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# Landslide Susceptibility Mapping in Nigeria Using Remote Sensing, GIS, and Machine Learning Models

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*Abstract* - **Landslide situations remain a significant concern in Nigeria, as they pose a great risk to human lives, property, and the natural environment, particularly in regions with steep slopes, heavy rainfall, and unfavorable human interference, including deforestation and urbanization. Nigeria's diverse geographical structure, ranging from urban areas such as Lagos and Abuja to rural regions, underscores the importance of accurate predictions for risk management and avoidance techniques. This research utilized remote sensing and GIS assessment to analyze landslide susceptibility in several regions of Nigeria. Data related to terrain, vegetation, soil moisture, and ground deformation were gathered using high-resolution satellite imagery from sources such as SPOT, ASTER, differential synthetic aperture radar interferometry (D-InSAR), and Landsat TM. GIS data layers included DEM, LULC, soil and geological maps, as well as hydrological maps and data. Methods applied in this study include logistic regression, STAT-R, frequency ratio, and the Random Forest tree-based model. The research produced detailed landslide susceptibility maps for various regions in Nigeria and identified significant factors such as slope, elevation, land use, precipitation, and access to transportation facilities. The Random Forest model demonstrated the most robust predictive capability. The integration of remote sensing with GIS was particularly significant, enhancing the precision of predictions and improving the efficacy of planning and management strategies. By incorporating remote sensing, GIS, and various machine learning algorithms, the researchers have developed a reliable tool for landslide risk prediction and management in Nigeria. Future research should focus on improving data quality and enhancing the generalizability of results to other regions.**
*Keywords:* **Landslide Susceptibility, Remote Sensing, GIS, Random Forest, Risk Management**

## I. INTRODUCTION

### *A. Background: Overview of Landslide Risks in Nigeria*

Landslides are a major natural disaster in Nigeria, with the potential to affect lives, property, and the environment. They are prevalent in regions characterized by steep slopes, high rainfall, and anthropogenic factors such as deforestation and urban development [20]. Areas most at risk include southeastern states and cities like Lagos and Abuja, due to increased development, improper land use, and poor drainage. Landslides can be deadly if vulnerable regions are not accurately predicted, which highlights the importance of risk assessment, early warnings, and planning for mitigation [12]. These models are useful to urban planners, policymakers, and disaster management agencies [1]. Landslide hazard maps are generated using remote sensing techniques and geographic information systems (GIS) as these tools provide comprehensive spatial data, enhancing model precision [23].

Reducing such risks requires community-based programs and awareness campaigns. Engaging local populations in monitoring landslide activities and sharing risk information can greatly improve preparedness and response [2]. Afforestation and controlled land use are sustainable land management measures that can help minimize landslides. The evolution of remote sensing and GIS has established them as the fundamental basis for landslide hazard assessment and management worldwide [3]. Various machine learning algorithms, including supervised (e.g., support vector machines) and unsupervised (e.g., K-means clustering), have been used to predict landslide susceptibility using remote sensing images and GIS data [8]. The integration of GIS, GPS, and remote sensing, commonly referred to as '3S technology,' is a valuable tool in regional landslide prediction [34].

The advent of GIS and satellite remote sensing has enabled the production of global maps for potential landslide hazards, particularly in regions such as the Pacific Rim, the Himalayas, and parts of North and South America. In landslide detection and monitoring, sophisticated approaches like differential synthetic aperture radar interferometry (D-InSAR) integrated with GIS are employed. Quantitative GIS models, such as fuzzy logic, logistic regression, and frequency ratio, have been applied in landslide susceptibility assessments in multiple regions [31]. In a similar study by [26], three machine learning algorithms - Naïve Bayes, Random Forest, and XGBoost - were evaluated for their effectiveness in identifying landslide susceptibility. The study found rainfall to be the major predictor of landslide frequency, with Random Forest demonstrating superior predictability. Landslides are also linked to human activities like deforestation and occur frequently in regions with steep slopes near transportation infrastructure [13].

In their study, O. Ozioko *et al.,* [29] applied methods such as HAHP and FR in GIS mapping, identifying factors like lithology, slope, and proximity to roads as significant influences on landslide hazard severity. The principal objective of this manuscript is to evaluate and compare the predictive models commonly used in landslide hazard assessment in Nigeria, focusing on their reliability and applicability to both urban and rural regions. The goal is to present findings on the use of remote sensing technology and GIS for landslide prediction and offer recommendations for optimal use in Nigeria. This review will compare and contrast the strengths and weaknesses of various models, suggest improvements, and discuss future research directions for enhancing landslide risk management in the country.

## II. METHODOLOGY

### *A. Data Sources*

#### *1. Remote Sensing Data Sources*

Data for studying landslide susceptibility can be obtained from high-resolution satellite imagery such as Landsat TM, ASTER, SPOT, and IRS P6, among others, for large-scale evaluation of terrain, vegetation, soil moisture, and other parameters. Aerial photographs are also useful as they provide additional information for detecting changes in terrain features and other small-scale features, offering better resolution compared to satellite data. Additionally, differential synthetic aperture radar interferometry (D-InSAR) can be employed to assess ground deformation and landslide movement, enabling precise measurements of Earth's surface displacement. This, in turn, facilitates the assessment and prediction of landslide activity [30].

#### *2. GIS Data Layers*

Landslide predictive GIS datasets include DEMs for slope and elevation, LULC for assessing the effects of human activities on the environment, and soil and geology for analyzing texture and formations. Information on drainage patterns, rainfall, and elevation helps in understanding the conditions under which landslides occur. The physical characteristics of infrastructure, such as roads and buildings, assist in evaluating the impact on living standards and in planning countermeasures.

### *B. Study Area*

#### *1. Characteristics of the Nigerian Regions Selected for the Study*

A cross-sectional survey of case studies conducted in Nigeria's six geopolitical zones demonstrates several applications of GIS and remote sensing (RS) in modeling landslide susceptibility. The research was carried out in Uyo, Akwa Ibom State, and Calabar, located in the South-South zone of Nigeria. It was established that a significant proportion of the areas investigated has high susceptibility to landslides due to factors such as slope, elevation, and human activities. In Awgu and Iva Valley, Enugu State, South-East Nigeria, rainfall was identified as the key predictor of landslides based on machine learning algorithms.

In the Eyinoke Hilly Area of Okeigbo, Ondo State, and Okemesi in Ekiti State (South-West), researchers using logistic regression models concluded that slope, elevation, and land use are significant predictors of landslide risk. In Jos Plateau, Plateau State (North-Central), the use of GIS and remote sensing techniques established that 87% of the area is characterized by low to very low elevation, leading to the conclusion that high-risk zones are associated with steep slopes and granitic rocks. Similarly, in Kogi and Benue States (North-Central), it was found that lineaments, steep slopes, proximity to transportation networks, and intensive cultivation contribute to the area's susceptibility to landslides. These studies highlight the need for localized research to enhance the understanding and management of landslide hazards in Nigeria.

### *C. Techniques*

#### *1. Remote Sensing Techniques*

Image classification, employing both supervised and unsupervised techniques, involves the analysis of satellite imagery and aerial photographs with the objective of identifying and categorizing different land cover types, as well as detecting changes over time. Change detection involves the comparison of multi-temporal remote sensing images to monitor landscape changes indicative of landslide activity, allowing for the assessment of their progression and impact. Radar interferometry (D-InSAR) is a technique that measures ground deformation and subtle terrain movements, providing high-precision data crucial for understanding landslide dynamics and supporting early warning systems [30].

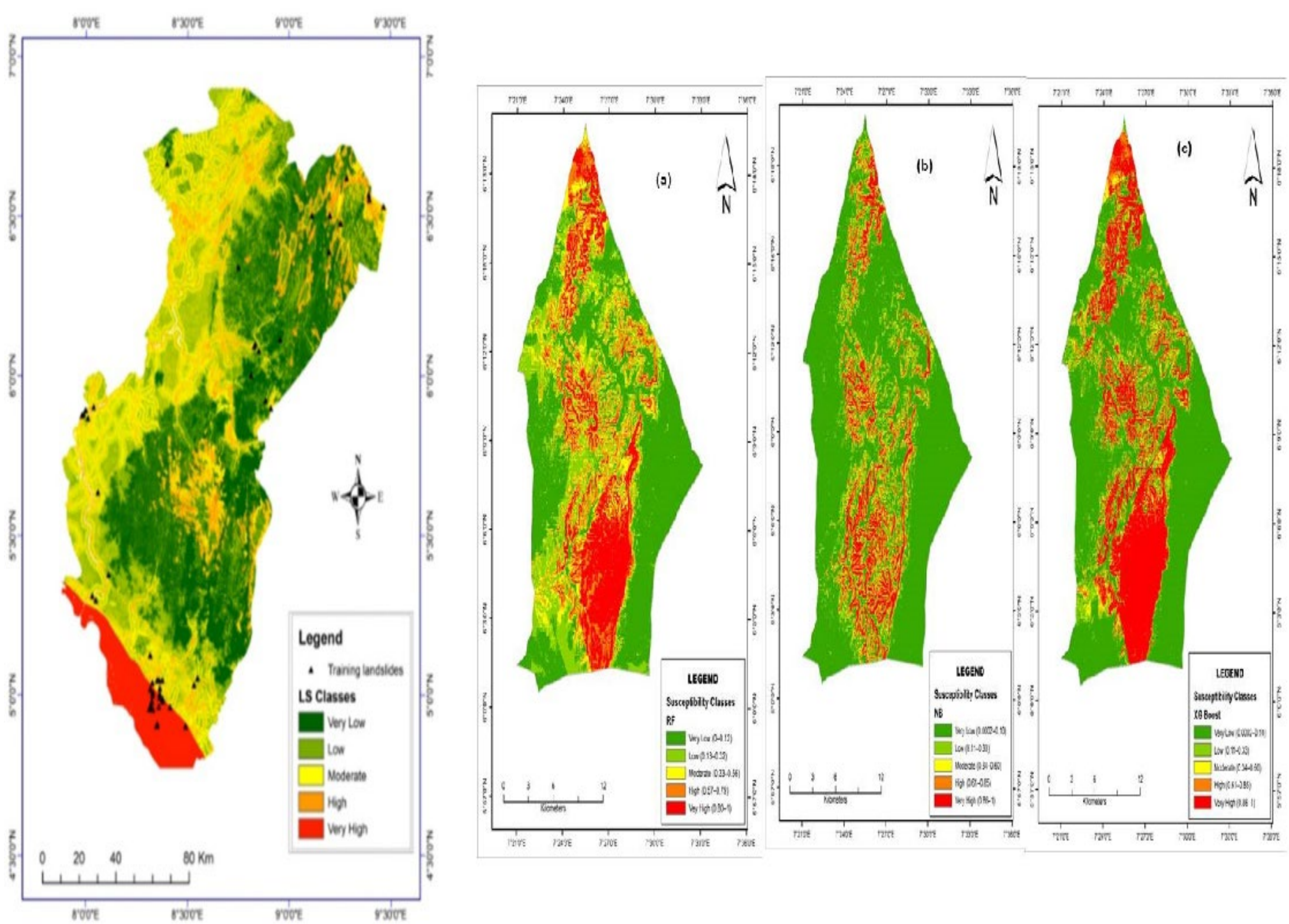
#### *2. GIS Data Layers*

In GIS, spatial analysis involves utilizing and analyzing various data layers, including DEMs, LULC maps, and hydrological data, to establish the level of susceptibility to landslides and their spatial distribution. The creation of landslide susceptibility maps is facilitated by the use of logistic regression, frequency ratio, and machine learning algorithms, such as SVM and Random Forest. These techniques employ environmental and geological predictors to generate the necessary maps. Multicriteria Decision Analysis (MCDA) is beneficial as it applies a logical structure to rank the relative importance of various factors involved in determining landslide susceptibility. These factors are then assigned weights proportional to their significance, and the overall effect is computed to generate susceptibility maps.

## III. RESULTS AND DISCUSSION

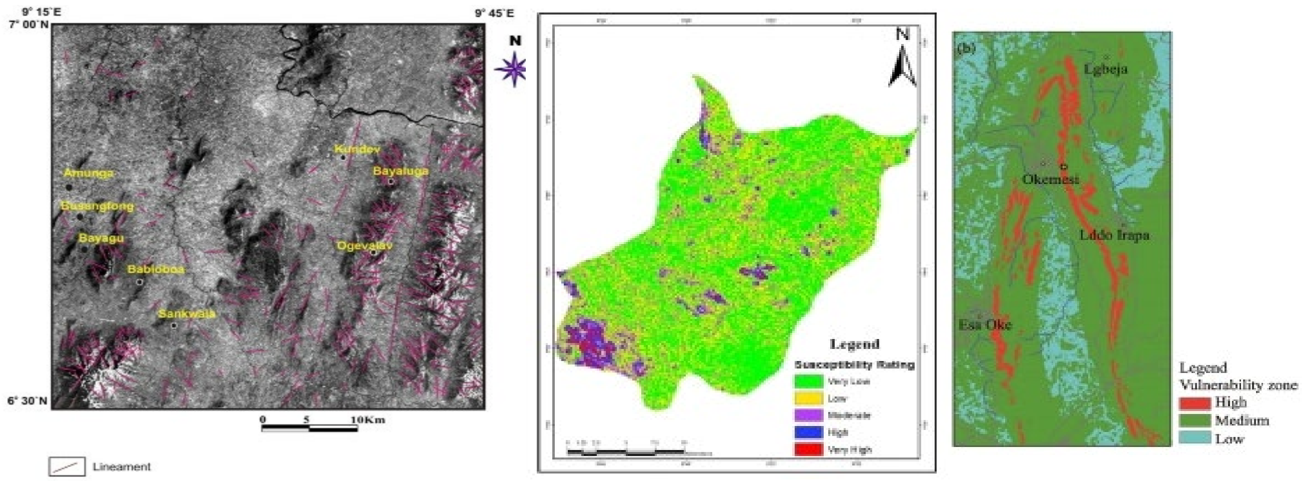
O. Ozioko *et al.,* [29] aimed to evaluate landslide susceptibility in the southeastern part of Nigeria, particularly in Iva Valley, using heuristic and bivariate statistical analysis in GIS. These methods involved field observations and surveys in combination with satellite imagery and Geographic Information System techniques to consider factors such as lithology, distance to the nearest drainage, altitude, slope, aspect, distance to the nearest road, land use, curvature, and distance to lineament. The efficacy of the developed models for landslide prognosis was evaluated using various analytical tools, including the confusion matrix and the area under the receiver operating characteristic curve (AUC ROC). The outcomes presented susceptibility maps detailing the level of vulnerability to landslides, which could be useful for development planning, control mechanisms, and risk assessment. However, it is important to note that the study provides insight into conditions in the specific region and may not be applicable to other areas. Related studies conducted in Kenya and Ethiopia have used GIS and statistical techniques with an emphasis on the influence of lithology and slope [25]. These studies also applied AUC for model validation, similarly to the approach used here. In a related study, J. Efiong *et al.,* [11] evaluated landslide susceptibility in Calabar, Cross River State, Southeastern Nigeria, employing remote sensing, GIS, and statistical techniques. The authors examined variables such as land use, lithology, slope, elevation, aspect, distance to roads, vegetation, curvature, and proximity to drainage. Statistical analysis for model accuracy was conducted using ROC and AUC. Despite limitations posed by the spatial resolution of remote sensing data, the study's results support infrastructure development and hazard mitigation efforts.

The rationale employed by U. E. Nnanwuba *et al.,* [26] was to determine the efficacy of various machine learning methodologies in quantifying the probability of landslide occurrence in the Awgu region, Southeastern Nigeria. The research combined fieldwork, multispectral analysis, bibliographic surveys, and machine learning to analyze factors such as rainfall, slope, altitude, aspect, land use, proximity to roads and watercourses, curvature, rock type, vegetation, and distance from watercourses.




(a) (b)

Fig. 1 (a) Landslide susceptibility index (LSI) map of Calabar, (South-South Nigeria) from Effiong, *et al.,* 2021;
(b) Landslide susceptibility index (LSI) map of Agwu, (South -East Nigeria) from Nnanwuba, *et al.,* 2022




(a) (b) (c)

Fig. 2 (a) Lineament on Filtered LandSat band 5, Indicating rapid Landslides are associated with Lineament in Benue Hills, (North-central Nigeria) from Igwe, O., *et al.,* 2016
(b) Landslide susceptibility Map of Jos (North-central Nigeria) Oluwafemi, *et al.,* 2018
(c) Landslide susceptibility index (LSI)Map of Ekiti, (Southwest Nigeria) from Akintan, O. B, *et al.,* 2023

TABLE I CHARACTERISTICS OF INCLUDED STUDIES

| **Author and Year** | **Study Objectives** | **Methodology** | **Study Location** | **Landslide Conditioning Factors** | **Metrics and Methods Used to Assess the Accuracy of Landslide Prediction Models** | **Implications to Landslide Risk Management** | **Challenges and Limitations of Study** |
|---|---|---|---|---|---|---|---|
| [29] | To assess landslide susceptibility using a geographic information system (GIS)-based heuristic approach coupled with bivariate statistical methods. | Field studies, analysis of satellite imagery, and application of heuristic and bivariate statistical techniques in GIS. | Iva Valley, Enugu, Southeast Nigeria | elevation, curvature, slope, aspect, land cover, distance from the road, distance from drainage, distance from lineament, lithology | Confusion matrix, AUC | Provides detailed susceptibility maps for informed planning and mitigation. | Limited to the specific study area; may not be generalizable. |
| [11] | To evaluate landslide susceptibility through the use of remote sensing and geographic information systems (GIS). | GIS, Remote sensing, statistical analysis. | Calabar, Cross River State, SouthSouth Nigeria. | slope, land use, elevation, aspect, distance from roads, lithology, vegetation, curvature, distance from drainage channels | ROC, AUC | Informs infrastructure development and hazard mitigation. | Limited spatial resolution of remote sensing data. |
| [26] | To compare machine learning algorithms for landslide susceptibility assessment. | Field investigation, remote sensing, literature review, machine learning algorithms | Awgu, Southeast Nigeria | rainfall, slope, elevation, aspect, land use, distance from roads, curvature, lithology, vegetation, distance from drainage | Confusion matrix, ROC, AUC | Supports landslide risk assessment and land management strategies. | The inherent limitations of machine learning models constrain the potential for further advancement. |
| [27] | Investigate landslide susceptibility through the application of machine learning | GIS, statistical methods, remote sensing, | Enugu, Southeast Nigeria | lithology, rainfall, distance from roads, aspect, vegetation, slope, elevation, | Kappa statistic, RMSE | Enhances understanding of landslide risks for | Potentially limited by the availability of high-resolution data. |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | and statistical techniques. | machine learning | | curvature, land use, distance from drainage | | improved land use planning. | |
| [18] | Application of remote sensing and GIS in landslide prediction | Remote sensing, GIS | Southeast Nigeria | distance from drainage, slope, distance from roads, vegetation, aspect, elevation, land use, curvature, lithology | Precision, recall, F1 score | It provides a conceptual framework for monitoring landslides and assessing associated risks. | Generalizing findings may be challenging due to regional differences. |
| [28] | To assess landslide susceptibility using remote sensing and geographic information systems (GIS). | Remote sensing, GIS | Jos Plateau, North Central Nigeria | elevation, distance from drainage, slope, aspect, land use, vegetation, distance from roads, curvature, lithology | ROC, AUC | Informs disaster management and urban planning. | The study is limited to the specific geologic and climatic conditions of the region. |
| [17] | Analyze factors associated with landslides using remote sensing and GIS. | Remote sensing (Landsat ETM+, ASTER GDEM), GIS | Benue Hills, North-central Nigeria | Structural trends, slope failures, lineaments, groundwater, geology | Sensitivity analysis, ROC | Provides insights for regional landslide risk mitigation. | Limited by the resolution of satellite imagery and DEM. |
| [33] | Predict landslide susceptibility using GIS and DEMs in Uyo. | GIS, DEMs, field observation | Uyo, Akwa Ibom State, South-South Nigeria | Slope, elevation, land use | RMSE, cross-validation | Useful for urban planning and infrastructure development. | May not account for all environmental variables influencing landslides. |
| [6] | Utilization of remote sensing and GIS for identifying potential landslide locations. | GIS, Remote sensing. | Jos Plateau, North Central Nigeria | distance from drainage, lithology, slope, elevation, land use, distance from roads, curvature, vegetation, aspect | Confusion matrix, AUC | Assists in identifying high-risk areas for preventive measures. | Limited by the quality and resolution of the remote sensing data used. |
| [13] | To ascertain the susceptibility of a given area to landslides by employing geographic information systems (GIS), remote sensing, and logistic regression models. | Remote sensing information, GIS, and logistic regression models | Okeigbo, Ondo State, South-West Nigeria | land use, aspect, slope, elevation, profile curvature, distance from road | Precision, recall, F1 score | Supports development planning and disaster preparedness. | Relies heavily on the quality of logistic regression models. |
| [5] | To predict landslide potential through the utilization of remote sensing and geographic information systems (GIS). | Remote sensing, GIS | Ekiti, Southwest Nigeria | slope, land use, elevation, aspect, distance from roads, lithology, vegetation, curvature, distance from drainage | Confusion matrix, ROC, AUC | Provides crucial data for infrastructure and urban planning. | May not account for all landslide-triggering factors. |
| [14] | Employ remote sensing and GIS to map landslide susceptibility. | Remote sensing information (SPOT 5, ASTER DEM), GIS | Jos South LGA, Plateau State, North-Central Nigeria | Land use, slope, aspect, elevation, distance from roads, lithology, vegetation, distance from drainage channels | ROC, AUC | Facilitates risk management and land-use policy formulation. | Limited by the spatial and temporal resolution of the satellite data. |

In a more recent study, V. E. Nwazelibe *et al.,* [27] employed machine learning and statistical techniques to analyze landslide susceptibility in Enugu, which is situated in the southeastern region of Nigeria. The influencing factors included rainfall, slope, elevation, aspect, land use, distance from roads, lithology, vegetation, curvature, and distance from drainage. The quality of the developed model was measured using the Kappa Statistic and Root Mean Square Error (RMSE). The study contributes to a more comprehensive understanding of potential landslide hazards and the integration of this knowledge into land use coordination. Nevertheless, the results may be influenced by the resolution of the data.

O. Igwe [18] used geospatial informatics techniques, including remote sensing and GIS, to forecast landslides in susceptible regions of Southeast Nigeria. The study focused on gradient, exposure, relief, land cover, distance to roads right-of-way, convexity, rock type, cover, and distance to water. The model was evaluated using precision, recall, and F1 scores. These findings may aid in understanding landslide monitoring and risk assessment, but the results may not be applicable to other regions. Similar studies in Cameroon using a combination of satellite imagery and GIS techniques demonstrated the significance of slope and lithology. Validation indicators, including precision, recall, and F1 score, were recommended by [32].

Similarly, O. A. Oluwafemi *et al.,* [28] analyzed landslide susceptibility in the Jos Plateau, North-Central Nigeria, employing remote sensing information and GIS. Factors considered included slope, aspect, elevation, land use, proximity to roads, curvature, rock type, vegetation, and distance from water bodies. The model's accuracy was assessed using the receiver operating characteristic (ROC) curve and the area under the ROC curve (AUC). The findings inform the development of more effective disaster management strategies and contribute to urban planning advancements. However, the research is limited to regional geologic and climatic conditions and may not be fully generalizable.

O. Igwe *et al.,* [17] integrated landslide factors and used remote sensing (Landsat ETM+, ASTER GDEM) and GIS in Benue Hill, North-Central Nigeria. Sensitivity analysis and the ROC test were employed to determine the accuracy of results derived from structural trends, slope failures, lineaments, groundwater, and geology interpretations. Although the research provides valuable insights into landslide hazards and safety measures at the regional scale, the precision of results is limited by the resolution of the satellite imagery and DEM used. Several factors influence the results, including the quality of satellite imagery and DEM resolution.

Ethiopian studies have focused on structural trends and geology when evaluating landslide threats, using sensitivity analysis and ROC analysis for validation [4]. Udosen *et al.,* [33] used GIS & DEMs and field observations in Uyo, Akwa Ibom State, South-South Nigeria, to determine the Susceptible Landslide Index. Variables considered included slope, elevation, and land use, with model performance assessed using RMSE and cross-validation. The research findings are useful for urban design and infrastructural planning, but the full range of environmental conditions affecting landslides cannot be fully described.

Bamisaiye [6] used remote sensing and GIS to predict future landslides on the Jos Plateau, North-Central Nigeria. The study focused on gradient, exposure, rainfall, land cover, proximity to roads, contour, geology, cover, and distance from water channels. The proposed model was evaluated using a confusion matrix and the area under the ROC curve, facilitating the identification of high-risk regions for preventive measures. However, results were somewhat constrained by data resolution.

In another study, Gbadebo *et al.,* [13] used remote sensing, GIS, and logistic regression models to estimate landslide susceptibility in Okeigbo, Ondo State, Southwest Nigeria. Factors analyzed included slope, elevation, aspect, profile curvature, distance from the road, and land use. Model performance was measured using cross-entropy, precision, recall, and F1 score. The study supports planning and disaster preparation, although the quality of logistic regression models is crucial.

In Zimbabwe, logistic regression has been used for susceptibility assessment, with precision, recall, and F1 score as evaluation metrics [10]. Research has also incorporated this technique alongside slope and land use [21]. O. B. Akintan *et al.,* [5] studied landslide susceptibility in Ekiti, Southwest Nigeria, using remote sensing and GIS (Figure 2c). Factors evaluated included gradient, altitude, exposure, land cover type, proximity to roads, parent material, vegetation canopy, contour, and drain distance. The study was useful for decision-making in infrastructure and urban planning, although it may not capture all potential slide triggers.

M. Rashwan *et al.,* [24] highlighted similar challenges in the comprehensive assessment of landslide susceptibility factors in their research on landslides in Egypt. The spatial distribution of landslide susceptibility in Jos South Local Government Area, Plateau State, North-Central Nigeria, was evaluated and predicted using remote sensing data (ASTER DEM, SPOT 5) and GIS. Factors considered included gradient, land cover, exposure, elevation, vegetation, proximity to roads, lithology, and distance to drainage channels. The study informed risk management strategies and land use policy development, but results were constrained by the spatial and temporal resolution of the satellite data.

## IV. CONCLUSION

The application of remote sensing and geographic information system (GIS) technologies in investigating landslides across various regions of Nigeria has demonstrated their efficacy in evaluating and mitigating natural disasters. These technologies enable the analysis of potentially problematic areas, thereby assisting in city planning and infrastructure development. Landslide susceptibility assessment, which includes factors such as slope, elevation, land use, and rainfall, has been validated through studies conducted at various sites across Nigeria, including Iva Valley, Calabar, Agwu, Enugu, Akwa Ibom, Okemesi, Kogi, Benue Hills, Ondo, and Jos Plateau. The incorporation of advanced techniques, such as machine learning algorithms and statistical models, has significantly enhanced the precision of forecasts and the generation of highly detailed susceptibility maps. However, the usefulness of these models is constrained by the quality and resolution of remote sensing data and the extent to which their results can be generalized across diverse geographical regions. Thus, localized studies are crucial as they help investigate specific causes of landslide risks in particular regions. Addressing issues such as data availability and variability in geographical and climatic conditions is essential to increase confidence in landslide prediction models. Therefore, integrating remote sensing with GIS, along with community participation and awareness, establishes a strong foundation for landslide vulnerability evaluation and management in Nigeria. Advances in remote sensing and spatial information utilization will enhance future prediction accuracy and improve the effectiveness of landslide impact mitigation strategies for at-risk communities.

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