Journal of Spatial Information Sciences

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JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
VOL. 2, ISSUE 3, PP 180–198, 2025 **DOI:** https://doi.org/10.5281/zenodo.17289828
PUBLISHED 02-10-2025

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LANDSLIDE SUSCEPTIBILITY MAPPING USING GIS-BASED MULTICRITERIA DECISION ANALYSIS: A CASE STUDY OF LOKOJA, NIGERIA

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DOI: https://doi.org/10.5281/zenodo.17289828

Abstract

Located between rivers and hills, Lokoja's development is advancing into hilly areas due to limited flat and safe land without recourse to the stability of the hills. The study aims to assess the structural stability of hilly areas through the production of landslide susceptibility maps using both a Geographic Information System and an analytical hierarchy process (AHP) model. Twelve data layers are exploited as the conditioning factors to detect the most susceptible areas. These factors include slope, aspect, plan curvature, land use and land cover, lithology, topographic wetness index, stream power index, distance to road, distance to stream, slope length, and fault. Subsequently, a Landslide susceptibility map was produced using a precise and conclusive weighted-overlay analysis of the AHP pair-wise evaluation methodologies to evaluate the effects of the conditioning factors. Results indicate that 5,703 hectares (32.34%) of the study area are 'not susceptible', 7,881 hectares (44.69%) are 'moderately susceptible', and 4,051 hectares (22.97%) are 'highly susceptible' to landslides. The study concludes that the susceptibility model is reliable for future decision-making, urban planning, and development in Lokoja, Kogi State, to reduce the risk of landslides in the region.

Keywords: Landslide susceptibility, Analytical Hierarchy Process (AHP), Landslide Hazards, Geographic Information System (GIS), Conditioning factors

1.0 Introduction

Landslides, a critical natural hazard in mountainous regions worldwide, have prompted significant global efforts over the past two decades to map their spatial distribution, driven by their devastating socioeconomic impacts,

ISSN: 2354-3361
DOI: https://doi.org/10.5281/zenodo.17289828
www.journals.unizik.edu.ng/jsis

including approximately 600 annual deaths and economic losses of 1–2% of gross national product in developing nations [1], [2], [3]. Governments and international research institutes have increasingly prioritized landslide hazard assessment to address not only the immediate risks of slope failures but also secondary economic threats, exacerbated by demographic pressures and mismanagement practices, such as illegal settlements, deforestation, and inadequate wastewater treatment [4], [5], [6]. This growing recognition of the far-reaching consequences of landslides underscores the urgent need for comprehensive research and effective mitigation strategies to safeguard vulnerable communities.

Landslide susceptibility mapping, a vital tool for mitigating landslide hazards, relies on a comprehensive understanding of slope movements and their controlling factors. The reliability of these maps depends on the quality and quantity of available data, the working scale, and the selection of appropriate analysis and modeling methodologies [7], [8]. As the foundational stage of landslide hazard mitigation, inventory and susceptibility mapping studies provide essential information to guide urban development and land-use planning decisions, significantly reducing potential damage and costs associated with landslides [9]. These maps are generated using various qualitative and quantitative approaches to ensure their effectiveness in supporting informed decision-making [8], [10].

Landslide susceptibility maps, essential for identifying, avoiding, or adapting to landslide risks, are developed using a variety of qualitative and quantitative approaches to produce reliable spatial outcomes for pinpointing high-risk areas. Studies such as [1] utilized GIS-based methods in central Italy's Umbria and Marche regions and summarized case studies along the Apennine Mountains, while other researchers (e.g. [11], [12], [13], [14], [15], [16], [17]) employed GIS and probabilistic models, often leveraging regional landslide inventories derived from aerial photographs and remotely sensed images. Statistical models, such as logistic regression (e.g. [18], [19], [20], [21]), the analytical hierarchy process (AHP) (e.g. [22], [23], [24], [25]), and evidential belief functions [26], [27], have been widely applied, alongside artificial intelligence methods, including fuzzy logic[19], [21], neural networks[19], [28], [29], and neuro-fuzzy logic [30], [31]. This paper aims to produce a landslide susceptibility map for part of Lokoja, Kogi State, using the AHP, contributing to effective hazard mitigation through informed land-use planning.

1.1 Statement of the Problem

Located between rivers and hills, Lokoja's development is advancing into hilly areas due to limited flat and safe land without recourse to the stability of the hills. This expansion into structurally unstable zones increases

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www.journals.unizik.edu.ng/jsis

landslide risks with potential severe socio-economic impacts. Challenges, including demographic pressure, illegal settlements, deforestation, and poor land use, aggravate slope instability [32]. Hence, there is a critical need for producing reliable landslide susceptibility maps through robust methodologies like GIS and the Analytical Hierarchy Process (AHP) to support sustainable urban planning and hazard mitigation.

2.0 Methodology

This study applies a Geographic Information System (GIS)-based multi-criteria decision analysis using the Analytical Hierarchy Process (AHP) to assess landslide susceptibility. The AHP method facilitates the systematic evaluation and weighting of various conditioning factors affecting landslide occurrence. Through pairwise comparisons and weighted overlay analysis within a GIS framework, the study synthesizes spatial data to produce a susceptibility map categorized into risk zones that support informed land-use planning and disaster mitigation decisions.

2.1 Study Area

Lokoja, the administrative capital of Kogi State in Nigeria's North Central geopolitical zone, spans latitudes from 7°39'60"N to 7°53'05"N and longitudes from 6°36'40"E to 6°47'27"E (Figure 1)[33]. Located close to the confluence of the Niger and Benue Rivers and adjacent to Mount Patti, its geography has shaped its linear urban development. The city is bordered by five local government areas—Adavi, Ajaokuta, Bassa, Koton-Karfe, and Lokoja itself, supporting its role as a regional hub (Figure 1(b)). Lokoja experiences distinct wet and dry seasons, with an average annual precipitation of 124.93 mm and a mean annual temperature of 29.16°C [34], [35]. A network of state roads and federal highways, including the A123 (Okene–Abuja Express Road) and A233 (Lokoja–Anyigba Road), ensures connectivity and accessibility to surrounding areas.

2.2 Preparations of Thematic Data Layers

This study considers twelve thematic data layers as conditioning factors for landslide susceptibility in the Lokoja region: slope, aspect, plan curvature, altitude, lithology, land use, lineaments, distance from rivers, distance from roads, stream power index (SPI), slope length (LS), and topographic wetness index (TWI). These preparatory factors, which influence the occurrence of landslides, were derived from available resources and field data, capturing the ground characteristics relevant to landslide susceptibility.

A. Slope Degree

The slope degree is a critical parameter in slope stability analysis due to its direct influence on the structural stability of mountainous areas [36], [9], [37]. For this study, a slope degree map (Figure 2a) of the Lokoja region

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PUBLISHED 02-10-2025

www.journals.unizik.edu.ng/jsis

was generated using a digital elevation model (DEM) and classified into six slope categories to support landslide susceptibility assessment.

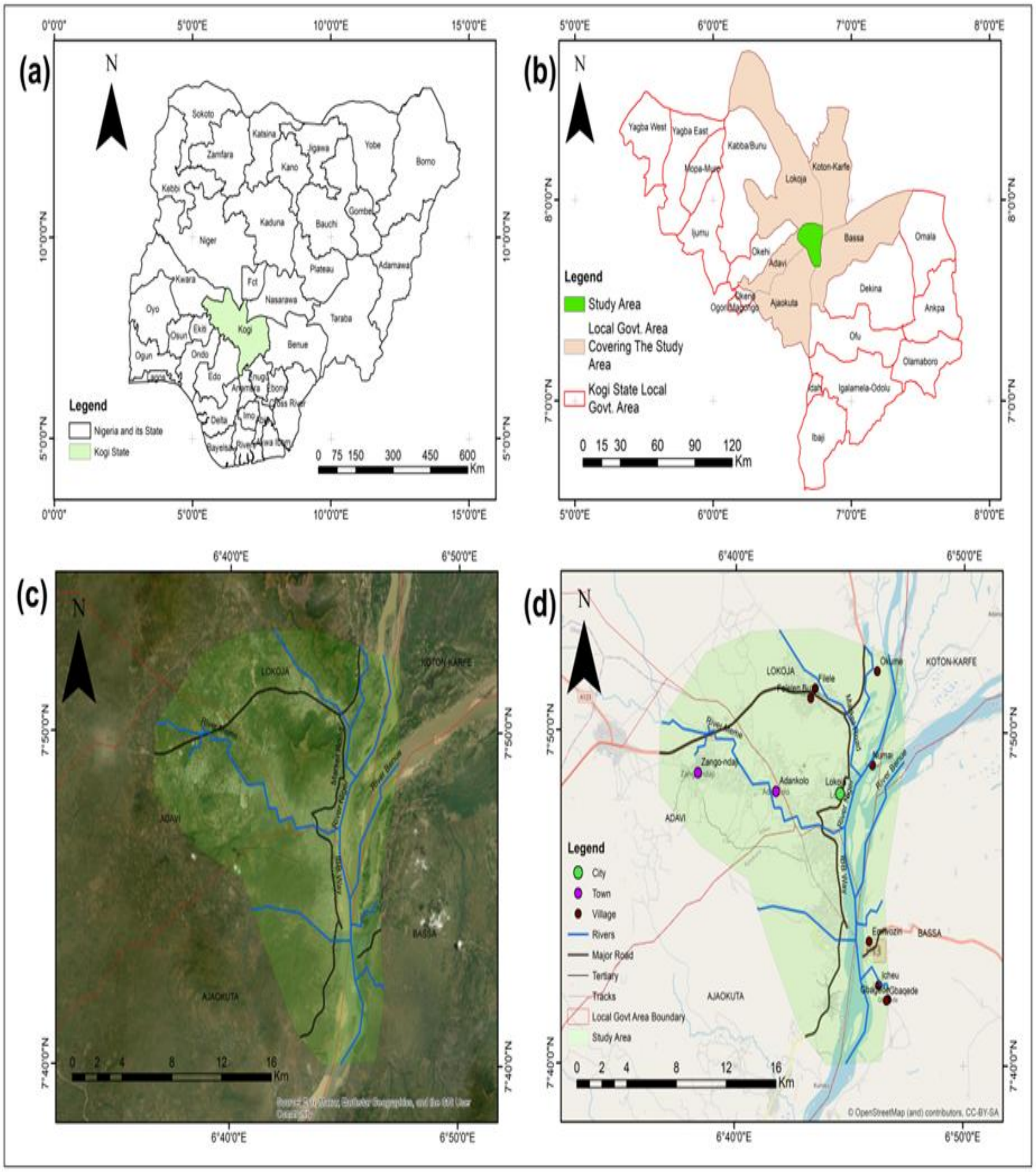

Figure 1: Map showing the (a) Administrative Map of Nigeria (b) Kogi State Local Government Administrative Map highlighting the Study Area, (c) Satellite Imagery of the Study Area, and (d) Street Map of the Study Area (Source: ESRI and Open Street Map)

B. Aspect

Aspect is widely recognized as a major landslide conditioning factor, and this parameter has been taken into account by numerous studies e.g. [9], [28]. Some meteorological events, such as rainfall, sunshine, and the

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morphological structure of the area, influence the propensity of landslides. Hillsides that receive dense rainfall reach saturation faster; however, this is also related to the slope's filtering capacity, which is controlled by a variety of parameters such as slope topography, soil type, permeability, porosity, humidity, organic ingredients, land cover, and climatic season. As a result, the slope-forming material's pore water pressure changes. The aspect map of the study area (Figure 2b) was created to demonstrate the relationship between aspect and landslides. The aspect map of the study area was created to demonstrate the relationship between aspect and landslides. Aspects are grouped into 9 classes.

C. Altitude

Altitude is a relevant landslide conditioning factor, and this study utilized a digital elevation model (DEM) with a 30 m by 30 m resolution [38] (Figure 2c) .

D. Distance To Road

Landslides may occur along the road and on the sides of slopes affected by roads, similar to the effect of distance from rivers [39], [40]. Roads built along slopes may cause a decrease in load on both the topography and the slope's heel. As a result, the Euclidean distance method in ArcGIS 10.8 was used along the road's path to assess the impact of the road on slope stability of slope (Figure 2d).

E. Distance To River

The saturation degree of the material on the slope is an important parameter that controls the stability of a slope [41]. Another important factor in slope stability is the slope's proximity to drainage structures. Streams can undermine stability by eroding slopes or saturating the lower part of the material, causing water levels to rise [42]. As a result, five distinct buffer zones were established within the study area to assess the extent to which the streams affected the slopes. The Euclidean distance method was used, and a visual inspection was performed to assess the relationship between the river and the landslide (Figure 2e).

F. Slope Length

The soil loss is caused by a combination of length (L) and slope steepness (S). The LS factor in the Universal Soil Loss Equation (USLE) measures the overland flow sediment transport capacity [43]. The slope length (Figure 2f) is the distance between the origin of the overland flow and the concentrated flow or dep location. The greater the slope length, the more water accumulates at the field's bottom, increasing erosion. It is also affected by the surface slope. According to [1], [44], there is a relationship between slide density and slope length.

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G. Plan Curvature

Plan Curvature is theoretically defined as the rate of change of a slope gradient or aspect, usually in one direction. The curvature value can be computed by taking the reciprocal of the radius of curvature in that direction [45]. As a result, while broad curves have low curvature values, tight curves have higher values. The curvature of a contour line formed by intersecting a horizontal plane with the surface is called plan curvature. The convergence or divergence of water during downhill flow influences plan curvature's (Figure 2g) influence on slope erosion processes [9], [46]. As a result, this parameter is one of the conditioning factors influencing landslide occurrence [45].

H. Land use/Land cover

Human activities have altered the land surface and caused significant damage to the natural environment, making it easier for landslides to form in conjunction with earthquake disturbances. Several studies have found a strong correlation between the distribution of landslides and land use changes. Land use is another factor that contributes to the occurrence of landslides [47], [48]. The Landsat image was supervised and classified using the Remap App [49], Four major land use/land cover classes were identified from the images, namely; bare ground, vegetation, water bodies, and built-up areas (Figure 2h)

I. Stream Power Index (SPI)

The stream power index (SPI) is a topographic attribute with multiple components. It is a measure of the erosive power of flowing water based on the assumption that discharge is proportional to the catchment area. It predicts net erosion in profile and tangential convexity areas (flow acceleration and convergence zones) and net deposition in profile concavity areas (zones of decreasing flow velocity). Stream power index (Figure 2i) was calculated based on the formula given by [43].

$$\text{SPI}= A_s - \tan\beta \qquad \text{(Equation 1)}$$

where A_s is the specific catchment's area and β is the local slope gradient measured in degrees.

J. Lineament

Lineaments are characterized by heavily fractured rocks and form a line or zone of weakness [50]. Generally, the greater the distance from tectonic structures, the fewer the number of landslides. Such phenomena are aided by selective erosion and water movement along fault planes. Aside from the major thrusts and faults derived from geological maps, some additional information about possible faults and structural dislocations was identified as lineaments using satellite imagery's image enhancement (filtering). The recognition of lineaments was done step

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by step from large to small scales, allowing for the generalization of many neighboring small-order lineaments while considering the spatial scale of the study (Figure 2j).

K. Topographic Wetness Index (TWI)

The topographic wetness index is another topographic factor in the runoff model (TWI) (Figure 2k) .It assesses the amount of water accumulated at a location based on both the upslope contributing area and the local slope [51], [52], [53].

$$\text{TWI}= ln\left(\frac{a}{tan\ \beta}\right) \qquad \text{(Equation 2)}$$

where a is the cumulative upslope area draining through a point (per unit contour length) and $tan\ \beta$ is the slope angle at the point. The $ln(\frac{a}{tan\ \beta})$ index reflects the tendency of water to accumulate at any point in the catchment (in terms of a) and the tendency of gravitational forces to move that water down the slope (expressed in terms of tan b as an approximate hydraulic gradient). Water infiltration primarily depends upon material properties such as permeability, pore water pressure, and effects on the soil strength [54].

L. Lithology

Another important factor in dealing with landslide susceptibility assessment and hazards is lithology [55]. Lithology (Figure 2l) influences the topography of the landscape and how seismic energy is transmitted, particularly through elastic and brittle/elastic rock properties, chemical weathering and its control of erosion and slope, fracture development and fault displacement, and seismic wave interactions with topography and lithological structures [56]. Although using rock mass rating with lithology factors to assess landslide hazards is reasonable, it cannot be applied to a large area due to insufficient field and laboratory data [57]. The sensitivity index of landslide occurrence of each rock type is calculated by comparing the landslide density in the area occupied by each rock type to determine the relative influence of bedrock lithology on the occurrence of landslides in a large area.

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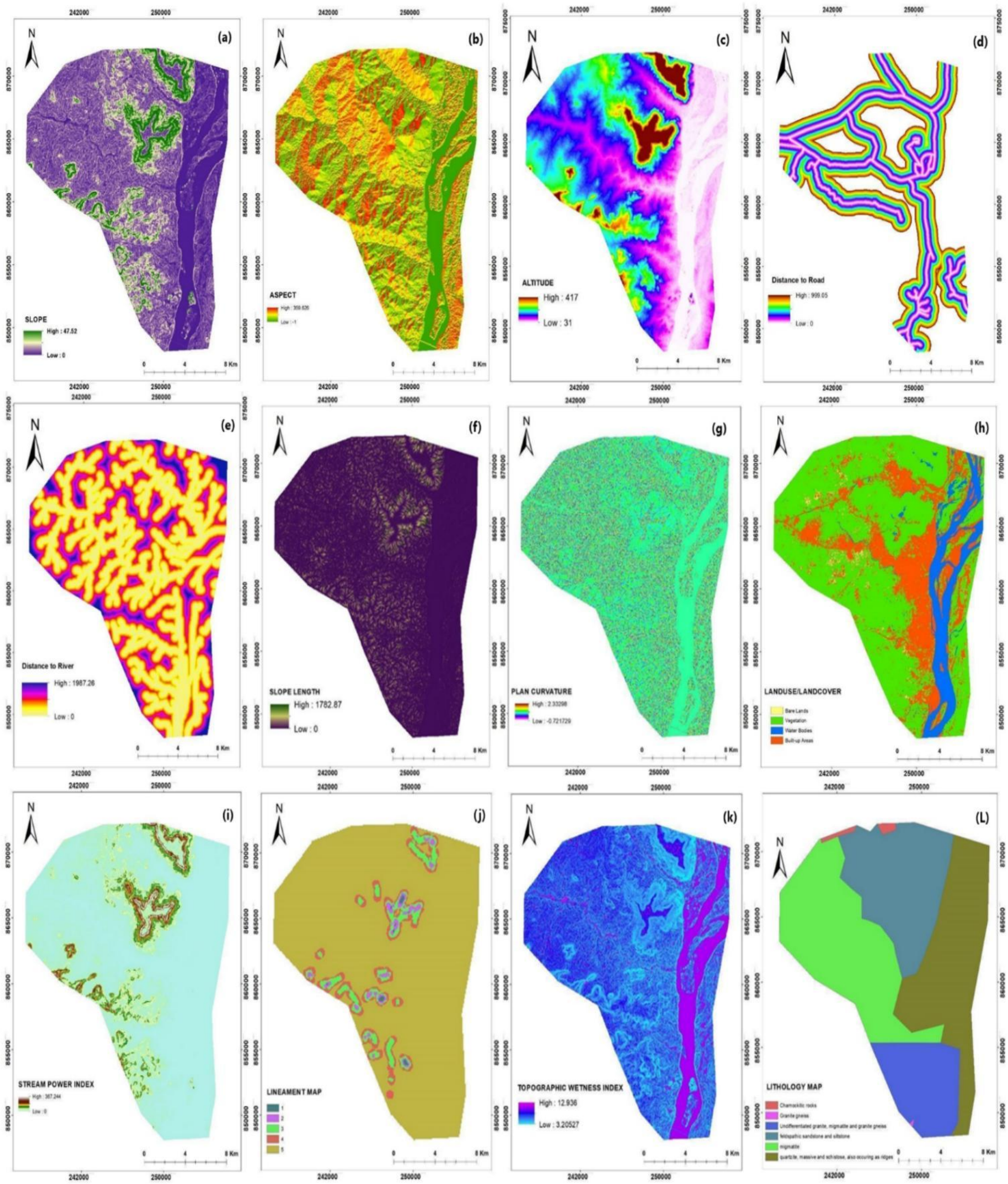

Figure 2: Map of (a) Slope, (b) Aspect, (c) Altitude(d) Distance to Road, and (e) Distance to River, (f) Slope Length, (g) Plan Curvature, (h) Land-use/Land-cover, (i) Stream Power Index(j) Lineament, (k) Topographic Wetness Index (TWI), and (l) Lithology

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2.3 Landslide Susceptibility Mapping

Application Of the Analytical Hierarchy Process (AHP)

The analytical hierarchy process (AHP) is a semi-qualitative method that involves a matrix-based pairwise comparison of the contribution of various landslide factors. AHP is a multi-objective, multi-criteria decision-making approach that allows the user to choose a preference scale from a set of alternatives [58]. It assists decision makers in determining which option best meets their objectives and their understanding of the problem. This mathematical technique is commonly used in site selection, suitability analysis, regional planning, routing modelling, and landslide susceptibility analysis, amongst others. The procedure consists of several steps: (1) breaking down a complex, unstructured problem into its component factors, which are the parameters chosen for this study; and (2) organizing these factors in a hierarchical order.; (3) assign numerical values based on subjective relevance to determine each factor's relative importance; and (4) synthesize the ratings to determine the priorities to be assigned to these factors [58]. When the factors are arranged in a hierarchical order, there should be a relative importance of one factor over another, resulting in a pair-wise comparison matrix with scores as given in the table below. Each factor is rated against every other factor in the construction of a pairwise comparison matrix by assigning a relative dominant value between 1 and 9 to the intersecting cell. When the vertical axis factor is more important than the horizontal axis factor, this value ranges between 1 and 9. The value, on the other hand, varies between the reciprocals 1/2 and 1/9. The effects of each parameter on the susceptibility of landslides relative to each other were first determined in these techniques by dual evaluation in map.

$$LSM_{AHP} = ((\text{Slope} \times W_{AHP}) + (\text{Aspect} \times W_{AHP}) + (\text{Altitude} \times W_{AHP}) + (\text{Plan Curvature} \times W_{AHP}) + (\text{Lithology} \times W_{AHP}) + (\text{Landuse} \times W_{AHP}) + (\text{Distance to River} \times W_{AHP}) + (\text{Distance to Road} \times W_{AHP}) + (\text{Lineament} \times W_{AHP}) + (\text{SPI} \times W_{AHP}) + (\text{TWI} \times W_{AHP}) + (\text{LS} \times W_{AHP})) \quad \text{(Equation 3)}$$

where W_{AHP} is the weightage for each landslide conditioning factor. The pixel values obtained are then classified into 4 classes (low, moderate, high, and very high) based on natural break to determine the class intervals in the landslide susceptibility map as shown in Table 1.

As shown in Table 2, the final result of the AHP model includes the weights of the derived factors, class weights, and a calculated consistency ratio (CR). The AHP method employs an index of inconsistency known as the consistency ratio (CR) to indicate the likelihood that the matrix judgments were generated at random [58].

$$CR = CI / RI \quad \text{(Equation 4)}$$

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Table 1: ***The Fundamental Scale Of Absolute Numbers/Scale Of Relative Importance*** [58]

Intensity of Importance	**Degree of Importance**	***Explanation***
1	Equally	Two activities contribute equally to the objective
3	Moderately	Experience and judgment slightly to moderately favour one activity over another.
5	Strongly	Experience and judgment strongly or essentially favour one activity over another.
7	Very strongly	An activity is strongly favoured over another, and its dominance is shown in practice.
9	Extremely	The evidence of favouring one activity over another is of the highest degree possible of an affirmation.
2, 4, 6, 8	Intermediate values	Used to represent compromises between the preferences in weights 1, 3, 5, 7, and 9
Reciprocals	Opposites	Used for inverse comparison

where RI is the average of the resulting consistency index based on the order of the matrix provided by [58] and CI is the consistency index, which can be expressed as;

$$CI = ((\lambda_{max} - n) / (n - 1)) \quad \text{(Equation 5)}$$

where λ_{max} is the largest or principal eigenvalue of the matrix and can be easily calculated from the matrix and n is the order of the matrix.

The consistency ratio, which generally ranges from 0 to 1, is a ratio between the matrix's consistency index and random index. A CR of 0.1 or less is considered to be a reasonable level of consistency [59]. A CR greater than 0.1 necessitates revision of the matrix judgment due to inconsistent treatment of specific factor ratings.

JOURNAL OF SPATIAL INFORMATION SCIENCES ISSN: 2354-3361
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3.0 Result

The values of spatial factor weights were defined using the AHP method. The acquired weights were used to calculate landslide susceptibility using a weighted linear sum procedure [60], [61]. The CR in this study is 0.066; the ratio indicates a reasonable level of consistency in the pair-wise comparison that is sufficient to recognize the factor weights. As a result, the weight corresponding to lithology is high, while the distance from faults is low (Table 6). The ratio reflects a reasonable level of consistency in the pairwise comparisons, sufficient to determine the class weights for AHP-based landslide susceptibility mapping, with all Consistency Ratios (CRs) below 0.1. The following equation was used:

$$\text{LSM} = \sum_{i=1}^{n}(R_i \times W_i) \quad \text{(Equation 6)}$$

Where R_i is the rating class for each layer and W_i is the weights for each of the landslides

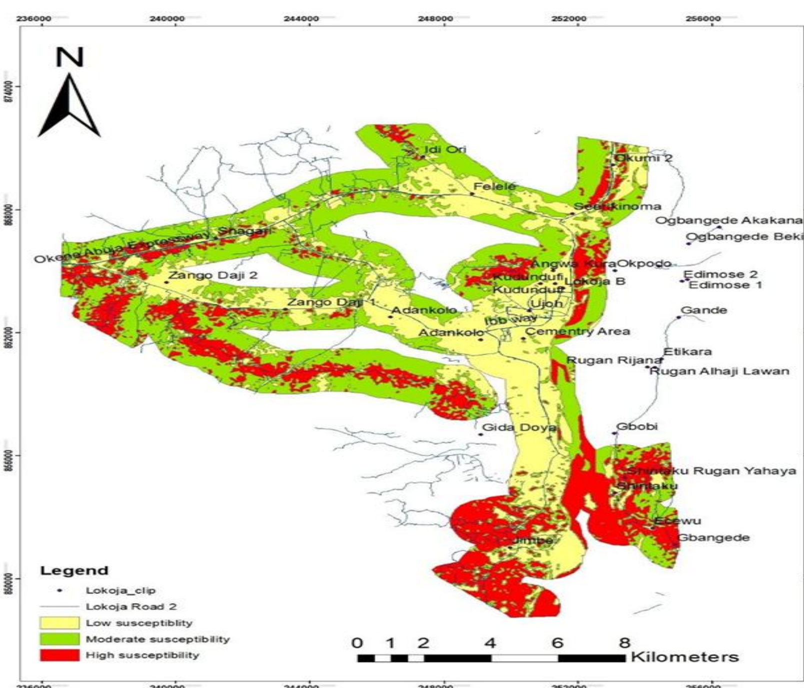

Figure 3: Landslide Susceptibility Map based on the analytical hierarchy process (AHP) model

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Table 2: The weight of each landslide conditioning factor by Analytical Hierarchy Process (AHP)

Criteria	Slope	Aspect	Altitude	Plan Curvature	Lithology	Land-use	Distance from river	Distance from road	Lineaments	Topographic Wetness Index (TWI)	Stream Power Index (SPI)	Slope length
Slope	1	6	5	2	0.333	3	6	3	6	4	5	3
Aspect	0.167	1	3	0.333	0.2	0.5	2	0.2	2	0.333	0.5	0.5
Altitude	0.2	0.333	1	0.2	0.167	0.25	0.5	0.2	3	0.333	0.5	0.5
Plan Curvature	0.5	3	5	1	0.5	5	6	3	6	5	7	7
Lithology	3	5	6	2	1	5	7	2	6	5	7	7
Land-use	0.333	2	4	0.2	0.2	1	2	0.333	2	0.333	2	2
Distance from river	0.167	0.5	2	0.167	0.143	0.5	1	0.2	2	0.25	0.5	0.5
Distance from road	0.333	5	5	0.333	0.5	3	5	1	5	2	4	4
Lineaments	0.167	0.5	0.333	0.167	0.167	0.5	0.5	0.2	1	0.333	0.5	0.333
Topographic Wetness Index (TWI)	0.25	3	3	0.2	0.2	3	4	0.5	3	1	4	2
Stream Power Index (SPI)	0.2	2	2	0.143	0.143	0.5	2	0.25	2	0.25	1	3
Slope length	0.333	2	2	0.143	0.143	0.5	2	0.25	3	0.5	0.333	1

Consistency Ratio: 0.066

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4.0 Discussion

The landslide susceptibility map generated through the integration of GIS and the Analytical Hierarchy Process (AHP) reveals significant spatial variations in risk across the Lokoja region, with approximately 22.97% of the area classified as highly susceptible, covering 4,051 hectares. This high-risk zone is predominantly associated with steep slopes, specific lithological formations, and proximity to rivers and roads, which align with the weighted contributions of these factors in the AHP model. The moderately susceptible areas, encompassing 44.69% of the study area (7,881 hectares), indicate transitional zones where urban expansion could exacerbate vulnerabilities if not managed properly, while the not non-susceptible regions (32.34%, or 5,703 hectares) offer safer grounds for development. These findings underscore the influence of topographic and anthropogenic factors, such as slope degree and distance to infrastructure, in amplifying landslide potential, consistent with prior studies like those by [9], [24], which emphasized the role of multi-criteria decision-making in hazard zoning.

The AHP-derived weights highlight lithology as the most influential factor, reflecting its control over soil strength, weathering, and erosion processes, which is supported by literature indicating that rock types significantly dictate landslide occurrence in hilly terrains [55], [56]. In contrast, lineaments (representing faults) received lower weights, suggesting that while structural weaknesses contribute to instability, their impact is secondary to hydrological and topographic elements like the Topographic Wetness Index (TWI) and Stream Power Index (SPI) in this region. This prioritization aligns with regional patterns observed in similar African contexts, where hydrological saturation from rivers like the Niger and Benue plays a pivotal role [35], [33], though it differs from tectonically active areas where faults dominate [50]. The consistency ratio of 0.066 affirms the reliability of these weights, enabling confident application for land-use planning, but it also points to the need for integrating dynamic factors like rainfall variability, which were not fully captured in the static model.

Despite the robustness of the model, its limitations stem from data resolution and the semi-qualitative nature of AHP, which relies on expert judgment and may introduce subjectivity, as noted by [23] and [25]. Although validation against historical landslide inventories was not conducted here due to data scarcity, such validation would enhance accuracy, in line with approaches used by [15] and [17]. Furthermore, the study's focus on static conditioning factors overlooks temporal triggers like seismic events or climate change-induced precipitation increases, which could alter susceptibility patterns [3], [6]. Overall, these results provide a foundational tool for mitigating socioeconomic impacts in Lokoja; however, future iterations should integrate hybrid machine learning models, such as neural networks [29], to improve predictive accuracy and effectively manage emerging risks associated with urban sprawl.

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5.0 Conclusion and Recommendation

This study successfully produced a landslide susceptibility map for part of Lokoja, Kogi State, by utilizing twelve conditioning factors processed through GIS and the AHP model, achieving a reliable zoning with a consistency ratio of 0.066. The map classifies areas as not susceptible (32.34%), moderately susceptible (44.69%), and highly susceptible (22.97%), providing critical insights into spatial risk distribution influenced by factors such as lithology, slope, and proximity to rivers. Through pairwise comparisons and weighted overlay analysis, the research contributes to the growing body of hazard assessment literature in developing regions, consistent with methodologies from [1]) and [8] and underscores the value of multi-criteria decision-making approaches.

The findings have significant implications for urban planning and disaster risk reduction in Lokoja, where rapid development in hilly areas increases vulnerability to landslides and associated economic losses. By identifying high-risk zones, the map supports strategies to prevent illegal settlements, strengthen infrastructure resilience, and promote sustainable land-use practices. These efforts contribute to safeguarding lives and minimizing secondary threats such as deforestation and inadequate wastewater management [4]. This proactive tool aligns with global efforts to mitigate natural hazards, particularly in riverine and mountainous environments such as Lokoja City, located at the confluence of the Niger and Benue rivers.

In conclusion, while the AHP-based susceptibility map provides a solid foundation for landslide mitigation, future research should incorporate real-time monitoring, higher-resolution data, and advanced models such as fuzzy logic or evidential belief functions [21], [27] to better capture dynamic triggering factors. Policymakers in Kogi State, along with government agencies and relevant stakeholders, are encouraged to adopt these susceptibility insights for zoning regulations and community education programs. Ultimately, this collaborative effort advances the goal of resilient development in landslide-prone areas, reducing devastating impacts on vulnerable populations and promoting long-term environmental stability.

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ISSN: 2354-3361
VOL. 2, ISSUE 3, PP 180–198, 2025
DOI: https://doi.org/10.5281/zenodo.17289828
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