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Remote Sensing and GIS-Based Landslide Susceptibility Mapping in the Eastern Region of Ghana Using Analytical Hierarchy Process

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Abstract

Landslides are among the most destructive natural hazards, causing significant damage to human life, infrastructure, and the environment. Assessing landslide susceptibility is essential for effective land-use planning and disaster risk reduction, particularly in regions with complex terrain and high rainfall. Using the Analytical Hierarchy Process (AHP) integrated with a GIS-based weighted overlay analysis method, this study develops a landslide susceptibility map (LSM) for Ghana's Eastern Region. Five conditioning thematic layers representing drainage density, soil, rainfall, slope aspect, and land use/land cover were derived from a digital elevation model (DEM), Landsat 9 imagery, rainfall, and soil datasets for the susceptibility analysis. Each factor was assigned a weight based on its influence on the occurrence of landslides using the AHP. Weighted thematic layers were combined to create the landslide susceptibility mapping, which was then classed into four susceptible classes: very low (VL) (5%), low (L) (37%), moderate (M) (56%) and high (H) (2%). The findings showed that the four most significant predisposing factors for landslides are rainfall, slope, soil, and geology. A landslide hazard zonation map was calculated to validate the percentage of territory covered by each danger class. The resulting susceptibility map provides important information for land-use planners, infrastructure development, and disaster risk management in the Eastern Region of Ghana.

Keywords: Natural hazards, Landslide susceptibility, Analytical Hierarchy Process, GIS, Remote Sensing

1 Introduction

Landslides are a highly destructive phenomenon that poses a significant threat to human life, infrastructure, and the environment worldwide (Thiery *et al.*, 2007). The severity of landslide impacts is worsened by the emission of greenhouse gases, which makes extreme weather events more frequent and intense, such as heavy downpours of rainfall that can trigger landslides (Chaturvedi *et al.*, 2014). Risk analysis of landslides is essential for developing efficient disaster management, as current methods are limited by their inability to predict landslide occurrences accurately (Corominas *et al.*, 2014). In the Eastern Region of Ghana, steep terrain, intense seasonal rainfall, and human activities such as deforestation and inappropriate land-use practices further increase slope instability and landslide susceptibility (Ampofo, 2022). These conditions highlight the need for reliable approaches to identify areas susceptible to future landslide occurrence.

Various approaches have been developed for landslide susceptibility assessment by integrating remote sensing, GIS, geophysical data, and machine learning techniques. The integration of remote sensing and geophysical data has improved the characterisation of landslide-prone areas (Hussain *et al.*, 2022), while GIS-based machine learning models, including Support Vector Machine (SVM) and Random Forest (RF), have enhanced susceptibility mapping through improved spatial prediction (Dindar and Alevkayalı, 2023). Recently, artificial intelligence techniques have been applied for landslide detection and prediction using remotely sensed data (Akosah *et al.*, 2024), whereas the combined use of GIS and machine learning has facilitated the analyses of various environmental and geological factors such as topography and land cover, controlling landslide occurrences (Chen *et al.*, 2018)

Developments in remote sensing technologies have significantly enhanced landslide detection, monitoring, susceptibility mapping, and hazard assessment. Techniques such as Synthetic Aperture Radar (SAR), Interferometric Synthetic Aperture Radar (InSAR), and Light Detection and Ranging (LiDAR), combined with machine learning and geospatial analyses, have improved landslide prediction, risk assessment, and early warning systems, thereby reducing potential loss of life and economic damage (Macciotta and Hendry, 2021). Zhao (2018) employed remote sensing methods for landslide detection, monitoring, and susceptibility modelling. Remote sensing techniques have also been widely applied for landslide recognition, monitoring, and susceptibility assessment (Scaioni *et al.*, 2014). Regional landslide assessment models developed have been used to evaluate landslides using remote sensing techniques, like inventory and susceptibility mapping (Lee *et al.*, 2018), while recent advances in remote sensing including InSAR, 3D modeling, and regional hazard assessment have further improved landslide assessment (Albanwan and Qin, 2024).

Despite these advances, landslide susceptibility assessment is still limited in many parts of Ghana, particularly in the Eastern Region, where increasing anthropogenic activities as well as complex environmental conditions underscore the need for reliable spatial decision-support systems. Therefore, this project aims to detect and map landslide-prone areas in the Eastern Region of Ghana using remote sensing data, GIS, and the AHP to support disaster risk reduction and sustainable land-use planning.

2 Study Area

2.1 Location

Situated in the southeast of Ghana, the Eastern Region is one of sixteen administrative regions that fall between latitudes 6° 29' 59.99" N and longitudes 0° 29' 59.99" E. It is well-known for its varied topography and geological features. The Bono East Region lies to the north, the Ashanti and Greater Accra Regions to the south and west, and the Volta Region to the east (Gyau-Boakye, 2001). Major urban centers include Koforidua, which is the regional capital, Nsawam, Akropong, and Aburi, which are connected by National highway roads and a network of feeder roads. Rural areas are connected via gravel roads, although access difficulties may persist in hilly regions such as the Akwapim-Togo Escarpment (Obuobie and Barry, 2012). The fact that this region is easily accessed from Accra and Kumasi means that there are easy logistics for fieldwork. Figure 1 presents the location map of the study area.

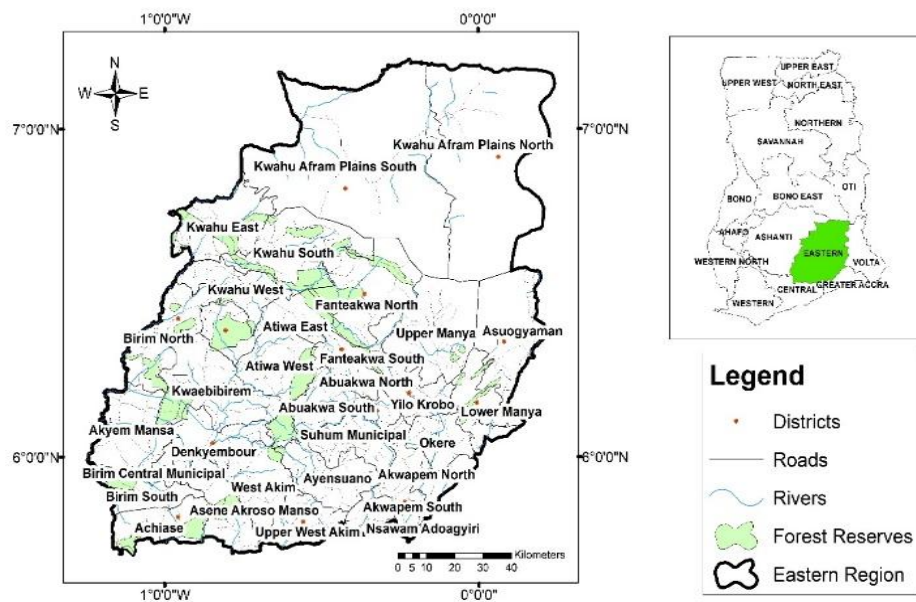


Figure 1 Location Map of the Eastern Region of Ghana

2.2 Climate, Vegetation and Land Use

The climate in this Region is tropical, marked by a bimodal rainfall pattern, which is observed between May and July, which is the major rainfall period, and the minor rainfall period also begins from September to October (Figure 2). The annual rainfall patterns often exceed 1,500 to 2000 mm, particularly during the major rainfall period, which increases the risk of landslides (Dumenu and Obeng, 2016). The inhabitants in urban areas such as Koforidua, the regional capital, and nearby rural communities depend heavily on agriculture, particularly cocoa and oil palm production, small-scale mining, and other land use practices that contribute to environmental degradation (Cobbina *et al.*, 2019). The widespread occurrence of unplanned settlements on steep slopes significantly increases the risk of landslide occurrences (Abbam *et al.*, 2018).

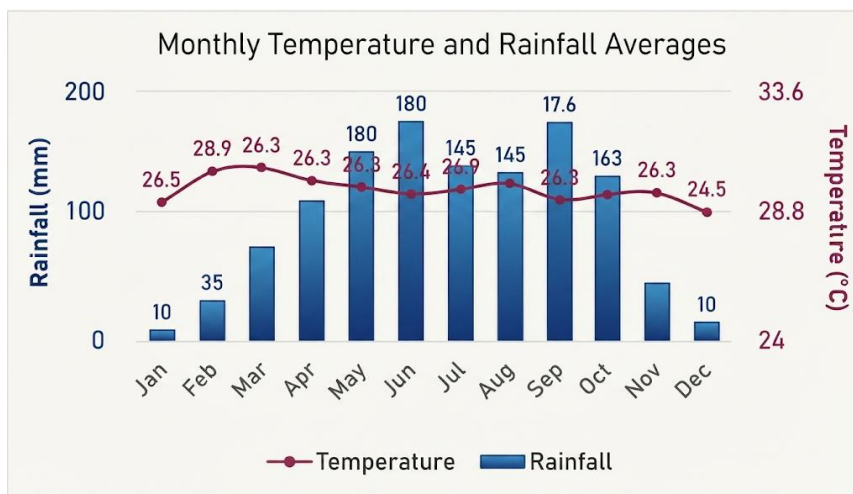


Figure 2 Rainfall Pattern in the Eastern Region of Ghana Showing Monthly trend of Rainfall and Temperature (Source: Musah *et al.*, 2018)

2.3 Topography and Drainage

The region features a highly divided topography dominated by the Akwapim-Togo Range, which extends in a southwest-northeast line for about 320,000 meters to the border of Togo, averaging 457 meters in height and mountain belt elevations up to 800 meters. Slopes that have an angle higher than 30 degrees are quite prevalent, especially in areas such as Aburi and Mpraeso. Plains characterized by flat topography can be found near the Volta River valley in the eastern side of Ghana. Among the key rivers in the region are the Volta River, the Birim River, and the Densu River, which drain into the Gulf of Guinea (Asante & Amuakwa-Mensah, 2014). Their tributaries including the Ayensu and Dodowa rivers experience seasonal discharges and heavy erosion during the rainy season.

2.4 Regional Geology

From a geological perspective, the Eastern Region of Ghana is situated in the West African Craton that mainly comprises Precambrian rocks from the Birimian Supergroup (2.2-2.0 Ga) and the Tarkwaian Group (Figure 3). This set of rocks was created as a result of volcanic and sedimentary rocks undergoing alteration through metamorphism (Black, 2013). On the other hand, the Akwapim-Togo Ranges belong to the Dahomeyide mobile Belt that was created as an outcome of the collision between the West African and Congo Cratons (600 Ma).

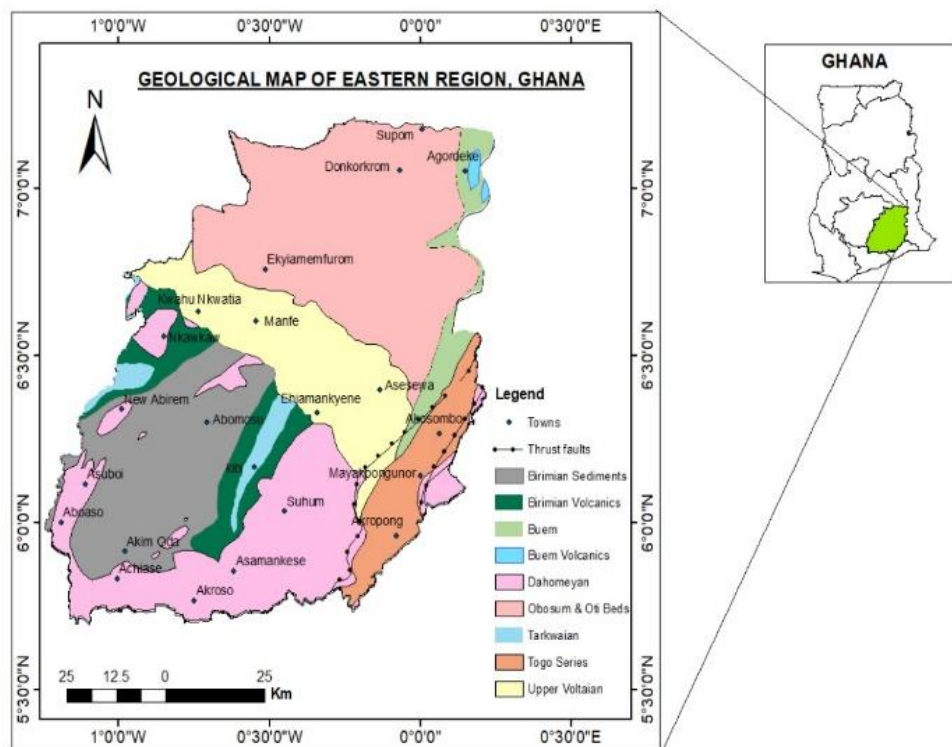


Figure 3 Geological Map of the Study Area

The geologic setting in this area involves highly weathered rocks such as phyllite, schist, quartzite, and meta-volcanics, as well as granitic intrusions. The geology of this area is complex, involving geological features like thrusts, fractures, and foliation in rocks that lead to unstable slopes subject to landslides

and rock falls (Black, 2013). The prolonged weathering of metamorphic rocks leads to the formation of thick clay soil deposits which may be susceptible to landslides, especially with high rainfall events. Figure 4 depicts a landslide event that occurred in Aburi, in the Eastern Region of Ghana (Bokpe, 2021)



Figure 4 A Picture of Aburi Landslide in the Eastern Region of Ghana

3 Materials and Methods

3.1 Data Source

Supplementary data included 5 SRTM DEMs tiles and 3 Landsat 9 scenes sourced from United States Geological Survey (USGS) Earth Explorer, with acquisition dates of 11-22 February 2000 and 27-28 January 2024, respectively. The datasets were mosaicked to provide complete coverage of the study area. The DEM provided a 3D topographic representation, while rainfall data from the Climate Research Unit (CRU) was processed using ArcGIS and the Inverse Distance Weighted (IDW) technique to create a rainfall map for the study area.

Soil data was sourced from the Food and Agriculture Organisation (FAO), while geological data were obtained from the Geology Department of the University of Mines and Technology. Drainage density was derived from the 30m-resolution SRTM DEM obtained from the USGS.

3.2 Data Processing

All spatial data processing, analysis, visualisation, and map production were performed in ESRI ArcGIS version 10.8. ESRI ArcGIS.

Pairwise comparison matrix

A pairwise comparison method based on AHP was used to determine the relative importance of the predisposing factors for the study (Saaty, 1980). In this study, five factors were used as predisposing factors: Aspect (A), Land Use/Land Cover (LULC), Soil (So), Drainage Density (DD), and Rainfall (R). This was done by comparing each pair of factors and assigning a relatively important score using a scale of 1-9. The pairwise comparison matrix was constructed based on expert knowledge and published literature, which is given by

$$a_{ij} = \frac{1}{a_{ji}}$$

Where i refers to the row and j refers to the column.

Figure 5 provides a flowchart of the procedures followed to produce the landslide susceptibility map of this study. The fundamental scale for pairwise comparison is shown in Table 1, and the matrix showing the pairwise comparison of the factors is in Table 2.

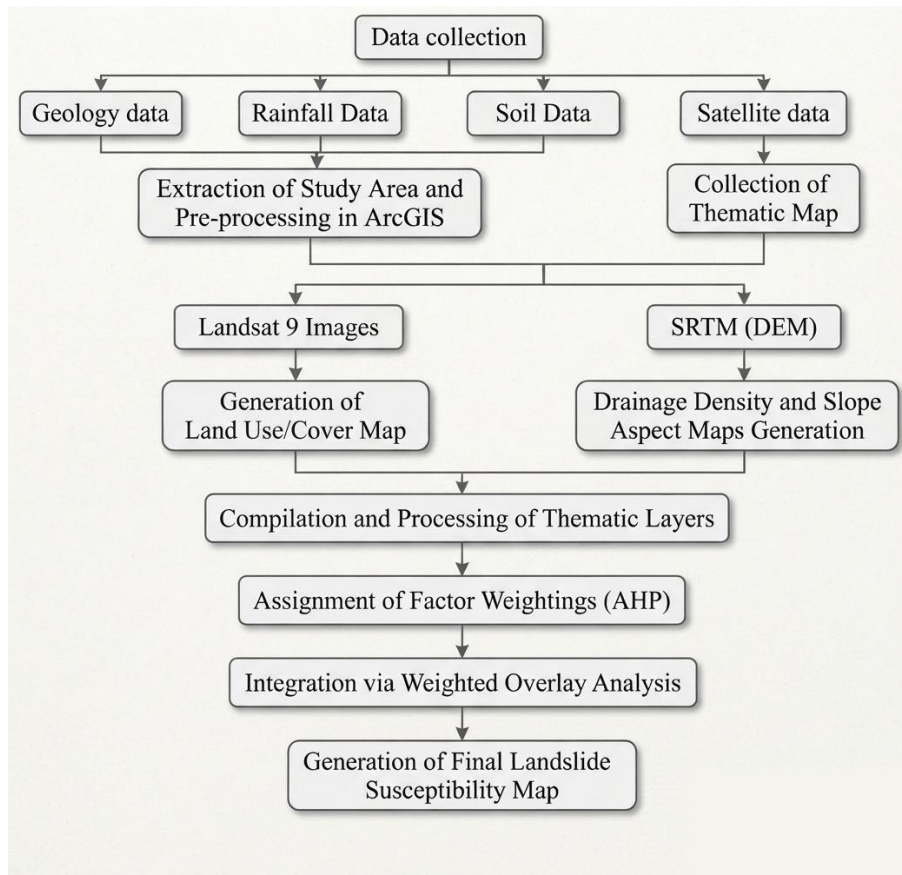


Figure 5 Flowchart for Landslide Susceptibility Map

Table 1 Fundamental Scale for Pairwise Comparison (Gerbo *et al.*, 2022)

Scales	Scale of relative importance	Descriptions
1	Equally	Two activities make an equal contribution to the goals.
3	Moderately	One activity is slightly to moderately favored over another by experience and judgment.
5	Strongly	One action is fundamentally or firmly favored over another by experience and judgment.
7	Very Strongly	The dominance of one activity over another is seen in practice.
9	Extremely Strong	There is the strongest possible expression of the preference for one activity over another.

2,4,6,8	Intermediate values	Compromises between the preferences in weights 1, 3, 5, 7, and 9.
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Table 2 The pairwise comparison matrix for the factors.

Comparison	R	A	So	LULC	DD
R	1	3	4	3	6
A	1/3	1	1/2	1	3
So	1/4	2	1	2	4
LULC	1/3	1	1/2	1	3
DD	1/6	1/3	1/4	1/3	1

Normalised comparison matrix

After comparing the importance of each factor to each other, the relative importance weight was computed from the geometric mean of the normalised comparison matrix. The normalised comparison matrix (Table 3) was obtained by summing the values in each column of the pairwise comparison matrix and dividing each value by the corresponding column sum, as expressed by:

$$N_{ij} = \frac{a_{ij}}{\sum_{i=1}^n a_{ij}}$$

Where:

a_{ij} is the original pairwise-comparison value in row i , column j ;

$\sum a_{ij}$ is the sum of values in column j , and

n_{ij} is the corresponding normalised value.

The relative weight of each conditioning factor was calculated as the arithmetic mean of the normalised values in its corresponding row:

$$w_i = \frac{\sum_{j=1}^n n_{ij}}{n}$$

Where:

n_{ij} is a normalized value in row i ,

n is the total number of factors, and w_i is the weight of factor i .

Table 3 Showing the Normalised Comparison Matrix of the factors

Comparison	R	A	So	LULC	DD
R	0.480	0.401	0.640	0.409	0.353
A	0.160	0.136	0.080	0.136	0.176
So	0.120	0.273	0.160	0.273	0.235

LULC	0.160	0.136	0.080	0.136	0.176
DD	0.080	0.045	0.040	0.045	0.059

Consistency calculation of the pairwise matrix

To ascertain any mistakes or inconsistencies in the pairwise matrix, the equation used for the Consistency Index (CI) is,

$$CI = \frac{\lambda_{\max} - n}{n - 1}$$

where n is the number of rows or columns and $\lambda_{\max}$ is the highest eigenvalue. The AHP uses the consistency ratio (CR) to assess how reliable the pairwise comparisons are. Consistent judgments are shown by a CR value ≤ 0.1 , which is generally regarded as satisfactory.

$$CR = CI/RI,$$

where CI stands for the Consistency Index and RI for the Random Consistency Index.

The RI values for various factors counts are shown in Table 4.

Table 4 Random Consistency Index (Saaty, 1980)

Number of Factors	1	2	3	4	5	6	7	8	9	10
Random Consistency Index	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

3.3 Overlay Analysis

A landslide susceptibility map was generated by integrating the five thematic layers, including Aspect, Rainfall, Land Use/Land Cover, Drainage Density, and Soil using ArcGIS's Weighted Overlay tool. The overlay weights were derived from the normalised AHP weights (Table 3). The susceptibility map was then reclassified into four susceptibility classes: Very Low, Low, Moderate, and High.

4 Results and Discussion

4.1 Weightage Calculation

Five landslide conditioning factors were assigned weights using the AHP, with rainfall receiving the highest weight, followed by soil, LULC, aspect, and drainage density. Their assigned weights, consistency assessment, and the resulting landslide susceptibility map are presented in the following sections.

4.1.1 Assigned Weight and Consistency Ratio (CR)

Table 5 shows the results of the AHP's operations on the specified landslide controlling factors. Rainfall, soil, Aspect, LULC, and Drainage Density in descending order. This shows that, among the given landslide predisposing factors, rainfall has the largest influence on landslides (Mahmud *et al.*, 2013).

Table 5 Weight of Factors

Predisposing Factors	Assigned Weight	Percentage weight (%)	Rank
Rainfall	0.458	45.82	1
Soil	0.212	21.21	2
Land use/ Land cover	0.138	13.78	3
Aspect	0.138	13.78	3
Drainage Density	0.054	5.39	5
Total	1.00	100.00	

$$\lambda_{\max} = 5.145$$

$$\text{Consistency Index (CI) was calculated as, } CI = \frac{\lambda_{\max} - n}{n - 1} = \frac{5.145 - 5}{5 - 1} = 0.036$$

$$\text{Consistency Ratio (CR) was calculated as, } CR = \frac{CI}{RI} = \frac{0.076}{1.12} = 0.032$$

For consistency in the pairwise matrix, the consistency Ratio (CR) must be less than or equal to 0.1 (Mihi *et al.*, 2022). Thus, the generated weight is said to be consistent and reasonable since the CR value is less than 0.1 (Gupta *et al.*, 2018).

4.2 Thematic Layers (Maps)

4.2.1 Rainfall

Rainfall is one of the primary factors influencing landslide occurrence, as prolonged or intense precipitation increases soil saturation and reduces slope stability. The rainfall map was categorised into five ranges (Figure 6): 6.68 – 8.184 mm (low rainfall), 8.185 – 9.688 mm (moderate rainfall), 9.689 – 11.19 mm (significant rainfall), 11.2 – 12.7 mm (high rainfall), 12.71 – 14.2 mm (very high rainfall). The map shows an increase in rainfall from north to south across the study area, with the highest rainfall occurring mainly in the central to southern portion, while the northern portion experiences comparatively lower rainfall. As rainfall received the highest AHP weight, the high-rainfall areas are expected to make greater contribution to landslide susceptibility.

4.2.2 Soil

The soil types in the study area, as shown in Figure 6, were categorised into four main classes: Loam, Sandy clay loam, Sandy loam, and Clay. The soil map demonstrates that sandy clay loam is the dominating soil type across the study area, with loam appearing in discontinuous patches in the central region. Clay and sandy loam are found in relatively limited areas on the eastern margin. As variations in soil type influence infiltration capacity and slope stability, it therefore contributes to the spatial variability of landslide susceptibility (Dai and Lee, 2002).

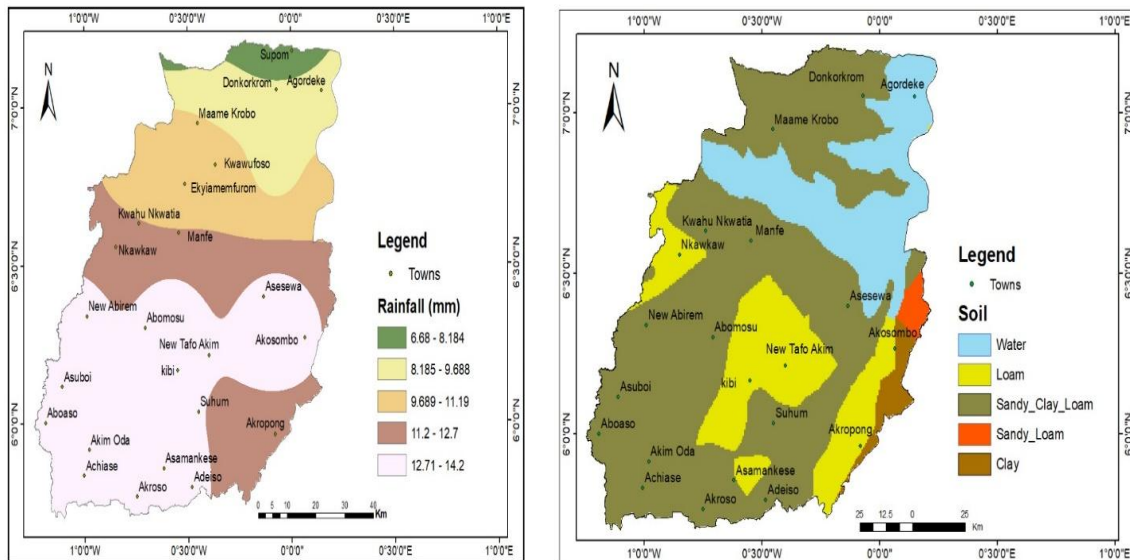


Figure 6 The Rainfall Map (left); Soil Map (right) of the Study Area

4.2.3 Slope Aspect

The direction of slopes is shown on the slope aspect map, which is produced using the DEM. Slope aspect is an important conditioning factor because it influences climatic variables such as solar radiation and precipitation, which in turn affect weathering processes and slope stability. For instance, south and southwest-facing slopes receive greater solar energy than slopes with other orientations. As seen in Figure 7, the slope aspect map was divided into ten classes: Flat (-1), North (0-22.5° and 337.5-360°), North-East (22.5-67.5°), East (67.5-112.5°), South-East (112.5-157.5°), South (157.5-202.5°), South-West (202.5-247.5°), West (247.5-292.5°), and North-West (292.5-337.5°).

The slope aspect map shows considerable spatial variation in slope orientation throughout the research area, with all aspect classes represented. Different slope orientations affect the quantity of solar energy and moisture received by specific slopes, which may contribute to variations in landslide susceptibility within the study area.

4.2.4 Land Use/ Land Cover

Land use/land cover plays a vital role in influencing landslide susceptibility. Areas with limited vegetation cover are generally more prone to soil erosion and slope instability, whereas dense vegetation with deep root systems helps reinforce soil and reduce erosion. Human activities such as deforestation, construction, and overgrazing further increase landslide susceptibility by removing protective vegetation cover. The land use/land cover map (Figure 7) was classified into four categories: Water Bodies, Built-Up Area, Vegetation Cover, and Barren Land.

Throughout the study area, vegetation is the dominant land cover, while built-up areas are concentrated around major settlements. Water bodies, such as the Volta Lake, occupy the eastern

portion of the study area, whereas barren land occurs in scattered patches. Thus, areas with less vegetation may be more prone to erosion and slope instability than highly vegetated areas, thereby influencing landslide susceptibility.

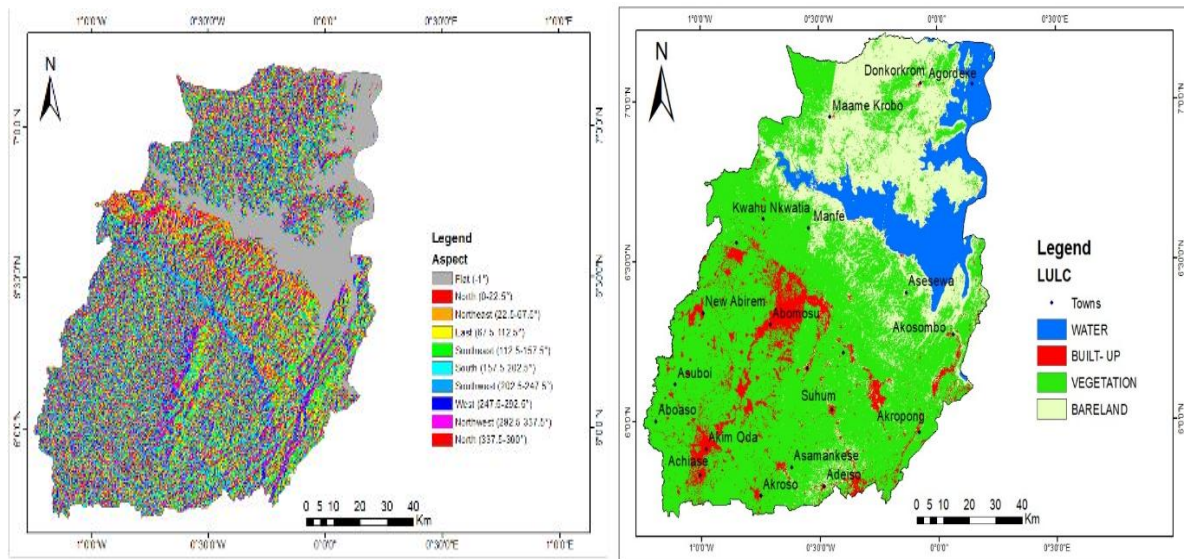


Figure 7 The Slope Aspect (left); Land Use/Land Cover Map (right) of the Study Area

4.2.5 Drainage Density

Drainage density represents the total length of streams and rivers per unit area and shows the degree of landscape fragmentation. High drainage density, when combined with steeper slopes, may increase surface runoff and slope instability, thereby increasing landslide susceptibility. As shown in Figure 8, the drainage density map was classified into five categories: Very low ($0-0.61 \text{ km/km}^2$), Low ($0.6-1.2 \text{ km/km}^2$), Moderate ($1.3-1.8 \text{ km/km}^2$), High ($1.9-2.4 \text{ km/km}^2$), and Very high ($2.5-3.8 \text{ km/km}^2$).

The drainage density map shows noticeable spatial variation across the study area. The dominating drainage density class is moderate, which covers much of the central region, while high and very high drainage density are localised mainly in the south and southeast parts of the study area. The northern section, in contrast, has low to very low drainage density. These variations suggest differences in landscape dissection, which may influence landslide susceptibility.

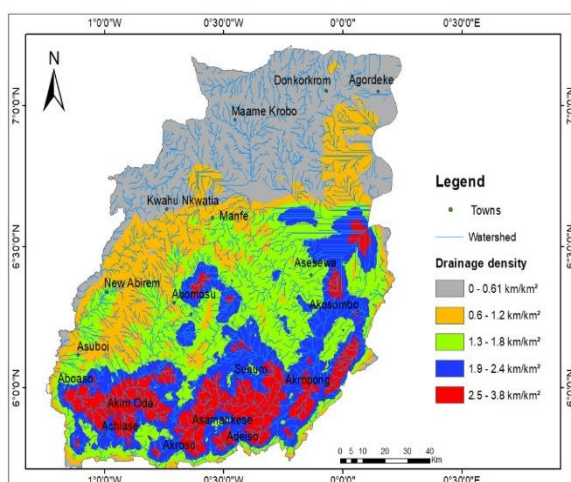


Figure 8 The Drainage Density of The Study Area

4.2.6 Identification of Landslide Prone Areas Using AHP

The integration of the five thematic layers using their assigned weights resulted in a landslide susceptibility map for the study area. As illustrated in Figure 9, the susceptibility map categorises the region into four distinct zones: very low, low, moderate, and high susceptibility to landslides.

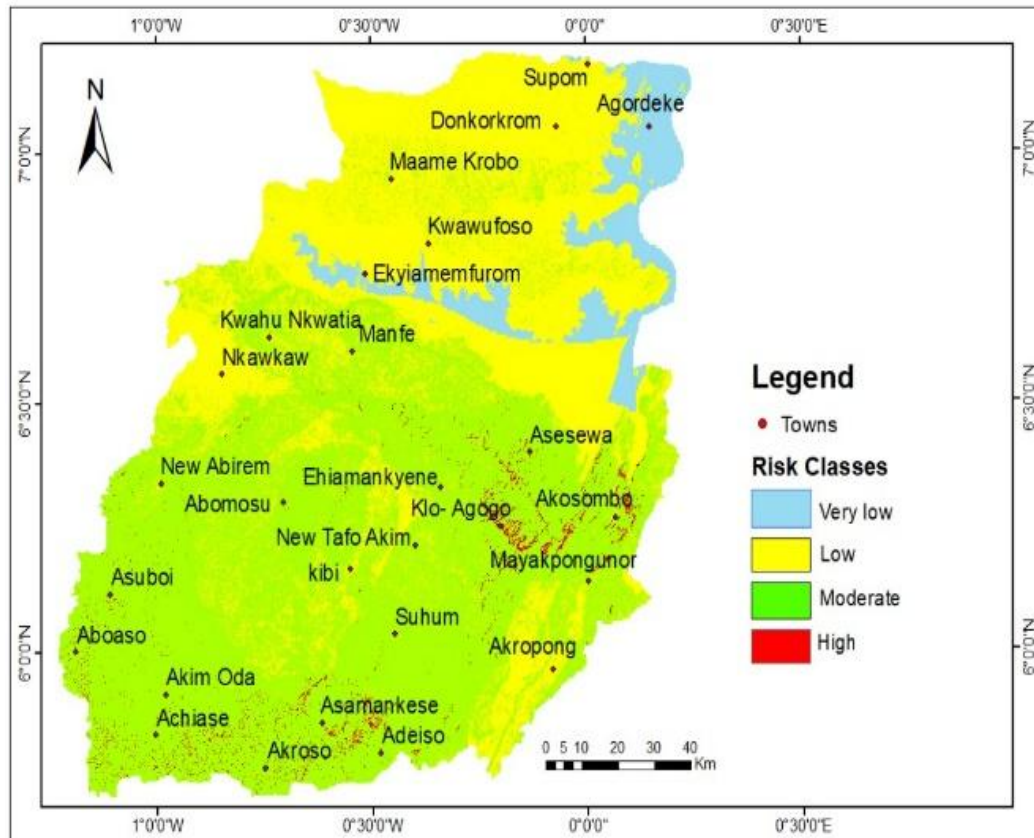


Figure 9 The Landslide Susceptibility Map for Eastern Region, Ghana

From Figure 9, it can be observed that the high landslide susceptibility zones are concentrated mainly in Asesewa, Ehiamankyene, Klobi-Agogo, Akosombo, and Mayakpongum as seen in red. The high-susceptibility zones primarily coincide with areas characterised by high rainfall, favourable soil conditions, higher drainage density, land use/land cover, and slope aspect. This is consistent with the assigned AHP weights where rainfall, soil and land use /land cover were assigned higher weights than the remaining conditioning factors. Furthermore, the majority of the research area falls within the moderate susceptibility class, indicated in green. This is explained by the fact that the majority of the land has moderate to high rainfall, soil and land use/land cover. In contrast, the bulk of the northern part of the study area is dominated by low and very low susceptibility classes due to its flat terrain and low drainage density. Table 6 and Figure 10 present the summary results of ranked areas and the corresponding percentage of risk rankings that were obtained in the study area.

Table 6 Summary Results of Ranked Areas

Risk Level	Area (km ²)	Percentage (%)
Very Low	1,022.16	5%
Low	6,986.39	37%
Moderate	10,530.78	56%

High	306.0136	2%
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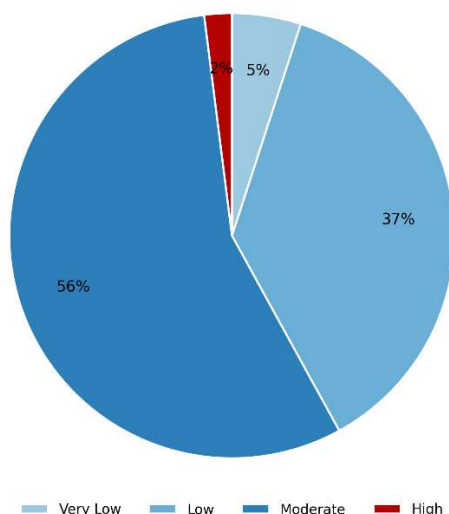


Figure 10 Landslide Susceptibility Classes Distribution and Percentage

5 Conclusions

While natural disasters are unavoidable, their impact can be reduced through proactive planning and preparedness, which can facilitate more effective recovery. Preparation of the landslide susceptibility map is vital in addressing the risk of landslide disasters, providing early warning systems, and pinpointing the landslide-prone areas. The preparation of a landslide susceptibility map makes it possible to identify landslide-prone areas, enabling preventive measures to minimise damage and loss of life. Identification of the landslide susceptibility zones using remote sensing technology helped save time, energy, and cost. Among the key conclusions are:

- The study demonstrated that rainfall, soil, slope aspect, land use and cover, and drainage density are the principal conditioning factors influencing landslide susceptibility in the study area. These factors were successfully integrated using the Analytical Hierarchy Process (AHP) and weighted overlay analysis to produce a landslide susceptibility map.
- Communities such as Asesewa, Akosombo, Ehiamankyene, Klo-Agogo, Mayakpongonor, Adubiase, Achiase, Akim Oda, Asuboi, Aboaso, Bepowase, and others are located within landslide-prone zones
- Rainfall was recognised as the most predisposing and contributing element to the research area's landslide potentials.
- The research region, which covers an area of 10,530.78 km², has a moderate landslide potential, according to the landslide susceptibility map.
- The findings of this study may support planners, disaster management agencies, and other stakeholders in land-use planning and sustainable development in the study area.

It is recommended that subsequent work into landslide susceptibility mapping could substitute the AHP method with Fuzzy Logic and the Maximum Entropy Model.

Statements and Declarations

Conflicts of interest/Competing interests

The authors declare that there is no competing interest for this research work.

Availability of data and material

The data used for the study can be made available upon request.

Ethical statement

The research was conducted in accordance to ethical standards.

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