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Landslides Susceptibility Mapping Using Analytic Hierarchy Process: Sahel of Algiers case study

Mira Filali [1] **and Fatma Zohra Belhadj**[2]

[1] PRAVDUR Laboratory, Faculty of Natural and Earth Sciences, Djilali Bounaama University of Khemis Miliana, Algeria.

[2] Built Environmental Research Lab, Faculty of Civil Engineering, University of Science and Technology Houari Boumediene, National Higher School of Public Works (ENSTP), Basic Infrastructure Department (DIB), Algeria.

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ABSTRACT: Geological hazards present a major challenge to the development of Algiers, the capital of Algeria, with landslides being particularly prevalent in the early terrain of the Sahel region. Comprehensive preliminary studies are essential for mapping zones vulnerable to slope instability and for mitigating their impacts. This study aims to produce a landslide susceptibility map for the Marly Sahel area using Geographic Information System (GIS) and Analytical Hierarchy Process (AHP) methodologies. Key factors considered in the susceptibility assessment include slope degree, lithology, distance to drainage, elevation, landuse and geotechnical parameters. The weight of each factor class was determined using the AHP technique integrated with the GIS functionalities. This process resulted in the generation of landslide Susceptibility maps, categorizing the area into five zones: very low, low, moderate, high, and very high susceptibilityThe analysis identified slope, lithology, cohesion, elevation and proximity to drainage as the most influential factors contributing to landslides occurrence. The study revealed that the northern and south-eastern parts of the area, particullary near valleys and drainage systems, are especialy susceptible to landslides. A landslide inventory map was employed to validate the susceptibility model, achieving a prediction rate of 0.75 based on the area under curve (AUC) technique. Despite limitations, such as the lack of landslide inventory data, this study underscores the critical importance of detailed landslide susceptibility mapping for effective hazard management and informed land-use planning in vulnerable regions.
Keywords: Landslide susceptibility, Sahel of Algiers, Geographic Information System (GIS), Analytic Hierarchy Process (AHP).

*Corresponding author. E-mail: m.filali@univ-dbkm.dz

1. Introduction

Landslides are complex natural hazards that can result in significant loss of life and property (Li et al., 2020). They occur when soil or rock is displaced by gravity, often triggered by various natural or human-induced factors (Filali et al., 2020; Kiernan et al., 2022), including heavy rainfall, earthquakes, volcanic activity, erosion, and human activities such as deforestation, mining, construction, and improper land use. The susceptibility of slopes vulnerability to landslides is often linked to the type of soil or rock present, such as clays, marl, gypsum, or loose formations that are prone to destabilization (El Jazouli et al., 2019). The occurrence and progression of landslides are influenced by several parameters like topography, geology, hydrology, erosion, urbanization, and meteorological conditions, with weather being the leading cause of many landslides events (Leonardi et al., 2022; Li et Chen, 2023).

Landslides are a common occurrence in northern Algeria, triggered by factors such as the region's geological composition, land morphology, hydrology, climate, and human activities (Senouci et al., 2021). Studies highlight frequent landslide events in area like Constantine, Medea, and Kabylie. Algiers, in particular experiences considerable damage to structures and infrastructure as a result of this geological hazard. Following Algeria's independence in 1962, rapid urbanization led to significant expansion into marginal lands southwest of Algiers's Sahel (coast), wich became increasingly suitable for construction. newly urbanized areas such as El-Achour, Daly-Brahim, Ouled-Fayet, Souidania, El Rahmania, Khraicia, and Sidi-Abdellah have since been impacted by landslides (Benbouras, 2022). These instability processes, whether superficial or deep (rotational or complex), are primarily observed in the Plaisancian marls and sandy clays, which form the transition zone between the Plaisancian and molassic Astien facies (Aymé, 1965; Filali et al., 2021).

Studing and analyzing landslides is essential todevelop susceptibility models and maps, that can help prevent or mitigate their devastating effects (Hua et al., 2021). These maps provide valuable insights for decision-makers, including planners and engineers, to identify suitable areas for development and minimize landslides impact (Thiery et al., 2021). Geographic information system (GIS) play a crucial role in managing spatial and temporal data, offering a pwerful platform for analyzing and interacting, with large datasets related to landslides (Li et al., 2019; Roccati et al., 2021). The growing application of GIS in landslide research underscores its critical role in the field. Its capacity to manage and integrate diverse data sources, along with supporting complex spatial analysis and visualization, makes GIS an indispensable tool for the studying geologic hazards (Sandeep & Shrivastava, 2022; Zangh et al., 2020).

Landslide susceptibility assessment methods can generally be classified into qualitative and quantitative approches (Kamran et al., 2021), including heuristic analysis, statistical analysis, and deterministic Analysis (Shano et al., 2020). The qualitative approch to landslide susceptibility mapping can be divides into two main categories: direct and indirect methods. The direct method, geomorphologic analysis, relies on expert knowledge and field experience to identify and map landslide susceptibility

(Xiao et al., 2020; Farook & Akram, 2021). The indirect methods, which are semi-quantitative, involve ranking parameters that influence landslide occurrence and assigning weight values based on expert judgment. These parameters can be assessed through expert opinion (knowledge-driven approach) or analytical techniques like the Analytical Hierarchy Process (AHP). The results of qualitative methods are largely influenced by expert knowledge, and notably, they do not require inventory maps for landslide susceptibility mapping (Vakhsoori et al., 2019).

In the quantitative approach to landslide susceptibility mapping includes deterministic and statistical methods. The deterministic method calculates safety factors to evaluate slope stability, typically applied to specific locations (Ghadrdan et al., 2021). In contrast, statistical methods, such as bivariate and multivariate techniques, Frequency Ratio (FR), Weight of Evidence (WoE), Artificial Neural Network (ANN), and Support Vector Machine (SVM), examine the relationships between conditioning factors and landslide distribution (Gentilucci et al., 2021). The choice of method depends on factors like the study area's scale, data availability, and the level of scientific knowledge. Additionnaly, Some qualitative methods such as analytic hierarchy process (AHP), analytic networks process (ANP), Fuzzy-AHP, become semi-quantitative when incorporating ranking and weighting (Bahrami et al., 2021).

The Analytic Hierarchy Process (AHP), developed by Saaty (1977), is a widely used Multi-Criteria Decision Analysis (MCDA) method employed by many researchers (Basu & Pal, 2020; Bahrami et al., 2021; Chanu & Bakimchandra, 2022; Liu et al., 2024). AHP simplifies complex problems involving multiple causative factors such as slope, drainage, lithology, and geology, by breaking them into simpler criteria and assigning weight based on their relative importance (Saaty, 1977). As part of MCDA, AHP provides a structured framework to integrate various criteria, and enables systematic comparison of factors through pairwise comparisons.

This process produces a comprehensive landslide susceptibility map, which is crucial for effective hazard management in vulnerable areas.

In Algeria, landslide susceptibility assessment is an emerging field. Several studies have used heuristic and statistical methods to identify vulnerable areas, particulary, in the eastern regions of the country (Sediki & Dehemi, 2022; Bourenane & Bouhadad, 2021; Hadji et al., 2018; Manchar et al., 2018). Notably, a study southeast of Algiers focused on landslide susceptibility, utilizing Hybrid meta-heuristic machine learning methods (Benbouras, 2022).

In this study, landslides are recognized as a complex natural phenomena influenced by various factors, including slope, hydrological characteristics, stratigraphic lithology, and geotechnical properties. As a result, the Analytic Hierarchy Process (AHP) was chosen for the following reasons:

1. Landslide occurrences data was gathered through a field survey, documenting 24 disaster sites. However, given the limited study area and insufficient samples size of landslide points, it was necessary to supplement and refine the data with the expertise of experienced professionals.

2. Information on landslide occurrences within the study area was recorded as points, indicating the location of past landslide events.

3. The implementation of AHP improved the evaluation process, enhancing accuracy by carefully adjusting and assigning appropriate weights to various factors.

By applying these methodologies, housing, and road authorities are empowered to formulate comprehensive strategic plans to mitigate the adverse impacts of landslides on human lives and property.

features recent quaternary alluvial deposits, including clay, silt, and gravel within the bassin, marine terraces to the north, and alluvial terraces near rivers. Tectonic activity in the region is evident in the tilted marine terraces and deformed alluvial deposits. The study area is located in the southwestern suburbs of Algiers, covering approximately 78.75 km2 and spans between 36°39' and 36°45' N longitude and 2°55' and 2°59'E latitude (Fig. 1). This region is well-known for its susceptibility to landslides,

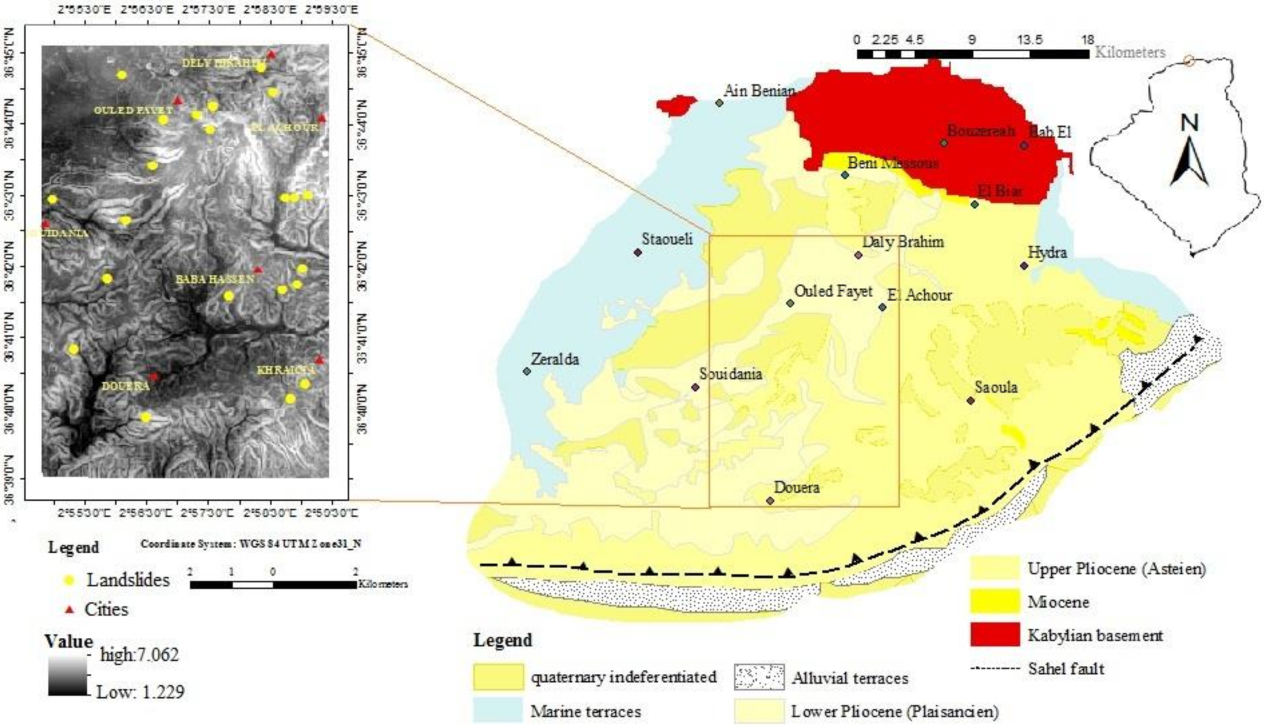


Figure 1:(a) Location map and (b) geological map (Royer et al 1961) related to study area

2. Study area

Algiers is situated in the sahel region of the northern Mitidja bassin, primarily composed of Plio-Quaternary deposits. The local geology

due to its geological and geomorphological features. Both climatic and anthropogenic factors also contribute to landslide occurrences in the area. Geologically, The Algiers region showcases a complex structure (Fig. 1), primarily consisting of a metamorphic dome borded by Tertiary and Quaternary sedimentary formations. The underlying metamorphic basement is composed of a highly tectonized crystalline rocks. These rock outcrops are located between Bouzareah and the port of Algiers.

The Tertiary period is characterized by the absence of Eocene and Oligocene deposits. It unconformably overlies the metamorphic basement and consists of the following layers:

- Lower Miocene, predominantly composed of sandstones. This layer is highly tectonized, with limited exposed outcrops.
- Lower Pliocene, primarily composed of marls and marly clays. these formations outcrops in the Sahel region, with a thickness exceeding 200 meters, and serve as the bedrock for much of the urban development. They are overlain by Astian sediments or more recent deposits. The marls form the tableland of EL Achour and Ouled fayet to the northeast, subjected to significant erosion (Royet et al., 1961).
- The recent deposits consist of fine sands, gravels, and pebbles.

The Sahel is characterized by a series of hills with a gradient ranging from 5% to 30%. The uplift of the Atlas Mountains, deriven by Astien tectonics, resulted in the formation of the Sahel anticline and the depression of Mitidja bassin (Royer et al., 1961;Aymé, 1956).

Landslides in the area display a wavy morphology and primarily occur within the weathered marl horizons. These horizons vary in weathering intensity, which in turn affects their strength properties and slope stability. The thickness of the weathered marl layers can reach up to 8 m in depth, even on slopes with an inclination greater than 10%.

3. Material and Methods

Landslide susceptibility mapping requires collection of data that influences the likelihood of landslides. The selection of specific factors depend on variables, such as the study area size of, the type of landslides, and the mechanisms of failure (Wang et al., 2019). However, there are no universal guidelines for selecting parameters that impact landslides in susceptibility mapping (Gaidzik & Ramírez-Herrera, 2021). Therefore, establishing a connection between causal factors and landslides remains both a critical and challenging task (Mind'je et al., 2020). A detailed flowchart outlining the entire process is provided in Figure 2.

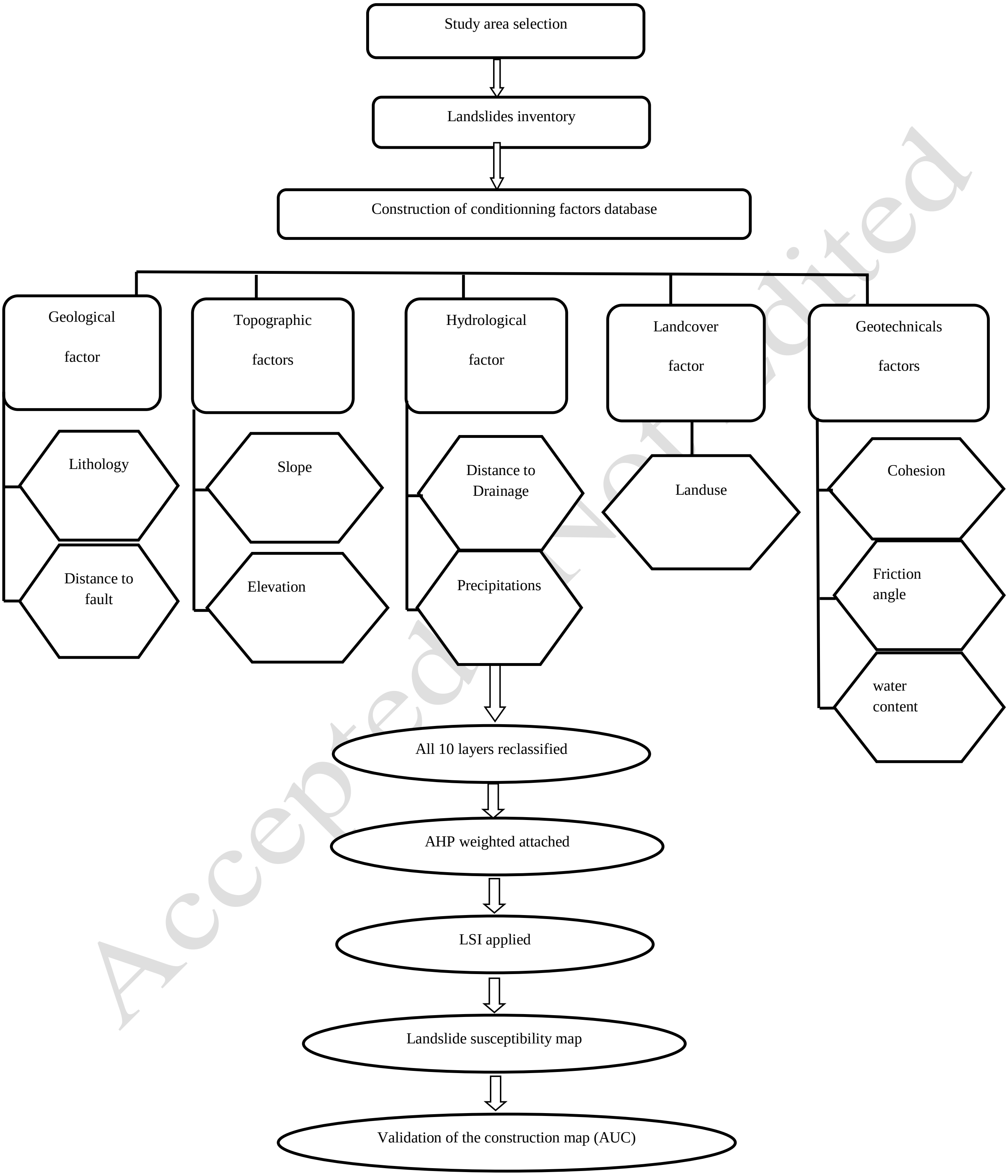


Figure 2: Flowchart outlining the steps involved in this study

3.1. Landslides inventory

Landslide inventory is a crucial component for landslide susceptibility modeling (Bera et al., 2021; Guri et al., 2015). It involves documenting past landslides occurences. In our study area, we identified 24 landslide events between 2011 and 2018 (Fig. 1). The landslide inventory map was compiled using multiple methods, including interviews with public administration personel, soil laboratories such as the National Laboratory of Habitat and Construction, and local residents of Algiers. The collected data were then validated through aerial photography, Google Earth, and field surveys.

The recorded cases occurred in urban areas, primarily within shallow layers ranging from a few decimeters to approximately 9 meters in depth, located within altered marly formations.

3.2. Predisposing factors

This study assessed and mapped the landslide susceptibility in the Sahel of Algiers by selecting key factors influencing slope stability, including slope, cohesion, friction angle, water content, land use, elevation, distance to the drainage network, and lithology. These factors, derived from expert knowledge and prior studies (Benbouras, 2022; Fell et al., 2008) were used to generate thematic layers from a 30 meters resolution digital elevation model (DEM) obtained from the Shuttle Radar Topography Mission (SRTM) database. The lithology layers were extracted from a 1:50,000-scale geologic map (Figure 4c). The layers were integrated using the AHP method in GIS environment(ArcGIS 10.8) through the Weighted Linear Combination (WLC) method (Ozdemir, 2020; Panchal & Shrivastava, 2022Liu et al., 2024). All factors were evaluated by experienced landslide experts and validated by numerous studies, forming the basis for their judgment.

3.2.1. Elevation

Elevation is a critical conditioning factor influencing landslide occurence, often indirectly affecting other elements such as slope, erosion and precipitations (Leonardo et al., 2022). Classifying local relief and identifying areas with maximum and minimum elevation within the terrain are essentiel practices. A grid map of elevation with a 5x5m cell size was generated, and the altitude was divided into fives as follows (fig. 3d): 53-162m; 126-154m; 154-179m; 179-208m and 208-269m

3.2.2. Slope

Slope plays a critical role in the formation, development, and susceptibility to landslides. Numerous studies have identified it as a key parameter in landslide susceptibility assessments (Mind'je et al., (2020); Liu et al., (2024)). As the slope angle increases, the risk of landslides increases, the likelihood of landslides also rises, as steeper slopes are more prone to instability. The slope angle can also influence moisture content and pore pressure, which are common contributors to landslides (Li et al., 2020). Consequently, slope angle is often used in landslide mapping to identify areas with a higher risk of landslides. In this study, a slope angle map was generated from the DEM and divided into five classes with intervals of 5% (Fig. 4a).

3.2.3. Distance to drainage

The occurrence of landslides is significantly influenced by the presence of rivers and their interaction with the surrounding landscape. Previous studies have shown that as the distance between a slope and the drainage network decreases, the likelihood of landslides increases (Anis et al., 2019; Huang et al., 2021) due to the impact of streams on slope stability.Erosion or undercutting by rivers can destabilize slopes (Foumelis et al., 2018), and streams can also saturate the lower part of the slope material (Nohani et al., 2019), leading to a loss of shear strength of the soil or rock. Therefore, considering the influence of rivers is crucial when assessing landslide risk in a given area. In this study, the distance to drainage was calculated by Euclidean distance in Arc GIS,and then reclassified into five classes: 0–130 m, 130–280 m, 280–420 m, 420–650 m, and 650–1670 m (Fig. 4b).

3.2.4. Lithology

A landslide is a geomorphological event closely tied to the lithological properties of the terrain. For this study, Lithological data were sourced from the 1: 50000-scale geological map of Algiers (Fig. 4c). The geological formations in thestudy area are relatively homogeneous from a litho-technical perspective. The Sahel region primarily consists of alluvial deposits, rocky formations, marls, sand, and sandstone (Filali et al., 2020)

3.2.5. Landuse

Landuse in a region indirectly reflects exposure to surface erosion and influences slope stability (Agrawal & Dixit, 2022). For the purposes of this study, land use was classified into seven categories: water, trees, crops, built areas, bare ground, rangeland and road (Fig. 4e)

3.2.6 Geotechnical criterion

In this research, we adopt a co-deterministic-statistical approach, integrating available geotechnical data. Which are crucial for assessing slope stability. Geotechnical data were obtained from various technical reports from public administration, soil laboratories, and companies. The key parameters used in this study include cohesion, friction angle, and water content. Average values from boreholes data (Fig. 3) were used to generate thematic layers (Fig. 4f, g and h). These vector layers were then converted into raster format and processed using ArcGIS software.

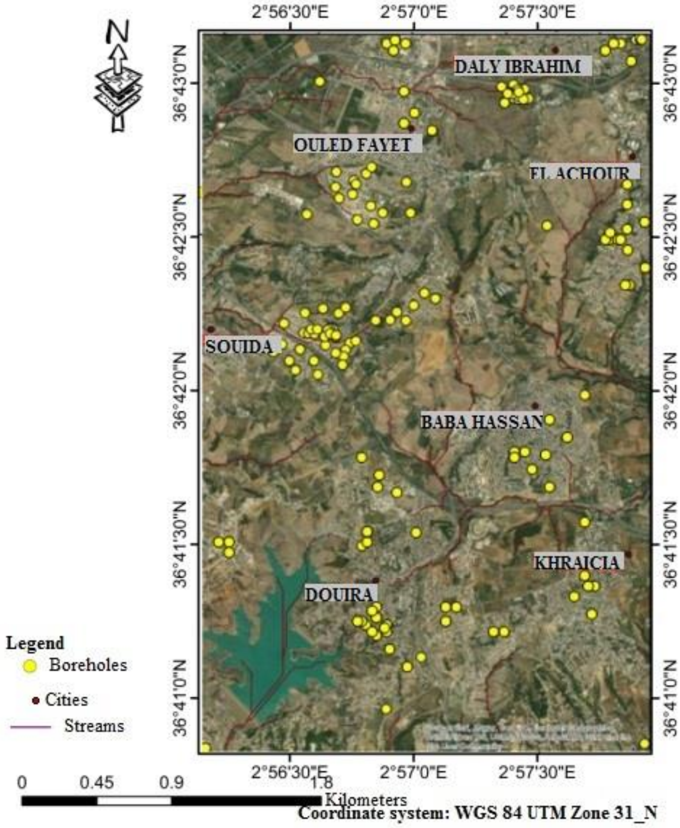


Figure 3: Location of boreholes in study area

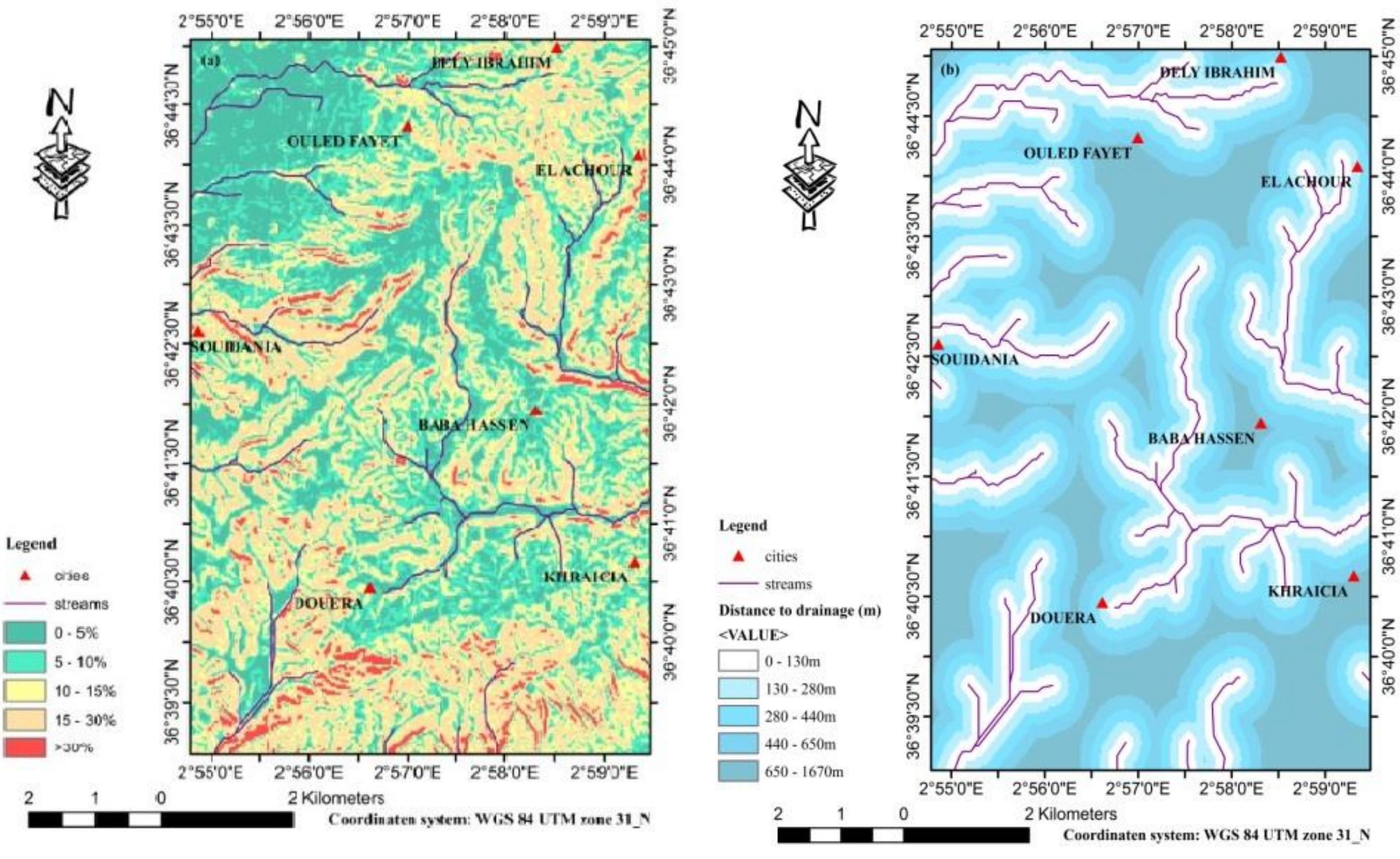
3.2.7 Distance to faults

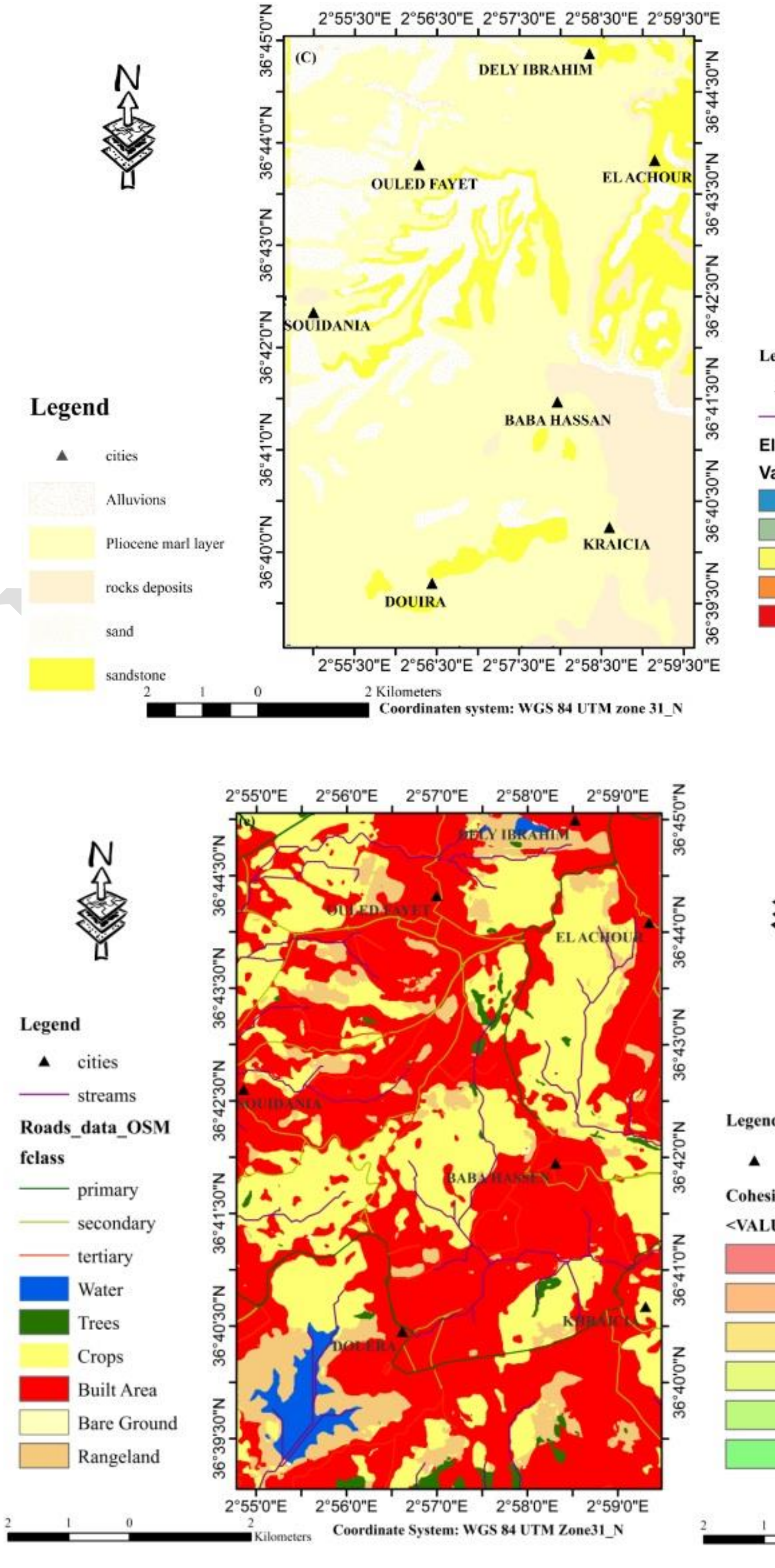
Geological fault zones are particulary vulnerable to landslides due to the reduction in rock strength caused by tectonic fractures (Vianello et al., 2023). The Algiers region contains several fault zones, predominantly oriented from east to west and north to south, such us the Sahel fault and Mitidja fault.In this study, fault zones were categorized into five categories to create a fault proximity map, using Euclidean distance analysis (Fig. 4i). This mapping was based on the geological map of Algiers.

3.2.8 Precipitations

Intense rainfall can greatly destabilize slopes by increasing pore water pressure through soil infiltration, which weakens shear strength and ultimately triggers landslides (Filali et al., 2020; Li et al., 2019).

To evaluate the impact of rainfall on landslide susceptibility in the study area, a high-resolution rainfall map was generated using the kriging interpolation method. Data from eight meteorological stations were used to model the annual rainfall distribution across the region. Rainfall events were further classified into five categories (Fig. 4j) to better understand their role in triggering landslides.




(C)
DELY IBRAHIM
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EL ACHOUR
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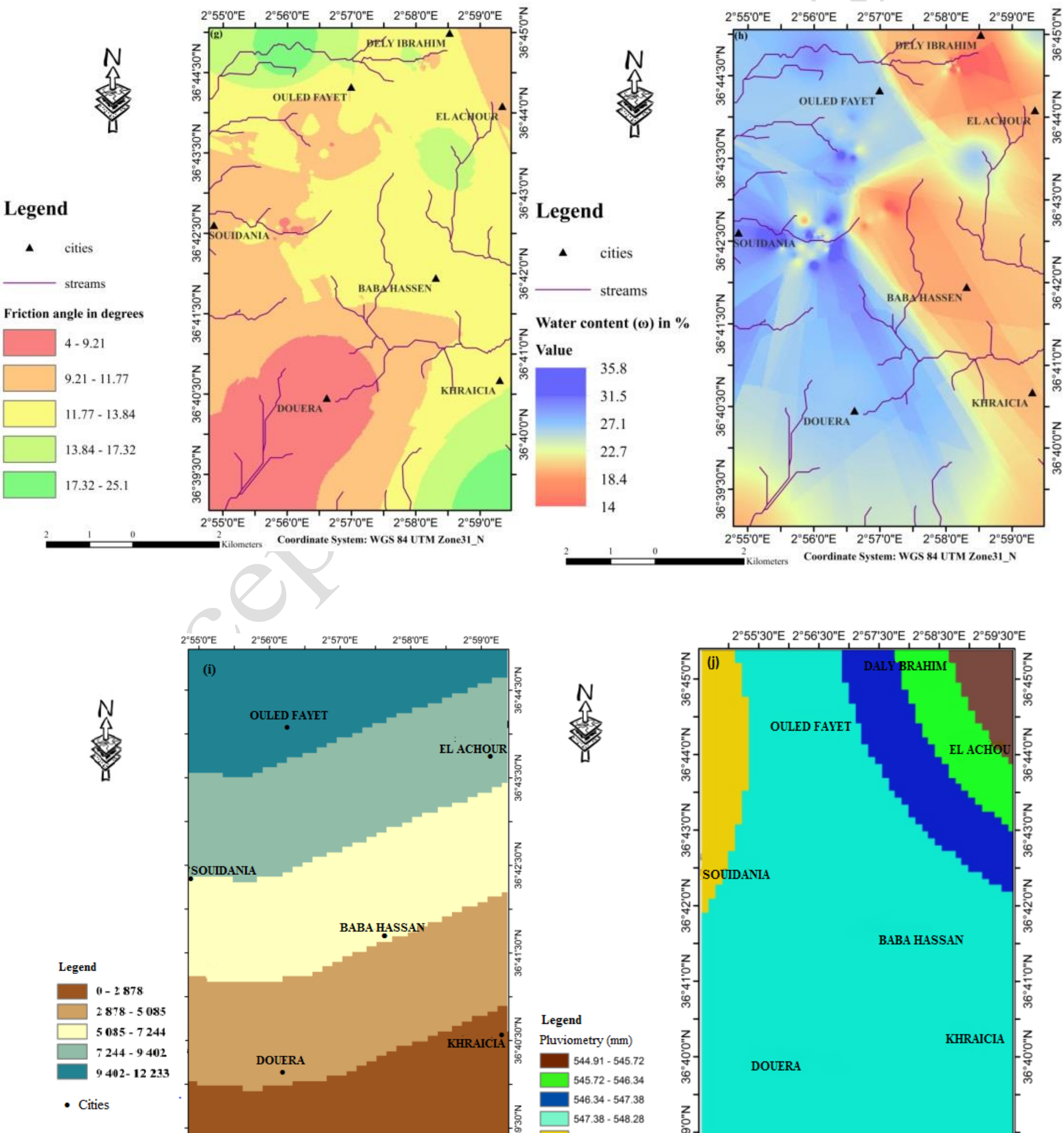
Coordinate System: WGS 84 UTM Zone31_N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DELY IBRAHIM
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Friction angle in degrees
4 - 9.21
9.21 - 11.77
11.77 - 13.84
13.84 - 17.32
17.32 - 25.1
Kilometers
Coordinate System: WGS 84 UTM Zone31_N
(h)
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cities
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Water content (ω) in %
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35.8
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27.1
22.7
18.4
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Coordinate System: WGS 84 UTM Zone31_N
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5 085 - 7 244
7 244 - 9 402
9 402- 12 233
Cities
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Pluviometry (mm)
544.91 - 545.72
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546.34 - 547.38
547.38 - 548.28

3.2.5 AHP technique

The weights of all parameters were determined using the Analytic Hierarchy Process (AHP), considering the local topographic and physical characteristics of the study area. Before generating the landslide susceptibility map, the weight and rating value of each factor were calculated. Each factor was divided into different classes and assigned a rating value from 1 to 9, following Saaty's fundamental scale (Table 1). Using the same procedure, weight values were determined to reflect the relative importance of each factor in comparison to the others. AHP, a A matrix exhibiting a consistency ratio (CR) below 0.10 indicates satisfactory consistency. Finally, the integration of various causative factors and classes into a single landslide susceptibility index (LSI) was achieved using a decision-making method based on pairwise relative comparisons, ensures consistency throughout the process. To assess the consistency of our expert judgement, the consistency index (CI) was calculated using following equation (1) (Saaty, 2001; Saaty, 1977).

$$CI = \frac{\lambda_{max} - N}{N - 1} \qquad (1)$$

Where λ_{max} is the maximum eigen value of the matrix, and N is the order of the matrix. The quality of the comparison is described by the consistency ratio (CR),which is calculated as the ratio of the (CI) and the random index (RI), as indicated in equation (2).

$$CR = \frac{CI}{RI} \qquad (2)$$

The average random consistency index (RI) is calculated from a randomly generated reciprocal matrices sample using scales 1/9, 1/8, 8, and 9 (Table 2).

This suggests that the computed weights for each factor are deemed acceptable weighted linear sum procedure as shown in equation (3)

Table 1 : Scale of preference between two parameters in AHP (Saaty, 1977).

Preference factor	Degree of preference	explanation
1	Equally	Two factors contribute equally to the objective
3	Moderately	Experience and judgment slightly to moderately favor one factor over another
5	Strongly	Experience and judgment strongly or essentially favor one factor over another
7	Very strongly	A factor is strongly favored over another and its dominance is showed in practice
9	Extremely	The evidence of favoring one factor over another is of the highest degree possible of an affirmation
2,4,6,8	intermediate	Used to represent compromises

Table 2 Random Consistency Index (RI) (Saaty, 2000).

N (number of factors)	1	2	3	4	5	6	7	8	9	10
Random Consistency Index (RI)	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

$$LSI = \sum_{j=1}^{n} W_j w_{ij} \qquad (3)$$

Where: Wj = weight value for parameter j; Wij = rating value or weight value of class I in parameter j; n = number of parameters. Landslide Susceptibility Index (LSI) values were classified into five categories: very low, low, moderate, high, and very high susceptibility.

The Weighted Linear Combination(WLC) method was employed to create the landslide susceptibility map, a widely used decision rule, particularly in GIS applications .

4. Results and Discussion

In this study, a GIS-based Analytic Hierarchy Process(AHP) was employed as a robust and comprehensive approach to assess the potentiel occurrence of landslides in the Sahel region of Algiers. Ten critical factors, known as landslide conditioning factors, wer carefuly selected for the susceptibility analysis. These factors include slope degree, distance to drainage, distance tofaults, precipitations, cohesion, internal friction angle, water content, elevation, landuse and lithology. Expert judgment, based on field observations and spatial analysis of each parameter, was Integrated to enhance the accuracy of the evaluation.

The relative importance of each factor was determined by constructing a pairwise comparison matrix, following Saaty's methodology (2001), as shown in Table 3.

Table 3: Pairwise Comparison Matrix, Factor Weights, and Consistency Ratio of Landslide Influencing Factors

	(S)	(L)	(P)	(LU)	(Dd)	(Df)	(E)	(C)	(F)	(W)	Weightage
slope (S)	1	3	5	7	7	7	9	9	9	9	0.345
Lithology (L)	0.33	1									0.211
Precipitations (P)	0.2	0.33	1								0.123
Landuse (LU)	0.14	0.2	0.33	1							0.079
Distance	0.14	0.2	0.33	0.33	1						0.065

drainage(Dd)											
Distance to faults (Df)	0.14	0.2	0.33	0.33	0.33	1					0.054
Elevation (E)	0.11	0.14	0.2	0.33	0.33	0.33	1				0.041
Cohesion (C)	0.11	0.14	0.2	0.33	0.33	0.33	0.33	1			0.033
Friction angle (F)	0.11	0.14	0.2	0.33	0.33	0.33	0.33	0.33	1		0.026
Water content (W)	0.11	0.14	0.2	0.33	0.33	0.33	0.33	0.33	0.33	1	0.0194
					λmax	**11.18**					
					CI	**0.132**					
					CR	**0.08**					

The analysis results indicate that the most influential factors affecting landslide susceptibility are those assigned the highest weights. Slope angle holds the highest weight at 0.345, underscoring its critical role in increasing gravitational instability. Steeper slopes are significantly more prone to failure. Lithology, with a weight of 0.211, ranks as the second most importante factor, as it governs the physical and mechanical behavior of the underlying geological materials. Weak or highly weathered formations, such as, clays and marls prevalent in the study area, are particulary susceptible to instability, especially when saturated by rainfall. Precipitation, with a weight of 0.123, further contributes to this susceptibility by enhancing pore water pressure and reducing soil shear strength. Precipitation plays a crucial role in reducing soil cohesion, thereby intensifying the risk of landslides. In the Algiers region, steep slopes composed predominanly of clayey and marly formations materials highly sensitive to water, contribute significantly to the frequency of landslide events . Moderate impact factors, such as land use (weight of 0.079), reflect the growing influence of urban expansion, which alters natural drainage patterns and further affects slope stability. Construction on unstable slopes, particularly in areas like Daly Brahim and Ouled Fayet, exacerbates landslide risk, while deforestation deriven by infrastructure development reduces the natural stability provided by vegetation. Distance to drainage (weight: 0.065), and distance to faults,

(weight:0.054) also emerge as a moderate contributors, particulary when combined with other destabilzing factors such as steep terrain or weak lithology. Minor factors like elevation with a weight of 0.041, influence susceptibility indirectly by affecting precipitation patterns and erosion processes. Geotechnical parameters, such as cohesion (weight: 0.033), friction angle (weight: 0.026), and water content (weight: 0.0194), exert a more localized influence, though their impact becomes critical under specific conditions. For example, in clayey rich, low cohesion coupled with a low friction angle significantly increases landslide susceptibility. Although water content, carries a relatively low weight, it remains a crucial factor during intense rainfall or in areas affected by infrastructure failures, such as leaking pipelines an issue frequently encountoured in Algiers. These factors collectively undermine soil stability and amplify landslide risks. The calculated Consistency Ratio (CR) of 0.088 confirms an satisfactory level of consistency in the AHP model, validating the reliability of the derived factor weights.

The susceptibility levels were categorized into five distinct zones: very low, low, moderate, high, and very high. As shown in Table 4, the moderate susceptibility zone is the most widespread in the Sahel region, covering 40.49% of the total area. This is followed by the high susceptibility zone, which accounts for 35.42%. The low susceptibility zone represents 29.58%, while the very high susceptibility zone covers 23.29% (equivalent to 12.33 km²).

Finally, the very low susceptibility zone represents the smallest portion of the study area, According to the susceptibility map (Fig. 5), areas with high vulnerability are primarely concentrated in the north and southestern parts of the study area, particularly along valleys withinhe 280 meters of the drainage network. Notably, regions such as Daly Brahim, Ouled fayet and el Achour regions exhibit elevated susceptibility due to their steep slopes (exceeding 30°), which promote both erosion and landslide activity. In contrast, the western parts of the study area display susceptibility levels ranging from very low to moderate, where precipitation often serves as the main triggering factor for landslides.

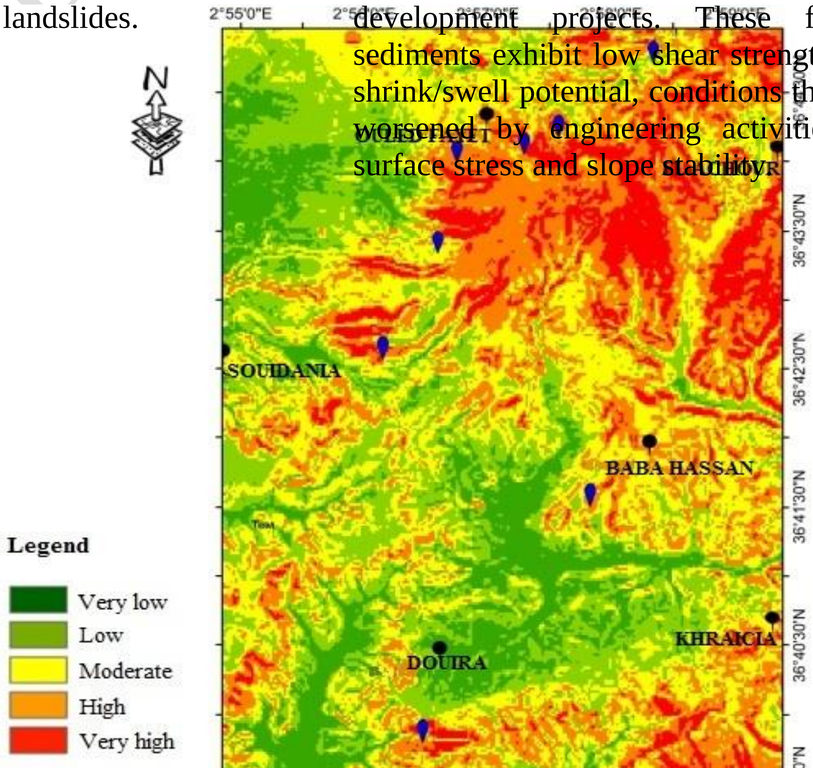
covering only 11.70% of the total surface. These results reveal that over three-quarters of the

Classe Susceptibility	Area (%)
Very low	11.7
Low	29.55
Moderate	40.49
High	35.42
Very high	23.29
Total	100.00

region (75.91%) lie within the moderate to high susceptibility zones, underscoring a substantial vulnerability to potential landslide. In contraste, zones with very low susceptibility are limited, indicating that stable terrain are restricted to a relatively samell portion of the area

Table 4: Susceptibility map classes Areas

The landslide susceptibility map reveals that clay-rich formations on steep slopes are particulary prone by to landslides. Outcropping units dominated by marls and clays have often been deforested and heavily affected by urban development projects. These fine grained sediments exhibit low shear strength and a high shrink/swell potential, conditions that are further worsened by engineering activities that alter surface stress and slope stability



Rock deposits and sandstones, known for their high mechanical strength, generally exhibit low susceptibility to landslide. However, they may become moderately involved when forming an inclined substratum beneath overlaying clayey or marly layers. In such cases, the instability of the upper layers can propagate downward, increasing overall landslide risk. Key contributing factors in the study area include slope, lithology,and cohesion, followed by distance to drainage, elevation, and landuse. Nonetheless, less influential preconditioning factors can still act as triggers under specific less conditions (Yong et al., 2022). For example, road excavations, additional construction on unstable slopes, or the accumulation of temporary surface water can initiate or accelerate landslide events.

In most cases, precipitation is the primary triggering factor for landslides in the study area. Its influence is indirectly related to lithology and elevation (Leonardo et al., 2022), Roads and fault lines are also recognized as significant contributors to landslide occurrence. The inclusion of these parameters improved the accuracy of the model. Moreover, several studies have consistently identified slope, lithology, land use, and distance to drainage as the most critical factors in landslide initiation (Liu et al., 2024). To evaluate the accuracy of the generated susceptibility map, the Receiver Operating Characteristic (ROC) curve was applied.

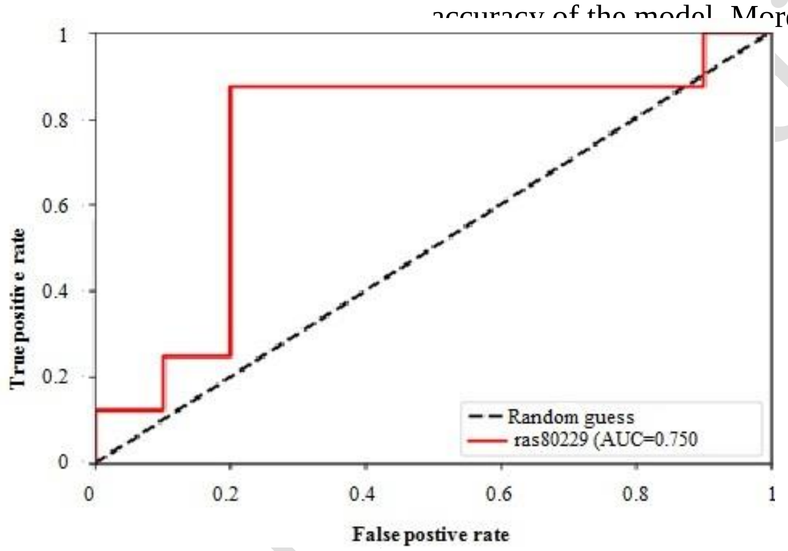


Figure 6. Receiver Operating Characteristic (ROC) curve assessment

The ROC curve is a widely used statistical tool to assess the performance of predictive models. It visually represents the relationship between the true-positive rate (sensitivity) and the false-positive rate (1 - specificity). The Area Under the Curve (AUC) is a key metric derived from the ROC curve, which measures the overall accuracy of the model. The AUC value ranges from 0.5 to 1, where values closer to 1 indicate a strong, reliable model, and values below 0.5 suggest a model that performs no better than random chance. In this study, the predictive maps achieved an AUC of 0.75 (Figure 6), indicating that the model is well-suited for landslide susceptibility mapping and performs effectively in identifying areas at risk.

5. Conclusion

Geological risks related to landslides present a considerable threat to the socio-economic stability of northern Algeria. However, research on landslides in the country remains limited and fragmented. Most studies have concentrated on the northeastern regions, leaving a gap in understanding landslide dynamics in other parts of the country. This study highlights that central Algeria is also significantly affected by slope movements, a region that has been largely overlooked in terms of foundational research, maps, and documentation. This lack of comprehensive data hinders the identification of landslide-prone areas and the development of effective mitigation strategies.

This article presents landslide susceptibility maps for the Sahel region of Algiers, located in northern Algeria. The Analytic Hierarchy Process (AHP) was used to analyze the relationship between landslide spatial distribution and predisposing factors. The susceptibility map, created by combining 10 parameters, demonstrated strong performance with an Area Under the Curve (AUC) value of 0.75, which is considered satisfactory. However, challenges remain in obtaining accurate data and selecting independent variables for analysis, particularly those believed to be causally linked to landslide occurrences.

The AHP methodology applied in this study operates within a rating-based framework, which is informed by expert opinions. While expert insights are invaluable, they introduce a degree of subjectivity. Variations in expertise and perspectives among experts can lead to differing opinions, potentially affecting the objectivity of the results and introducing uncertainty into the analysis. It is crucial to recognize that the reliability of the findings is closely tied to the quality of the landslide location data, particularly the landslide inventory map.

The findings from this research will play a crucial role in the development of new regulations for land protection, infrastructure, and land management. These results will be valuable for local administrations, decision-makers, and planners, particularly when utilizing advanced AHP and GIS techniques to guide effective planning and decision-making processes.

6. Nomenclature.

RI:	Random Consistency index.
LSI:	Linear weight sum
CR	Consistency ratio
CI	Consistency index
λ_{max}	Eigen value
Wj:	weight value for parameter j
AUC:	Air under curve.
AHP	Analytic Hierarchy Process

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