

High-Resolution Landslide Susceptibility Assessment along a Mountain Road Corridor in Carbonate Terrains Using Handheld SLAM LiDAR and GIS-Based AHP: Northeastern Iraq

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Abstract

Corridor landslides in road networks as well as rock slope instabilities on mountains roads represent hazards for transport systems in many areas, especially in karst terrains where slope behavior depends on discontinuities, bedding structure, and stress changes due to the removal of material during excavation. Slope instabilities on roads cuts occur often in northeast Iraq; nevertheless, their corridor vulnerability assessment is still limited due to the absence of topographic datasets for steep slopes. The present research has developed a methodology for evaluation of landslide risk along the Dokan-Topzawa road route (1.8 km) employing portable handheld Simultaneous Localization and Mapping (SLAM) Light Detection and Ranging (LiDAR) system coupled with Analytical Hierarchy Process (AHP) analysis utilizing GIS. LiDAR data (~ 400 million point cloud) have been processed to construct the Digital Elevation Model (DEM) from which nine conditioning factors related to geomorphology, geology, and environment have been extracted. The weight values of the factors have been obtained using AHP technique with an acceptable consistency ratio (CR = 0.02), which further have been combined into Landslide Susceptibility Index (LSI) with a weighted linear combination technique at 10 meter resolution. The resultant susceptibility map categorized the area into four susceptibility categories namely very low, low, moderate and high susceptibility zones. High susceptibility zones comprised 37.4% of the study area whereas zones having moderate and high susceptibility constituted 51.9% of the area. The landslide site investigations revealed that observed sites of landslides were situated in zones of moderate to high susceptibility. Profile interpretation through LiDAR and site investigations confirmed that factors influencing slope instability were mainly fractured limestone, unfavorable beddings towards the road, steepness of slope and seepage through discontinuities.

Keywords: Fractured Limestone, Road Cuts, SLAM LiDAR, Slope Instability, Zagros Mountains

1. Introduction

The instability of rock slopes within mountainous road alignments can be identified as a geomorphological threat to the transportation network and community security, especially considering that excavation of road alignments within such environments usually creates intersections between slopes and weak structural discontinuities in the rock mass [1] and [2]. Instability potential usually escalates as a function of both gravitational and hydrological processes since excavations tend to create steeper natural slopes and expose discontinuities [3] and [4]. The most common failure mechanisms in carbonate terrains include

planar sliding, wedge failure, toppling, and rockfall, while slope behavior is largely governed by bedding planes, joint systems, and excavation-induced stress redistribution [5].

Fractured limestone rocks, dating back to the Late Cretaceous period, have often been identified as being responsible for landslides occurring in the cuts made on roads in the Kurdistan Region of Iraq [6]. The landslides that occur along the road network of Dokan are controlled by the bedrock, as well as structural controls [7]. Several studies conducted earlier took into account the problem of landslides as well as slope stability at Dokan and its adjacent areas

located in the Iraqi Zagros region. Thus, there were four cases of landslides associated with road cuts that occurred along the road from Dokan to Surdesh analyzed with the use of stereographic projection and the Landslide Possibility Index [8]. Moreover, rock slope instability in the southwest limb of the Kosret anticline in the vicinity of Dokan was assessed with kinematic analysis of bedding and joints [9]. In terms of a wider scale, namely the Kurdistan Region, a novel automatic approach to detecting landslides by applying QuickBird satellite images and ASTER DEM was developed [10]. Moreover, landslide susceptibility models together with ROC analysis were used for Mawat, NE Iraq [11]. These studies have contributed greatly to our understanding of landslides, structurally induced slope instability, and regional landslide susceptibility in the Iraqi Zagros. However, most of the previous studies have been undertaken at individual slope sites or at a regional scale, employing DEMs of medium resolution and traditional topographic data sets. In contrast, the current study is geared toward corridor-level susceptibility mapping of the Dokan -Topzawa road corridor employing Simultaneous Localization and Mapping (SLAM) handheld LiDAR data. The processed SLAM LiDAR point cloud contained approximately 400 million points, corresponding to a mean point density of approximately 1,180 points/m². This dense dataset enabled detailed representation of steep slopes, narrow road cuts, and discontinuity-controlled cliffs in carbonate rocks, particularly in areas affected by recent road construction.

However, a proper estimation of landslide susceptibility in such settings needs topographic datasets of high resolution to detect near-vertical rock walls, scarping structures controlled by fracturing, and small-scale curvatures [12] and [13]. Conventional DEMs are inadequate for conducting corridor-based investigations because they cannot define the geometrical configuration of restricted road cuts and artificially constructed steep slopes [14]. Geomorphic investigations indicate that poor resolution of spatial analysis results in the concealment of instability-causing features [15].

In terms of recent developments in landslide risk evaluation, there is a growing trend toward the adoption of LiDAR-based DEM data sets, as well as point clouds of a relatively high density [14] and [15]. In addition, LiDAR technologies have been extensively used for the detection of landslide scarps, evaluation of discontinuity-based landslides, and morphometric evaluation of slopes in mountainous areas [16] and [17]. The main advantage of using these types of data is the fact that they retain small-scale topographic features like fracture-based scarps,

tension cracks, and slope breaks. LiDAR sensors using SLAM technology enable the collection of high-density 3D point cloud data in confined spaces. This approach is well suited for assessing landslide susceptibility in difficult terrain, narrow road sections, and steep rock faces where GNSS signal availability might be poor [9] and [18]. According to recent investigations, handheld SLAM LiDAR allows for collecting ultra-high-resolution topographic data in such confined areas as road cuttings, tunnels, and steep mountain slopes covered with forests [19] and [20].

Nevertheless, the application of mobile SLAM LiDAR technology for assessing the susceptibility to landslides within corridors is still relatively unknown, especially in the case of Iraq's Zagros Mountains area, where there are not many landslide inventories or high-resolution terrain datasets available. Thus, combining highly dense terrain information obtained from SLAM with GIS-based landslide susceptibility modeling can be an attractive solution. The study is designed to assess corridor-scale landslide susceptibility using SLAM LiDAR data within a GIS-supported AHP framework. The SLAM LiDAR-derived DEM was used to generate the terrain factors, which were weighted within the AHP framework to calculate the landslide susceptibility index (LSI) along the Dokan–Topzawa corridor.

2. Study Area, Data and Methods

2.1 Study Area

This study focuses on an area covering an approximately 1.8 km long stretch of the road that runs from Dokan to Topzawa, located in the Sulaymaniyah Province of northeastern Iraq. The corridor is shown on the map using the geographic coordinate system (WGS84) and is situated within 44°58'20"E to 44°59'30"E longitude and 35°56'30"N to 35°56'50"N latitude (Figure 1). This study takes into account not only road cuts but also the slopes of natural origin, as the corridor is about 200 m wide on either side of the road. The very uneven topography of the area, with elevation of road cuts more than 70 m above ground level and steep slopes ranging between steep and very steep, favors gravitational instability, particularly in relation to the intersection of the excavation area with unfavorable discontinuities [21] and [22]. From the geological point of view, the corridor area is mainly composed of bedded and fractured limestone from the Kometan Formation with highly developed jointing systems and local interbedded soft clays [23]. This lithology strongly affects slope stability because joints create weak structural planes that facilitate the formation and release of blocks from the slopes [8] and [9].

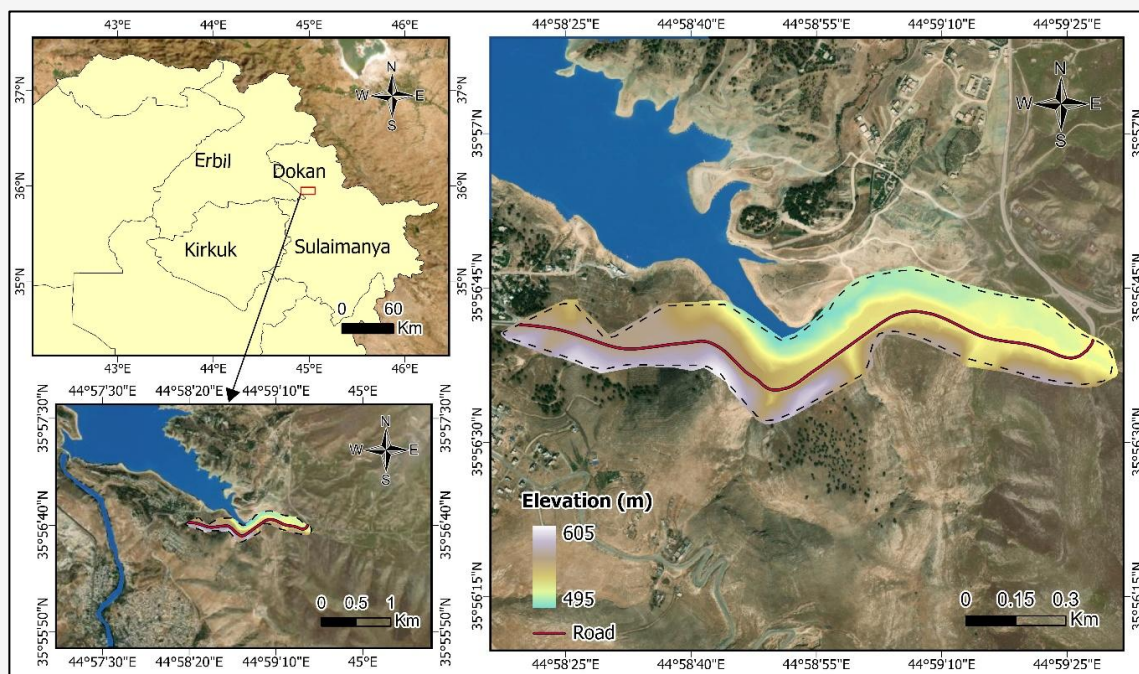


Figure 1: Dokan–Topzawa road corridor, northeastern Iraq

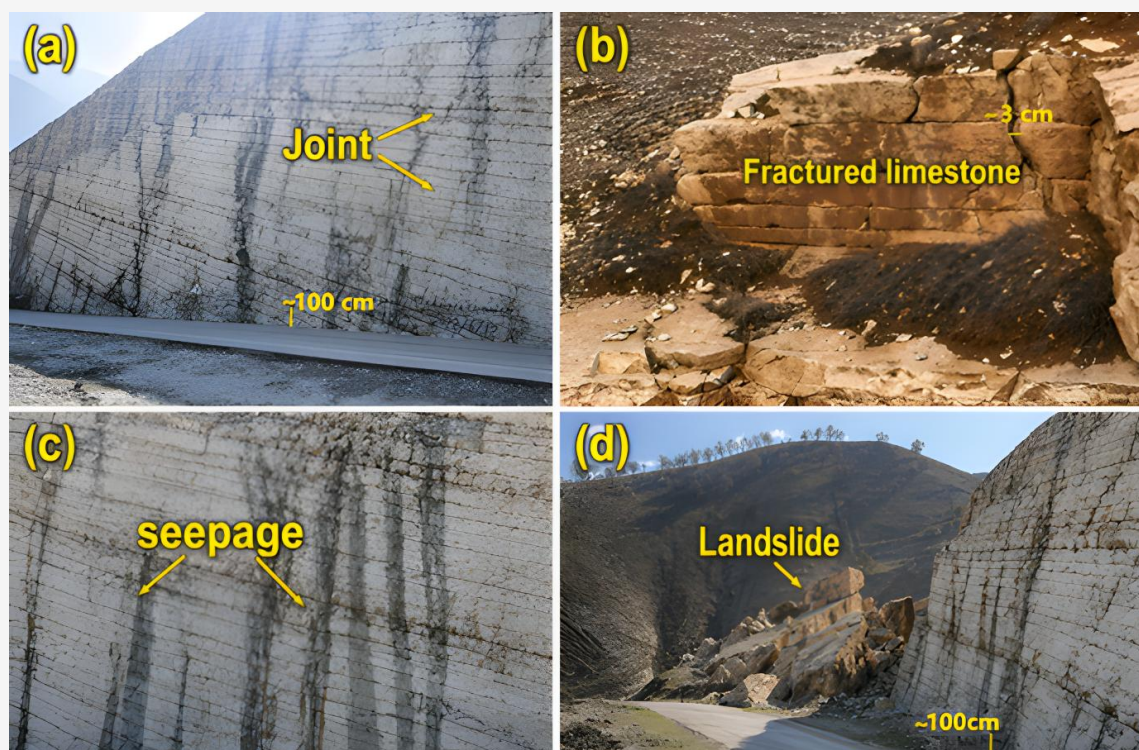


Figure 2: Field observations:

(a) jointed limestone, (b) fractured limestone, (c) seepage, and (d) slope instability

Observations taken in the corridor show the occurrence of open joints, fractured limestone, seepage, and slope instability characteristics as shown in Figure 2(a), 2(b), 2(c) and 2(d). Joints, as

seen in Figure 2(a) and 2(b), are structural discontinuities in bedded limestone that lead to the formation of weak layers in the slope face. The approximate field-scale measurements (~100 cm) in

Figure 2(a) and 2(d) have been included for a better visualization of the dimensions of the exposed rock slopes. Fractured limestone, as shown in Figure 2(b), has an approximate fracture width of (~3 cm). Seepage, as illustrated in Figure 2(c), is due to water moving along the rock discontinuities due to seepage in upslope regions. The displaced rock mass is an example of slope instability related to fractured bedding planes Figure 2(d).

2.2 Overall Workflow

The general approach that was applied during this investigation is shown in Figure 3. It starts with the collection of high-density point cloud data, with a mean density of approximately 1,180 points/m², using a handheld SLAM LiDAR device along the Dokan–Topzawa road corridor. Furthermore, Sentinel-2 remote sensing images are employed to compute normalized Difference Vegetation Index (NDVI). The NDVI values were calculated from Sentinel-2 Band 8 (Near Infrared) and Band 4 (Red) according to [24], using Equation 1:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Equation 1

Where:

NDVI = Normalized Difference Vegetation Index
NIR = Spectral reflectance from Band 8 of Sentinel-2 imagery
RED = Spectral reflectance from Band 4 of Sentinel-2 imagery

The Topographic Position Index (TPI), which is included as a topographic conditioning factor in the workflow, is a measure of the elevation of a grid cell relative to the mean elevation of its neighboring cells; its calculation is described in Section 2.5. The AHP weight-sensitivity analysis and bootstrap validation were performed in Python using the Notebook environment within ArcGIS Pro 3.4.

The LiDAR point cloud underwent registration, noise filtration, and removal of outliers before creating a DEM. The terrain, geology, and environmental conditions for the study area were extracted from the DEM and other available datasets. These parameters were normalized and weighted based on the AHP. After weighing the factors, an integration was performed, and the LSI was computed.

2.3 Handheld SLAM LiDAR Data Acquisition and Processing

The topographic data for the road corridor were obtained using a portable LiDAR device (Stonex SLAM LiDAR) based on a SLAM procedure. Such an approach allows achieving both sensor trajectory and three-dimensional reconstruction without depending on continuous GPS signals [20]. Consequently, this methodology has proved to be very successful in mapping areas with restricted road corridors with steep rocky slopes. The post-processing of the LiDAR point cloud entailed optimization of the sensor trajectory, alignment of all point clouds, filtering of noise, and their further integration into one point cloud using the Stonex SLAM post-processing software and ArcGIS Pro 3.4. The processed point cloud contained approximately 400 million points, corresponding to an average point density of approximately 1,180 points/m². This density enabled accurate representation of artificial road cuts, natural slopes, and fracture-controlled geomorphological features that are not adequately represented by conventional DEM acquisition methods [25]. In the process of field data collection, the STONEX X120GO SLAM LiDAR sensor was hand-carried and operated by a field operator. The operator walked along one side of the road and returned along the opposite side and accessible slope margins, while safe and accessible areas above the slope were surveyed as well. This resulted in overlapping scans of the road surface, downslope topography, and road-cut slopes. Circular loop-closure paths were conducted at intervals of about 100 m in order to reduce longitudinal trajectory drift [26]. As the operator advanced along the corridor, overlapping scans from new viewpoints allowed terrain obscured from earlier positions to be captured. Thus, the upper-slope terrain shown in Figures 5(b)–5(e) was captured from multiple viewpoints and incorporated into the merged point cloud. The SLAM LiDAR dataset provided sufficient positional accuracy for slope-scale geomorphological analysis. Absolute georeferencing of the point cloud was performed using ground control points (GCPs), rather than the internal GNSS receiver of the X120GO. Seven GCPs located along the survey corridor were measured independently with a Leica Viva GS15 differential GNSS receiver, and their X, Y, and Z coordinates were recorded in the WGS 1984 UTM Zone 38N coordinate system. Corresponding points were manually identified within the SLAM point cloud. Initially, four points were used to transform the point cloud into the GNSS coordinate system, whereas the remaining three points were temporarily withheld for an independent geometric check.

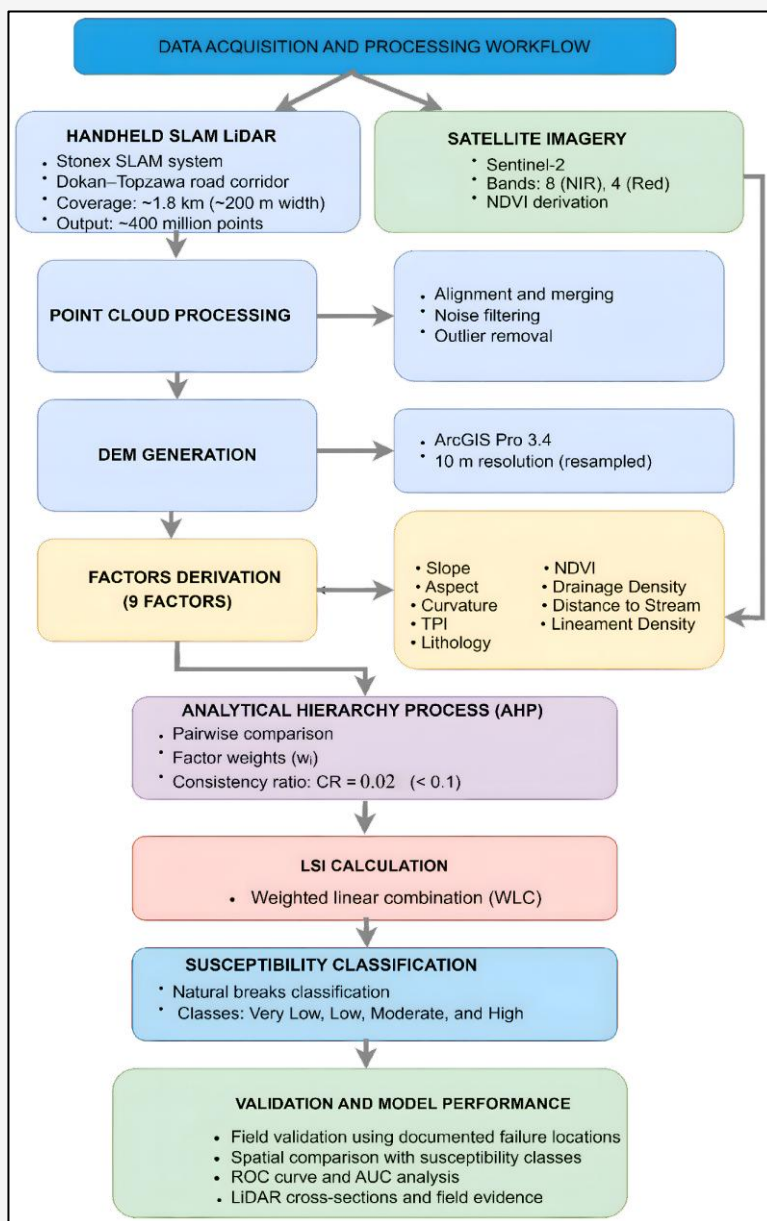


Figure 3: Landslide susceptibility assessment workflow

The 3D inter-point distances forming the triangle among the three check points were compared between the GNSS measurements and the transformed LiDAR point cloud, resulting in an average discrepancy of approximately 2 cm. Following this verification, all seven points were incorporated into the final georeferencing adjustment. This distance discrepancy was negligible relative to the 10 m working resolution used in the susceptibility analysis [27].

2.4 DEM Generation and Working Resolution

The digital elevation model (DEM) was generated from the post-processed handheld LiDAR point

cloud. For landslide susceptibility modeling, the DEM was resampled to a 10×10 m working grid. This resolution provided stable terrain-derivative calculations while maintaining spatial consistency among all conditioning factors used in the model. Although handheld LiDAR provided a sub-meter level detail on terrain representation, slope, aspect, and curvature derivatives were prone to being sensitive to micro-topography and noise in case of their calculation using too fine a resolution (e.g., 1×1 m). For that reason, a 10×10 m working resolution was used to decrease the impact of micro-topography and obtain geomorphologically significant derivative maps [27][28] and [29]. Additionally, a 10 m

resolution ensured consistency in data processing between Sentinel-2-derived NDVI raster images obtained from satellite imagery collected in April 2024 to provide clearer representation of surface conditions [30].

2.5 Landslide Conditioning Factors and Factor Derivation

The conditioning factors that were used for topography included slope gradient, slope aspect, profile curvature, and the Topographic Position Index (TPI). The selection of such factors was intended to reflect slope geometry, relative relief, and surface curvature concerning gravitational processes [28]. The slope gradient is regarded as one of the main factors causing landslides, especially those occurring in road-cuttings, whereas profile curvature and TPI help identify areas of material concentration and dispersal. For hydrological conditioning factors, drainage density and distance to streams were used as they indicated surface water runoff concentration and the possibility of water infiltration into the ground. Such conditioning factors are especially important for fractured limestone terrains, as the infiltration process along fractures could affect slope stability in hydro-mechanical processes [3].

For structural and geological conditioning factors, lithology and lineament density were considered. Lineament density characterized discontinuity density, while lithology distinguished between intact and fractured limestone. These conditioning factors are significant for slope dynamics along road sections [31] and [32]. Lineaments were manually identified using the LiDAR-generated DEMs with enhanced hillshading effect, complemented by the use of high-resolution imagery from Google Earth [16]. Hillshade rendering was employed to highlight topographic breaks, trace fracture lines, and linear geomorphic structures related to geological discontinuities. The identified lineaments were then digitized as polylines in ArcGIS Pro 3.4 and converted to a raster of lineament density through spatial density analysis, as commonly used in geomorphology [17] and [28]. Four categories of lithologic units were distinguished based on the type of rock, fracturing intensity, weathering traits, and field observations, namely unfractured limestone, moderately fractured limestone, highly fractured limestone, and limestone with clay interbeds.

Vegetation coverage was quantified based on the NDVI layer acquired from Sentinel-2 satellite images, computed through Equation 1. The topography-related parameters, such as slope, aspect,

and profile curvature, were created using the LiDAR DEM through typical geographic information system (GIS) techniques commonly used for landslide susceptibility mapping [28]. The TPI of each grid cell was calculated according to [33], considering its elevation relative to neighboring cells, using Equation 2:

$$TPI = z_0 - \bar{z}_n$$

Equation 2

Where:

z_0 = Elevation of the target cell

$\bar{z}_n$ = Mean elevation of the neighboring cells

The role of surface water was determined through drainage density, which was calculated according to [34], using Equation 3:

$$D_d = \frac{\sum L_s}{A}$$

Equation 3

Where:

$\sum L_s$ = Total length of streams

A = Corresponding basin area

The drainage density represents runoff intensity and areas likely to receive groundwater recharged due to slope instability [34].

2.6 Factor Standardization and Classification Thresholds

For evaluating the importance of the conditioning factors, the pairwise comparison matrix applied a simple scale of AHP importance from 1 to 5 [35]. After weighting, the conditioning factor maps were converted to a set of susceptibility influences from very low [1] to very high [9]. The continuous factors, such as the slope, profile curvature, TPI, NDVI, drainage density, distance to stream, and lineament density, were resampled into new values following the Natural Breaks (Jenks) classification method [36][37] and [38]. However, directional and categorical factors such as aspect and lithology were classified based on their engineering-geological importance, literature findings, and fieldwork knowledge. Greater susceptibility values were provided to those factors that create better environmental conditions for slope failure, especially fractured carbonate rocks and structural discontinuities [17] [39] and [40].

Slope-class ratings were not assumed to be directly proportional to slope angle. The 30–60° slope class was assigned the highest rating (9) based on the field observations and the occurrence of unstable road-cut slopes within this range. In contrast, a slightly lower rating (7) was assigned to the 60–75° slope class because some near-vertical limestone slopes, including cross-section b–b', remained stable where slope and discontinuity orientations were not kinematically favorable for sliding.

The thresholds and susceptibility grades for each variable have been included in Appendix A (Table A1). The chosen landslide conditioning variables and the respective data sources and units of measure have been summarized in Table 1.

2.7 Analytical Hierarchy Process

The AHP method was used for establishing the weights of the landslide controlling factors based on pairwise comparisons [41]. This method involves comparing one factor with all others to determine how important the factor is in relation to slope failure control. For ease of analysis and to minimize subjective judgment in evaluating the factors, a simplified AHP ranking scale of 1 to 5 was used in this study. The complete pairwise comparison table and associated weights of each factor can be found in Table 2. The consistency ratio (CR) of the pairwise comparisons were determined according to [41], using Equation 4:

$$CR = \frac{CI}{RI}$$

Equation 4

Where:

CI = Consistency index

RI = Random index

The value of the consistency ratio calculated for the final 9-factor comparison matrix was found to be 0.02, which is less than the accepted threshold of 0.10 recommended. The pairwise comparisons were

developed in line with the traditional AHP procedure, based on field observations, geomorphic knowledge of the slope instability processes, and lessons learnt from existing landslide susceptibility studies. Relatively higher importance was attributed to factors such as slope, lithology, and structural characteristics (lineament density), owing to the fact that the main reason behind slope instability along the study corridor is the occurrence of steeply dissected fractured carbonate slopes. This is evident from the results of morphometric-based studies [42]. Slope has been assigned the highest weight, followed by lithology and lineament density. Other factors, including hydrological and environmental characteristics, have been assigned moderate weights, while terrain features have been assigned relatively lesser weights.

2.8 Landslide Susceptibility Index and Classification

The LSI is calculated using the method of weighted linear combinations, where the relative importance of each conditioning factor to the instability of the slopes can be taken into account when computing the susceptibility of using Equation 5.

$$LSI = \sum_{i=1}^n w_i r_i$$

Equation 5

Where:

w_i = Weight assigned to the *i*-th conditioning factor using AHP

r_i = Rating value of the *i*-th conditioning factor
 $i = 1, 2, 3, \dots, n$ (number of conditioning factors)

This equation takes into consideration the importance of different conditioning factors to generate one susceptibility index value [43]. The weighted overlay model has been run in ArcGIS Raster Calculator with the use of standardized factor rasters and their AHP weightings.

Table 1: Selected landslide conditioning factors, their data sources, and corresponding units used in the susceptibility analysis

No.	Conditioning factor	Data source	Unit
1	Slope	LiDAR-derived DEM	Degree (°)
2	Lithology	Literature review and field observations	Categorical
3	Lineament density	LiDAR-derived DEM and remote sensing interpretation	km/km ²
4	Drainage density	Streams derived from LiDAR DEM	km/km ²
5	NDVI	Sentinel-2 imagery	Unitless
6	Distance to Stream	Streams derived from LiDAR DEM	Meters (m)
7	Topographic Position Index (TPI)	LiDAR-derived DEM	Unitless
8	Profile curvature	LiDAR-derived DEM	1/m
9	Aspect	LiDAR-derived DEM	Degree (°)

Table 2: AHP pairwise comparison matrix and normalized weights

Factor	Slope	Lithology	Lineament Density	Drainage Density	NDVI	Distance to Stream	TPI	Profile curvature	Aspect	Weight
Slope	1	2	2	3	4	4	4	5	5	0.28
Lithology	0.5	1	1	2	2	2	3	3	3	0.16
Lineament Density	0.5	1	1	1	1	2	2	2	2	0.12
Drainage Density	0.333	0.5	1	1	1	1	1	2	2	0.09
NDVI	0.25	0.5	0.5	1	1	1	2	2	2	0.09
Distance to Stream	0.25	0.5	1	1	1	1	1	1	1	0.08
TPI	0.25	0.333	0.5	1	1	0.5	1	1	1	0.06
Profile curvature	0.2	0.333	0.5	0.5	1	0.5	1	1	2	0.06
Aspect	0.2	0.333	0.5	0.5	1	0.5	1	0.5	1	0.05

The obtained continuous LSI raster has then been classified into four classes based on the Natural Breaks (Jenks) classification approach, which maximizes the difference between adjacent intervals [36]. Finally, the resultant map included zones of very low, low, moderate, and high susceptibility. The obtained LSI values have been interpreted in terms of relative landslide susceptibility and not in probabilistic terms of an expected landslide event.

2.9 AHP Weight-Sensitivity Analysis

OAT sensitivity analysis was used to measure the effects of variations in factor weights on the LSI outputs. Each of the nine factors were independently varied by -20% , -10% , $+10\%$, and $+20\%$. This produced a total of 36 scenarios. In each scenario, the other eight factor weights were proportionally rescaled to ensure that their total sum remained 1.0. RMSE, the Pearson correlation coefficient, and the maximum percentage of cells that changed susceptibility class were calculated relative to the baseline model in Python for each scenario. The original susceptibility-class boundaries (3.90, 4.80, and 5.20) were kept fixed across all scenarios. Factor-level results are shown in Appendix B (Table B1).

2.10 Validation Using Field Inventory and ROC-AUC Analysis

Model validation involved the use of field inventory observations along with the Receiver Operating Characteristic (ROC) analysis and its accompanying measure of Area Under the Curve (AUC). These methods are frequently utilized in evaluating landslide susceptibility [43] and [44]. Altogether, there were 43 validation points in the study corridor, categorized into two classes: relatively stable points (Class 0) and relatively unstable or unstable points (Class 1). Unstable points referred to those that fell within or close to the documented locations of

landslides, while relatively stable points indicated otherwise. The ROC curve was plotted based on a comparison between the binary classification of points and LSI values from the landslide susceptibility map. The AUC value obtained was used as a measure of validation [43]. The uncertainty in the AUC was evaluated through a stratified percentile bootstrap approach using 10,000 iterations in Python. The observations in each category were sampled separately with replacement so that the original numbers of stable (32) and unstable (11) observations were retained in each iteration. The 2.5th and 97.5th percentiles of the bootstrapped AUC distribution were used to determine the 95% confidence interval.

3. Results

3.1 Conditioning Factor Maps

Spatial representation of the nine conditioning factors employed for the landslide susceptibility assessment is provided in Figure 4. These factors include slope, lithology, lineament, NDVI, drainage density, distance from the stream, TPI, profile curvature, and aspect. The slope map Figure 4(a) depicts that areas with steep slopes are mainly confined to the road-cut zones and valley side slopes, with occasional presence of nearly vertical slopes along the limestone outcrops. The lithology map Figure 4(b) reveals that moderately to highly fractured limestones dominate the majority of the area, while clay-bearing interbeds exist in some portions. The lineament map Figure 4(c) shows the location of structural discontinuity and fracture zones throughout the corridor. The lineament density index was then computed from this layer and employed as one of the conditioning factors in the susceptibility assessment [45] and [46]. This is characterized by relatively high values along the middle and eastern parts of the corridor.

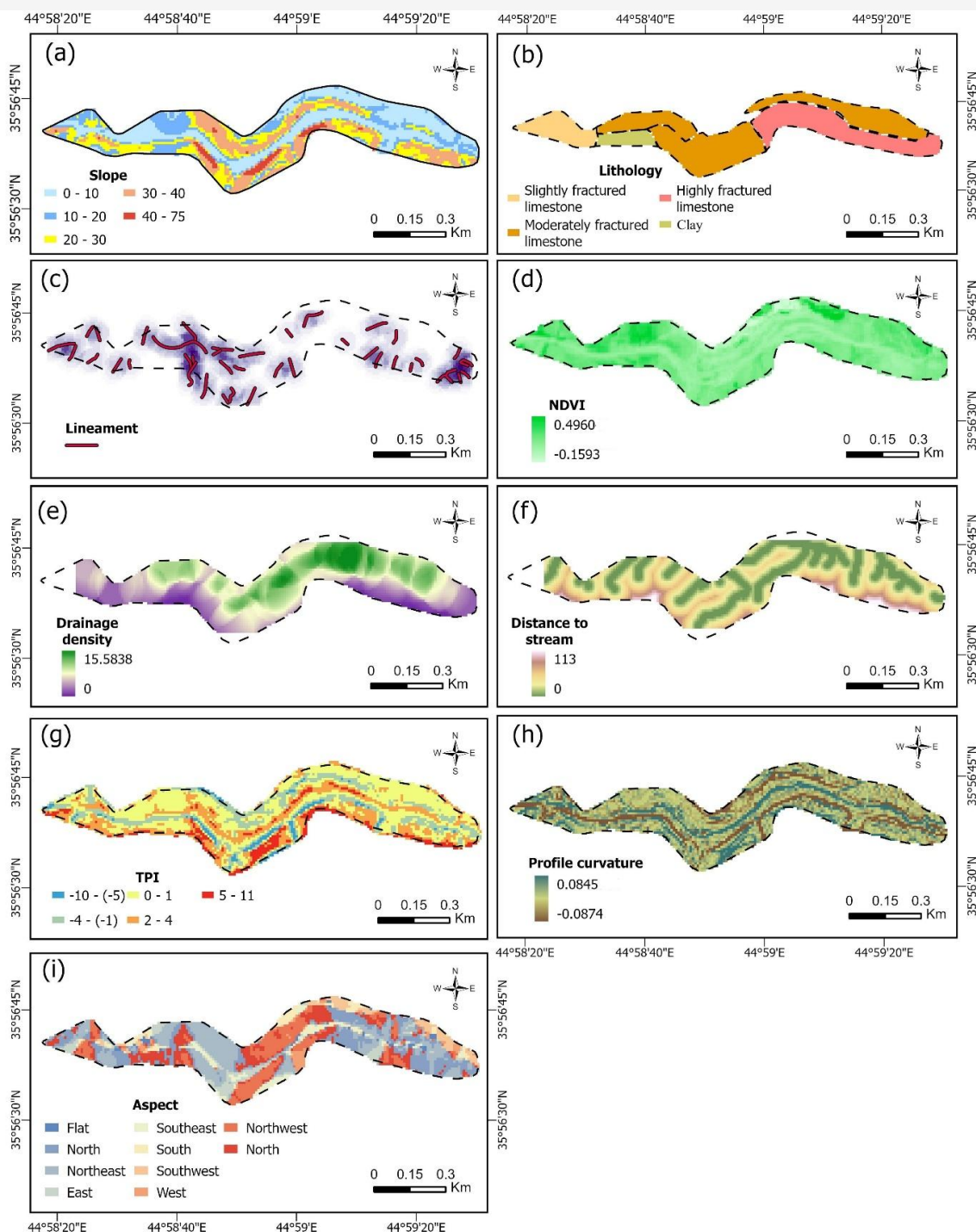


Figure 4: Landslide conditioning factor maps: (a) slope, (b) lithology, (c) lineament density, (d) NDVI, (e) drainage density, (f) distance to streams, (g) TPI, (h) profile curvature, and (i) aspect

The NDVI values Figure 4(d) have a range of around -0.159 to 0.496 , signifying the existence of sparse to moderately dense vegetation in relation to the exposed rocky environment. Conditioning factors for hydrology, such as drainage density and distance to stream Figure 4(e) and (f), demonstrate spatial

differences within the corridor. The range of values for drainage density lies between 0 and about 15.58, with high values being found in areas with dissection slopes and localized convergence areas for streams. Distance to stream varies between 0 and about 113 meters. Terrain variables like TPI and profile

curvature Figure 4(g) and 4(h) vary significantly throughout the corridor, as the area consists of ridges, valleys, convex slopes, and concave slopes alternately. TPI varies from -10 to 11, while profile curvature values fall between approximately -0.087 and 0.084. The aspect map Figure 4(i) indicates dominance of north and northeast aspects for the majority of the corridor, whereas there is a change towards north-western aspects in accordance with the curvature of the road alignment.

3.2 Cross-Section Analysis

Further analysis of the slope morphology was achieved by generating five characteristic cross-sections derived using the LiDAR-derived DEM Figure 5(a), 5(b), 5(c), 5(d), and 5(e). The selected cross-sections traverse the upper part of the slope, the road bench, and the downslope sections. Some of their main features have been outlined in Table 3. Sections a-a' and b-b' (Figure 5(a) and 5(b)) can be considered to represent stable slopes. Section a-a' (Figure 5(a)) presents a fairly uniform slope profile with the upper gradient value of approximately 36%, which becomes progressively smaller to the bottom

at around 20%. Section b-b' (Figure 5(b)) represents the slope profile with changing geometry without any traces of slope disturbances; the upper gradient values reached approximately 220% (approximately 65° slope angle).

On the other hand, sections c-c', d-d', and e-e' (Figure 5(c), 5(d), and 5(e)) are characterized by an irregular geomorphology. Section c-c' (Figure 5(c)) depicts an area affected by landslides located above the road, with gradients ranging from 44% at the upper part to approximately 54% at the lower section. Section d-d' (Figure 5(d)) is represented by an extremely steep upper part above the road and a lower part ranging from 92% that forms a scarp-like head zone. Section e-e' (Figure 5(e)) demonstrates an extremely steep slope, with an upper gradient of about 50% and a lower part of 66%. Generally, the unstable slope sections are characterized by irregular slope geometries, slope breaks, and a steeper lower slope section, while stable sections are depicted by smooth and continuous profile features. The unstable slope sections c-c', d-d', and e-e' are represented by areas of medium-high susceptibility depicted in Figure 6.

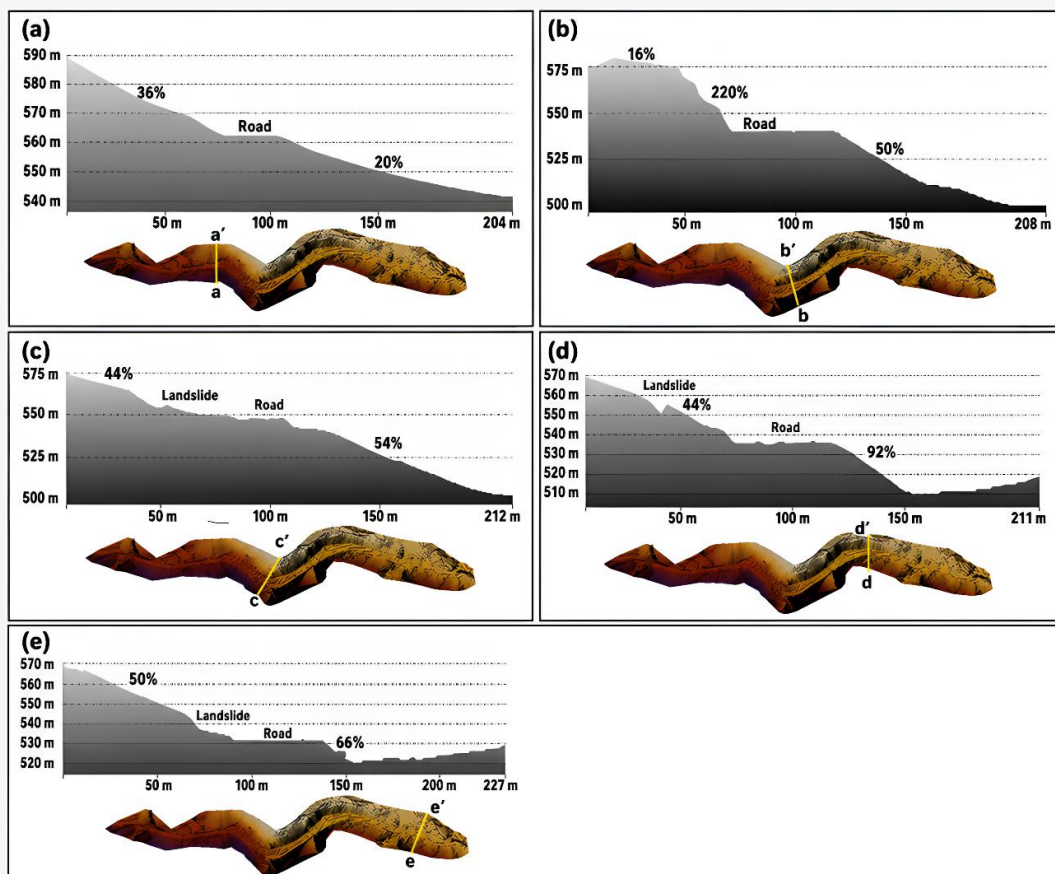
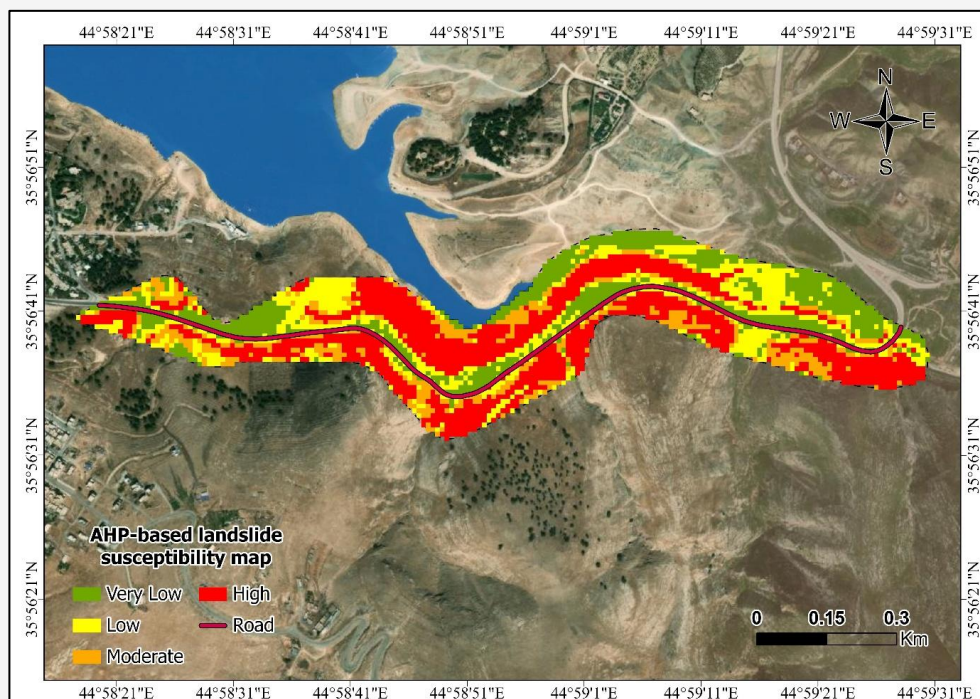


Figure 5: LiDAR-derived cross-sectional profiles along the study corridor (a) section a-a', (b) section b-b' (c) section c-c', (d) section d-d', and (e) section e-e'

Table 3: Characteristics of LiDAR-derived cross-sections (a–a' to e–e') along the study corridor

Section	Profile length (m)	Upper slope gradient (%)	Lower slope gradient (%)	Stability condition	Geomorphic observation
a–a'	~204	~36	~20	Stable	Smooth, continuous slope
b–b'	~208	~220	~50	Stable	Continuous profile without landslide evidence
c–c'	~212	~44	~54	Unstable	Landslide-affected zone above the road
d–d'	~211	~44	~92	Unstable	Scarp-like head zone (landslide)
e–e'	~227	~50	~66	Unstable	Structurally controlled landslide

**Figure 6:** AHP-based landslide susceptibility map of the study corridor

3.3 Landslide Susceptibility Zonation

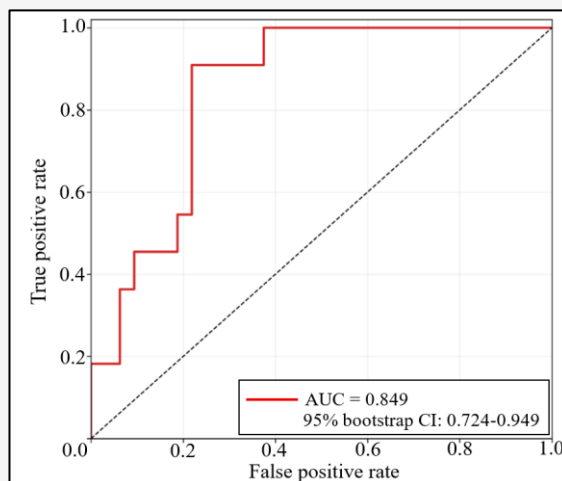
Landslide Susceptibility Map (Figure 6) obtained through the use of the LSI, an index based on AHP, indicates the distribution of landslide susceptibility within the study corridor. Using the LSI ratings determined for each pixel within the corridor, the study corridor was categorized into four different classes of susceptibility: very low, low, moderate, and high susceptibility. High susceptibility zones have been observed to occur mostly along road cuttings and fractured limestone outcrops, especially in places where unfavorable structures intersect drainage lines (Table 4). Statistically, the largest percentage (37.4%) of the corridor belongs to the high susceptibility category, followed by the very low (25.7%), low (22.4%), and moderate (14.5%) susceptibility categories. Landslides that have occurred within the area occur within moderate to high susceptibility zones.

3.4 AHP Weight-Sensitivity Results

The OAT analysis demonstrated that the model remained stable across the 36 weight-variation scenarios. Under the $\pm 10\%$ variations, Pearson correlation coefficients remained at or above 0.9985, while the maximum class change was 7.37%. The high-susceptibility proportion ranged from 35.41% to 39.99%, remaining close to the 37.4% reported for the baseline susceptibility map. Under the more conservative $\pm 20\%$ variations, the minimum Pearson correlation was 0.9929, the maximum class change reached 15.75%, and the high-susceptibility proportion ranged from 32.89% to 42.81%. The greatest response occurred when the slope weight was reduced by 20%, whereas TPI produced the lowest maximum class change (1.87%). Factor-level results are presented in Appendix B (Table B1).

Table 4: Area and percentage distribution of landslide susceptibility classes

Susceptibility Class	LSI Range	Area (m ²)	Percentage (%)
Very Low	1.78 – 3.90	86,700	25.7
Low	3.90 – 4.80	75,800	22.4
Moderate	4.80 – 5.20	49,100	14.5
High	5.20 – 6.90	126,200	37.4
Total	—	337,800	100

**Figure 7:** Receiver Operating Characteristic (ROC) curve used to validate the AHP-based landslide susceptibility model (AUC = 0.849; 95% bootstrap CI: 0.724–0.949)

3.5 Model Validation Results

Figure 7 shows the ROC curve and the area under the ROC curve (AUC). The AUC for the model was 0.849 (95% bootstrap CI: 0.724–0.949), indicating good discrimination between stable and unstable validation points [44] and [47]. Despite the high AUC, the relatively wide confidence interval reflects uncertainty associated with the limited validation sample.

4. Discussion

As observed from the susceptibility patterns across the study corridor, slope morphology, fractured limestone lithology, and structural discontinuity appear to be the key determinants of slope instability as observed in the case of fractured carbonate rocks [48] and [49]. Specifically, slopes that feature road cuts at high angles of intersection with unfavorably oriented bedding planes and joints reduce the stability of rock masses, an instability mode that has been observed before in limestone rock slope hazards [21] and [22]. With the use of LiDAR using the SLAM technique, it was possible to achieve a very detailed terrain mapping of nearly vertical slopes and discontinuity-driven micro-terrain features that are not commonly obtained from DEMs. This allows the analysis of slope breakages and structurally controlled features in a more precise manner compared to conventional DEM analysis [50].

The cross-sections obtained through this technique reveal directly the slope failure mechanisms in areas where there are steep road cuts and nearly vertical slopes. This is aligned with current advances in landslide investigation methods, in which the significance of obtaining highly detailed three-dimensional measurements to analyze failure geometries of rock slopes [51] and [52]. The characteristics revealed by the cross-sections further substantiate the susceptibility assessment since unstable areas present irregular geometry and steeper slopes than stable ones.

The highly refined topography extracted from the LiDAR survey, on the other hand, forms the basis for better susceptibility modeling due to its accuracy in depicting terrain conditions, which is important for mapping landslide-prone areas within narrow road corridors [20] and [27]. In addition, the application of the AHP-LSI model proved to be efficient as a screening technique for detecting landslide-prone areas within linear transport corridors. The total percentage area occupied by the moderately and highly susceptible zones (51.9%) is similar to previous AHP-based results conducted in the carbonate mountainous regions of the wider Zagros area, where highly susceptible areas usually occupy between 40% to 60% of the investigated transport corridor or watershed areas [12] and [53]. This may be an indication of the similarity of geological and

geomorphological characteristics of the entire Zagros region. Such a trend has also been reported in recent corridor-scale and transportation-specific landslide studies [7] and [14].

In particular, this method will be useful in areas where detailed landslide inventories have not been established since it facilitates the identification of the relative hazard characteristics in a corridor system [38][43] and [54]. Noting that moderate and highly susceptible zones constitute about 51.9% of the corridor, the presence of all observed failures in both categories shows spatial agreement between the observed failures and the susceptibility classification [43]. It is also important to highlight that the study corridor includes all three known landslides in the area, making up all the verified landslides recorded along the 1.8 km studied corridor. This does not permit statistical validation using a large sample, but it demonstrates spatial agreement between all verified landslide locations and the areas classified as having moderate or high susceptibility. Thus, no verified landslide occurred outside these two categories. This type of analysis provides preliminary spatial validation in narrow corridor studies where the number of documented landslides is naturally limited [43]. The method used is typical of other vulnerability assessments in the corridors under complex structural conditions of mountain areas, which also employ a limited number of landslides for validation. In particular, road corridor vulnerability can be validated using some known cases of road failures, which provide spatial correspondence between actual road failures and highly vulnerable areas as a preliminary validation approach for linear infrastructural projects [14]. With an AUC value of 0.849, the model can be said to perform well in discriminating between stable and unstable sites [44] and [47]. However, a fairly wide 95% bootstrap confidence interval (0.724–0.949) reflects uncertainty in the estimated model performance. Such uncertainty is likely influenced by the limited validation sample, since the 11 unstable validation points correspond to only three landslide locations and may exhibit spatial dependence within each location. Therefore, the confidence interval at the point level may not fully reflect uncertainty at the site level. The validation should consequently be considered preliminary, and additional independent landslide locations are required to assess the model's broader generalizability.

Moreover, field observations reveal that locations that have been identified as exhibiting high susceptibility tend to be associated with fractured limestone formations, discontinuities, seepage areas, and rockfall accumulation sites, thus offering more

validation to the spatial relevance of the susceptibility models. Seepage is evidenced by the intrusion of water into the formation due to the presence of discontinuities, leading to weakening in terms of shear strength, making it easier to initiate slope failures, especially along steeper slopes created by road cuts. Such vulnerability categories are meant to be seen as relative indices of susceptibility towards instability rather than definitive statements about the occurrence of landslides and are meant mainly to draw attention to those areas that need further evaluation. This approach makes the model quite ideal for a rapid landslide hazard analysis as well as the prioritization of mitigation efforts within transportation corridors where there is no existing inventory information.

While it is true that the AHP model is subjective in its nature, based on the results of sensitivity analysis, the general pattern of susceptibility is relatively resilient and stable, especially when the weights change within $\pm 10\%$. The higher sensitivity demonstrated under the $\pm 20\%$ weight changes can be regarded as a conservative scenario that is not characteristic of normal model performance. The most influential factor was slope, which is consistent with its highest weight and the field observations demonstrating instability along steep road sections. In contrast, the low sensitivity associated with TPI variations indicates that this factor has a limited effect on the overall classification.

5. Conclusions

This study addresses the knowledge gap related to corridor-scale landslide susceptibility assessment by integrating portable SLAM LiDAR with GIS-based AHP along the Dokan–Topzawa road corridor. The dense LiDAR point cloud provided a detailed representation of steep road cuts, near-vertical slopes, and structural features that were inadequately captured by conventional DEMs, while the susceptibility assessment was conducted using a 10×10 m working grid. The processed point cloud contained approximately 400 million points with an average density of about 1,180 points/m², enabling the derivation of nine conditioning factors representing the topographic, geological, hydrological, and environmental characteristics of the corridor. From the findings, it is evident that susceptibility is strongly influenced by the combined effects of slope faces that have been excavated at a steep geometry, fractured limestone geology, unfavorable bedding angles, and drainage. Combined areas that are moderately and highly susceptible account for about 51.9% of the corridor, implying the influence of strong geological and geomorphological factors. This observation has been further validated

by LiDAR profile sections and ground observations. The model's spatial relevance is supported by its agreement with the recorded landslides, as all the failures occurred in areas of moderate to high susceptibility. Validation using the receiver operating characteristic area under the curve showed an AUC of 0.849 (95% bootstrap CI: 0.724–0.949). Although the data were relatively limited, the spatial correlation indicates preliminary internal validity. The sensitivity analysis further demonstrated that the model remained stable under the tested AHP weight variations, particularly within the $\pm 10\%$ scenarios. The suggested methodology can be particularly helpful in areas with less data, since the combination of handheld LiDAR scans with GIS analysis makes it possible to quickly determine hazardous zones. In general, the proposed methodology is quite effective for conducting landslide susceptibility assessment along mountainous transportation corridors characterized by complex geological conditions.

References

- [1] Kromer, R., A., Hutchinson, D., J., Lato, M., J., Gauthier, D. and Edwards, T., (2015). Identifying Rock Slope Failure Precursors Using LiDAR for Transportation Corridor Hazard Management. *Engineering Geology*, Vol. 195; 93-103. <https://doi.org/10.1016/j.enggeo.2015.05.012>.
- [2] Mavrouli, O., Corominas, J., Ibarbia, I., Alonso, N., Jugo, I. and Ruiz, J., (2019). Integrated Risk Assessment Due to Slope Instabilities in the Roadway Network of Gipuzkoa, Basque Country. *Natural Hazards and Earth System Sciences*, Vol. 19(2); 399-419. <https://doi.org/10.5194/nhess-19-399-2019>.
- [3] Kim, J., M., Kim, M., S., Kim, M., J. and Park, W., H., (2025). Hydro-mechanical Numerical Evaluation of Rainfall-Induced Fully Coupled Groundwater Flow, Land Deformation, and Failure Potential in a Variably Saturated Heterogeneous Hill Slope. *Environmental Earth Sciences*, Vol. 84(5). <https://doi.org/10.1007/s12665-024-11986-4>.
- [4] Wang, B., Zuo, Q., Deng, M., Yi, Q., Ruan, D. and Liang, Z., (2025). Study on the Deformation Mechanism of Chair-Like Bedding Rock Landslides under the Coupling Effect of Geological and Hydrological Factors. *Engineering Geology*, Vol. 344. <https://doi.org/10.1016/j.enggeo.2024.107832>.
- [5] Ankah, M. L. Y. and Kincal, C., (2022). Stability Analysis of Rock Slopes Using Kinematic Analysis and Numerical Modeling: Foça-Bağarası State Highway, Turkey. *Modeling Earth Systems and Environment*, Vol. 8(4); 5225-5233. <https://doi.org/10.1007/s40808-022-01454-y>.
- [6] Bahrami, S., Rahimzadeh, B. and Khaleghi, S., (2020). Analyzing the Effects of Tectonic and Lithology on the Occurrence of Landslide along Zagros Ophiolitic Suture: A Case Study of Sarv-Abad, Kurdistan, Iran. *Bulletin of Engineering Geology and the Environment*, Vol. 79(3); 1619-1637. <https://doi.org/10.1007/s10064-019-01639-3>.
- [7] Zhao, S., Zeng, R., Zhang, Z., Meng, X., Qi, T. and Long, Z., (2024). Landslide Mapping and Causes of Landslides in the China–Nepal Transportation Corridor Based on Remote Sensing Technology. *Remote Sensing*, Vol. 16(2). <https://doi.org/10.3390/rs16020356>.
- [8] Sissakian, V. K., Omer, S. A. and Mohamed, D. S., (2018). Assessment of Dukan Landslides, West of Sulaimani City, the Kurdistan Region, Northeast Iraq. *UKH Journal of Science and Engineering*, Vol. 2(1); 28-37. <https://doi.org/10.25079/ukhjse.v2n1y2018.pp28-38>.
- [9] Zarraq, G. A., (2021). Slope Stability Analysis of the Southwestern Limb of Kosret Anticline in Dokan, Northeastern Iraq. *The Iraqi Geological Journal*, Vol. 54(2A); 34-48. <https://doi.org/10.46717/igj.54.2A.3Ms-2021-07-24>.
- [10] Othman, A. A. and Gloaguen, R., (2013). Automatic Extraction and Size Distribution of Landslides in Kurdistan Region, NE Iraq. *Remote Sensing*, Vol. 5(5); 2389-2410. <https://doi.org/10.3390/rs5052389>.
- [11] Othman, A. A., Gloaguen, R., Andreani, L. and Rahnama, M., (2015). Landslide Susceptibility Mapping in Mawat Area, Kurdistan Region, NE Iraq: A Comparison of Different Statistical Models. *Natural Hazards and Earth System Sciences*, Vol. 15; 215-227. <https://doi.org/10.5194/nhessd-3-1789-2015>.
- [12] Ali, Z., Faeq Ibrahim, G., R., Kiss, K. and Pirisi, G., (2025). Comparable Analysis of Analytical Hierarchy Process and Fuzzy Logic Methods Based on GIS and Remote Sensing for Anticipating Landslide Susceptibility in the Iraqi Kurdistan Region, Koya District. *Geocarto International*, Vol. 40(1). <https://doi.org/10.1080/10106049.2025.2540881>.
- [13] Chen, Y., (2025). Spatial Prediction and Mapping of Landslide Susceptibility Using Machine Learning Models. *Natural Hazards*, Vol. 121(7); 8367-8385. <https://doi.org/10.1007/s11069-025-07132-3>.

- [14] Singha, N. and Sarkar, S., (2024). Modelling Landslide Susceptibility along Major Transportation Corridor in Darjeeling Himalayas Using GIS-Based MCDA Approaches. *Modeling Earth Systems and Environment*, Vol. 10(3); 3197-3218.
- [15] Qiu, H. and Wei, Y., (2025). Landslide Geomorphology: Pattern, Process and Stability. *Journal of Earth Science*, Vol. 36(1); 327-332. <https://doi.org/10.1007/s12583-024-0131-z>.
- [16] Farmakis, I., Hutchinson, D., J., Vlachopoulos, N., Westoby, M. and Lim, M., (2023). Slope-Scale Rockfall Susceptibility Modeling as a 3D Computer Vision Problem. *Remote Sensing*, Vol. 15(11). <https://doi.org/10.3390/rs15112712>.
- [17] Jaboyedoff, M., Oppikofer, T., Abellán, A., Derron, M., H., Loye, A. and Metzger, R., (2012). Use of LiDAR in Landslide Investigations: A Review. *Natural Hazards*, Vol. 61(1); 5-28. <https://doi.org/10.1007/s11069-010-9634-2>.
- [18] Bendezu de la Cruz, M. A. B., (2021). *Evaluation of LiDAR Systems for Rock Mass Discontinuity Identification in Underground Stone Mines from 3D Point Cloud Data*. Master's Thesis. Department of Mining Engineering, West Virginia University, USA.
- [19] Fahle, L., Holley, E. A., Walton, G., Petruska, A. J. and Brune, J. F., (2022). Analysis of SLAM-Based LiDAR Data Quality Metrics for Geotechnical Underground Monitoring. *Mining, Metallurgy & Exploration*, Vol. 39(5); 1939-1960. <https://doi.org/10.1007/s42461-022-00664-3>.
- [20] Strzabala, K., Cwiąkała, P. and Puniach, E., (2024). Identification of Landslide Precursors for Early Warning of Hazards with Remote Sensing. *Remote Sensing*, Vol. 16(15). <https://doi.org/10.3390/rs16152781>.
- [21] Hungr, O., Leroueil, S. and Picarelli, L., (2014). The Varnes Classification of Landslide Types, an Update. *Landslides*, Vol. 11(2); 167-194. <https://doi.org/10.1007/s10346-013-0436-y>.
- [22] Guzzetti, F., Carrara, A., Cardinali, M. and Reichenbach, P., (1999). Landslide Hazard Evaluation: A Review of Current Techniques and Their Application in a Multi-scale Study, Central Italy. *Geomorphology*, Vol. 31(1-4); 181-216. [https://doi.org/10.1016/S0169-555X\(99\)00078-1](https://doi.org/10.1016/S0169-555X(99)00078-1).
- [23] Othman, A., Obaid, A., Al-Manmi, D., Al-Maamar, A., Hasan, S. and Liesenberg, V., (2021). New Insight on Soil Loss Estimation in the Northwestern Region of the Zagros Fold and Thrust Belt. *ISPRS International Journal of Geo-Information*, Vol. 10(2). <https://doi.org/10.3390/ijgi10020059>.
- [24] Rouse Jr. J., W., Haas, R. H., Deering, D. W., Schell, J. A. and Harlan, J. C., (1974). *Monitoring the Vernal Advancement and Retrogradation of Natural Vegetation*. NASA/GSFC Type III Final Report, Greenbelt, MD, USA.
- [25] Hussain, Y., Schlögel, R., Innocenti, A., Hamza, O., Iannucci, R. and Martino, S., (2022). Review on the Geophysical and UAV-Based Methods Applied to Landslides. *Remote Sensing*, Vol. 14(18). <https://doi.org/10.3390/rs14184564>.
- [26] Zhao, X., Ren, X., Li, L., Wu, J. and Zhao, X., (2024). PA-SLAM: Fast and Robust Ground Segmentation and Optimized Loop Detection Laser SLAM System. *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 60(5); 5812-5822. <https://doi.org/10.1109/TAES.2024.3397962>.
- [27] Ahmed, M., Titti, G., Trevisani, S., Borgatti, L. and Francioni, M., (2025). Is Higher Resolution Always Better? A Comparison of Open-Access DEMs for Optimized Slope Unit Delineation and Regional Landslide Prediction. *Natural Hazards and Earth System Sciences*, Vol. 25(7); 2519-2539. <https://doi.org/10.5194/nhess-25-2519-2025>.
- [28] Florinsky, I., (2016). *Digital Terrain Analysis in Soil Science and Geology*. 2nd ed., Academic Press, London.
- [29] Abdulrahan, Z. O., Al Nuaimy, Q. A. M. and Mezaal, M. R., (2025). Soil Erosion Assessment for the Eastern Part of Daquq District Using a RUSLE Model-Based GIS. *International Journal of Computational and Experimental Science and Engineering*, Vol. 11(1). <https://doi.org/10.22399/ijcesen.1187>.
- [30] Abad, L., Hölbling, D., Spiekermann, R., Prasicek, G., Dabiri, Z. and Argentin, A. L., (2022). Detecting Landslide-Dammed Lakes on Sentinel-2 Imagery and Monitoring Their Spatio-Temporal Evolution Following the Kaikōura Earthquake in New Zealand. *Science of the Total Environment*, Vol. 820. <https://doi.org/10.1016/j.scitotenv.2022.153335>.
- [31] Jassim, H. M., (2021). Slope Stability Analysis of Haibat Sultan Road Cut, Kurdistan Region, Iraq Using a Field Method. *Iraqi Geological Journal*, Vol. 54(1F); 98-109. <https://doi.org/10.46717/igj.54.1F.9ms-2021-06-29>.
- [32] Sissakian, V. K., Ahad, A. D. A. and Hamid, A. T., (2011). Geological Hazards in Iraq, Classification and Geographical Distribution. *Iraqi Bulletin of Geology and Mining*, Vol.

- 7(1); 1-28. <https://ibgm-iq.org/ibgm/index.php/ibgm/article/view/137>.
- [33] Weiss, A., (2001). *Topographic Position and Landforms Analysis*. Poster Presentation, ESRI User Conference, San Diego, CA.
- [34] Horton, R. E., (1945). Erosional Development of Streams and their Drainage Basins; Hydrophysical Approach to Quantitative Morphology. *Geological Society of America Bulletin*, Vol. 56(3); 275-370. [https://doi.org/10.1130/0016-7606\(1945\)56\[275:EDOSAT\]2.0.CO;2](https://doi.org/10.1130/0016-7606(1945)56[275:EDOSAT]2.0.CO;2).
- [35] Al-Kakey, O. H., Othman, A. A. and Merkel, B. J., (2023). Identifying Potential Sites for Artificial Groundwater Recharge Using GIS and AHP Techniques: A Case Study of Erbil Basin, Iraq. *Kuwait Journal of Science*, Vol. 50(1B). <https://doi.org/10.48129/kjs.11917>.
- [36] Jenks, G. F., (1967). The Data Model Concept in Statistical Mapping. *International Yearbook of Cartography*, Vol. 7; 186-190.
- [37] Arabameri, A., Saha, S., Roy, J., Chen, W., Blaschke, T. and Tien Bui, D., (2020). Landslide Susceptibility Evaluation and Management Using Different Machine Learning Methods in the Gallicash River Watershed, Iran. *Remote Sensing*, Vol. 12(3). <https://doi.org/10.3390/rs12030475>.
- [38] Ayalew, L. and Yamagishi, H., (2005). The Application of GIS-Based Logistic Regression for Landslide Susceptibility Mapping in the Kakuda-Yahiko Mountains, Central Japan. *Geomorphology*, Vol. 65(1-2); 15-31. <https://doi.org/10.1016/j.geomorph.2004.07.006>.
- [39] Cruden, D., M. and Varnes, D., J., (1996). Landslides: Investigation and Mitigation. Chapter 3- Landslide Types and Processes. *Transportation Research Board Special Report No. 247*, 36-75.
- [40] Hoek, E. and Bray, J. D., (1981). *Rock Slope Engineering*. 3rd ed., Institution of Mining and Metallurgy, London.
- [41] Saaty, T. L., (1980). *The Analytic Hierarchy Process*. McGraw-Hill, New York, USA.
- [42] Qader, W. M., Noori, A. M., Omer, F. M., Al Nuaimy, Q. A. M. and Saed, F. G., (2023). Soil Erosion Susceptibility Mapping by Analyzing Morphometric Parameters Using ALOS PALSAR DEM and GIS Techniques for Rawanduz River Basins in Iraq. In: *Selected Studies in Geomorphology, Sedimentology, and Geochemistry*. Springer, Cham, 89-93. https://doi.org/10.1007/978-3-031-43744-1_19.
- [43] Reichenbach, P., Rossi, M., Malamud, B., D., Mihir, M. and Guzzetti, F., (2018). A Review of Statistically-Based Landslide Susceptibility Models. *Earth-Science Reviews*, Vol. 180; 60-91. <https://doi.org/10.1016/j.earscirev.2018.03.004>.
- [44] Yesilnacar, E. and Topal, T., (2005). Landslide Susceptibility Mapping: A Comparison of Logistic Regression and Neural Networks Methods in a Medium Scale Study, Hendek Region, Turkey. *Engineering Geology*, Vol. 79(3-4); 251-266. <https://doi.org/10.1016/j.enggeo.2005.02.002>.
- [45] Yalcin, A., (2008). GIS-Based Landslide Susceptibility Mapping Using Analytical Hierarchy Process and Bivariate Statistics in Ardesen, Turkey: Comparisons of Results and Confirmations. *Catena*, Vol. 72(1); 1-12. <https://doi.org/10.1016/j.catena.2007.01.003>.
- [46] Pourghasemi, H. R., Pradhan, B. and Gokceoglu, C., (2012). Application of Fuzzy Logic and Analytical Hierarchy Process to Landslide Susceptibility Mapping at Haraz Watershed, Iran. *Natural Hazards*, Vol. 63(2); 965-996. <https://doi.org/10.1007/s11069-012-0217-2>.
- [47] Pradhan, B. and Lee, S., (2010). Landslide Susceptibility Assessment and Factor Effect Analysis: Backpropagation Artificial Neural Networks and Their Comparison with Frequency Ratio and Bivariate Logistic Regression Modelling. *Environmental Modelling & Software*, Vol. 25(6); 747-759. <https://doi.org/10.1016/j.envsoft.2009.10.016>.
- [48] Brideau, M. A., Yan, M. and Stead, D., (2009). The Role of Tectonic Damage and Brittle Rock Fracture in the Development of Large Rock Slope Failures. *Geomorphology*, Vol. 103(1); 30-49. <https://doi.org/10.1016/j.geomorph.2007.07.020>.
- [49] Stead, D. and Wolter, A., (2015). A Critical Review of Rock Slope Failure Mechanisms: The Importance of Structural Geology. *Journal of Structural Geology*, Vol. 74; 1-23. <https://doi.org/10.1016/j.jsg.2015.02.002>.
- [50] Glenn, N. F., Streutker, D. R., Chadwick, D. J., Thackray, G. D. and Dorsch, S. J., (2006). Analysis of LiDAR-Derived Topographic Information for Characterizing and Differentiating Landslide Morphology and Activity. *Geomorphology*, Vol. 73(1-2); 131-148. <https://doi.org/10.1016/j.geomorph.2005.07.006>.

- [51] Abellan, A., Oppikofer, T., Jaboyedoff, M., Rosser, N., Lim, M. and Lato, M., (2014). Terrestrial Laser Scanning of Rock Slope Instabilities. *Earth Surface Processes and Landforms*, Vol. 39; 80-97. <https://doi.org/10.1002/esp.3493>.
- [52] Jaboyedoff, M., Bu, F., Chalé, A., Choanji, T., Derron, M. H. and Fei, L., (2024). *Toward the Assessment of the Rockfall Sources Hazard Failure Using 3D Point Clouds and Remote Sensing Techniques*. In: New Challenges in Rock Mechanics and Rock Engineering. CRC Press, 39-60.
- [53] Doski, J. A. H., (2025). Landslide Susceptibility Evaluation in the Mountainous Terrain of the Zagros Fold-Thrust Belt: A Case Study from Kurdistan, Northern Iraq. *Natural Hazards*, Vol. 121(20); 23647-23685. <https://doi.org/10.1007/s11069-024-07069-z>.
- [54] Lee, S., (2019). Current and Future Status of GIS-Based Landslide Susceptibility Mapping: A Literature Review. *Korean Journal of Remote Sensing*, Vol. 35(1); 179-193. <https://doi.org/10.7780/kjrs.2019.35.1.12>.

Appendix A: Factor Classification Thresholds and Susceptibility Ratings

Table A1: Classification thresholds and susceptibility ratings assigned to each conditioning factor used in the AHP-based landslide susceptibility analysis

Factor	Class Range / Category	Rating	Interpretation
Slope (°)	0 – 5	1	Very low susceptibility
	5 – 15	3	Low susceptibility
	15 – 30	5	Moderate to high susceptibility
	30 – 60	9	Very high susceptibility based on observed road-cut instability
	60 – 75	7	High susceptibility depending on discontinuity orientation
Aspect (°)	0 – 45	9	Very high susceptibility
	45 – 135	5	Moderate susceptibility
	135 – 225	1	Very low susceptibility
	225 – 315	5	Moderate susceptibility
	315 – 360	7	High susceptibility
Profile Curvature	–0.087 – (–0.039)	1	Very low susceptibility
	–0.039 – (–0.014)	3	Low susceptibility
	–0.014 – 0.003	5	Moderate susceptibility
	0.003 – 0.022	7	High susceptibility
	0.022 – 0.085	9	Very high susceptibility
TPI	–10.03 – (–4.52)	1	Very low susceptibility
	–4.52 – (–1.43)	3	Low susceptibility
	–1.43 – 0.86	5	Moderate susceptibility
	0.86 – 3.50	7	High susceptibility
	3.50 – 11.43	9	Very high susceptibility
NDVI	–0.159 – (–0.028)	9	Very high susceptibility
	–0.028 – 0.103	7	High susceptibility
	0.103 – 0.234	5	Moderate susceptibility
	0.234 – 0.365	3	Low susceptibility
	0.365 – 0.496	1	Very low susceptibility
Drainage Density	0 – 3.12	1	Very low susceptibility
	3.12 – 6.23	3	Low susceptibility
	6.23 – 9.35	5	Moderate susceptibility
	9.35 – 12.47	7	High susceptibility
	12.47 – 15.58	9	Very high susceptibility
Distance to Stream (m)	0 – 22.63	9	Very high susceptibility
	22.63 – 45.25	7	High susceptibility
	45.25 – 67.88	5	Moderate susceptibility
	67.88 – 90.51	3	Low susceptibility
	90.51 – 113.14	1	Very low susceptibility
Lineament Density (km/km ²)	0 – 5.08	1	Very low susceptibility
	5.08 – 10.15	3	Low susceptibility
	10.15 – 15.23	5	Moderate susceptibility
	15.23 – 20.30	7	High susceptibility
	20.30 – 25.38	9	Very high susceptibility
Lithology	Slightly fractured limestone	3	Low susceptibility due to a relatively intact rock mass
	Moderately fractured limestone	5	Moderate susceptibility associated with increased discontinuities
	Highly fractured limestone	7	High susceptibility due to pervasive fracturing and reduced rock strength
	Clay-rich interbeds	9	Very high susceptibility due to weak layers and low shear strength

Appendix B: AHP Weight-Sensitivity Analysis

Table B1: Factor-level summary of the AHP weight-sensitivity analysis

	Baseline weight	Tested weight range	Maximum RMSE	Minimum Pearson	Maximum class change (%)	High-class range (%)
Slope	0.2827	0.2262 – 0.3392	0.1698	0.9929	15.7490	32.89 – 42.81
Lithology	0.1594	0.1275 – 0.1913	0.0575	0.9988	4.4997	37.15 – 38.25
Lineament	0.1216	0.0973 – 0.1459	0.0759	0.9986	6.8976	35.08 – 40.11
Drainage	0.0919	0.0735 – 0.1103	0.0523	0.9988	4.6773	36.83 – 38.78
NDVI	0.0893	0.0714 – 0.1072	0.0661	0.9999	5.5654	35.26 – 40.14
Distance to	0.0771	0.0617 – 0.0925	0.0568	0.9993	4.6773	36.97 – 38.81
TPI	0.0629	0.0503 – 0.0755	0.0275	0.9997	1.8650	37.69 – 37.83
Profile	0.0621	0.0497 – 0.0745	0.0289	0.9997	2.0130	37.66 – 37.80
Aspect	0.053	0.0424 – 0.0636	0.0326	0.9996	2.9899	36.83 – 38.54

Note: Each factor weight was independently varied by –20%, –10%, +10%, and +20%, while the remaining weights were proportionally rescaled to maintain a total weight of 1.0. The original class boundaries (3.90, 4.80, and 5.20) were held constant across the 36 OAT sensitivity scenarios