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SPATIAL ASSESSMENT OF LANDSLIDE SUSCEPTIBILITY IN THE LOWER ASTORE VALLEY, GILGIT-BALTISTAN, PAKISTAN, USING GIS AND THE ANALYTIC HIERARCHY PROCESS

Sundas Mehreen[1], Tehreem Nawaz[2], Tanveer Ul Haq[*3]

[1,2]*Department of Environmental Sciences, COMSATS University Islamabad, Abbottabad Campus, Abbottabad 22010, Pakistan*

[*3]*State Key Laboratory of Geohazard Prevention and Geoenvironment Protection, Chengdu University of Technology, Chengdu 610000, Sichuan, China*

[*3] tanveerulhaq961@gmail.com

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landslide susceptibility; geographic information system (GIS); Analytic Hierarchy Process (AHP); Astore Valley; susceptibility index; mountain environment.

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Tanveer Ul Haq

Abstract

Landslides are among the major geomorphological hazards affecting mountainous regions, where steep terrain, geological conditions, and human activities contribute to slope instability. This study assesses landslide susceptibility along the Ramghat-Eidgah corridor in the lower Astore Valley, Gilgit-Baltistan, Pakistan, using a Geographic Information System (GIS) integrated with the Analytic Hierarchy Process (AHP). Seven landslide-conditioning factors were considered: slope, aspect, lithology, land cover, distance to faults, distance to roads, and distance to streams. Spatial datasets derived from a 30-m ASTER Digital Elevation Model, satellite imagery, geological information, and mapped infrastructure and drainage features were processed and integrated in ArcGIS. AHP was used to assign relative weights to the conditioning factors, with slope receiving the highest weight (0.40), followed by lithology (0.29), land cover (0.09), distance to faults (0.06), distance to streams (0.06), aspect (0.06), and distance to roads (0.04). The weighted factors were combined to generate a landslide susceptibility index, which was classified into four categories: low, moderate, high, and very high. The resulting map indicates that 17.59% of the study area falls within the low-susceptibility class, 32.31% within the moderate class, 32.87% within the high class, and 17.22% within the very-high class. Thus, approximately 50.10% of the mapped area is classified as having high to very high landslide susceptibility. Predictive performance was evaluated using a 70:30 data partition and the ArcSDM tool in ArcGIS. The resulting area under the receiver operating characteristic curve (AUC) was 0.700, indicating a moderate level of discrimination. The resulting landslide susceptibility map provides a spatial basis for identifying areas with different levels of relative landslide susceptibility. It can support land-use planning, infrastructure development, and the prioritization of areas for field investigation and risk-reduction measures in the study area.

1. INTRODUCTION

Landslides are among the most widespread geomorphic hazards in mountainous regions, where steep relief, active tectonics, fractured bedrock, intense weathering, and concentrated surface-water flow interact to produce unstable slopes. They include processes such as rock falls, rock slides, debris slides, earth slides, and debris flows, which differ in material, movement mechanism, velocity, and impact. Their consequences extend beyond direct damage to buildings and infrastructure: slope failures can sever roads, interrupt access to health and education services, damage agricultural land, obstruct rivers, and generate cascading hazards. In high-relief regions, where settlements and transport corridors are commonly constrained to narrow valley floors, even localized slope failures may have disproportionate socioeconomic effects (Aleotti & Chowdhury, 1999; Guzzetti et al., 1999; Dai et al., 2002; Hungr et al., 2014; McColl, 2022).

The spatial occurrence of landslides is controlled by interactions between predisposing terrain conditions and triggering processes. Predisposing conditions include slope gradient and morphology, lithology, geological structure, soil properties, drainage, land cover, and human modification of slopes. Triggers such as intense or prolonged rainfall, snowmelt, and earthquakes can temporarily increase driving stresses or reduce material strength. The relative importance of individual factors varies among physiographic settings and landslide types. Conditioning factors should therefore be selected with reference to local geomorphology and the scale and quality of available data, rather than adopted uncritically from another region (Varnes, 1978; Cruden & Varnes, 1996; Glade et al., 2005; van Westen et al., 2008; Fell et al., 2008; Reichenbach et al., 2018; McColl, 2022).

Landslide susceptibility mapping identifies the relative spatial propensity for landsliding as a function of terrain conditions. It addresses where landslides are more likely to occur, whereas a complete landslide-hazard assessment also considers the probability of occurrence within a specified time period and the expected magnitude or intensity. Risk assessment further requires information on exposed people and assets and their vulnerability. A susceptibility index derived from static terrain layers cannot, on its own, forecast the timing of a failure or quantify expected losses (Fell et al., 2008; van Westen et al., 2008; Corominas et al., 2014; Reichenbach et al., 2018; Shano et al., 2020).

Geographic information systems (GIS) and remote sensing are widely used in regional landslide studies because they allow terrain, geological, hydrological, land-cover, and infrastructure information to be assembled and analysed within a common spatial framework. Digital elevation models (DEMs) support the derivation of terrain attributes such as slope and aspect, while optical satellite imagery assists in identifying landslide features, land-cover patterns, and changes in surface conditions. Field observations and GPS surveys remain important for checking image interpretations and improving the positional and thematic reliability of landslide inventories. The usefulness of a susceptibility model nevertheless depends on the scale, completeness, and positional accuracy of both the inventory and the conditioning layers (Carrara et al., 1991; Guzzetti et al., 1999; van Westen et al., 2008; Saleem et al., 2019; Reichenbach et al., 2018).

Approaches to susceptibility assessment include expert-based geomorphological mapping, heuristic index methods, bivariate statistical models, multivariate statistical models, and machine-learning techniques. Frequency-ratio and weights-of-evidence methods estimate associations between landslide occurrence and conditioning-factor classes; logistic regression and other multivariate methods model relationships among multiple predictors; and machine-learning approaches can represent nonlinear interactions when adequate training data are available. Reviews indicate that no single method is universally superior: performance is influenced by inventory quality, mapping units, predictor selection, spatial scale, validation design, and the geomorphological relevance of the input data (Carrara et al., 1991; Lee & Talib, 2005; Ayalew & Yamagishi, 2005; Yalcin, 2008; Reichenbach et al., 2018; Ado et al., 2022).

The Analytic Hierarchy Process (AHP) is a multi-criteria decision-making method commonly used in GIS-based susceptibility mapping. It converts pairwise expert judgments about the relative importance of criteria into a normalized priority vector, allowing multiple thematic layers to be combined in a weighted overlay. AHP can be useful where detailed landslide inventories or long event records are limited because it provides a transparent framework for integrating expert knowledge. However, the resulting weights depend on the judgments used to construct the comparison matrix. Consistency checking is therefore essential; a low consistency ratio indicates internal coherence of the judgments, not empirical predictive accuracy of the final map (Saaty, 1977, 1980, 2008; Malczewski, 2006; Chandio et al., 2013; Mandal & Mandal, 2018).

Studies in the Himalayan and Karakoram mountain belts demonstrate the relevance of GIS-based susceptibility mapping in regions where rugged topography, active structures, variable lithology, and road development combine to create slope-instability concerns. In northern Pakistan, researchers have used remote sensing and GIS to map landslides and evaluate the influence of slope, aspect, geology, land cover, and proximity to roads, faults, and drainage. Kanwal et al. (2017) applied an AHP-based approach in the Shigar and Shyok basins, while Iqbal et al. (2021) assessed susceptibility along the Dubair–Dudishal section of the Karakoram Highway. More recent work along the Karakoram Highway has compared statistical and machine-learning approaches and used remote-sensing observations for validation (Kulsoom et al., 2023; Iqbal et al., 2024; Abbas et al., 2024). These studies provide regional methodological context, but their results cannot be transferred directly to the lower Astore Valley because factor relationships and model performance are spatially dependent (Kanwal et al., 2017; Afzal et al., 2022; Kulsoom et al., 2023; Abbas et al., 2024).

Astore is a relevant setting for this type of assessment. The valley occupies a high-relief landscape within the broader Himalayan–Karakoram region, where steep slopes, river incision, complex geological units, and tectonic structures shape the terrain. Roads and settlements are concentrated along the valley corridor, increasing the potential consequences of slope instability. Previous work has applied GIS and AHP to landslide susceptibility in the Astore region (Afzal et al., 2022), providing a regional point of comparison. The present study focuses on the lower valley reach between Ramghat and Eidgah and uses a seven-factor model comprising slope, aspect, lithology, land cover, distance to faults, distance to roads, and distance to streams (Searle et al., 1999; DiPietro et al., 2000; Robertson & Collins, 2002; Zanchi & Gaetani, 2011; Afzal et al., 2022).

Despite the growing application of susceptibility mapping in northern Pakistan, local-scale assessments remain constrained by incomplete landslide inventories, variable data resolution, limited field verification, and inconsistent reporting of model validation. A map generated through weighted overlay can be useful for screening, but its reliability cannot be judged solely from factor weights or visual appearance. Good practice requires transparent documentation of the inventory, mapping unit, data sources, factor classification, weighting procedure, class thresholds, and validation strategy. Published reviews emphasize the need to evaluate model fit, prediction performance, spatial error patterns, and uncertainty (Reichenbach et al., 2018; Fleuchaus et al., 2021; Ado et al., 2022; Chicas et al., 2024).

Against this background, this study examines landslide susceptibility in the lower Astore Valley, from Ramghat to Eidgah, using GIS and AHP. The study has three objectives: (1) to compile and map landslide locations using satellite-image interpretation supported by field and GPS observations; (2) to prepare thematic layers representing seven selected conditioning factors; and (3) to integrate these layers using AHP-derived weights to produce a four-class susceptibility map. The analysis is intended as a regional screening assessment to support the prioritization of field inspection and land-use planning. It is not a time-dependent hazard forecast because it does not incorporate temporal triggering probabilities or a landslide-magnitude model.

2. Study Area

The study area extends from Ramghat to Eidgah in the lower Astore Valley, Gilgit-Baltistan, Pakistan. Astore is a high-mountain valley, with elevations ranging broadly from approximately 2,600 to 8,000 m across the wider valley region. The lower valley is characterized by a narrow river corridor bordered by steep, rugged slopes. The Astore River and its tributary channels form an important part of the local drainage network.

The regional setting is tectonically complex and lies within the broader Himalayan–Karakoram collision zone. Major regional structures, including the Main Mantle Thrust and other fault and shear-zone systems, characterize the regional geological framework. Lithological contrasts, structural discontinuities, river incision, and human modification of slopes may contribute to local instability. The analysis incorporates distance to mapped faults, streams, and roads as spatial conditioning variables. Regional geological and geomorphological studies provide context for the structural and topographic controls relevant to northern Pakistan (Searle et al., 1999; Afzal et al., 2022). The geographical location and extent of the study area are shown in Figure 1.

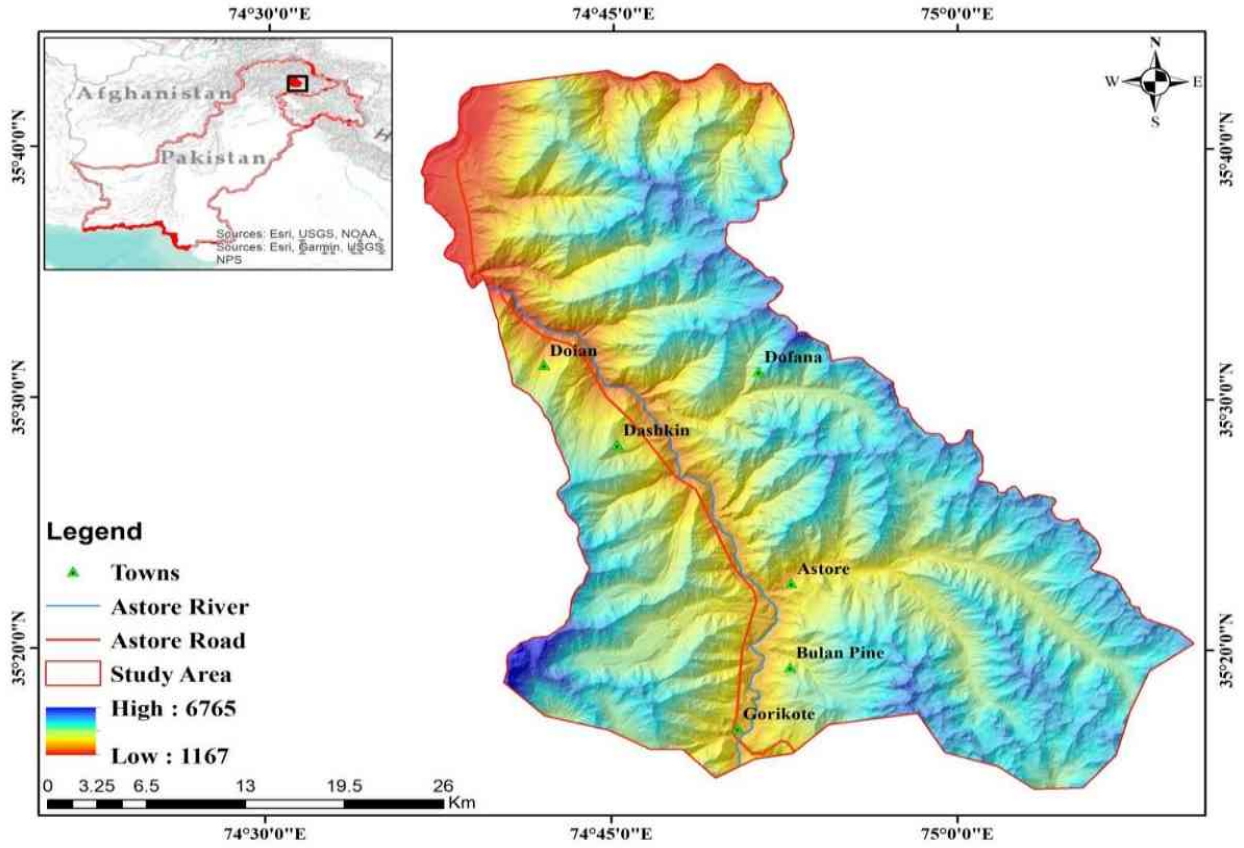


Figure 1. Location of the study area showing the Ramghat-Eidgah corridor in the lower Astore Valley, Gilgit-Baltistan, Pakistan.

3. Data and methods

3.1. Data sources and preparation

A 30-m ASTER-derived Digital Elevation Model (DEM) was used to derive slope and aspect. Landsat-8 satellite imagery and Google Earth imagery were interpreted to map land-cover patterns and identify landslide features. Geological maps provided lithological information, while mapped faults, roads, and stream networks were used to generate the corresponding distance-based conditioning layers. ArcGIS was used to process and integrate the spatial datasets and

prepare the thematic layers required for landslide susceptibility assessment. Field observations and GPS measurements were used to verify mapped landslide locations and refine the landslide inventory. All spatial datasets were referenced to the WGS 1984 UTM Zone 43N coordinate reference system, and area measurements were expressed in square kilometres (km²).



Figure 2. Methodological workflow adopted in this study.

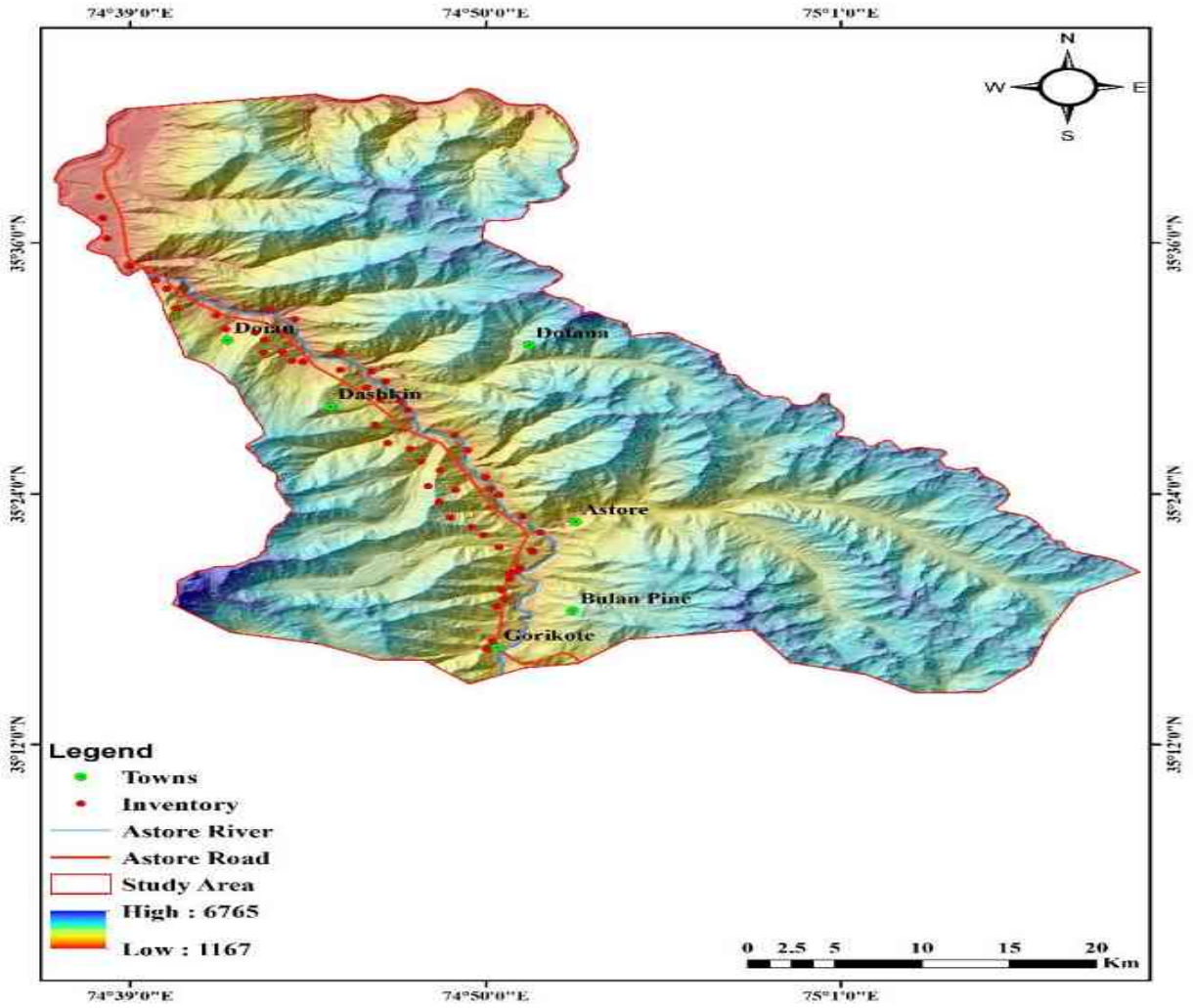


Figure 3. Spatial distribution of the mapped landslide inventory, settlements, roads and river network in the study area.

3.2. Landslide inventory

The landslide inventory was prepared by visually identifying landslide features in satellite imagery and Google Earth, followed by field checking using GPS. The inventory provides the spatial reference for examining landslide distribution in relation to the seven conditioning factors. Field observations indicate that many mapped landslides lie close to riverbanks and that some occur near the road corridor. A total of 70 landslide locations were identified and included in the landslide inventory. These locations were used as the reference dataset for the landslide susceptibility assessment and subsequent model validation.

3.3. Landslide-conditioning factors

Seven conditioning factors were selected for the analysis. Slope and aspect were derived from the DEM. Lithology represents differences in material type and geological structure, while land cover represents surface conditions and human land use. Distance-to-fault, distance-to-road, and distance-to-stream layers were generated to represent proximity to mapped structures, infrastructure, and drainage channels. Road excavation and changes in drainage can influence slope stability,

while stream erosion and bank undercutting can affect slopes adjacent to channels.

Table 1. Conditioning factors, data sources, and roles in the susceptibility model.

Conditioning factor	Source / derivation	Role in the model
Slope angle	30-m ASTER-derived DEM	Terrain steepness
Slope aspect	30-m ASTER-derived DEM	Slope orientation and exposure
Lithology	Geological mapping	Spatial variation in rock/material type
Land cover	Landsat-8 and Google Earth interpretation	Surface cover and land-use condition
Distance to fault	Mapped fault network and GIS distance analysis	Proximity to structural discontinuities
Distance to road	Road network and GIS distance analysis	Proximity to road cuts and infrastructure
Distance to stream	Stream network and GIS distance analysis	Proximity to channel erosion and riverbanks

3.4. Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) was used to assign relative importance to the seven landslide-conditioning factors. The factors were compared pairwise using Saaty's numerical preference scale (1–9), and the comparison matrix was normalized to derive the priority weights (Saaty, 1980). The consistency ratio (CR) was calculated to evaluate the internal consistency of the pairwise comparisons. The calculated CR was 0.03, which is below the commonly accepted threshold of 0.10, indicating an acceptable level of consistency among the pairwise judgments. The derived factor weights are presented in Table 2. Slope received the highest weight (0.40), followed by lithology (0.29), while the remaining five factors collectively accounted for 0.31. The highest class-level weights for the individual conditioning factors are summarized in Table 3.

Table 2. Relative weights assigned to the seven landslide-conditioning factors using AHP.

Factor	AHP weight	Relative rank
Slope	0.40	1
Lithology	0.29	2
Land cover	0.09	3
Distance to faults	0.06	4 (tied)
Distance to streams	0.06	4 (tied)
Aspect	0.06	4 (tied)
Distance to roads	0.04	7
Total	1.00	–

Table 3. Highest class-level weights identified for the seven landslide-conditioning factors.

Factor	Class with highest reported class weight	Class weight
Slope	40°–50°	0.29
Aspect	Southeast	0.28
Lithology	Quaternary deposits	0.37
Land cover	Barren land	0.40
Distance to fault	<50 m	0.49

Distance to road	<100 m	0.42
Distance to stream	<20 m	0.39

3.5. Landslide Susceptibility Index (LSI)

The weighted-overlay method was applied in ArcGIS to integrate the seven landslide-conditioning factors and generate the landslide susceptibility index (LSI). Each factor was assigned a relative weight derived from the Analytic Hierarchy Process (AHP), while individual classes within each factor were assigned scores according to their relative contribution to landslide susceptibility. The weighted scores of the conditioning factors were combined to calculate the LSI for each raster cell.

$$LSI = \sum_{i=1}^{7} W_i S_i \quad (1)$$

where LSI is the landslide susceptibility index, (W_i) is the AHP-derived weight assigned to the (i)th conditioning factor, and (S_i) is the GIS-based class score assigned to the corresponding spatial class of that factor. The summation represents the weighted contribution of all seven conditioning factors to the final landslide susceptibility index.

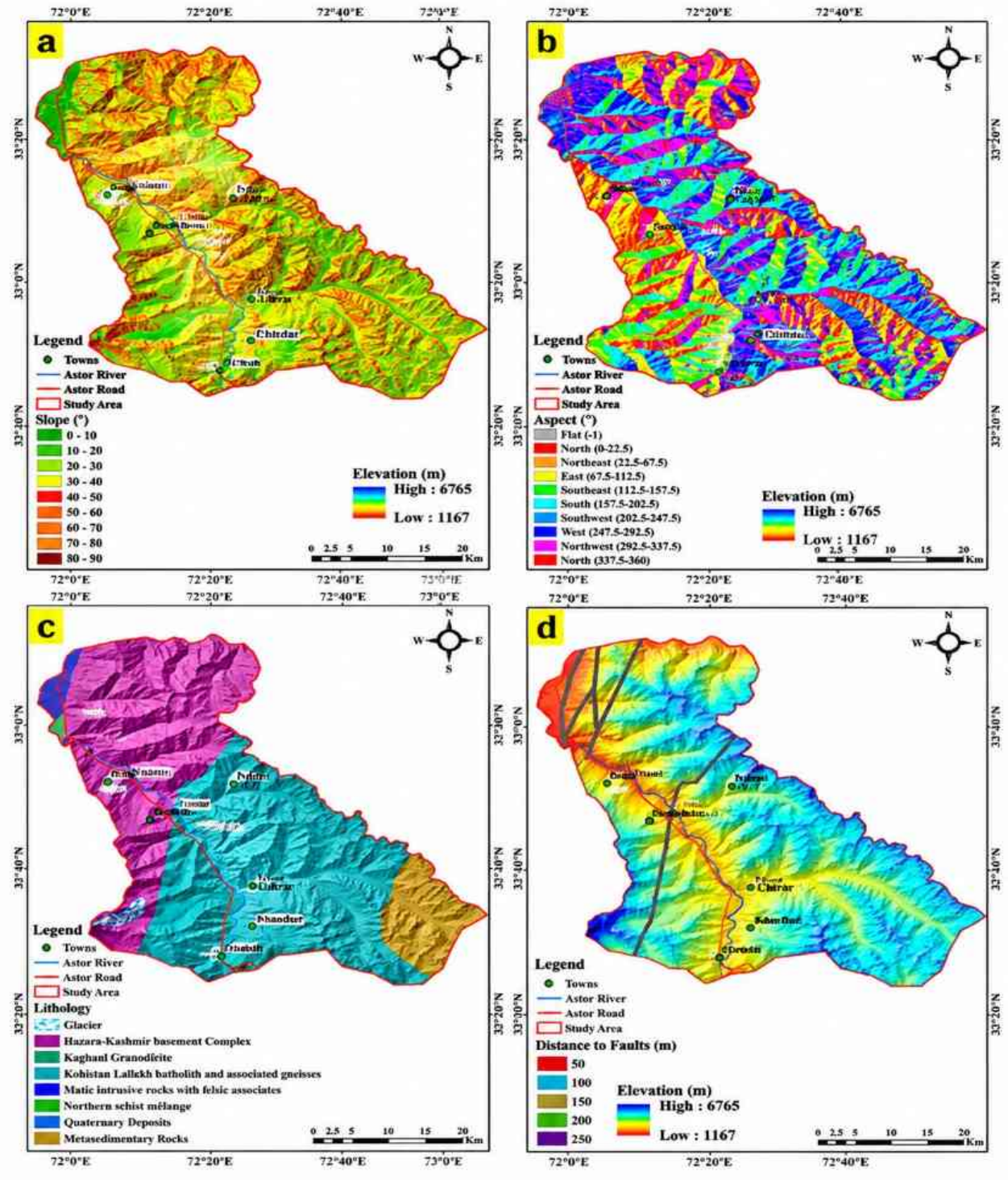
4. Results

4.1. Landslide inventory and spatial pattern

The landslide inventory provides an overview of the spatial distribution of identified landslide occurrences within the lower Astore Valley. The mapped locations highlight areas affected by slope instability and provide an important basis for examining the relationship between landslide occurrence and various terrain, geological, and environmental factors. The inventory was used as a reference for the GIS-based susceptibility assessment and for understanding the spatial patterns of landsliding across the study area.

4.2. Conditioning-factor patterns

The slope analysis assigns the largest class weight to slopes of 40°-50° (0.29), followed by 50°-60° (0.23) and 30°-40° (0.19). The slope map and corresponding class-weight graph are shown in Figure 4. For lithology, Quaternary deposits have the largest reported class weight (0.37). Barren land is the highest-weighted land-cover class (0.40), followed by agricultural/irrigated land (0.30).


a
Legend
Towns
Astor River
Astor Road
Study Area
Slope (°)
0 - 10
10 - 20
20 - 30
30 - 40
40 - 50
50 - 60
60 - 70
70 - 80
80 - 90
Elevation (m)
High : 6765
Low : 1167
Chitrdar
b
Legend
Towns
Astor River
Astor Road
Study Area
Aspect (°)
Flat (-1)
North (0-22.5)
Northeast (22.5-67.5)
East (67.5-112.5)
Southeast (112.5-157.5)
South (157.5-202.5)
Southwest (202.5-247.5)
West (247.5-292.5)
Northwest (292.5-337.5)
North (337.5-360)
Elevation (m)
High : 6765
Low : 1167
c
Legend
Towns
Astor River
Astor Road
Study Area
Lithology
Glacier
Hazara-Kashmir basement Complex
Kaghani Granodiorite
Kohistan Lallakh batholith and associated gneisses
Matic intrusive rocks with felsic associates
Northern schist mélange
Quaternary Deposits
Metasedimentary Rocks
Chitrar
Phandur
d
Legend
Towns
Astor River
Astor Road
Study Area
Distance to Faults (m)
50
100
150
200
250
Elevation (m)
High : 6765
Low : 1167
Chitrar
Drosh
72°0'E
72°20'E
72°40'E
73°0'E
33°20'N
33°0'N
32°40'N
32°20'N
N
S
W
E
0 2.5 5 10 15 20 Km

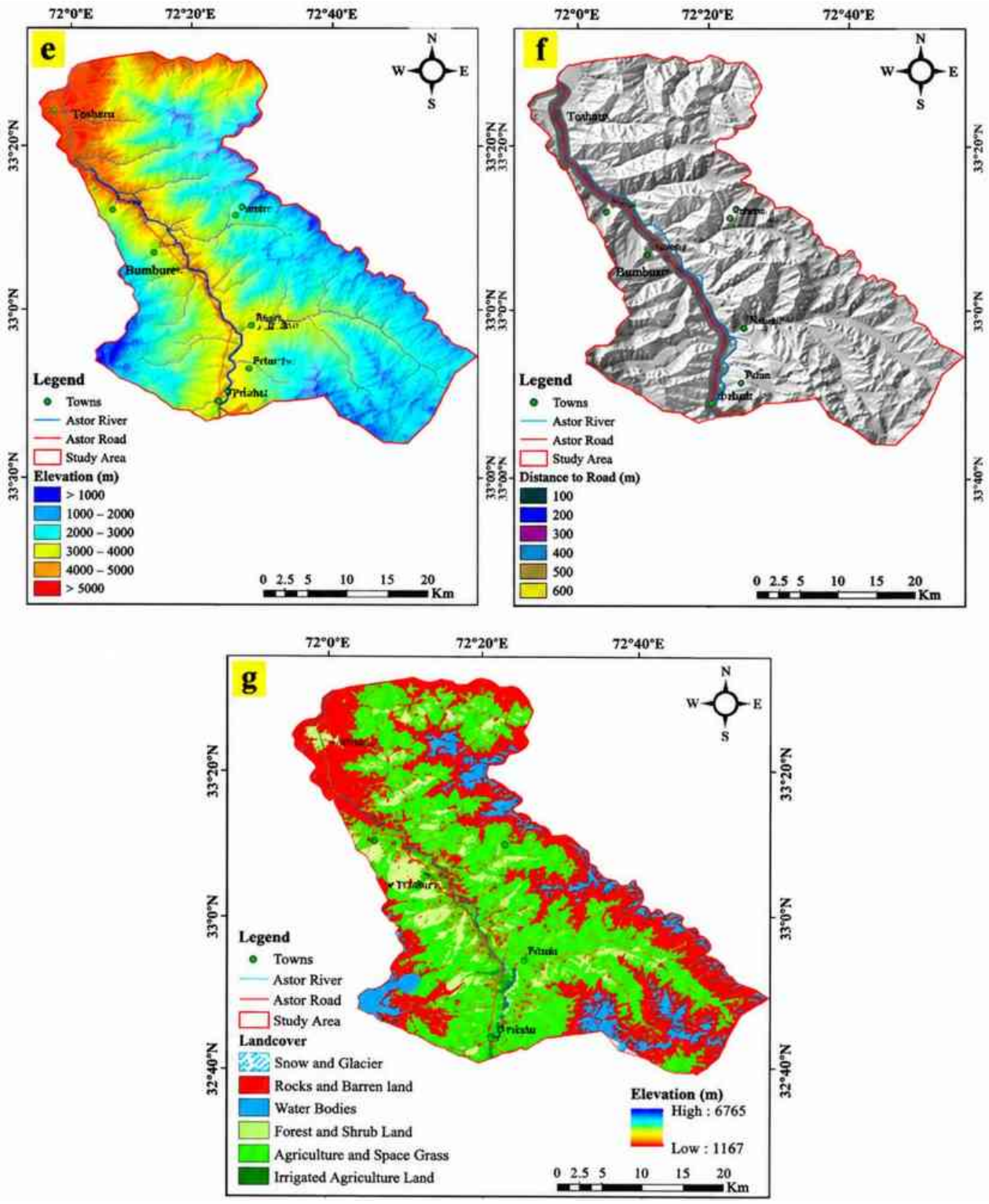


Figure 4. Spatial distribution of selected terrain and environmental characteristics of the study area: (a) slope, (b) aspect, (c) lithology, (d) distance to faults, (e) elevation, (f) distance to roads, and (g) land cover. Note: elevation is shown as contextual information and is not listed among the seven model factors.

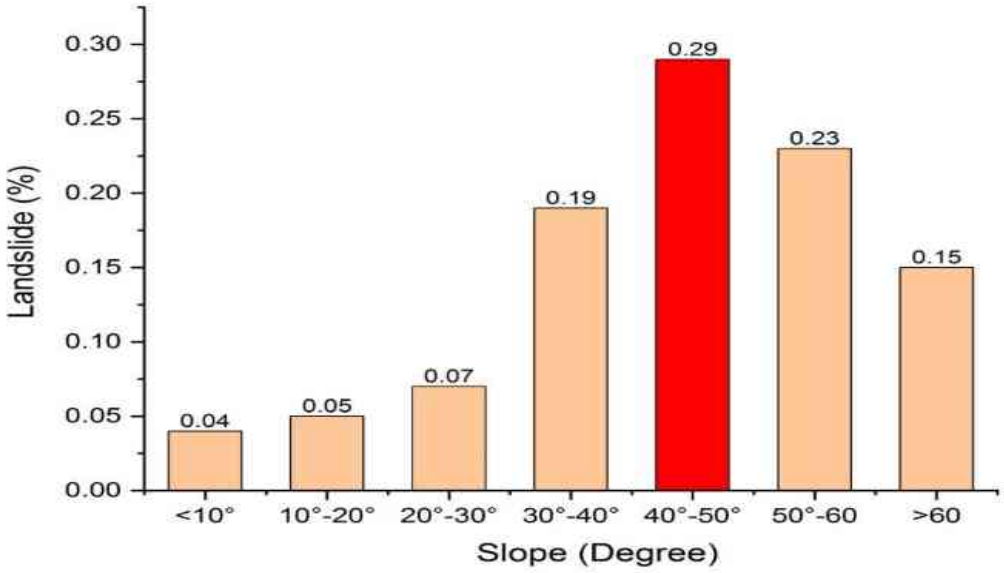


Figure 5. AHP class weights associated with slope angle.

For distance to faults, the class within 50 m has the highest reported weight (0.49). For distance to roads, the class within 100 m has the highest reported weight (0.42). For distance to streams, the class within 20 m has the highest reported weight (0.39), followed by the 20-40 m class (0.28). These weights assign greater relative susceptibility to areas close to mapped faults, roads, and streams within the model.

The class-level weight results indicate that southeast-facing slopes received the highest weight (0.28), followed by east-facing slopes (0.22). This suggests that southeast-facing slopes were assigned the greatest relative importance among the aspect classes in the AHP-based susceptibility assessment.

4.3. AHP weights and susceptibility map

The AHP results indicate that slope (0.40) and lithology (0.29) received the highest factor weights, highlighting their dominant contributions to the landslide susceptibility assessment. Land cover was assigned a weight of 0.09, while distance to faults, distance to streams, and aspect each received 0.06. Distance to roads had the lowest weight of 0.04.

The landslide susceptibility index (LSI) ranges from 1.988 to 18, and the resulting susceptibility map was classified into four categories: low, moderate, high, and very high. According to the raster attribute table, the low-susceptibility class covers 245.135 km² (17.59%), the moderate-susceptibility class covers 450.182 km² (32.31%), the high-susceptibility class covers 458.034 km² (32.87%), and the very-high-susceptibility class covers 239.964 km² (17.22%). The total mapped area is approximately 1,393.314392 km². Combined, the high- and very-high-susceptibility classes cover approximately 697.997 km², representing 50.10% of the study area. The spatial distribution of the four susceptibility classes is presented in Figure 7.

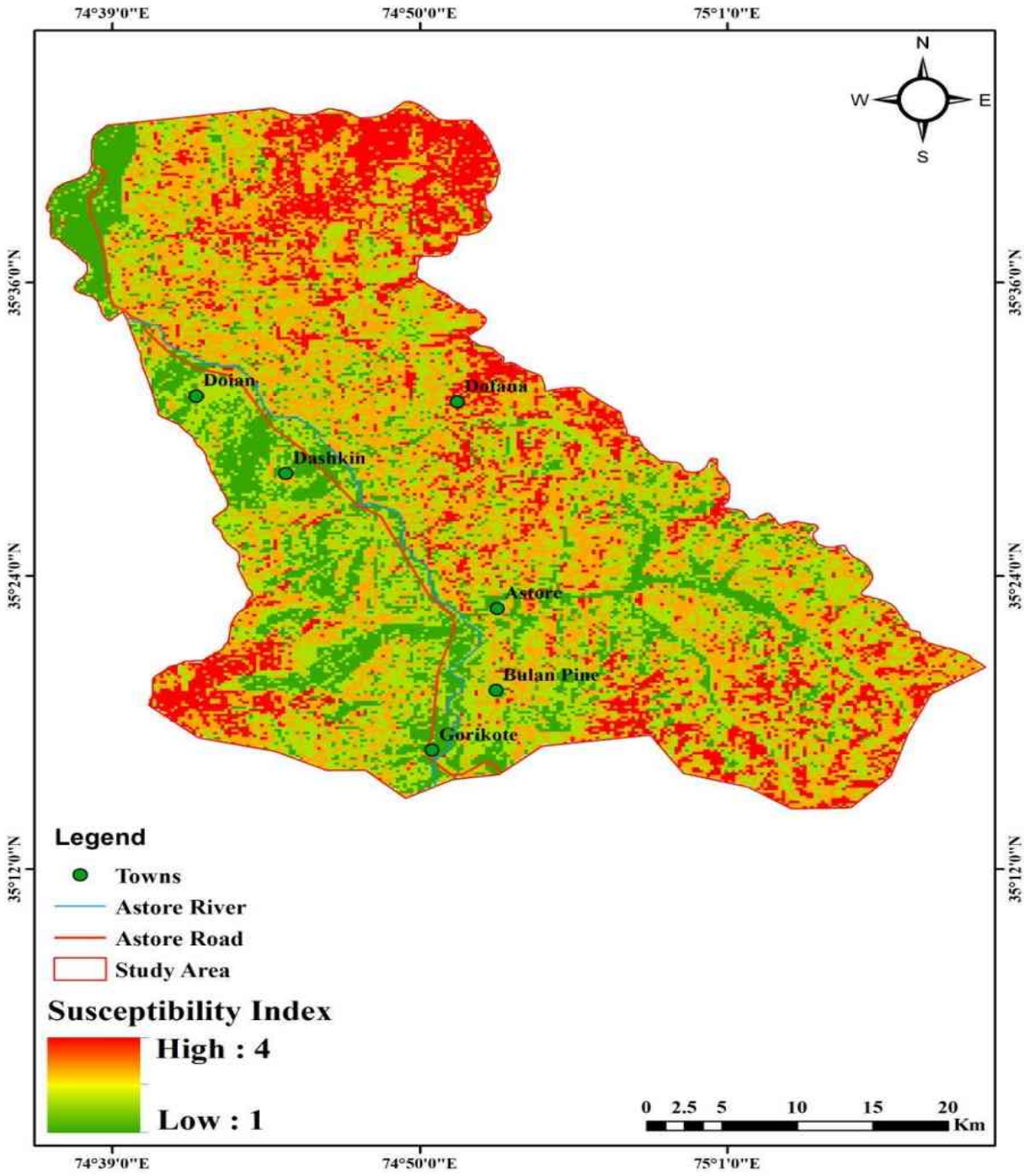


Figure 6. Continuous landslide susceptibility index (LSI) map (reported index range: 1.988–18).

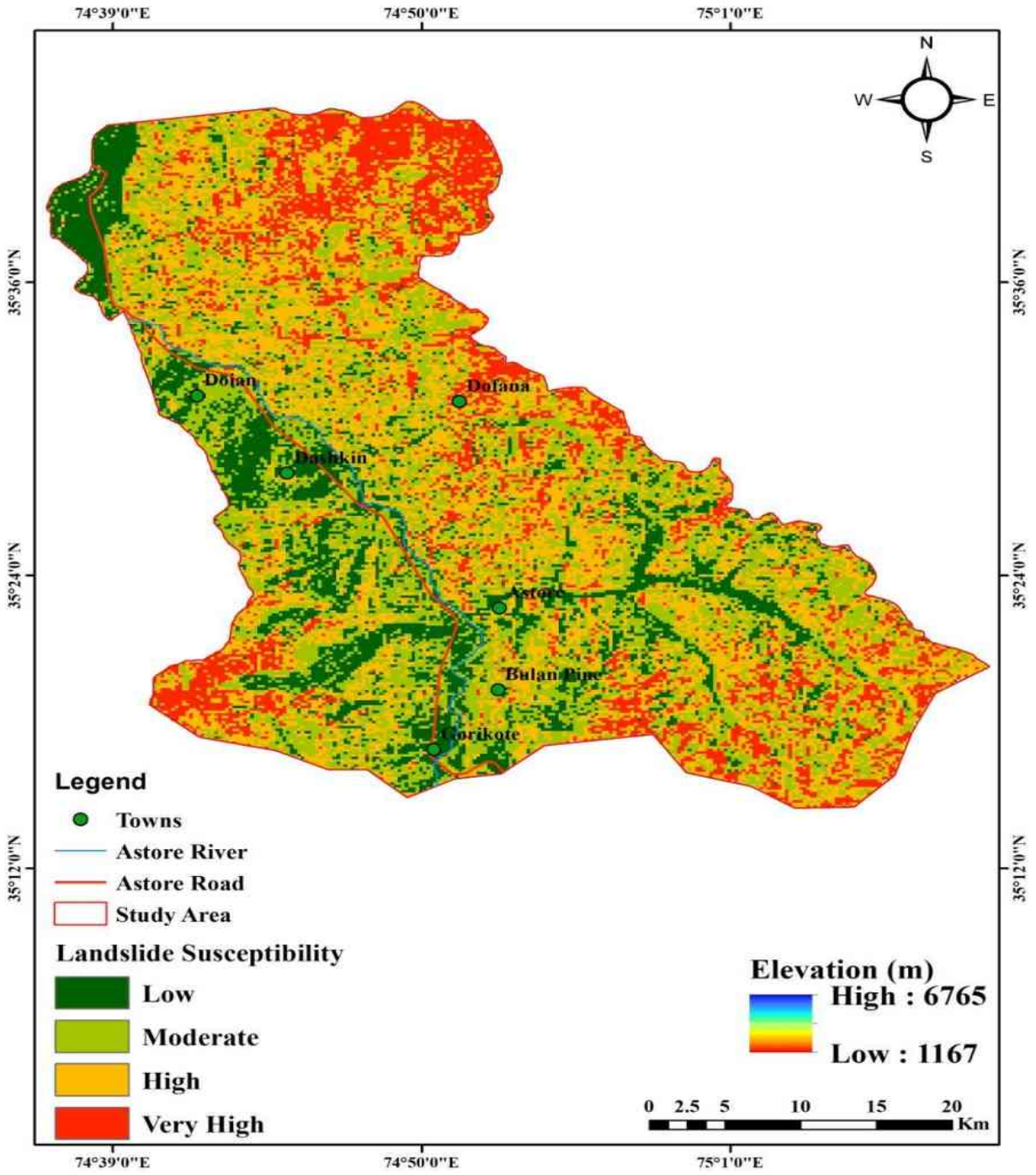


Figure 7. Landslide susceptibility map of the lower Astore Valley showing low, moderate, high and very high susceptibility classes.

4.4. Susceptibility-class area and ROC validation

The predictive performance of the landslide susceptibility model was evaluated using a 70:30 training–validation data partition. A total of 70 landslide locations were included in the inventory and randomly divided into two non-overlapping subsets using the ArcSDM tool in ArcGIS. Of these, 49 landslide locations (70%) were used for model development, while the remaining 21 locations (30%) were reserved for validation. The

validation locations were excluded from the training dataset, ensuring that the two subsets comprised distinct, non-overlapping landslide locations. For ROC analysis, ArcSDM randomly generated non-landslide locations across the study area, excluding the mapped landslide locations. The Receiver Operating Characteristic (ROC) curve was used to assess the model's predictive performance, yielding an Area Under the Curve (AUC) value of 0.700.

Table 4. Spatial distribution of landslide susceptibility classes in the lower Astore Valley.

Susceptibility class	Area (Km^2)	Area (%)
Low	245.135	17.594
Moderate	450.181990	32.310
High	458.033563	32.874
Very high	239.963685	17.223
Total	1,393.314392	100.000

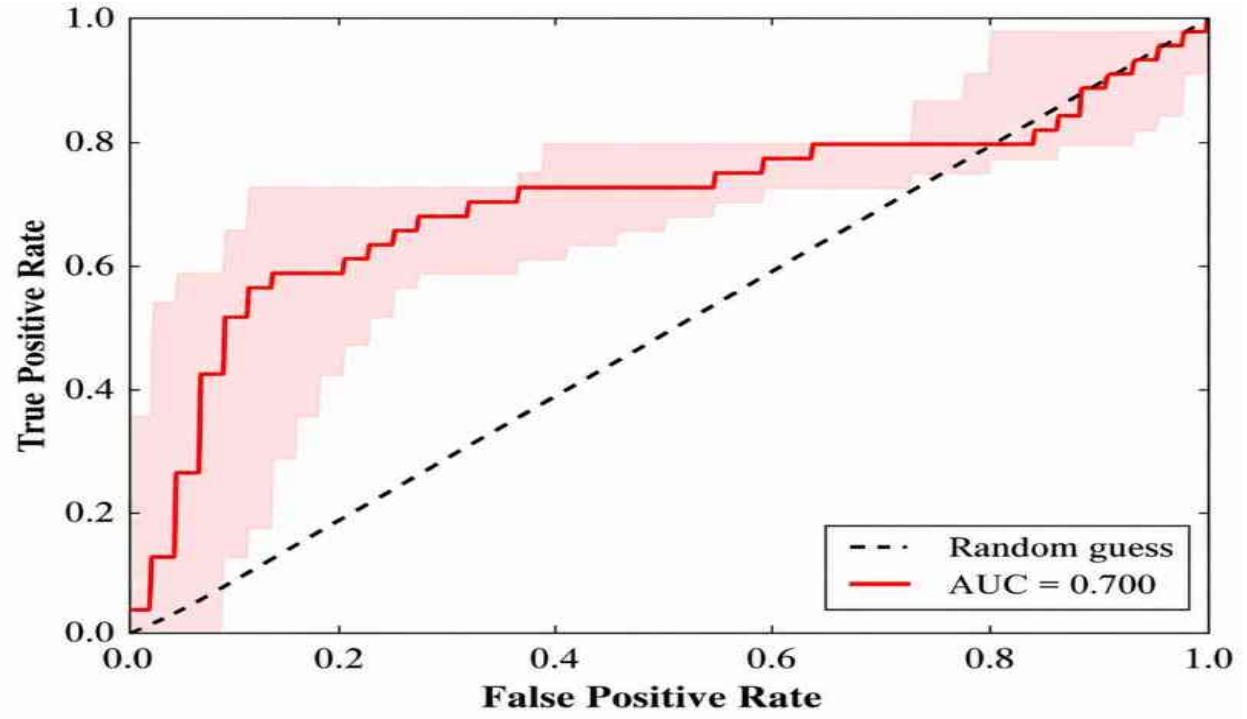


Figure 8. Receiver operating characteristic (ROC) curve for the susceptibility model (author-reported AUC = 0.700).

Table 5. Summary of the ROC validation result reported by the authors.

Validation measure	Reported value	Interpretation / qualification
Area under the ROC curve (AUC)	0.700	Moderate discrimination

5. Discussion

The AHP results identify slope angle and lithology as the two most influential conditioning factors in the lower Astore Valley landslide susceptibility model. This is consistent with the geomorphological characteristics of the study area, where steep slopes contribute to gravitational instability, while lithological properties influence

material strength, weathering, and structural discontinuities. The importance of these factors is supported by previous studies on landslide processes and susceptibility assessment (Fell et al., 2008; McColl, 2022). Similar findings have also been reported in regional studies from northern Pakistan and the Karakoram, although the relative importance of individual factors varies according to local conditions and modelling approaches (Kanwal et al., 2017; Afzal et al., 2022; Kulsoom et al., 2023).

Proximity to faults, roads, and streams also contributes to the spatial distribution of susceptibility. Field observations indicate that several mapped landslides occur close to riverbanks, while others are located near roads. River erosion may remove material from slope toes and reduce slope stability, whereas road construction can modify natural slope geometry and drainage conditions. Fault-related fracturing may also contribute to weakened rock masses. These interpretations are consistent with previous research on hillslope erosion and road-related slope instability (Fox & Wilson, 2010; Yalcin, 2008). However, these spatial associations should not be interpreted as direct evidence of causation.

Land cover represents another contributing factor, with barren land receiving the highest class weight. This suggests an association between exposed ground conditions and the susceptibility pattern identified by the model. Nevertheless, land-cover weights reflect the adopted AHP assessment and should not, by themselves, be taken as proof that barren land or vegetation disturbance directly causes slope failure.

The susceptibility map indicates the relative spatial propensity for landsliding under the terrain and conditioning factors included in the analysis. It does not establish when a landslide will occur or quantify its magnitude and potential consequences. Accordingly, the results are interpreted as landslide susceptibility rather than time-dependent hazard or risk zonation.

The model was evaluated using a random 70:30 partition of the 70 mapped landslide locations. Of these, 49 locations were used for model development, while the remaining 21 locations were reserved for validation. The validation locations were excluded from the training dataset, ensuring that the same landslide locations were not used in both subsets. However, because the partition was random, spatial independence between the training and validation datasets cannot necessarily be assumed.

6. Conclusions

This study applied a GIS-based Analytic Hierarchy Process to assess landslide susceptibility along the Ramghat-Eidgah corridor in the lower Astore Valley, Gilgit-Baltistan, Pakistan. Seven conditioning factors-slope, aspect, lithology, land cover, distance to faults, distance to roads, and distance to streams-were integrated to produce a landslide susceptibility map. The AHP results identified slope (0.40) and lithology (0.29) as the most influential factors within the adopted model, highlighting the importance of terrain steepness and geological materials in the spatial distribution of landslide susceptibility.

The resulting map classified the study area into four susceptibility categories. High-susceptibility areas account for 32.87% of the mapped area, while very-high-susceptibility areas cover 17.22%. Combined, these two classes represent approximately 50.10% of the study area. The remaining area is classified as moderate susceptibility (32.31%) and low susceptibility (17.59%). These findings identify substantial portions of the study corridor that warrant attention in land-use planning, infrastructure management, and field investigation.

The model was evaluated using a random 70:30 partition of the 70 mapped landslide locations, with 49 locations used for training and 21 separate, non-overlapping locations reserved for validation. Although the validation locations were excluded from model development, the random partition does not necessarily establish spatial independence between the two datasets.

The resulting susceptibility map provides a spatial framework for prioritizing areas that require attention in land-use planning, infrastructure development, and landslide risk-reduction efforts in the lower Astore Valley. In particular, it can help guide field verification and detailed slope-stability investigations, including the inspection of road

cuts, drainage conditions, and riverbank erosion. However, the map represents relative landslide susceptibility based on the conditioning factors considered in this study; it does not predict the timing or probability of future landslide events and should not be treated as a time-dependent hazard forecast or a quantitative risk assessment. Site-specific geotechnical investigations remain necessary for engineering and land-use decisions.

7. Practical implications and recommendations

Future studies should improve landslide inventory documentation and use updated, reliable spatial datasets. The AHP class-level scores and LSI reclassification thresholds should be clearly reported to enhance reproducibility. Spatially independent validation and additional field investigations are also recommended to improve model reliability. Finally, comparisons with other susceptibility assessment methods and periodic map updates may further strengthen landslide susceptibility assessment in the region.

Data availability

The landslide inventory, conditioning-factor data, model outputs, and validation results generated during this study are available from the corresponding author upon reasonable request, subject to the data-sharing conditions of the supporting research projects and any restrictions applying to third-party datasets.

Author contributions

Sundas Mehreen: Conceptualisation, Methodology, Investigation, Software, Formal analysis, Data curation, Visualisation, and Writing, original draft. Tehreem Nawaz: Conceptualisation, Funding acquisition, and Writing, review and editing. Tanveer ul Haq: Conceptualisation, Supervision, and Writing, review and editing. All authors reviewed and approved the final manuscript.

Declaration

Declaration of Competing Interests

The authors declare that they do not have known competing financial interests or personal relations that could have influenced the work reported in this paper.

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