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Article

Keywords: Susceptibility mapping, Disaster Risk Reduction, Multi-criteria decision-making methods, Machine Learning, Karakoram Highway

Posted Date: October 19th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11104077/v1>

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Additional Declarations: No competing interests reported.

Integrated debris-flow susceptibility assessment along the Karakoram highway using statistical, multi-criteria, and explainable machine-learning models

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Abstract

Globally, Debris Flows are the most abundant geomorphological hazard, causing significant loss of life and severe damage to infrastructure, especially in mountainous areas. The Karakoram Highway (KKH), which passes through rugged terrain, plays a vital role in the China-Pakistan Economic Corridor and is particularly vulnerable due to extreme topographic relief, active neotectonics, and complex hydrometeorological conditions. Besides its strategic significance, the regional-scale susceptibility mapping that systematically compares with a subjective, expert-driven approach with a data-driven machine learning model remains limited in the area. In this study, a comparative debris-flow susceptibility framework was developed using an independently compiled inventory of 104 occurrences, including 62 field-verified sites and 42 remotely identified sites. An integrated analytical framework was used to compare multi-criteria decision-making methods (AHP and ANP), the Statistical Frequency Ratio (FR) approach, and machine-learning algorithms (XGBoost and Random Forest) across thirteen geo-environmental conditioning factors and to evaluate regional debris-flow susceptibility. The results indicate that Random Forest achieved the highest AUC (0.852), followed by XGBoost (AUC = 0.839), FR (AUC = 0.784), ANP (AUC = 0.775), and AHP (AUC = 0.766). The Debris flow hazard in this area is frequently controlled by topographical factors, including elevation and slope, combined with intense seasonal precipitation. The resulting high-resolution susceptibility maps support disaster risk

reduction, resilient infrastructure development, and targeted emergency response strategies for the China-Pakistan Economic Corridor (CPEC).

Keywords

Susceptibility mapping; Disaster Risk Reduction; Multi-criteria decision-making methods; Machine Learning; Karakoram Highway

1. Introduction

Debris flow is a rapid mass movement process characterized by its high destructive potential, capable of transporting large volumes of sediment over long distances and causing severe damage to infrastructure and humans (Trujillo-Vela et al., 2022; Dowling and Santi, 2014). In mountainous terrains, debris flow is categorized as the most lethal and frequently occurring disaster worldwide (Zhou et al., 2022). In recent years, the frequency and magnitude of debris flows have increased due to severe weather variability and a progressive rise in seismic activity (Tang et al., 2025). Recent analysis demonstrates that the Himalayan and Hindu-Kush ranges are facing a significant rise in climate-driven geohazards, emphasizing the urgent need for improvement in monitoring and prediction frameworks (Amaratunga et al., 2023). However, the principal causes include sudden, intense precipitation, rapid snowmelt, and earthquake-related disturbances, as well as human-related alterations, including unplanned development and deforestation, which further enhanced the soil erosion on steep slopes (Wu et al., 2019). The northern mountainous belts of the China-Pakistan Economic Corridor (CPEC) rank among the most geologically dynamic and unstable regions in the worldwide. This region is characterized by pronounced topographic relief, ongoing active neotectonic deformation, and elevated ground stress, making it extremely susceptible to debris-flow disasters (Li et al., 2023). In the northern mountainous region of Pakistan, heavy rainfall on April 2, 2016, triggered widespread slope failures at more than 100 locations, including Kohistan and Dasu regions, along the Karakoram Highway, blocking the highway for more than two weeks and resulting in 16 fatalities (Ali et al., 2021a). The approximately 1,200 kilometers (km) Karakoram Highway (KKH) begins in Kashghar, Xinjiang province, passes the Khunjerab Pass, and continues southward to Besham, North Pakistan (Gao et al., 2021).

The tectonically active geomorphology of the Western Himalayas, marked by rapid uplift and deep river incision, creates favorable conditions for frequent slope instability and mass-movement activity (Kashyap and Behera, 2024). Owing to these conditions, the Karakoram Highway (KKH) has long been affected by severe geological hazards throughout its transboundary corridor. Between 2008 and 2011, around 150 debris-flow events were reported along

the highway (Liao et al., 2013). The Xinjiang section has been repeatedly impacted by damaging events, including the March 2015 debris flow near the Akto–Shufu county border, which trapped over 300 vehicles and about 600 people; the July 2016 event in Yecheng County that claimed 35 lives, and the July 2017 mud-rock flow in Bulunkou Township that buried road segments and left more than 1,000 travelers stranded (Qing et al., 2020a). Due to active tectonics, steep topography, and a very delicate landscape, the mountainous terrains of northern Pakistan are equally vulnerable to these catastrophic events (Shah et al., 2025). In 2010, a massive slope failure and subsequent flow at Attabad blocked the Hunza River, submerging a large section of the KKH and disrupting international trade for months. The floods in Pakistan in 2022, which killed over 1,500 people and impacted an estimated 33 million, highlighted the critical necessity for a thorough, multi-scale hazard assessment of the transboundary regions (Khan et al., 2022). In addition, the 2025 rainfall season is a major compound climate risk event that demonstrates how extreme weather can result in concurrent fatalities, infrastructure failure, and agricultural losses. Furthermore, extensive displacement and over 1,000 fatalities between June and October 2025; the tragedy also damaged over 100 medical facilities and almost 230,000 houses (WHO 2025; OCHA 2025b). (NDMA 2025a) reported 2,811 km of compromised roads and 790 damaged bridges as evidence of the widespread degradation of the built environment. These losses were deeply multisectoral, encompassing crop damages (US\$1.23 billion / PKR 422.65 billion), road infrastructure (PKR 187.75 billion), housing (PKR 91.20 billion), and critical public service facilities (OCHA 2025c; NDMA 2025a).

The establishment of resilient land-use frameworks and integrated disaster risk reduction significantly depends on the spatial assessment of debris flow susceptibility. Subsequently, susceptibility mapping is broadly regarded as a significant strategy for reducing the socio-economic consequences and fatalities associated with debris flow and landslides in mountainous regions (Haijun, 2024; Zhao et al., 2020; Marsala et al., 2019; Qiu et al., 2024). In recent decades, modern analytical approaches have been widely used by researchers to evaluate the debris flow across various regions of the world. Traditional statistical and multi-criteria models are widely used for debris flow susceptibility evaluation, including the Analytical Hierarchy Process (AHP) (Yalcin, 2008), Fuzzy Logic models, Network analysis, and the information value approach (Chang and Chao, 2006; Qin et al., 2019; Qing et al., 2020a). The recent study applies multicriteria decision-making together with a hybrid analytical framework and advanced machine learning models to map debris flow susceptibility. However, these subjective methods often have difficulty capturing the complex non-linear association among geo-environmental factors and debris flow initiation. Although statistical methods, including Frequency Ratio (FR), offer more objectivity, in contrast, Machine learning (ML)

algorithms, such as XGBoost (XGB) and Random Forest (RF), have brought superior predictive performance and higher accuracy in spatial modelling. Recent studies demonstrate that comparative ensemble machine learning frameworks significantly outperform single models by lowering variance and enhancing generalization over a variety of terrains (Fang et al., 2021; Wei et al., 2022). Although sophisticated machine learning (ML) techniques like Random Forest (RF) and XGBoost (XGB) have shown great predictive power in spatial modeling, their use in debris flow susceptibility modeling requires careful consideration of their inherent limitations (Li et al., 2025). Random Forest (RF) effectively manages high-dimensional geo-environmental data and minimizes overfitting; however, it occasionally has trouble with spatial extrapolation, and its forecast reliability is diminished in geomorphic terrain outside of its training area (Deng et al., 2022; Xu et al., 2024). On the other hand, XGBoost's performance is susceptible to hyperparameter adjustment and may be overfit when trained on noisy, inadequately regularized datasets. XGBoost uses gradient boosting to handle unbalanced datasets and captures non-linear correlations, producing extremely accurate bounds (Zhang et al., 2019; Tian et al., 2026).

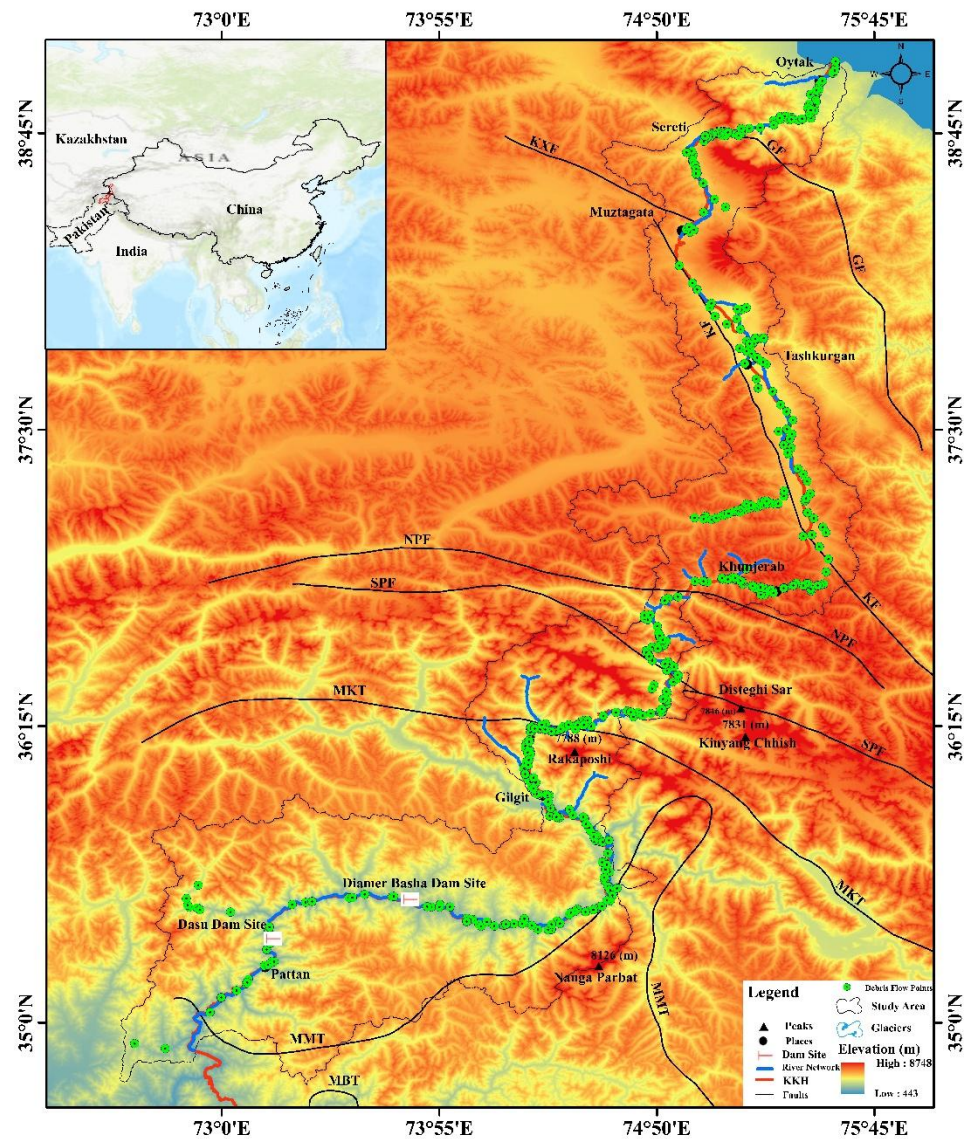
In comparison to deterministic models, these models have frequently been regarded as non-transparent approaches due to limited interpretability and their inability to explicitly describe the underlying physical processes. Recent research uses Interpretable AI approaches (SHAP) to overcome this problem. Comprehensive studies evaluating the performance of subjective models (AHP, ANP), advanced machine learning models (RF, XGBoost), and objective statistical methods (FR) throughout this transboundary corridor are still lacking, despite the strategic importance of the KKH. This study attempts to identify the primary factors influencing debris flow initiation along the Karakoram Highway (KKH) by applying a variety of techniques, such as the Analytical Hierarchy Process (AHP), Analytical Network Process (ANP), statistical methods like Frequency Ratio (FR), and advanced machine learning XGBoost (XGB). This study aims to identify the main factors controlling debris flow initiation along the Karakoram Highway (KKH) by integrating multiple approaches, including the Analytical Hierarchy Process (AHP), Analytical Network Process (ANP), statistical analysis through the Frequency Ratio (FR) model, and the advanced machine learning technique XGBoost (XGB). Debris flow susceptibility was evaluated using a high-resolution hybrid framework that combines thirteen geo-environmental parameters, allowing topographic, lithological, and long-term climatic controls to be represented within a single assessment structure. Through the evaluation of prediction accuracy (ACC) and Area Under the Curve (AUC), it is discovered that the existing methods provide a strong decision-support basis for disaster risk reduction and resilient infrastructure development across the important international corridor

China-Pakistan. Additionally, this system is scalable and transferable to other tectonically active and climatically sensitive mountainous places worldwide due to its modular architecture and reliance on globally accessible data.

2. Study Area

This study area is located in the active tectonic zone of the northwest Himalayan belt, extending from northern Pakistan to northwestern China. The Karakorum Highway, which is about 1200 km long, starts from Kashgar in Xinjiang and passes through the Khunjerab Pass and ends in the northwest of Pakistan's Besham area. The KKH plays an important strategic and economic role in the Asian highway network, as an important land connection between China and South Asia (Zhao et al., 2019). The corridor passes through the roughest and highest terrain in the world, where three mountains collide with each other: the Karakoram, the Himalaya, and the Hindukush. Hence, the landscape is characterized by steep terrain, continuous tectonic activity, and an active landscape-forming process (Qing et al., 2020b).

This study area is experiencing strong uplift and is damaged by the major fault system (Figure 1), resulting in a rugged glacier-dominated landscape and frequent moderate to strong earthquakes (Huang, 2024). Notable tectonic uplift and major fault systems have created the glacier-dominated landscape with frequent to moderate earthquakes. The study area's elevation profile displays extreme variability, with a maximum peak of 8,748 m and a minimum of 443 m. Regions with high relief, high ground stress, and steep gradients are among the most hazardous for debris flow. Such high-relief environments, combined with high ground stress and steep gradients, make this region one of the most susceptible zones for debris-flow disasters globally (Yang et al., 2011).



139 **Figure 1.** Geographical and topographic setting of the study area along the Karakoram Highway (KKH), extending
140 from Oytak to Besham, with major faults, river networks, glaciers, and key geographic features

141 Mean annual rainfall across the corridor varies extensively, ranging from an arid minimum of 81.6 mm to a
142 maximum of 1544 mm in more humid sections. Furthermore, seasonal melting of extensive snow and glacier cover in
143 the upstream basins, particularly during the summer, enhances runoff generation and contributes significantly to the
144 initiation of flash floods and debris flows (Jiang et al., 2021).

145 **3. Methods and Materials**

In this study, a GIS-based integrated framework was developed for debris flow susceptibility mapping along the Karakoram Highway by combining multi-criteria decision-making methods (MCDM) approaches, statistical analysis, and machine learning techniques.

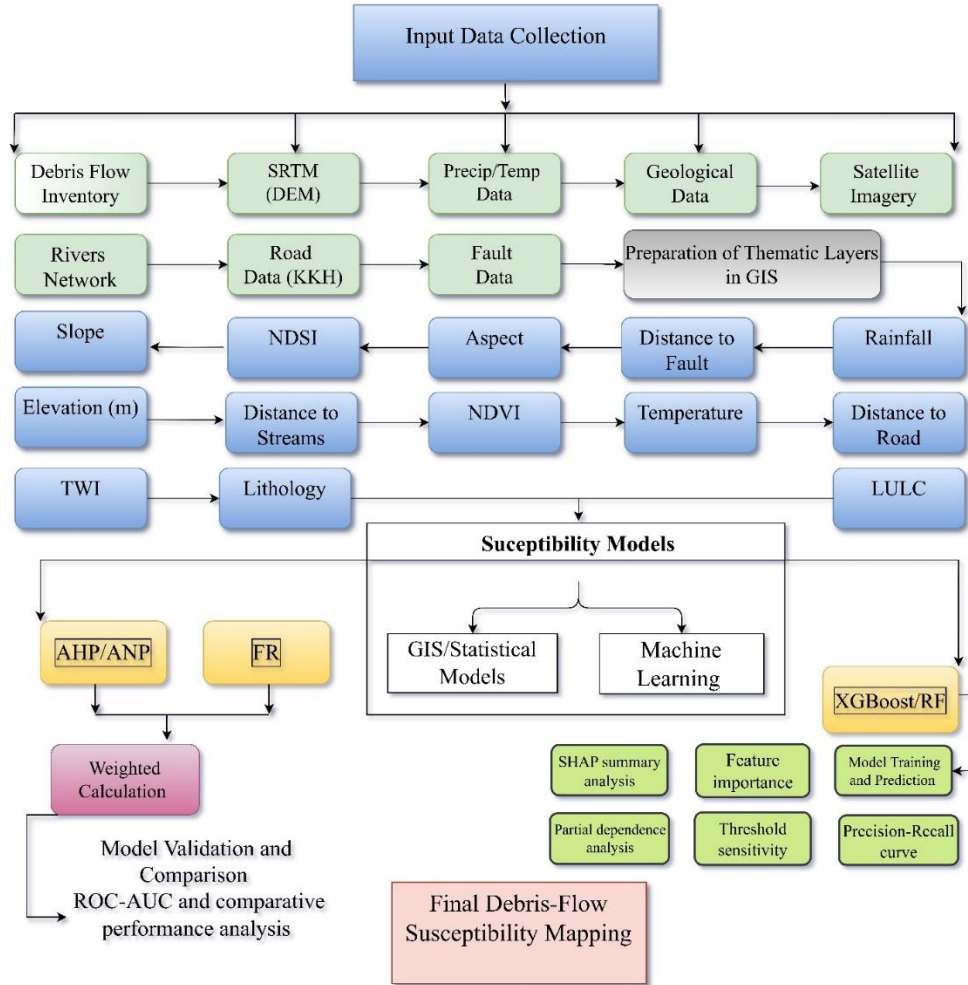


Figure 2. Methodological framework for debris flow susceptibility index mapping

The Analytical Hierarchy Process (AHP), Analytic Network Process (ANP), and Frequency Ratio (RF) methods were applied as Knowledge-driven and statistical approaches, while Random Forest (RF) and Extreme Gradient Boosting (XGBoost) models were employed as data-driven machine learning approaches. The proposed frameworks integrate a debris flow inventory with thirteen conditioning factors representing topographic, hydrologic, climatic, geological, environmental, and anthropogenic characteristics to generate susceptibility maps. Debris flow hazard susceptibility maps based on multiple causative and influencing factors. This methodological framework comprises four main stages shown in Figure 2: (i) Preparation of the debris flow inventory and conditioning factors datasets; (ii) Development of Susceptibility models using MCDM, statistical, and Machine learning approaches; (iii)

Model verification, implementation, and validation for performance assessment of the results; and (iv) Evaluation and comparison for model performance using predictive accuracy ACC and the AUC.

3.1 Data Collection

Reliable, comprehensive, and well-structured datasets are essential for accurate debris flow susceptibility mapping and hazard assessment. In this study, a multi-criteria approach was adopted by integrating data collected from national and international sources with field-based observations. The relevant conditioning factors were prepared and analyzed using geospatial techniques, and their influence on debris-flow susceptibility was evaluated through different modelling approaches. All spatial data were processed and analyzed using ArcMap, Python, and RStudio. A detailed description of the datasets, including their sources, temporal coverage, spatial resolution, and derived parameters, is provided in Table 1.

Table 1. Description, source, and preprocessing characteristics of datasets used for debris-flow susceptibility modelling.

Dataset	Temporal coverage	Derived conditioning factors	Preprocessing	Native Resolution	Model resolution	Source
SRTM DEM		Elevation, Slope, Aspect	10 m resampling; terrain derivation	30 m	10 m	USGS Earth Explorer
Sentinel-2 MSI	2017-2024	NDSI	Reflectance processing; index calculation	10 m	10 m	USGS Earth Explorer
Precipitation Data	2000-2024	Mean Annual Precipitation	10 m resampling	Native resolution	10 m	Copernicus CDS
Temperature Data	2000-2024	Mean Annual Temperature	10 m resampling	Native resolution	10 m	ECMWF ERA5-Land
Geological Data	—	Geological Mapping	Rasterization; reclassification	Vector	10 m	China Geological Survey; LGED
Fault Data	—	Distance to Fault	Euclidean; rasterization	Vector	10 m	GSCloud
Road Data	—	Distance to Road	Euclidean distance; rasterization	Vector	10 m	Actual road data source

Esri Land Cover	2017-2024	LULC	Classification and reclassification	10 m	10 m	Esri Living Atlas
Sentinel-2 SR	2017-2024	NDVI	NDVI calculation	10 m	10 m	Google Earth Engine

170

171 **3.1.1 Debris Flows Inventory Development**

172 A debris-flow inventory was independently developed for the study area by integrating field investigation

173 with multi-temporal remote-sensing interpretation (Figure 3). Given the large spatial extent of the Karakoram

174 Highway corridor and the difficulty of accessing many mountainous locations, high-resolution satellite imagery and

175 historical Google Earth images were used to complement field observations and improve the spatial coverage of the

176 inventory. A total of 104 debris-flow occurrences were identified, of which 62 locations were verified through field

177 investigations, while the remaining 42 locations were identified from Google Earth and high-resolution satellite

178 imagery. The remote-sensing interpretation focused on geomorphological characteristics indicative of debris-flow

179 activity, including source-area slope disturbance, channelized flow paths, changes in surface texture or vegetation

180 cover, disturbed channel surfaces, and recognizable depositional features. Multi-temporal imagery was examined to

181 improve the identification of features that may have been modified or obscured in more recent images. Remotely

182 interpreted locations were compared with field observations where available, and locations showing unclear or

183 ambiguous signatures were re-examined before inclusion in the final inventory. The resulting inventory therefore

184 integrates field- verified and remotely interpreted debris-flow occurrences distributed across the study area corridor.

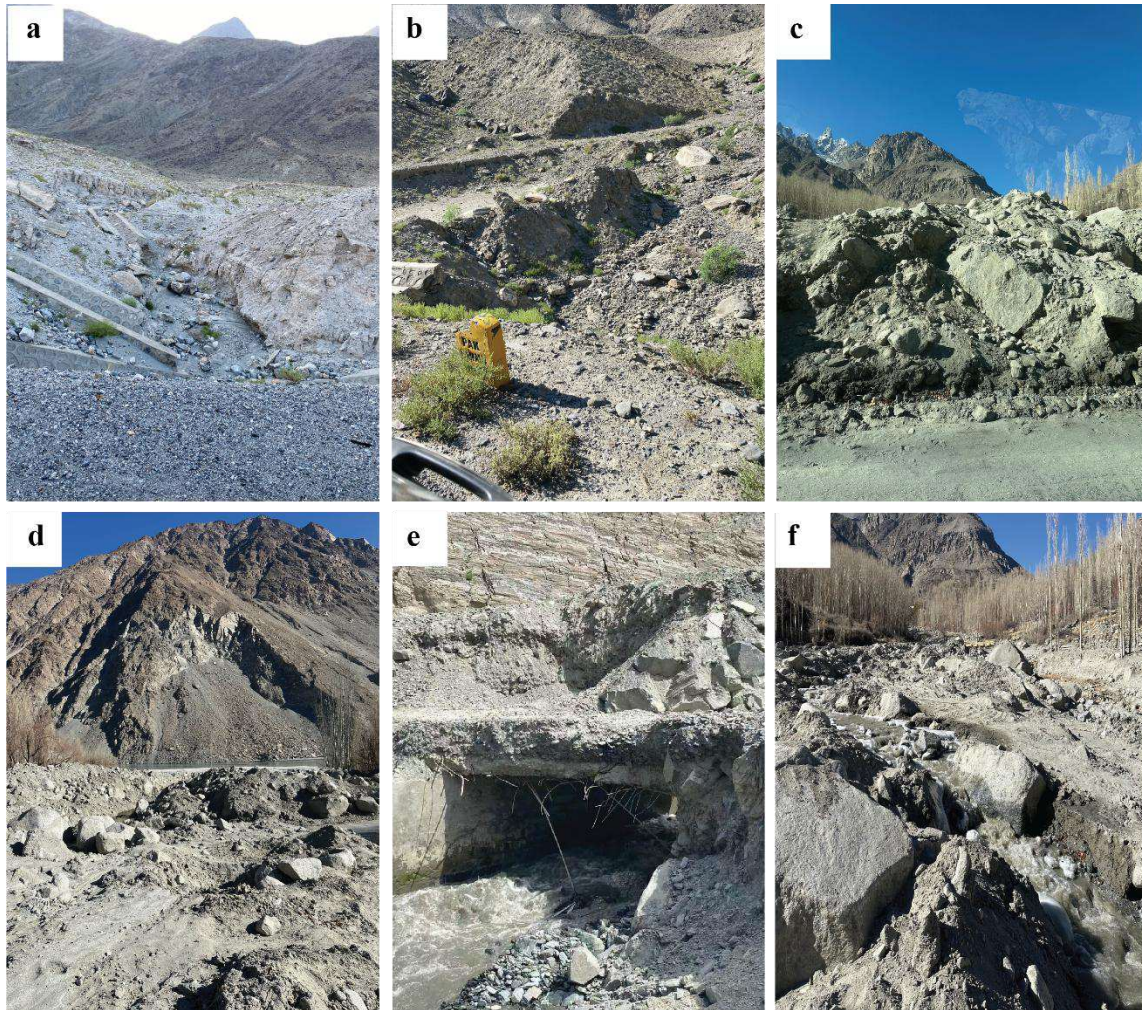


Figure 3. Field-based evidence of debris-flow occurrence recorded through inventory preparation, including source areas and erosional sections in the upper slope zone b, c), and debris-flow deposition channel infilling and sediment accumulation in down-slope areas to the valley bottom.

3.2 Debris-Flow Conditioning Factors

The selection of debris-flow controlling factors is a crucial step in susceptibility modeling and mapping, with previous studies examining various geo-environmental variable and their influence on debris-flow occurrence (Xiong et al., 2020). Debris flows are controlled by the interaction of terrain conditions, climatic factors, surface characteristics, and human activities (Zhao et al., 2022). In this study, parameters such as elevation, topographic wetness index, drainage pattern, lithology, temperature, precipitation, distance to faults and roads, land use/land cover, NDVI, and NDSI were considered to represent the main conditions influencing debris-flow initiation and movement in the study area.

3.2.1 Elevation

Elevation (Fig. 4a) is an important indicator in the study of DFS, which indirectly affects the occurrence of debris flow by affecting rainfall distribution, vegetation cover, land use, and soil moisture (Chen et al., 2024). When the elevation difference in an area is huge, elevation becomes the most important factor affecting the occurrence of geohazards (Xie et al., 2021). Elevation is a fundamental input for accurate spatial modeling, from which many important terrain-related and hydrological factors can be derived. The maximum elevation in the study area is 8748 m, and the minimum is 443 m.

3.2.2 Slope

Slope gradient is a key geomorphological factor governing slope stability, runoff concentration, and the mobilization of loose materials (Li et al., 2024). Slope represents the terrain gradient and is a key factor in debris-flow initiation, whereas steeper slopes increase gravitational potential energy, promoting slope instability and a higher likelihood of debris flows (Lang et al., 2024).

3.2.3 Aspect

Aspect represents the orientation of a slope and is influenced by factors such as rainfall patterns, solar radiation exposure, prevailing wind direction, and processes, including frost action (Aksoy and Ercanoglu, 2012; Chen et al., 2020).

3.2.4 Topographic Wetness Index (TWI)

The TWI indicates how water landscape affects zones of water concentration and runoff paths (Dash et al., 2022; Haijun et al., 2024). In this study, TWI was calculated from the DEM using Eq. (3) in ArcGIS.

$$TWI = \ln\left(\frac{\alpha}{\tan \beta}\right) \quad (1)$$

3.2.5 Normalized Vegetation Index (NDVI)

The Normalized Vegetation Index (NDVI) was derived from Sentinel-2 surface reflectance harmonized imagery obtained from 2017 to 2024 at a spatial resolution of 10 meters through Google Earth Engine. Vegetation reduces surface erosion by strengthening the soil through root reinforcement, minimizing surface erosion and significantly contributing to slope stability. As NDVI accurately measures vegetation density and subtly indicates the degree of human disturbance, it was chosen as a main assessment factor, as it effectively quantifies vegetation density and indirectly reflects the extent of human disturbance (Zheng et al., 2025). NDVI was calculated as Eq (ii)

$$NDVI = \frac{NIR - R}{NIR + R} \quad (2)$$

where R denotes the pixel value of the red spectral band, and NIR denotes the pixel value of the near-infrared band.

3.2.6 Drainage Pattern

Streams play a significant role in the initiation and mobilization of debris flows. During or after intense rainfall events, stream channels convey concentrated surface runoff that can trigger debris-flow initiation and subsequently facilitate the downslope transport of mobilized material along established flow paths. The current research used a proximity-based parameter, represented as buffer zones surrounding stream channels, to assess the impact of streams on the occurrence of debris flows (Zhao et al., 2022).

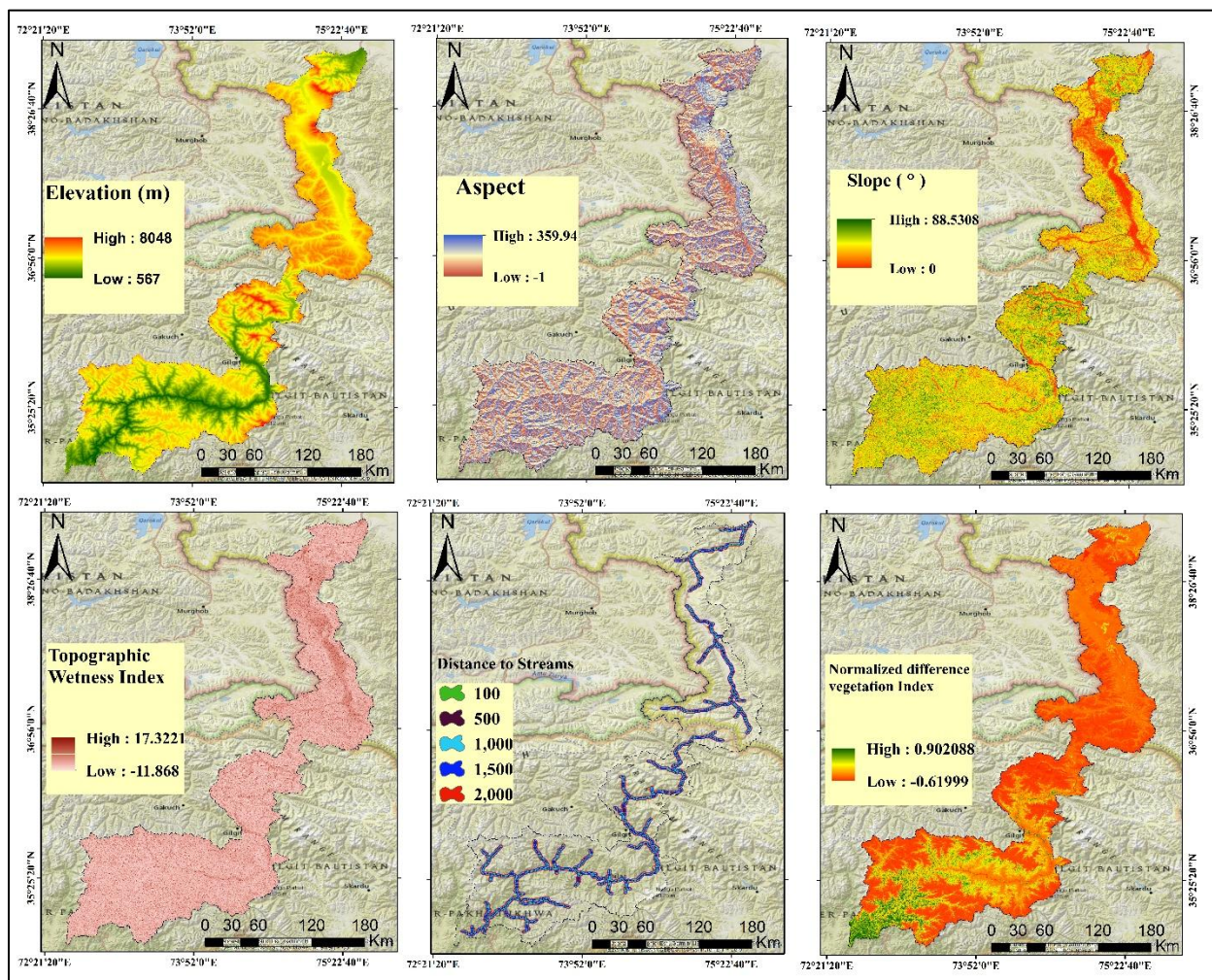


Figure 4. Thematic maps of the thirteen causative factors used in the susceptibility analysis: (a) Elevation, (b) Aspect, (c) Slope, (d) Topographic Wetness Index (TWI), (e) Distance from Streams, (f) Normalized Difference Vegetation Index (NDVI),

3.2.7 Normalized Snow Index (NDSI)

The Normalized Snow Index (NDSI) was derived from Sentinel-2 MSI imagery with a Spatial resolution of 10 meters, obtained during 2017- 2024. Using GIS to describe the Snow and glacier cover in the upstream basin, as characterized by NDSI, and their seasonal melting during the summer period can significantly enhance runoff production, thereby increasing the likelihood of floods and debris-flow activity (Nisar Ali Shah et al., 2025).

$$NDSI = \frac{\text{Band3} - \text{Band11}}{\text{Band3} + \text{Band11}} \quad (3)$$

3.2.8 Land Cover/Land Use (LULC)

Land use regulates vegetation cover, surface roughness, and soil stability; it has a significant impact on debris-flow susceptibility. Land use changes, such as increased agricultural production, urbanization, and deforestation, can worsen soil erosion and decrease landscape resilience, making debris flow more vulnerable. (Liu et al., 2025).

3.2.9 Lithology

Since different types of rock react differently to weathering, erosion, and movement, lithology is a crucial conditioning factor in debris-flow susceptibility assessment (Li et al., 2024). Lithology also plays a significant role in controlling slope stability and determining the availability of material for debris-flow initiation (Ming et al., 2014).

3.2.10 Distance to Fault

The presence of Fault alters geological conditions and can create favorable settings for the development of secondary hazards, especially debris flows (Qiu et al., 2022; Gao and Ding, 2022). The distance to faults was derived by generating buffer distances from fault lines within a Fig (I) GIS environment.

3.2.11 Mean Annual Temperature

In geological hazard susceptibility, the mean land surface temperature is a useful indicator, as it reflects surface characteristics, vegetation cover, soil moisture conditions, and thermal controls on the surface processes (Bian et al., 2024).

3.2.12 Mean Annual Precipitation

Rainfall is a primary trigger of slope stability (Wang et al., 2016). Debris-flow disasters are primarily triggered by intense rainfall events. In the study area, mean annual rainfall varies widely, ranging from a minimum of 81.6 mm to a maximum of 1544 mm. Prolonged rainfall increases water storage in the soil, while short- duration intense rainstorms generate rapid surface runoff; thus, both processes are favorable to debris-flow initiation (Wang et al., 2020).

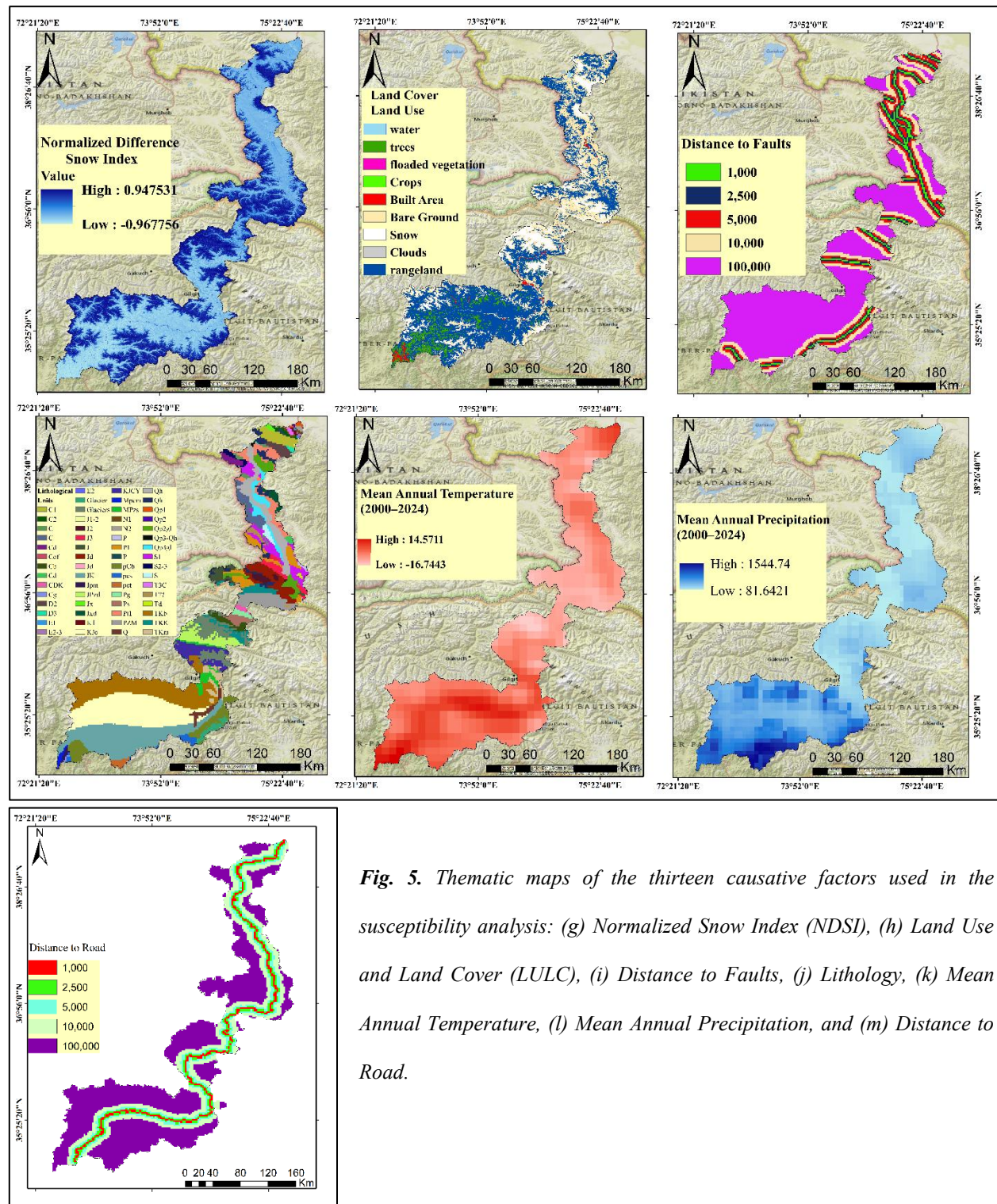


Fig. 5. Thematic maps of the thirteen causative factors used in the susceptibility analysis: (g) Normalized Snow Index (NDSI), (h) Land Use and Land Cover (LULC), (i) Distance to Faults, (j) Lithology, (k) Mean Annual Temperature, (l) Mean Annual Precipitation, and (m) Distance to Road.

Proximity to roads strongly influences slope stability, as road construction in mountainous terrains disrupts natural slope equilibrium. Road construction alters natural drainage systems and intensifies erosion processes, which can reduce slope stability and increase debris-flow susceptibility (Youssef et al., 2016). Therefore, distance to roads was included as a conditioning factor to represent anthropogenic influences on slope processes, as widely reported in previous studies.

3.3 Application of Machine Learning in Debris-flow Susceptibility Mapping (XGBoost, RF)

3.3.1 XGBoost-Based Susceptibility Analysis

Xtreme Gradient Boosting (XGBoost) is a scalable boosting algorithm method that integrates a scalable boosting algorithm (Chen and Guestrin, 2016a). Boosting regularization allows us to control overfitting, which helps improve our models. XGBoost is widely used for supervised learning tasks, including both classification and regression. XGBoost supports iterative cross-validation during the boosting process, which supports objectively determining the optimal number of boosting iterations within a single training method, thereby improving model efficiency in spatial modeling applications (Cao et al., 2020). The primary objective of the XGBoost technique is to minimize the loss function through gradient descent, thereby helping to address the overfitting problem. The fundamental principle of XGBoost lies in combining a weak learner through ensemble boosting, which leads to improved performance. The primary objective of the XGBoost algorithm is to minimize the loss function through gradient-based optimization, thereby reducing overfitting. In addition, XGBoost achieves higher prediction accuracy through the integration of bootstrap aggregation and a set of weak learners (Kumar et al., 2024).

3.3.2 Random Forest (RF) based susceptibility analysis

Random forest (RF) is an ensemble-learning method (Biau and Scornet, 2016; Cao et al., 2020). For a classification problem, the RF operates by constructing a multitude of decision trees and outputs the results by taking the majority votes (Ho, 1998). Each tree is built using a bootstrap sample of the observations and a random subset of features, and the final classification is determined by majority voting among all trees in the forest. The overall misclassification error estimated from out-of-bag (OOB) samples is used to evaluate generalization performance and assess variable importance. Feature randomness and bagging together enhance the robustness and predictive accuracy of the Random Forest model (Biau and Scornet, 2016).

3.4 GIS-integrated Multi-Criteria Decision-Making Approaches for Debris-flow Susceptibility Mapping (FR, AHP, ANP)

3.4.1 Frequency Ratio (FR) Based Susceptibility Assessment

The Frequency Ratio (FR) method is a widely used bivariate statistical technique for susceptibility assessment. It quantifies the relationship between debris flow occurrence and individual classes of each conditioning factor. The frequency ratio is calculated using the following equation (Rehman et al., 2025).

$$FR_i = \left(\frac{D_i/D}{A_i/A} \right) \quad (4)$$

Where D_i is the number of debris flow occurrences within class i , D is the total number of debris-flow occurrences in the study area, A_i is the area occupied by class i , and A is the total study area. In raster-based GIS analysis, the area proportions can equivalently be presented by the corresponding number of pixels. The FR value expresses the strength of association between debris-flow occurrence and each class of conditioning factor. Values greater than 1 indicate a relatively stronger association with debris-flow occurrence, whereas values less than 1 indicate a weaker association.

3.4.2 Analytical Hierarchy Process (AHP) based factors weighting

The Analytical Hierarchy Process (AHP) is a multi-criteria, expert-opinion-based decision-making approach widely used to assess debris-flow hazard susceptibility (Kumar and Sarkar, 2023). This approach follows a structured framework that involves defining the problems and objectives, identifying alternative options, constructing a pairwise comparison matrix, deriving factor weights, and determining the final priority rankings (Saaty, 2008). The combined effect of multiple factors causes debris-flow initiation (Li et al., 2021). The AHP methods quantify the relative importance and relationship between conditioning factors and debris-flow occurrence (Qiao et al., 2019; Sun et al., 2021).

3.4.3 Analytical Network Process Interdependencies and Susceptibility Evaluation

The Analytical Network Process (ANP) is another multi-criteria decision-making (MCDM) technique and represents an extension of the Analytic Hierarchy Process (AHP). Unlike AHP, ANP is capable of modeling complex interrelationships by incorporating both direct interactions and feedback dependencies among conditioning factors (Saaty, 2004). ANP is mainly used when simple hierarchical comparisons are insufficient, as it allows the importance of criteria to change depending on the changes being estimated (Adams et al., 2023).

3.5 Dataset Partitioning and Model Validation Strategy

The prepared inventory and conditioning factor datasets were divided into training and testing subsets using stratified random sampling. Seventy-five percent (75%) of the samples were used for model development, while

twenty-five percent (25%) were reserved for independent testing. A fixed random seed (random state 42) was applied to ensure reproducibility and consistent sample distribution among different modelling approaches. The same partitioning strategy was applied to susceptibility models, allowing a consistent comparison of their predictive performance.

4. Results

The debris-flow susceptibility results were generated using different modelling approaches, including GIS-based multicriteria decision-making methods (AHP and ANP), and statistical bivariate analysis (Frequency Ratio, FR), and Machine learning algorithms (Extreme Gradient Boosting, XGBoost, and Random Forest, RF). All models were developed using the same dataset containing thirteen key conditioning factors, ensuring a consistent basis for comparison among the susceptibility results. The final outputs were generated as raster maps with a spatial resolution consistent with the input thematic layers.

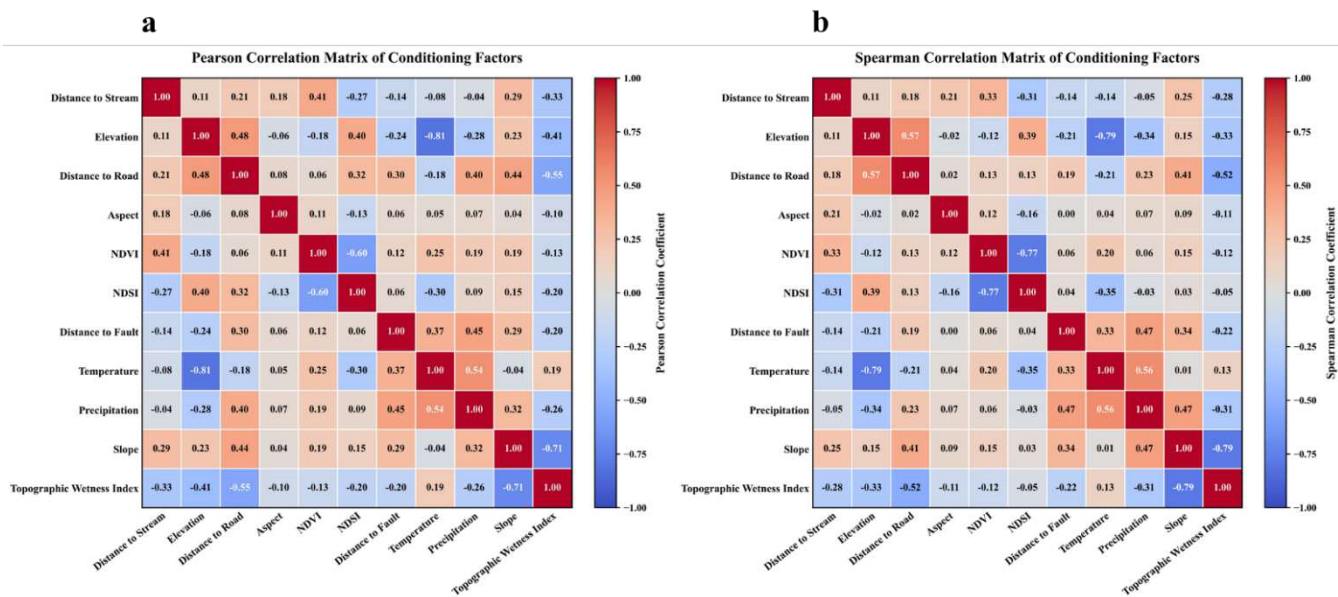


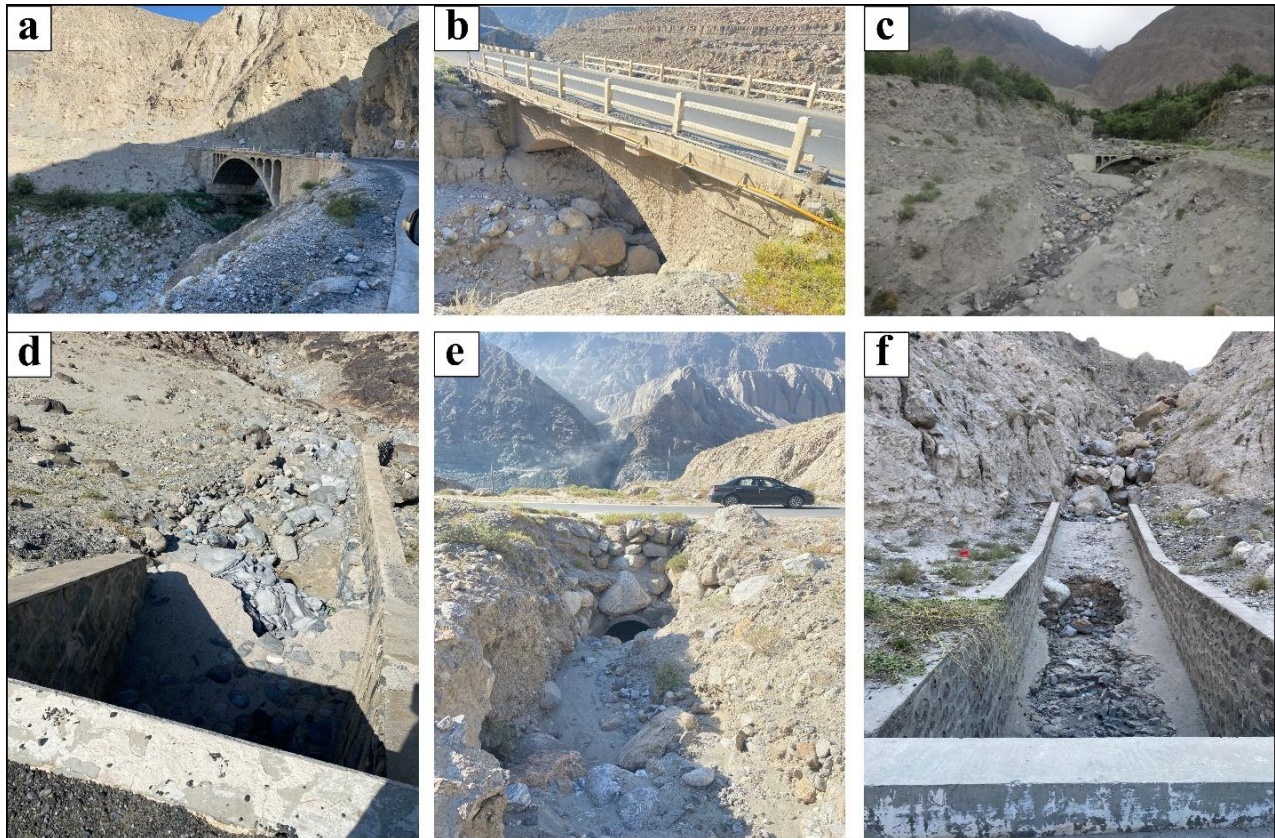
Figure 6. Pearson (a) and Spearman (b) correlation matrices showing the relationships among the thirteen conditioning factors used for debris-flow susceptibility modelling. The heatmaps illustrate the strength and direction of linear and rank-based associations between variables, providing an assessment of inter-factor relationships and potential multicollinearity among the selected conditioning factors.

4.1. Inventory balance and predictor diagnostics

The compiled inventory used for model training and testing was well balanced, with nearly equal numbers of debris-flow and non-debris samples. This distribution reduces the risk of class-dominance bias and makes comparative evaluation more reliable, particularly for recall- and precision-based metrics. Screening of the predictor set further indicated that the selected conditioning factors were suitable for multi-model analysis. Pairwise Pearson and Spearman correlation analyses reveal that several variables exhibit geomorphically meaningful associations, while no widespread evidence of severe redundancy or multicollinearity is observed among the selected conditioning factors. The strongest relationships occur among the hydro-topographic variables, particularly TWI, stream distance, slope, precipitation, elevation, and temperature, as expected in a mountainous corridor where high relief energy, runoff concentration, and snowmelt-driven hydrological processes contribute to debris-flow initiation. The Pearson and Spearman correlation matrices also revealed that the conditioning factors were correlated, though not to a degree that indicates extreme redundancy. Moderate positive and negative correlations existed among hydrological, topographic, and climatic factors, which is expected in a steep mountain environment where slope, drainage, elevation, moisture status, and cryospheric conditions tend to vary jointly. However, the overall correlation levels remained below those typically associated with severe multicollinearity, indicating the predictor variables still provided complementary information. This outcome is a significant finding because susceptibility mapping benefits from predictor sets that are physically linked but not redundant (Guzzetti et al., 2006; Reichenbach et al., 2018).

4.2. Spatial Distribution of Debris-Flow Susceptibility

Different structural variations over the KKH corridor were highlighted by the debris-flow susceptibility maps computed using various models (Figure 9). The landscape is significantly weighted toward the "Low" (28.67%) and "High" (32.53%) susceptibility classes using the Analytic Hierarchy Process (AHP) model (Figure 6d), which displays a thorough regional distribution. The most conservative hazard estimate was generated using the Analytic Network Process (ANP) model (Figure 9c), which considered factor interdependencies into consideration. Only 3.02% of the study area was classed as "very high" susceptibility, with the great majority falling into the "low" (39.00%) and "moderate" (22.07%) categories.



376 **Figure 7.** Field observations demonstrating the effects of debris flow: a), b), and c) bridges, d) and f) culverts, and e)
 377 underpasses.

378 The ANP map's network weighting may unduly smooth out local geomorphic extremes since it visually
 379 underrepresents the danger intensity in recognized, active tributary connections. The Frequency Ratio (FR) statistical
 380 model (Figure 9e) showed considerable sensitivity to localized topographic factors as compared to the subjective
 381 models. FR clearly identified drainage lines and steep slopes by computing direct bivariate connections. Nevertheless,
 382 this method led to a discernible overestimation of extreme hazard zones, designating 15.26% of the corridor as "very
 383 high" susceptibility. The FR map visually displays 'very high' pixels dispersed widely throughout the upper
 384 catchments, including remote locations with inadequate access to the roadway or material supply. Ultimately, the most
 385 highly organized and geomorphologically realistic spatial patterns were produced by the machine learning models.

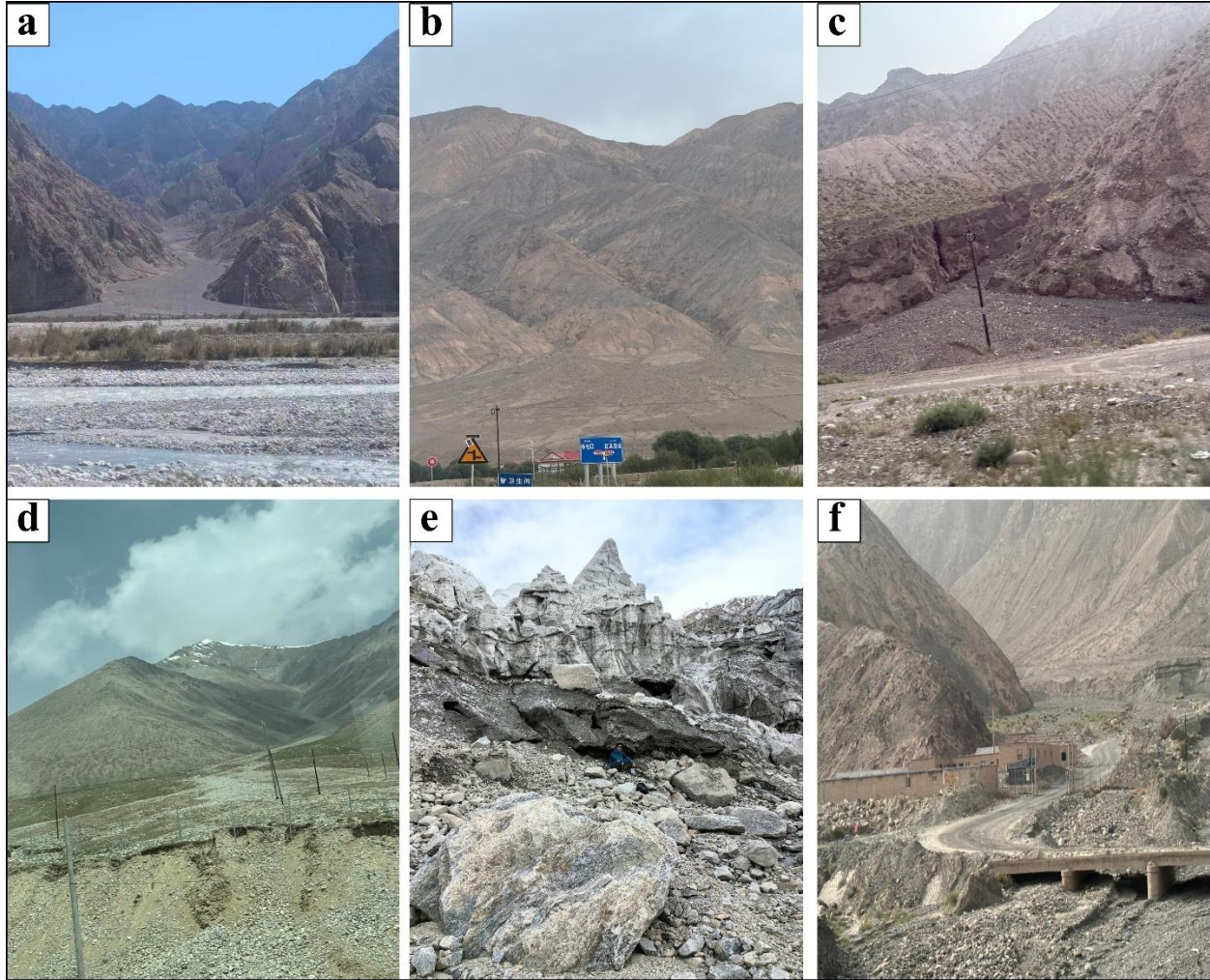


Figure 8. Field photographs of debris flow events in the study area: a, b,c, and d) show depositional surfaces, e) debris flow deposits, and f) debris flow affecting road infrastructure.

Non-linear environmental controls were successfully captured by the Random Forest (RF) model (Figure 9b), which restricted "very high" zones (11.57%) to real geomorphic bottlenecks and assigned a significant amount of the terrain to the "moderate" transitional class (36.08%). This spatial accuracy was further improved using Extreme Gradient Boosting (XGBoost) (Figure 9a). XGBoost focused "high" (23.54%) and "very high" (17.94%) probabilities strictly around important valley corridors, road-aligned sectors, steep tributary junctions, and active fault buffers, as opposed to a diffuse distribution. In contrast, both ML models accurately and confidently categorized remote, stable terrain outside of the main drainage networks as having "very low" susceptibility, demonstrating their greater capacity to map interconnected, systemic hazard routes as opposed to isolated terrain characteristics.

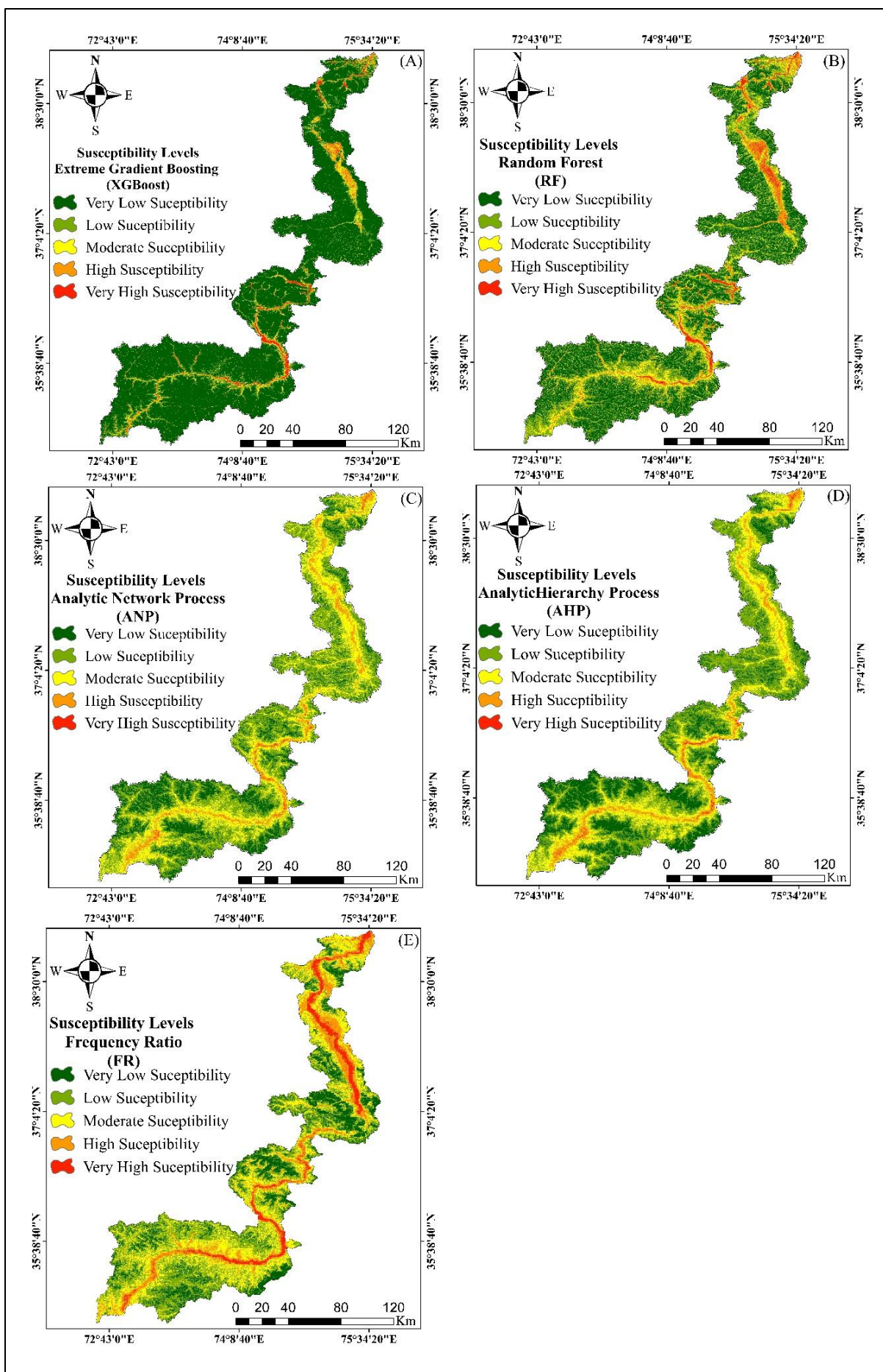


Figure 9. Final debris-flow susceptibility maps generated using different modelling approaches: (a) Extreme Gradient Boosting (XGBoost), (b) Random Forest (RF), (c) Analytic Hierarchy Process (AHP), (d) Analytic Network Process (ANP), and (e) Frequency Ratio (FR), showing the spatial distribution of five susceptibility classes across the Karakoram Highway corridor.

4.3. Comparative Distribution of Susceptibility Classes

The percentage distribution of susceptibility classes for each of the five models used, AHP, ANP, Frequency Ratio (FR), Random Forest (RF), and XGBoost, is shown in Table 2 and Figure 10. The distribution of susceptibility varies noticeably amongst the various modeling techniques, according to the data. A comparatively greater percentage of the research area is classified into the low and moderate susceptibility classes by AHP and ANP.

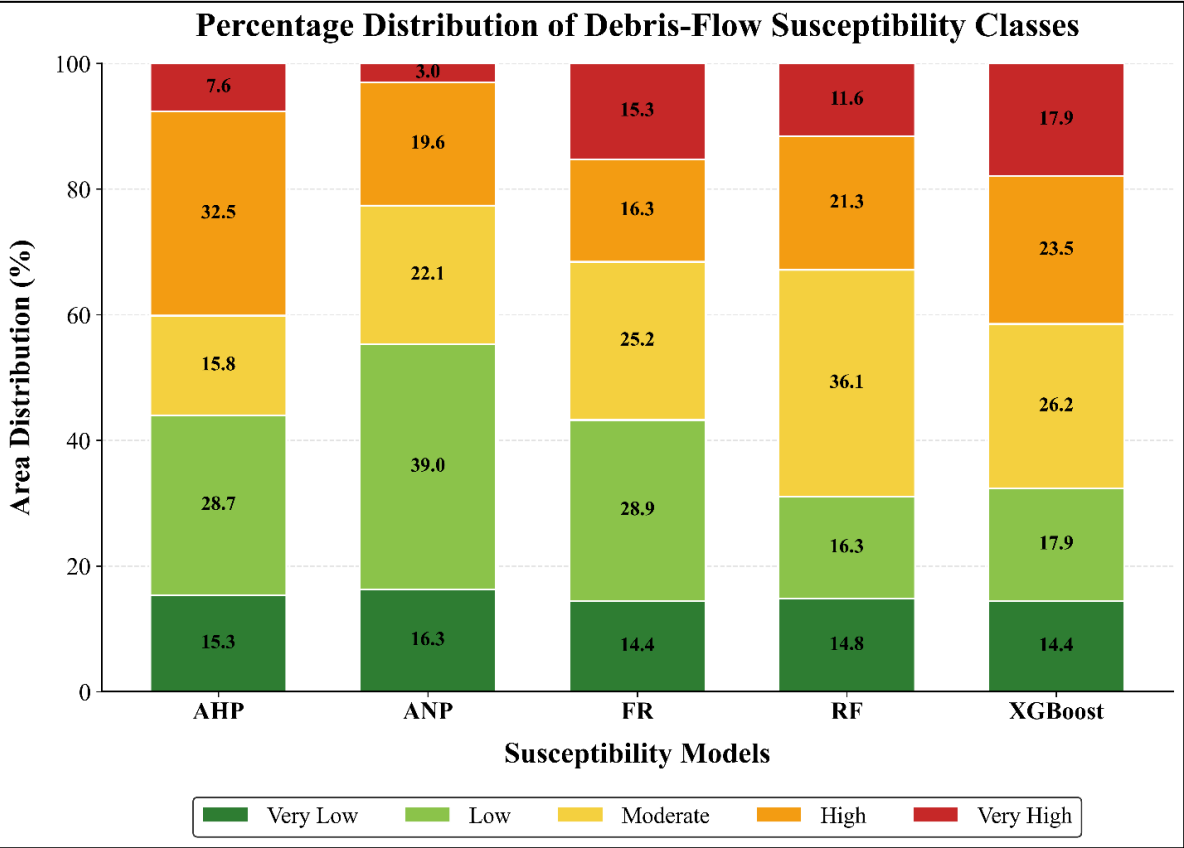


Figure 10. Comparative distribution of debris-flow susceptibility classes derived from different modelling approaches along the Karakoram Highway corridor. The stacked bar chart presents the percentage proportion of five susceptibility categories (Very Low, Low, Moderate, High, and Very High) predicted by the Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Frequency Ratio (FR), Random Forest (RF), and Extreme Gradient

Boosting (XGBoost) models. The variation in susceptibility-class proportions highlights the differences in spatial hazard classification among the applied modelling techniques.

On the other hand, throughout the Karakoram Highway corridor, the Frequency Ratio and Random Forest models identify high-susceptibility zones, which are primarily linked to steep slopes, dense drainage networks, and structurally controlled mountainous terrain. In geomorphically unstable catchments, the XGBoost model identifies localized high-susceptibility zones while highlighting wider low-susceptibility areas. Very high susceptibility zones make up smaller portions of the study area in all models, suggesting that debris-flow events are not evenly distributed throughout the corridor but rather spatially concentrated inside particular high-risk terrain segments. Comparatively, to conventional concentrated high-susceptibility zones, which is indicative of their increased ability to capture nonlinear, knowledge- driven methods, the machine learning models generally perform better in finding geographic interactions among conditioning elements.

Table 2. *Percentage distribution of debris-flow susceptibility classes derived from different models along the Karakoram Highway (KKH)*

Susceptibility Classes	AHP (%)	ANP (%)	FR (%)	RF (%)	XGBoost (%)
Very Low	15.33	16.29	14.40	14.78	14.42
Low	28.67	39.00	28.85	16.27	17.92
Moderate	15.84	22.07	25.18	36.08	26.18
High	32.53	19.63	16.31	21.29	23.54
Very High	7.64	3.02	15.26	11.57	17.94

4.4. Comparative Predictive Performance and Model Validation

The XGBoost confusion matrix produced nineteen (19) true negatives, twenty-four (24) true positives, and two (2) false negatives at the optimum decision threshold of 0.515, indicating a high level of sensitivity for debris-flow detection. This pattern is important from a hazard-management perspective because missing active or potentially

hazardous locations is generally more costly than issuing a limited number of false alarms. The XGBoost output remained extremely competitive and demonstrated a strong balance between discrimination and spatial interpretability, despite RF's slightly higher AUC.

Table 3. Summary of ROC-AUC values used to rank the five debris-flow susceptibility models.

Model	Validation indicator	Value
Random Forest	ROC-AUC	0.852
XGBoost	ROC-AUC	0.839
Frequency Ratio	ROC-AUC	0.784
ANP	ROC-AUC	0.775
AHP	ROC-AUC	0.766

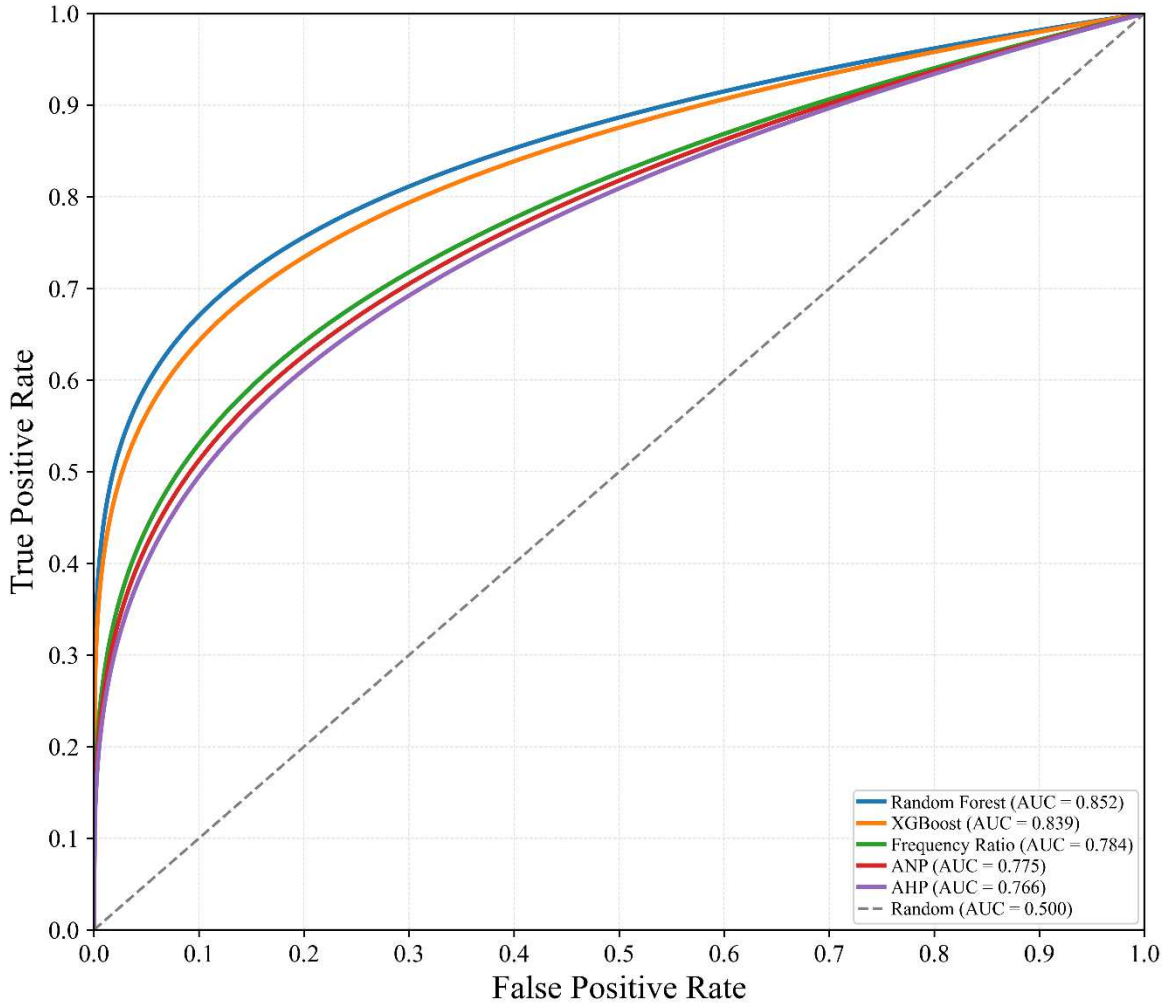


Figure 11. Receiver operating characteristic (ROC) curves comparing the predictive performance of five debris-flow susceptibility models. The corresponding area under the curve (AUC) values quantify the ability of AHP, ANP, Frequency Ratio (FR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) approaches to discriminate between debris-flow and non-debris-flow locations along the Karakoram Highway corridor.

4.5 Precision-Recall Curve and Threshold Sensitivity Analysis

The Precision-Recall curves provide further information about the capacity of machine-learning models for classification. With an area under the precision-recall curve of roughly 0.794, the Random Forest model shows predictive performance over a range of recall levels. Similarly, with an average accuracy score of 0.784, the XGBoost model finds consistent precision values over a wide variety of recall thresholds. Both machine-learning models offer reliable prediction performance overall, according to the precision-recall study, with XGBoost showing a marginally

better balance between precision and recall. The graph indicates strong identification of debris-flow-prone locations by demonstrating that the model maintains reasonably high precision even as recall grows. The threshold sensitivity study shows how changes in the classification threshold affect the performance indicators. Precision gradually rises while recall falls as the threshold rises, illustrating the common trade-off between these two measurements. The balance between precision and recall is reflected in the F1-score, which is comparatively stable at lower thresholds and progressively declines as the threshold rises. The ideal threshold value of 0.515 achieves a balance between reducing incorrect predictions and precisely recognizing debris-flow occurrences.

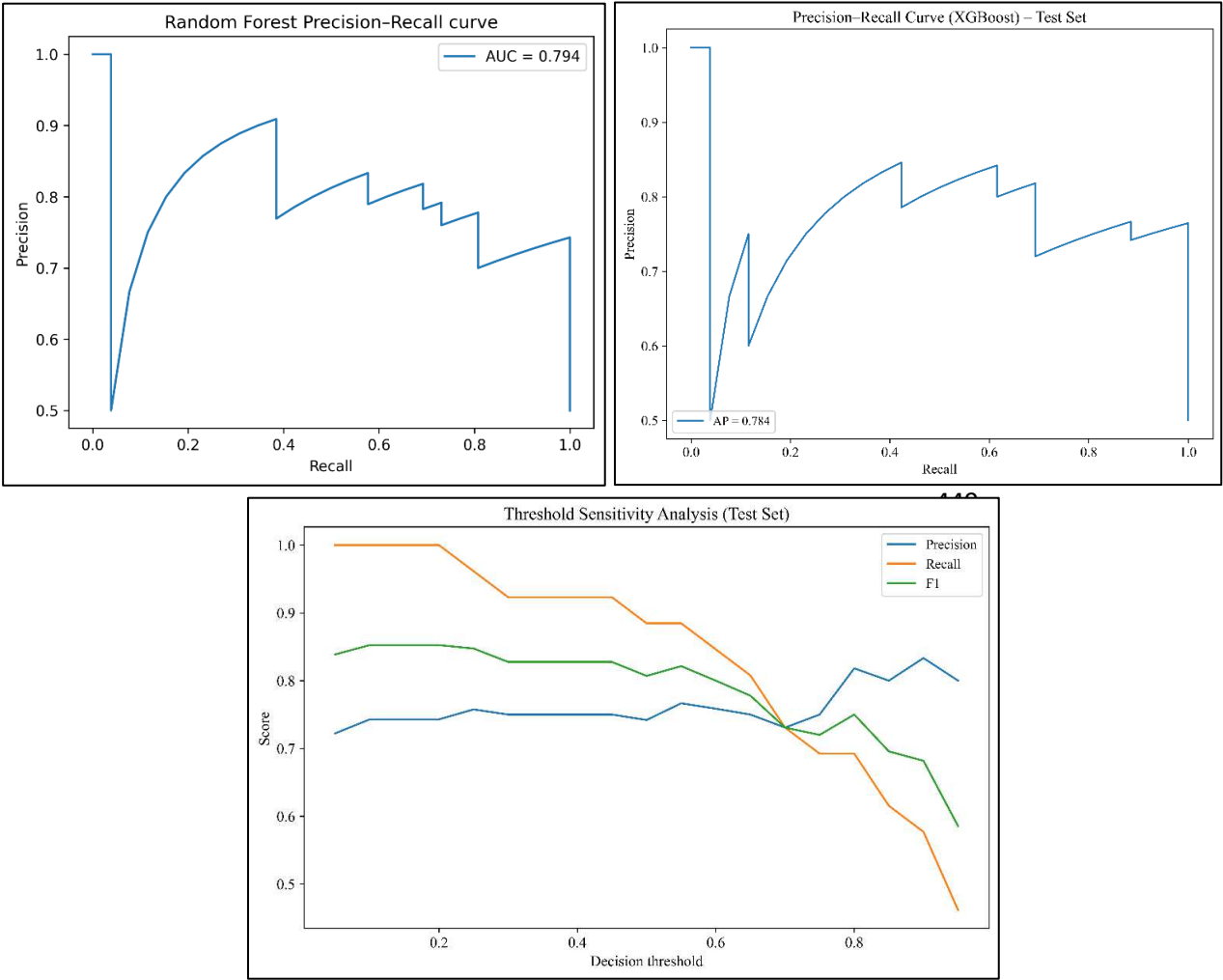


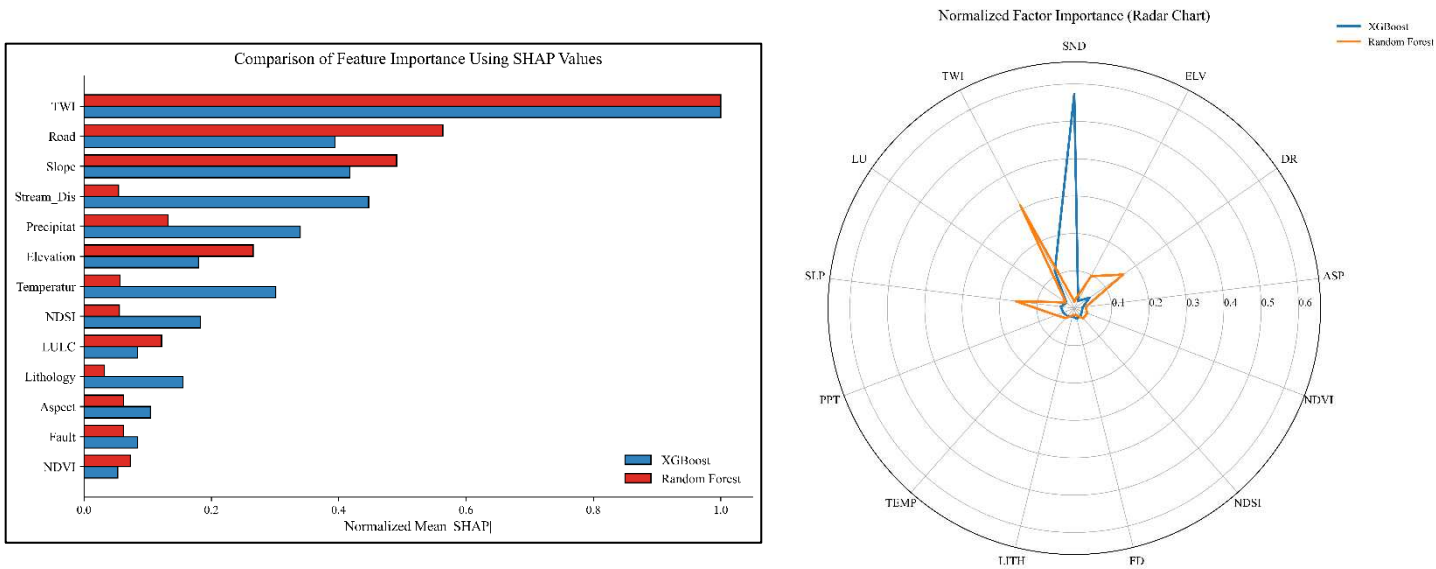
Figure 12. Precision-recall curves for debris-flow susceptibility models: (a) Random Forest; (b) XGBoost; (c) Threshold sensitivity analysis.

458 **Table 4.** Performance evaluation metrics of debris-flow susceptibility models

Model	AUC	Accuracy	Precision	Recall	F1 Score
XGBoost	0.852	0.788	0.742	0.885	0.807
Random Forest	0.839	0.769	0.733	0.846	0.786
Frequency Ratio	0.784	0.808	0.750	0.923	0.828

459 **4.6 Comparative Importance of Conditioning Factors**

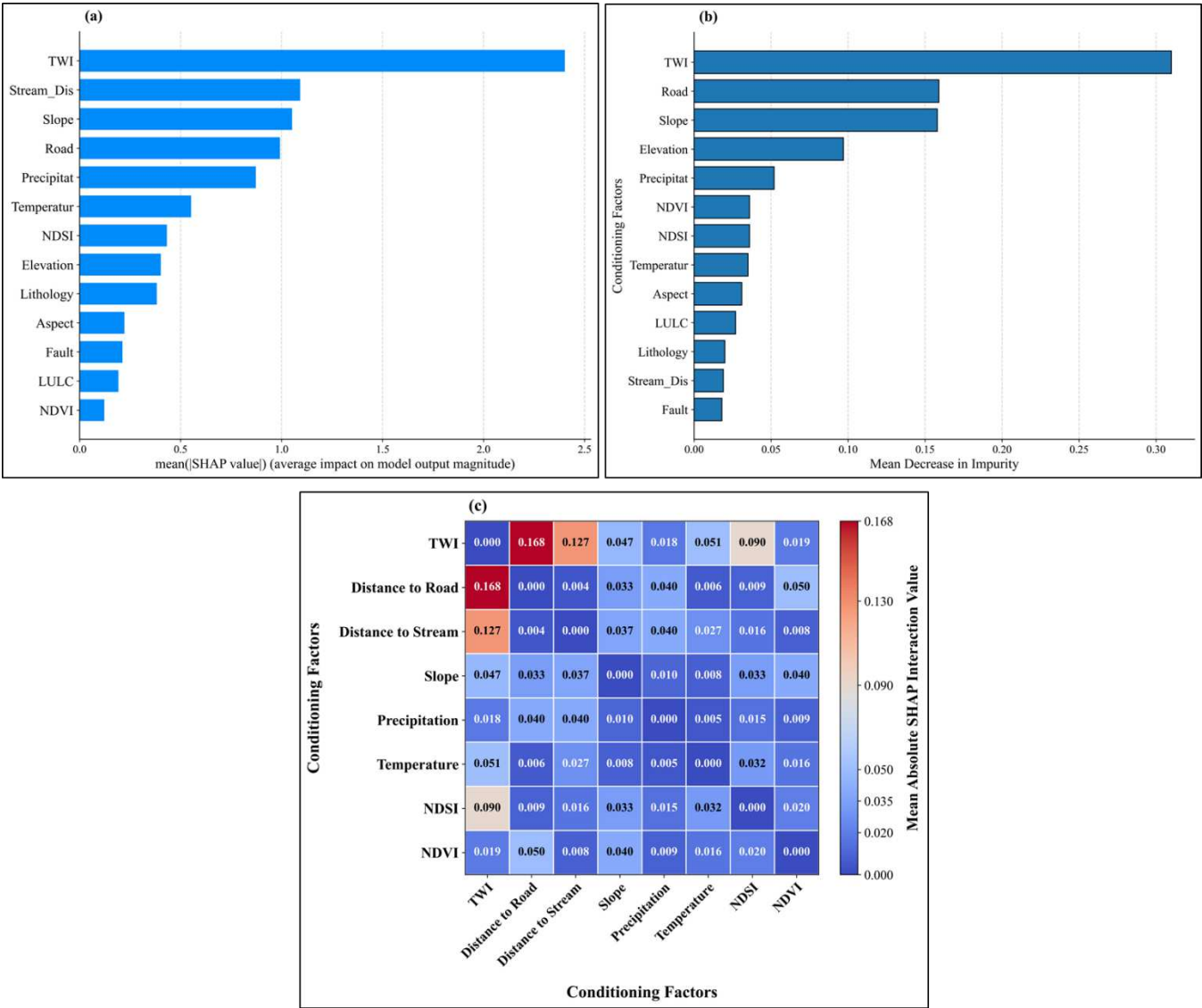
460 Hydrological and geomorphological factors continuously dominate susceptibility prediction, according to the
461 comparison of models. Across several models, variables including precipitation, slope, stream distance, and TWI are
462 highly significant. Conversely, vegetation-related factors like LULC, NDVI, and NDSI typically have lower
463 significance values. The findings imply that the main factors influencing the study area's susceptibility to debris flows
464 are hydrological processes and terrain form. The findings show that the most important variables influencing debris-
465 flow susceptibility in the research area are slope, elevation, precipitation, and distance to streams (Fig. 13 b). The
466 relevance of water accumulation in initiating debris-flow processes is highlighted by hydrological indicators like the
467 Topographic Wetness Index (TWI), which also exhibit high importance values.



468 **Figure 13.** Comparative importance of conditioning factors: (a) Factor importance from RF and XGBoost; (b) Radar
 469 chart of RF and XGBoost results.

470 **4.7. Explainable Machine-Learning Interpretation**

471 The variable-importance outputs from both XGBoost and Random Forest are broadly consistent and point to
 472 a hydrotopographic control regime. Under SHAP-based ranking, TWI emerged as the most influential variable in
 473 XGBoost, followed by stream distance, slope, road proximity, precipitation, temperature, and NDSI.



474 **Figure 14.** Model interpretation and explainability analyses: (a) global SHAP feature importance for the Extreme
 475 Gradient Boosting (XGBoost) model, (b) Random Forest feature importance based on the mean decrease in impurity
 476 (MDI), and (c) SHAP interaction heatmap showing the strongest pairwise interactions among the top eight
 477 conditioning factors.

The XGBoost gain plot, however, places stream distance first and TWI second, showing that predictor ranking is sensitive to the chosen importance metric. Random Forest returned a similar hierarchy, with TWI, stream distance, slope, and road-related effects dominating the model response. This agreement across models indicates that the most susceptible sectors are those in which moisture accumulation, short travel distances to active channels, steep gradients, and anthropogenic slope disturbance occur simultaneously. The interaction analysis adds an important process-level interpretation. The strongest pairwise effect was observed for TWI x Road (0.168), followed by TWI x Stream distance (0.127) and TWI x NDSI (0.090). Moderate but still meaningful interactions were identified for TWI x Temperature (0.051), Road x NDVI (0.050), and TWI x Slope (0.047). These results indicate that hydrological concentration alone does not account for the observed susceptibility pattern. Instead, moisture accumulation becomes especially hazardous where it is coupled with road disturbance, close channel connectivity, steep terrain, and cryosphere-related runoff contributions.

4.8 SHAP Summary Analysis of Conditioning Factors

Figure 15 represents the SHAP summary plot, which provides a summary of the influence of the conditioning factors on the debris flow susceptibility predicted by the model using the Random Forest algorithm. The distribution of the SHAP values on the horizontal axis represents the strength and direction of the influence of the conditioning factors on the model output. In accordance with the analysis, the Topographic Wetness Index (TWI), slope, and distance to streams are significant factors in the occurrence of debris flows throughout the study area. Higher values of these factors are generally associated with greater susceptibility; this is due to the significant influence of hydrological accumulation and terrain steepness on the initiation of debris-flow processes. Climatic factors, on the other hand, play an important role in the prediction of the model. On the other hand, vegetation-related factors like LULC and NDVI contribute comparatively less to the prediction of susceptibility. Overall, the SHAP analysis verifies that the Karakoram Highway corridor's debris-flow susceptibility is dominated by topography and hydrological factors.

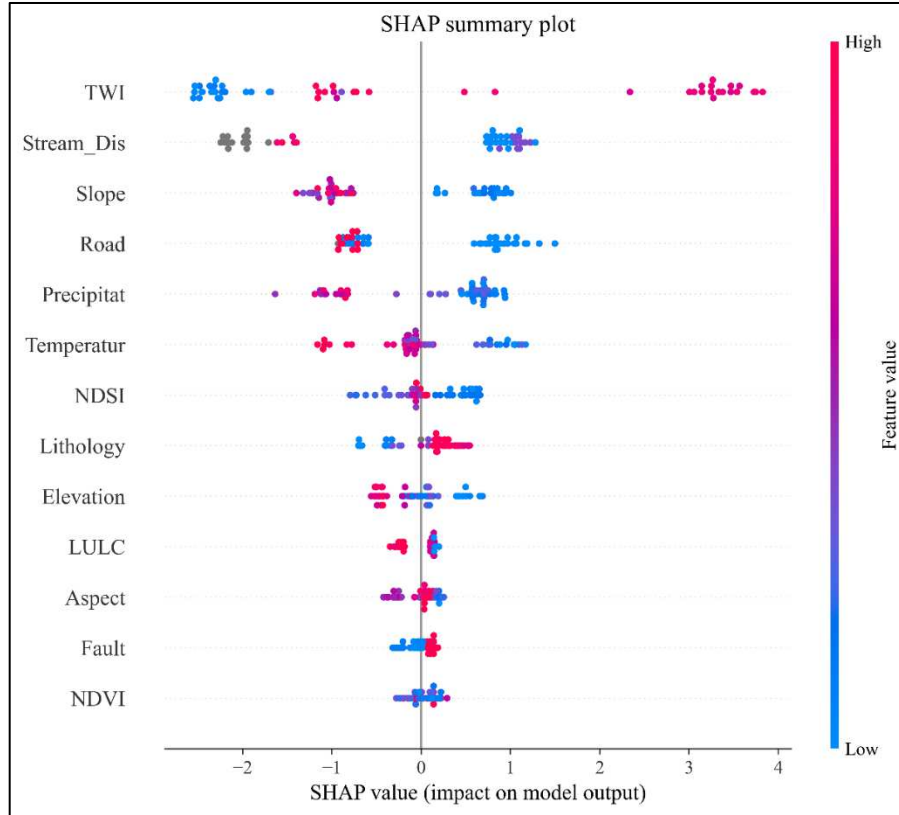


Figure 15. SHAP summary plot showing the global contribution of conditioning factors to debris-flow susceptibility prediction

4.9 Local SHAP Explanation of Model Prediction

The local SHAP descriptions provide an understandable explanation of the influence of individual conditioning factors on the prediction of debris flow susceptibility at specific locations. Figures (a) and (b) show the contribution of the conditioning factors for two specific examples, one being non-debris and the other being debris flow. In the non-debris sample (Figure a), some of the factors, such as TWI, distance to streams, slope, precipitation, road proximity, and elevation, contribute negatively to the prediction of susceptibility at the location. The negative SHAP values show that the environmental conditions are less favorable for the initiation of the debris flows in this region. However, some variables, such as lithology and NDVI, have contributed slightly to the increase in the prediction value, although the effect is very small. Overall, the local SHAP analysis illustrates the potential for interpretable machine learning approaches to improve understanding of the internal decision-making process of the Random Forest model, through quantifying the contribution of each conditioning factor to a particular prediction. This

is seen to improve the level of transparency associated with susceptibility modelling and to provide a greater level of understanding regarding the environmental factors that affect debris flows.

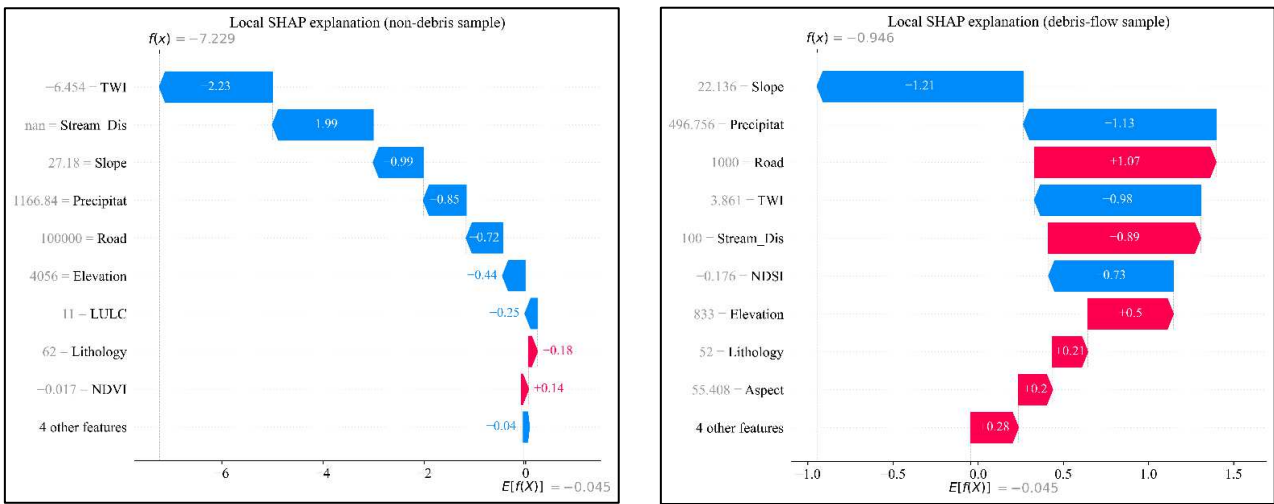


Figure 16. Local SHAP waterfall plots illustrating the contribution of individual conditioning factors to model predictions for (a) a non-debris-flow sample and (b) a debris-flow sample. Blue bars represent factors that decrease the predicted susceptibility, whereas red bars indicate factors that increase it; the cumulative contributions shift the model output from the baseline value, $E[f(X)]$, to the final prediction, $f(x)$, for each sample.

4.10 Partial Dependence Analysis

The partial dependence plots illustrate the relationship between individual conditioning factors and the predicted debris-flow susceptibility. The results indicate that the susceptibility generally increases with increasing slope gradients, whereas it decreases with an increase in distance from the streams, highlighting the importance of terrain steepness and hydrological connectivity in controlling model responses. Non-linear response patterns were observed for variables such as temperature and precipitation, demonstrating the complex interactions among environmental conditions that influence the spatial variability of debris-flow susceptibility.

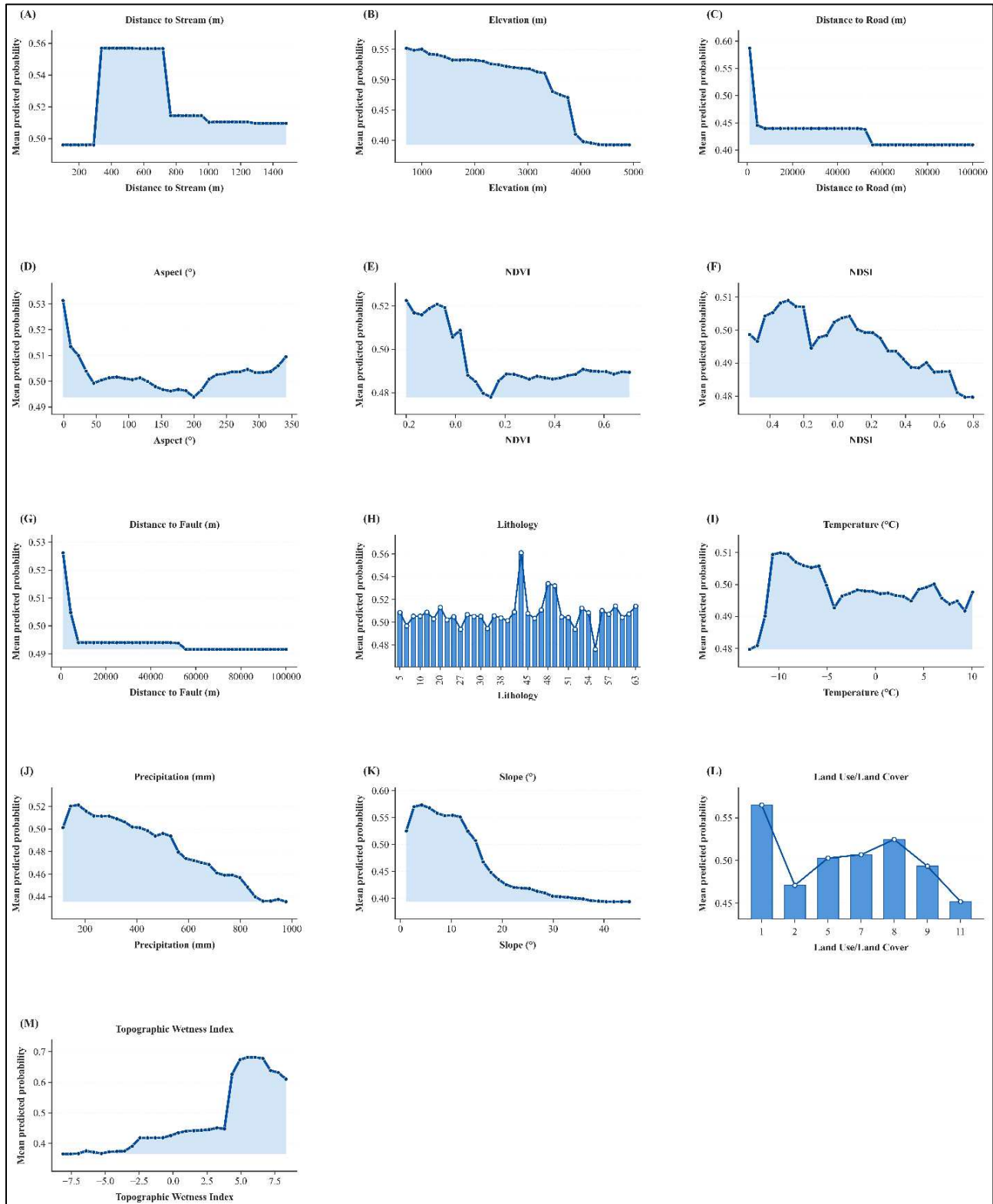


Figure 17. The relationship between specific conditioning parameters and anticipated debris-flow vulnerability is displayed using partial dependence graphs. (A) distance to stream, (B) elevation, (C) distance to road, (D) aspect, (E)

normalized difference vegetation index (NDVI), (F) normalized difference snow index (NDSI), (G) distance to fault, (H) lithology, (I) temperature, (J) precipitation, (K) slope, (L) land use/land cover (LULC), and (M) topographic wetness index (TWI). The curves represent the average marginal effect of each conditioning factor on the predicted probability of debris-flow susceptibility while holding all other variables constant.

5. Discussion

The strong performance of Random Forest and XGBoost is consistent with the complex processes governing debris-flow occurrence in steep mountain environments. Factors such as slope gradient, drainage concentration, sediment availability, rainfall input, snow and ice conditions, and local human disturbance interact in threshold-like, non-linear ways to initiate debris flows. Ensemble tree methods are especially effective in this context because they can represent non-monotonic responses, interaction terms, and abrupt variable thresholds without imposing strong parametric assumptions (Breiman, 2001; Chen and Guestrin, 2016b). In addition to their higher predictive accuracy, these ensemble models demonstrate a strong ability to capture complex nonlinear interactions among conditioning factors, which are characteristic of debris-flow initiation in high-mountain environments. By contrast, weighting-based approaches such as AHP and ANP are structurally less flexible and therefore struggle to reproduce the compound controls that govern sediment mobilization and channelized mass-flow response.

The stronger performance of the machine-learning models is also in line with previous susceptibility studies showing that ensemble methods frequently outperform simpler bivariate or expert-based approaches when the predictor space is heterogeneous and process coupling is strong (Bui et al., 2016; Reichenbach et al., 2018; Chen et al., 2024). In the present study, the narrow range between Random Forest and XGBoost suggests that both algorithms learned the dominant hazard controls effectively, whereas the clear gap between these models and Frequency Ratio indicates the added value of flexible decision boundaries.

In addition, the present study provides a notable contribution to understanding the debris flow hazard susceptibility, which marks a critical gap in the existing literature. Although the area is already vulnerable to debris flow (Nisar Ali Shah et al., 2025). Though the changing climate conditions, including extreme precipitation and warming temperatures, make the area more prone to debris flow hazards and risk (Ahmed et al., 2020; Atiq and Mahmood, 2022). Existing studies on the debris flow along the KKH are limited to hazard assessment (Derbyshire et al., 2001; Qing et al., 2020; Ali et al., 2022; Reicherter, 2025; Shah et al., 2025). Therefore, a comprehensive debris

flow hazard susceptibility assessment in the context of climate change is the need of the future policymaking and risk reduction strategies.

The analysis indicates that the primary organizing principle of susceptibility in the research corridor is hydro-topographic connectedness in the study area. The runoff converges where channels can entrain and transfer sediment, and where hillslopes are steep enough to encourage both failure and rapid sediment delivery are all described by TWI, stream distance, and slope. Strong correlation between TWI and stream distance implies that moisture contents along the channel network become particularly critical. Shorter sediment-routing distances increase the mobilization of loose material by concentrating runoff and cause debris flows. With high susceptibility zones concentrated in geomorphically unstable catchments with steep slopes, narrow valleys, and highly dissected drainage networks, the spatial distributions of susceptibility further show that debris-flow occurrence is extremely localized rather than uniform. These results are consistent with the broader geomorphic knowledge that the interaction between source areas, drainage channels, and downstream confinement controls debris flows rather than the slope angle alone (Guzzetti et al., 2006; Hungr and Leroueil, 2014). Because debris-flow processes are controlled by compound effects rather than isolated variables, this further emphasizes the significance of considering factor interactions and nonlinear relationships into account. Beyond evaluating predictive performance, interpreting the contribution of individual conditioning factors is essential for understanding the mechanisms controlling debris-flow susceptibility. Recent advances in explainable machine learning approaches have demonstrated that SHAP-based methods can effectively quantify the influence of predictor variables and identify complex nonlinear interactions within geohazard systems (He et al., 2025a).

In this study, the integration of SHAP analysis provides additional insight into the role of conditioning factors and improves the physical interpretations of machine-learning-based susceptibility predictions along the Karakoram Highway. This explainable framework also helps identify how individual conditioning factors contribute differently to susceptibility variations, providing a deeper understanding of the mechanisms represented by machine learning predictions rather than relying only on conventional feature-ranking methods (Zhu et al., 2024; He et al., 2025b). Road proximity is one of the most influential variables across the interpretation outputs, and its interactions with TWI were the strongest detected signal. This result is highly significant for the Karakoram Highway environment. Mountain roads frequently disturb slope equilibrium through excavation, unloading, artificial drainage concentration, spoil deposition, and the exposure of weak materials. Where these disturbances coincide with naturally convergent runoff

pathways, the likelihood of debris-flow initiation and the remobilization increases sharply. The mapped concentration of high-susceptibility cells along the highway corridor, therefore, appears to reflect both natural process concentration and infrastructure-induced amplification.

In the cold and high- altitude area where there is a seasonal snowfall and increasing rainfall, which altered the loose sediments to form a potential debris flow (Liu and He, 2024). This is because the area is already highly fractured, as the study area is situated in between the Indian Plate to the South and the Asian Plate to the north (Akram and Zeeshan, 2018). The major Faults such as the Main Boundary Thrust (MBT), the Main Mantle Thrust (MMT), the Kamila shear zone, the MKT, MMT, Kalagile Fault, the Gheezi Fault, the Tashkorgan Fault, the Kongor shan Fault, the Shan_ti Fault, and the Tahanman Fault pass through it. When the rainwater trapped in the fracture and freezes in winter, it creates more fractures (Wang et al., 2020). The problem get more in the spring when the upper layer of the soils gets thaws into the slurry mud, but the layer under this is hard, which creates a slippery surface (Gatto, 2000; Tian et al., 2017). Due to this, when even in the small rain, the slope gets weakened and collapses into the dangerous mudslides, and the water has plenty of loose material to pick up and carry on down the hill. As a lot of loose material sources are present at high altitudes, and when they get charged, more potential energy will be converted into kinetic energy, therefore creating a heavy debris flow.

The study area revealed that the majority of areas with a high risk of debris flow occur along valley floors close to roadways and tributary intersections. This has significant implications for risk reduction along KKH. High-risk and low-uncertainty areas are designated as priority zones for field check and preventative interventions like drainage control and slope stabilization. The findings also demonstrated that development disrupts the natural drainage and slope. For improved planning, the focus should move from a general regional assessment to a specific high-risk location. Measures such as longer culverts, protection barriers, and slope reinforcement should be deployed at these crucial points. In order to keep the highway safe during severe weather, dependable high-risk locations should be given priority for an early warning system based on rainfall. Corridor-scale hazard reduction is directly impacted by the spatial concentration of high and very high susceptibility along valley floors, stream mouths, and road-adjacent sectors. High-susceptibility, low-uncertainty zones represent robust priority areas for field validation, targeted mitigation, and slope drainage interventions. In contrast, high-susceptibility, high-uncertainty zones highlight locations where additional data and validation are required before finalizing engineering measures. This differentiation

is critical for effective risk governance, as it integrates both hazard intensity and confidence in its spatial characterization.

The KKH serves as the logistical core of the China-Pakistan Economic Corridor (CPEC) and is more than just a regional route. It is a vital, linear transboundary artery. Infrastructure resilience is therefore greatly impacted by the geographical concentration of "high" and "very high" susceptibility zones along valley floors, stream mouths, and road-adjacent sectors. The main "pinch points" where this linear infrastructure is vulnerable are tight gorges, bridges, culverts, and underpasses. These locations serve as structural bottlenecks where debris flows frequently overtop or destroy the road prism (Figure 7). Strategies for mitigation should focus on upgrading the volumetric capacity of culverts at identified high-susceptibility tributary junctions, constructing deflection berms or rigid barriers at high-risk debris fans, and reinforcing over-steepened cut slopes with retaining structures. Moreover, the high-susceptibility-low-uncertainty zones mapped by XGBoost should be targeted for the implementation of dynamic early warning systems (EWS) calibrated to local rainfall thresholds, so that this critical international supply chain remains operational during extreme hydro-meteorological events.

5.3 Limitations and future research

Although the results are reliable, some limitations should be noted. First, the inventory data and raster-based predictors represent a specific time period, whereas debris-flow systems are dynamic and may change with changing climate variation, land-cover disturbance, and road modifications. Second, pixel-based susceptibility maps simplify process chains that include initiation, entrainment, and runout, and therefore cannot fully substitute for detailed event-based process modelling. Third, some conditioning factors likely function at multiple scales, so future work should more explicitly test for scale-sensitivity. Future studies may further improve model robustness by incorporating spatial cross-validation strategies to assess model transferability across different environmental settings. Finally, the uncertainty map shows some still ambiguous transition areas that would benefit from further field validation or higher resolution event inventories. Future studies could improve the framework by incorporating rainfall intensity-duration thresholds, event chronology, multi-temporal road-construction data, and physically based runout modelling. Yet, the current findings illustrate that the ensemble learning and explainable-AI-based outputs are a transparent and practically usable basis for the debris-flow susceptibility assessment.

649 **Declaration**

650 **Funding Declaration**

651 This work was supported by the department of Civil and Environmental Engineering, College of Engineering, King
652 Faisal University, Al-Ahsa, Saudi Arabia. The funding was received by Aftab Ahmed Khan

653 **Competing Interests Declaration**

654 The authors declare no competing interests.

655 **Data Availability Declaration**

656 The datasets used during the current study are available from the corresponding author on reasonable request.

657 **Consent to Publish Declaration**

658 Not applicable.

659 **Consent to Participate Declaration**

660 Not applicable.

661 **Ethics Declaration**

662 Not applicable.

663 **6. Conclusions**

664 This study reveals that debris-flow susceptibility along the Karakoram Highway corridor is controlled by
665 complex interactions among hydro-topographic conditions, climatic variability, cryospheric influence, and human
666 activities associated with infrastructure development. The findings indicate that debris-flow initiation is primarily
667 associated with the combined effects of moisture accumulation, steep terrain, concentrated runoff pathways, and
668 anthropogenic modification of unstable slopes. Interaction analysis revealed that the strongest contributions to
669 susceptibility arise from the coupled relationships between TWI and road proximity, TWI and stream distance, and
670 TWI and NDSI. This demonstrates that debris-flow occurrence is critical where hydrological concentration coincides
671 with unstable slopes, channel connectivity, and snow- or temperature-sensitive hydrological processes. The applied
672 models indicate that the ensemble machine-learning approaches, particularly Random Forest and XGBoost, produced
673 substantially stronger predictive performance comparatively to the other techniques. Random Forest achieved the
674 highest discriminatory capability, while XGBoost demonstrated superior overall predictive efficiency through a
675 balanced representation of precision and recall. The comparable and consistently strong performance of both ensemble
676 models confirms the robustness of the identified susceptibility patterns and highlights the reliability of nonlinear

machine-learning frameworks for debris-flow assessment. Spatially, the susceptibility indexes indicate that moderate to high susceptibility zones extend across a considerable portion of the highway corridor; however, very high susceptibility is mainly concentrated within steep and confined mountainous catchments.

These critical areas are predominantly distributed along the main drainage-aligned transportation corridor and associated tributary systems rather than occurring randomly throughout the region. The integration of susceptibility and uncertainty analysis further strengthens the practical applicability of the results by distinguishing areas with reliable hazard prediction from locations where additional field-based verification remains necessary. Consequently, the computed susceptibility maps provide a scientifically defensible basis for prioritizing monitoring programs, drainage management, slope stabilization, and transportation route planning along the Karakoram Highway. The study also emphasizes the need of accounting for nonlinear relationships and factor interactions in debris-flow susceptibility modelling. In this regard, interpretable ensemble-learning methods provide clear advantages over traditional statistical and expert-based approaches by improving both predictive capability and process understanding. Overall, the findings demonstrate that machine-learning approaches provide a reliable and operationally applicable framework for debris-flow susceptibility assessment in complex high-mountain environments, while also supporting hazard mitigation, infrastructure resilience, and disaster-risk reduction along the Karakoram Highway corridor and other comparable mountainous regions worldwide.

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