https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

Integrating multidimensional factors through Bayesian Belief Networks for landslide and debris-flow risk reduction in subtropical zones

Kinh Bac Dang[1], Hieu Nguyen[1,*], Thanh Dat Do[1], Thi Phuong Nga Pham[1], Tuan Linh Giang[1,2], Thi Dieu Linh Nguyen[1], Huu Hao Ngo[3], Giuseppe Forino[4]

[1] *VNU University of Science, Vietnam National University, 334 Nguyen Trai, Thanh Xuan, Hanoi, Vietnam*

[2] *VNU Institute of Vietnamese Studies and Development Science (VNU-IVIDES), Vietnam National University, 336 Nguyen Trai, Thanh Xuan, Hanoi, Viet Nam*

[3] *Centre for Technology in Water and Wastewater, School of Civil and Environmental Engineering, University of Technology Sydney, Sydney, NSW 2007, Australia*

[4] *School of Science, Engineering & Environment, University of Salford, Manchester M5 4WT*

Correspondence to: Hieu Nguyen (nguyenhieu@hus.edu.vn)

Abstract. Current forecasting models for landslides and debris flows mostly look at environmental or socio-economic factors on their own. They rarely combine both into a single probabilistic framework that might give warning in complicated and uncertain situations. This constraint is especially clear in Vietnam, where intense subtropical rain, steep and extensively dissected mountainous terrain, and quick changes in land use and infrastructure are the main causes of landslides and debris flows. This research introduces a novel approach using a Bayesian Belief Network (BBN) to enhance landslide-risk prediction through the integrated analysis of environmental and socioeconomic data. The developed BBN model incorporates inputs from diverse sources, including Geographic Information Systems (GIS), remote sensing, and field survey observations. Structural Equation Modeling was employed to align the BBN with established relationships between landslides and influencing factors. The analysis explored different scenarios by combining rainfall intensity with land-use patterns and assessing the protective role of embankments. Results indicate that precipitation exceeding 130 mm over a period longer than three days markedly increases the likelihood of landslides and debris flows, particularly in agricultural regions. Gabion embankments were found to be highly effective in mitigating risks to both human safety and built environments.

Keywords: *Natural hazard, Susceptibility, Risk, Modelling, Scenario.*

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

1. Introduction

Various disasters such as landslides and debris flows have significantly impacted human lives and infrastructure in mountainous regions (Barnard et al., 2001; Ren, 2015). These hazards commonly occur on steep slopes and are primarily triggered by disturbances to the critical balance of forces within slope materials. According to the European Civil Protection and Humanitarian Aid Operations – European Commission (2022)[1], up to 78.3% of global landslides in 2021 occurred in Asia. The consequences of these events can be catastrophic: landslides and debris flows claimed more than 1,500 lives in China in July 2010; 5,000 lives in December 1941 and 600 lives in August 1971 in Peru; over 1,100 lives in the Philippines in 2006; and nearly 2,000 lives in Italy in September 1963 (Kang et al., 2023; Palumbo et al., 2024).

In Vietnam, records from the Ministry of Natural Disaster Prevention and Search and Rescue indicate that the aftermath of Typhoon Yagi in 2024 resulted in human and economic losses amounting to 40 trillion VND (approximately US$1.63 billion), with 329 fatalities and over 2,000 people affected. The primary causes were increased precipitation and prolonged rainfall during the tropical cyclone, combined with human-induced slope disturbances due to construction activities (Tu et al., 2016; Yamasaki et al., 2021).

To mitigate such risks, many countries have developed models and maps aimed at predicting and warning against landslides and debris flows (Shirzadi et al., 2017; Zhao and Lu, 2018). However, these tools have often failed to deliver practical results, a limitation attributed by researchers to the selection of inappropriate input variables and the use of unsuitable modelling approaches. Consequently, there is a pressing need for more robust and reliable decision-support tools that can effectively guide disaster prevention and warning efforts across diverse topographic, environmental, and climatic conditions.

A comprehensive analysis of contributing factors is essential for developing such tools for landslide and debris-flow risk assessment. Geographic Information Systems (GIS) have traditionally served as platforms for integrating various qualitative and quantitative datasets through weighting systems to enhance risk estimation (Barman et al., 2023; Hung et al., 2015; Nichol et al., 2019). Among the commonly used methods, the Analytic Hierarchy Process (AHP) and its fuzzy logic extension (Fuzzy-AHP) account for approximately 15% of risk assessments (Kayastha et al., 2013; Mondal and Maiti, 2012; Saleem et al., 2020).

Statistical models, which are more effective in handling data with complex correlations, constitute another important approach (Damm and Klose, 2015). Linear statistical methods have remained the

[1] https://www.statista.com/statistics/267833/number-of-people-affected-by-major-dry-landslides-worldwide/

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

dominant analytical tools for hazard assessments, contributing to 20.51% of modelling approaches, while probabilistic methods account for 12.82% (Fig. 1). Techniques such as multiple linear regression, Bayesian probability, and ROC-plane analysis have proven successful in estimating the likelihood of landslide and debris-flow occurrences (Moriguchi et al., 2023; Song et al., 2012). For instance, geostatistical analyses in Ghana have revealed that landslide susceptibility is not solely dependent on temporal increases in rainfall intensity, but also on geological parameters and their interactions (Segue et al., 2024).

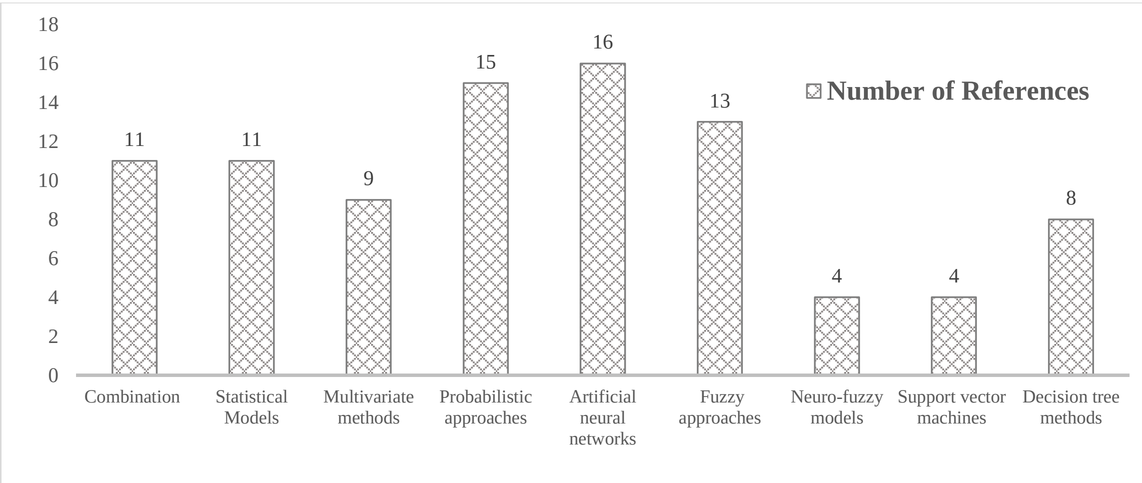

Figure 1. Frequency of research methods in assessing risks of landslides and debris.

To date, higher-order machine learning algorithms such as Decision Trees (accounting for 10.26%), Support Vector Machines (5.13%), and more advanced models like XGBoost have begun to be incorporated into geostatistical modeling frameworks to improve predictive capabilities (Bui et al., 2020). These point-based machine learning and artificial intelligence approaches are well suited to the problem because the datasets typically involve numerous interrelated variables, enabling focused, point-by-point prediction (Ma et al., 2021; Models, 2021). Despite progress in developing risk assessment procedures, accurate prediction of landslides remains a significant challenge. This difficulty arises primarily from the multitude of interacting factors that contribute to mass movement, including diverse natural and environmental conditions as well as human activities (Ngo et al., 2025). Consequently, further research and methodological advancements are required to enhance model performance, improve forecast accuracy, deepen our understanding of landslide mechanisms, and develop more effective strategies for risk reduction.

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

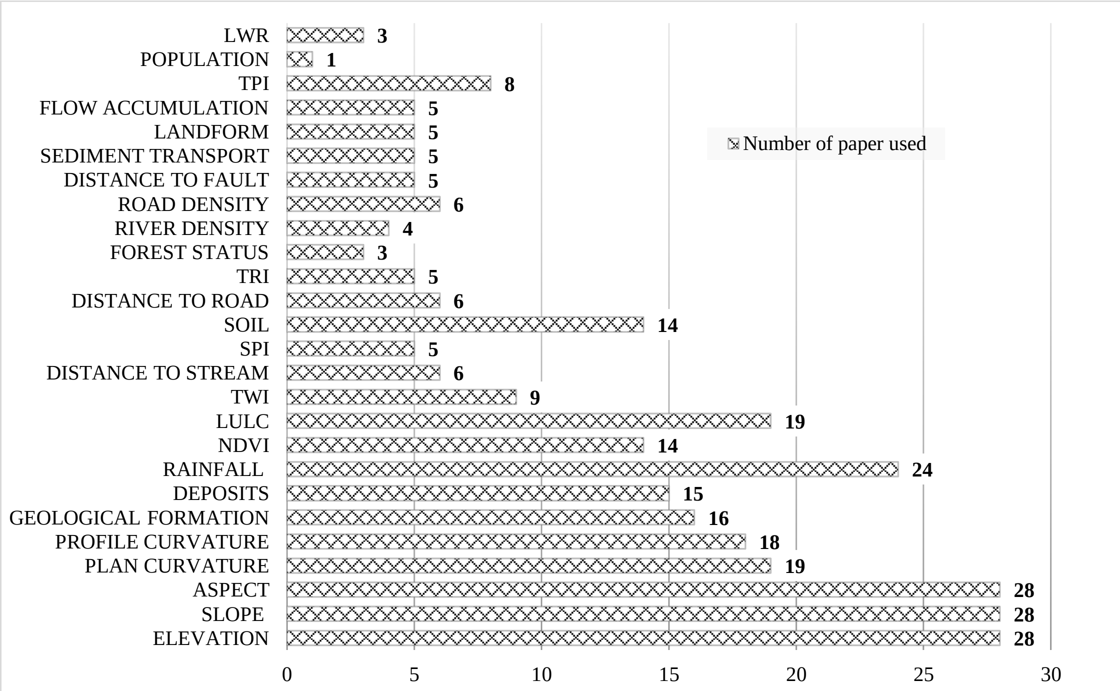

Figure 2. The number of studies using different factors in assessing risks of landslides and debris flows.

Regarding factors used to assess landslide and debris flow hazards in previous studies, a wide range of variables have been considered across tropical and temperate regions, including hazard intensity, triggering mechanisms, and environmental conditions (Ngo et al., 2025). Most of studies identified precipitation and tectonic activity as primary triggering factors (Fig. 2). Heavy or prolonged rainfall saturates soils, increases pore-water pressure, and destabilizes rock formations, thereby disturbing slope equilibrium (Islam and Ryan, 2016). Natural and environmental factors particularly geomorphological, geological, and hydrological variables were cited in more than 50% of studies. These factors contribute to slope instability by inducing fractures and cracks in rock masses and reducing slope strength, often exacerbated by seismic activity (Kuschel et al., 2024). Among these, topographic features such as elevation, slope, and lithology were most frequently included, appearing in over 90% of studies, highlighting their importance in predicting landslides and debris flows (Sun et al., 2024; Yang et al., 2024). Geological deposit characteristics were reported in 50% of studies, reflecting their role in determining the permeability and mechanical stability of slope materials.

In addition, human activities including road construction, urbanization, and land-use changes have increasingly been incorporated into hazard assessment models. Variables such as distance to road

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

networks and land use/land cover (LULC) were used in more than 60% of studies, underscoring the anthropogenic contribution to altered runoff patterns, enhanced surface flow, and reduced slope stability (Agboola et al., 2024; Bachri et al., 2021). Remote-sensing indices, such as vegetation cover (NDVI), built-up index (NDBI), and related indicators, were applied in approximately 45% of studies (Wang et al., 2019). However, population-related variables (e.g., settlement distribution) remain largely underexplored, limiting accurate assessment of the social impacts of landslide hazards in mountainous regions (FAO, 2010). The frequency of these variables across studies reflects both their prevalence and the intricate interconnection between natural and anthropogenic drivers of landslide and debris-flow risks.

Building on this foundation, the present study develops a Bayesian Belief Network (BBN) model to predict landslide and debris-flow risks by integrating environmental and socio-economic factors. Structural Equation Modeling (SEM) is applied to align the internal dependencies within the BBN framework to empirically identified relationships (Dang et al., 2025a). SEM further facilitates the identification of direct and indirect interactions among topographic, hydrological, and geological variables influencing susceptibility. Section 2.3 and 3.2 present the proposed BBN model, incorporating GIS and Sentinel-2 remote-sensing data. Section 3.3 details the sensitivity analysis results and their implications for hazard risk levels, while Section 3.4 reports on scenario analysis under varying environmental and land-use conditions. Finally, the performance of the BBN model is demonstrated through hazard zoning applications, showing its effectiveness as a decision-support tool for risk estimation and sustainable development.

2. Material and methods

2.1. Case study

According to statistical data and research in Vietnam, landslides and debris flows frequently occur along transportation routes in the provinces of Lai Chau, Dien Bien, Son La, Hoa Binh, Lao Cai, Yen Bai, and Phu Tho (Hung et al., 2015) (Fig. 3). These hazards are concentrated in complex, deeply dissected mountainous terrain characterized by severe erosion and geological fragmentation. Due to the highly variable topography, landslides and debris flows occur in a chaotic and largely uncontrollable manner, causing extensive damage to human life and property (Tien Bui et al., 2012). Official records indicate approximately 8,500 landslide and debris flow sites in the northwestern region during the 2010s (Dang et al., 2018, 2025b), with more than 2,700 debris flows exceeding 100,000 m^3 in volume. Using high-resolution remote sensing imagery such as VNREDSat-1 and SPOT-5, Ghasemian et al. (2020) identified and manually interpreted landslides and debris flows larger than 20 m² in this region. More than 2,000 cases detected through remote sensing were subsequently verified by field surveys, which also documented over 600 additional sites inaccessible for direct field investigation.

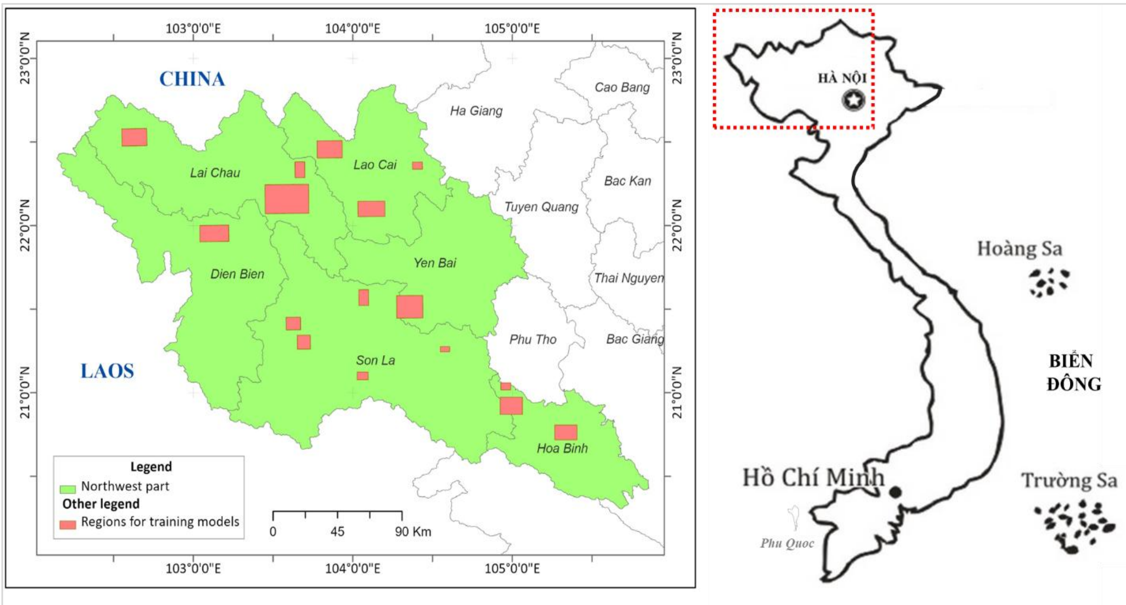

Figure 3. Location of landslides and debris flows detected from images collected from Maxar Technology and CNES/Airbus sources from 2010 to 2024.

Key research areas include the Hoa Binh and Son La hydropower reservoirs, national highways 6, 12, and 4D, as well as critical zones such as Muong Lay, where numerous landslides and debris flows occur on slopes ranging from 35° to 45°, particularly within tectonic destruction zones (Hang et al., 2021; Nguyen et al., 2021). Large-scale debris flows have been recorded from Tam Duong, Than Uyen, and Tan Uyen to highland communes in Phong Tho (Lai Chau), as well as in key locations such as Nam Lay and Muong Lay (Dien Bien) and Muong Te (Son La) (Dang et al., 2024). A high density of landslides is concentrated in areas characterized by rugged terrain and geologically vulnerable conditions.

Despite the increasing frequency and severity of these hazards, the application of artificial intelligence (AI) and remote sensing technologies remains limited in Vietnam (Dang et al., 2025b). The use of high-resolution remote sensing data and AI-based approaches is still rare due to technological challenges (Ngo et al., 2025). Current efforts primarily focus on developing risk zoning maps, forecasting events, and reducing damage caused by mass movements (Duc et al., 2023; Luu et al., 2023; Thanh et al., 2020). However, these studies need to be further expanded and refined, particularly in remote and difficult-to-access mountainous regions (Nguyen et al., 2025). Enhancing the application of advanced technologies

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

in landslide and debris-flow research is essential to improve forecasting accuracy, strengthen disaster prevention and mitigation strategies, and support sustainable socio-economic development in Vietnam.

2.2. BBN development for warning landslides and debris flows

Step 1: Identification of Influencing Factors

The primary objective of the model is to support managers, experts, and decision-makers in anticipating and issuing warnings about potential landslides and debris flows. An initial compilation of influencing factors was carried out based on previous research, literature, and specialized documents. These sources covered a wide range of aspects including physical characteristics, climatic variables, hydrological parameters, and infrastructure conditions related to landslide and debris flow hazards (Tien Bui et al., 2017; Yousefi and Imaizumi, 2024).

Subsequently, through consultations with experts and local management agencies, a refined list of critical factors was developed. This process involved meetings and interviews held in 2023 and 2024 with officials from governmental and non-governmental departments, sectoral organizations, and scientists from research institutes and local environmental management agencies. For example, the selection of natural and environmental factors were reviewed by experts in Vietnam Academy of Science and Technology and Vietnam National University, whereas the selection of social factors were reviewed by experts in Vietnam Academy of Social Sciences. Some factors related to construction activities were reviewed by experts in University of Transport and Communications. During this stage, certain components were either included or excluded; for example, the role of solar radiation in water accumulation was critically examined. The outcome was a finalized list of major influencing factors, which served as the foundation for constructing the conceptual hazard-warning model.

Step 2: Development of a Conceptual Model

Conceptual models are essential tools for examining and evaluating the complex interactions between natural and anthropogenic factors that influence the occurrence and risk of landslides and debris flows. In this study, the conceptual model was designed to transform geological, climatic, hydrological, and land-cover information into specific variables within a Bayesian Belief Network (BBN), thereby enhancing predictive capability and risk assessment.

The model integrates multiple dimensions of risk, including susceptibility, hazard, resilience, and vulnerability, as illustrated in Fig. 4. Key inputs encompass data on the distribution and frequency of landslides and debris flows, climatic and geological conditions, triggering factors, and elements at risk. Importantly, vulnerability is explicitly incorporated to capture the ability of communities to withstand or mitigate the impacts of such hazards (Agboola et al., 2024; Luu et al., 2023).

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

Specifically, landslide and debris flow risks are influenced by a combination of pre-transported material conditions, hydrological settings, surface properties, climatic drivers, and exposure factors (Highland, 2008; Palumbo et al., 2024; Shirzadi et al., 2017). Among these, topographic, geomorphologic, and lithologic characteristics strongly determine slope stability, material transport, drainage density, and soil-water dynamics (Ngo et al., 2025). Surface resistance - shaped by vegetation cover and human interventions - further modifies hazard likelihood (Tran et al., 2025). Meanwhile, rainfall intensity, weathering, and other climatic parameters act as dominant triggers.

Equally critical are the exposure and resilience dimensions, which reflect population density, existing protective infrastructure, and community preparedness. These elements determine not only the potential scale of damage but also the capacity of vulnerable groups to recover (Alam and Ray-Bennett, 2021; Chen et al., 2024b).

The subsequent step involves the integration and analysis of data corresponding to these components, which provides the basis for operational hazard prediction and early-warning systems.

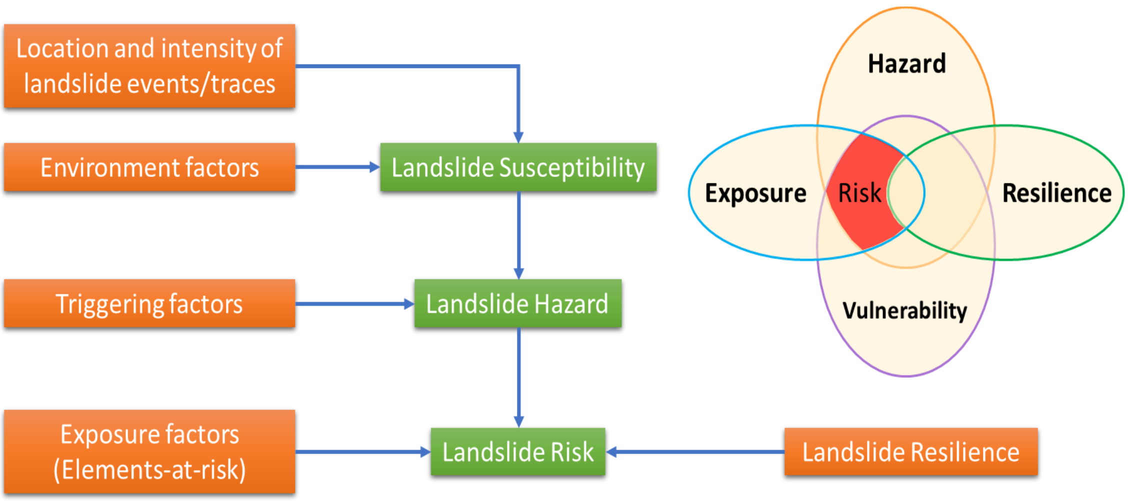

Figure 4. Conceptual network depicting the relations between environmental and human-derived factors with landslide susceptibility, hazard, and risk.

Step 3: Data collection

Landslide and debris flow warnings are influenced by geological, geomorphological, meteorological, hydrological, land cover and land use, and infrastructure conditions (Fig. 5).

Geological and Geomorphological Factors

The first group of data relates to surface features and geological structures, including DEM, geological faults, and lithological types (Liu et al., 2025). DEM provides essential information on elevation and

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

terrain shape, enabling the calculation of parameters such as slope, aspect, and curvature indices, which are critical in identifying areas vulnerable to landslide and debris flow hazards (Borgomeo et al., 2014; Nichol et al., 2019). Faults, as structural discontinuities within the earth's crust, are highly susceptible to natural forces (Moore and Sawyer, 2016). Lithological types determine the water retention capacity and stability of soils, both of which are crucial in assessing slope stability (Tu et al., 2016). Collectively, these data define the geomorphological and geological characteristics that distinguish stable areas from unstable ones.

Meteorological and Hydrological Factors

Rainfall, flow accumulation, the Terrain Wetness Index (TWI), and proximity to rivers are fundamental triggers of landslides and debris flows (Jin et al., 2025). Intense or prolonged rainfall saturates soils, reducing shear strength and resistance to mass movement. Flow accumulation and TWI highlight zones with high water buildup potential, increasing susceptibility to slope failure (Mckean and Roering, 2004; Yousefi et al., 2025). Areas adjacent to rivers are particularly prone to erosion, further heightening the risk of slope instability. This group of factors is central to evaluating meteorological and hydrological triggers of landslide and debris flow events.

Land Cover and Land Use Factors

Remote sensing indices such as NDVI, BSI, and NDBI, along with land use/land cover (LULC) data, provide valuable insights into slope stability (Tran et al., 2024; Wang et al., 2019). NDVI measures vegetation density, which is inversely correlated with landslide occurrence, as dense vegetation particularly forest cover stabilizes slopes through root reinforcement (Tawalo et al., 2025). Conversely, BSI and NDBI highlight bare land and urbanized areas, both highly susceptible to slope failures due to the absence of vegetation cover. These datasets are therefore indispensable for assessing the influence of anthropogenic and natural land cover factors on slope hazards.

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

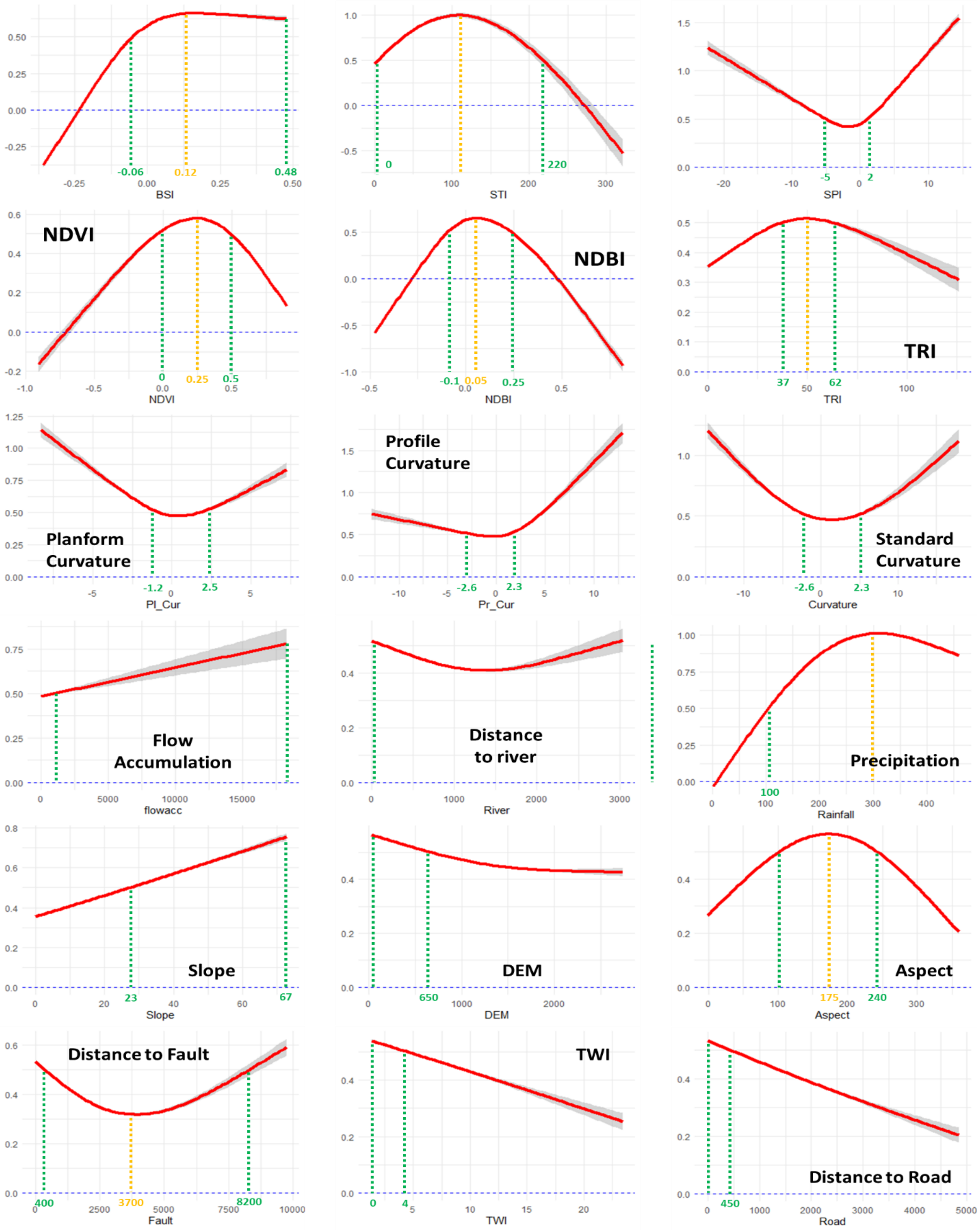

Figure 5. Correlation lines (Red) between independent variables with landslide hazard.

The regions between green lines are thresholds of landslide hazard higher than 50%. The yellow lines

230 are peak of landslide hazard in each variable.

Infrastructure Factors

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

Infrastructure-related data, such as "distance to roads," reflect the impact of human activities on slope stability (Barnard et al., 2001; Stark et al., 2026). Slopes adjacent to roads are often destabilized due to excavation, construction, and traffic, making them more vulnerable to shallow landslides. Consequently, monitoring and assessing infrastructure-related impacts are vital for anticipating and mitigating risks in areas with high human activity and traffic (Bachri et al., 2021).

Integration for Hazard Warning Models

Through the integrated use of these datasets within a Bayesian Belief Network model, it is possible to generate highly accurate landslide and debris flow warnings. The combined consideration of geological, geomorphological, meteorological, hydrological, land use, and infrastructure factors enhances the reliability of hazard prediction and provides a robust framework for risk management.

Step 4: Preprocessing of Data for BBN Model

According to the application of landslide hazard warning in BBN model construction, a key challenge is defining well-coordinated relationships among input variables (Lan et al., 2021; Xiao et al., 2023). To address this, two techniques were employed: the Structural Equation Model (SEM) and multivariate regression, both of which assess interrelationships between variables and eliminate redundant or insignificant factors (Rai et al., 2024). SEM, in particular, is useful for identifying causal relationships among input variables (Bac and Bao, 2020; Dang et al., 2021).

The process began with an analysis of correlation coefficients to select strongly associated variables. SEM then used this correlation matrix to characterize relationships based on parameters such as correlation coefficients, Akaike's Information Criterion (AIC), and Bayesian Information Criterion (BIC). Relationships were retained only if the correlation coefficient was statistically significant ($p \leq 0.05$) for the given dataset and both AIC and BIC values were low.

In parallel, multivariate regression was applied to examine the linear relationship between the dependent variable (landslide risk) and the independent variables. This step identified which predictors had the strongest influence on landslide risk. Variables lacking statistical significance were eliminated based on regression coefficients, p-values, and R^2 values. This refinement optimized the set of input variables by retaining only those with meaningful predictive power.

The SEM and multivariate regression analyses were conducted in R-Studio (version 2024.12.0+467; Zhao, 2014). The validated variables were then integrated into a BBN model using Netica software (Netica, 2010) to simulate relationships and improve accuracy in risk estimation for landslides and debris flows. By combining SEM and multivariate regression, the approach enhances both the efficiency and the reliability of the BBN model by incorporating only critical independent variables.

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

Subsequent to building the conceptual model, preparing data and analyzing the variables, the final stage is to develop and model the BBN for landslide and debris-flow risk assessment. This process starts with the construction of the Conditional Probability Table (CPT) (Kleemann et al., 2017), in which the frequencies of landslides and debris-flows, environmental conditions, triggering factors, exposure factors and resilience in order to evaluate the risk of landslides and debris-flows.

Allocations for land use, topography, environment, and other factors are spatially combined within the study area to determine the percentage of high-risk zones from which the basic CPT is derived. This provides scientific evidence of how landslide risk depends on the prevalence of favorable and triggering factors (Ding et al., 2025; Liang et al., 2025). However, the BBN model building process does not end with the construction of CPTs but needs to go in checking loops between the steps to be approved by the experts and the stakeholders (Chen et al., 2024a). Model evaluation includes the examination of sensitivity using the values as mutual information and entropy reduction to establish the extent to which each factor is sensitive to landslide and debris-flows risk. Uncertainty reduction is calculated by the formula:

$$E = H(M) - H(N) = \sum_m \sum_n \frac{P(m,n)[P(m,n)]}{P(m)P(n)} \qquad (1)$$

H(M|N) is the amount of uncertainty that is left in node M after the receipt of new data. Once the BBN model is set, the network can estimate the posterior probability of landslide and debris flow conditions, and then issue early warnings for decision makers in risk mitigation (Landuyt et al., 2015). Training and testing of BBN model facilitates full incorporation of risk factors in to enable proper forecasting of landslide and debris flow hazards which in turn reduces damage and protects the community.

2.3. Scenario development

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

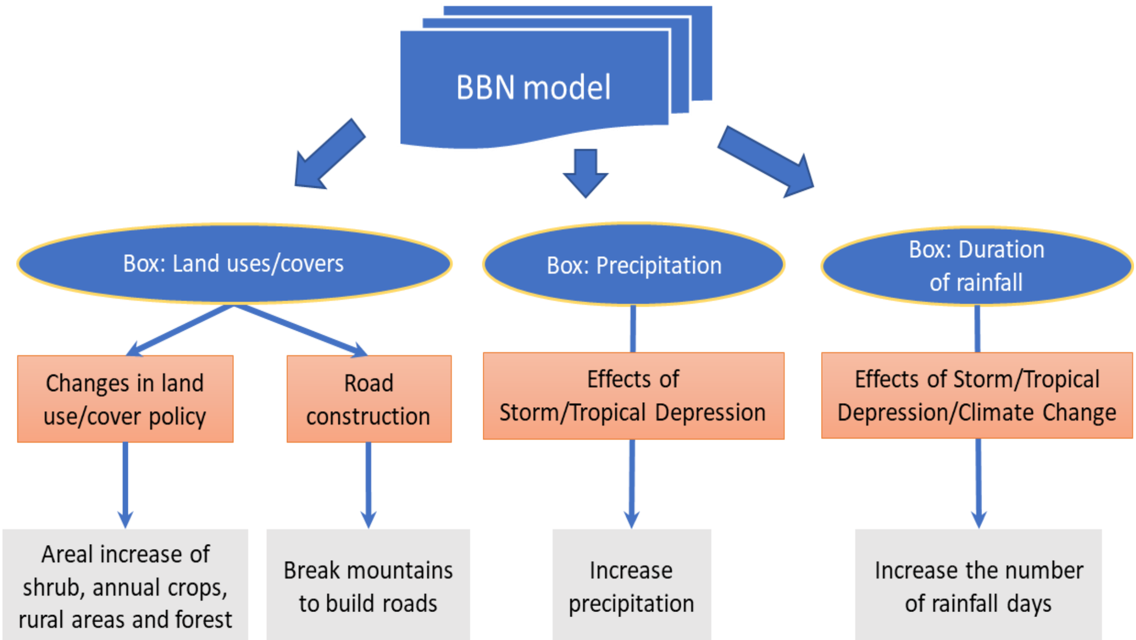

Figure 6. Framework to generate scenarios based on changes in boxes: Land uses/covers, precipitation and duration of rainfall days.

Scenarios generated in the BBN model for landslide and debris flow hazard prediction represent a crucial step in understanding influencing factors and assessing associated risks (Song et al., 2012; Sun et al., 2021) (Fig. 6). In particular, land use/land cover (LULC) change and climate change significantly affect landslide risk.

Regarding LULC change, alterations in land use policies such as the expansion of shrubland, annual crops, rural settlements, or forests or the construction of roads by cutting through mountains can substantially modify terrain structure and topsoil properties (Alvarez Jaimes et al., 2025). These changes may decrease soil water permeability, increase slope steepness, and reduce soil stability, thereby elevating the likelihood of landslides and debris flows.

Similarly, climate change and associated extreme weather events exert profound impacts. Increased rainfall, a greater number of rainy days, and more frequent storms or tropical depressions can lead to soil saturation (Jin et al., 2025). Since most soils exhibit low bearing capacity when moist especially when waterlogged these conditions greatly heighten the probability of landslide and debris flow occurrences.

By constructing such scenarios within the BBN framework, it becomes possible to model the interdependencies among these factors and assess how landslide and debris flow risks vary under different conditions. This approach enables the identification of the most vulnerable areas, thereby

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

supporting authorities and stakeholders in planning mitigation measures and improving disaster management strategies. Furthermore, scenario-based modeling informs the adaptation of land use planning and construction policies, and provides valuable insights for long-term climate change risk management.

3. Results

3.1. Statistical analysis of interdependences as a basis to parameterize the BBN

According to the developed SEM model (Appendix A), three primary parameters related to landslide and debris flow hazards are water/flow, pre-transported materials, and land use/cover. Based on the statistical analysis, the Stream Power Index (SPI) was selected as the key indicator for water/flow, the Sediment Transport Index (STI) for materials, and the Bare Soil Index (BSI) for land use/cover.

In the SEM model, various topographic factors and their relationship with SPI were examined. The analysis shows that slope has a minor but positive influence on SPI, with a coefficient of 0.07, indicating that stream power slightly increases as slope becomes steeper. This relationship is highly statistically significant (***). The Topographic Wetness Index (TWI) exhibits a stronger positive effect, with a coefficient of 0.45, suggesting that increased soil moisture enhances stream power. By contrast, curvature has a negative coefficient of -0.29, meaning that, other conditions being equal, convex curvature reduces stream power.

Overall, the model indicates that slope, TWI, and curvature collectively account for 46% of the variation in SPI ($R^2 = 0.46$), demonstrating their indirect but substantial influence on water/flow dynamics relevant to landslide and debris flow hazards.

The SEM model analyzing the relationships between related hazards and pre-transported materials based on topographic and geological factors is presented in the second group. The variables DEM, Fault, and Aspect directly influence TRI and "Distance to rivers" with coefficients of –0.01, 0.47, 0.03, and –0.18, respectively, with DEM exerting the strongest effect. Slope is further influenced by TRI with a coefficient of 0.52. Under the combined effects of TRI and distance to rivers, slope shows a strong relationship with flow accumulation and the Topographic Wetness Index (TWI). Geological characteristics, flow accumulation, and TWI together contribute 40% to the variability of the Sediment Transport Index (STI), although STI is less directly affected by flow accumulation and TWI.

Land use/land cover (LULC) change increases vegetation density, as indicated by its positive effect on NDVI (0.08), and reduces the Normalized Difference Built-up Index (NDBI) by –0.03, reflecting a decrease in built-up areas. Roads also exert a minor influence on NDBI. Both NDVI and NDBI exhibit

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

autoregressive relationships. The dependent variable Bare Soil Index (BSI) explains 89% of its variance through NDVI and NDBI, with regression coefficients of –0.02 and 0.95, respectively, indicating that BSI increases with increasing NDBI and decreases as NDVI rises.

The final part of the SEM model illustrates the relationships among STI, SPI, BSI, rainfall, and the occurrence of landslide and debris flow hazards. Hazard occurrence is most strongly influenced by BSI (0.93), followed by rainfall (0.42), SPI (0.34), and STI (0.27). Overall, the model explains 54% of the variance in landslide and debris flow hazards, as indicated by the coefficient of determination ($R^2 = 0.54$).

3.2. Parameterization of the BBN with classified data

The BBN model diagram (Fig. 7) illustrates the expanded framework of landslide risk assessment and highlights the numerous natural and anthropogenic factors involved. Geo-environmental attributes, which are essential for understanding landslide susceptibility, were incorporated into the model's development. The "Rise" component is further classified into four categories, where geomorphological factors play a critical role in influencing water accumulation and soil erosion. These factors originate from variations in river density, soil and rock types, and the distribution of pre-transported materials, all of which are shaped by underlying geological structures and available resources. Based on the physical properties of soils and rocks in a given geological context, these variables are key to determining the degree of landslide susceptibility in an area.

Additionally, other components of the model address the contribution of water flow and the integration of rainfall amount and duration to evaluate the combined effects of climate and hydrological conditions on landslide and debris-flow hazards. The rainfall classification values applied in the model range from 1 to 460 mm, with rainfall duration spanning from 1 to 7 days. Furthermore, boxes representing land use and land cover types are included to assess the impact of human activities on landslide risk. These categories encompass various land types such as urban and rural areas, forests, and croplands, providing a comprehensive understanding of anthropogenic influences on landslide hazards.

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

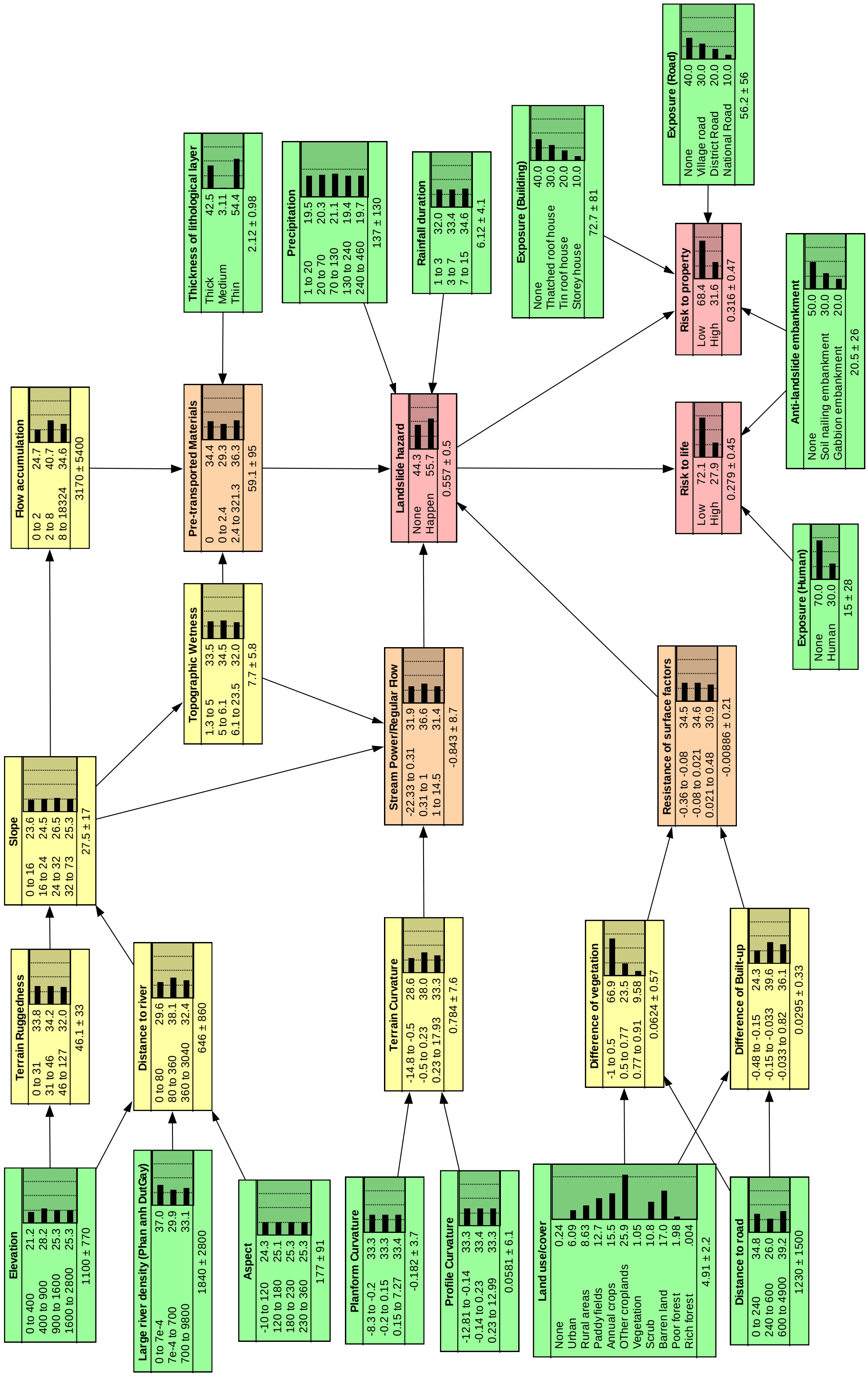

Figure 7. BBN model for predict landslide hazards and their risk to life and property.

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

The additional exposure factors include buildings, roads, and residents, which are categorized to assess their impact on human life and property. The model also incorporates intermediate variables, such as surface resistance and flow capacity, which facilitate the estimation of landslide occurrence probability. These variables help quantify the extent to which human-induced factors contribute to landslide risk. Furthermore, the model accounts for landslide probability, potential losses related to human life and preventive infrastructure, as well as the effectiveness of protective measures such as embankments and soil reinforcement. Consequently, this framework is valuable not only for hazard prediction but also for comprehensive risk management, particularly in environments where the complex interplay between natural and anthropogenic factors must be thoroughly examined.

3.3 Sensitivity analysis

The sensitivity analysis table compares the effect of all the identified parameters on some specified BBN nodes that relate to landslide risk, life risk and property risk (Tab. 1). Thus, the higher the perceived rainfall and property risks, the higher the perceived landslide risk. With a belief variance of 0.09 for both correlation between the perceived precipitation and risk to property with related hazards. The correlation coefficient is 0.385 with precipitation and 0.368 with risk to property. Despite this, it means that monitoring rainfall or reducing property exposure is a good strategy in minimizing land slide risk. While those that include rainfall duration and materials before transportation have variance of 0.01, which indicate a very small impact, below 2%. Landslide risk was also the most strongly associated with risk to life with a variance of 0.06 and a proportion of 30.7%.

Table 1. Sensitivity analysis for BBN nodes.

No.	Node	Variance of Beliefs	Mutual Relation Percentage
A	***Sensitivity of 'Landslide and debris flow hazards' to a finding at another node:***		
1	Precipitation	0.09	38.5
2	Risk to property	0.09	36.8
3	Risk to life	0.08	30.7
4	Resistance of surface factors	0.01	3.16
5	Difference of Built-up	0.01	2

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

6	Rainfall duration	0.01	1.76
7	Pre-transported Material	0.01	1.04
B	***Sensitivity of 'Risk to life' to a finding at another node:***		
1	Landslide and debris flow hazards	0.06	30.7
2	Risk to property	0.04	21.2
3	Precipitation	0.02	11.8
4	Anti-landslide embankment	0.01	6.32
5	Exposure (Human)	0.01	2.92
C	***Sensitivity of 'Risk to property' to a finding at another node:***		
1	Landslide and debris flow hazards	0.080	36.8
2	Risk to life	0.046	21.2
3	Precipitation	0.031	14.2
4	Anti-landslide embankment	0.017	7.87
5	Resistance of surface factors	0.003	1.16
6	Exposure (Road)	0.002	1.01

Concerning risk to property, this variable exhibited a considerable influence on the risk to life, with a coefficient of 0.04 (proportion 21.2%), indicating that property risk contributes to human risk in an indirect manner. Rainfall also had a significant effect (variance 0.02, proportion 11.8%), demonstrating that weather conditions are an important factor in risk assessment and mitigation. The risk to property itself is substantial, as changes in landslide risk levels can have major impacts on property damage (variance 0.080, proportion 36.8%). Moreover, property risk also contributes to risk to life, with a variance of 0.046 and a proportion of 21.2%. The regression analysis further showed that climate change can affect losses of both life and property, with a variance of 0.031 (14.2%). Although less significant, factors such as landslide resistance and surface characteristics are also relevant and should be considered in strategies aimed at minimizing overall risk.

3.4. Results of scenarios

Fig. 8 presents the results of landslide hazard analysis scenarios based on the developed BBN model. The input factors considered include land-use change, road construction, rainfall, and rainfall duration, with the aim of assessing the probability of landslide occurrence under different

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

conditions and across various areas. The analysis first examines the probability of landslides based on land-use type and distance from roads. Results show that the likelihood of landslides increases significantly in areas close to roads (<240 m), reaching about 57%, and the risk tends to rise with higher built-up land density or when forest land is converted to agricultural land. For example, in forested areas, the probability of a landslide is about 50%, whereas in scrubland or agricultural land, it increases to approximately 60%. These findings clearly demonstrate that human activities, particularly land-use change and infrastructure development, substantially influence the probability of landslides and debris flows, especially near transportation networks. Additionally, rainfall conditions play a crucial role: precipitation intensity and duration significantly increase the probability of landslide occurrence.

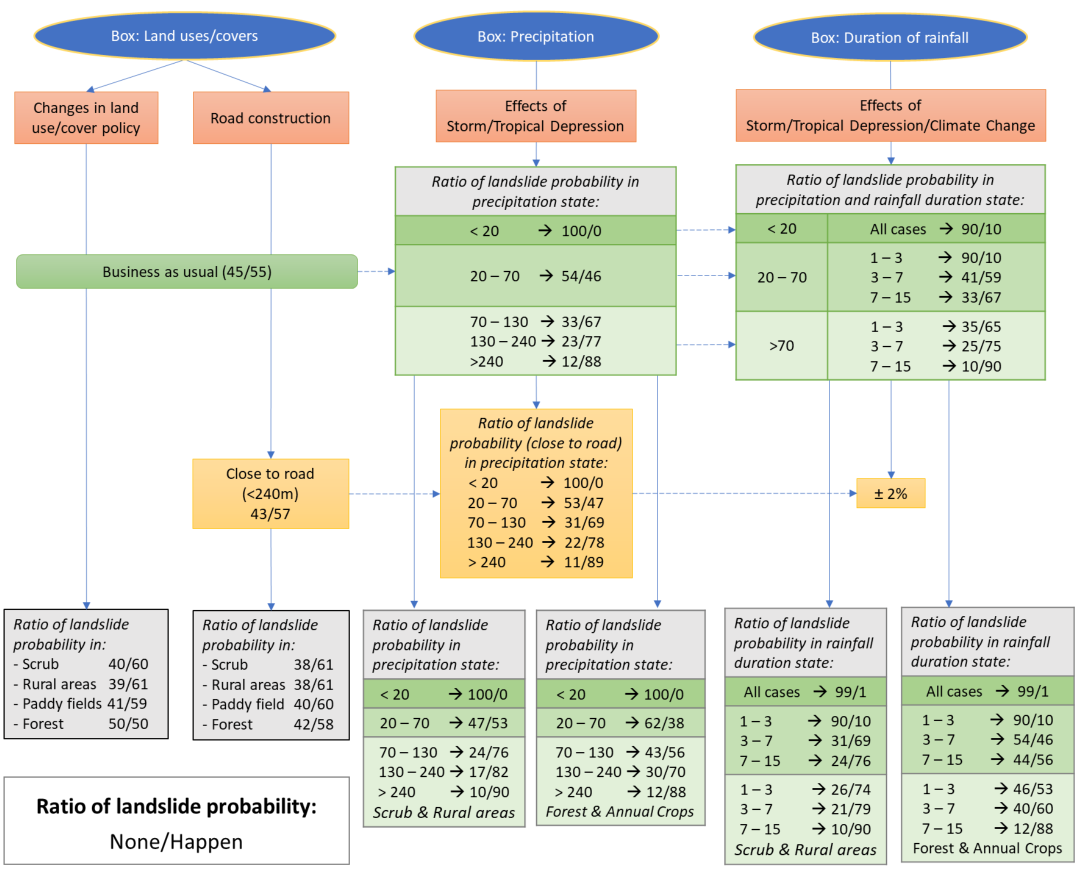

Figure 8. Scenario results to predict the probability of landslide hazards in different changes in land uses/covers, increase of precipitation and duration of rainfall days.

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

At low rainfall levels (<20 mm), the risk of landslides is minimal, with an extremely low probability ratio (100/0). However, as rainfall increases particularly when it exceeds 240 mm, this risk rises sharply, with the probability ratio reaching 12/88. This clearly demonstrates that areas exposed to intense and consecutive rainfall are highly vulnerable to landslide occurrences, especially when the terrain is steep or lacks vegetation cover. Extended rainfall duration further compounds the risk, as prolonged precipitation leads to greater water accumulation in the soil, increasing instability. A positive statistical correlation is observed between precipitation amount and landslide probability at daily, daily accumulation, and total rainfall scales. When storm events last longer than 7–15 days, the probability ratio becomes extremely high ranging from 75% to 90% particularly in areas with easily erodible soils such as agricultural or bare lands. These findings underscore the importance of forecasting and issuing warnings for prolonged and continuous rainfall events to mitigate potential damage. Moreover, when considering different land use types under varying rainfall conditions, the probability of landslide occurrence becomes more complex. In scenarios where rainfall exceeds 240 mm and persists for 7–15 days, scrubland and agricultural land exhibit a very high landslide risk, reaching up to 90%. Although forested areas and perennial crops show greater resistance, the risk remains at a hazardous level (60–88%) under conditions of heavy and prolonged rainfall.

Table 2. Probability of risk to life under the protection of different anti-landslide embankment.

Case	Exposure (to human)	Anti-landslide embankment	Probability of risk to life	
			Low (%)	High (%)
1	None	None	46	54
2	None	Soil nailing embankment	73	27
3	None	Gabion embankment	91	9
4	Human	None	19	81
5	Human	Soil nailing embankment	45	55
6	Human	Gabion embankment	64	36

Tab. 2 presents the probability of risk to human life when exposed to landslide and debris flow hazards under different types of embankment protection. The values are calculated based on the highest probability scenario of the “Landslide and debris flow hazards” category. The results

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

indicate that, in the absence of people or civil structures at the site (Exposure: None), the use of embankments significantly reduces the risk when people pass through or conduct livelihood activities nearby. Without any protective structure, the risk reaches 54%; however, with the application of a soil nailing embankment, this risk decreases to 27%, and the use of a gabion embankment provides the highest level of safety, reducing the risk to just 9%. In contrast, when human presence is involved (Exposure: Human), the risk increases substantially. In the absence of protective structures, the risk ratio rises to 81%, indicating a high likelihood of severe impacts from landslides. With engineering interventions, the risk is significantly mitigated: soil nailing embankments reduce the risk to 55%, while gabion revetments lower it further to 36%. These results highlight the crucial role of engineering measures such as gabion and soil nailing embankments in protecting human life in areas prone to frequent landslides.

Table 3. Probability of risk to building and road under the protection of different anti-landslide embankment.

Case	Exposure (to Building)	Exposure (to Road)	Anti-landslide embankment	Probability of risk to property	
				Low (%)	High (%)
1	None	None	None	50	50
2	None	None	Soil nailing embankment	80	20
3	None	None	Gabion embankment	99	1
4	None	Village road	None	15	85
5	None	Village road	Soil nailing embankment	35	65
6	None	Village road	Gabion embankment	75	25
7	None	District road	None	20	80
8	None	District road	Soil nailing embankment	45	55
9	None	District road	Gabion embankment	85	15
10	None	National road	None	30	70
11	None	National road	Soil nailing embankment	60	40
12	None	National road	Gabion embankment	95	5
13	Thatched roof house	None	None	25	75

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

14	Thatched roof house	None	Soil nailing embankment	55	45
15	Thatched roof house	None	Gabion embankment	85	15
16	Thatched roof house	Village road	None	15	85
17	Thatched roof house	Village road	Soil nailing embankment	45	55
18	Thatched roof house	Village road	Gabion embankment	85	15
19	Thatched roof house	District road	None	20	80
20	Thatched roof house	District road	Soil nailing embankment	45	55
21	Thatched roof house	District road	Gabion embankment	85	15
22	Thatched roof house	National road	None	30	70
23	Thatched roof house	National road	Soil nailing embankment	60	40
24	Thatched roof house	National road	Gabion embankment	95	5
25	Tin roof house	None	None	15	85
26	Tin roof house	None	Soil nailing embankment	45	55
27	Tin roof house	None	Gabion embankment	75	25
28	Tin roof house	Village road	None	10	90
29	Tin roof house	Village road	Soil nailing embankment	35	65
30	Tin roof house	Village road	Gabion embankment	75	25
31	Tin roof house	District road	None	15	85
32	Tin roof house	District road	Soil nailing embankment	40	60
33	Tin roof house	District road	Gabion embankment	80	20
34	Tin roof house	National road	None	35	65
35	Tin roof house	National road	Soil nailing embankment	65	35
36	Tin roof house	National road	Gabion embankment	90	10
37	Store house	None	None	5	95
38	Store house	None	Soil nailing embankment	35	65
39	Store house	None	Gabion embankment	65	35
40	Store house	Village road	None	1	99
41	Store house	Village road	Soil nailing embankment	25	75
42	Store house	Village road	Gabion embankment	65	35
43	Store house	District road	None	10	90

44	Store house	District road	Soil nailing embankment	35	65
45	Store house	District road	Gabion embankment	75	25
46	Store house	National road	None	30	70
47	Store house	National road	Soil nailing embankment	55	45
48	Store house	National road	Gabion embankment	85	15

Similarly, Tab. 3 presents the risk probability for assets (including buildings and roads) under different scenarios of landslide exposure and with various types of anti-landslide embankments. The results show that, without any protective structure, the risk to assets is significantly high, particularly in areas near major roads or critical buildings. For example, storehouses face a risk level as high as 95% without protection, which decreases to 65% with a soil-nailing embankment and further to 35% with a gabion embankment. Likewise, the probability of pavement failure drops markedly when protective measures are implemented during road construction. A village road, for instance, exhibits a 99% risk without protection, but this reduces to 75% with soil-nailing embankments and 35% with gabion embankments. Larger roads, such as national highways, show a similar trend, with the risk falling from 70% (no protection) to 45% (soil nailing) and 15% (gabion).

These preliminary findings indicate that both structural type and construction quality play pivotal roles in determining risk levels. Small houses with thatched or tin roofs are far more vulnerable to cyclones compared to well-built permanent structures, especially warehouses. Nevertheless, anti-landslide measures, particularly gabion revetments, substantially mitigate high-risk conditions for assets. In practice, implementing protective structures such as soil-nailing and gabion revetments not only minimizes property damage but also enhances the safety and resilience of urban infrastructure and transportation systems in landslide-prone areas.

4. Discussion

4.1. Advancements in the Developed BBN Model

The developed BBN model incorporates a wider range of natural and anthropogenic variables than earlier models proposed by Depina et al. (2020) and Hao et al. (2023) for landslide risk warning. It has been significantly enhanced to improve both its accuracy and practical utility. Unlike

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

previous approaches, the BBN model presented in this study is designed for application at an international scale, particularly in subtropical regions, and integrates fundamental geographical and climatic parameters such as slope, elevation, rainfall, soil moisture, and terrain curvature. These additional variables have been demonstrated based on the SEM model to play a critical role in predicting landslide risk across large spatial scales, outperforming earlier models developed by Lan et al. (2021) and Xiao et al. (2023), which were mainly applied to local settings. As several variables overlap with those used in previous studies, earlier methodological frameworks can still be retained and updated in line with this new version.

A key advancement of the present model is the integration of remote sensing data with GIS records and additional information collected from surveys conducted among officials and local residents. Remote sensing and GIS datasets provide comprehensive, large-scale spatial coverage, which greatly enhances environmental monitoring and facilitates targeted interventions, as demonstrated by Mondini et al. (2013). Furthermore, stakeholder interviews capture qualitative, perception-based information that cannot be fully expressed numerically, offering valuable insights into how communities perceive risk and the impacts of human activities, as suggested by Sun et al. (2021). In addition, advanced analytical tools such as sensitivity analysis and multivariate scenario optimization, as applied by Xiao et al. (2023), were incorporated to enhance model performance under dynamic conditions such as changing temperature regimes or terrain variability. As a result of these improvements, the BBN model extends beyond simple prediction. It now supports the generation of a broader and more diverse range of response options tailored to the specific conditions of different regions. This represents a major step forward compared to previous models, which often relied on single-variable or linear approaches inadequate for capturing the complexity of real-world systems.

4.2. Contributions to Disaster Risk Reduction

The enhanced BBN model can be applied to evaluate the contribution of human-made infrastructures to prevent landslide and debris flow risks by accommodating uncertainty and multidimensional datasets. It represents a novel addition to the BBN framework compared with earlier models. By simulating variables such as housing type (e.g., thatched-roof houses, tin-roof houses, storage buildings), geographical location, and proximity to hazard-prone areas, the model can estimate potential casualties and structural damage. For example, the annual probability of debris flow destruction is eight times higher for thatched-roof houses than for reinforced storage facilities. Similarly, the model predicts that reinforced national roads can reduce 80% the risk, whereas village roads face a 70% disruption risk. Simulation results also reveal that employing gabion embankments can reduce the probability of landslides impacting facilities within a 500 m radius by approximately 60%.

The BBN framework also enables cost–benefit analyses of different mitigation options, supporting more effective disaster-risk-reduction planning. A case study conducted in the mountainous north-western region of Vietnam demonstrated that the likelihood of residential property damage dropped from 70% to 30%, and mortality risk decreased from 15% to 5% following the installation of gabion and soil nailing embankments. Accordingly, the model not only forecasts risk but also informs the design of effective mitigation strategies.

Beyond risk assessment, the GIS-based hazard mapping based on the BBN model provides spatially explicit data to guide infrastructure development in landslide-prone areas. High-risk zones can be clearly delineated to restrict hazardous development and protect vital resources such as forests and water supplies. The model also aids government agencies in implementing ecological strategies for prevention - such as reforestation, installation of natural drainage systems, and slope stabilization - while promoting the use of environmentally friendly construction materials. Moreover, its early warning capabilities strengthen community resilience by safeguarding vulnerable groups and reducing losses of life and property during disasters.

The BBN model further supports scenario analysis to evaluate how urbanization and natural resource exploitation influence landslide risk. Decision-makers can use this capability to balance development needs with environmental protection. By integrating essential data for urban planning, watershed management, and environmental conservation, the model helps anticipate the consequences of factors such as climate change, infrastructure density, and agricultural practices. These analyses can inform solutions including reforestation, construction of eco-friendly drainage systems, and restrictions on building in hazardous areas.

To achieve the above results, the model in the future should incorporate additional data streams from geotechnical sensors, weather radar, and satellite observations to improve accuracy and support rapid emergency response. Enhanced methods for managing large and complex datasets, along with user-friendly visualization tools, are also essential to support decision-making by authorities and communities. Moreover, the model should integrate long-term climate, social, and

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

economic projections and be compatible with hydrological and climate models to enhance its decision-support capabilities. Finally, incorporating feedback from real-world landslide and debris flow events will allow continuous refinement of the model's performance.

These improvements not only increase the model's practical value but also ensure that it becomes a powerful tool for balancing economic development, environmental protection, and community safety advancing progress toward sustainability.

5. Conclusions

This study demonstrates the value of Bayesian Belief Network (BBN) models in advancing our understanding of the factors that heighten the likelihood of landslides and debris flow hazards, along with their associated risks to people and property. The findings highlight that the north-western region of Vietnam is particularly vulnerable, with hazard occurrence strongly influenced by human-driven factors such as climate change (manifested in increased precipitation and prolonged rainfall), land-use change, and road construction. The sensitivity analysis underscores the critical role of land use/cover and embankment type in minimizing property exposure and reducing overall landslide risk. Specifically, the results reveal that cumulative rainfall exceeding 130 mm over three consecutive days substantially raises the probability of landslides and debris flow, especially in cultivated and farming areas. Importantly, gabion embankments were shown to provide highly effective protection against both casualties and structural damage. Beyond identifying risk factors, this research emphasizes the scale of danger posed by such hazards and the urgent need for proactive mitigation measures, such as protective slopes and appropriate land-use planning. Overall, the study affirms that BBN models are powerful tools for hazard assessment, regulation, and risk management. By integrating environmental, climatic, and anthropogenic factors, they can equip decision-makers with robust, evidence-based insights to guide policies, improve resilience, and safeguard both communities and ecosystems.

Author contributions: Kinh Bac Dang: Funding acquisition, project administration, data curation, methodology, software, writing – original draft. Hieu Nguyen: Conceptualization, supervision, methodology, writing –review and editing. Thanh Dat Do: Methodology, resources, validation, writing – review and editing. Thi Phuong Nga Pham: Methodology, data curation, formal analysis, writing – review and editing. Tuan Linh Giang: Data curation, formal analysis,

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

writing – review and editing. Thi Dieu Linh Nguyen, Huu Hao Ngo, and Giuseppe Forino: Conceptualization, methodology, writing – review and editing.

Acknowledgments

This research was funded by the research project QG.24.75 of Vietnam National University, Hanoi.

References

Agboola, G., Beni, L. H., Elbayoumi, T., and Thompson, G.: Optimizing landslide susceptibility mapping using machine learning and geospatial techniques, Ecol. Inform., 81, 102583, https://doi.org/10.1016/j.ecoinf.2024.102583, 2024.

Alam, E. and Ray-Bennett, N. S.: Disaster risk governance for district-level landslide risk management in Bangladesh, Int. J. Disaster Risk Reduct., 59, 102220, https://doi.org/10.1016/j.ijdrr.2021.102220, 2021.

Alvarez Jaimes, M. A., Roman Quintero, D. C., Ortiz Contreras, J. D., Bedoya Rios, D. F., and Tapias Camacho, M. A.: Implications of landslide runout modeling for vulnerability assessment: Benchmarking from a case study in the andean region, Int. J. Disaster Risk Reduct., 131, 105920, https://doi.org/10.1016/J.IJDRR.2025.105920, 2025.

Bac, D. K. and Bao, D. Van: Analyzing Bio-Geo-Chemical Factors in Relation to Land Use Trends on Basalt Terrain in Dong Nai and Nearby Areas, VNU J. Sci. Earth Environ. Sci., 36, 79–89, https://doi.org/10.25073/2588-1094/vnuees.4542, 2020.

Bachri, S., Shrestha, R. P., Yulianto, F., Sumarmi, S., Utomo, K. S. B., and Aldianto, Y. E.: Mapping landform and landslide susceptibility using remote sensing, gis and field observation in the southern cross road, Malang regency, East Java, Indonesia, Geosci., 11, 1–15, https://doi.org/10.3390/geosciences11010004, 2021.

Barman, J., Soren, D. D. L., and Biswas, B.: Landslide Susceptibility Evaluation and Analysis: A Review on Articles Published During 2000 to 2020, 211–220 pp., https://doi.org/10.1007/978-3-031-15377-8_14, 2023.

Barnard, P. L., Owen, L. A., Sharma, M. C., and Finkel, R. C.: Natural and human-induced landsliding in the Garhwal Himalaya of northern India, Geomorphology, 40, 21–35, https://doi.org/https://doi.org/10.1016/S0169-555X(01)00035-6, 2001.

Borgomeo, E., Hebditch, K. V, Whittaker, A. C., and Lonergan, L.: Characterising the spatial distribution, frequency and geomorphic controls on landslide occurrence, Molise, Italy, Geomorphology, 226, 148–161, https://doi.org/10.1016/j.geomorph.2014.08.004, 2014.

Bui, D. T., Tsangaratos, P., Nguyen, V. T., Liem, N. Van, and Trinh, P. T.: Comparing the prediction performance of a Deep Learning Neural Network model with conventional machine learning models in landslide susceptibility assessment, Catena, 188, https://doi.org/10.1016/j.catena.2019.104426, 2020.

Chen, F., Jia, H., Du, E., Chen, Y., and Wang, L.: Modeling of the cascading impacts of drought and forest fire based on a Bayesian network, Int. J. Disaster Risk Reduct., 111, https://doi.org/10.1016/j.ijdrr.2024.104716, 2024a.

Chen, M., Tang, C., Xiong, J., Chang, M., and Li, N.: Spatio-temporal mapping and long-term evolution of debris flow activity after a high magnitude earthquake, Catena, 236, https://doi.org/10.1016/j.catena.2023.107716, 2024b.

Damm, B. and Klose, M.: The landslide database for Germany: Closing the gap at national level, Geomorphology, 249, 82–93, https://doi.org/10.1016/j.geomorph.2015.03.021, 2015.

Dang, K. B., Burkhard, B., Müller, F., and Dang, V. B.: Modelling and mapping natural hazard regulating ecosystem services in Sapa, Lao Cai province, Vietnam, Paddy Water Environ., 16, 767–781, https://doi.org/10.1007/s10333-018-0667-6, 2018.

Dang, K. B., Nguyen, T. T., Ngo, H. H., Burkhard, B., Müller, F., Dang, V. B., Nguyen, H., Ngo, V. L., and Pham, T. P. N.: Integrated methods and scenarios for assessment of sand dunes ecosystem services, J. Environ. Manage., 289, 112485, https://doi.org/10.1016/j.jenvman.2021.112485, 2021.

Dang, K. B., Nguyen, C. Q., Tran, Q. C., Nguyen, H., Nguyen, T. T. T. T., Nguyen, D. A., Tran, T. H., Bui, P. T., Giang, T. L., Lenh, T. A., Ngo, V. L., Yasir, M., Nguyen, T. T. T. T., Ngo, H. H., Quan, C., Cuong, Q., Nguyen, H., Thuy, T., and Hao, H.: Comparison between U-shaped structural deep learning models to detect landslide traces, Sci. Total Environ., 912, 169113, https://doi.org/10.1016/j.scitotenv.2023.169113, 2024.

Dang, K. B., Pham, T. T., Phan, T. T. H., Nguyen, M. H., Pham, T. P. N., Hoang, T. T., Hoang, T. H. N., Nguyen, T. H. T., Nguyen, T. H., Le, Q. D., Tran, N. B. Van, and Tran, T. K. B.: Bayesian Belief Network for Assessing Conservation and Tourism Development in UNESCO Geoparks, Geoheritage, 17, https://doi.org/10.1007/s12371-025-01083-8, 2025a.

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

Dang, K. B., Hoang, T. T. H., Nguyen, H., Vu, K. C., Giang, T. L., Damien, C., Nguyen, T. D. L., and Do, T. N.: Integrating remote sensing and artificial intelligence for landslide detection and susceptibility analysis along tourism routes in Da Bac district, Hoa Binh province, Vietnam, Vietnam J. Earth Sci., 47, 430–446, 2025b.

Depina, I., Oguz, E. A., and Thakur, V.: Novel Bayesian framework for calibration of spatially distributed physical-based landslide prediction models., Comput. Geotech., 125, 103660, https://doi.org/10.1016/j.compgeo.2020.103660, 2020.

Ding, J. W., Lu, D. G., and Dong, Y.: Seismic spatiotemporal assessment of indoor occupant casualties in regional buildings: A Bayesian network approach incorporating population density dynamics, Int. J. Disaster Risk Reduct., 126, 105637, https://doi.org/10.1016/J.IJDRR.2025.105637, 2025.

Duc, D. M., Minh, V. C., Yen, H. H., Loc, N. T., and Duc, D. M.: Analysis of landslide kinematics integrating weather and geotechnical monitoring data at Tan Son slow moving landslide in Ha Giang province, Vietnam J. Earth Sci., 45, 131–146, 2023.

FAO: The role of forests and forestry in the prevention and rehabilitation of lanslides in Asia, For. ans landslides, Cent. people For. FAO, 2010.

Ghasemian, B., Asl, D. T., Pham, B. T., Avand, M., Nguyen, H. D., and Janizadeh, S.: Shallow landslide susceptibility mapping: A comparison between classification and regression tree and reduced error pruning tree algorithms, Vietnam J. Earth Sci., 42, 208–227, 2020.

Hang, H. T., Hoa, P. D., Tru, V. N., and Phuong, N. V.: Landslide Susceptibility Mapping Along National Highway-6, Hoa Binh Province, Vietnam Using Frequency Ratio Model And Gis, Int. J. GEOMATE, 21, 84–90, https://doi.org/10.21660/2021.85.j2222, 2021.

Hao, J., Liu, L., Long, Z., Chu, Y., Zhang, D., Chen, X., and Huang, C.: Scenario deduction of Natech accident based on dynamic Bayesian network: A case study of landslide accident in a liquor storage tank area in Guizhou Province, China, J. Loss Prev. Process Ind., 83, 105067, https://doi.org/10.1016/j.jlp.2023.105067, 2023.

Highland, L. M.: Introduction The Landslide Handbook-A Guide to Understanding Landslides, Landslide Handb. - A Guid. to Underst. Landslides, 4–42, 2008.

Hung, P. Van, Soon, P. Q., and Dung, N. Van: The study evaluated arming of risk of lanslide in Hoa Binh and Son La reservoir hydropower area on the basis of analyzing high-resolution remote sensing and geographic information systems, Vietnam J. Earth Sci., 37, 193–203, 2015.

Islam, T. and Ryan, J.: Chapter 5 - Hazard Identification—Natural Hazards, in: Hazard Mitigation in Emergency Management, edited by: Islam, T. and Ryan, J., Butterworth-Heinemann, 129–170, https://doi.org/https://doi.org/10.1016/B978-0-12-420134-7.00005-9, 2016.

Jin, B., Zeng, T., Liu, S., Li, Y., Gui, L., Zhao, B., Yin, K., Catani, F., and Peduto, D.: Quantitative risk assessment for rainfall-induced landslides of transmission line towers: the case of Chongqing national transmission protection regions, Int. J. Disaster Risk Reduct., 128, 105715, https://doi.org/10.1016/J.IJDRR.2025.105715, 2025.

Kang, Y., Lu, Z., Zhao, C., and Qu, W.: Inferring slip-surface geometry and volume of creeping landslides based on InSAR: A case study in Jinsha River basin, Remote Sens. Environ., 294, 113620, https://doi.org/10.1016/j.rse.2023.113620, 2023.

Kayastha, P., Dhital, M. R., and Smedt, F. De: Computers & Geosciences Application of the analytical hierarchy process (AHP) for landslide susceptibility mapping : A case study from the Tinau watershed , west Nepal, Comput. Geosci., 52, 398–408, https://doi.org/10.1016/j.cageo.2012.11.003, 2013.

Kleemann, J., Celio, E., and Fürst, C.: Validation approaches of an expert-based Bayesian Belief Network in Northern Ghana, West Africa, Ecol. Modell., 365, 10–29, https://doi.org/10.1016/j.ecolmodel.2017.09.018, 2017.

Kuschel, E., Tolle, F., Klaus, V., Laa, U., Prokop, A., Friedt, J. M., Bernard, E., and Zangerl, C.: Meteorological factors control debris slides and debris flows in a high-Arctic glacier basin (Ny-Ålesund, Svalbard), Geomorphology, 467, https://doi.org/10.1016/j.geomorph.2024.109492, 2024.

Lan, M., Zhu, J., and Lo, S.: Hybrid Bayesian network-based landslide risk assessment method for modeling risk for industrial facilities subjected to landslides, Reliab. Eng. Syst. Saf., 215, 107851, https://doi.org/10.1016/j.ress.2021.107851, 2021.

Landuyt, D., Van der Biest, K., Broekx, S., Staes, J., Meire, P., and Goethals, P. L. M.: A GIS plug-in for Bayesian belief networks: Towards a transparent software framework to assess and visualise uncertainties in ecosystem service mapping, Environ. Model. Softw., 71, 30–38, https://doi.org/10.1016/j.envsoft.2015.05.002, 2015.

Liang, S., Peng, L., Yang, G., Zhang, H., and Jin, Y.: Modeling residents' long-term adaptation to geohazards in mountainous regions using agent-based models and Bayesian networks, Int. J. Disaster Risk Reduct., 119, 105279, https://doi.org/10.1016/J.IJDRR.2025.105279, 2025.

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

Liu, D., Liu, D., He, C., Zhang, C., Jin, W., Sa, W., Xing, X., Wu, C., Tan, C., Qin, Y., Xiang, B., and Shao, J.: An integrated framework to quantitatively analyze the potential threat of landslide-triggered outburst flood hazard chain, a case study in Danba, China, Int. J. Disaster Risk Reduct., 130, 105864, https://doi.org/10.1016/J.IJDRR.2025.105864, 2025.

Luu, C., Ha, H., Bui, Q. D., Luong, N. D., Khuc, D. T., Vu, H., and Nguyen, D. Q.: Flash flood and landslide susceptibility analysis for a mountainous roadway in Vietnam using spatial modeling, Quat. Sci. Adv., 11, 100083, https://doi.org/10.1016/j.qsa.2023.100083, 2023.

Ma, Z., Mei, G., and Piccialli, F.: Machine learning for landslides prevention: a survey, Neural Comput. Appl., 33, 10881–10907, https://doi.org/10.1007/s00521-020-05529-8, 2021.

Mckean, J. and Roering, J.: Objective landslide detection and surface morphology mapping using high-resolution airborne laser altimetry, Geomorphology, 57, 331–351, https://doi.org/10.1016/S0169-555X(03)00164-8, 2004.

Models, M. L.: Automated Landslide-Risk Prediction Using Web GIS and Machine Learning Models, 1–32, 2021.

Mondal, S. and Maiti, R.: Landslide Susceptibility Analysis of Shiv-Khola Watershed, Darjiling: A Remote Sensing & GIS Based Analytical Hierarchy Process (AHP), J. Indian Soc. Remote Sens., 40, 483–496, https://doi.org/10.1007/s12524-011-0160-9, 2012.

Mondini, A. C., Marchesini, I., Rossi, M., Chang, K. T., Pasquariello, G., and Guzzetti, F.: Bayesian framework for mapping and classifying shallow landslides exploiting remote sensing and topographic data, Geomorphology, 201, 135–147, https://doi.org/10.1016/j.geomorph.2013.06.015, 2013.

Moore, Z. T. and Sawyer, D. E.: Assessing post-failure mobility of submarine landslides from seismic geomorphology and physical properties of mass transport deposits: An example from seaward of the Kumano Basin, Nankai Trough, offshore Japan, Mar. Geol., 374, 73–84, https://doi.org/10.1016/j.margeo.2016.02.003, 2016.

Moriguchi, N., Ito, L., and Tokai, A.: Risk assessment of chemical release accident triggered by landslide using Bayesian network, Sci. Total Environ., 890, 164321, https://doi.org/10.1016/j.scitotenv.2023.164321, 2023.

Netica: Netica-J Reference Manual, 119, 2010.

Ngo, V. L., Nguyen, H., Dang, K. B., Giang, T. L., Dang, V. B., Do, T. H., Nguyen, M. H., Dang, N. V., and Dao, M. D.: Advancing debris flow detection based on deep learning model and high-

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

resolution images, Vietnam J. Earth Sci., 42, 290–214, 2025.

Nguyen, H., Dang, K. B., Giang, T. L., Dang, V. B., Dang, N. V., and Dao, M. D.: Exploring Various Deep Learning Models for High-Precision Landslide Tracing in Very-High Resolution Remote Sensing Imagery, J. Indian Soc. Remote Sens., https://doi.org/10.1007/s12524-025-02267-z, 2025.

Nguyen, M. D., Thang, N. Van, Wakai, A., Sato, G., Karnjana, J., Hung, H. V., Ho, L. S., Prakash, I., Quang, H. T., and Pham, B. T.: Identification, monitoring, and assessment of an active landslide in tavan-hauthao, sapa, laocai, vietnam – a multidisciplinary approach, J. Disaster Res., 16, 501–511, https://doi.org/10.20965/JDR.2021.P0501, 2021.

Nichol, J. E., Shaker, A., and Wong, M.-S.: Evaluation of the Global Satellite Mapping of Precipitation (GSMaP) data on sub-daily rainfall patterns in Vietnam, Geomorphology, 44, 94–104, https://doi.org/https://doi.org/10.15625/2615-9783/16980, 2019.

Palumbo, M., Ascione, A., Santo, A., and Santangelo, N.: Evaluation of sediment budgets in catchments prone to flash flood-related debris flows: A case study from the southern Apennines (Italy), Geomorphology, 454, https://doi.org/10.1016/j.geomorph.2024.109174, 2024.

Rai, S. C., Pandey, V. K., Sharma, K. K., and Sharma, S.: Landslide susceptibility analysis in the Bhilangana Basin (India) using GIS-based machine learning methods, Geosystems and Geoenvironment, 3, 100253, https://doi.org/10.1016/j.geogeo.2024.100253, 2024.

Ren, D.: Storm-triggered landslides in warmer climates, Storm-Triggered Landslides Warmer Clim., 1–365, https://doi.org/10.1007/978-3-319-08518-0, 2015.

Saleem, J., Ahmad, S. S., and Butt, A.: Hazard risk assessment of landslide-prone sub-Himalayan region by employing geospatial modeling approach, Nat. Hazards, 102, 1497–1514, https://doi.org/10.1007/s11069-020-03980-3, 2020.

Segue, W. S., Njilah, I. K., Fossi, D. H., and Nsangou, D.: Advancements in mapping landslide susceptibility in Bafoussam and its surroundings area using multi-criteria decision analysis, statistical methods, and machine learning models, J. African Earth Sci., 213, 105237, https://doi.org/10.1016/j.jafrearsci.2024.105237, 2024.

Shirzadi, A., Shahabi, H., Chapi, K., Bui, D. T., Pham, B. T., Shahedi, K., and Ahmad, B. Bin: A comparative study between popular statistical and machine learning methods for simulating volume of landslides, Catena, 157, 213–226, https://doi.org/10.1016/j.catena.2017.05.016, 2017.

Song, Y., Gong, J., Gao, S., Wang, D., Cui, T., Li, Y., and Wei, B.: Susceptibility assessment of earthquake-induced landslides using Bayesian network: A case study in Beichuan, China, Comput. Geosci., 42, 189–199, https://doi.org/10.1016/j.cageo.2011.09.011, 2012.

Stark, T. D., Estes, K. D., Silver, R. C., Holman, E. A., Leshchinsky, B. A., and Vahedifard, F.: Objective versus subjective landslide risk: A case of Cache Creek Landslide in California, Int. J. Disaster Risk Reduct., 132, 105910, https://doi.org/10.1016/J.IJDRR.2025.105910, 2026.

Sun, D., Xu, J., Wen, H., and Wang, D.: Assessment of landslide susceptibility mapping based on Bayesian hyperparameter optimization: A comparison between logistic regression and random forest, Eng. Geol., 281, 105972, https://doi.org/10.1016/j.enggeo.2020.105972, 2021.

Sun, D., Ding, Y., Wen, H., Zhang, F., Zhang, J., Gu, Q., and Zhang, J.: SHAP-PDP hybrid interpretation of decision-making mechanism of machine learning-based landslide susceptibility mapping: A case study at Wushan District, China, Egypt. J. Remote Sens. Sp. Sci., 27, 508–523, https://doi.org/10.1016/j.ejrs.2024.06.005, 2024.

Tawalo, A., Tsinidis, G., and Urciuoli, G.: Numerical framework for risk assessment of buried natural gas pipelines subjected to landslide-induced deformations due to rainfall infiltration: The Miscano landslide case, Int. J. Disaster Risk Reduct., 129, 105776, https://doi.org/10.1016/J.IJDRR.2025.105776, 2025.

Thanh, D. Q., Nguyen, D. H., Prakash, I., Jaafari, A., Nguyen, V. T., Phong, T. V., and Pham, B. T.: GIS based frequency ratio method for landslide susceptibility mapping at Da Lat City, Lam Dong province, Vietnam, Vietnam J. Earth Sci., 42, 55–66, 2020.

Tien Bui, D., Pradhan, B., Lofman, O., Revhaug, I., and Dick, O. B.: Landslide susceptibility assessment in the Hoa Binh province of Vietnam: A comparison of the Levenberg-Marquardt and Bayesian regularized neural networks, Geomorphology, 171–172, 12–29, https://doi.org/10.1016/j.geomorph.2012.04.023, 2012.

Tien Bui, D., Tuan, T. A., Hoang, N. D., Thanh, N. Q., Nguyen, D. B., Van Liem, N., and Pradhan, B.: Spatial prediction of rainfall-induced landslides for the Lao Cai area (Vietnam) using a hybrid intelligent approach of least squares support vector machines inference model and artificial bee colony optimization, Landslides, 14, 447–458, https://doi.org/10.1007/s10346-016-0711-9, 2017.

Tran, A. T., Pham, V. H., Tran, T. T., Nguyen, T. A. N., Nguyen, V. D., Pham, T. H., and Tran, V. P.: Landslide susceptibility in Phuoc Son, Quang Nam: A deep learning approach, Vietnam J. Earth Sci., 47, 39–57, 2025.

Tran, V. A., Khuc, T. D., Truong, X. Q., Nguyen, A. B., and Phi, T. T.: Application of potential

https://doi.org/10.5194/egusphere-2026-160
Preprint. Discussion started: 27 January 2026

machine learning models in landslide susceptibility assessment: A case study of Van Yen district, Yen Bai province, Vietnam, Quat. Sci. Adv., 14, 100181, https://doi.org/10.1016/j.qsa.2024.100181, 2024.

Tu, T. Van, Duc, D. M., Tung, N. M., and Cong, V. D.: Preliminary assessments of debris flow hazard in relation to geological environment changes in mountainous regions, North Vietnam, Vietnam J. Earth Sci., 38, 257–266, https://doi.org/10.15625/0866-7187/38/3/8712, 2016.

Wang, Y., Wang, X., and Jian, J.: Remote sensing landslide recognition based on convolutional neural network, Math. Probl. Eng., 2019, https://doi.org/10.1155/2019/8389368, 2019.

Xiao, P., Wang, T., Tian, Y., Xie, X., You, J., Tan, X., and Chen, H.: A Bayesian Network-Based Inhibition Model of the Rainstorm–Landslide–Debris Flow Disaster Chain in Mountainous Areas: The Case of the Greater Bay Area, China, Water (Switzerland), 15, https://doi.org/10.3390/w15173124, 2023.

Yamasaki, T., Sato, G., Kimura, T., Hung, H. V., Manh, N. D., Ozaki, T., Yokoyama, O., Tosa, S., and Wakai, A.: Landslide process revealed by mineralogical properties of landslide deposits in the sa pa district, Vietnam, J. Disaster Res., 16, 556–560, https://doi.org/10.20965/JDR.2021.P0556, 2021.

Yang, Z. qiang, Qi, W. wen, Xu, C., and Shao, X. yi: Exploring deep learning for landslide mapping: A comprehensive review, China Geol., 7, 330–350, https://doi.org/10.31035/cg2024032, 2024.

Yousefi, S. and Imaizumi, F.: Assessing the impact of sediment characteristics on vegetation recovery in debris flow fans: A case study of the Ohya Region, Japan, Ecol. Eng., 209, https://doi.org/10.1016/j.ecoleng.2024.107408, 2024.

Yousefi, S., Imaizumi, F., and Takayama, S.: Spatial distribution and transport characteristics of debris flow sediment using high resolution UAV images in the Ohya debris flow fan, Geomorphology, 469, 109533, https://doi.org/10.1016/j.geomorph.2024.109533, 2025.

Zhao, C. and Lu, Z.: Remote sensing of landslides-A review, Remote Sens., 10, 8–13, https://doi.org/10.3390/rs10020279, 2018.

Zhao, Y.: R and Data Mining: Examples and Case Studies, 1–160, https://doi.org/10.1016/B978-0-12-396963-7.00001-5, 2014.