# Integrating multidimensional factors through Bayesian Belief Networks for landslide risk reduction in subtropical zones

**Abstract:**

Current forecasting models for landslides 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. This research introduces a novel approach using a Bayesian Belief Network (BBN) to enhance landslide hazard prediction and risk assessment 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, 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, Hazard, Risk, Modelling, Scenario.

**Highlights**

- BBN model for landslide risk predictions was developed.
- Based on GIS, remote sensing, and interview data, 28 input factors were collected.
- BBN were validated based on SEM, multivariate regression and sensitivity analysis.
- Subtropical rainfall higher than 130mm during three-day periods increase the risk.
- Implementation of Gabion embankments can reduce human and infrastructure risks.

## 1. Introduction

Landslides are defined as the downslope movement of soil, rock, or debris under the influence of gravity, encompassing various types such as rotational, translational slides, and debris flows. Various disasters such as landslides have significantly impacted human lives and infrastructure in mountainous regions (Barnard et al., 2001; Ren, 2015). The consequences of these events can be catastrophic: landslides 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).

At the regional scale, landslides are particularly prevalent in Asia, where up to 78.3% of global landslide events in 2021 were recorded, according to the European Civil Protection and Humanitarian Aid Operations – European Commission (2022)[1]. These hazards commonly occur on steep slopes and are primarily triggered by disturbances to the critical balance of forces within slope materials.

In Vietnam, records from the Ministry of Natural Disaster Prevention and Search and Rescue indicate that the aftermath of landslides and floods occurring during Typhoon Yagi in 2024

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

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. Some provinces recorded more than 1,000 landslide events (such as in Lao Cai and Yen Bai provinces) (Nguyen et al., 2026). 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 landslide hazards (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 risk assessment. Geographic Information Systems (GIS) have traditionally served as platforms for integrating various qualitative and quantitative datasets through weighting systems to enhance hazard 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 landslide hazard or susceptibility 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 dominant analytical tools for hazard assessments, contributing to 20.51% of modelling approaches, while probabilistic methods account for 12.82% (Byrraju, 2019). Techniques such as multiple linear regression, Bayesian probability, and ROC-plane analysis have proven successful in estimating the likelihood of landslide 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).

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 hazard assessment and prediction 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.

Regarding factors used to assess landslide 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 (Zhao and Lu, 2018). 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 (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 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 hazards.

Therefore, this study develops a Bayesian Belief Network (BBN) model to predict landslide hazards and assess associated risks by integrating multidimensional factors. Landslide risk is considered as the combination of hazard, exposure, and vulnerability, often expressed as: Risk =

Hazard × Exposure × Vulnerability. Accordingly, input multidimensional factors include: (i) geomorphological factors (e.g., slope, curvature, drainage density), (ii) geological and material properties (e.g., soil and rock types, pre-transported materials), (iii) triggering factors (e.g., rainfall intensity and duration), and (iv) exposure-related variables (e.g., population, infrastructure, land use). Based on a developed Structural Equation Modeling (SEM), the internal dependencies between four components were identified and integrated in the BBN framework (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 and risk assessment, 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 frequently occur along transportation routes in the provinces of Da river basin, including Lai Chau, Dien Bien, Son La, Hoa Binh, Yen Bai, and Phu Tho (Hung et al., 2015) (Figure 1). Some other landslides in Lao Cai province were also added to increase the number of the input data. These hazards are concentrated in complex, deeply dissected mountainous terrain characterized by severe erosion and geological fragmentation. Due to the highly variable topography, landslides 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 sites in the northwestern region during the 2010s (Dang et al., 2018, 2025b), with more than 2,700 landslides exceeding 100,000 m³ in volume. Using high-resolution remote sensing imagery such as VNREDSat-1 and SPOT-5, Ghasemian et al. (2020) identified and manually interpreted landslides 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.

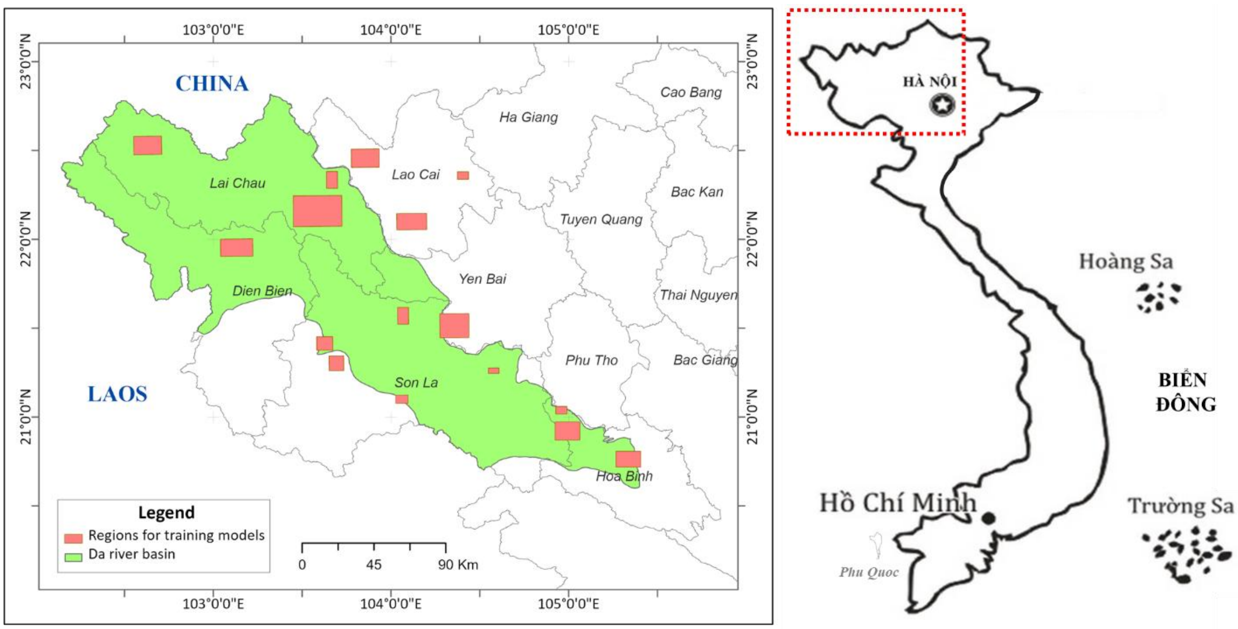


**Figure 1.** Location of landslides detected Worldview-2 images on Google Earth Pro software from 2010 to 2024.

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 occur on slopes ranging from 35° to 45°, particularly within tectonic destruction zones (Hang et al., 2021; Nguyen et al., 2021). Large-scale landslides 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 in landslide 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

A Bayesian Belief Network (BBN) is a graphical model that shows how variables are connected to each other and how they cause each other. Unlike black-box models such as Random Forest or Neural Networks, BBN provides transparent and interpretable results, which are particularly important for risk communication and decision-making (Dang et al., 2025a). BBN can also be used to perform probabilistic inference in the face of uncertainty, and scenario-based analysis (e.g., with different rainfall conditions), which are necessary to landslide hazard and risk assessment. The following benefits make BBN more appropriate in this research where both interpretability and combining various groups of factors are needed.

In a BBN model, each node has a conditional validation table (CPT) linked to it. This table shows how likely it is that a variable will happen based on its nodes. This model allows for validation inference, which means that changing one variable (like rainfall) could change the performance of other variables (like hazard and risk) through the network. This study employs Bayesian Belief Networks (BBNs) to examine evolving environmental, climatic, and socioeconomic circumstances to establish a land base and subsequently evaluate the risk to the computing network and assets. BBN models are developed through four steps, from determining factors, building a theoretical model, gathering multidimensional data, to the final model. The detail of each step can be explained as follows:

**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. In this study, warning refers to the process of identifying and communicating the probability of landslide occurrence (hazard) and its potential impacts (risk) in advance, in order to support timely decision-making and risk mitigation. The selection of variables was based on three main criteria: (i) statistical significance identified through SEM and multivariate regression analysis, (ii) data availability and spatial consistency, and (iii) relevance to landslide processes as reported in previous studies. 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 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 was reviewed by experts in Vietnam Academy of Science and Technology and Vietnam National University, whereas the selection of social factors was 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. 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 for landslide hazard and subsequent risk assessment .

The model integrates multiple dimensions of risk, including susceptibility, hazard, resilience, and vulnerability, as illustrated in **Figure 2**. Key inputs encompass data on the distribution and frequency of landslides, climatic and geological conditions, triggering factors, and elements at risk. Specifically, landslide hazard is 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.

Importantly, vulnerability is not included in the model as a separate variable, but is reflected indirectly through the characteristics of the affected objects. (Agboola et al., 2024; Luu et al., 2023). These characteristics include the type of structure, the quality of infrastructure, and the presence of protective measures such as dikes or embankments, thereby determining the level of damage when the same level of danger occurs. Different objects such as roads, houses, or people will have different levels of vulnerability, and this is reflected in the model results through the risk to life and the risk to property.

Equally critical are the exposure and resilience dimensions, which reflect population density, existing protective infrastructure, and community preparedness. Resilience is the ability of a system or structure to withstand and recover from the impact of landslides. 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).

In this study, the risk framework follows the widely accepted formulation in which risk is a function of hazard, exposure, and vulnerability. 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.

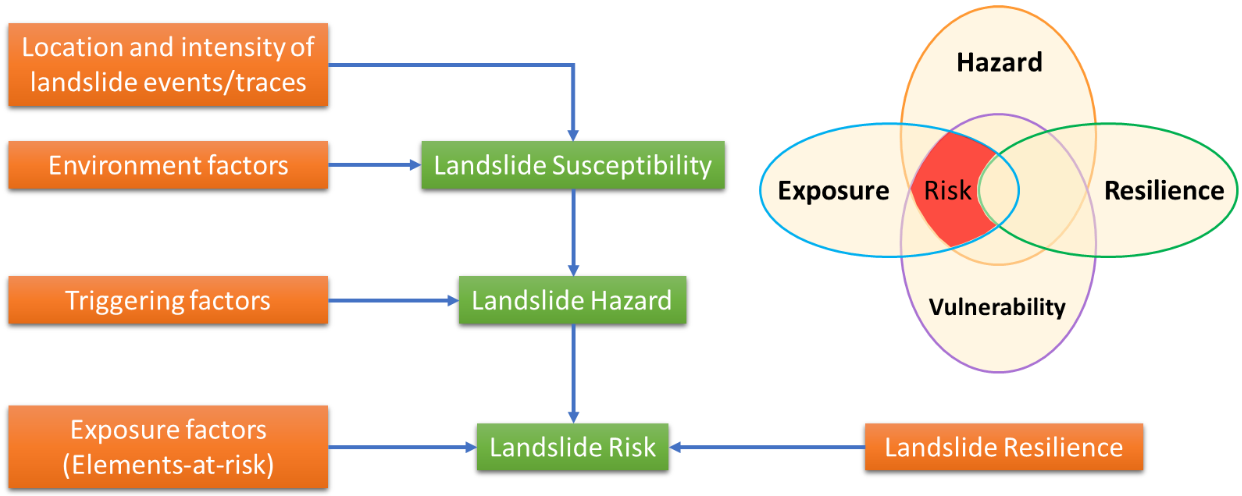


**Figure 2.** Conceptual framework linking hazard, exposure, and vulnerability in the assessment of landslide risk.

**Step 3: Data collection**

Landslide warnings are influenced by geological, geomorphological, meteorological, hydrological, land cover and land use, and infrastructure conditions (Figure 3). This Figure refers to the range of input variable values at which the probability of a landslide hazard surpasses 50%. It was run based on the Bayesian Network Model's (BBN) probabilistic response curves. It shows the conditions under which the chance of a landslide is highest. When we say "landslide hazard greater than 50%", it means that the BBN model's posterior probability is greater than 0.5, which means that under certain conditions (like rainfall, slope, or land use), the chance of a landslide is higher than the chance of it not happening. The graphs in the figure are constructed from sensitivity analysis and response analysis of the BBN model, where each curve represents the change in the probability of a landslide with respect to one input variable, while other variables are kept constant or according to their initial distribution. The vertical dashed lines represent ranges of values corresponding to levels of probability of interest (e.g., 50%), thereby defining the influence thresholds of each factor.

In this study, the spatial resolution is defined by the raster datasets used in the analysis, which were standardized to a resolution of 30x30 m. Accordingly, a grid-based mapping unit (pixel-based approach) was adopted, where each cell represents the smallest spatial unit for analysis and developing BBN model. Five input data groups were obtained, including:

<u>Geological and Geomorphological Factors</u>

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 terrain shape, enabling the calculation of parameters such as slope, aspect, Terrain Ruggedness Index (TRI), and curvature indices, which are critical in identifying areas vulnerable to landslide 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.

<u>Meteorological and Hydrological Factors</u>

Rainfall, flow accumulation, the Terrain Wetness Index (TWI), and proximity to rivers are fundamental triggers of landslides (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 build-up 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 likelihood of slope instability (hazard). This group of factors is central to evaluating meteorological and hydrological triggers of landslide 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.

Infrastructure Factors

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).

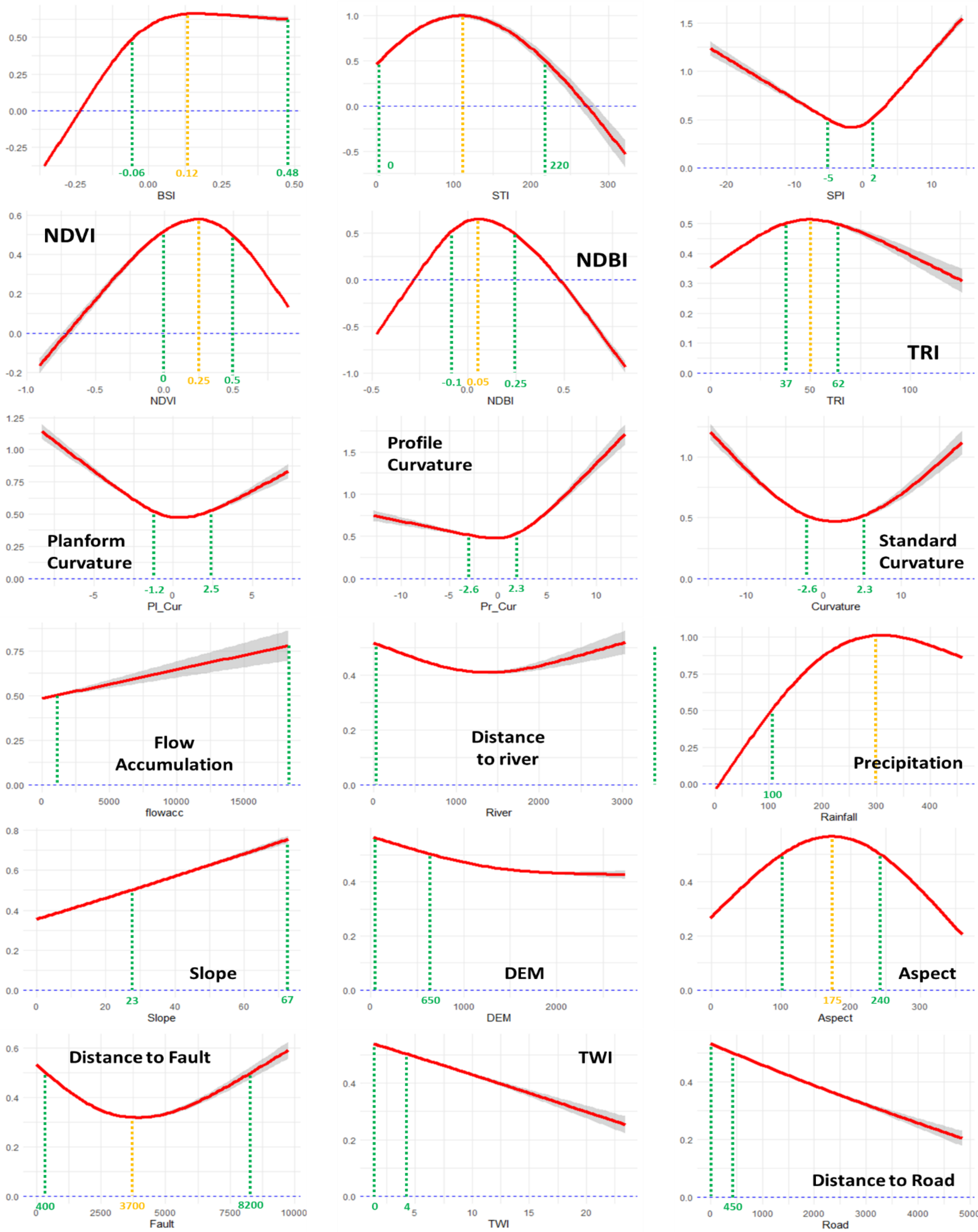


**Figure 3.** Correlation lines (Red) between independent variables with landslide hazard. The regions between green lines are thresholds of landslide hazard higher than 50%. The yellow lines are peak of landslide hazard in each variable.

Discretization of Input Factors

The input variables of the BBN model are classified into multiple value ranges (also known as states) to enable calculating probabilities. This classification is founded on real information, by examination of the dispersion of values of every variable (e.g., frequency of appearance, variety of fluctuation), instead of expert choice. In other instances, reference thresholds used in scientific literature and common geomorphological features of the study region are used to modify the classification ranges, as opposed to arbitrarily binned, to make results objectively and interpretably. As an example, with the slope variable, the data is examined to define frequent range of values, and sorted into levels as; low (0–16°), medium (16–32°), and high (>32°). These ranges do not only indicate the real distribution of the data, but also are related to the geomorphological features, with steep-slope areas being more likely to have landslides.

Likewise, in the case of the cumulative rainfall variable, the data are processed to identify characteristic thresholds which are further broken down into levels like: small (less than 100 mm), medium (100-200 mm) and large (greater than 200 mm). These ranges represent varying amounts of rainfall in reality and enable one to easily define conditions under which the threat of landslides is at its highest when it is subjected to extended conditions of heavy rainfalls.

Integration of Factors for Landslide Hazard Assessment and Warning

Five field trips were procedure from 2023 to 2025 to employ in three aspects: (i) to aid in the construction of the BBN structure by confirming the significance and orientation of relationships among variables; (ii) to instruct and calibrate CPTs where observational data exist (e.g., by relating rainfall, slope, land use conditions to observed landslides); and (iii) to provide an independent validation check of the model, by comparing model. Through the integrated use of these datasets within a BBN model, it is possible to generate highly accurate landslide warnings. The combined consideration of geological, geomorphological, meteorological, hydrological, land use, and infrastructure factors enhances the reliability of landslide hazard prediction and supports risk management. Additionally, different categories of exposed elements (e.g., residential buildings, roads, and human presence) are treated separately in the model to reflect their varying vulnerability levels.

**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). In the BBN framework, exposure is represented by elements such as population, buildings, and road infrastructure. Vulnerability is characterized by the susceptibility of these elements to damage, which is reflected through variables such as building types, infrastructure conditions, and the presence of protective measures (e.g., embankments). To address their relations, 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). Therefore, the SEM is employed as a pre-statistical analysis method to determine and confirm the associations between input variables, and determine their relative effect. The results of SEM (together with multivariate regression) are used to support the selection of variables and the definition of network structure (i.e., directional relationships between nodes) in the BBN.

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 hazard / occurrence probability) 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 for landslide hazard prediction.

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 landslide hazard estimation (or occurrence probability). There were two primary steps in the modeling process. The BBN model was first used to figure out the hazard, which is the chance of a landslide happening in certain environmental conditions and with certain triggering effects. Second, this hazard was paired with things like population, buildings, and infrastructure that could make it worse to figure out how dangerous it was to life and property. In this study, the usual formula is used to define risk as follows: Risk = Hazard × Exposure × Susceptibility. 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.

Subsequent to building the conceptual model, preparing data and analyzing the variables, the final stage is to develop and model the BBN for landslide risk assessment. The relationships between variables in the BBN network are represented through conditional probability tables (CPTs). This process starts with the construction of the Conditional Probability Table (CPT) (Kleemann et al., 2017), in which the frequencies of landslide, environmental conditions, triggering factors, exposure factors and resilience in order to evaluate landslide hazard. In this study, the CPTs were constructed based on statistical analysis results (SEM and multivariate regression) combined with observational data to ensure the objectivity and consistency of the model. This approach helps to limit reliance on mere expert opinions. For example, for the "Landslide hazard" node, the CPT table was constructed based on the relationship between variables such as rainfall, slope, and land use. For instance, when rainfall is high (>240 mm), the slope is steep (>30°), and the area is agricultural land, the probability of a landslide can reach over 80%. Conversely, under conditions of low rainfall (<50 mm), a small slope (<15°), and forest cover, this probability drops below 20%. These probability values are not assigned subjectively but are derived from data and statistical relationships that have been tested through SEM and multiple regression.

Furthermore, spatial allocations of land use, topography, environmental conditions, and other factors are integrated across the study area to determine the proportion of high-risk zones, from which the baseline CPTs are 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). The BBN model development 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 landslides 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 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 landslide hazards, thereby supporting risk reduction and community protection.

### 2.3. Scenario development

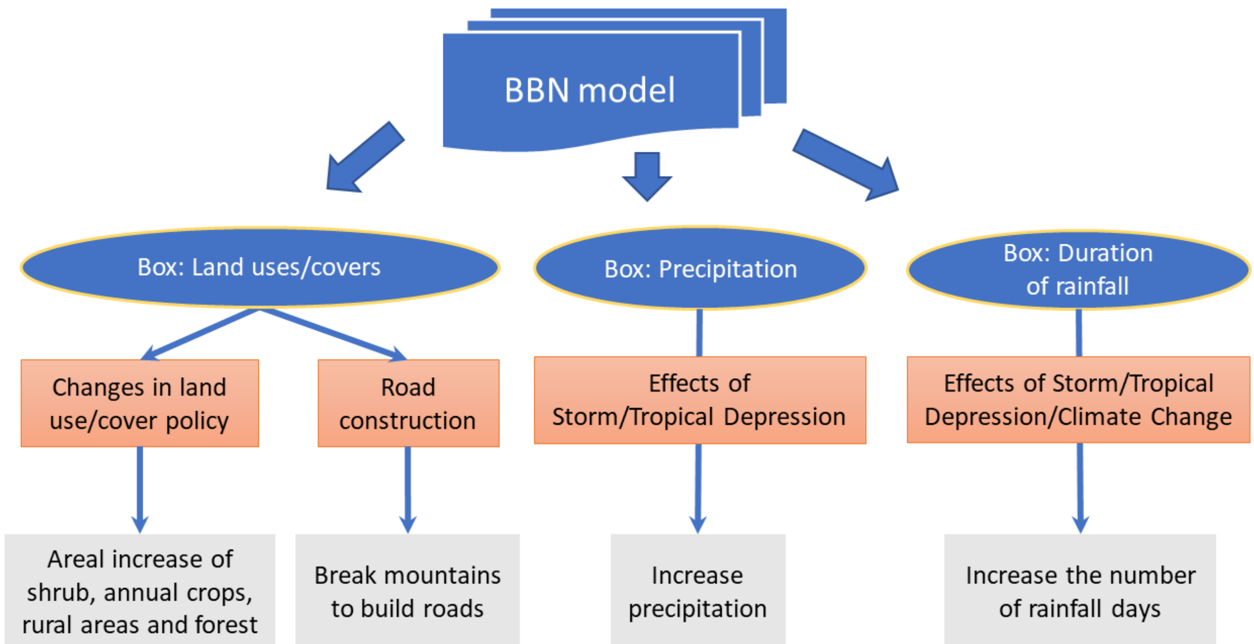


**Figure 4.** Framework to generate scenarios based on changes in boxes: Land uses/covers, precipitation and duration of rainfall days.

Scenarios generated in the BBN model for landslide hazard prediction represent a crucial step in understanding influencing factors and assessing associated risks (Song et al., 2012; Sun et al., 2021) (Figure 4). 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.

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 hazard and associated risks.

By constructing such scenarios within the BBN framework, it becomes possible to model the interdependencies among these factors and assess how landslide risks vary under different conditions. This approach enables the identification of the most vulnerable areas, thereby 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 hazards, 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 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 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 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 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 (Figure 5) illustrates the expanded framework for landslide hazard and risk assessment and highlights the numerous natural and anthropogenic factors involved. This Figure shows the different states and probability distributions of each variable in the BBN model. Each value class is based on the data, and the percentage values show how likely or how much each state contributes to the landslide risk. Importantly, its information is not the result of subjective classification. It is a quantitative representation of the model's probabilistic relationships. In this study, landslide hazard is first estimated through environmental and triggering factors, and subsequently combined with exposure and vulnerability components to derive risk to life and property. The "Landslide hazard" node is under effects of 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 susceptibility and hazard levels in an area. For example, some areas with steep slopes (>30°), high river density, and loose or weathered materials have high probability of landslides (more than 70–80%) when it rains heavily (>240 mm). On the other hand, other areas with slight slopes (less than 15°), more stable lithology, and less drainage can have lower probability of landslides, usually less than 20–30%. It shows how strongly geomorphological and geological settings affect slope stability.

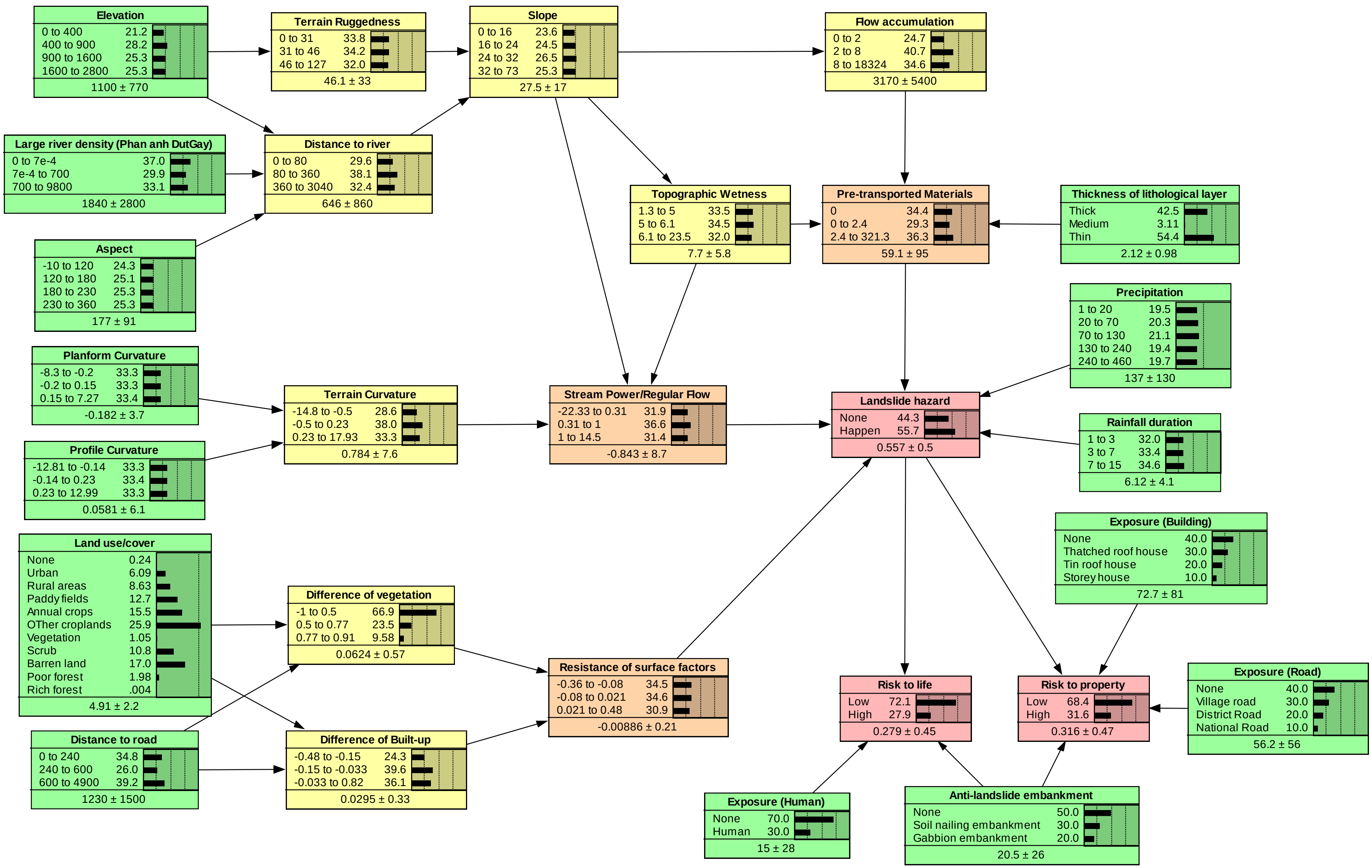


**Figure 5.** BBN model for predict landslide hazards and their risk to life and property.

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 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 hazard. 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.

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 hazard. 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 hazard, life risk and property risk (Table 1). The sensitivity analysis indicates that precipitation (variance = 0.09) and risk to property (variance = 0.09) are the most influential variables controlling landslide risk, with higher contributions than rainfall duration and pre-transported materials (variance ≈ 0.01). With a belief variance of 0.09 for both the relationship between precipitation and landslide hazard, and between risk to property and landslide hazard. 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 landslide 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 hazard 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 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 |
| 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 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 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 |

The results demonstrated that hazard alone does not determine risk; instead, the interaction between landslide hazard and exposure (e.g., roads and buildings) significantly amplifies potential damage. 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%), shows a stronger influence on landslide hazard (correlation coefficient = 0.385) compared to its indirect contribution to risk through exposure, highlighting its dominant role as a triggering factor rather than a direct determinant of damage. Interestingly, rainfall duration and pre-transported materials exhibit relatively low influence (variance ≈ 0.01), suggesting that, in the study area, short-term intense precipitation plays a more critical role than prolonged rainfall or sediment conditions. 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

Figure 6 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 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 landslide hazard 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, especially near transportation networks. Additionally, rainfall conditions play a crucial role: precipitation intensity and duration significantly increase the probability of landslide occurrence.

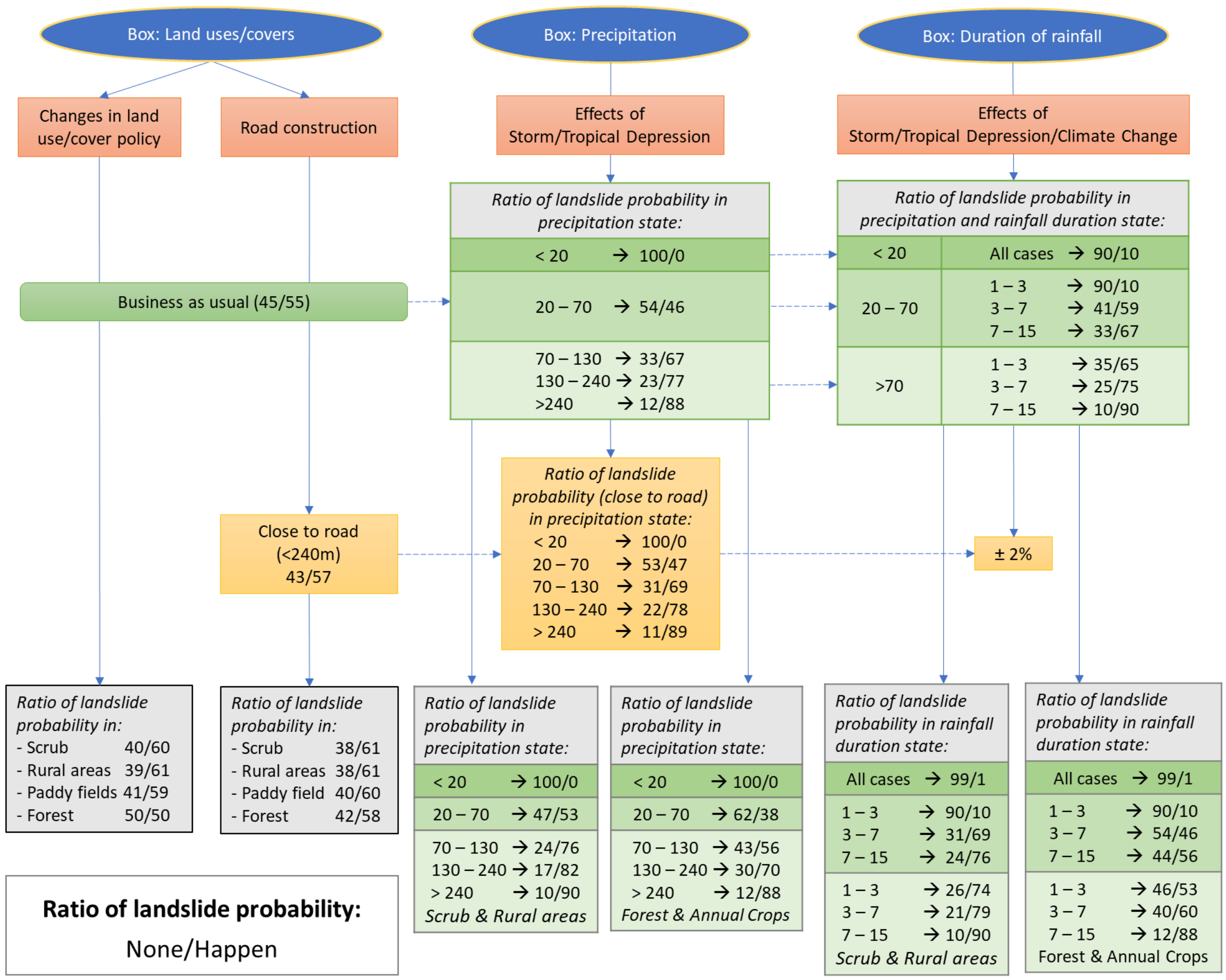


**Figure 6.** Scenario results to predict the probability of landslide hazards in different changes in land uses/covers, increase of precipitation and duration of rainfall days.

At low rainfall levels (<20 mm), the probability of landslide occurrence is minimal, with an extremely low probability ratio (100/0). However, as rainfall increases — particularly when it exceeds 240 mm — this probability 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 hazard, 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 hazard, reaching up to 90%. Although forested areas and perennial crops show greater resistance, the risk remains at a hazard 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 |

Table 2 presents the probability of risk to human life when exposed to landslide hazards under different types of embankment protection. The values are calculated based on the highest probability scenario of the “Landslide hazards” category. The results 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 level 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 |
| 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, Table 3 presents the probability of risk to assets (including buildings and roads) under different scenarios of landslide exposure and with various types of anti-landslide embankments. These differences reflect variations in vulnerability, as different types of buildings and infrastructures exhibit different resistance to landslide impacts. 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 landslide impacts 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.

**3.5. Landslide probability maps based on precipitation scenarios**

In order to respond to the spatial interpretation of the results, landslide hazard maps were created of the Da River basin in three accumulation scenarios of rainfall (70–130 mm, 130–240 mm, and >240 mm) based on the application of the developed BBN model (Figure 7). The lower rainfall does not provide high probability of landslide hazard as explained above. These maps give a clear cartographic illustration of the spatial variations of landslide hazard in the study area in various rainfall conditions.

Landslide hazard is restricted in steep slope areas and areas with high drainage density under low rainfall conditions (70-130 mm) especially in portions of Lai Chau (Muong Te district), Yen Bai (Mu Cang Chai district) and Dien Bien. The regions have moderate level of hazard through geomorphological features even in the conditions of relatively low rainfall.

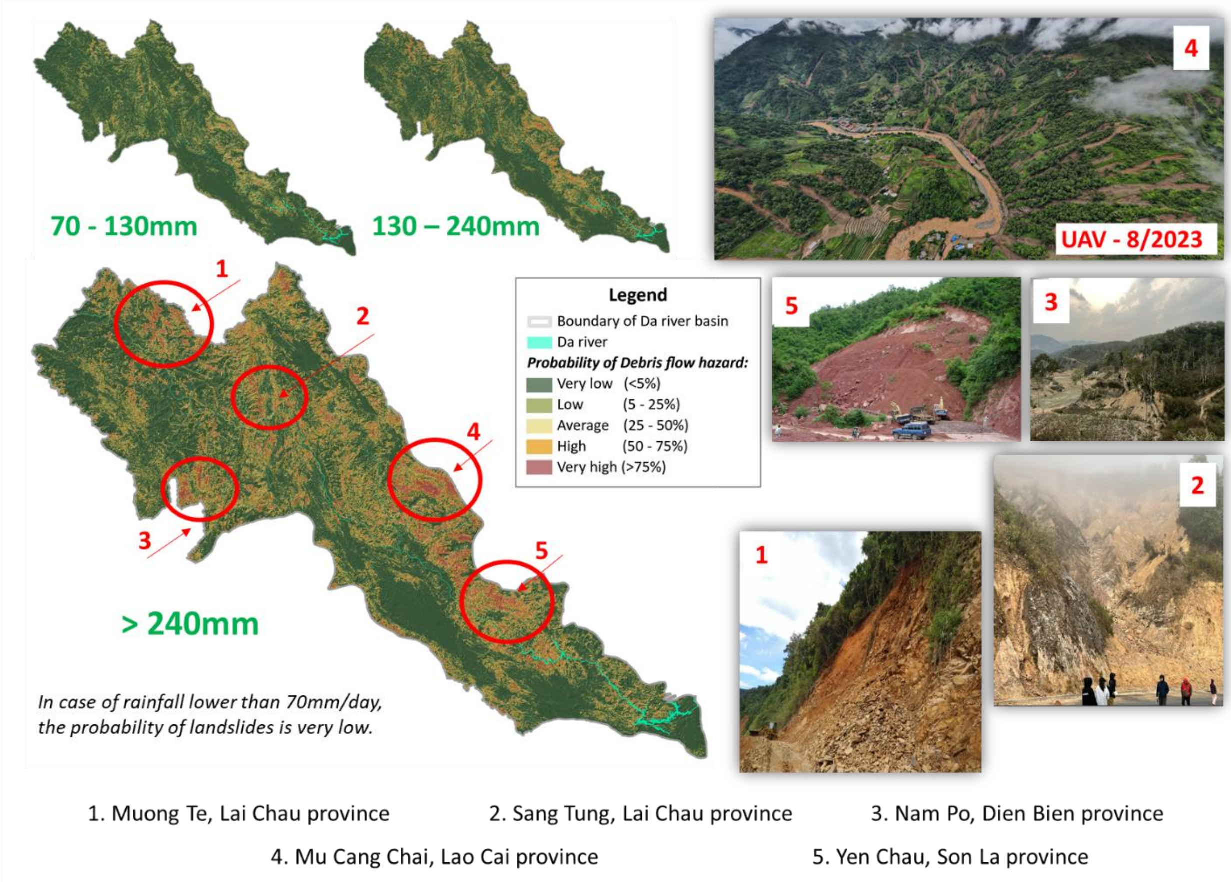


**Figure 7.** Probability map of landslide occurring in three rainfall scenarios based on BBN model in the Da river basin.

At a rainfall greater than 130-240 mm, the area of landslides hazard is larger. The areas with high hazard zones start developing along the river valleys and mountainous areas, particularly in the north-western section of the basin and regions where there are high land-use activities. The result of the increased rainfall is an increase in soil moisture and decreased slope stability, which produces a measurable change in the moderate to high hazard levels in a more extensive region.

Landslide hazard is extensive and very high in most areas of the basin in the high rainfall situation (>240 mm). The most vulnerable zones around Lai Chau, Son La and southeastern towards Hoa Binh are significantly high due to the extended and strong rainfall which floods the soil and slopes making them unstable. Previously known moderate or high hazard regions in the lower rainfall conditions convert to very high hazard regions, suggesting an extreme nonlinear relationship between landslide processes and intensity of rainfall.

These scenario-based maps are a clearer depiction of the spatial dynamics of landslide hazard to rainfall variability, and better represented visually over tabular or diagram-based results. The findings indicate that short-term rainfall events (1-3 days) are a highly important triggering factor, and hazard patterns are highly determined by the interplay between the intensity of rainfall and the underlying geomorphological characteristics.

# 4. Discussion

## 4.1. Comparison with formal networks/frameworks

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

Even though the classification of the input factors can bring a level of uncertainty, because of the choice of the class size and separation criteria, this problem is clearly resolved in the BBN framework by sensitivity analysis. The sensitivity analysis quantifies the impacts of each variable and its state on the output (landslide hazard and risk) in terms of mutual information, and entropy reduction, to determine the most influential variables and the importance of different classification schemes on the model results.

When the findings indicate that the main variables (e.g., rainfall, slope, and land use) have a high and consistent impact under various circumstances in classifications, the model can be regarded as robust and not highly relying on preliminary assumptions. On the other hand, in cases where a variable has been found to be very sensitive as a result of categorization, the classification scheme is re-considered and revised to represent the data distribution in a more accurate way.

Thus, sensitivity analysis can not only determine the most significant controlling factors but also is an internal control mechanism of the model, which can reduce bias and make the results more reliable. Due to such advancements, BBN model goes beyond mere prediction, and it is used to create more adaptable and contextual response strategies to suit various conditions in the region. 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 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 landslide occurrence and associated damage 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 landslide occurrence and its impacts on 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 landslide hazard but also assesses 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-hazard 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.

Additionally, the scenario-based landslide hazard maps (Figure 7) offer an effective foundation on how the disaster risk can be reduced in the Da River basin since they help to clearly show the spatial distribution of the hazard under various rainfall conditions. These maps can be used to locate the priority areas in which to monitor and intervene, especially those zones which regularly have high levels of hazard. Besides, the specified rainfall thresholds (70-130 mm, 130-240mm, and above 240mm over a 13days period) can be used to facilitate threshold-based early warning and response planning. The spatial outputs also provide scientific basis of land-use planning to assist the authorities in controlling the development in high-risk regions and focus on mitigation strategies.

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 economic projections and be compatible with hydrological and climate models to enhance its decision-support capabilities. Finally, incorporating feedback from real-world landslide 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 increase the probability of landslide hazards and their associated risks to people and property. The findings highlight that the Da river basin 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 thereby reducing overall landslide risk. Specifically, the results reveal that cumulative rainfall exceeding 130 mm over three consecutive days substantially raises the probability of landslide, 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 to predict hazard and assess risk, they can equip decision-makers with robust, evidence-based insights to guide policies, improve resilience, and safeguard both communities and ecosystems.

## Software and data availability

Name of model: BBN-landslide

Developers: Hieu Nguyen and Kinh Bac Dang

Contact: hieunguyen@hus.edu.vn and dangkinhbac@hus.edu.vn

Data and model availability: https://github.com/dangkinhbac/BBN_landslide.git

Date first available: February 21, 2025

Software required: Netica

Software availability: https://www.norsys.com/netica.html

Operating Systems: Windows

Cost: Free and payment options, detail in https://www.norsys.com/purchase_order_info.htm

## Declarations

**Competing interests:** The authors declare no competing interests.

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## CRediT author statement

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

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