A PROBABILISTIC FRAMEWORK FOR ESTIMATING LANDSLIDE PROBABILITY USING MAJOR TRIGGERING FACTORS

MOHAMMAD RAHAL[1], SHAZA SOLEIMAN[2] & BASSAM HUSSEIN[3]
[1]Phoenicia University, Lebanon
[2]Lebanese International University, Lebanon
[3]The International University of Beirut, Lebanon

ABSTRACT

Landslide probability estimation is crucial for risk assessment and mitigation, yet existing approaches often fail to effectively quantify the combined influence of multiple triggering factors. This study introduces a novel probabilistic methodology that explicitly incorporates three primary landslide triggers: heavy rainfall, significant earthquakes and severe human activity. The proposed framework calculates landslide probability by integrating conditional probability theory with dependency coefficients that capture trigger interactions. Unlike conventional models that assume independence among triggers, this approach accounts for both interdependent and counteracting interactions, leading to a more realistic assessment of landslide likelihood. The methodology employs Poisson-distributed event probabilities to estimate the annual occurrence of each trigger, while historical landslide records are used to derive conditional probabilities of failure. Additionally, a buffer-based approach is introduced to estimate landslide spatial impact on the total study area. This comprehensive methodology enhances predictive accuracy by integrating empirical observations, statistical probability models, and expert reasoning where necessary. The proposed framework provides geotechnical engineers and decision-makers with a systematic tool for landslide risk assessment and hazard mitigation.

Keywords: landslide probability, rainfall, earthquake, human activity, risk estimation, Poisson distribution.

1 INTRODUCTION

Landslides are among the most common and devastating geological hazards causing significant loss of lives and major economic damage every year in communities globally. Previous studies have reported that the 17% of fatalities, attributed to natural hazards worldwide, are caused by landslides [1]. Different natural phenomena and human disturbances trigger landslides. Natural triggers include meteorological changes, such as intense or prolonged rainfall or snowmelt, and rapid tectonic forcing, such as earthquakes or volcanic eruptions. On the other hand, human-induced disturbances include land use changes, deforestation, excavation, changes in the slope profile and irrigation [2]. Due to the diverse range of natural and human-induced triggers, accurately assessing landslide risk remains a complex task [3]. It has been recognized that considerable uncertainties exist in models and parameters that are commonly used for landslide risk estimation [4]. Thus, traditional methods, whether qualitative, semi-quantitative, or quantitative, often struggle with handling uncertainties in input data [5]. Particularly, regional landslide susceptibility assessments are complex, as they must consider a wide range of contributing factors [3]. Given these challenges, probabilistic analysis is gaining more attention in landslide hazard assessment, as it allows for the consideration of estimation uncertainties and the spatial variability of geological, geotechnical, geomorphological, and seismological parameters [6].

Landslide probability estimation involves inherent uncertainties that can be addressed using different probabilistic approaches. Lee, in one of his research works, broadly classified

WIT Transactions on The Built Environment, Vol 217, © 2025 WIT Press
www.witpress.com, ISSN 1743-3509 (on-line)
doi:10.2495/ERES250011

these approaches into objective and subjective probabilities [7]. Objective probability is based on observed data or experiments and represents the relative frequency of landslide occurrences over multiple instances. It is considered measurable and verifiable through empirical studies. Conversely, subjective probability relies on expert judgment and available knowledge to quantify uncertainty. This approach is particularly useful when empirical data are scarce or incomplete, allowing practitioners to incorporate expert assessments into probability estimates [7]. Despite their applicability, both objective and subjective probability approaches are constrained by data availability and the inherent uncertainties in landslide occurrence and triggering conditions.

2 LITERATURE REVIEW

Various methodologies have been developed to improve the accuracy of landslide probability estimation and hazard assessment. These methodologies can be classified into six main categories based on their principles and data utilization. The categories differ in data requirements and applicability to various geographical regions. This section provides an overview of the major methods for estimating landslide probability.

2.1 Empirical (historical) methods

Historical records of landslide occurrences, along with quantitative stability analyses, provide a basis for objectively estimating event probabilities. However, probabilistic assessments of landslide hazards that are based on historical records are difficult to apply, because most landslide records cover short periods of historical time and small geographic areas. Furthermore, landslide records often do not contain information regarding date of occurrence [8]. Landslide inventories can be created by gathering historical records of past events or by interpreting aerial photographs, supplemented with field verification. The way landslides are represented on inventory maps varies depending on the scale of failures and the nature of the study, ranging from detailed depictions of landslides to simplified point representations indicating their locations [9].

2.2 Heuristic (expert-based) methods

Probability assessments can be based on expert judgment, utilizing existing knowledge and experience from similar projects and locations. This method, known as subjective probability assessment, depends on the evaluator's confidence in predicting whether a landslide will occur or not [10]. One of the most widely used heuristic approaches is the analytic hierarchy process (AHP). AHP is a semi-qualitative method, which involves a matrix-based pair-wise comparison of the contribution of different factors for landsliding. It is a multi-objective, multi-criteria decision-making approach, which enables the user to arrive at a scale of preference drawn from a set of alternatives [11]. Another commonly applied method is weighted overlay analysis, where multiple thematic layers such as lithology, land use, and rainfall intensity are combined with assigned weights based on expert opinions to produce a slope stability susceptibility map [12]. Despite their qualitative nature, heuristic models can be combined with data-driven and deterministic methods to enhance the accuracy of slope stability assessments, particularly in regions with limited historical data or high geological complexity [11].

2.3 Deterministic (process-based) models

Deterministic, process-based models are widely used in geotechnical engineering to assess slope stability by simulating the fundamental physical processes governing slope behaviour. These models incorporate triggering factors such as rainfall infiltration, changes in groundwater levels, seismic activity, and external loading to evaluate failure mechanisms [13]. Deterministic models rely on mathematical formulations that integrate geotechnical and hydrological properties to estimate the factor of safety (FoS), a key parameter in stability assessments. Numerical approaches, such as the finite element and finite difference methods, allow for more advanced analyses by considering heterogeneous soil conditions, complex slope geometries, and dynamic loading effects [14]. These techniques enable engineers to model stress distribution, strain development, and failure surfaces with greater accuracy. Furthermore, in seismic stability analysis, deterministic models incorporate pseudo-static or fully dynamic considerations to account for earthquake-induced accelerations and their impact on slope stability [15]. However, the reliability of these models is highly dependent on accurate input parameters derived from site-specific investigations, laboratory testing, and empirical correlations.

2.4 Statistical models (bivariate and multivariate)

Bivariate analysis is among the most basic statistical methods and is widely applied across various disciplines. Several bivariate statistical analysis (BSA) techniques have been developed, including the frequency ratio (FR), weight of evidence (WoE), and evidential belief function (EBF) [16]. The theoretical formulation of FR, along with its application in landslide susceptibility and flood mapping, has been documented in studies by Yilmaz [17] and Tehrany et al. [18]. This method represents the ratio of the area where an event has occurred to the total study area [17]. The WoE method, on the other hand, is a data-driven approach grounded in Bayesian probability theory. To apply WoE, two key parameters, positive weight (W^+) and negative weight (W^-), must be calculated [19]. A more advanced approach is multivariate analysis, which evaluates the combined influence of multiple interrelated factors on slope failure. In this method, landslides are considered the result of various environmental variables that change across space and time. Multivariate analysis allows the estimation of the relative weight of each contributing factor by means of statistical procedures such as multiple regression or discriminant analysis. These procedures have already been applied in landslide susceptibility assessment, demonstrating that they are capable of successfully predicting slope failures using either categorical data, or quantitative terrain parameters [20]. Other statistical methods, such as logistic regression, are also used in landslide susceptibility mapping to model the relationship between landslide occurrence and factors like slope angle, aspect, and lithology [21].

2.5 Simulation models (Bayesian, Monte Carlo)

Monte Carlo simulation (MCS) and Bayesian networks (BNs) are two powerful probabilistic methods for landslide probability estimation, each offering unique advantages in dealing with uncertainty and variability [22]. Marin and Mattos [23] utilized MCS in a physically based landslide susceptibility analysis, where multiple realizations of geotechnical parameters, such as soil strength and hydrological conditions, were generated to capture the inherent uncertainties in slope stability modelling. By running thousands of simulations, they provided a probabilistic distribution of failure likelihood rather than a deterministic safety factor, enhancing risk assessment. Vogel et al. [24] applied BN learning for natural hazard analysis, demonstrating its capability in integrating expert knowledge with observational data. The BN approach structures causal relationships among landslide-influencing factors, such as precipitation, slope angle, and soil properties, updating probability distributions dynamically as new data becomes available.

2.6 Data-driven models

Within the last decade, with the advancement of artificial intelligence (AI), state-of-the-art, data-driven, and computationally powerful methods have started to emerge on the horizon. Once such methods are trained using a required amount of data, they are showing promising results in predicting landslides. Currently, the development of AI methods is highly dynamic in almost every section of academia and industry, and landslide susceptibility mapping (LSM) is following a similar trend [25].

The fuzzy set theory developed by Zadeh [26] and different fuzzy logic operators discussed later use the combination of fuzzy membership functions related to landslide causative factors, namely the fuzzy AND, fuzzy OR, fuzzy algebraic sum, and the fuzzy gamma (γ) operator [27]. In landslide susceptibility mapping, spatial objects on a map are considered as members of a set [28]. The Artificial Intelligence (AI), Deep Learning (DL) and Machine Learning (ML) modelling techniques, namely boosted regression tree (BRT), random forest (RF), logic regression (LR) and support vector machines (SVM), convolution neural network (CNN), deep convolution neural network (DCNN), backpropagation neural network (BPNN) and U-Net model, fuzzy expert system (FES), extreme learning machine (ELM), artificial neural network (ANN), explainable artificial intelligence (XAI), and certainty factor–random (CF–RF) hybrid, have been successfully used with remote sensing datasets from different sources to map the susceptibility of landslides and predict and monitor landslide deformation zones [29].

3 RESEARCH GAPS AND PROPOSED APPROACH

While existing methods contribute significantly to landslide risk analysis, their effectiveness varies depending on data availability, scale, and the complexity of triggering interactions. Despite advancements in landslide probability estimation, many models oversimplify the relationships between multiple triggering factors by assuming independence or assigning static weights. For example, traditional, statistical, and deterministic approaches often fail to explicitly account for conditional dependencies among key triggers, leading to potential inaccuracies in risk assessment. Additionally, while machine learning techniques have been applied to landslide susceptibility mapping, they typically require extensive training data and do not inherently capture the probabilistic nature of landslide occurrences.

To address these limitations, this study proposes a probabilistic framework that integrates elements from the historical, heuristic, and deterministic categories discussed in the literature review. By incorporating conditional probability theory and dependency coefficients, the framework enhances landslide probability estimation by explicitly modelling the interactions between multiple triggering factors. The proposed model enhances predictive accuracy, providing a more systematic, adaptable, and evidence-based approach to landslide risk assessment.

4 PROPOSED METHODOLOGY

In a previous study by Morgan [30], landslide risk was defined in terms of either property damage or loss of life through the following two equations. When considering the annual probability of loss of life for a specific individual, landslide risk is expressed as:

$$R(DI) = P(H) \times P(S \mid H) \times P(T \mid S) \times V(L \mid T) \tag{1}$$

where $R(DI)$ represents the annual probability of loss of life, $P(H)$ is the annual probability of the landslide event, and $P(S|H)$ is the probability of spatial impact given the event. For property damage, the equivalent expression is:

$$R(PD) = P(H) \times P(S \mid H) \times V(P \mid S) \times E \tag{2}$$

where $R(PD)$ is the annual loss of property value.

The focus of the current study is on the probability aspect of landslides, specifically the terms $P(H) \times P(S|H)$, which remain consistent in both equations. The objective is to understand how to quantify these two probability terms. This study quantifies landslide probability by integrating Poisson-distributed event probabilities [31] with dependency coefficients for three major triggering factors: heavy rainfall (R), significant earthquakes (E), and severe human activity (A). Heavy rainfall, particularly intense rainfall over a short period, can destabilize slopes and is a common triggering factor in high-precipitation regions. Significant earthquakes induce landslides by shaking the ground and loosening soil and rock, especially in hilly and mountainous areas. Severe human activities such as deforestation, mining, road construction, and improper land use can also disturb slope stability, increasing the likelihood of landslides. The inclusion of these factors reflects the real-world understanding that landslides are typically triggered by a combination of natural and anthropogenic causes. For the current study, the overall probability of a landslide impact is defined as $P(L)$, and is expressed as:

$$P(L) = P(H) \times P(S \mid H) \tag{3}$$

Given that the focus is on the three triggering factors, $P(H)$ is defined as:

$$P(H) = P(L \cap R) + P(L \cap E) + P(L \cap A) - \Delta P \tag{4}$$

where ΔP accounts for overlapping contributions (dependencies) between triggering factors.

Substituting this into the equation for $P(L)$, we get:

$$P(L) = (P(L \cap R) + P(L \cap E) + P(L \cap A) - \Delta P) \times P(S \mid H) \tag{5}$$

In this study, the expression for ΔP, is given by:

$$\Delta P = P(L \cap R \cap E) + P(L \cap R \cap A) + P(L \cap E \cap A) \tag{6}$$

For simplicity, the ΔP equation accounts for dependencies between a landslide and two triggering factors at a time, rather than all three simultaneously. This assumption is reasonable and reflects a realistic approach to capturing the most significant interactions without overcomplicating the analysis.

Finally, substituting the expression for ΔP into the equation for $P(L)$, we obtain:

$$P(L) = \big(P(L \cap R) + P(L \cap E) + P(L \cap A) - P(L{\cap}R{\cap}E) - P(L{\cap}R{\cap}A) - P(L{\cap}E{\cap}A)\big) \times P(S|H) \quad (7)$$

The following sections will detail the computation of each term in the $P(L)$ equation.

4.1 Estimating the probability of a landslide associated with a triggering factor

The flowchart in Fig. 1 illustrates how the probability of a landslide associated with a triggering factor (F) will be computed for each of the three triggering factors considered in this study, as discussed in the following subsections.

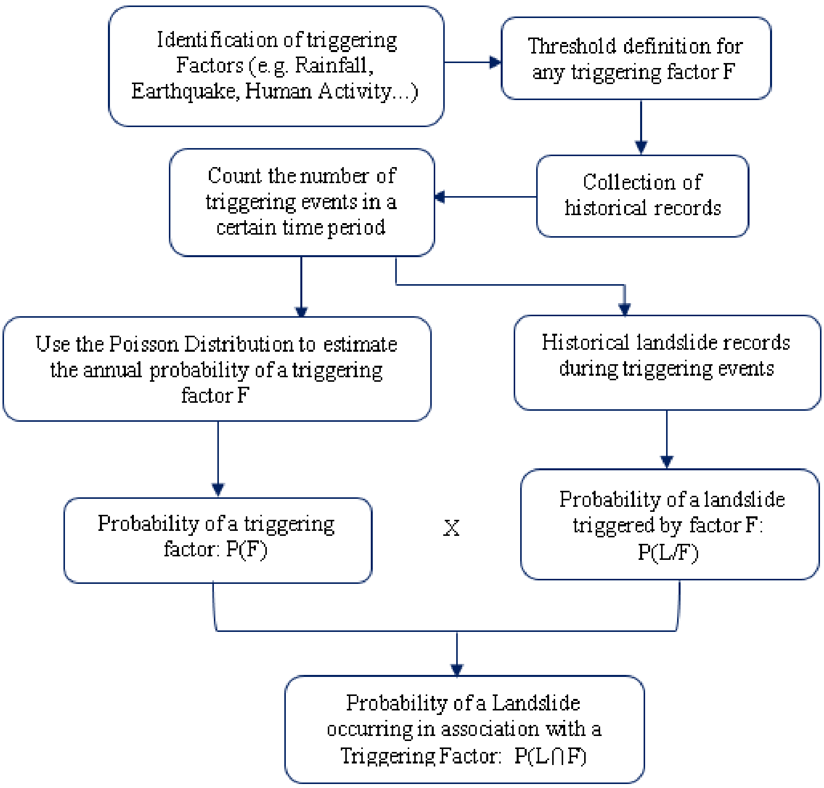

Figure 1: Probability of a landslide associated with a triggering factor.

4.1.1 $P(L{\cap}R)$: Landslides triggered by heavy rainfall

Using conditional probability, the probability of a landslide occurring due to heavy rainfall is expressed as:

$$P(L{\cap}R) = P(L|R)P(R) \quad (8)$$

To calculate the annual probability of heavy rainfall, $P(R)$, a threshold must first be defined based on local climate conditions or historical records (e.g., $R \geq 50$ mm/day, $R \geq 100$ mm/day, or other region-specific criteria). Once the threshold is established, historical rainfall data for a specific region over a defined period (e.g., 10 or 20 years) should be gathered. During this period, the number of heavy rainfall events is counted, and the average annual occurrence (λ) is determined as:

$$\lambda = \frac{\text{Number of heavy rainfall}}{\text{Total years}} \tag{9}$$

Assuming rainfall occurrences follow a Poisson distribution, the probability of at least one heavy rainfall in a given year is:

$$P(R) = 1 - e^{-\lambda} \tag{10}$$

The Poisson distribution is chosen because it effectively models the occurrence of rare, independent events over a fixed time period, such as heavy rainfall exceeding a defined threshold. It assumes that these events occur randomly but at a constant average rate, making it a suitable choice for estimating the probability of extreme weather events [31].

To determine $P(L|R)$, landslide records triggered by heavy rainfall must be examined over the same defined period (e.g., 10 or 20 years) to ensure a consistent time limit of analysis. The probability is estimated as:

$$P(L|R) = \frac{\text{Landslides caused by heavy rainfall}}{\text{Total heavy rainfall events}} \tag{11}$$

With $P(L|R)$ and $P(R)$ computed, $P(L \cap R)$ can be determined.

4.1.2 $P(L \cap E)$: Landslides triggered by significant earthquakes

Similarly, using conditional probability, the probability of a landslide occurring due to significant earthquakes is given by:

$$P(L \cap E) = P(L|E)P(E) \tag{12}$$

To determine the annual probability of significant earthquakes, $P(E)$, a threshold magnitude must be chosen based on historical records and expert recommendations (e.g., $M \geq 4.0$ or $M \geq 5.0$). Based on this threshold, historical earthquake data for a specific region over a defined period (e.g., 20 years) is recorded, and the average annual occurrence (λ) is calculated by dividing the total number of significant earthquake events by the length of the period.

Assuming a Poisson distribution, $P(E)$ is then calculated as:

$$P(E) = 1 - e^{-\lambda} \tag{13}$$

To estimate $P(L|E)$, records of landslides triggered by significant earthquakes are reviewed over the same defined period, and the probability is determined as:

$$P(L|E) = \frac{\text{Landslides caused by significant earthquakes}}{\text{Total significant earthquake events}} \tag{14}$$

With $P(L|E)$ and $P(E)$ computed, $P(L \cap E)$ can be then determined.

4.1.3 $P(L \cap A)$: Landslides triggered by human activities

Following the same approach, the probability of a landslide occurring due to severe human activity is given by:

$$P(L \cap A) = P(L|A).P(A) \tag{15}$$

To estimate the annual probability of severe human activity, $P(A)$ a threshold must first be established to define what qualifies as a 'severe' event. Unlike rainfall or earthquakes, where intensity is naturally measured (e.g., mm/day, magnitude), human activities require defining severity based on observable impact. A severe human activity event could be defined using one or more of the following measurable criteria:

- Deforestation rate: Removal of a certain area of forest per year (e.g., ≥ 10 hectares).
- Major construction projects: Large-scale infrastructure development (e.g., projects covering ≥ X square kilometres).
- Excavation or earthworks: Volume of soil displaced beyond a critical limit (e.g., ≥ Y cubic metres).
- Urban expansion: Increase in impervious surface (e.g., roads, buildings) beyond a set percentage over time.

Other relevant criteria may also be considered depending on the specific context of the analysis.

Once the threshold is set, historical records from sources such as satellite imagery, land-use change reports, environmental impact assessments, and government records should be reviewed over a defined period (e.g., 20 years). The number of years where at least one severe human activity event occurred is counted, and the total number of events over that period is recorded. Using these records, the average number of severe human activity events per year (λ) is calculated as:

$$\lambda = \frac{\text{Total severe human activity events}}{\text{Total years}} \tag{16}$$

Assuming a Poisson distribution, the probability of at least one severe human activity event occurring in a given year is:

$$P(A) = 1 - e^{-\lambda} \tag{17}$$

To determine $P(L|A)$, records of landslides triggered by severe human activity must be reviewed over the same defined period. The number of landslides caused by these activities is divided by the total number of severe human activity events, providing an estimate of $P(L|A)$. With $P(L|A)$ and $P(A)$ computed, $P(L \cap A)$ can be determined.

4.2 Estimating ΔP

As mentioned at the beginning of the methodology, ΔP is given by:

$$\Delta P = P(L \cap R \cap E) + P(L \cap R \cap A) + P(L \cap E \cap A) \tag{18}$$

This relationship can be effectively visualized using a Venn diagram, as shown in Fig. 2. In this representation, the landslide event serves as the sample space, while the three intersecting sets correspond to the three triggering factors. The three yellow shaded areas in the diagram illustrate the components of the ΔP equation, with each one representing the intersection between two triggering factors, excluding the region where all three factors overlap. Since

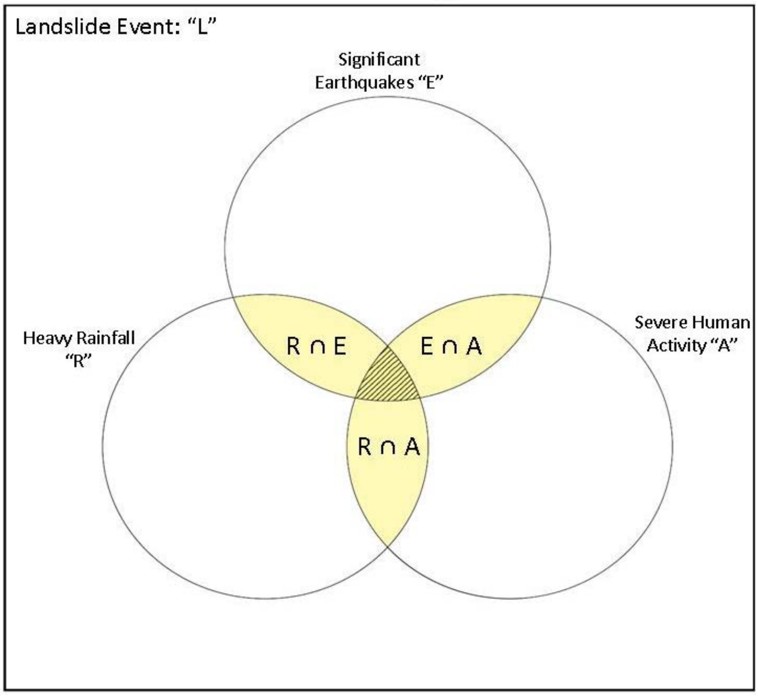

Figure 2: Venn diagram of landslide triggers.

the landslide is considered the sample space, each yellow shaded area in the figure also denotes the intersection of a landslide occurrence with two triggering factors simultaneously. These three yellow regions correspond directly to the three components of the ΔP equation, each capturing the probability of a landslide conditioned on the simultaneous presence of two specific factors.

By applying the definition of conditional probability, ΔP can be rewritten as:

$$\Delta P = P(L|R,E)P(R \cap E) + P(L|R,A)P(R \cap A) + P(L|E,A)P(E \cap A) \tag{19}$$

A key consideration in this formulation is how dependencies between different factors are treated. To balance model accuracy and practical feasibility, the assumption of independence in intersection probabilities is made, where the joint occurrence of rainfall and earthquakes, rainfall and human activity, and human activity and earthquakes is assumed to be independent. This assumption simplifies the estimation of intersection probabilities and avoids introducing additional dependency parameters, which may be difficult to quantify with available data. Therefore,

$$P(R \cap E) = P(R)P(E), P(R \cap A) = P(R)P(A), P(E \cap A) = P(E)P(A) \tag{20}$$

The values of these probabilities are obtained from the previous sections of the methodology.

While the occurrence of any two events may be relatively independent, especially if they are driven by separate geophysical and meteorological processes, their combined effect on landslides is the primary concern. Landslides are influenced by these factors in a complex and dependent manner. Thus, while the intersection terms are treated as independent, dependencies are incorporated into the landslide conditional probabilities:

$$P(L|R,E), P(L|R,A), P(L|E,A) \tag{21}$$

These terms account for how the combined effects of rainfall, human activity, and earthquakes contribute to landslide susceptibility, capturing their interactions in a physically meaningful way. For example, the probability of a landslide occurring given that both heavy rainfall (R) and severe human activity (A) have taken place is estimated as:

$$P(L|R,A) = P(L \mid R) \cdot P(L \mid A) \cdot \rho L,RA \tag{22}$$

where:

- $P(L|R)$ and $P(L|A)$ are computed from the previous section of the methodology.
- $\rho L,RA$ represents the interaction strength between heavy rainfall (R) and severe human activity (A) in triggering landslides (L). It adjusts how much more (or less) likely a landslide is to occur when both triggers happen together, compared to treating them as independent.

To determine this dependency factor, a qualitative scale is established to guide expert reasoning, as proposed in Table 1.

Table 1: Interpretation of $\rho L,RA$ values and their expected interaction effects on landslide probability.

$\rho L,RA$ value	**Interpretation**	**Expected interaction effect**
1.0	No dependency (independent)	Heavy rainfall and severe human activity do not influence each other in triggering landslides.
1.0–1.5	Weak positive dependency	The combined effect slightly increases landslide likelihood beyond what would be expected if they acted independently.
1.5–3.0	Moderate positive dependency	The combined effect increases landslide likelihood more than would be predicted by their independent probabilities alone.
> 3.0	Strong positive dependency	The interaction significantly amplifies landslide probability, making it much greater than what independent effects would suggest.
0.5–1.0	Weak negative dependency	The combined effect slightly reduces landslide probability compared to what would be expected from independent effects.
< 0.5	Strong negative dependency	Some factors reduce the landslide probability when both triggers are present, possibly due to counteracting influences.

The same procedure is applied to estimate $P(L|R,E)$ and $P(L|E,A)$. Once these values are obtained, they are substituted into the ΔP equation to calculate the overall value.

4.3 Estimating $P(S|H)$

In cases where detailed landslide data is unavailable, a buffer-based approach can be employed to approximate the probability that a given area will be affected by a landslide. This method estimates the probability $P(S|H)$ by defining a predefined buffer zone around landslide-prone areas, accounting for potential runout distances and secondary impacts. The first step in this approach is identifying landslide-prone areas. These areas are determined using terrain analysis, historical landslide records, and susceptibility maps, focusing on locations with steep slopes, unstable soils, or a history of past landslides. Once these regions are established, a buffer zone is defined to account for landslide impact. Its extent is selected based on typical landslide runout distances, which represent the expected distance that debris will travel downslope. This distance can be determined using empirical models, past landslide events, or expert judgment. The resulting buffer zone includes both the landslide-prone area and its surrounding region, which may be impacted by landslide-induced debris flow [32]. A similar application of this buffer-based approach can be found in a study on monsoon-triggered landslides [33], where the authors delineated a buffer region around each landslide to account for the potentially affected surroundings. Their conceptual illustration is presented in Fig. 3. To compute the probability $P(S|L)$, the total area covered by the buffer (including landslide-prone regions) is divided by the total study area:

$$P(S|H) = \frac{\text{Total buffer area (including landslide prone areas)}}{\text{Total study area}} \tag{23}$$

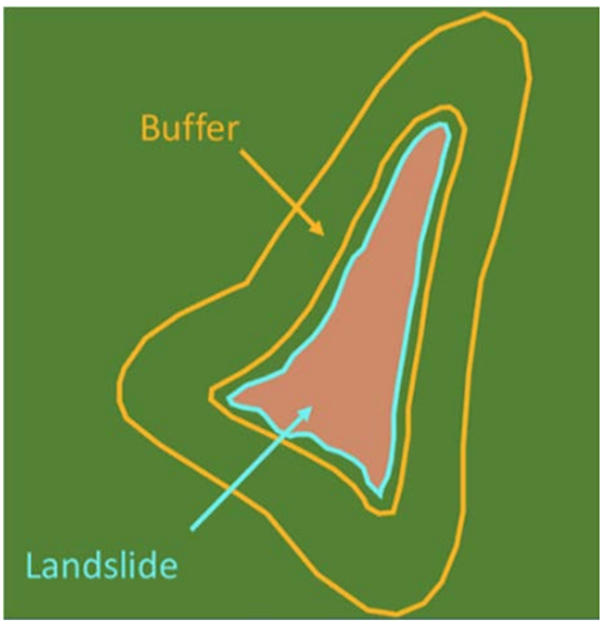

Figure 3: Landslide-prone area and surrounding buffer zone.

This ratio provides an approximation of the proportion of the study region at risk due to both direct landslides and their secondary effects. Where data is available, validation and sensitivity analysis can be performed to improve the estimation. The buffer distance can be validated using historical landslide cases, and a sensitivity analysis can be conducted by varying the buffer distance and assessing its effect on $P(S|H)$. This step ensures the robustness of the probability estimate. The buffer-based approach offers a simplified yet effective means of estimating landslide impact probability, particularly in scenarios where detailed hazard modelling is not feasible.

With all components of eqn (5) determined using the proposed methodology, the final values can now be substituted into the equation to compute the overall probability of a landslide impact at a given location, $P(L)$. The following flowchart (Fig. 4) visually summarizes the process of obtaining $P(L)$, beginning with the calculated probability of a landslide occurring in association with a triggering factor, which is the final node in the flowchart of Fig. 1.

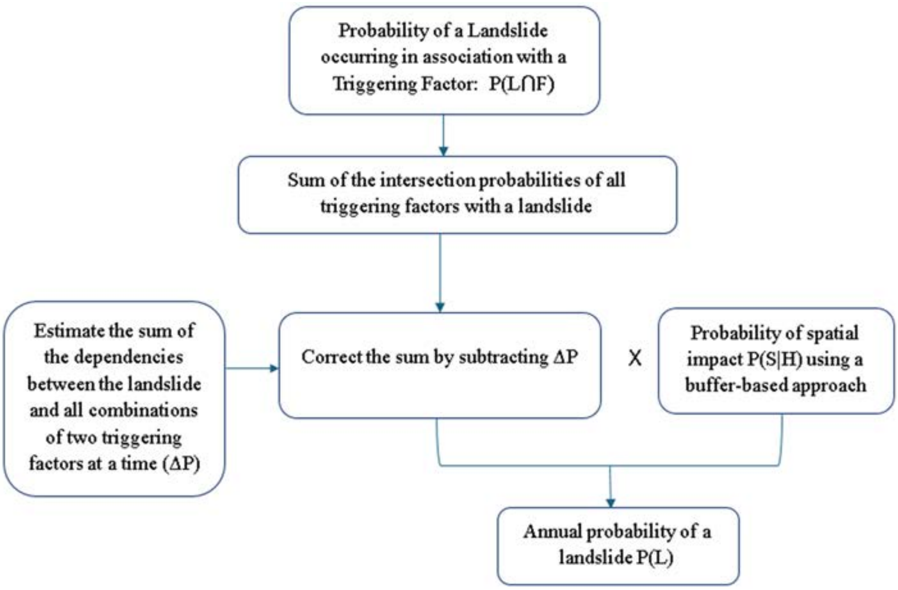

Figure 4: Annual probability of a landslide $P(L)$.

5 CONCLUSION

This study introduces a probabilistic framework for landslide probability estimation that systematically integrates subjective probability assessment with the quantitative impact of heavy rainfall, significant earthquakes and severe human activity as primary triggering factors. To estimate the likelihood of each triggering event, the framework employs Poisson-distributed event probabilities. Unlike conventional approaches that either rely solely on historical landslide records or assume independent triggering effects, this methodology enhances predictive accuracy by incorporating conditional probability theory and dependency coefficients to capture the complex interactions between these factors. Additionally, the approach accounts for the probability of spatial impact given an event through a buffer-based method. By explicitly modelling direct probabilities, interaction effects, and spatial probability, this structured and adaptable model effectively blends expert judgment and historical data with quantitative estimations, offering a comprehensive tool for landslide hazard assessment. Beyond enhancing predictive accuracy, the proposed methodology directly addresses the probability component of the landslide risk equation introduced at the beginning of the methodology, by estimating both the annual probability of a landslide event and its spatial impact. Building on this foundation, future research should prioritize enhancing the dependency coefficients using machine learning techniques and real-world datasets, as well as incorporating additional geotechnical parameters to improve probability estimation. Furthermore, a complementary methodology should be developed to assess the consequences component of the landslide risk equation, enabling complete risk assessment. Finally, a case study should be conducted to integrate probability and consequences estimations, applying the full risk assessment framework to diverse geological settings and validating its effectiveness in real-world scenarios.

REFERENCES

[1] Haque, U. et al., The human cost of global warming: Deadly landslides and their triggers (1995–2014). *Science of the Total Environment*, **682**, pp. 673–684, 2019.

[2] Guzzetti, F., Reichenbach, P., Cardinali, M., Galli, M. & Ardizzone, F., Probabilistic landslide hazard assessment at the basin scale. *Geomorphology*, **72**(1–4), pp. 272–299, 2005.

[3] Ercanoglu, M. & Gokceoglu, C., Assessment of landslide susceptibility for a landslide-prone area (north of Yenice, NW Turkey) by fuzzy approach. *Environmental Geology*, **41**, pp. 720–730, 2002.

[4] Cassidy, M.J., Uzielli, M. & Lacasse, S., Probability risk assessment of landslides: A case study at Finneidfjord. *Canadian Geotechnical Journal*, **45**(9), pp. 1250–1267, 2008.

[5] Rahal, M., Soleiman, S. & Hussein, B., Comprehensive methodology for landslide risk assessment using fuzzy logic systems: A step-by-step approach. *Proceedings of the 9th World Congress on Civil, Structural, and Environmental Engineering (CSEE 2024)*, London, 152, 2024.

[6] Refice, A. & Capolongo, D., Probabilistic modeling of uncertainties in earthquake-induced landslide hazard assessment. *Computers and Geosciences*, **28**(6), pp. 735–749, 2002.

[7] Lee, E., *Landslide Risk Assessment: The Challenge of Estimating the Probability of Landsliding*, Geological Society of London, 2009.

[8] Coe, J.A., Michael, J.A., Crovelli, R.A., Savage, W.Z., Laprade, W.T. & Nashem, W.D., Probabilistic assessment of precipitation-triggered landslides using historical records of landslide occurrence, Seattle, Washington. *Environmental and Engineering Geoscience*, **10**(2), pp. 103–122, 2004.

[9] Wright, R.H., Campbell, R.H. & Nilsen, T.H., Preparation and use of isopleth maps of landslide deposits. *Geology*, **2**(10), pp. 483–485, 1974.

[10] Lee, E.M. & Jones, D.K., *Landslide Risk Assessment*, ICE publishing, 2023.

[11] Pourghasemi, H.R., Pradhan, B. & Gokceoglu, C., Application of fuzzy logic and analytical hierarchy process (AHP) to landslide susceptibility mapping at Haraz watershed, Iran. *Natural Hazards*, **63**, pp. 965–996, 2012.

[12] Tešić, D. et al., Landslide susceptibility mapping using AHP and GIS weighted overlay method: A case study from Ljig, Serbia. *Serbian Journal of Geosciences*, **6**(1), pp. 9–21, 2020.

[13] Sannino, G., Bordoni, M., Bittelli, M., Meisina, C., Tomei, F. & Valentino, R., Deterministic physically based distributed models for rainfall-induced shallow landslides. *Geosciences*, **14**(10), p. 255, 2024.

[14] Griffiths, D. & Lane, P., Slope stability analysis by finite elements. *Geotechnique*, **49**(3), pp. 387–403, 1999.
[15] Sarma, S., Seismic stability of earth dams and embankments. *Geotechnique*, **25**(4), pp. 743–761, 1975.
[16] Yalcin, A., GIS-based landslide susceptibility mapping using analytical hierarchy process and bivariate statistics in Ardesen (Turkey): Comparisons of results and confirmations. *Catena*, **72**(1), pp. 1–12, 2008.
[17] Yilmaz, I., Landslide susceptibility mapping using frequency ratio, logistic regression, artificial neural networks and their comparison: A case study from Kat landslides (Tokat—Turkey). *Computers and Geosciences*, 35(6), pp. 1125–1138, 2009.
[18] Tehrany, M.S., Pradhan, B. & Jebur, M.N., Spatial prediction of flood susceptible areas using rule based decision tree (DT) and a novel ensemble bivariate and multivariate statistical models in GIS. *Journal of Hydrology*, **504**, pp. 69–79, 2013.
[19] Bonham-Carter, G.F., Agterberg, F.P. & Wright, D.F., Weights of evidence modelling: A new approach to mapping mineral potential. *Statistical Applications in the Earth Sciences* (eds F.P. Agterberg & G.F. Bonham-Carter), Geological Survey of Canada, pp. 171–183, 1990.
[20] Baeza, C. & Corominas, J., Assessment of shallow landslide susceptibility by means of multivariate statistical techniques. *Earth Surface Processes and Landforms: The Journal of the British Geomorphological Research Group*, **26**(12), pp. 1251–1263, 2001.
[21] Ayalew, L. & Yamagishi, H., The application of GIS-based logistic regression for landslide susceptibility mapping in the Kakuda-Yahiko Mountains, Central Japan. *Geomorphology*, **65**(1–2), pp. 15–31, 2005.
[22] Ismail, S., Nehme, H., Hussein, B. & Hajj-Hassan, M., Integration of Monte Carlo simulation tool for forecasting medical equipment risks in HIQMA system. *2016 3rd Middle East Conference on Biomedical Engineering (MECBME)*, pp. 10–15, 2016.
[23] Marin, R.J. & Mattos, Á.J., Physically-based landslide susceptibility analysis using Monte Carlo simulation in a tropical mountain basin. *Georisk: Assessment and Management of Risk for Engineered Systems and Geohazards*, **14**(3), pp. 192–205, 2020.
[24] Vogel, K., Riggelsen, C., Korup, O. & Scherbaum, F., Bayesian network learning for natural hazard analyses. *Natural Hazards and Earth System Sciences*, **14**(9), pp. 2605–2626, 2014.
[25] Kudaibergenov, M. et al., Application of artificial intelligence in landslide susceptibility assessment: Review of recent progress. *Remote Sensing*, **17**(1), p. 34, 2024.
[26] Zadeh, L.A., Fuzzy sets. *Information and Control*, **8**(3), pp. 338–353, 1965.
[27] Kayastha, P., Application of fuzzy logic approach for landslide susceptibility mapping in Garuwa sub-basin, East Nepal. *Frontiers of Earth Science*, **6**, pp. 420–432, 2012.
[28] Tangestani, M., Landslide susceptibility mapping using the fuzzy gamma approach in a GIS, Kakan catchment area, southwest Iran. *Australian Journal of Earth Sciences*, **51**(3), pp. 439–450, 2004.
[29] Kim, J.-C., Lee, S., Jung, H.-S. & Lee, S., Landslide susceptibility mapping using random forest and boosted tree models in Pyeong-Chang, Korea. *Geocarto International*, **33**(9), pp. 1000–1015, 2018.
[30] Morgan, G., Evaluating total risk to communities from large debris flows. *Proceedings of the Geohazards-92 Symposium*, BiTech Publishers, pp. 225–236, 1992.

[31] Tay, L.T., Alkhasawneh, M.S., Lateh, H., Hossain, M.K. & Kamil, A.A., Landslide hazard mapping of Penang Island using Poisson distribution with dominant factors. *J. Civ. Eng. Res.*, **4**, pp. 72–77, 2014.
[32] Saha, A.K., Arora, M.K., Gupta, R.P., Virdi, M. & Csaplovics, E., GIS-based route planning in landslide-prone areas. *International Journal of Geographical Information Science*, **19**(10), pp. 1149–1175, 2005.
[33] Burrows, K., Marc, O. & Remy, D., Using Sentinel-1 radar amplitude time series to constrain the timings of individual landslides: A step towards understanding the controls on monsoon-triggered landsliding. *Natural Hazards and Earth System Sciences*, **22**(8), pp. 2637–2653, 2022.