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GIS-Based Multi-Criteria Evaluation (MCE) for Landslide Susceptibility Mapping: A Review

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Abstract— This Landslides are among the most destructive natural hazards, posing significant risks to human life, infrastructure, and the environment. Accurate landslide susceptibility mapping (LSM) is essential for effective disaster risk reduction and land-use planning. This review paper explores the application of Geographic Information System (GIS)-based Multi-Criteria Evaluation (MCE) methods in landslide susceptibility mapping. It synthesizes current methodologies, evaluates the effectiveness of various decision-making techniques—such as the Analytical Hierarchy Process (AHP), Weighted Linear Combination (WLC), and fuzzy logic—and highlights their integration with spatial data layers representing key landslide conditioning factors (e.g., slope, soil type, rainfall, land use, geology). The review also addresses challenges related to data quality, subjective weighting, and model validation, while discussing advancements in machine learning integration and hybrid approaches. Overall, this paper provides a comprehensive overview of the strengths and limitations of MCE-based LSM frameworks, offering recommendations for future improvements in predictive accuracy and practical implementations.

Keywords: Landslide Susceptibility Mapping, Geographic Information System (GIS), Multi-Criteria Evaluation (MCE), Analytical Hierarchy Process (AHP), Weighted Linear Combination (WLC).

1. INTRODUCTION

Landslides represent a persistent and widespread natural hazard, especially in mountainous and geologically unstable regions, resulting in extensive damage to infrastructure, environmental degradation, and, most critically, loss of human lives (Parise, 2000; Girma et al., 2015; Leulalem et al., 2020). Defined as the downslope movement of rock, debris, or soil under the force of gravity (Cruden&Varnes, 1996), landslides are often triggered by a combination of natural and anthropogenic factors—including intense or prolonged rainfall, seismic activity, rapid snowmelt, deforestation, and unregulated land development. These events may occur in various forms such as flows, slides, topples, or falls, with many instances involving complex interactions among multiple movement types (Crozier, 1986; Dikau et al., 1996). To mitigate their impact, landslide susceptibility mapping (LSM) has emerged as a fundamental tool in hazard assessment and land-use planning. LSM enables the identification and spatial classification of areas at risk, providing decision-makers with vital information for implementing risk reduction strategies. A susceptibility map integrates various conditioning factors—including slope angle, lithology, hydrology, vegetation cover, and human land use—to estimate the likelihood of future landslide occurrences (Brabb, 1984; Guzzetti et al., 2005, 2006). Over the years, multiple LSM techniques have been developed, ranging from qualitative geomorphological approaches to quantitative statistical and physically based models. Despite their differences, these methods generally rest on two key assumptions: (1) landslides leave observable geomorphic signatures that can be detected via field surveys or remote sensing, and (2) landslide processes are governed by physical laws that can be modeled through empirical, deterministic, or statistical frameworks (Cruden&Varnes, 1996).

In alignment with these principles, recent studies have increasingly adopted GIS-based Multi-Criteria Evaluation (MCE) frameworks to enhance the precision and applicability of LSM. As described in the abstract, the integration of GIS with decision-making techniques such as the Analytical Hierarchy Process (AHP), Weighted Linear Combination (WLC), and fuzzy logic allows for the systematic combination of multiple spatial data layers that represent key conditioning parameters (e.g., topography, rainfall, geology, and land cover). This approach enhances the objectivity of susceptibility assessments and enables better visualization and interpretation of complex spatial patterns. Nevertheless, challenges remain. Issues such as subjective weighting of criteria, varying data resolution, and limited validation against historical landslide inventories continue to affect model reliability. Recent advancements involving machine learning algorithms and hybrid models have shown promise in addressing some of these limitations, offering improved predictive capabilities and adaptability across diverse geographical contexts. Thus, this review not only underscores the importance of LSM in disaster risk management but also critically evaluates the current GIS-based MCE methodologies. By synthesizing the strengths and limitations of existing frameworks, the paper contributes valuable insights into enhancing predictive accuracy and operational implementation of landslide susceptibility mapping.

1.1 Challenges and Advances in GIS-MCE for Landslide Susceptibility Mapping

Landslides remain among the most destructive natural hazards, threatening human lives, damaging infrastructure, and disrupting ecosystems, especially in mountainous and tectonically active regions. As climate change accelerates the frequency of extreme rainfall events and anthropogenic land-use changes continue to disturb

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natural slopes, the need for reliable landslide susceptibility mapping (LSM) becomes increasingly critical. Geographic Information System (GIS)-based Multi-Criteria Evaluation (MCE) methods have emerged as powerful tools in this context, allowing the integration of spatial datasets and expert judgment to model terrain instability across diverse geographic settings. However, several methodological and technical challenges continue to hinder the effectiveness and reproducibility of GIS-MCE frameworks. One of the most debated issues is the weight assignment of causative factors. Traditionally, methods such as the Analytical Hierarchy Process (AHP) have been widely used to allocate weights to conditioning factors like slope, lithology, land use, and rainfall. Despite its popularity, AHP is fundamentally subjective and expert-driven, which may introduce bias and reduce the generalizability of the model. Recent studies suggest integrating objective statistical techniques—such as Frequency Ratio (FR) or Information Value (IV)—to refine the weighting process and minimize subjectivity, resulting in better hybrid MCE models (Koldasbayeva et al., 2024; Frontiers in Earth Science).Another key concern is the quality, completeness, and resolution of input datasets. Landslide inventories, which form the basis for model training and validation, are often incomplete, imbalanced, or poorly georeferenced, especially in data-scarce regions. This not only affects the validity of the LSM but also introduces spatial bias in predictive outputs (Bola et al., 2024; *Nature Geoscience*). To address this, Reliability-Based Sampling (RBS) and ensemble learning approaches have been proposed to improve the robustness of training datasets and account for uncertainties in landslide occurrence (ScienceDirect, 2024). Moreover, the integration of Machine Learning (ML) techniques into the MCE framework has opened new possibilities for automatic weight generation and feature importance estimation. Techniques such as Random Forest (RF) and Extreme Gradient Boosting (XGBoost) have demonstrated high predictive accuracy and are capable of quantifying the influence of each conditioning factor objectively (Zhao et al., 2024; *MDPI Remote Sensing*). These data-driven models outperform traditional AHP-based approaches in many complex terrains but are often criticized for their black-box nature. To bridge this gap, researchers have begun incorporating explainable AI (XAI) techniques like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to improve the interpretability of ML-driven LSMs (Chen & Fan, 2024; *arXiv*). This helps planners and policymakers not only rely on model outputs but also understand why certain regions are classified as high-risk, thus increasing the trust and usability of LSMs in real-world planning. Lastly, the standardization of modeling protocols and reporting frameworks is gaining attention. Variability in spatial resolution, classification thresholds, and validation metrics can lead to inconsistent interpretations across studies. To mitigate this, the adoption of process-oriented standards like CRISP-DM (Cross-Industry Standard Process for Data Mining) is being promoted to ensure reproducibility, documentation clarity, and methodological transparency (Frontiers in Environmental Science, 2024).

2. METHODOLOGICAL SOLUTIONS FOR ENHANCED GIS-MCE PERFORMANCE

Normally, for reliably selecting training (landslide) and non-landslide samples, ampling strategy profoundly affects model accuracy in geomorphologically varied regions: reproducible, representative sampling in homogeneous units improves performance AUC gains of up to 9% and Kappa by 17%. Repeat sampling (20×) at 95% confidence maintains stable metrics. Two-Level Random Sampling (2LRS): This algorithm divides landslide polygons into distinct training and testing subsets, reducing spatial overlap and overfitting compared to random sampling Science. Meanwhile for utilizing ensemble and averaging strategies to mitigate model variance were combining predictions from different ML models (e.g., RF, SVM, GBDT) into an average ensemble notably raises overall AUC (e.g. ~0.91), outperforming individual models. In another way the feature selection and model interpretability were conducted as effective factor selection methods (e.g., Information Gain, RFE, LASSO, PSO) improve ML/DL model accuracy by isolating key conditioning variables,explainable AI tools like TreeSHAP elucidate factor importance in models such as XGBoost, identifying top influential variables like slope, elevation, and Topographic Wetness Index (TWI), and SHAP, LIME, DeepLIFT enhance transparency in ML/DL models—balancing interpretability and accuracy, especially when reducing conditioning factor complexity. Lastly, the optimal terrain unit design and slope-based sampling were note as one of the goof solution for automatic extraction and optimization of slope units using DEM-driven hydrological segmentation improve susceptibility modeling. Negative (non-landslide) sample selection guided by certainty-factor-based prior knowledge enhances model robustness.

2.1 Advanced Approaches and Data Strategies in GIS-Based MCE for Landslide Susceptibility Mapping

Recent innovations in GIS-based Multi-Criteria Evaluation (MCE) for Landslide Susceptibility Mapping (LSM) have sought to overcome critical limitations in data quality, model interpretability, and predictive accuracy. Four major directions—data enhancement, ensemble modeling, feature transparency, and deep learning integration—are reshaping the field and offering more robust, transferable models.

- Addressing Data Scarcity and Improving Sampling Validity

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In data-poor environments, innovative approaches are being developed to maintain model performance. For instance, geodiverse extrapolation techniques, tested in Northern Morocco, show that models trained across heterogeneous geomorphological regions can still maintain acceptable performance (AUC 0.65–0.85), depending on the algorithm and validation method used (Benabdelouahab et al., 2024). Moreover, modular, transparent machine learning workflows, particularly Python-based frameworks for Random Forest LSM, are gaining popularity. These systems emphasize flexibility in data preprocessing and reproducibility, aligning with the FAIR data principles (Findable, Accessible, Interoperable, and Reusable) to improve model sharing and refinement (Mokhtari et al., 2024, SpringerLink).

- Leveraging Ensemble and Machine Learning Techniques for Balanced Predictive Power

Ensemble learning methods such as stacking, bagging, boosting, and majority voting are improving the balance between accuracy and interpretability. In Jiuzhaigou, China, the integration of SHAP (SHapley Additive exPlanations) into ensemble pipelines has enhanced model transparency (Wang et al., 2024). At a national scale, stacking models like CatBoost and XGBoost, fed with 30 spatial predictors, achieved high accuracy (AUC ~0.89) in South Korea—identifying elevation and soil depth as major drivers (Park et al., 2024). In the Himalayas, hybrid bagging-Random Forest models reached an exceptional AUC of 0.947 in Shimla district, outperforming many traditional techniques in terms of precision and F1 scores (Kumar et al., 2024, ADS Abstract Service). Additionally, comprehensive post-earthquake evaluations in Nepal show that Random Forest outperformed other models (e.g., logistic regression, XGBoost), achieving recall values of ~91%, a critical factor for minimizing false negatives in hazard scenarios (Zhao et al., 2024, MDPI).

- Enhancing Feature Selection and Interpretability through Explainable AI (XAI)

The adoption of TreeSHAP and SHAP values has provided a clearer picture of the most influential factors driving landslides. In optimized XGBoost models, SHAP revealed that slope, elevation, and Topographic Wetness Index (TWI) are dominant contributors, helping eliminate redundant variables and boosting AUC to as high as 0.97 (Li et al., 2024). In complex terrains like the Three Gorges, comparative testing of CNNs, XGBoost, and SVMs—augmented with SHAP, LIME, and DeepLIFT—demonstrated a trade-off between using many features (19) for accuracy versus a selected few (9) for interpretability (Chen & Fan, 2024). Cross-national studies, including from Turkey, consistently advocate for the use of SHAP to interpret ensemble models such as RF, LightGBM, and XGBoost. These studies often confirm the importance of elevation and lithology as core predictors (Demir et al., 2024).

- State-of-the-Art Deep Learning for High-Precision Mapping

Deep learning (DL) has recently shown transformative potential in LSM. A hybrid model that combines Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and attention-based U-Net architecture achieved nearly 99% classification accuracy and an AUC of ~0.988 when tested in the Western Ghats. This marks a major leap in spatial resolution and the precision of hazard prediction (Raj et al., 2024).The evolution of GIS-based MCE in LSM is being driven by the convergence of reliable data practices, ensemble ML models, explainable AI, and deep learning. These approaches are enhancing both the accuracy and interpretability of landslide models, especially in geologically diverse and data-scarce regions. The integration of SHAP-based explanations, modular workflows, and hybrid ensembles represents a major step forward in operationalizing LSM for effective disaster risk reduction.

2.2. The Multi Criteria Evalution (MCE)using AHP Method

The The landslide susceptibility of Kullu Valley in the Himachal Himalayas was assessed using a combination of Analytical Hierarchy Process (AHP), Frequency Ratio (FR), and a hybrid spatial MCE geostatistical method, as documented by Meena et al. (2019). This region is prone to rockfalls, rock slides, and debris flows, causing significant economic damage and concern for both authorities and geoscientists. Accurate mapping depends heavily on terrain classification. Meena et al. utilised nine distinct landform units defined by the Geological Survey of India (GSI) including active floodplains, alluvial plains, piedmont slopes, glaciated zones, and highly dissected terrains—to identify areas most susceptible to slope failure. Specifically, the highly and moderately dissected zones, along with glaciated terrain, were found to be particularly landslide-prone eplus.Using a GPS-based inventory of 149 landslide locations, they generated buffer zones around linear features like faults that strongly influence susceptibility. Statistical weighting confirmed that proximity to faults was a primary determinant of slide risk.heir validation results showed AUC values of 0.797 for AHP, 0.907 for FR, and 0.910 for the hybrid SMCE approach—demonstrating that while AHP requires expert judgment and is more time-consuming, the hybrid method offered the highest predictive accuracy in this context.

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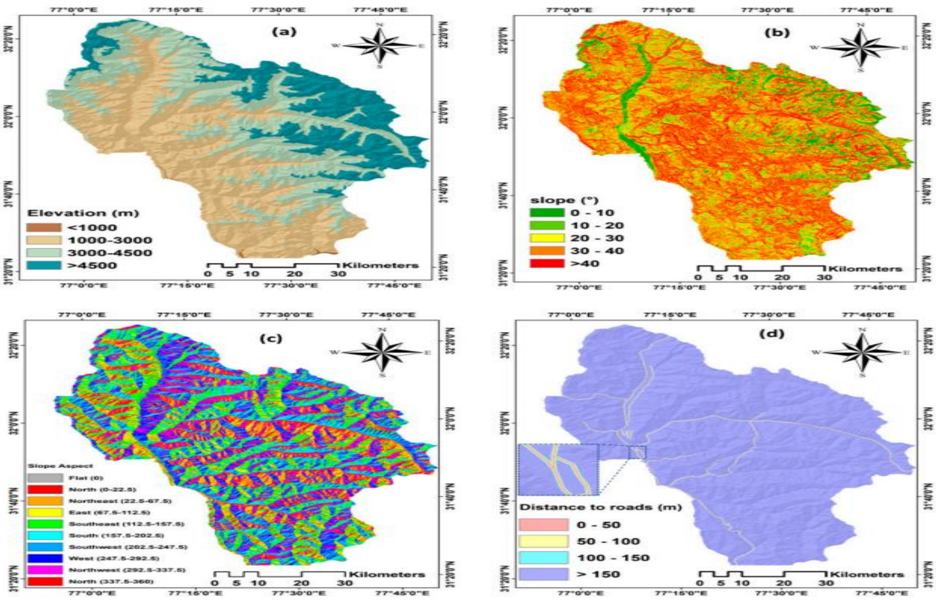

Figure 1. Kullu valley's landform resulted from GSI

Spatial Multi-Criteria Evaluation (MCE) is a methodological approach that integrates multiple thematic layers typically in the form of composite index maps—to assess the extent to which specific spatial criteria are met within a particular geographic area. These outputs play a pivotal role in supporting strategic planning and informed decision-making processes, particularly in contexts involving complex spatial dynamics (Rahman &Saha, 2008). The theoretical basis for MCE is rooted in the Analytic Hierarchy Process (AHP), a structured decision-making framework first introduced by Saaty (1980). AHP facilitates the decomposition of complex problems into a hierarchy of sub-problems, enabling pairwise comparisons and the assignment of relative weights to each criterion. This ensures a rational and consistent evaluation of multiple, and often conflicting, criteria. The implementation of MCE within a GIS environment typically involves several critical stages, including problem tree analysis, criteria standardization, weighting, and spatial overlay or map generation. In the problem analysis phase, goals and relevant criteria are systematically defined and grouped into thematic clusters—usually representing factors (that support the objective) or constraints (that limit it) (Sharifi&Retsios, 2004). Each criterion is then standardized to a common scale, allowing for comparison and integration into the final decision-making framework (Hizbaron et al., 2011). AHP, in particular, has gained widespread acceptance as a powerful and adaptable tool for spatial decision-making, especially when dealing with uncertain or qualitative inputs. It excels in scenarios involving multi-criteria and multi-objective problems, such as land-use planning, disaster risk assessment, and suitable site selection for infrastructure or development projects (Ghorbanzadeh et al., 2023; Barona &Ghorbanzadeh, 2019). One of the core strengths of AHP lies in its integration of expert judgment—incorporating both quantitative datasets and qualitative insights provided by domain specialists. This enhances the reliability and contextual relevance of the final decision outputs (Saaty, 2008). Furthermore, when coupled with GIS, AHP enables spatially explicit modeling, where decision outcomes are visualized in map form, making it easier for policymakers, planners, and stakeholders to interpret and act upon the results (Malczewski, 2020). Recent studies have further refined the MCE-AHP framework by integrating fuzzy logic, machine learning algorithms, and ensemble modeling techniques to increase predictive accuracy and reduce uncertainty—particularly in landslide susceptibility mapping, flood hazard assessment, and climate resilience planning (Zhao et al., 2022; Khosravi et al., 2023).In this study, the research methodology focuses on identifying decision alternatives and systematically comparing various parameters by leveraging a detailed landslide inventory dataset, as presented in Table 1. The comparative analysis of these parameters is conducted through the Analytic Hierarchy Process (AHP), which involves assigning relative weights to each factor using pairwise comparison matrices informed by expert judgment.

A core component of AHP is the principle of transitivity, which ensures logical consistency in comparisons. According to this principle, if one factor (e.g., f1) is more important than another (f2), and f2 is more important than a third factor (f3), then f1 must logically be more important than f3 (i.e., f1 > f2 and f2 > f3 implies f1 > f3). This transitive relationship is fundamental in preserving the internal consistency of the decision matrix. Consistency is not merely theoretical—it has practical implications for the reliability of the model. For example, if f1 is judged to be twice as important as f2 (f1 = 2 × f2), and f2 is considered four times more important than f3 (f2 = 4 × f3), then it logically follows that f1 should be eight times more important than f3 (f1 = 8 × f3) to maintain consistency within the hierarchy (Malczewski et al., 2020). Inconsistencies in these relationships can undermine the credibility of the weighting process and lead to flawed decision outcomes.The use of expert-driven pairwise comparisons within the AHP framework enables a structured quantification of subjective judgments, facilitating a transparent, replicable,

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and rational decision-making process. This is particularly vital in spatial decision problems like landslide susceptibility mapping, where multiple interdependent environmental and geomorphological factors must be assessed in a coherent and logical manner.Consistency Ratio (CR): In practical AHP applications, the consistency of the matrix is quantified using a Consistency Ratio (CR). A CR value below 0.10 is generally considered acceptable, indicating that the judgments made are consistent enough to be valid.

Real-World Implication: When used correctly, this process ensures that the final weighted ranking of conditioning factors (e.g., slope, rainfall, geology, land use) for landslide susceptibility is logically sound and defensible.

Table 1. Pairwise comparison point-based rating scale of AHP

Importance	Definition	Explanation
1	Equal importance	Contribution to objective is equal
3	Moderate importance	The attribute is slightly favoured over another
5	Strong importance	The attribute is strongly favoured over another
7	Very strong importance	The attribute is very strongly favoured over another
9	Extreme importance	Evidence favouring one attribute is of the highest possible order of affirmation
2,4,6,8	Intermediate values	When compromise is needed

Therefore, it is essential to evaluate the consistency of expert judgments within the comparison matrices at every stage of the analysis. Inconsistencies arise when the largest eigenvalue (λ_max) of a matrix exceeds the number of

$$CR = (\lambda max - n)/\mathrm{RI}(\mathrm{n}-1)\text{.................................}(1)$$

The Random Index (RI) represents the average consistency index derived from randomly generated pairwise comparison matrices. For matrices of varying sizes (n = 2 to 9), the corresponding RI values are 0.00, 0.52, 0.89, 1.11, 1.25, 1.35, 1.40, and 1.45, respectively (Ghorbanzadeh et al.). A consistency ratio (CR) below 0.10 is generally regarded as acceptable, whereas a CR exceeding 0.10 indicates a significant inconsistency in the judgment matrix (Saaty, T. L. (1980).

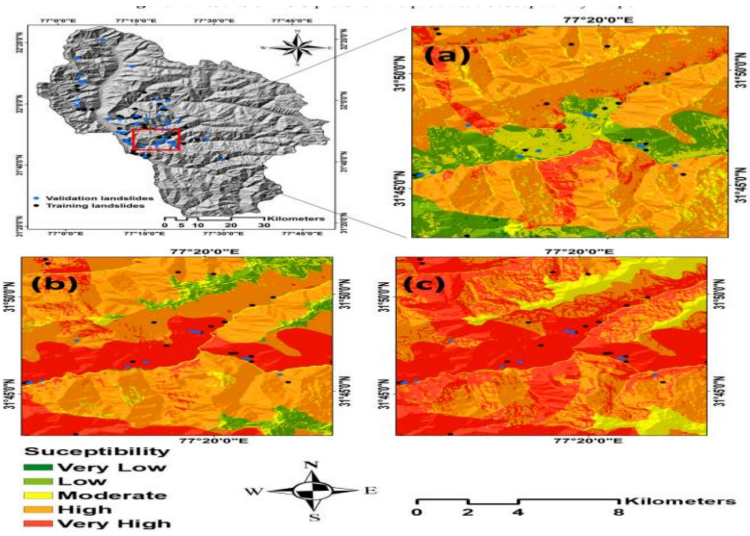

Figure.2. An enlarged sub-area from the resulting LSMs generated based on (a). AHP, (b) FR and (c) Hybrid SMCE Method models (Source; Sansar et al)

The The study utilized the Area Under the Curve (AUC) approach to validate the results, achieving an AUC value of 0.797, indicating acceptable predictive performance of the Analytical Hierarchy Process (AHP) in landslide susceptibility mapping (LSM) for the Kullu Valley in the Himalayas. The applied methodology demonstrates high

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transferability and potential applicability in other regions for disaster risk reduction and land-use planning. However, despite its advantages, AHP presents several notable limitations. The reliance on expert judgment introduces subjectivity, which may affect the objectivity and reproducibility of results (Ghorbanzadeh et al., 2021). Furthermore, AHP involves complex mathematical operations, such as eigenvalue computations and matrix algebra, which can be error-prone, especially when handling high-dimensional data (Saaty, 1980; Malczewski, 2006).Moreover, AHP struggles with modeling uncertainty and capturing dynamic or probabilistic variations inherent in geohazard data, which may undermine the robustness of the model outputs (Rehman et al., 2023). Another inherent limitation is its inability to effectively represent interdependencies or nonlinear interactions among criteria, which are often significant in environmental processes like landslides (Chakraborty& Joshi, 2022).

2.2. The Multi Criteria Evalution (MCE) using FRMethod

The **Frequency Ratio (FR) model** is a widely utilized geospatial statistical method for evaluating the likelihood of spatial phenomena, such as landslide occurrences, by analyzing their association with various conditioning factors (Girma et al., 2021). The influence or weight of each conditioning factor can be estimated by calculating the ratio of landslide occurrences to the total spatial extent of the study area. This approach is particularly effective in establishing quantitative correlations between specific environmental factors and landslide distribution, thus providing valuable insights into the spatial patterns of landslide susceptibility (Cruden&Varnes, 1996).

In the computation process, the landslide inventory data is intersected with thematic layers representing conditioning variables such as slope, lithology, land cover, and distance from roads or faults. For each class within a conditioning factor, the frequency ratio is calculated by dividing the proportion of landslides in that class by the proportion of the area that the class occupies in the entire study region. An FR value greater than 1 indicates a positive relationship with landslide occurrence, while a value less than 1 suggests a lower likelihood (Crozier, 2005).Despite its simplicity and transparency, the FR model assumes statistical independence among factors and does not account for potential interactions between variables. However, it remains a preferred method due to its low computational demands and effectiveness in preliminary landslide susceptibility mapping. To improve its predictive performance, the FR model is often integrated with machine learning algorithms or multi-criteria decision-making methods (Chen et al., 2023; Pham et al., 2021).

A final susceptibility map can be generated by employing a linear combination of the sum of each factor's contributions as equation bellow;

$$LSMFR = FRw1 + Frw2 + FRw3 + \ldots + FRw9 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

Where FRw1 is the corresponding FR weight for the ith factor. FR weights indicate a higher correlation of that class in triggering landslides.In summary, the Frequency Ratio (FR) model serves as an effective geospatial tool for assessing the probability of landslide occurrences based on various conditioning factors. This method quantifies the influence of each factor by calculating the ratio between observed landslide events and the overall extent of the study area. It is particularly useful for establishing statistical correlations between landslides and different classes of contributing factors, thereby enhancing our understanding of their spatial relationships.

The computation of FR weights involves several steps: identifying the proportion of landslide inventory points within each class of the conditioning factors, overlaying these with the spatial datasets to determine the area ratio for each class, and finally deriving the FR value by dividing the landslide density by the area density within the same class. This process enables the identification of areas more susceptible to landslides.

Overall, the FR model provides a systematic and quantitative framework for landslide susceptibility mapping. Its straightforward implementation and the inclusion of a mathematical expression make it a practical and insightful tool for predicting landslide-prone zones and understanding the spatial dynamics of landslide triggers.

2.3. Hybrid Spatial Multi-Criteria Evaluation (SMCE) Integrated with Frequency Ratio (FR)

Frequency Ratio (FR) approach to enhance landslide susceptibility mapping. Instead of treating conditioning factors simply as raster layers, SMCE incorporates them in diverse formats—lines, points, and polygons—allowing for richer spatial modeling. Through GIS, these input layers are grouped, weighted, standardized (to a uniform 0–1 scale), and transformed into composite index maps that reflect the influence of each factor on landslide susceptibility.When SMCE is fused with FR, the result is a powerful hybrid framework (often referred to as SMCE–FR) that captures both expert-based multi-criteria weighting (via AHP) and empirical factor–landslide correlations (via FR). The outcome enables creation of composite susceptibility maps that are both interpretable and accurate. For instance, in the Kullu Valley, the hybrid SMCE approach produced an AUC of 0.910, surpassing standalone AHP (0.797) and FR (0.907) performance level.

2.3.1. Detailed Workflow and Theoretical Basis

a. Problem Definition and Factor Selection: Conditioning factors relevant to landslides (e.g., slope, lithology, distance to faults) are identified and grouped hierarchically, as per AHP methodology.
b. Weighting and Standardization:
    - AHP provides expert-driven weights through pairwise comparisons.

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- FR calculates weights based on the ratio of landslide occurrence in each factor class relative to its area coverage.

c. Composite Map Generation: These standardized and weighted layers are aggregated with GIS overlays to produce a composite susceptibility map.
d. Validation and Interpretation: The resulting maps visually and quantitatively depict where landslide criteria are strongly or weakly satisfied across the study area, serving as key inputs for mitigation and spatial planning.

Compare to recent methodsmore recent studies continue to build on the hybridization concept, Wu et al. (2024) introduced a hybrid model integrating logistic regression and physically based slope-stability analysis, explicitly modelling soil parameter uncertainty, and showing improved predictive performance over standalone models.Chen & Fan (2024) combined explainable AI techniques (e.g., SHAP, LIME) with machine learning classifiers to enhance both prediction accuracy and interpretability in landslide susceptibility modelling echoing the hybrid aim of clarity and performance.These modern advancements confirm that integrating diverse modeling techniques whether statistical, physical, or AI-driven offers robustness comparable to SMCE FR, especially when accounting for uncertainty and complex interactions among factors. Hybrid SMCE - FR marries expert-based AHP weighting with empirical FR weighting, yielding more reliable and interpretable susceptibility maps. The method has demonstrated superior predictive power (AUC up to 0.910) compared to standalone models in real-world case studies like Kullu Valley. Recent research expands on this concept by integrating physical slope models, machine learning, and explainable AI, all aiming to balance interpretability, validation, and accuracy.

3. CONCLUSION

The integration of the Spatial Multi-Criteria Evaluation (SMCE) method with the Frequency Ratio (FR) model offers a powerful, transparent, and adaptable approach for landslide susceptibility mapping. By combining expert judgment through AHP with data-driven statistical analysis, the hybrid model enhances both the interpretability and accuracy of hazard assessments. Its ability to incorporate diverse spatial datasets and normalize them into a coherent decision-making framework makes it especially valuable for complex terrains and regions lacking dense data coverage. While machine learning models may provide slightly higher predictive accuracy, the hybrid SMCE–FR method remains highly effective for practical applications in land-use planning, risk mitigation, and disaster preparedness due to its clarity, flexibility, and ease of implementation. This makes it a reliable tool for both researchers and decision-makers in geospatial hazard analysis.

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