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Review

Nature-Based Solutions for Large-Scale Landslide Mitigation: A Review of Sustainable Approaches, Modeling Integration, and Future Perspectives

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Abstract

Landslides rank among the most frequent and devastating natural hazards globally, causing significant loss of life and property. As a result, landslide susceptibility assessment has become a central focus in geohazard research, which is devoted to preventing and alleviating the frequent occurrence of landslides. Numerous analytical models have been applied to evaluate landslide susceptibility, including Frequency Ratio (FR), Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), and various hybrid and neural network-based approaches. This review synthesizes current progress in integrating Nature-based Solutions (NBS) with modeling and policy frameworks, highlighting their potential to provide cost-effective, sustainable, and adaptive alternatives to conventional landslide mitigation strategies. Based on a systematic review of 127 peer-reviewed publications published between 2023 and 2025, selected from Web of Science, ScienceDirect, MDPI, Springer, and Google Scholar using predefined keywords and screening criteria, this study reveals that the most frequently used conditioning factors in landslide susceptibility modeling are slope (96 times), aspect (77 times), elevation (77 times), and lithology (77 times). Among modeling approaches, Random Forest (RF), Support Vector Machine (SVM), hybrid models, and neural network models consistently demonstrate high predictive performance. Despite the expanding body of literature on NBS, only 2.3% of all NBS-related studies specifically address landslide mitigation. The existing literature primarily concentrates on assessing the biophysical effectiveness of interventions such as vegetation cover, root reinforcement, and forest-based stabilization using a range of predictive modeling techniques. However, significant gaps remain in the integration of economic valuation frameworks, particularly cost–benefit analysis (CBA), to quantify the monetary value of NBS interventions in landslide risk reduction. This highlights a critical area for future research to support evidence-based decision-making and sustainable risk governance.

Keywords: landslide; literature review; sensitivity analysis; nature-based solutions (NBS)

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1. Introduction

Climate change and rapid urbanization have brought great challenges to the sustainable development of cities, and human beings are facing more severe and frequent natural disasters, such as droughts, floods, heat waves, and other extreme weather events. Rainfall-induced landslides have emerged as a major natural hazard in many parts of the world, causing thousands of deaths and billions of dollars in economic losses [1]. In Malaysia, landslides represent the second most significant natural disaster after flooding, making it a persistent threat to lives, infrastructure, and the economy [2,3]. These events not only destroy built environments but also lead to loss of life, environmental degradation, and severe disruption to economic activities. Some of the most damaging landslides have occurred in areas such as Pos Dipang, Bukit Antarabangsa, and Cameron Highlands. Between 1973 and 2007, landslide-related incidents were estimated to have caused economic losses totaling approximately USD 1 billion [4,5].

Landslide susceptibility assessment is a cornerstone of geohazard research, which is devoted to preventing and alleviating the frequent occurrence of landslides [6]. A wide variety of models have been developed to evaluate landslide susceptibility, which can generally be categorized into three groups. First, statistical models such as Frequency Ratio (FR), Weight of Evidence (WoE), and Logistic Regression (LR) are commonly employed for probabilistic analysis. Second, machine learning (ML) techniques, including neuro-fuzzy systems, Decision Trees (DTs), and Support Vector Machines (SVMs), have been widely used for pattern recognition and classification [6]. Third, deep learning (DL) approaches, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have recently gained prominence for their ability to handle large, complex datasets and capture nonlinear spatial relationships [7]. Landslide susceptibility models generate a Landslide Susceptibility Map (LSM) by integrating various landslide conditioning factors (such as slope, aspect, lithology, and land use) and predict the occurrence of landslides in the future [8,9]. GIS-based landslide sensitivity models have been developing rapidly. Recent studies have been systematically examined to identify trends in model usage frequency, performance evaluation, and the selection of conditioning factors. This analysis provides valuable insights into the current state of the field and supports effective strategies for future landslide susceptibility assessments.

Nature-Based Solutions (NBS) are regarded as a sustainable, resilient, and cost-effective urban development strategy that contributes to obtaining a high-quality living environment and benefits for healthier, more sustainable cities. It has been promoted by many policymakers, governance bodies, and other relevant organizations, mainly as a development strategy around ecological engineering, green infrastructure, blue infrastructure, or blue–green infrastructure [10,11]. After the introduction of NBS by the European Commission and the International Union for Conservation of Nature, research on NBS has also aroused great interest in academia [12]. Nature-based Solutions (NBS) have shown significant potential in mitigating the impacts of hydro-meteorological hazards, including floods, droughts, heatwaves, and landslides [13,14].

Despite the growing number of review papers on landslide susceptibility assessments, several critical gaps persist. Previous reviews have generally treated landslide susceptibility modeling and Nature-Based Solutions (NBS) as separate areas of research, lacking an integrated perspective that connects predictive modeling with ecological stabilization strategies. In addition, limited attention has been given to the economic valuation of NBS interventions, particularly through cost–benefit analysis, which is essential to evaluate their financial viability and long-term sustainability. Few comparative analyses have focused on recent (2023–2025) developments in machine learning and deep learning models, especially under changing climatic conditions that significantly influence landslide dynamics.

Moreover, existing reviews seldom provide a systematic analysis of conditioning factors and model performance within the context of NBS-based slope stabilization. Therefore, this study addresses these gaps by presenting an integrated and up-to-date review that links landslide susceptibility modeling, NBS applications, and economic considerations to support sustainable and evidence-based landslide risk reduction.

This study presents a comprehensive literature review of recent research focused on the application of NBS for landslide risk mitigation. The review examines current research progress, identifies prevailing methodologies and implementation approaches, and outlines prospective directions to inform and guide future studies in this domain.

2. Materials and Outline

We examined different scientific databases, including Google Scholar, Web of Science, Science Direct, MDPI, and Springer databases, to identify and screen articles consistent with prescribed terms or related articles [15]. The review process focused on two primary research themes. The first theme addressed landslide susceptibility analysis, emphasizing comparative studies that evaluated two or more landslide models. This approach enabled a rigorous comparison of model performance and effectiveness. To ensure the inclusion of the most recent methodological advancements, this review focused on peer-reviewed literature published from January 2023 to 30 August 2025 that was retrieved using keywords such as "landslide," "GIS," "sensitivity analysis," and "compare." The search strategy employed Boolean operators, combining conditional factors as follows: "Landslide" AND "GIS" AND "Sensitivity analysis" AND "Compare."

The second theme explored the application of Nature-based Solutions (NBS) in landslide risk mitigation. Search terms included "Nature-based solution," "landslide," and "slope stability," along with specific NBS strategies such as "forest" and "vegetation." These terms were applied across the same databases to capture studies that investigated ecological and sustainable approaches to slope stabilization and landslide prevention. The Boolean search string used was "Nature-based solution" AND "Landslide" AND "Slope stability" OR ("Forest" OR "Vegetation").

From both search themes, a total of 510 studies were initially identified, comprising 280 peer-reviewed articles under Theme 1 and approximately 230 studies under Theme 2. After removing duplicates and screening titles and abstracts for relevance, 127 studies were retained for detailed review. Overall, these 127 papers were systematically reviewed and categorized into modeling and ecological NBS approaches. The reviewed literature collectively provides a comprehensive overview of current research on landslide susceptibility modeling and the use of Nature-based Solutions in landslide mitigation, while also identifying key trends, knowledge gaps, and directions for future research.

3. Results

This review examines and analyzes 97 articles on landslide model comparison since 2023 to obtain the latest research progress of landslide sensitivity analysis. Each of these comparative studies involves at least two or more landslide sensitivity analysis models to compare the performance of simulated landslides. Therefore, the following will describe the research situation regarding the landslide sensitivity analysis model over the past year, as well as the database required to build the model. The remaining articles conduct discussion regarding Nature-Based Solutions in landslide risk mitigation.

3.1. Conditional Factors for Landslide Sensitivity

In the establishment of a landslide sensitivity evaluation model, one of the most important steps is to select the appropriate factors affecting the occurrence of landslides [16,17].

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The selection of factors is usually based on the analysis of the nature of landslide occurrence and the characteristics of geology and geomorphology, hydrology, and human influence in the study area [18]. In general, when preparing a database of landslide-related parameters, selected relevant landslide triggers are based on knowledge gained from the literature, the availability of data, and the analysis of the study area [19]. The selection of landslide factors varies across different studies, and there is no unified standard for selecting or determining the effective factors for a landslide. Therefore, analyzing and providing a set of common factors that can be used for landslide sensitivity assessment will help to select input variables for landslide models more conveniently and quickly in future studies [6].

Landslide factors are usually classified into seven different categories: topography, geology, soil, hydrology, traffic, forest, and land use. Previous literature reviews have analyzed the conditioning factors used in landslide susceptibility models, revealing that topographic, geological, hydrological, and land use factors are among the most frequently considered [20,21]. This review also analyzes and compiles the latest findings by counting the frequency of each factor reported in the literature, as illustrated in Figure 1. Among these, topographic factors are typically derived from Digital Elevation Model (DEM) data, including variables such as elevation, slope, aspect, curvature, and geomorphology. The curvature factor is often further divided into specific forms such as profile curvature, plan curvature, general curvature, terrain curvature, and tangential curvature [22].

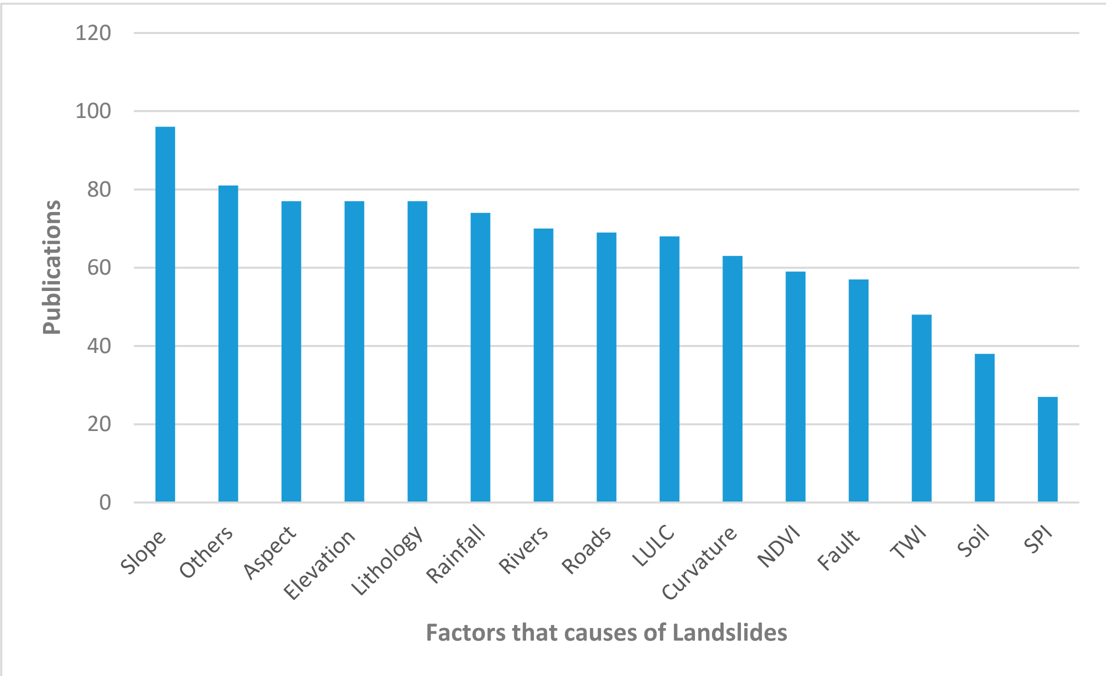

Figure 1. Number of published articles on factors as causes of landslides. Abbreviations: LULC = Land Use/Land Cover; NDVI = Normalized Difference Vegetation Index; TWI = Topographic Wetness Index; and SPI = Stream Power Index.

The results indicate that topographic and geological factors are among the most widely used in landslide susceptibility analyses. As illustrated in Figure 1, slope is the most frequently employed factor, appearing in nearly 100 publications, followed by aspect, elevation, and lithology, each cited in approximately 75–80 studies. These parameters are fundamental in almost all models, highlighting their critical role in defining slope instability.

Geological factors, such as lithology and proximity to faults, are prominently featured in approximately 60–70 publications. Lithology serves as the primary internal factor, offering the material foundation for landslides by determining rock strength, permeability, and susceptibility to weathering [23,24]. Conversely, proximity to faults serves as a structural geological factor; fault zones generally weaken the rock mass and create discontinuities, thereby increasing the likelihood of slope instability [25,26]. Hydrological factors, including distance to rivers, river density, and rainfall, are moderately represented, with each factor discussed in approximately 50–70 studies. Among these, distance from rivers and rainfall data are frequently utilized, while the Topographic Wetness Index (TWI), which assesses soil moisture and water accumulation potential [27], is less commonly employed in landslide susceptibility mapping, appearing in 48% of previous studies. In contrast, the Stream Power Index (SPI) estimates the erosive capacity of surface water flow [28,29], and soil-related variables such as soil type, texture, and properties, which influence infiltration and shear strength [24,30], are less frequently utilized, appearing in fewer than 40 studies.

Traffic-related factors typically encompass road density and proximity to roads, with the latter being highlighted in approximately 69 studies, underscoring its significance in representing anthropogenic influences on slope stability [31,32]. Within the domain of land use, both land use and land cover (LULC) are generally considered, with LULC being more extensively examined in 68 studies due to its consequential hydrological and mechanical impact on slopes [33]. Factors related to forest and vegetation often include vegetation type, vegetation density, forest type, and the Normalized Difference Vegetation Index (NDVI). Among these, NDVI is most frequently utilized, appearing in roughly 60 studies [31,34]. Higher vegetation density in these areas contributes to greater soil stability [35,36]. In addition to the primary categories of landslide conditioning factors, such as topography, geology, soil, hydrology, traffic, land use, and vegetation, rainfall data also play a pivotal role. They are frequently incorporated into landslide susceptibility assessments due to their impact on slope instability.

Overall, the analysis highlights that the most common landslide factors in the past year (from 2023) were slope (96 times), aspect (77 times), elevation (77 times), and lithology (77 times); they remain the dominant factors in landslide susceptibility studies, while hydrological and anthropogenic factors such as rainfall (74 times), rivers (70 times), roads (69 times), LCLU (68 times), Curvature (63 times), NDVI (59 times), distance to fault (57 times), TWI (48 times), Soil (38 times), and SPI (27) also play critical but slightly less emphasized roles.

3.2. Models and Methods Applied to Landslide Susceptibility and Trends

Geographic Information System (GIS)-based landslide susceptibility models are generally classified into four main categories: knowledge-driven, data-driven, machine learning, and hybrid approaches. Knowledge-driven models depend on expert judgment to assign weights to conditioning factors [37], while data-driven models apply statistical analyses to quantify the relationship between landslide occurrences and causal variables [38]. Machine learning models, as an advanced extension of data-driven methods, are capable of capturing complex and nonlinear relationships among influencing factors [32,34]. With recent methodological progress, hybrid models have been developed to combine two or more approaches, utilizing their respective strengths while minimizing individual limitations [39]. In total, 97 comparative studies encompassing 66 distinct models were reviewed.

As summarized in Table 1, the Random Forest (RF) model was the most frequently applied, appearing in 27 studies, followed by Logistic Regression (LR) with 23 occurrences. Both the Support Vector Machine (SVM) and Frequency Ratio (FR) models were each reported 16 times, while the Artificial Neural Network (ANN) appeared in 10 studies. These five models were the most widely adopted in recent landslide susceptibility assessments, highlighting their reliability and consistent performance across various study areas.

Table 1. Number of published articles from 2023 until now for the landslide susceptibility models.

Methods	Models	No Publication	References or Performance AUC
Knowledge Driven (Subjective)	Analytical Hierarchy Process (AHP)	9	[23,33,40–45]
	Weighted Overlay Method (WOM)	2	[46,47]
	Fuzzy Logic (FL)	1	[44]
	Interval AHP (IAHP)	1	[48]
	Multi-influencing Factor (MIF)	1	[23]
	Multi-Criteria Decision Making (MCDM)	1	[45]
	Multi-Criteria Analysis (MCA)	1	[49]
	Physically based probabilistic modeling of Rainfall Landslides using Simplified Transient Infiltration Model (PRL-STIM)	1	[50]
	Interval Number Distance-Based Region Growing (IDRG)	1	[48]
	Fast Shallow Landslide Assessment Model (FSLAM)	1	[51]
	Multi-Objective Decision Optimization (MODO)	1	[43]
Data Driven/ Statistical (Objective)	Logistic Regression (LR)	23	[28,30,39,49,52–69]
	Frequency Ratio (FR)	15	[24,39,41,46,53,55–58,62,70–74]
	Information Value (IV)	6	[41,55,57,58,67,68]
	Weight of Evidence (WOE)	4	[58,60,67,68]
	Index of Entropy (IOE)/Shannon Entropy (SE)	1	[58]
	Certainty Factor (CF)	2	[29,75]
	Equal Weight Method (EWM)	1	[37]
	Dempster–Shafer Theory (DS)	1	[75]
Machine Learning	Random Forest (RF)	26	[26–31,49,54,57,61,63–66,69–71,76–85]
	Support Vector Machines (SVMs)	17	[27,28,30,49,57–59,61,64,69,71,77,78,83,84,86,87]
	Artificial Neural Networks (ANNs)	8	[33,61,62,70,87–90]
	Multi-Layer Perceptron (MLP)	7	[29,56,68,71,77,78,85]
	XGBoost	7	[30,52,63,77,82,91,92]
	Deep Neural Network (DNN)	6	[53,59,80,81,89,93]
	Convolutional Neural Network (CNN)	5	[52,93–96]
	Bayesian Networks (BNs)	4	[58,89,93,97]
	Decision Trees (DTs)	4	[29,54,58,98]
	K-Nearest Neighbor (KNN)	3	[27,77]
	Naïve Bayes (NB)	2	[29,62]
	Artificial Bee Colony (ABC)	2	[87,99]
	Gradient-Boosting Decision Tree (GBDT)	2	[83,85]
	Adaptive Boosting (AdaBoost)	2	[31,85]
	Stochastic Gradient Boosting (SGB)	1	[87]
	MultiBoost (MAB)	1	[26]
	Elman Neural Network (ENN)	1	[89]
	Maximum Entropy (ME)	1	[55]
	Long Short-Term Memory (LSTM)	1	[59]
	Artificial Fish Swarm (AFS)	1	[99]

Table 1. *Cont.*

Methods	Models	No Publication	References or Performance AUC
	Information value (IV) with ML (SVM, LR, RF, MLP)	4	[28,40,67,68]
	Weight of Evidence (WoE) with Logistic Regression (LR) and MLP	3	[60,67,68]
	Fuzzy multi-criteria decision-making (Fuzzy-AHP)	2	[100,101]
	Frequency Ratio with Analytical Hierarchy Process (FR-AHP)	2	[73,102]
	Cuckoo optimization algorithm (COA) with MLP	2	[90,103]
	Physically based probabilistic model (PPM) with a convolutional neural network (CNN)	1	[38]
	Frequency Ratio coupled with Random Forest (FR-RF)	1	[66]
	Analytical Hierarchy Process (AHP) with Shannon entropy (SE)	1	[42]
	Artificial Neural Networks (ANNs) with MLP	1	[104]
	Earthworm Optimization Algorithm (EWA) with MLP	1	[104]
	Particle Swarm Optimization (PSO) with MLP	1	[104]
	Biogeography-Based Optimization (BBO) with MLP	1	[104]
Hybrid	Backtracking search algorithm (BSA) with MLP	1	[90]
	Convolutional Neural Network (CNN) with Beluga Whale Optimization (BWO)	1	[95]
	Convolutional Neural Network (CNN) with Coati Optimization Algorithm (COA)	1	[95]
	Convolutional Neural Network (CNN) with long short-term memory (LSTM)	1	[93]
	Time-distributed convolutional neural network (TD-CNN)	1	[105]
	Bidirectional Gated Recurrent Unit (Bi-GRU)	1	[105]
	Multi-scale convolutional neural network (MSCNN)	1	[105]
	Biogeography based optimization (BBO) and differential evolution (DE)	1	[106]
	Bidirectional long short-term memory (LD-BiLSTM)	1	[107]
	Geographically Weighted Regression (GWR) with Tabular Network (TabNet)	1	[80]
	Random Forest (RF) with Forest by Penailing Attributes (FPA)	1	[26]
	MultiBoost (MAB) with Forest by Penailing Attributes (FPA)	1	[26]
	SailFish Optimizer (SFO) with MLP	1	[103]
	Transient rainfall infiltration and grid-based regional slope stability (TRIGRS) with RF	1	[34]

3.3. Knowledge-Driven Method

Among the knowledge-driven approaches, the Analytical Hierarchy Process (AHP) remains the most widely applied method, reported in nine publications. Other decision-based techniques, such as the Weighted Overlay Method (WOM), Multi-Criteria Decision

Making (MCDM), and Multi-Influencing Factor (MIF) models, have been employed less frequently, each appearing in only one or two studies. While these heuristic approaches are particularly useful in data-scarce regions, their application has declined in recent years due to their subjective reliance on expert judgment and the potential variability introduced by qualitative weighting procedures.

Analytical Hierarchy Process (AHP)

The primary role of AHP in the landslide susceptibility model is to systematically derive the relative weights of the evaluation factors (Landslide Conditioning Factors, or LCFs) [100]. As illustrated in Figure 2, AHP is a multi-level hierarchical structure, consisting of overall goals, standards, and suitability levels. Each level of this hierarchical structure has a clear correlation [108]. It structures the problem hierarchically and assesses the relative importance of causative factors through pairwise comparisons [109], thereby revealing the interrelationships among parameters influencing landslide occurrence. Although AHP is simple, transparent, and relatively effective [94], it is often criticized for its dependence on expert judgment and limited capacity to handle uncertainty [79]. Additionally, the traditional AHP framework struggles to manage ambiguity because it expresses qualitative insights and preferences as crisp values, leading to a high degree of subjectivity during criteria normalization. This limitation is addressed by the Fuzzy–AHP approach [100]. Consequently, AHP is increasingly employed in combination with statistical and data-driven models, such as FR–AHP, Fuzzy–AHP, and AHP–SE, to enhance model reliability and predictive accuracy. Notably, Hoa et al. [42] reported that the integrated AHP–SE model outperformed its individual components, achieving an AUC value of 0.876, which falls within the range typically classified as very good performance.

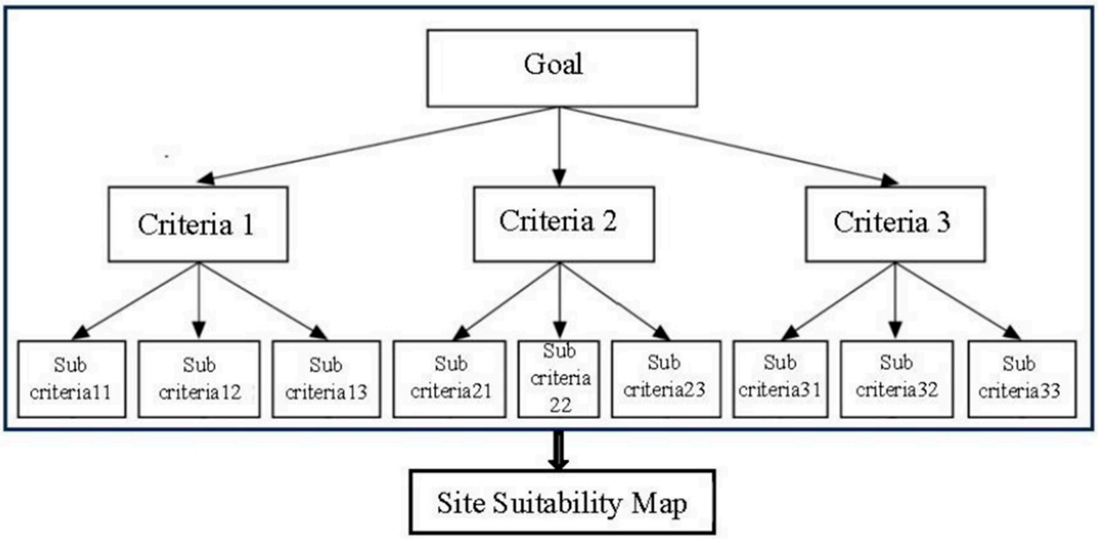

Figure 2. The AHP system used for suitability analysis [108].

3.4. Data-Driven Method

Data-driven and statistical approaches have gained prominence in recent years due to their objectivity, reproducibility, and quantitative rigor. Among these, Logistic Regression (LR) has emerged as the most widely applied model, appearing in 23 studies. The Frequency Ratio (FR) method is also prevalent, being employed in 16 studies, followed by Information Value (IV) in 6 and Weight of Evidence (WOE) in 4. Other probabilistic methods, including Shannon Entropy (SE), Certainty Factor (CF), and Dempster–Shafer Theory (DS), have been used less frequently, each reported in one or two studies.

3.4.1. Logistic Regression (LR)

Logistic Regression (LR) is a widely utilized multivariate statistical technique for modeling the probability of landslide occurrence as a function of multiple conditioning factors [63]. It transforms a linear combination of predictors into a probability value between 0 and 1, quantifying both the strength and direction of each factor's influence [30,56]. Due to its simplicity, interpretability, and efficiency, LR is often used as a benchmark against advanced machine learning (ML) models such as Random Forest (RF), Support Vector Machine (SVM), and Artificial Neural Network (ANN) [61]. However, its linear nature limits its ability to capture complex nonlinear relationships. To address this, LR has been extended through models like Kernel Logistic Regression and Logistic Model Tree (LMT) [76], or integrated into hybrid frameworks. Notably, P. Zhao et al. [28] reported that the IVM–LR model achieved the highest AUC value (0.998), representing an 18.53% improvement over the traditional standalone LR model (AUC 0.842).

3.4.2. Frequency Ratio (FR)

The Frequency Ratio (FR) model is a bivariate statistical method that evaluates the relationship between landslide occurrences and conditioning factors [56]. It compares the frequency of landslides within each factor class to their overall spatial distribution, where higher FR values indicate stronger associations [63]. This method effectively identifies the relative contribution of each factor or class to landslide susceptibility, providing a simple yet robust framework for spatial prediction. Comparative studies have shown that FR performs competitively, often exceeding conventional models such as Informative Value (IV) in predictive accuracy [55,74]. For instance, Ke et al. [73] demonstrated that the hybrid FR–MIV–BP model achieved the highest or second-highest accuracy among tested models, with FR1–MIV–BP and FR2–MIV–BP models yielding accuracies of 0.908 and 0.898, respectively, closely matching actual landslide distributions. The FR1–MIV–BP (Feature Reduction 1–Multi-Input Variable–Backpropagation) model uses a single-stage feature reduction to select important input variables, whereas the FR2–MIV–BP (Feature Reduction 2–Multi-Input Variable–Backpropagation) model applies a two-stage feature reduction for more refined input selection. Both models then utilize BP neural networks for prediction, with FR2–MIV–BP typically offering higher accuracy due to enhanced feature selection.

3.5. Machine and Deep Learning Algorithms

The machine learning (ML) category represents the dominant trend in current landslide research. The Random Forest (RF) model has emerged as the most frequently applied algorithm, with 26 publications, followed by Support Vector Machine (SVM) (17). Other widely used models include Artificial Neural Networks (ANNs) (8), Multi-Layer Perceptron (MLP) (7), Deep Neural Networks (DNNs) (6), Convolutional Neural Networks (CNNs) (5), and ensemble techniques such as XGBoost (7) and AdaBoost (2). Less commonly, researchers have explored models like K-Nearest Neighbor (KNN), Decision Tree (DT), Bayesian Networks (BNs), and Gradient Boosting Decision Tree (GBDT). These models are preferred for their ability to capture complex nonlinear relationships among landslide conditioning factors.

3.5.1. Random Forest

The Random Forest (RF) model is a nonparametric ensemble learning algorithm that constructs multiple decision trees using bootstrap sampling and aggregates their outputs through majority voting to generate final predictions [82,85]. Efficient in handling large datasets, the model reduces overfitting and quantifies the relative importance of conditioning factors [27,63]. Among 97 reviewed studies, 20 reported RF as achieving the highest predictive accuracy for landslide susceptibility mapping. For instance, C. Chen et al. [54] found that RF achieved an AUC of 0.938 and an overall accuracy (ACC) of 0.880, outperforming LR (AUC = 0.918) and DT (AUC = 0.905). Similarly, Yu et al. [85] compared RF with LR, SVM, and MLP, reporting that RF attained the highest AUC (0.92) and F1-score (0.85) for landslide classification. These findings reaffirm RF's robustness, generalization capability, and reliability across diverse geomorphological conditions [61].

3.5.2. Support Vector Machine (SVM)

A Support Vector Machine (SVM) is a nonlinear machine learning algorithm proposed by Vapnik. It maximizes the boundary between classes by distinguishing the classes with the optimal hyperplane. The data closest to the hyperplane are called support vectors, which are very suitable for the processing of small sample datasets. SVM also uses different kernels (kernel functions) to quantify the similarity of data in the spatial region, including linear (LN), polynomial (PL), radial-based function (RBF), and Sigmoid (SIG). Among them, the kernel function based on RBF is the most used kernel in landslide sensitivity evaluation research and outperforms other kernels [110,111]. When compared against Logistic Regression (LR) and Random Forest (RF), SVM typically performs well. In one analysis, SVM achieved an ROC AUC of 0.96 and an F1-score of 0.92, outperforming Multi-Criteria Analysis (MCA) results significantly [49]. SVM and its coupled models have been observed to delineate larger areas of high susceptibility zones in certain regions compared to other models [57]. However, some comparisons indicate that SVM models may overestimate the proportions of high and very high susceptibility classes compared to Random Forest models [49].

3.5.3. Artificial Neural Network (ANN)

The neural network algorithm is among the most widely used and highest-performing approaches for landslide susceptibility analysis. In certain studies, its predictive accuracy has even surpassed that of Random Forest (RF) and Support Vector Machine (SVM) models. Commonly applied neural network architectures include the Convolutional Neural Network (CNN), Artificial Neural Network (ANN), and Deep Neural Network (DNN), with CNN and ANN being the most frequently adopted in existing research.

Convolutional neural network (CNN) technology represents the most prominent deep learning framework, capable of processing high-dimensional spatial data and automatically extracting complex features such as edges, textures, and spatial patterns [112–114]. Through convolutional, pooling, and fully connected layers, CNNs effectively capture spatial dependencies in raster-based landslide data, enabling superior classification performance compared to conventional machine learning models [89].

The Artificial Neural Network (ANN), a feed-forward network comprising input, hidden, and output layers, employs nonlinear activation functions to model complex relationships among conditioning factors [115,116]. ANN-based models frequently outperform traditional statistical methods such as Logistic Regression (LR), Frequency Ratio (FR), Decision Tree (DT), Weights of Evidence (WOE), and Maximum Entropy (ME) [72]. For instance, Abdollahizad et al. [71] reported that the Multilayer Perceptron (MLP) model achieved the highest prediction accuracy (87.06%), exceeding SVM (80.0%) and RF (76.67%). Nevertheless, recent findings suggest that CNN architecture generally outperforms ANN in capturing spatial dependencies, yielding higher overall accuracy in landslide susceptibility modeling [24,89].

Deep Learning (DL) models, as an advanced subset of ANNs, further enhance the capacity to model complex nonlinear relationships [52]. Although DL algorithms significantly improve predictive precision, they require substantial data and computational resources compared to models such as SVM or RF. Interestingly, Rihan et al. [81] conclude that the RF model outperformed the Deep Neural Network (DNN), achieving a higher AUC–ROC value (0.95 vs. 0.88), emphasizing the influence of data characteristics and context on model performance. Moreover, J. Li et al. [80] found that the specialized deep neural network TabNet achieved the highest AUC (0.9828), significantly surpassing both DNN and ResNet models, highlighting that deep learning architectures differ considerably in their effectiveness when applied to structured tabular data.

A significant drawback of CNNs (and deep learning in general) is their high computational cost and the crucial need for extensive training data [34,39]. In environments where data is scarce, researchers often prefer simpler yet robust models such as Random Forest (RF) or Artificial Neural Network (ANN)/Multilayer Perceptron (MLP), which deliver reliable performance with less data and reduced computational costs [34]. Both traditional machine learning methods (SVM, CART) and deep learning approaches encounter persistent challenges related to overfitting and limited interpretability. ANN models, in particular, require extensive tuning of parameters, including learning rate, number of hidden layers, and activation functions, to achieve optimal performance. Nevertheless, ANN remains a highly effective tool for landslide susceptibility prediction, and its performance can be significantly enhanced through metaheuristic optimization [117].

In conclusion, CNN and other deep learning architectures represent the state-of-the-art for feature extraction and spatial pattern recognition when adequate data and computational resources are available. However, optimized ANN/MLP models offer a more practical and reliable alternative for resource-constrained applications, maintaining strong predictive capability with comparatively lower data requirements [34,117]. In this review, we differentiate ANN, MLP, and DNN based on their network architecture and complexity. ANN refers to general neural network models, MLP denotes ANNs with one or more hidden layers, and DNN represents deep architectures with multiple hidden layers capable of capturing complex relationships. Hybrid models combining ANN and MLP or integrating neural networks with other methods are explicitly indicated in Table 1 to clarify the combination strategy used in the literature.

3.6. Hybrid Approaches

Hybrid models have gained increasing prominence in landslide susceptibility analysis, integrating multiple algorithms to enhance predictive accuracy and generalization. More than 20 hybrid configurations have been reported, including IV–LR, FR–AHP, Fuzzy–AHP, CNN–LSTM, and AHP–Shannon Entropy combinations. Notably, FR–RF and IV–ML (SVM, LR, RF) integrations demonstrate superior robustness and adaptability in heterogeneous terrains [28]. Hybrid deep learning frameworks, such as Multi-Scale CNN (MSCNN), Bidirectional LSTM (Bi-LSTM), and TabNet–GWR, further exemplify the growing sophistication of data-driven landslide modeling [80,84,107].

The integration of statistical and machine learning methods has also yielded substantial improvements in quantifying the relationship between landslide occurrences and conditioning factors. For instance, W. He et al. [57] demonstrated that the FR–RF model achieved the highest prediction accuracy (AUC = 0.949) among comparable single and coupled models. Although the inclusion of a weaker learner (FR) may slightly reduce the performance of a stronger model (RF), it enhances the interpretability and weighting of input factors.

Hybridization of physical and data-driven approaches has likewise shown promising results. A proposed Physically Based Probabilistic Model (PPM)–CNN framework for rainfall-induced landslide mapping improved predictive accuracy (AUC = 0.85) compared to standalone CNN (AUC = 0.61) and PPM (AUC = 0.74) models [50]. Similarly, combining multiple algorithms (ensemble learning) or optimizing internal parameters through metaheuristic algorithms can produce superior hybrid models. For example, Z. Chen and Song [95] reported that the CNN–COA model achieved higher accuracy (AUC = 0.919) than CNN–BWO (AUC = 0.906) and standalone CNN (AUC = 0.805), illustrating that optimization enhances model precision and reduces overfitting.

According to the statistics and summary of comparative articles, the hybrid model and Neural network model have shown excellent performance in landslide sensitivity analysis research in the last year, compared with other models. In the future, the analysis and upgrading of these two methods may become one of the cores.

3.7. Model Selection Guidance

The previous section provided a detailed overview of each methodology for landslide susceptibility analysis, demonstrating that machine learning, deep learning, and hybrid approaches are more complex to implement but generally yield superior predictive performance. Before analyzing with a selected model, several critical factors must be carefully considered. Among these, data availability plays a central role: knowledge-driven or simple statistical models are typically preferred when datasets are limited, whereas machine learning and deep learning approaches achieve optimal performance with large, high-quality datasets. Knowledge-driven and statistical models are often employed in data-scarce environments, where limited geotechnical data is available [118]. Statistical models can provide reliable outputs, especially when using binary classification algorithms, which are effective for regional-scale analysis [119]. However, this model may not capture complex, nonlinear relationships as effectively as ML and DL [119]. Ado et al. [120] reported that ML and DL models thrive on large datasets, achieving high accuracy and reliability in susceptibility mapping, often exceeding an AUC of 0.90. Recent advancements include hybrid models that combine statistical and ML techniques, enhancing predictive capabilities even in data-limited scenarios. Despite their advantages, these models require meticulous data preparation and normalization to optimize performance [121].

System complexity also influences model choice. Simple systems may be adequately captured using statistical approaches, while highly complex systems with nonlinear or high-dimensional relationships often require machine learning or deep learning techniques. Machine learning is particularly useful in scenarios where the system exhibits a high degree of interconnectivity and dependency among components, as seen in naturally occurring systems like the human body and environmental systems [122]. These models can learn patterns from large datasets, making them suitable for tasks such as prediction, classification, and anomaly detection in complex systems. For instance, a study demonstrated that a DL model achieved an accuracy of 92.12% in predicting landslide susceptibility, significantly surpassing traditional models [123].

The purpose of the study is another important consideration. For predictive tasks, models that generalize well, such as machine learning or deep learning, are appropriate. The selection of relevant factors significantly influences model accuracy. For instance, using autoencoder-based methods for DL models has been shown to enhance prediction performance, while traditional factor selection methods may reduce accuracy [124]. In contrast, if the goal is to understand underlying mechanisms or provide explanatory insights, knowledge-driven or interpretable data-driven models are preferable. For instance, a knowledge graph can summarize relationships between landslide entities and rules, enhancing interpretability [125]. While knowledge-driven and interpretable models provide valuable insights, they may require extensive domain expertise and data, which can limit their applicability in rapidly changing environments. Balancing complexity and interpretability remains a challenge in landslide susceptibility modeling.

Consideration of available resources and technical expertise is essential when selecting modeling approaches for landslide susceptibility. Advanced models, such as deep learning (DL) architectures, require substantial computational power, including access to GPUs, and extensive datasets for training. For example, Convolutional Neural Networks (CNNs) and hybrid models like CNN–LSTM have demonstrated impressive accuracy rates of up to 98.80%, but their implementation demands significant technical proficiency [126]. In contrast, simpler models like Naïve Bayes and Support Vector Machines (SVMs) are less resource-intensive and easier to implement, yielding satisfactory performance with accuracy rates of 87.52% for DL versus 92.12% for SVM [123]. While advanced models like DL offer higher accuracy and advanced capabilities, their complexity may present challenges in regions with limited computational resources or technical expertise. Therefore, it is crucial to adopt a balanced approach that integrates both technological advancements and practical constraints in landslide susceptibility modeling. By carefully considering factors such as data availability, system complexity, study objectives, and available resources, researchers can select the most appropriate modeling approach that aligns with the specific requirements of their study, as illustrated in Figure 3.

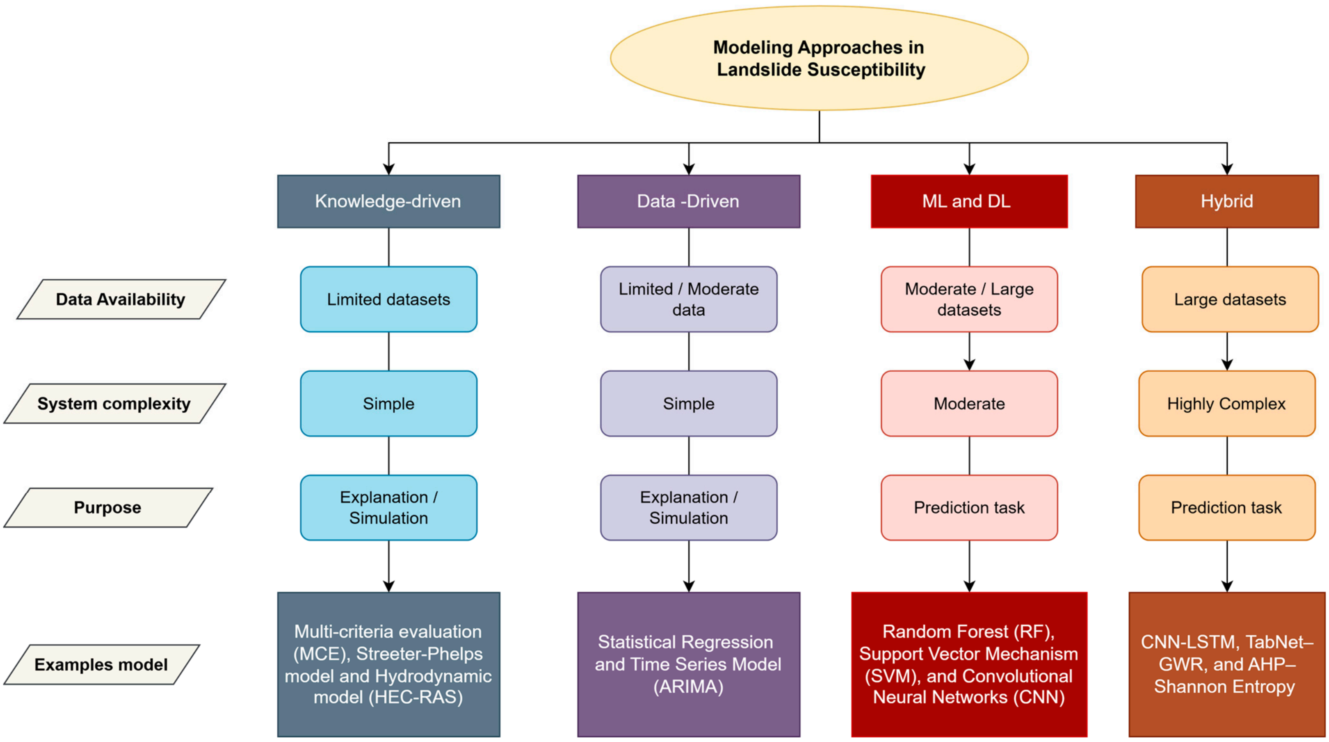

Figure 3. Consideration for choosing the right modeling for landslide susceptibility analysis.

3.8. Comparative Evaluation Metrics of Landslide Susceptibility Analysis Models

At present, it is very common and important to study the effectiveness of landslide models. With the emergence of numerous new and improved models, it is not possible to directly determine which approach is most effective for landslide prediction. A fundamental and critical aspect of such research is the application of appropriate verification methods to quantitatively demonstrate the differences in predictive accuracy among models. This process can also guide future studies by identifying and eliminating less effective approaches. The following are the comparative evaluation metrics most frequently adopted in landslide susceptibility analysis models, as shown in Figure 4.

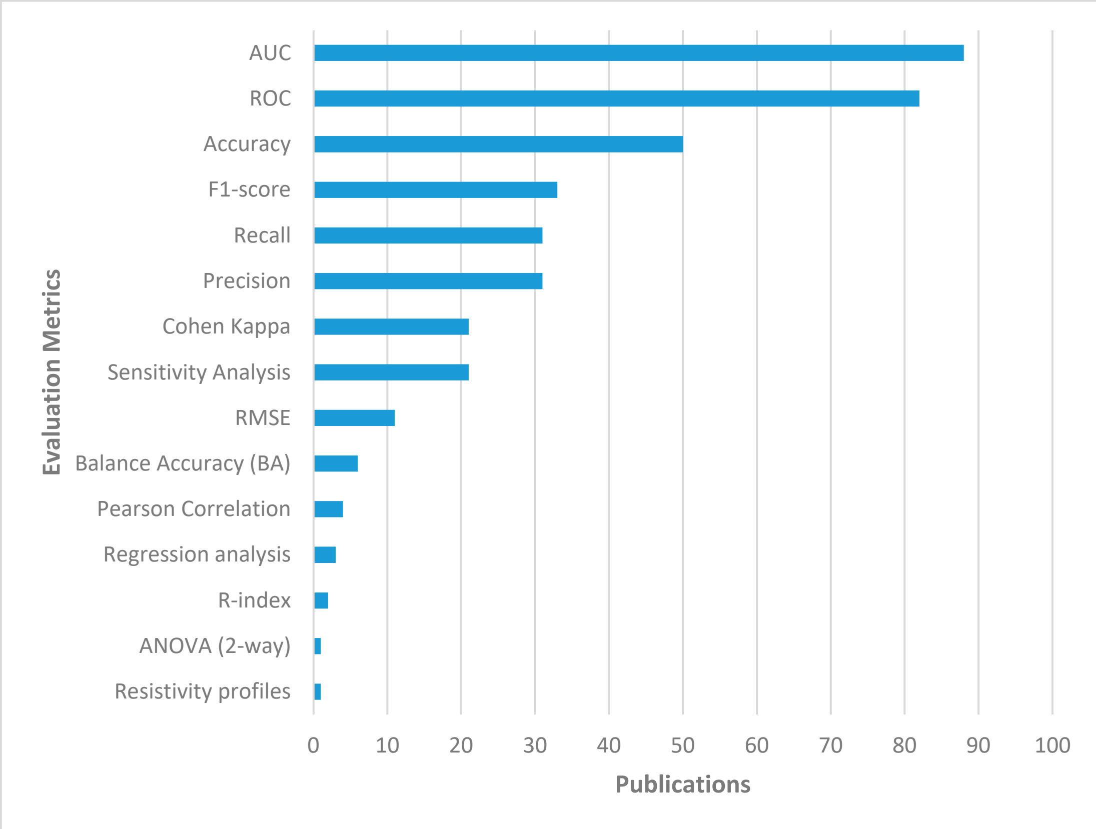

Figure 4. Number of publications used for evaluation metrics in the landslide susceptibility analysis.

3.8.1. Receiver Operating Characteristic–Area Under the Curve (ROC–AUC)

Among various evaluation metrics, the Receiver Operating Characteristic–Area Under the Curve (ROC–AUC) value [127] is the most frequently used, as illustrated in Figure 3. This metric serves as the predominant performance indicator, appearing in nearly all reviewed studies (approximately 90 publications). These metrics are highly esteemed for their robustness in assessing classification performance independent of threshold selection, thereby establishing them as the preferred standard for model validation in landslide susceptibility mapping. However, its applicability depends on the context of the data, especially when dealing with imbalanced datasets. In such cases, ROC–AUC is particularly useful as it helps evaluate the model's ability to correctly classify landslides (positives) versus non-landslides (negatives), despite imbalances in the dataset. The Receiver Operating Characteristic (ROC) curve is a graphical representation derived from a confusion matrix, plotting sensitivity against specificity on its horizontal and vertical axes, respectively. The Area Under the Curve (AUC) refers to the area under the Receiver Operating Characteristic curve (ROC), which is a widely used method for verifying and comparing the performance of models in landslide susceptibility assessment. It comprises true positive (TP) values and true negative (TN) values. Specifically, the true positive (TP) represents the accurately predicted number of landslides, while the true negative (TN) denotes the accurately predicted total number of non-landslides [128,129]. The calculation formula is shown in Equation (1):

$$AUC = \sum TP + \sum TN/(P+N) \tag{1}$$

P and N represent the total number of landslides and non-landslides. Its value ranges from 0.5 to 1.0, and if we construct inaccurate models, its AUC is less than equal to 0.5. Conversely, if it is a perfect model, the AUC is 1 [130]. The relationship between AUC and model prediction accuracy is as follows: Excellent: 0.9–1; Very good: 0.8–0.9; Good: 0.7–0.8;

Average: 0.6–0.7; And Poor: 0.5–0.6 [131]. According to the AUC value, we counted the models with high accuracy in landslide simulation validated in previous studies, that is, the models with the best performance [132].

Following AUC and ROC, Accuracy (50 times), F1-score (33 times), Recall (31 times), and Precision (31 times) are the next most widely used metrics, reflecting the growing emphasis on balanced classification performance, especially in datasets with imbalanced classes.

Sensitivity (also referred to as the true positive rate) represents the proportion of actual landslide occurrences that are correctly identified by the model, while specificity (true negative rate) measures the proportion of non-landslide areas that are correctly classified. In the ROC curve, sensitivity is plotted against 1—specificity across different classification thresholds, allowing an assessment of the trade-off between correctly detecting landslides and minimizing false alarms.

3.8.2. Overall Accuracy (OA)

Overall Accuracy (OA) is used to measure the proportion of true results (both TP and TN) among the total number of cases examined. It indicates how well the model works. The formula given shows the accurate work in Equation (2):

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{2}$$

True Positive (TP) refers to instances correctly classified under the positive label. True Negative (TN) denotes the number of instances accurately classified under the negative label. False Positive (FP) indicates the number of instances incorrectly classified under the negative label, while False Negative (FN) represents the number of instances incorrectly classified under the positive label [87]. These metrics are commonly used in scenarios where the data classes are balanced. In datasets with an imbalance between landslide and non-landslide cases, relying solely on OA could be misleading as it may overestimate the performance of a model that predicts the majority class most of the time. Models optimized through Hyper-parameter Optimization (HPO) typically demonstrate enhanced accuracy; for example, the BO–SVM model achieved an accuracy of 89.53%, surpassing the default model's accuracy of 84.91% [32]. In a comparative analysis of Multi-Criteria Decision Analysis (MCDA) models, GIS–TISSA exhibited the highest accuracy (0.869), followed by F–AHP (0.856) and AHP (0.855) [101].

3.8.3. F1-Score

The F1-score represents the harmonic mean of Precision and Recall, as expressed in Equation (3). It provides a balanced evaluation of model performance, particularly useful when class distributions are imbalanced [89]. A model with an F1-score approaching 1 is generally considered highly reliable [82].

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{3}$$

The F1-score is widely employed to comprehensively assess model performance across varying hyperparameter configurations [32]. In an integrated physically based and machine learning (ML) model, optimization achieved an F1-score of 0.949, indicating strong predictive capability [34]

3.8.4. Recall

Recall quantifies the model's ability to correctly identify positive instances, such as landslide occurrences, and is defined in Equation (4):

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

This metric is critical in landslide susceptibility modeling, as it emphasizes minimizing false negative cases where actual landslides are not detected [133]. In an optimized hybrid (physically based and ML-based) model, the feature selection process improved Recall to 0.984, highlighting its enhanced sensitivity and detection capability [34].

3.8.5. Precision

Precision is used to assess the model's accuracy in predicting positive labels [89], specifically the fraction of correctly predicted landslides (TP) amongst all instances predicted as landslides (TP + FP), as shown in Equation (5):

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

Precision, along with other metrics, is used to assess the effectiveness of HPO techniques on ML algorithms like XGBoost [32]. Further, this metric also identifies the landslide areas with a low False Positive rate, known as low false alarms [59,106].

3.8.6. Cohen's Kappa Coefficient

Cohen's Kappa Coefficient has been applied in approximately 21 publications for evaluating landslide susceptibility models. This metric assesses the consistency of classification results while accounting for the probability of agreement occurring by random chance [80,87]. The coefficient is defined by Equation (6):

$$k = \frac{Po - Pe}{1 - Pe} \tag{6}$$

where k represents the Kappa statistic, Po denotes the proportion of observed agreement, and Pe indicates the proportion of agreement expected by chance. Cohen's Kappa is particularly useful for evaluating the degree of agreement between model predictions and ground truth data (GTS) or for assessing classification consistency between different models [134].

Metrics such as RMSE (Root Mean Square Error), Balance Accuracy (BA), and Pearson Correlation appear less frequently based on this review, mainly in studies integrating regression-based or continuous susceptibility mapping approaches. Regression analysis, R-index, ANOVA (2-way), and Resistivity profiles are rarely applied, representing less conventional or more specialized methods of validation, often used in hybrid or physically based models. Overall, Figure 3 highlights that AUC and ROC dominate as the principal evaluation criteria in landslide susceptibility modeling, while the inclusion of multiple complementary metrics (F1-score, Precision, Recall) reflects a broader methodological trend toward comprehensive, multi-metric model evaluation to ensure reliability and predictive robustness.

3.8.7. Data Dependency for Metrics Evaluation

The performance of all these metrics is highly data-dependent. For example, ROC–AUC depends on the quality of both the positive and negative samples. Inaccurate or incomplete data can lead to misleading AUC values. Similarly, models using SVM or

Random Forest are sensitive to the amount and quality of training data. Insufficient data, particularly in regions prone to landslides but lacking extensive historical data, may impair the reliability of these models. It is crucial to ensure that the dataset accurately reflects the range of landslide conditions, as models trained on non-representative data may not generalize well to real-world conditions.

Moreover, the F1-score is sensitive to both Precision and Recall, and in cases of imbalanced data, a model that overpredicts the majority class (non-landslide areas) will show a poor F1-score. Similarly, Cohen's Kappa is particularly sensitive to data imbalances, as it accounts for the agreement occurring by chance, which can obscure meaningful differences between models if the dataset is skewed.

3.8.8. Interpretability and Overfitting Risk in Evaluation Metrics

Interpretability is another important consideration when choosing an evaluation metric. Simpler models like Naïve Bayes or Logistic Regression are often more interpretable than machine learning models like SVM or Random Forest. In regions where the decision-makers lack technical expertise, simpler models that provide clear insights into the influence of conditioning factors on landslide susceptibility may be more practical, even if they offer slightly lower predictive accuracy. However, more complex models like Deep Learning (DL) approaches (such as CNN and hybrid CNN–LSTM models) often achieve higher accuracy but at the cost of interpretability. These models are considered "black-box" models, meaning that while they may deliver precise results, they do not readily explain how they arrived at a prediction. In practice, this can limit their usefulness in regions where stakeholders require transparent, understandable reasons behind model predictions. Additionally, overfitting remains a significant risk, especially for more complex models. Deep learning models, while powerful, require substantial computational resources, large datasets, and significant technical expertise to prevent overfitting. Without proper tuning and validation (cross-validation), DL models can memorize training data instead of learning the underlying patterns, leading to poor performance on unseen data. For instance, models like CNN–LSTM, despite achieving high accuracy (up to 98.80%), risk overfitting if they are not appropriately regularized or validated. Conversely, simpler models like SVM are less prone to overfitting in small datasets but may not capture complex relationships between factors influencing landslide susceptibility.

To mitigate overfitting, cross-validation and regularization techniques should be employed, especially for models with a high number of parameters, like deep learning models. Using ensemble methods, such as Random Forest or Gradient Boosting, can help reduce overfitting by combining multiple models' outputs, thus improving generalization.

Each model has its unique paradigm, data, and operational requirements; it is necessary to conduct a comparative analysis and critical discussion of these model methods. Table 2 systematically compares the four types of landslide models mentioned above, Analytic Hierarchy Process (AHP), data-driven methods, machine/deep learning algorithms, and hybrid methods, in order to more clearly clarify the specific advantages and disadvantages of each model, as well as the conditions or reasons for the success or failure of the model simulation.

Table 2. Comparative analysis of landslide susceptibility modeling approaches.

Model Type	**Analytical Hierarchy Process (AHP)**	**Data-Driven Methods**	**Machine and Deep Learning Algorithms**	**Hybrid Approaches**
Paradigm	Structured conversion of expert judgment into factor weights.	Establishes probabilistic relationships based on statistical theory and historical data.	Automatically extracts complex patterns and features from data.	Integrates principles or outputs from different paradigms.
Advantages	1. Low data dependency; Simple calculation; 2. Clear weight calculation process; 3. Effectively integrating qualitative issues	1. Relatively simple model; 2. High efficiency in simulation calculation; Effectively tests key influencing factors.	1. Easily capture complex relationships, handle high-dimensional data (remote sensing images); 2. High prediction accuracy; 3. Automatically perform data feature extraction	1. Reduce the uncertainty of a single model; 2. Effectively handle ordinary quality data; 3. Improve the accuracy of the model
Limitations	1. Subjective and dependent on expert opinions; 2. Static model and requires re-evaluation of expert opinions for updates.	1. Sensitive to data; 2. Weak in handling complex relationships; 3. The relationship of influencing factors directly affects the performance of the model	1. "Black-box situation": Poor explanatory ability, resulting in mechanical analysis; 2. High requirements for data quality and quantity; 3. Complex calculations, with a high risk of overfitting.	1. Model design lacks a unified framework and is highly subjective; 2. Increases the amount of data calculation and verification work; 3. There is a risk of combining the shortcomings of different models.

Note: This synthesis was developed through an analysis and consolidation of the key discussion presented in the selected literature.

4. Research on NBS for Landslide Mitigation

4.1. Overview of NBS

Nature-Based Solutions (NBS) have become a cornerstone of modern environmental policy, offering an innovative approach to tackling multiple challenges posed by natural disasters, including landslides. Originating from the World Bank's 2008 initiative, NBS focuses on leveraging natural processes to address environmental, social, and economic challenges in a sustainable manner [135]. NBS is guided and promoted by many influential intergovernmental institutions in the world, such as the World Bank, the International Union for Conservation of Nature, the European Union (EU), etc. In particular, the European Commission (EC) attaches great importance to the development of NBS, and the goals of NBS application they envision mainly include four parts: to balance the relationship between nature and human society; to build a resilient urban ecosystem; to stimulate economic development; and to improve the quality of life, health and well-being of the population [136]. The NBS concept proposed by the International Union for Conservation of Nature is now widely accepted, which is "Nature-based Solutions are actions to protect, sustainably manage, and restore natural and modified ecosystems that address societal challenges effectively and adaptively, simultaneously benefiting people and nature" (source: (IUCN) https://www.iucn.org/our-work/nature-based-solutions, accessed on 25 October 2025). In summary, NBS provides a strategy that is closely integrated with natural factors to adapt to future extreme changes, address future social and economic challenges, improve the human living environment, and reduce the impact of climate change on the environment. The focus is on providing planning solutions for the development of smart and sustainable cities in the future [137].

NBS has been widely used in urban planning [138,139] and hydro-meteorological risk reduction. The results show that NBS can effectively improve urban resilience and provide a valuable method for sustainable urban development and effectively reduce the impact of climate change and population growth on the urban environment. This is to realize the goal of NBS to improve the quality of life, health, and well-being of urban ecosystem residents [140,141]. What is more closely related to this paper is the research of NBS for hydro-meteorological risk reduction. For risk reduction, NBS is divided into large-scale NBS and small-scale NBS, where the study area of large-scale NBS includes mountainous areas, river corridors, and coastal regions, while small-scale NBS is usually used in the urban or local area, like green roofs, green walls, swales, etc., such as in Figure 5 [13].

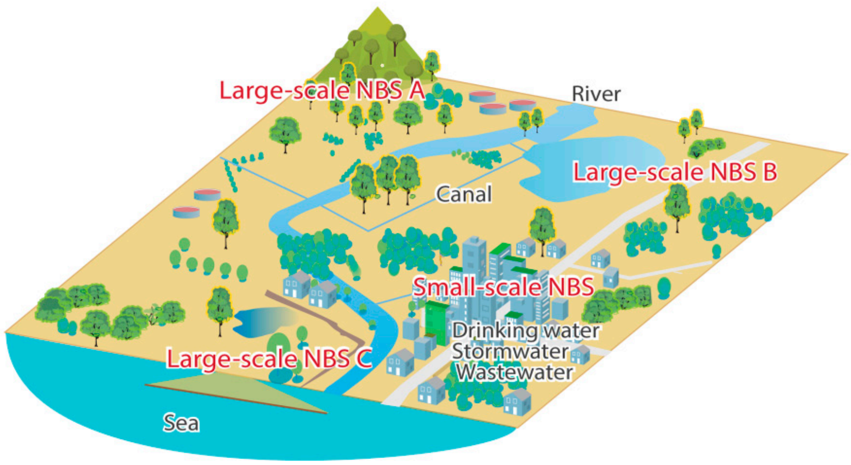

Figure 5. Display of large-scale NBS and small-scale NBS [13].

NBS studies on disaster risk mitigation include floods [142], droughts [143], heat-waves [144], landslides [145], storm surges [146], and coastal erosion [147]. Kumar et al. [148] reviewed the research of NBS on the mitigation of hydro-meteorological risk and summarized the proportion of different natural disasters (Figure 6). Among them, the proportion of flood research was higher than that of other natural disasters, while the proportion of NBS applied to landslides was only 2.3% [149]. The highest proportion is in the aspect of the monitoring method (44.7%). The method used by NBS to mitigate landslides is introduced in detail in Section 4.2.

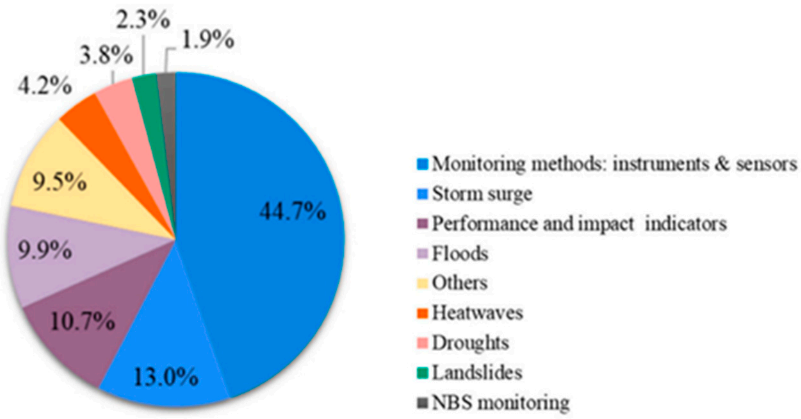

Figure 6. The proportion of different themes in the study of reducing hydro-meteorological risk by NBS [148].

In the context of landslide mitigation, NBS represents a revolutionary shift, offering long-term, cost-effective alternatives to traditional methods. This section delves into the application of NBS for landslide management, emphasizing its potential to stabilize slopes and prevent landslide occurrence through natural and integrated approaches.

4.2. Application on NBS for Landslide Mitigation

The application of NBS to landslide risk is mainly for landslide management. Quantifying the impact of NBS strategies or measures in the landslide process is the focus of the research. If the results show a decreasing trend of landslide activities compared with the situation before the implementation of NBS, it can provide evidence and support for the effectiveness of NBS in landslide mitigation. This section reviews approximately 30 relevant studies (2023–2025) and discusses the underlying mechanisms through which NBS contribute to landslide stabilization, types of Nature-Based Solutions (NBS) and the approaches used to evaluate their economic value.

4.2.1. Mechanism of Landslide Mitigation by Nature-Based Solution (NBS)

Vegetation plays a pivotal role in Nature-Based Solutions (NBS) for landslide mitigation by enhancing slope stability through both mechanical and hydrological processes [150].

- **Mechanical Reinforcement**

The primary mechanical contribution comes from the plant root network, which reinforces the soil matrix. Root systems contribute significantly to slope stabilization by increasing soil shear strength through root cohesion and tensile resistance. The interlocking of roots with soil particles provides an anchoring effect that resists downslope movement, a process widely referred to as root reinforcement [151]. Empirical studies have demonstrated that large roots are the primary contributors to this mechanical stability, exerting greater tensile strength and shear resistance than finer roots [152]. Consequently, the selection of vegetation species with robust root systems has become a key focus in bioengineering applications [153]. For instance, species such as Vetiveria zizanioides (vetiver grass) have been effectively employed for shallow slope stabilization under rainfall-induced conditions due to their high root tensile strength and modulus [154].

- **Hydrological Regulation**

Vegetation also influences slope hydrology by modulating water flow and storage within the soil. Plant canopies and litter layers intercept rainfall, reduce surface runoff, and minimize erosion [155]. Meanwhile, root networks alter the hydraulic conductivity of soil, promoting deeper infiltration while regulating pore water pressure distribution [156]. Through evapotranspiration, vegetation reduces volumetric water content within the soil matrix, thereby mitigating the risk of slope failure under wet conditions. Collectively, these hydro-mechanical effects improve slope stability and reduce landslide susceptibility [157].

4.2.2. Nature-Based Solutions for Landslide Mitigation

Nature-Based Solutions (NBS) for landslide mitigation primarily leverage the stabilizing functions of vegetation (Green approaches) and integrate these natural elements with engineered or biodegradable materials (Hybrid approaches) to manage shallow landslides, erosion, and hydro-geological hazards [158].

Green Approaches

Green approaches utilize natural processes and living elements, particularly vegetation, to provide both mechanical and hydrological stabilization [157]. These methods are often grouped under soil and water bioengineering (SWBE) techniques [159]. The following section discusses the measures that have been highlighted in this review: vegetative measures and soil and water bioengineering (SWBE) techniques.

Vegetative Measures

Vegetative measures are defined as NBS for landslide risk reduction. They are generally suitable for slopes with gradients less than 50% [158]. Afforestation, Reforestation, and Forest Management: the strategic planting or preservation of living vegetation or forest improves soil stability by minimizing run-off, increasing soil strength through roots, and preserving biological processes [156]. Protection forests are recognized as efficient ecosystem-based solutions for reducing geo-hydrological hazards, mainly those occurring at shallow strata [157]. For instance, Devanand et al. [158] developed a novel methodology for the spatial allocation of these measures for landslide risk reduction in the Portofino promontory, Italy. Landslide susceptibility mapping was incorporated and was used to create a toolbox ESRI ArcGIS (Pro 3.3) environment to aid decision-makers in the planning and implementation of large-scale NBS. The spatial allocation toolbox was applied to the case study Portofino promontory, Liguria region, Italy, and 70% of the area was found to be highly susceptible to landslides.

Soil and Water Bioengineering (SWBE) Techniques

SWBE technology specifically combines plants as usable biological materials in combination with inert materials (such as wood and stone) to achieve stability (technical function), ecological restoration, and aesthetic value [160]. SWBE is usually divided into soil biological engineering (SBE) and water biological engineering (WBE). SBE deals with the stabilization of shallow landslides and the prevention of surface erosion. WBE is applied to protect and stabilize riverbanks. These characteristics are usually applicable to areas with a steeper slope ($\geq$50%), as in these areas the effect of relying solely on vegetation measures is often insufficient [161]. Preti et al. [159] calculated the safety factor (FS) based on SSAP2010 software to assess the slope stability in north-western Tuscany, Italy. The aim was to monitor the technical effect of SWBE on the influence of shallow landslides. This project verified that with the development of vegetation and the intervention of SWBE technology, the FS in the study area increased over time, which had a significant effect in reducing natural risks and slope instability.

Hybrid Approaches

Hybrid approaches combine NBS (green or blue) with engineered structures or inert materials. Mitigation measures to reduce landslide hazards usually also include drainage systems, drainage ditches, geotextiles, etc., which are commonly used to treat and mitigate landslide activities caused by weather factors (persistent rain) [162]. The integrated solution involves considering the synergistic benefits of NBS and gray infrastructure in disaster management (the comparison between NBS and common solutions is shown in Table 3). For example, geotextiles are widely used in soil bioengineering, used to improve the stability of geotechnical structures and slopes by promoting soil reinforcement and exhibiting excellent drainage capabilities. Geotextiles have effectively improved the carrying capacity of the soil on the slope, improving the soil's ability to resist external loads and the stability of the slope, thus reducing the trigger of landslides [163]. Such methods are only applicable to shallow landslide mechanisms; some studies have focused on researching and evaluating environmental characteristics and setting decision-making conditions, helping decision-makers select appropriate solutions. For instance, selecting a hybrid disaster response mechanism that enhances drainage capacity through the synergy of vegetation and geotextiles to reduce the occurrence of landslides, or establishing a single infrastructure that would have a better effect on disaster prevention [164].

https://doi.org/10.3390/su18010308

Table 3. Comparison between NBS and gray solutions [165].

NBS	Common Solutions
Enhancing biodiversity, bringing environmental benefits and improving landscapes.	The destruction of landscapes and ecosystems incurs environmental costs.
The performance and long-term effectiveness of NBS facilities are less predictable due to a lack of operational experience and scientific data.	The facilities are operational and can prevent specific types of disasters, but they are unable to handle disasters beyond that scale.
More suitable for situations with a smaller population size.	Considering densely populated areas, the purpose of this arrangement is to protect residents from the impact of disasters.
Will not cause any damage to the environment.	When constructing infrastructure, may damage the existing ecosystem or landscape.
Improve the landscape and promote the development of green tourism industry.	Public investments that will temporarily increase local income.
The growth cycle must be taken into account. Seasonal changes represent a potential limitation.	Poor adaptability, and the "locking" of positions restricts the prevention range.

Blue and Green–Blue Approaches (Water Management)

While often part of engineered solutions, water management measures are critical to addressing rainfall-induced shallow landslides and are often incorporated into NBS projects. Water management typically involves managing rainfall infiltration, improving drainage or addressing groundwater issues to control water volume and preventing landslides. Rainfall infiltration can lead to soil saturation and increase pore water pressure. Compared with not considering the infiltration of rainfall, appropriate management or slowing down the infiltration process can slow down the rate of decline in the stability of landslides [166]. Such studies support the implementation of drainage measures. A well-planned sustainable drainage system (SuDS) can restore the hydrological conditions of the region. B. Chen and Chui, 2025 [167], employed the Storm Water Management Model (SWMM) with Modflow and Scoops3D for hydrological simulation and slope stability analysis, confirming that the implementation of SuDS effectively reduced runoff, increased groundwater reserves, and enhanced slope safety. In addition, the study on the stability of river basin slopes will utilize hydrological models to assess the risk of landslides. For instance, Petpongpan et al. [168] applied a BTOPMC model to conduct runoff simulation in the Yom River Basin and landslide risk assessment. The risk map obtained from the experimental simulation is similar to the landslide risk map provided by the Land Development Department of Thailand, proving that the simulation results are trustworthy.

4.2.3. NBS Economic Value Assessment

Beyond the environmental and social benefits, it is crucial to assess the economic value of NBS in landslide mitigation. Cost–benefit analysis (CBA) is a widely recognized method for evaluating the financial viability of NBS, ensuring that resources are allocated efficiently for risk mitigation. In the context of landslide mitigation, CBA compares the costs of implementing NBS measures with the potential financial savings from reduced landslide damage [169]. The evaluation of economic value also provides intuitive support for the establishment of policies or measures [170]. Cost–benefit analysis (CBA) is a very popular economic evaluation method, which is recognized as a more standardized and reliable analysis tool, and is widely used in the decision-making stage, that is, for the feasibility analysis of various measures and facilities [170,171]. The purpose of CBA is mainly to provide and promote the most efficient resources or allocation applied to various realistic projects. It monetizes all costs and benefits and selects the best economically sustainable solution, which will be applied to projects as an alternative to other methods [171,172].

In the research on the application of NBS and mitigation of natural disasters, CBA mostly appears in the mitigation of floods [17,173,174]. The specific CBA method is described as shown in Figure 7. The whole analysis process is to compare the economic benefits of the Business as Usual (BAU) measure and the NBS measure. BAU usually refers to grey infrastructure. The evaluation process is composed of four parts: Co-benefits, Avoided Damage Costs, the Cost of Implementation, and Opportunity Costs. Co-benefits refer to the additional environmental, economic, and social benefits arising from any part that can be assessed monetarily and will be considered in CBA. Avoided Damage Costs represent gains after taking different strategies to reduce related risks. Implementation Cost is the necessary cost for NBS implementation and subsequent maintenance. Finally, Opportunity Costs are indirect costs. The implementation of NBS requires land acquisition, so it is necessary to give up the development of some facilities, resulting in a certain amount of abandonment costs [175]. Aggregate all the benefits and costs defined above, and the ratio between them is the most basic indicator in CBA, namely the cost–benefit ratio (BCR). A BCR between 2 and 5 is considered economically effective, and a BCR above 5 is considered to have a high level of cost-effectiveness [176].

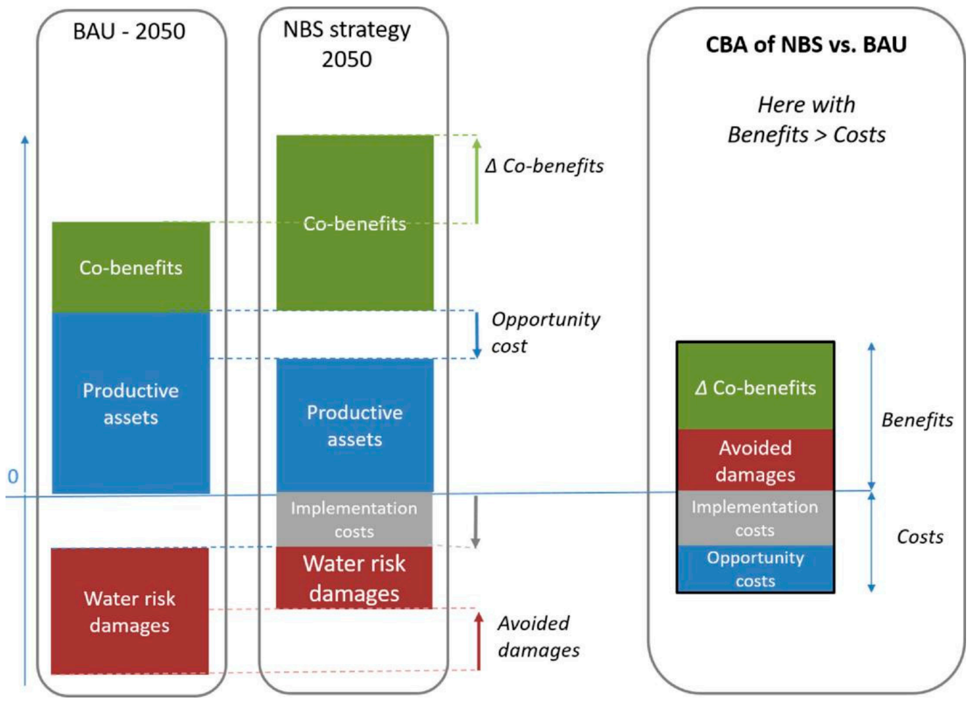

Figure 7. NBS economic value evaluation—Cost–benefit analysis principle [175].

Salbego et al. [177] evaluated the economic benefits of landslide prevention measures (drainage works). They demonstrated through CBA that implementing simple drainage works can save up to EUR 3 million in preventing and treating landslides [178]. Hostettler et al. [176] assessed the effectiveness of soil bioengineering in mitigating shallow landslide events. A hybrid method was proposed in the whole experiment, including contour planting, pile walls with plants, fascines, and a drainage system. This strategy was applied to two landslide-prone areas in the Olancho department in Honduras, one near a school and the other containing two homesteads. Both CBAs show that bioengineering measures are cost-effective for mitigating landslide emergencies, with a cost–benefit ratio of 4.5 for the vicinity of the school and a BCR of 6 for the homestead, both demonstrating a high level of cost-effectiveness [176]. Grima et al. [179] pay the opportunity cost to farmers and pastoralists living in the Colombian Andes, thereby facilitating the construction of forest corridors by preserving forests or reforestation along roads. It turns out that vegetation and forests provide a cost-effective ecosystem service for preventing landslides. Compared to the value citizens pay for landslide damage, forests are 16 times more cost-effective, mitigating the economic damage caused by landslides [179]. Figure 8 shows clearly the linking of the integrated framework of this review paper.

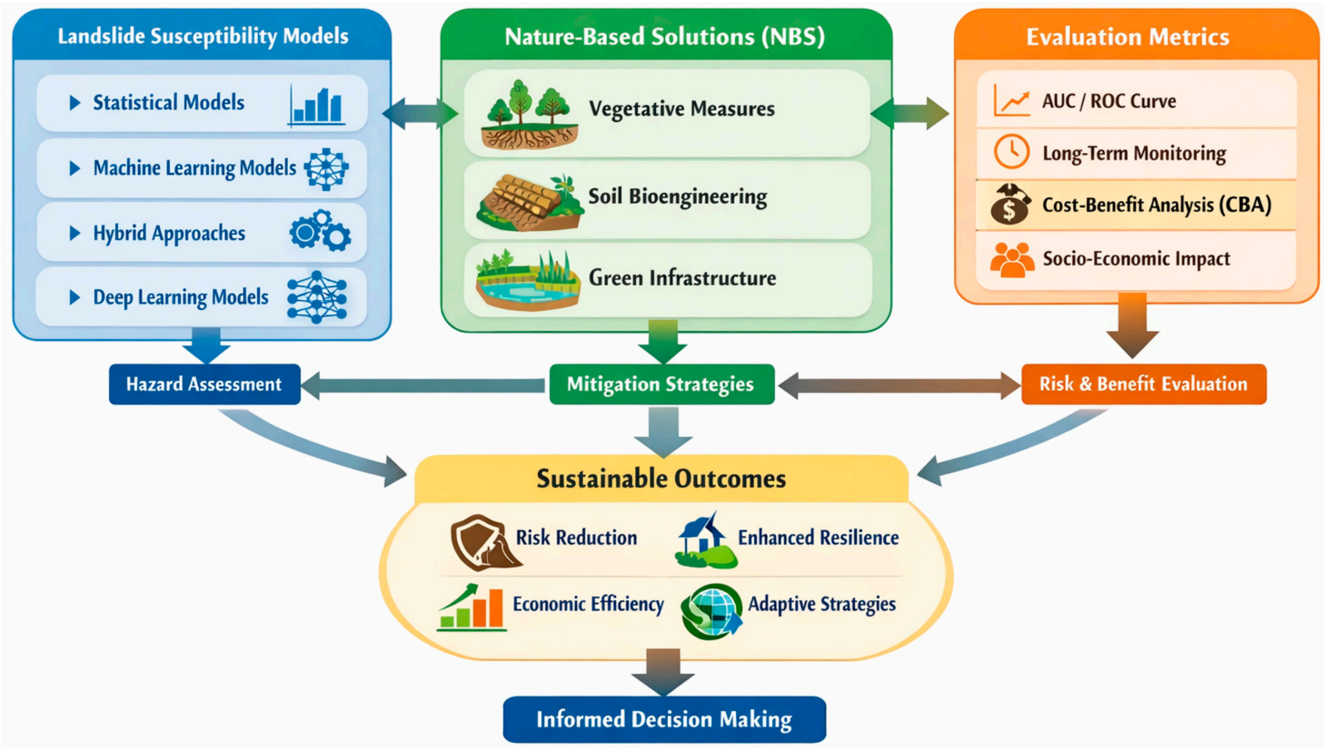

Figure 8. Integrated framework for landslide mitigation.

4.3. Connection Between Landslide, NBS, and Modeling Tools

Section 4.2 provides a detailed account of several cases where NBS has been attempted for landslide management. However, in some questionnaire surveys, it was found that the public's doubts about the effectiveness of NBS led them to still prefer grey engineering solutions [180]. And the landslide sensitivity analysis model can also be applied to evaluate the effectiveness of NBS in slope reinforcement and landslide mitigation. Hoyek et al. [181] used the landslide model as an assessment tool and employed Linear Regression (LR), Random Forest (RF), and Support Vector Regression (SVR) to evaluate the effect of floodplain restoration in NBS on improving the river ecosystem. Furthermore, Emeka et al. [182] used the AHP model to verify the impact of four major hydroseeded vegetations (ryegrass, rye corn, signal grass, and couch) on landslides in Sarten, Malaysia, and the results showed that couch vegetation had a better inhibitory effect on landslides than the other three [182]. There are many kinds of landslide sensitivity analysis models with high selectivity, which provide technical support for evaluating the effectiveness of NBS in landslide mitigation.

In the analysis of landslide sensitivity, choosing the appropriate factors is the foundation of the landslide model [183]. For the selection of the impact factor, based on the main environmental causes that can induce landslides, appropriate environmental factors are chosen as the evaluation indicators for the landslide sensitivity analysis, so as to obtain the corresponding landslide sensitivity map, which can be applied for analysis, research and prevention of the occurrence of catastrophic landslides [184]. From this, we can establish the relationship diagram among the three, as shown in Figure 9, which presents the causes of the landslide and the connection between NBS and the model tools. In the landslide model, we include positive influencing factors (NBS) and negative influencing factors (inducing factors). Based on these influencing factors, we design multiple scenarios to apply in the model, obtaining the corresponding landslide sensitivity maps. Finally, through comparison, we evaluate the role of NBS in disaster prevention and mitigation [185]. In addition, there are numerous types of landslide sensitivity models. Before evaluating the effectiveness of NBS, it is necessary to assess the performance of the models to ensure the validity of the simulation results [158].

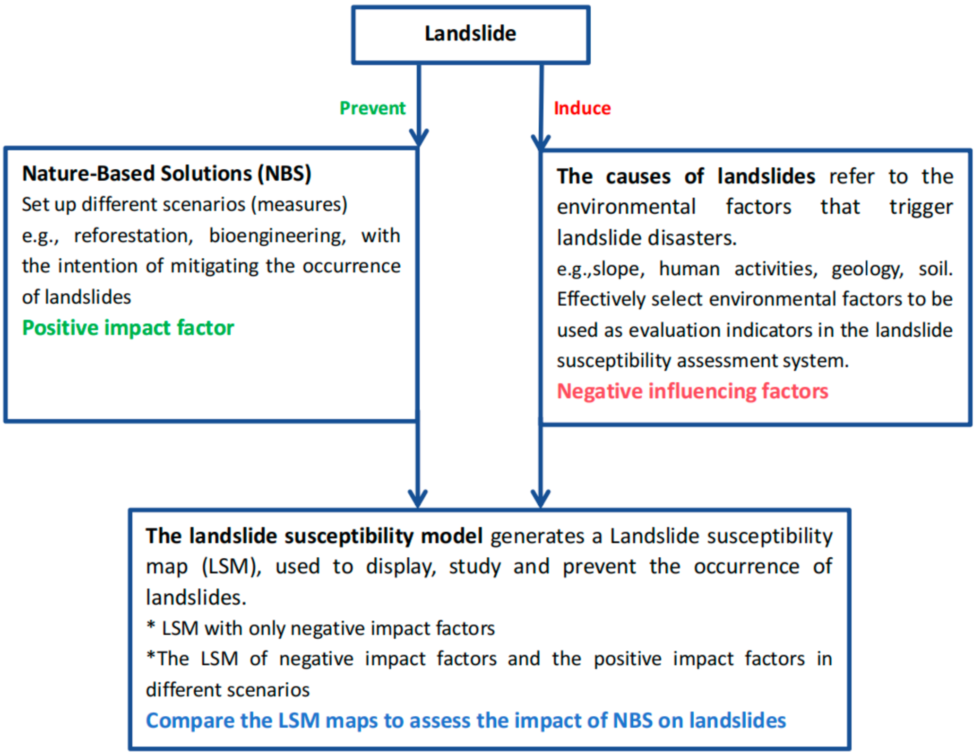

Figure 9. The framework to show connection between landslide causes, NBS approaches, and modeling tools. The synergistic framework integrating non-contact measurement, numerical simulation, and nature-based solutions (NBS) for sustainable landslide mitigation.

4.4. Integrating Non-Contact Measurement and Numerical Simulation for Large-Scale Landslide Management

NBS holds great potential as a sustainable paradigm for landslide risk reduction. Beyond ecological and bioengineering interventions, advances in numerical simulation and non-contact measurement have increasingly contributed to sustainable large-scale landslide mitigation. However, for reliable large-scale application, it is necessary to establish quantitative and predictable research on complex slope systems. Relying solely on empirical methods or traditional monitoring limits the ability to optimize different methods, predict disasters, and verify the long-term performance of disaster reduction measures (including NBS). Considering the integration of other sustainable methods such as non-contact measurement techniques and advanced numerical simulation can address these limitations and enhance the predictability and adaptability of landslide disaster reduction research.

4.4.1. Non-Contact Measurement

With the rapid development of remote sensing (RS), photogrammetry, laser, and radar technologies, non-contact monitoring methods have been widely applied in the deformation monitoring of reservoirs, dams, buildings, and geological disaster. Compared with "single-point monitoring", non-contact measurement technology can conduct high-frequency and high-precision data collection (of terrain and landform) in large areas or dangerous areas that are difficult to access and provide crucial data support for the sustainability of landslide disaster prevention [186]. The technology mainly consists of Interferometric

Synthetic Aperture Radar (InSAR) [187], Light Detection and Ranging (LiDAR) [188], and Ground-Based Synthetic Aperture Radar (GB-SAR) [189], etc. For instance, Ge et al. [190] proposed a method for monitoring the deformation effect of landslides using ground laser scanning (TLS) technology. By fitting multidimensional stereographs, they generated a three-dimensional (3D) point cloud model to simulate the displacement of the landslide at different time intervals. The displacement results were ultimately verified based on the monitoring data from the Global Navigation Satellite System (GNSS). The results confirmed that the average deformation value in this area was -0.2041 m. Finally, the displacement map was drawn to display the displacement and deformation conditions within the study area, enabling rapid identification of landslide activities and timely warnings. The overall study proved that TLS makes point cloud analysis more feasible and efficient and improves the accuracy in landslide monitoring.

4.4.2. Numerical Simulation

Landslide research, based on the underlying driving mode of the analysis method, is divided into two categories: data-driven methods and physical-driven methods [191]. The data-driven technology (including the landslide susceptibility analysis model, in Section 3) directly analyzes the patterns and correlations between environmental factors and historical landslide events from observed or simulated data, thereby completing tasks like susceptibility mapping, scenario generation, or feature identification. In contrast, physical-driven numerical simulation reconstructs the real-time state of landslides and simulates future evolution and movement by calculating explicit physical principle equations (e.g., continuum mechanics, hydrology and soil dynamics, etc.), capturing the complete evolution process of geological disasters to verify the validity of scenarios [192]. This type of method includes depth-resolved wave models [193], soil-water coupling models [194], depth-integrated continuum methods (DICMs) [195], etc. Ge et al. [196] studied the energy evolution during the rock avalanches by combining field investigation and numerical simulation. The three-dimensional discrete element code (3DEC) is one of the most widely applied numerical methods in the field of rock mechanics. It simulated the expansion process of the Jiweishan rock avalanche and verified the numerical simulation results based on field observation data. The results proved that the volume of the rock has a significant impact on the dynamic characteristics and energy transfer of the rockfall. As the volume increases, the energy transfer becomes more obvious, resulting in a greater movement distance of the rockfall. Therefore, by reducing the volume of unstable rock masses, the hazards caused by rockfalls can be mitigated.

During the review of the article, these methods usually take into account the deep synergy in practice. For instance, Necula et al. [197] utilize multi-temporal InSAR techniques and slope numerical modeling (2D Finite Difference code) to analyze the most active areas of landslides and their potential failure mechanisms. Synergistic development enhances the predictability, adaptability, and sustainability of landslide prevention research. Therefore, the optimization of landslide disaster mitigation in the future mainly lies in considering the synergy of different approaches (Figure 10). Non-contact measurement provides high-quality spatio-temporal data of the slope, serving as the input data for validating numerical simulations. Different simulation implementations calibrate models and conduct scenario tests, aiming to reflect the mechanical state of the real landslide and the effects of different intervention schemes, providing a scientific basis for the design of NBS. The final implementation was based on the optimal solution derived from the simulation to complete the landslide disaster mitigation work. Its performance was evaluated through continuous non-contact measurements to assess the ability to reduce risks, thereby forming an integrated framework for sustainable landslide disaster mitigation.

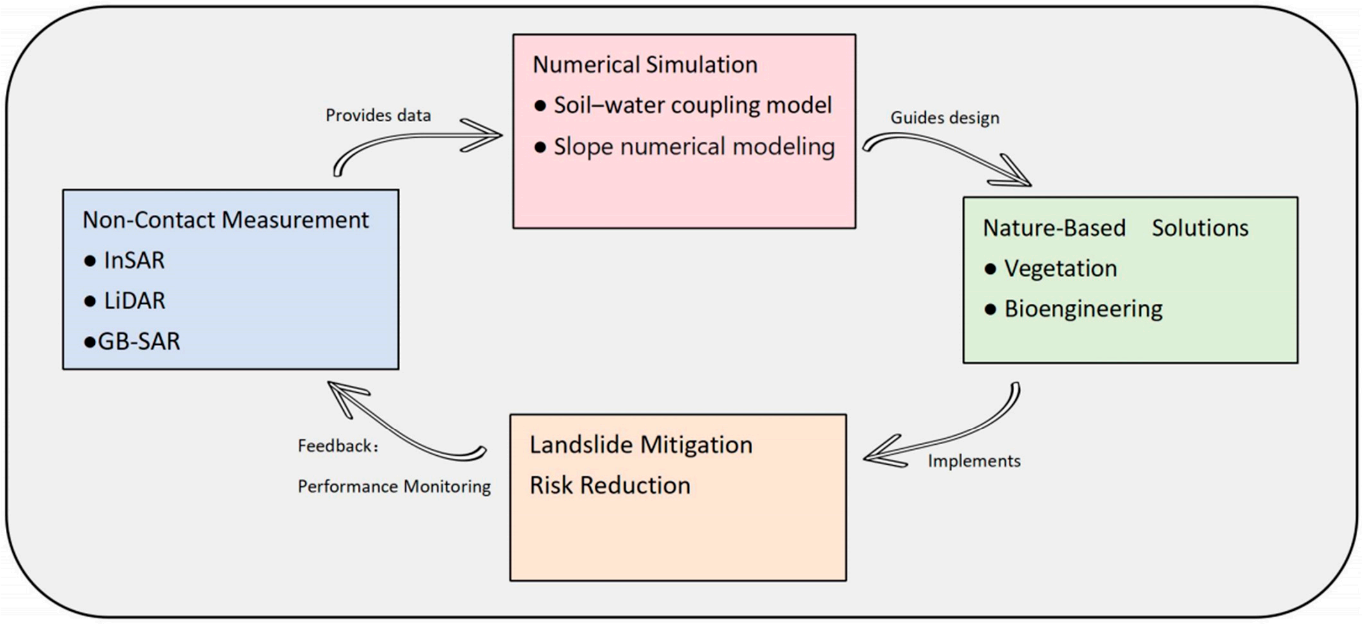

Figure 10. The synergistic framework integrating non-contact measurement, numerical simulation, and nature-based solutions (NBS) for sustainable landslide mitigation.

5. Conclusions

This review synthesizes recent advances in landslide susceptibility modeling and the application of Nature-based Solutions (NBS) for landslide risk reduction, highlighting current practices, limitations, and emerging research needs. Several key conclusions can be drawn:

There are no fixed and unified landslide condition factors in existing studies, which are generally determined subjectively through the specific conditions of the study area. In this paper, the occurrence frequency of all landslide factors was counted: the dominant factors in landslide susceptibility studies include slope (96 times), aspect (77 times), elevation (77 times), and lithology (77 times). In future studies, researchers can prioritize whether these factors are suitable for application in their study area.

In landslide research, a variety of modeling approaches are employed, and achieving high-precision simulation results depends critically on model performance. This study examines both the utilization frequency and performance of commonly applied landslide models. The performance of the model is typically evaluated using a comprehensive multi-index model to ensure the reliability and accuracy of the simulation results. However, in the modeling of landslide susceptibility, AUC and ROC remain the most important evaluation criteria. Among them, the hybrid model and the neural network model have performed exceptionally well in the research of landslide susceptibility analysis. In the future, the analysis and improvement of these two methods may become one of the core contents.

Compared with other hydro-meteorological risks, NBS has less research (2.3%) on reducing landslide risk. Most of the studies focused on evaluating the effectiveness of NBS-based measures to mitigate landslides using different models or algorithms, and studies on vegetation roots and soil bioengineering were the most popular. Among all the studies, the proportion of shallow landslides is relatively high, while there is a lack of research on the application of NBS for intermediate- and deep-level landslides. Some articles have dealt with deep landslides, but they have mainly focused on exploring the impact of rainfall on deep landslides. Research on landslides in the intermediate layer is even more scarce. In the future, emphasis should be placed on researching how NBS can be adjusted to mitigate the hazards of intermediate landslides or deep landslides or to evaluate the effectiveness of NBS in dealing with intermediate landslides or deep landslides.

The public acceptance of general infrastructure (gray facilities) is higher than that of NBS, mainly due to the lack of knowledge about NBS and its "uncertainty". In the future, the landslide sensitivity model can be used as a tool to assess the role of NBS in landslide prevention and control. In addition to this, it should be noted that the economic value (cost–benefit analysis) of NBS should be considered in the study of reducing landslide risk, so as to monetize the ability of NBS in reducing landslide, which can provide more intuitive evidence support. In addition, more attention should be paid to socio-economic trade-offs. The impact of NBS on the economy should comprehensively assess the environment, people's livelihoods, and disaster prevention. Rational and comprehensive planning schemes should be developed that are more acceptable and conducive to development by the public. As well, appropriate consideration of the coordinated development of NBS and gray infrastructure should be given. NBS can complement, not replace, engineering solutions. Will this hybrid solution enhance the popularity and effectiveness of NBS in the future? The proposed solution lacks long-term monitoring research in the process of landslide mitigation and control. It is unknown whether NBS can operate stably and safely in the long term and effectively manage disasters in landslide prevention. More research is still needed in the future to prove its stability. All of the above are the research directions of NBS in landslide disasters in the future. Future research should integrate multi-hazard simulation, climate scenario analysis, and socio-economic valuation to strengthen the implementation of NBS within national adaptation strategies.

Looking forward, future research should prioritize the following:

i The integration of NBS with hybrid and gray infrastructure solutions rather than treating them as standalone alternatives;
ii Multi-hazard and climate change-informed modeling frameworks to assess NBS performance under future rainfall and extreme-event scenarios;
iii The application of socio-economic valuation to support policy uptake and national adaptation strategies;
iv Long-term empirical monitoring to evaluate the durability, stability, and safety of NBS in landslide-prone areas;
v Future research should actively consider the sustainability and synergy potential of landslide analysis methods to enhance the scientific depth of the studies and their relevance to society.

Overall, strengthening the linkage between advanced landslide susceptibility modeling, NBS effectiveness assessment, and socio-economic evaluation will be essential to enhance the scientific credibility, practical applicability, and public acceptance of NBS for sustainable landslide risk management.

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