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Hybrid landslide susceptibility modelling for rainfall-triggered landslides in forested slopes: a review for bridging physics-based and machine learning methods

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Abstract

Background: Managing the risk of shallow landslides is important for any land use in steep terrain. This is especially true for plantation forestry in New Zealand, where construction of forest roads or clear-fell harvesting can exacerbate both frequency and scale of rainfall-induced shallow landslides. In forestry, landslide susceptibility mapping has typically been completed using heuristic field-based methods. Geospatial empirical and statistical models, mainly based on past storm events have predictive performance at scale but are limited by their lack of physical grounding. Conversely, deterministic physics-based slope stability methods, while interpretable, require detailed geotechnical data that are not available at operational scales. Recent advances in hybrid models offer a pathway to combine the mechanistic transparency of physics-based methods with the flexibility of data-driven geospatially based algorithms.

Methods: This review evaluates recent research on hybrid landslide susceptibility modelling for rainfall-triggered shallow landslides, with a particular focus on applications relevant to plantation forestry. Using a structured literature search across major databases from 2010 to 2024, 94 peer-reviewed studies were used to inform the development of six recurring categories of hybrid integration: physically derived features, physics-guided loss or constraint functions, physics-inspired or interpretable network architectures, physics-guided sample selection, physics-driven metaheuristic optimisation, and joint susceptibility-intensity modelling. The characteristics, strengths, opportunities and limitations of each category were synthesised based on the reported model structure, type of physical integration, interpretability, scalability, and relevance to operational forestry applications.

Results: Hybrid models demonstrate a strong potential to enhance slope-stability assessment in forestry operations by reducing data demands, improving interpretability, and enabling physically consistent, large-area mapping. The unique nature, strengths, opportunities and limitations of each hybrid model category are outlined and compared.

Conclusions: The findings highlight the opportunity to transition towards interpretable neural-network modelling approaches that learn relationships between environmental variables while embedding physically meaningful geotechnical and hydrological processes within the model structure. Successful development would support forestry land managers identify localised shallow landslide risk to support the operational planning.

Keywords: Forestry; hybrid modelling; interpretable neural networks; landslide risk; machine learning; rainfall-induced landslides

Introduction

Shallow landslides are a dominant erosion process on steep slopes in New Zealand, where plantation forestry often occupies terrain that is highly susceptible to rainfall-triggered slope failures (Marden et al. 2006; Basher et al 2008; Phillips et al. 2012). Shallow landslide events threaten soil productivity, water quality, and downstream infrastructure, representing a major challenge for sustainable forest management (Crozier 2005; Smith et al 2023). For the forest industry, construction of infrastructure such as roads and landings, as well as clear-fell harvesting, can directly add to that risk (e.g. O'Loughlin 1974; Phillips et al 2012; Griffiths et al. 2020).

The need for identifying and mapping landslide susceptibility has long been considered critical for forest management in steep terrain (Pearce & Gage 1977; Phillips et al. 2024), whereby Marden et al. (2005) proposed that detailed terrain stability mapping be mandatory in erodible steep lands. Smith (2024) provided a thorough review of the possible implementation of national and international approaches as they relate to New Zealand plantation forestry. Internationally, examples from Oregon, USA (OSG 2003), Washington, USA (WDNR 2016) and British Columbia, Canada (ABCFP 2008) show that with expertise and over time such processes can be formalised within a regulatory framework. These established detailed evaluation processes attempt to combine heuristic experience from steep slope forestry with deterministic geotechnical engineering fundamentals.

Heuristic (field-based) approaches

A heuristic approach to identify landslide-prone areas relies on field observations, qualitative overlays and expert judgment (Marden et al. 2015; Smith 2024). Crozier and Glade (2005) provided an early review of heuristic mapping approaches, highlighting that although these models can offer useful preliminary risk assessments, their predictive performance often deteriorates when extrapolated beyond calibration areas. Typical methods involve manually defined slope thresholds, geomorphological mapping, and land use assessments (e.g. Kritikos & Davies 2015; Smith 2024), and involve simplified thresholds and assumptions about factor interactions that limit their reproducibility across different regions (Phillips et al 2017). They might require expert-based zonation maps that combine slope thresholds, lithology, soil drainage classes, and land cover to generate landslide hazard zoning, making them intuitive for experienced users but prone to expert bias (Smith 2024; Kritikos & Davies 2015).

For forestry land-use in New Zealand, the National Environmental Standard for Plantation Forestry (NES-PF) established land-use classes into four 'Erosion Susceptibility Classification' (ESC) categories (Bloomberg et al. 2011). This was based on the existing land use capability (LUC) system that was first published in 1969, with the most recent update in 2009 (Lynn et al. 2021). The ESC 'red' category denoted Very High erosion risk and has served as a proxy for both landowners and regulatory agencies to apply different risk mitigation strategies to mitigate accelerated erosion and shallow landslide risk. However, the broad soil mapping of the LUC provides both uncertainty and little detail at a scale appropriate for operational planning by forest managers (Basher & Barringer 2017).

Deterministic (geotechnical) approaches

Physics-based geotechnical models simulate slope stability through mechanistic equations that represent the balance between driving and resisting forces acting on a potential sliding mass. Many regional landslide susceptibility models rely on limit-equilibrium formulations that compute a Factor of Safety (FS), although other numerical approaches such as finite-element modelling are also widely used in geotechnical slope-stability analysis. They typically incorporate soil strength, soil cohesion, slope angle, soil friction angle, pore-water pressures, and other hydrological factors (Marden 2012; Phillips et al. 2012). These deterministic models simulate slope stability by explicitly solving geotechnical and hydrological equations, most often via the calculation of a Factor of Safety (FS). To support wide-scale professional application for geotechnical engineers, such models are utilised as software programmes. An example is the SHALSTAB model that integrated steady-state hydrological assumptions with slope stability analysis based on terrain and soil properties (Montgomery & Dietrich 1994). Pack et al. (1998) introduced SINMAP, an extension of SHALSTAB, that incorporates probabilistic uncertainty into FS estimates and has been used for mapping shallow landslide susceptibility in forested environments. Another example is Scoops3D that calculates three-dimensional FS values across complex terrain using Bishop's Simplified Method (e.g., Wang et al. 2024). Although originally developed for site-specific analysis, newer adaptations have incorporated Scoops3D outputs into machine learning (ML), bridging toward the concept of hybrid modelling.

TRIGRS (Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability Model) extends deterministic models by dynamically simulating transient pore-water pressure changes during rainfall events (Baum et al. 2008). By incorporating these principles into a grid-based framework, TRIGRS enables temporal modelling of rainfall-triggered shallow landslides.

Geospatial statistical models

The recent expansion of geospatial capabilities provides new and detailed data from sources such as satellite (Rosser et al. 2019) or LiDAR (Xu et al. 2025) technologies. Using this detailed information, geospatial statistical models can establish correlations between known landslide occurrences and conditioning factors such as slope, terrain curvature, rainfall, and land cover. Example techniques include Logistic Regression, as applied by Schicker and Moon (2012) to regional landslide susceptibility mapping in the Waikato Region, New Zealand. Generalized Additive Models (GAM) allow more flexible nonlinear relationships between environmental factors and landslide occurrence compared to standard logistic regression. This has offered improved fitting without requiring deep ML methods (Persichillo et al. 2016).

Geospatial statistical and empirical models provide useful baselines for landslide susceptibility mapping, particularly where datasets are moderate and the aim is transparent, interpretable results. In New Zealand forestry logistic regression has been used for making detailed regional slope stability risk maps and remains the most interpretable and transferable of these approaches (e.g. Smith et al. 2021; Spiekermann et al. 2023; Brenning 2005).

Machine-learning models

The application of Machine Learning (ML) models to support shallow landslide identification has become dominant due to their ability to discover nonlinear patterns in complex, high-dimensional datasets without requiring explicit physical assumptions. The approach uses algorithms to predict landslide susceptibility based on historical patterns and high-dimensional datasets. Widely used ML models include Random Forest, where Catani et al. (2013) showed it to outperform traditional statistical methods by capturing complex interactions between terrain, lithology, and land cover. Support Vector Machines (SVM) deal with nonlinear boundaries and high-dimensional input spaces, outperforming logistic regression in predictive performance (Brenning 2005). Sahin (2020) implemented XGBoost models for regional landslide susceptibility, where an Ensemble Tree Boosting method showed superior predictive performance compared to RF and SVM, especially when handling imbalanced datasets.

Conforti et al. (2014) employed basic Artificial Neural Networks (ANNs) alongside statistical methods to predict landslide-prone areas. Although ANNs captured complex relationships, their lack of transparency posed challenges for operational use in forestry planning. Adnan Ikram et al. (2024) advanced landslide susceptibility modelling by combining Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) for dynamic spatio-temporal prediction. Their deep learning framework incorporated sequences of rainfall and environmental variables, achieving high accuracy in temporal landslide forecasting.

Machine learning models offer substantial improvements in predictive accuracy and scalability for landslide susceptibility mapping (Table 1). However, their reliance on large training datasets and the black-box nature of their algorithms underscores the need for the introduction of physics-informed and interpretable hybrid approaches. While each modelling paradigm has advanced the field, gaps remain, particularly in balancing scalability, interpretability, and physical realism, key requirements for operational applications in forestry and other dynamic landscapes.

Hybrid models

The complementary strengths and limitations of physics-based and data-driven approaches have led to a growing interest in hybrid frameworks that integrate geotechnical principles with the flexibility of data-driven algorithms within machine-learning architectures (Pei & Qiu 2024; Youssef et al. 2023). Such frameworks aim to preserve the mechanistic rigour of slope-stability theory while exploiting the pattern-recognition power of modern algorithms applied to geospatial datasets (Wang et al. 2024; Dahal & Lombardo 2024; Youssef et al. 2023). Recent comparative analyses consistently confirm that hybrid models outperform purely data-driven or deterministic approaches by combining physical interpretability with predictive scalability (e.g., Ye et al. 2025; Sachinthaka et al. 2025; Jiang et al. 2026; Al-Najjar et al. 2025).

Despite growing international progress, no review has systematically examined how these hybrid methods are structured, what types of physical information

TABLE 1: Summary of approaches used in landslide susceptibility assessment

Approach	Description	Strengths	Limitations	Example Studies
Heuristic (field-based)	Qualitative, expert-driven assessments using checklists, slope thresholds, or empirical overlays	Simple, intuitive, low data requirements	Subjective, non-transferable, lacks predictive rigour	Crozier & Glade (2005), Kritikos & Davies (2015), Simon Smith (2024)
Deterministic (geotechnical)	Simulates slope stability using soil mechanics and hydrology to compute FS or displacement	Mechanistic, physically grounded, interpretable	Requires detailed inputs (soil, depth), limited scalability	SHALSTAB (Montgomery & Dietrich, 1994); SINMAP (Pack et al. 1998); Newmark Method, Scoops3D, Bishop's Simplified Method (Bishop 1955)
Geospatial/statistical	Correlates landslide presence with conditioning factors using regression or statistical inference	Transparent, easy to interpret, moderate data needs	Assumes linearity, sensitive to input data and sampling bias	WoE (Schicker & Moon 2012); GAM (Persichillo et al. 2016) Logistic Regression (Smith et al. 2023, Spiekermann et al. 2023)
Machine-learning	Learns complex patterns from high-dimensional data without explicit physical assumptions	High accuracy, handles non-linearity, scalable	Often a "black box"; limited interpretability; needs large datasets; challenging to operationalise in forestry settings	RF (Catani et al. 2013); XGBoost (Sahin 2020); ANN (Conforti et al. 2014); SNN (Youssef et al. 2023)

they integrate, or how applicable they are to forestry. This review addresses that gap by systematically synthesising recent advances in hybrid and physics-informed landslide-susceptibility modelling. The goal is to support a conceptual foundation for developing next-generation tools for landslide-risk assessment and planning in New Zealand's rainfall-sensitive steep slope forested landscapes.

Methodology

This review adopted a semi-systematic approach following the SALSA and PRISMA frameworks to ensure transparency and reproducibility (Grant & Booth 2009; Page et al. 2021). The goal was to identify peer-reviewed studies that combine physics-based and data-driven approaches for landslide susceptibility modelling, particularly rainfall-triggered shallow landslides in forestry landscapes.

The search was conducted in early 2025, using the Scopus, Web of Science, and Google Scholar databases. The following Boolean combination of keywords was applied to titles, abstracts and keywords: ("hybrid" OR "physics-informed" OR "physics-based" OR "physics-guided") AND ("machine learning" OR "neural network" OR "XGBoost" OR "Random Forest") AND ("landslide" OR "slope stability" OR "susceptibility") AND ("rainfall" OR "shallow" OR "forestry").

The search was restricted to English-language publications from 2010 to 2024. Reference lists of selected papers were also screened to identify additional relevant studies. Studies were included if they:

- analysed rainfall-triggered or shallow landslides;
- employed hybrid, physics-informed, or physics-guided machine-learning approaches;
- provided quantitative results or model-validation metrics; and
- presented sufficient methodological detail for appraisal.

Excluded were papers that:

- focused exclusively on earthquake-induced landslides;
- used purely deterministic physics-based models without data integration; or
- relied solely on statistical or heuristic mapping lacking any physical component.

Applying the inclusion criteria, 94 peer-reviewed studies were identified and used to inform the qualitative synthesis and development of the six hybrid-model categories. For each selected study, the following information was extracted:

- geographical location and spatial scale;
- triggering mechanism (rainfall or mixed);
- input datasets (e.g. terrain, soil, geology, precipitation);
- modelling approach (physics-based, ML, or hybrid type); and
- evaluation metrics (e.g., AUC, accuracy, precision, recall, confusion matrix).

Hybrid and physics-informed model categories

From the literature search, six categories were developed based on repeatedly observed patterns. 'Hybridisation' is not a single process but occurs at different integration levels between physical and data-driven components. Therefore, the categories were developed according to where and how physical knowledge is introduced into the ML workflow:

1. Physically derived features used as ML inputs.
2. Physics-guided loss or constraint functions.
3. Physics-inspired or interpretable network architectures.
4. Physics-guided sample selection.
5. Physics-based metaheuristic optimisation; and
6. Joint susceptibility-intensity modelling.

Each category represents a distinct integration stage. The following sections describe these category differences and highlight the strengths and opportunities for each.

1. Physically derived features as ML inputs

One of the most direct strategies for integrating physical knowledge into machine-learning models is to incorporate physically derived variables or hydrological indices as input features alongside traditional geospatial predictors (e.g., slope, curvature, and soil texture). Examples of physically derived variables include the SHALSTAB and Scoops3D outputs. The physical parameters are only used as model inputs without modifying the algorithm. This approach enriches the feature space with geotechnical information, allowing data-driven algorithms to learn physically meaningful patterns without explicitly solving slope-stability equations.

Several studies have demonstrated the effectiveness of this approach. Pei & Qiu (2024) combined simplified hydrological modelling with XGBoost, using FS values derived from steady-state infiltration assumptions to improve the physical consistency and generalisation of susceptibility predictions. Wang et al. (2024) incorporated FS maps from Scoops3D stability analysis into Random Forest and XGBoost frameworks, enhancing the robustness and interpretability of rainfall-induced shallow landslide predictions. Liu et al. (2023) similarly developed a physics-informed data-driven model by integrating FS outputs from Jibson (2007) into a Random Forest classifier, showing improved model stability and spatial transferability. Cheon et al. (2025) further demonstrated the use of physics-based FS computations within a neural-network architecture for real-time landslide monitoring in mountainous terrain.

In forestry applications, this strategy is particularly attractive because it leverages existing physics-based terrain analyses (e.g., SHALSTAB or SINMAP outputs) as spatially continuous proxy layers. In many steep forested landscapes, direct soil and hydrological measurements remain limited, which constrains the application of fully parameterised physics-based models at operational scale. Combined with high-resolution digital elevation models (DEMs) and rainfall data, FS-based hybrid inputs enable scalable susceptibility mapping across large forest estates while maintaining geotechnical interpretability. In a New Zealand forestry context, a study by Hashemi and Visser (2026) demonstrates how GIS-derived environmental layers and relevant geotechnical parameters can be combined in a Python-based workflow to generate regional-scale FS estimates that can support landslide susceptibility assessment and serve as physically meaningful inputs for machine-learning models.

2. Physics-guided loss or constraint functions

A more advanced hybridisation strategy involves embedding physical constraints directly into the loss function of a ML model. In conventional ML models, loss functions such as Mean-Squared Error or cross-entropy focus purely on minimising statistical prediction error. In contrast, physics-guided loss formulations add a regularisation term derived from geotechnical principles, such as the FS or stress-strain relationships, thereby guiding the learning process toward physically plausible solutions.

Dahal and Lombardo (2024) developed a physics-regularised neural network where constraint violations (e.g., FS>1 for stable cells) contributed to the total loss, improving both interpretability and predictive stability. Pei & Qiu (2024) also utilise physically derived inputs, their work qualifies as a distinct integration category because they additionally modify the loss function itself. Their physics-guided loss formulation augments the XGBoost objective with FS-based penalties, ensuring that unstable slopes (FS<1) are not misclassified as stable. This represents a fundamentally different integration mechanism from simply providing FS as an input feature. Karniadakis et al. (2021) demonstrated that embedding physical constraints directly into the loss function substantially improves model robustness, especially in data-sparse conditions, providing a strong conceptual basis for landslide-susceptibility applications.

Physics-guided loss functions therefore represent a technically demanding yet powerful method of embedding domain knowledge within ML models. Their adoption is an opportunity for physically consistent landslide susceptibility and other geotechnical applications, particularly where purely empirical models struggle to generalise across diverse terrain such as New Zealand's forested hill country.

3. Physics-inspired or interpretable network architectures

A deeper level of integration between physical understanding and data-driven modelling is achieved through physics-inspired network architectures, where the structure of a neural network is designed to mimic or constrain physical processes. Rather than treating the model as a generic black box, the architecture itself encodes aspects of slope-stability mechanics or hydrological behaviour, constraining how information flows through the network.

In such architectures, intermediate layers or subnetworks can represent physically meaningful components; for example, hydrology, soil mechanics, or terrain morphology whose outputs are later combined to estimate overall slope stability. This modular structure mirrors how different processes contribute to landslide initiation.

For implementing this approach, Youssef et al. (2023) proposed the Superposable Neural Network (SNN) in which features are grouped into interpretable subnetworks representing physical themes such as hydrological control, terrain geometry, and land-cover stability. These subnetworks are superposed to form a composite susceptibility prediction, preserving explainability while maintaining competitive accuracy. Dahal and Lombardo (2024) designed custom neural architectures in which intermediate outputs corresponded to variables like shear stress or water-table depth, producing physically traceable model behaviour. In related Earth-science applications, Physics-Informed Neural Networks (PINNs) explicitly embed partial-differential-equation constraints into the learning process, demonstrating how network design can directly encode governing equations (Raissi et al. 2019).

Physics-inspired architectures provide a promising frontier for landslide-susceptibility modelling as it combines the flexibility and scalability of deep learning with the credibility and mechanistic transparency required for risk management in forest operations. However, practical adoption remains limited by computational cost and the need for well-parameterised physical priors, particularly across data-sparse forest landscapes such as those in New Zealand.

4. Physics-guided sample selection

Another hybridisation strategy integrates physical reasoning at the data-sampling stage, where training and validation samples are selected or weighted based on slope-stability conditions predicted by deterministic models. Instead of relying solely on random or balanced sampling of landslide and non-landslide points, this approach uses physically meaningful indicators such as the Factor of Safety (FS) or hydrological thresholds to ensure that the dataset reflects realistic slope-stability dynamics.

Physics-guided sampling improves both class balance and physical interpretability by excluding terrain zones that are physically implausible (e.g., flat areas with FS $\gg$ 1 or digital artefacts). Models learn to discriminate within geotechnically meaningful ranges. The resulting datasets emphasise boundary conditions near instability thresholds, which are most relevant for risk assessment.

Liu et al. (2023) and Fu et al. (2025) highlight that carefully selecting non-landslide samples based on stability criteria or information-value thresholds substantially improves prediction accuracy and reduces spatial bias in machine-learning susceptibility maps. Dou et al. (2023) further demonstrated that physically consistent sample selection mitigates model overfitting and enhances transferability across diverse terrains. Wang et al. (2024) adopted a physics-based strategy in which unstable pixels (FS < 1) from Scoops3D outputs served as positive samples and stable ones (FS > 1.5) as negatives in an XGBoost framework.

For forestry applications, physics-guided sampling offers a practical advantage. It enables regional-scale models to capture slope-stability variability across different terrain, soil, and rainfall conditions without exhaustive field inventories. By screening DEM-derived layers using FS-based stability outputs, forest managers can generate balanced, physically meaningful datasets.

5. Physics-based metaheuristic optimisation

Metaheuristic optimisation algorithms, such as Genetic Algorithms (GA), Particle Swarm Optimisation (PSO), and Ant Colony Optimisation (ACO), have become increasingly popular in landslide-susceptibility modelling for fine-tuning model parameters while respecting physical constraints. In hybrid frameworks, these algorithms function as physics-guided search engines, embedding geotechnical thresholds (e.g., minimum Factor of Safety, cohesion limits, or hydraulic-conductivity ranges) directly into the optimisation process.

For example, Adnan Ikram et al. (2024) developed an evolutionary-optimised neural network that incorporates soil-strength constraints during the parameter search step. Their PSO-based model restricted parameter updates to physically possible nature-inspired algorithms domains, reducing the risk of overfitting to non-physical correlations. Pei and Qiu (2024) combined physics-informed loss functions with metaheuristic hyper-parameter tuning, allowing the model to converge toward solutions that were both physically consistent and statistically optimal. Liu et al. (2023) similarly demonstrated that embedding FS-based physical priors into the learning process of ML models enhances robustness and generalisation. Dahal and Lombardo (2024) further illustrated how PINN-based optimisation can impose stability-related constraints on the training objective, effectively integrating the governing slope-stability equations into the learning process.

Metaheuristics can also be applied to optimise the FS computation itself, as shown by Wang et al. (2024), who employed GA to calibrate shear-strength parameters in Scoops3D before using the resulting FS map as an ML input. For forestry slope management, this approach offers strong potential in areas where soil or geotechnical properties vary widely or remain poorly constrained. Embedding physically constrained optimisation enables models to adapt to spatial heterogeneity in plantation landscapes while maintaining geotechnical realism.

6. Joint susceptibility-intensity modelling

A different hybridisation strategy is to jointly model landslide initiation susceptibility with intensity-related outcomes, linking physics-based process outputs to geospatial statistical or machine-learning predictors. In practice, this means combining a susceptibility component (probability of landslide initiation) with intensity proxies, potential runout extent, or physically derived FS margins. The objective is to move beyond “where failures may occur” toward “how severe they may be,” while retaining geotechnical consistency.

Two common workflows are used. The first is sequential (two-stage) pipelines: a physics-based module (e.g., SHALSTAB, SINMAP, Scoops3D) generates FS or stability margins that inform a statistical or ML model of landslide initiation, and a second module estimates intensity using physically motivated metrics (e.g., hydrologic loading indices) or empirical scaling relationships (e.g., frequency-area distributions). The second is a constrained single-stage learning: an ML model predicts the probability of landslide initiation while being standardised by physics-based terms in the objective (FS thresholds, stability constraints), effectively tying probability and intensity signals within the same optimisation.

Recent studies illustrate these ideas: Wang et al. (2024) used Scoops3D-derived FS within tree-based ML classifiers, improving physical realism of initiation mapping; Pei and Qiu (2024) imposed FS-based penalties in the loss function to keep predictions aligned with stability conditions; and Dahal and Lombardo (2024) showed how physics-informed neural networks can embed governing mechanics directly into training. Classic intensity measures such as shown by Jibson (2007) and landscape-scale scaling relations by Malamud et al. (2004) provide practical proxies that can be fused with susceptibility predictions to help prioritise mitigation actions.

For planning forestry operations such as road construction, joint frameworks are attractive because they produce actionable layers: initiation probability for planning and severity surrogates (e.g., potential displacement/runout). Key challenges include propagation of uncertainty between modules, scale mismatch (cell-scale physics vs. landscape-scale ML), and limited intensity ground truthing. Addressing these requires clear reporting of uncertainty, harmonised spatial resolution between components, and, where possible, hierarchical designs (local FS constraints informing regional susceptibility) to preserve physical meaning while remaining scalable.

Discussion

The integration of physical principles with ML represents a promising evolution in landslide-susceptibility modelling, particularly for rainfall-triggered shallow failures in forested steep slope terrain. The hybridisation strategies reviewed in this study demonstrate that physics-informed machine learning can support this development. By embedding geotechnical variables into model training and validation, hybrid approaches improve both interpretability and generalisation.

A key challenge remains the alignment of spatial scales between physically derived inputs and ML features derived from geospatial datasets. Physics-based models typically operate at slope or small catchment scales, whereas ML models often generalise across large regions. Future hybrid frameworks should explicitly address this scaling issue, possibly through multi-resolution architectures or hierarchical FS feature integration, where local slope stability informs broader spatial predictions. In forested environments, rainfall-soil interactions can be influenced by vegetation processes such as canopy interception, root reinforcement, and changes in soil moisture dynamics.

Another major opportunity lies in enhancing model interpretability. Superposable Neural Network (SNN) and physically constrained architectures like PINNs provide templates for achieving transparency without sacrificing accuracy. These frameworks allow each subnetwork or node to represent a physically meaningful process, such as hydrological loading, soil shear strength, or vegetation reinforcement, making outputs more intuitive for decision-makers.

Although most hybrid landslide-susceptibility models reviewed were developed in diverse geomorphological settings, their methodological advances have clear opportunities for New Zealand plantation forestry. Steep terrain, highly erodible sedimentary lithologies, and intense rainfall events create conditions where shallow landslides are a persistent management challenge. Hybrid modelling frameworks that combine physically meaningful parameters with scalable machine-learning algorithms offer a pathway to develop operational tools capable of supporting forest planning and risk management. Approaches that incorporate physically derived features such as factor-of-safety estimates or hydrological indices can help bridge the gap between regional-scale susceptibility mapping and the site-specific geotechnical understanding required for forestry operations.

Physics-informed ML approaches can deliver tangible operational benefits for forest managers. They can produce spatially continuous risk maps that integrate digital terrain data, rainfall records, and soil information into an interpretable decision-support framework. Such hybrid tools are particularly valuable where traditional field assessments are cost-prohibitive or not feasible. Despite these advantages, the development of hybrid models remains relatively young and standardised evaluation frameworks are still lacking. Few studies have quantified uncertainty propagation from physical parameters into ML predictions.

Future developments should prioritise interpretable and physics-aligned neural architectures, quantification of uncertainty in hybrid modelling frameworks, and integration with high-resolution remote-sensing data. By uniting geotechnical theory and machine-learning adaptability, hybrid models represent not only an academic advance but also a practical evolution toward transparent, data-driven decision support for improved forest land management.

Conclusions

Landslide-susceptibility modelling is undergoing a rapid transformation driven by the convergence of physics-based reasoning and machine-learning innovation. This review has outlined how hybrid and physics-informed approaches bridge mechanistic understanding and predictive power, offering scalable and interpretable tools for rainfall-triggered shallow landslides in forested terrain.

Six principal integration strategies were identified and collectively these approaches demonstrate that embedding geotechnical principles within artificial intelligence workflows can enhance interpretability, improve scalability and provide risk assessment at finer resolutions.

For New Zealand's forestry sector, where shallow, rainfall-triggered failures are a persistent post-harvest challenge, hybrid models provide a pathway toward efficient and evidence-based slope-risk management.

Competing interests

The authors declare that they have no competing interests

Authors' contributions

MH conceptualised and designed the review, conducted the literature search and study screening, developed the review framework and hybrid-model categories, synthesised and interpreted the literature, and drafted and revised the manuscript. RV contributed to the conceptual development of the review, supervised the research, provided critical intellectual input, and reviewed and edited the manuscript. Both authors read and approved the final manuscript.

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