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REVIEW ARTICLE

Evolution and critical evaluation of deterministic physically based rainfall-induced landslide susceptibility mapping: a mixed review

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Abstract

Physically-based models play a critical role in assessing rainfall-induced landslide susceptibility, offering valuable insights into landslide hazard prediction and risk mitigation. This study conducts a scientometric and systematic review of deterministic, physically-based, rainfall-induced landslide susceptibility mapping, synthesising research trends and advancements in this domain. A comprehensive literature search, conducted through the Scopus database following PRISMA guidelines, identifying 70 key studies for in-depth analysis. The findings reveal significant progress, including the integration of climate change projections, enhanced real-time monitoring systems, and advancements in high-resolution data processing. Despite these developments, challenges persist in achieving a balance between model complexity and practical applicability. This review highlights the need for standardised validation protocols, robust uncertainty analysis, and interdisciplinary approaches that merge physical modelling with machine learning techniques. By evaluating the evolution and current state of deterministic physically-based landslide modelling, this study provides a valuable reference for researchers and practitioners, contributing to the advancement of more reliable and accessible landslide susceptibility assessments.

Keywords Landslide susceptibility · Physically-based deterministic models · Rainfall-induced landslides · Hydrological approaches

1 Introduction

Natural hazards have become more frequent over the past two decades, posing significant risks to human lives, infrastructure, and the environment (Kumari et al. 2025). Among the various natural hazards, landslides have led to some of the most prevalent natural disasters

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(Alcántara-Ayala 2025; Qiu and Wei 2025). Earthquakes and rainfall are widely recognised as primary triggers of landslides (McColl 2022). Among these landslides, rainfall-induced landslides are more common and tend to be shallow landslides, involving shallow soil (up to 2–3 m) (Ran et al. 2018; Tohari 2018). Rainfall-induced landslide occurrence represents the final stage of a sequential process that begins with rainfall infiltration, which progressively weakens the slope and ultimately leads to failure (Cotecchia et al. 2016; Shroder 2021). On the other hand, landslide susceptibility is the likelihood of a landslide occurring in an area on the basis of local terrain conditions (Brabb 1984). Therefore, accurately modeling landslide occurrence is crucial for effective land-use planning, as it aids in hazard assessment and mitigation strategies (Wang and Nanehkaran 2024).

Landslide susceptibility mapping (LSM) methods, often called modelling methodologies, have evolved with time (Liu et al. 2023). Broadly, they can be categorised into qualitative, semi-quantitative, and quantitative as described by Das et al. (2023). Among these, Physically Based Deterministic Models (PBDM) fall under quantitative methods, as they quantify the balance of forces acting on slopes, typically using a Factor of Safety (FS) to assess local stability or instability (Bednarik et al. 2024). These methods are grounded in fundamental geotechnical and hydrological principles, incorporating key parameters such as rainfall infiltration, soil strength, groundwater dynamics, and topographic conditions to simulate slope stability (Ebrahim et al. 2024; Sannino et al. 2024). Unlike empirical or statistical approaches, PBDMs provide a process-driven analysis of landslide mechanisms, offering greater reliability and predictive accuracy, particularly in regions with limited historical landslide data (Fumagalli 2025). Furthermore, Ciurleo et al. (2017) emphasised that PBDMs can accurately depict the actual physical processes triggering landslides compared to empirical or statistical models.

Recent climate change trends have significantly altered rainfall patterns, leading to increased cumulative precipitation and a higher frequency of extreme weather events (Ebi et al. 2021; Oguz et al. 2024). These changes have substantially contributed to the rise in rainfall-induced landslides, as prolonged and intense precipitation accelerates soil saturation, increases pore-water pressure, and reduces slope stability (Fumagalli 2025). Apart from the above mentioned advantages, PBDMs are considered the most effective tools for rainfall-induced LSM (Ebrahim et al. 2025; Zhao et al. 2025).

PBDMs have gained widespread acceptance within the engineering and scientific communities for landslide susceptibility analysis (Sannino et al. 2024). These models are not only applied at local scales but are also increasingly used for larger regional assessments, as they effectively capture the dynamic variability of slope stability conditions. The integration of remote sensing technologies has further enhanced their applicability over large areas, enabling comprehensive landslide monitoring in locations where traditional ground-based surveys are impractical (Ji and Cui 2023). PBDMs are particularly valuable for disaster preparedness and policy planning, as they can predict landslide occurrences in advance, assisting in the development of early warning systems (Park et al. 2019a, b; Sannino et al. 2024).

Despite the increasing use of PBDMs in rainfall-induced LSM, there remains a fragmented understanding of their effectiveness, input parameter sensitivity and implementation challenges, particularly across hydrological and geotechnical contexts. Most existing studies often focus on specific models or case studies, making it difficult to establish a comprehensive comparison of methodologies (Sannino et al. 2024). To address this gap, this review is structured into two complementary components. First, a scientometric analysis provides a quantitative overview of the field's evolution, highlighting publication trends, geographic distribution, and emerging research themes. Second, a systematic review offers a critical evaluation of physically-based models, organised into four thematic clusters based on their hydrological modelling approach. This review synthesises their methodological foundations and performance characteristics. The primary objective is to establish a structured framework for understanding and comparing PBDMs in rainfall-induced landslide contexts. Special attention is given to the evolution of technical modelling strategies, from early steady-state hydrological assumptions to more complex transient and multi-layer infiltration schemes, as well as to the assumptions embedded in infinite slope and three-dimensional failure analyses. Recent advancements, such as the integration of machine learning to improve predictive capacity, the use of probabilistic techniques like Monte Carlo simulations to quantify parametric uncertainty, and the gradual incorporation of non-stationary climate scenarios, reflect a field in transition toward more adaptable and operationally relevant frameworks. By critically evaluating these developments through a clustered model analysis, this review offers a comprehensive reference to support future model selection, refinement, and implementation in real-world hazard mitigation strategies.

2 Methodology

The literature reviews help to elaborate a comprehensive synthesis of a topic of interest, underpinning the construction of scientific knowledge, where new theories and opportunities for future research can then arise (Snyder 2019). The traditional literature review assesses the mastery of a topic; in contrast, a systematic review of the literature involves a comprehensive analysis of all available information in response to a research question (Snyder 2019; Miller 2024). This research study adopted two methods, including scientometric analysis (Ivancheva 2008; Nath and Jana 2021) and a systematic review using the PRISMA 2020 method (Page et al. 2021). Combining scientometric techniques with systematic reviews creates a solid state-of-the-art, contributing to research advances with new and significant research trends. Furthermore, the systematic review and the scientometric techniques examine patterns and trends, providing the basis for identifying future research directions (Donthu et al. 2021). The scientometric analysis uses quantitative analysis to widely describe, appraise, and verify scientific publications across many science and engineering disciplines (Van Raan 1997). This technique provides a statistical summary and a graphical representation of various aspects of published research, whereas manual and traditional review papers fail to do so (Ellegaard and Wallin 2015).

Researchers have published numerous studies in the field of landslide research. Therefore, it is vital to choose the most reliable and relevant databases for the data analysis. The two most effective, comprehensive, and objective databases for conducting literature searches in the field of geological and geotechnical engineering are Scopus and Web of Science (Mongeon and Paul-Hus 2016). Scopus has a wider coverage and bibliometric data compared with the Web of Science (Bergman 2012; Baas et al. 2020), and was therefore utilised as the search database for this study. The preliminary bibliometric data search in the Scopus database was conducted in January 2025.

The Scopus database search string titles, abstracts, and keywords selected using AND Boolean operator to gather the data (TITLE-ABS-KEY (landslide* OR "slip" OR landslip* OR "slope") AND (susceptib* OR predict* OR model* OR map*) AND (physical based OR "Geotechnical") AND ("rainfall" OR "precipitation" OR "rain-induced" OR "rainfall-induced" OR "rainfall-triggered" OR "rain induced" OR "rainfall-induced" OR "rainfall triggered")). By employing these keywords, it was ensured that the search strategy would result in a comprehensive and relevant collection of studies for this literature review, enabling a thorough analysis of the trends, methods, and findings. The PRISMA 2020 method was employed in the document selection process, as shown in Fig. 1 (Page et al. 2021).

An initial search in the Scopus database yielded a total of 825 documents. Although various additional filters, such as document type, source type, and publication year, are available, they were not applied at this stage, except for the inclusion criteria of publications from the year 2000 onward and those written in English. The documents published before the year 2000 were excluded as recent literature reflects the current state-of-the-art, and ensures that analysis is based on the most up-to-date and impactful research findings (Bornmann and Mutz 2015).

At the screening stage, 536 records were eliminated after the title and abstract review process. During that process, articles related to marine and submerged landslides, lake sediments, ecosystems, erosion, deforestation, and human settlement were identified and

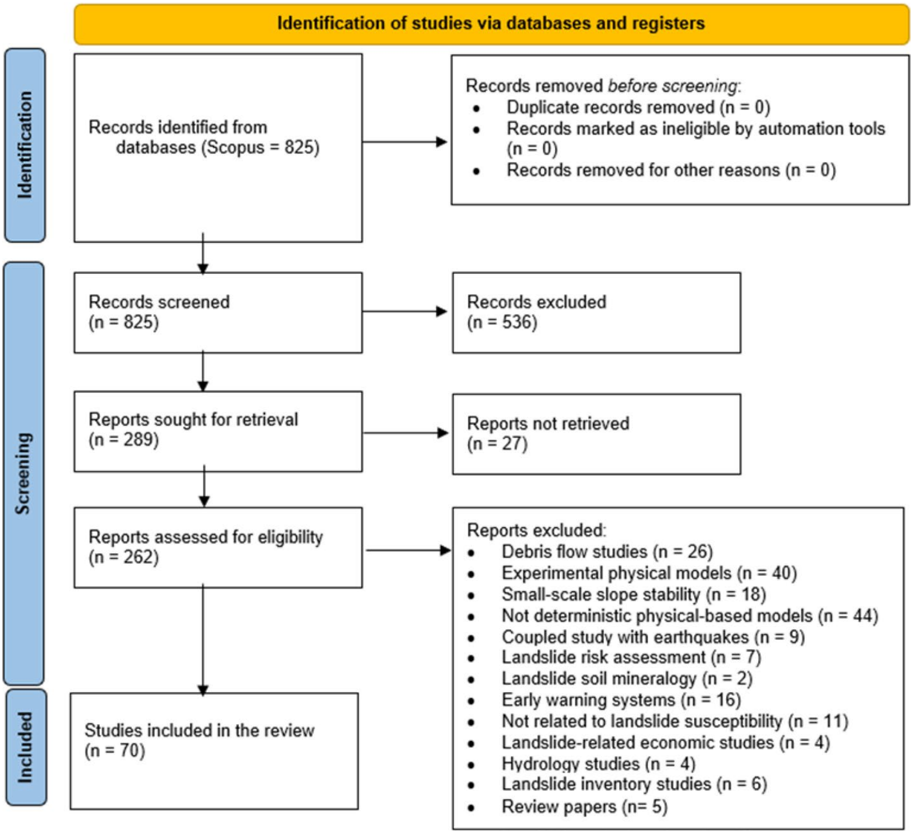

Fig. 1 Prisma flow diagram for the study

excluded as they are irrelevant to the specific focus of this study. Among the retained studies, 27 records were not retrieved at the next stage of the screening process. Those documents were missing parts of bibliographic information (i.e., author, title, publication year, DOI, affiliation, abstract, or keywords) or full text. For the final retrieval, 262 studies were assessed for eligibility for the analysis. At this stage, 189 studies were eliminated as those were not directly relevant to rainfall-induced PBDMs, resulting in a total of 70 documents for final analysis and review. All the final studies were downloaded and indexed into the EndNote reference manager for reading and content analysis. Vos-Viewer and R-Studio were employed for the Scientometric analysis, including annual publication trend, documents published by countries, and the most trending topics.

3 Scientometric analysis

A scientometric analysis provides a comprehensive overview of the research landscape on rainfall-induced PBDMs. It highlights how the research interest in the field has evolved, which countries are leading in publication and collaboration, and which topics and keywords are currently emerging or dominant within the literature. This limited but targeted analysis identifies key shifts in the field from early emphasis on core physical modelling concepts to more recent attention toward data integration and climate-related challenges. These insights provide a foundation for the subsequent systematic review, which adopts a cluster-based framework to critically evaluate PBDMs.

3.1 Annual publication trend

The amount of annual scientific publications on PBDMs have exhibited a fluctuating yet overall increasing trend from 2008 to 2024. Although the initial search was conducted for the period 2000 to 2025, the earliest publications that met the inclusion and exclusion criteria emerged only in 2008. In the early years (2008–2014), publication numbers were low and inconsistent, indicating limited research interest in the research area (Dahal et al. 2008; Tsai and Chen 2010). However, from 2015 to 2019, the trend stabilised, likely influenced by increased data availability, improved computational tools, and growing awareness of climate-induced landslide hazards (Tsai et al. 2015; Park et al. 2019a, b). A significant increase in 2019, and particularly from 2020 onwards, reflects a growing focus on PBDM research, as shown in Fig. 2. The highest number of publications occurred between 2021 and 2023, driven by advancements in methodologies and greater attention to LSM (Feng et al. 2023; Al-Najjar et al. 2024; Oguz et al. 2024). Although a decline is observed in 2024, this may be attributed to indexing delays or ongoing peer-review processes, which commonly affect the most recent year in bibliometric datasets. Thus, the overall trend, as shown by the regression line in Fig. 2, supports a growing academic interest in PBDMs and reflects their increasing relevance for both scientific understanding and practical landslide hazard mitigation. This growth aligns with global efforts in disaster risk reduction, the integration of climate scenarios into geotechnical modelling, and interdisciplinary research initiatives. The trend line illustrates the increasing focus on PBDMs, which are becoming both a scientific priority and a practical tool for landslide hazard mitigation.

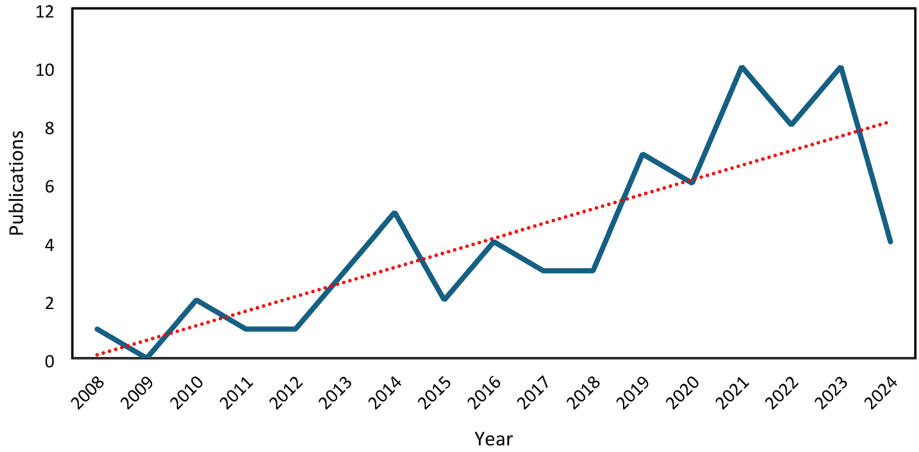

Fig. 2 Scientific production per year

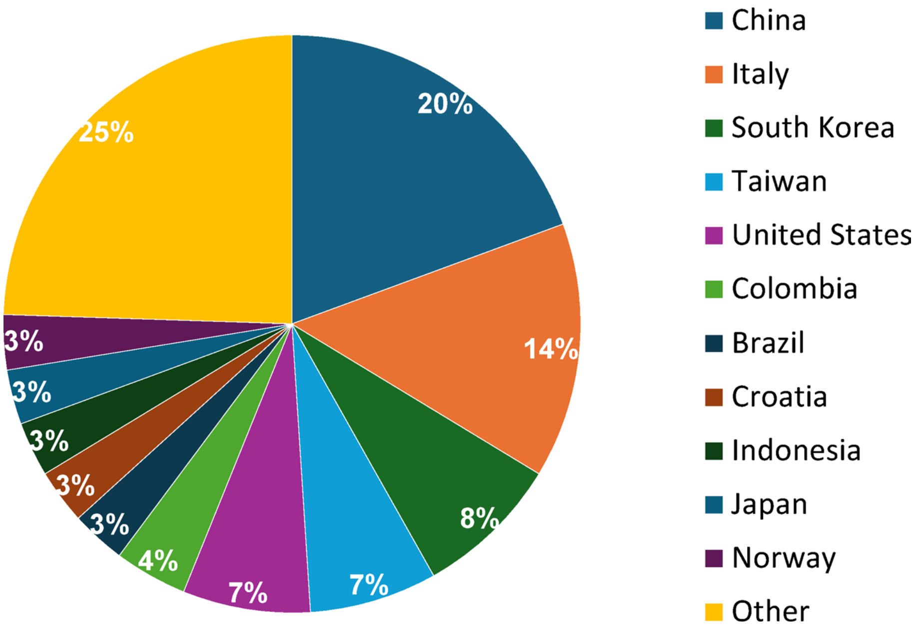

Fig. 3 Documents by countries, most relevant countries

3.2 Documents by countries

Certain countries have made and continue to make higher contributions to the current research domain compared to others. In the VoS-Viewer software, the Bibliographic coupling tool was employed to identify the leading contribution countries. A country's minimum quantity of papers was set at 3, and 11 of the 30 countries met this condition. As shown in Fig. 3, China has the highest number of documents (Lin et al. 2021; Wang et al.

2023), followed by Italy and South Korea (Wei et al. 2021). This dominance indicates a strong regional focus on landslide susceptibility, possibly due to the significant impact of landslide disasters in these countries. Countries like Brazil (de Melo et al. 2021), Colombia (Ortiz-Giraldo et al. 2023), and Norway (Oguz et al. 2024) also contribute actively, reflecting their geographical vulnerability to rainfall-induced landslides and the need for advanced predictive models.

On the other hand, when examining citation impact and collaborative influence, a different pattern emerges as shown in Table 1. Despite publishing fewer papers, the United States exhibits the highest total link strength (377.09) and a high citation count (322), indicating significant international collaboration and scholarly influence. In this context, link strength refers to the frequency and intensity of co-authorship connections between countries in the dataset. Similarly, Italy ranks second in both citations (567) and link strength (354.13), suggesting a strong balance between productivity and impact. Croatia and Norway, with only three publications each, also demonstrate high link strength values (167.67), underscoring their integration into global research networks. Furthermore, the “Other” category (25%) in Fig. 3 represents the collective contribution of 19 additional countries that each had fewer than 3 qualifying studies. These include several regions in South and Southeast Asia, Africa, and Central America, which were represented in the initial search but ultimately filtered out based on our strict inclusion criteria.

3.3 Most trending topics and keywords

The trend topics analysis reveals a clear evolution of research priorities in PBDM rainfall-induced LSM. As shown in Fig. 4, early studies (pre-2015) focused on fundamental geotechnical parameters such as shear strength, soil properties, and slope stability, forming the foundation of physically-based modelling. Post-2016, a shift toward GIS-based modelling, hydrological modelling, and trigger mechanisms is evident, emphasizing multi-disciplinary integration. More recently, machine learning (ML), mapping algorithms, and probabilistic forecasting have emerged as dominant themes, reflecting the growing reliance on data-driven techniques. This trend underscores the need for hybrid models that combine traditional geotechnical analysis with advanced computational approaches for improved predictive accuracy.

In the VoS-Viewer software, the co-occurrence tool was employed to identify the most used keywords in the research domain. A minimum number of occurrences was set at 3,

Table 1 Bibliographic coupling of countries

Country	Documents	Citations	Total link strength
China	19	545	323.73
Italy	14	567	354.13
South Korea	8	231	210.87
Taiwan	7	121	19.23
United States	7	322	377.09
Colombia	4	107	114.67
Brazil	3	62	97
Croatia	3	54	167.67
Indonesia	3	143	12
Japan	3	136	69.78
Norway	3	54	167.67

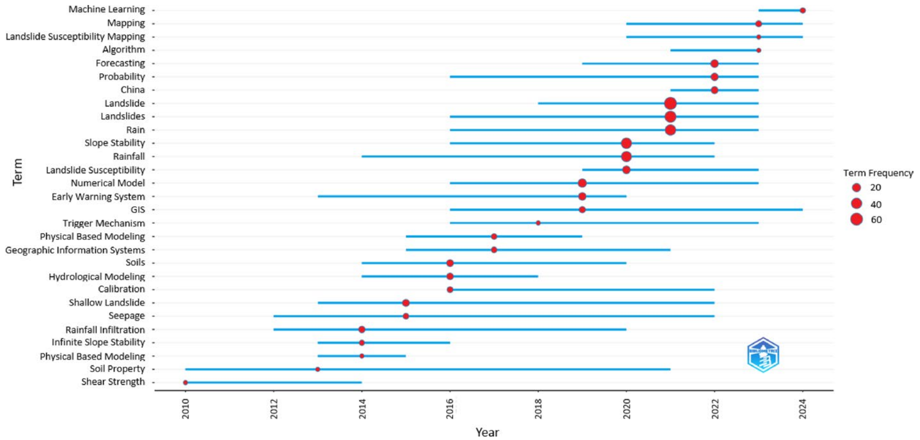

Fig. 4 Most trending topics, using the bibliometric tool

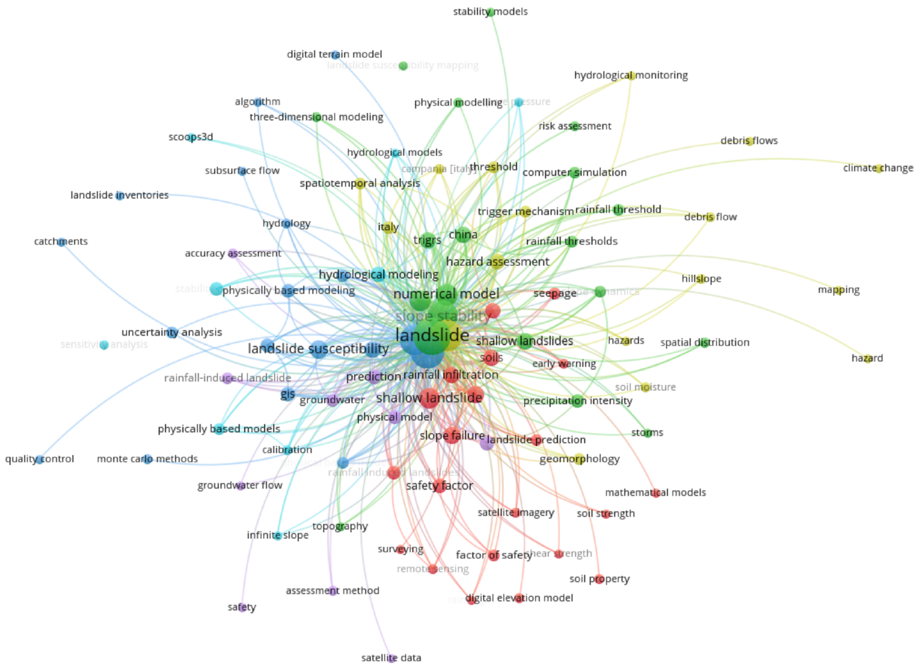

Fig. 5 Keyword co-occurrence overlay visualisation, using the Vos-Viewer tool

and 96 out of 724 keywords met this condition. While the terms "landslide", "rainfall", and "landslide susceptibility" appear as dominant nodes, indicating their centrality in this research domain, as shown in Fig. 5. One of the most critical observations from the keyword co-occurrence network is the marginal positioning of the keyword "climate change" despite its increasing global relevance. This shows that, although researchers recognise the impact of climate variability on landslides, physically-based models have not yet fully included climate change scenarios or changing rainfall patterns. The weak connections also suggest that “climate change” is a relatively new addition to this field and has not been deeply integrated into the main modelling approaches. Bridging this gap is essential to develop landslide models that are not only based on strong physical principles but also able to reflect future conditions driven by climate change, which is crucial for long-term hazard planning and adaptation.

4 Systematic review

Rainfall-induced PBDMs generally consist of two critical components: a hydrological module that simulates rainfall infiltration, groundwater flow, and pore pressure variations, and a slope stability module based on mechanical equilibrium and failure (Sannino et al. 2024). Figure 6 presents the distribution of these PBDMs utilised across studies included in this systematic review. The analysis highlights Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability (TRIGRS) as the predominant choice, followed by Stability Index Mapping (SINMAP), indicating their wide acceptance and robust applicability among researchers. Furthermore, frequent use of customised models suggests the need for tailored solutions in diverse geographic and climatic contexts.

Notably, all PBDMs reviewed in this systematic analysis adopt the infinite slope failure mode combined with the Limit Equilibrium Method (LEM) for slope stability calculations. This commonality underscores the widespread applicability of infinite slope assumptions in modelling shallow rainfall-induced landslides, due to their simplicity and computational efficiency, particularly when addressing extensive geographical areas. While these deterministic models consistently employ the infinite slope failure mode and LEM methods, they differ significantly in their hydrological modelling approaches. Hence, they were grouped into four distinct clusters, based on the hydrological modelling approach used, as shown in Fig. 7. Specifically, hydrological representations vary from simplified steady-state infiltration models (e.g., SINMAP, SHILTAB, SLIP) that efficiently capture long-term hydrological conditions, to advanced transient infiltration models (e.g., TRIGRS, HISSM, SUSHI)

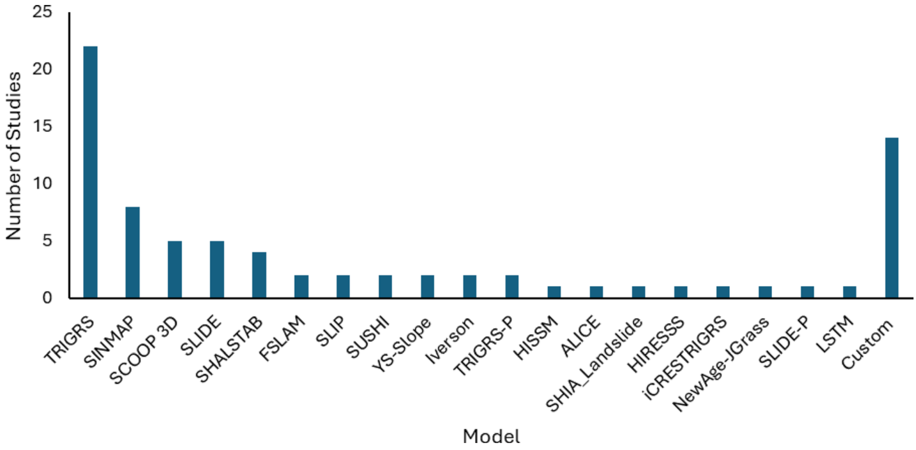

Fig.6 Identified PBDMs for rainfall-induced landslide susceptibility mapping

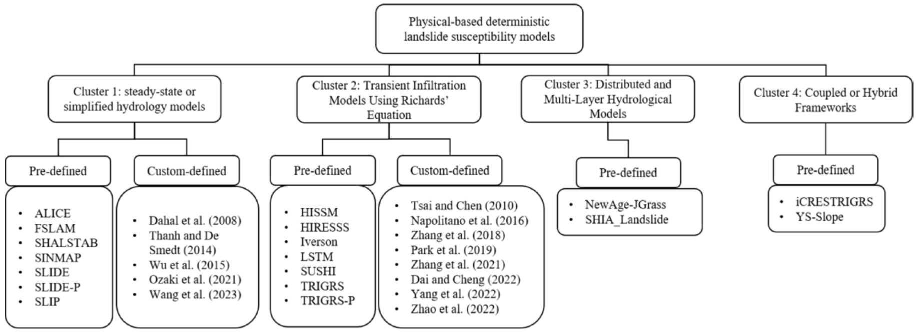

Fig. 7 Outline of clusters of different PBDMs

employing Richards' equation for precise simulation of temporal pore pressure variations. Additionally, some models incorporate multi-layered or distributed hydrological systems (e.g., SLIDE, SHIA_Landslide) to better represent complex subsurface flow processes. Understanding these methodological distinctions is critical, as they directly influence each model's predictive accuracy, applicability, and sensitivity to geotechnical and climatic parameters, as evidenced in the respective studies reviewed.

To facilitate a clearer understanding and comparison among the various PBDM landslide susceptibility models reviewed, Table 2 provides a systematic synthesis of their defining hydrological and geotechnical characteristics. The table explicitly contrasts the four model clusters steady-state, transient, multi-layer distributed, and hybrid frameworks in terms of their hydrological approaches, temporal infiltration dynamics, slope stability methodologies, and practical applicability. This structured comparison serves as a foundation for the subsequent detailed evaluations in the systematic review section, highlighting methodological strengths, limitations, and recommended areas for model enhancement.

4.1 Cluster 1: models using steady-state or simplified hydrology

Steady-state or simplified hydrological models assume that infiltration or groundwater flow reaches equilibrium quickly and remains constant over time (Rushton 2004). These assumptions drastically reduce computational demands and data requirements, making such models especially suitable for regional-scale applications and data-scarce environments. However, they often sacrifice precision in simulating rapid pore pressure responses during intense or short-duration rainfall events (Durmaz et al. 2023). Among the models that adopt this hydrological framework, Fast Shallow Landslide Assessment Model (FSLAM) offers a hybrid approach by combining a steady-state slope-parallel groundwater flow model (inspired by TOPMODEL) with a simplified vertical infiltration model based on the SCS-CN method (Ma et al. 2023). This integration allows it to represent both antecedent and event-based hydrological controls, bridging the gap between spatial realism and computational efficiency (Durmaz et al. 2023). Stability Index Mapping (SINMAP), like FSLAM, uses a steady-state assumption for subsurface flow but does so with a stricter focus on topographic control (Sinarta et al. 2017). It calculates the hydrological driving forces using the ratio of contributing area to local slope, assuming saturation develops under constant recharge. Its probabilistic formulation, incorporating input uncertainty, makes it ideal for

Table 2 Summary of the clustering methods

Feature cluster	Cluster 1 steady-state/simplified	Cluster 2 transient (Richards')	Cluster 3 multi-layer/distributed	Cluster 4 coupled/hybrid
Hydrological modeling approach	Steady-state or simplified infiltration	Richards' Eq. transient infiltration	Distributed (multi-layer or tank models)	Coupled (multiple modules)
Time dependency of infiltration	No	Yes	Yes	Varies (often yes)
Pore pressure representation	Static or index-based	Dynamic and temporally varying	Dynamic, spatially and vertically varying	Dynamic, module-dependent
Slope stability analysis	Infinite slope (LEM)	Infinite slope (LEM)	Infinite/local FS	Infinite slope/local/3D/probabilistic
Climate change adaptability	Limited	Limited, some recent adaptations	Moderate (dependent on data quality)	Moderate to High (scenario-driven)
Vegetation and ecological effects	Generally, not included	Limited, model-specific (e.g., HISSM)	Limited	Module-dependent
Uncertainty quantification capability	Rarely included	Probabilistic versions available (e.g., TRIGRS-P)	Occasionally applied	Often included (probabilistic hybrids)
Computational efficiency	High (fast)	Moderate	Low (computationally demanding)	Low (highly demanding)
Data input demands	Minimal (basic topographic and soil data)	Moderate-high (soil hydraulic properties)	High (high-resolution spatial/soil data)	Very High (multiple data streams)
Typical application scale	Regional screening	Catchment-scale to site-specific	Catchment to basin	Site-specific or complex scenarios
Key strengths	Fast, easy screening	Accurate for short-duration rainfall events	Captures complex subsurface flows	Highly adaptable, scenario-oriented
Primary limitations	Oversimplified, insensitive to temporal variations	Data-intensive, higher computational demands	Difficult calibration in sparse-data areas	Complex integration, reduced generalisability

terrain-based, large-area assessments, although it lacks sensitivity to rainfall duration or intensity (Lin et al. 2021).

Building upon the infinite slope model, Slope Infiltration Distributed Equilibrium (SLIDE) simplifies infiltration further by directly correlating rainfall depth to changes in apparent cohesion and saturation (Giraldo et al. 2021; Luo et al. 2021). Its probabilistic extension, SLIDE-Probabilistic (SLIDE-P), enhances this by allowing input parameters (e.g., cohesion, friction angle) to vary randomly through Monte Carlo simulations. Though both models assume steady-state infiltration without simulating lateral or transient flow, SLIDE-P introduces robustness by accounting for parameter uncertainty, thereby improving predictive reliability in heterogeneous terrains (Liao et al. 2012). In a similar vein, Shallow Landslide Instability Prediction (SLIP) also employs an infinite slope framework but introduces a time-dependent saturation function (Ono et al. 2014). This function dynamically responds to accumulated rainfall and drainage while avoiding full transient flow modelling. It is conceptually similar to SLIDE but includes a more explicit representation of temporal hydrologic changes, making it better suited for simulating evolving conditions during prolonged rainfall events (Gatto 2023).

The Assessment of Landslides Induced by Climatic Events (ALICE) model is a physically based, deterministic system developed by the French Geological Survey (BRGM) for assessing susceptibility to rainfall-induced landslides (Vandromme et al. 2020). While it offers greater structural flexibility in addressing both shallow and deep-seated landslides through two-dimensional slope profiles, it typically relies on static or user-defined water table depths. Although it can be integrated with external hydrological models for dynamic simulations, its default application often reflects simplified assumptions, categorizing it similarly to other models. ALICE distinguishes itself by accommodating a broader range of landslide geometries, yet it shares the same hydrological limitations commonly found in this model cluster (Vandromme et al. 2020). Shallow Landslide Stability (SHALSTAB) maintains the use of steady-state infiltration and flow-routing algorithms to delineate areas prone to saturation (Kim et al. 2019). It excels in catchment-scale hazard mapping, especially where DEM and soil parameters are available, but like SINMAP, it lacks dynamic rainfall-response capabilities (Lee et al. 2020).

In addition to well-known models like SINMAP and FSLAM, several researchers have developed custom PBDMs that utilize steady-state or simplified hydrology to reflect the hydrology conditions and data limitations. Wang et al. (2023) introduced a model tailored for granite-derived residual soils in South China, integrating a modified SCS-CN infiltration model with an equilibrium slope stability equation that includes a macropore coefficient to account for vegetation root-enhanced permeability. The model estimates effective rainfall per slope unit and does not simulate time-dependent infiltration, aligning it with steady-state hydrology principles. Ozaki et al. (2021) proposed a deterministic GIS-based model using a simple seepage prediction equation that estimates wetting front depth from cumulative rainfall and porosity under the assumption of vertical-only water movement. This model bypasses transient unsaturated flow and uses a modified infinite slope formula for safety factor estimation. Thanh and De Smedt (2014) calculated a wetness index using a steady-state topography-driven flow model, and pore pressure is estimated through equilibrium between infiltration and contributing area flow. This approach follows the logic of SHALSTAB and SINMAP but in a custom GIS format for Vietnam's A Luoi District.

Dahal et al. (2008) applied a hydrological model to estimate saturated depth from terrain curvature and slope angle under continuous rainfall. The model uses a steady-state throughflow concept, where saturation depth increases proportionally with rainfall duration and is inserted into a one-dimensional infinite slope formula. Their GIS-based approach includes error propagation to evaluate model uncertainty. Wu et al. (2015) developed a physically-based threshold model coupling the Mohr–Coulomb criterion with a Darcy-based simplified infiltration function. The model defines saturation evolution as a sum of exponentially decaying rainfall increments, allowing the derivation of a rainfall intensity-duration threshold curve. It assumes infiltration proceeds vertically and reaches equilibrium quickly, thus qualifying as simplified hydrology.

In all the models, steady-state or simplified hydrological formulations (such as constant rainfall inputs, vertical-only flow, absence of lateral redistribution, and empirical infiltration models) are employed to reduce computational burden and make models operable in data-scarce regions. However, this comes with trade-offs, including limited transient response simulation and dependence on empirical parameter calibration. Despite these limitations, such models provide valuable frameworks for landslide early warning and regional susceptibility mapping, especially where full hydrological datasets or high-resolution temporal rainfall records are unavailable.

4.2 Cluster 2: transient infiltration models using Richards' equation

Models in this cluster simulate transient, variably saturated infiltration processes using formulations derived from Richards' equation, which governs unsaturated flow in porous media. Richards' equation combines Darcy's law for unsaturated flow with the continuity equation to describe how water moves vertically through soil, accounting for changes in volumetric water content and pressure head over time (Sugawara and Sayama 2024). These models are generally more physically realistic than steady-state approaches, offering greater accuracy in predicting shallow landslides especially during intense or short-duration rainfall. Steady state flow occurs when the magnitude and direction of flow is constant with time throughout the entire domain. Conversely, transient flow occurs when the magnitude and direction of the flow change with time. In other words, the hydraulic head doesn't change with time in a steady state flow system but does change during transient flow. This does not mean that in a steady state system there is no movement of groundwater, it simply means that the amount of water within the domain remains the same, and that the amount of water that flows into the system is the same amount as flows out.

Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability Model (TRIGRS) is a widely used model that solves a one-dimensional, linearised form of Richards' equation, accounting for both steady-state antecedent moisture and transient pressure changes during rainfall (Al-Najjar et al. 2024; Oguz et al. 2024; Tan et al. 2024). It offers two boundary condition options: (1) an infinite-depth assumption (allowing free drainage) or (2) a finite impermeable basal boundary, depending on the presence of bedrock or contrasting hydraulic layers. TRIGRS uses analytical solutions for infiltration and links them to an infinite slope stability model, computing the FS at each grid cell and depth interval across large spatial domains (Oguz et al. 2024). TRIGRS-P, an extension of TRIGRS, introduces probabilistic modelling using Monte Carlo simulations, thereby quantifying uncertainties in geotechnical and hydrological inputs (e.g., cohesion, friction angle, saturated hydraulic conductivity) (Sinarta et al. 2017). This results in a probabilistic distribution of FS, providing outputs such as the probability of failure for given rainfall conditions. TRIGRS-P retains the same infiltration framework as TRIGRS, but its added stochastic component significantly enhances its utility for hazard assessments where data uncertainty is high (Chen et al. 2019).

The Iverson model (Iverson 2000), foundational to TRIGRS, offers a semi-analytical solution to the Richards' equation under the assumption of saturated initial conditions and short-term rainfall. The Iverson model proposed a linear diffusion equation for pressure head, justified when capillarity dominates over gravity flow in near-saturated soils. A defining feature of Iverson's model is the "beta line correction" that limits unrealistic pressure heads at shallow depths, a problem that occurs when using simplified infiltration models without ponding constraints (Tsai and Chiang 2013).

Saturated Unsaturated Simulation for Hillslope Instability (SUSHI) represents a more advanced physically-based approach, using a two-dimensional finite difference scheme to solve Richards' equation for both saturated and unsaturated flow (Capparelli and Versace 2011, 2014). Unlike TRIGRS, which simplifies lateral flow, SUSHI simulates downward and lateral flow components, accounting for soil heterogeneity, irregular slope geometries, and variable boundary conditions. It couples this infiltration model with a geotechnical module based on the LEM. SUSHI is especially notable for handling volcaniclastic soils and layered profiles, where matrix suction above the water table contributes significantly to shear strength (Capparelli and Versace 2011, 2014).

High Resolution Slope Stability Simulator (HIRESSS) also applies a simplified analytical solution to Richards' equation, similar in philosophy to the Iverson model, but optimized for high-performance computing (Rossi et al. 2013). It assumes wet initial conditions, applying a linear diffusion approximation and computing infiltration-induced pressure changes with time. A unique feature of HIRESSS is its integration of Monte Carlo simulations directly into the model core, allowing it to generate spatially distributed probabilistic FS maps in near real-time. This makes HIRESSS especially well-suited for operational landslide early warning systems over large, mountainous catchments.

According to Abdollahi et al. (2024), Hydrological Infiltration Slope Stability Model (HISSM) is particularly valuable for analysing the susceptibility of post-wildfire, rainfall-triggered shallow landslides at a regional scale. The model employed in this study integrates hydromechanical processes, vegetation reinforcement, and post-wildfire recovery effects to assess landslide susceptibility. Long Short-Term Memory (LSTM) based landslide prediction models, though primarily machine learning (ML) driven, incorporate physically-based transient infiltration outputs as inputs. In the model proposed by Huang (2023), subsurface flow is modelled using a finite element solution of Richards' equation, and the resulting dynamically unstable area is fed into a LSTM neural network. This integration allows the LSTM to learn from physically meaningful patterns of moisture build-up and slope instability, offering time-series prediction of landslide onset and duration. This hybrid method preserves physical interpretability while enhancing prediction precision, especially in data-scarce or complex geomorphic settings.

In addition to widely established models, several custom models have been developed that fall under the category of transient infiltration models utilizing Richards' equation. These models are often tailored to address specific regional conditions, soil types, or uncertainty quantification needs. For instance, Dai and Cheng (2022) designed a dynamic soil moisture model for landslide-prone mountainous regions, leveraging Richards' equation to simulate vertical infiltration processes. Their model incorporated climate-sensitive feedbacks to capture rapid hydrological responses under varying rainfall and temperature conditions. Similarly, Zhao et al. (2022) employed a one-dimensional Richards equation in conjunction with the Gardner model for soil–water retention and hydraulic conductivity to evaluate the temporal evolution of slope stability under random rainfall patterns. Park et al. (2019a, b) developed a physically-based model integrating Richards' equation with a fuzzy-based Monte Carlo simulation, allowing for regional-scale landslide susceptibility assessment under parameter uncertainty. Yang et al. (2022) presented a high-resolution, physically-based approach using HYDRUS-2D to model transient unsaturated flow and link it with local FS analysis, explicitly coupling Richards' equation with suction stress-based failure criteria. Furthermore, Tsai and Chen (2010) emphasized the importance of considering the variation of unit weight and unsaturated shear strength as a function of soil saturation in Richards-based infiltration models, addressing key gaps in prior formulations that often assumed constant material properties. Collectively, these custom models expand the application of Richards' equation by incorporating enhanced realism and uncertainty treatment, offering valuable tools for site-specific landslide hazard prediction.

Models in this cluster share a common theoretical foundation in Richards' equation, enabling detailed simulation of transient unsaturated–saturated pore water dynamics. However, they differ in numerical complexity, treatment of uncertainty, dimensionality (1D vs. 2D), computational efficiency, and coupling strategies. While TRIGRS and TRIGRS-P are widely used for regional applications due to their efficiency and flexibility, models like SUSHI and HIRESSS provide greater physical realism and probabilistic capabilities, albeit with higher computational demand. Emerging hybrid models, such as the LSTM-integrated approach, reflect a growing trend toward physics-informed machine learning in landslide prediction.

4.3 Cluster 3: distributed and multi-layer hydrological models

Distributed and multi-layer hydrological models represent a significant advancement in physically based landslide modelling by integrating spatially distributed rainfall-runoff processes with multi-layer soil moisture storage and transfer schemes (Aristizábal et al. 2016). Unlike simpler 1D infiltration or steady-state models, these approaches simulate vertical and lateral water movement across heterogeneous landscapes, providing a more realistic representation of pore water pressure build-up in response to rainfall.

Shallow Instability Analysis for Landslide (SHIA_Landslide) is a conceptual and physically based model designed for tropical and mountainous catchments, combining a grid-based five-tank hydrological system with a classic infinite slope stability analysis (Aristizábal et al. 2016). Each tank simulates different hydrological components: interception, surface runoff, gravitational storage, aquifer flow, and channel flow, allowing for vertical infiltration and lateral redistribution. The soil profile is discretized into residual soil, saprolite, and bedrock layers, each with distinct hydraulic conductivities. The model dynamically estimates perched water table heights and compares them against critical saturation thresholds to assess slope failure potential (Aristizábal et al. 2016).

The New Age Hydrological Modelling System within the JGrass GIS Framework (NEWAGE-JGrass) integrates simplified but distributed physically-based models (M1 to M3) within a modular GIS-based hydrological framework. Where M1 (Steady-State Flow) assumes that water movement reaches equilibrium instantly, making it efficient for long-term landslide susceptibility assessments, but less accurate for short-term predictions. M2 (Transient Flow) incorporates time-dependent infiltration dynamics, allowing it to capture pore-water pressure fluctuations during high-intensity rainfall, improving the accuracy of real-time landslide forecasting. M3 (Hybrid Approach) combines steady-state groundwater movement with transient surface infiltration, balancing computational efficiency and accuracy for regional-scale susceptibility mapping (Formetta et al. 2016).

These models offer improved accuracy for rainfall-induced landslide prediction in heterogeneous environments by explicitly modelling multi-layer infiltration and lateral subsurface flow. However, their higher computational demand and need for detailed input data may limit application in data-poor settings. Their strength lies in combining hydrological realism with spatial scalability, making them valuable tools for hazard mapping and early warning systems in complex terrains.

4.4 Cluster 4: coupled or hybrid frameworks

Coupled or hybrid modelling frameworks have emerged as a robust approach for simulating rainfall-induced landslides, particularly in contexts where the isolated application of hydrological or geotechnical models may yield limited predictive performance (Kim et al. 2014). These frameworks integrate physically-based hydrological processes with slope stability analysis, enabling more comprehensive simulation of the dynamic interactions between rainfall infiltration, pore pressure evolution, and slope failure. A notable example is the Yonsei-Slope (YS-Slope) model, which couples a modified Green-Ampt infiltration formulation with a two-dimensional groundwater flow model based on Darcy's law, implemented within a GIS environment (Kim et al. 2014). The hydrological module captures the time-dependent evolution of both the wetting front and rising groundwater table, allowing for concurrent simulation of unsaturated and saturated flow conditions. These dynamics are linked to an enhanced infinite slope model that accounts for matric suction, vegetative surcharge, and root reinforcement. This coupling enables the model to simulate multiple landslide initiation mechanisms, including those driven by perched water tables and shallow infiltration, making it particularly effective in regions with complex hydrogeological settings and variable soil profiles (Jeong et al. 2018).

The Integrated Coupled Routing and Excess Storage–Transient Rainfall Infiltration and Grid-Based Regional Slope-Stability (iCRESTRIGRS) framework effectively integrates the Coupled Routing and Excess Storage (CREST) distributed hydrological model with the well-established TRIGRS model, which analyses transient infiltration and slope stability. CREST computes spatially distributed rainfall-runoff processes, encompassing interception, infiltration, soil moisture dynamics, and the routing of surface and subsurface flow through a variable infiltration capacity approach. This hydrological output is then utilized to dynamically drive TRIGRS, which calculates transient pore water pressure and factors of safety over time and space (Zhang et al. 2016). The coupling of these models enhances the representation of spatial heterogeneity in hydrological responses and the temporal variability in slope stability, thus improving the model's predictive capabilities for cascading hazard events. In a case study of Hurricane Ivan in North Carolina, the framework demonstrated superior performance compared to standalone TRIGRS, achieving higher true positive rates and reducing false alarms in landslide predictions (Zhang et al. 2016).

Although Slope Stability Calculations Organized on Personal Computers in 3D (Scoops3D) lacks a standalone hydrological component, it is widely used in coupled frameworks where hydrological inputs such as transient pore pressure or water table depth are provided by external models like TRIGRS. Scoops3D performs a three-dimensional limit equilibrium analysis using spherical slip surfaces and evaluates FS across complex terrains, making it suitable for both shallow and deep-seated failure analysis (Tran et al. 2022; Durmaz et al. 2023). In coupled setups, TRIGRS simulates transient infiltration using Richards' equation, and Scoops3D utilizes the resulting piezometric surfaces for 3D slope stability prediction (Palazzolo et al. 2021). This integration improves spatial prediction accuracy and allows modelling of retrogressive, multi-stage landslides, especially when Scoops3D is used iteratively to update terrain and FS maps (Tran et al. 2022). Optimization techniques, such as genetic algorithms, have further enhanced Scoops3D's performance by calibrating search grid parameters for better agreement with observed failures. Despite high data and

Table 3 Summary of methodological gaps and recommendations in rainfall-induced PBDMs

Identified gap	Models affected	Recommendation
Limited treatment of transient infiltration or temporal pore pressure variation	SINMAP, SHILTAB, SLIP, ALICE	Adopt models with transient hydrology (e.g., TRIGRS, Iverson), particularly for short-duration, high-intensity rainfall events
Lack of uncertainty quantification	Most steady-state models	Incorporate probabilistic extensions (e.g., TRIGRS-P, Slide-P) or Monte Carlo simulations
Absence of climate change scenario integration	Almost all except recent TRIGRS versions	Integrate non-stationary rainfall patterns via downscaled GCM or stochastic climate generators
Low adaptability to vegetation or wildfire effects	All except HISSM	Include dynamic vegetation effects, root reinforcement, and post-wildfire soil property shifts
Limited model validation and benchmarking	General issue across the literature	Encourage standardized datasets, validation with observed landslide events, and model intercomparison exercises
Restricted spatial scalability or resolution issues	SLIP, ALICE, NewAge-JGrass	Employ modular or nested multi-scale modeling strategies for broader application and computational efficiency

computational demands, Scoops3D, when used within hybrid systems, offers a robust physically based framework for rainfall-induced landslide susceptibility analysis.

As highlighted in the preceding sections, each model cluster exhibits distinct methodological strengths and limitations in representing rainfall-induced landslide susceptibility. While the scientometric analysis revealed early signals of emerging but underexplored themes such as uncertainty quantification, climate change integration, and vegetation effects, the systematic review enabled a deeper evaluation of these challenges across specific models. Table 3 synthesizes the key gaps identified and discussed throughout the review, along with corresponding recommendations to enhance the adaptability, transparency, and predictive strength of physically based models. These insights are intended to guide future research and practical implementation toward more climate-resilient and interoperable landslide susceptibility frameworks.

5 Emerging trends and the future directions

PBDMs for rainfall-induced landslide susceptibility have progressively evolved, moving from simpler, steady-state hydrological methods to more advanced, interdisciplinary frameworks. Early models such as SHALSTAB (Kim et al. 2019) and SINMAP (Sinarta et al. 2017) primarily relied on simplified hydrological assumptions and infinite slope stability methods, providing foundational yet limited predictive insights. The incorporation of advanced hydrological techniques marked a significant progression. Models utilizing Richards' equation, notably TRIGRS (Al-Najjar et al. 2024; Oguz et al. 2024), SUSHI (Capparelli and Versace 2011, 2014), and Iverson's model (Tsai and Chiang 2013; Tsai et al. 2015), effectively captured transient infiltration processes, significantly improving prediction realism and accuracy. The field further advanced with probabilistic modelling approaches like HIRESSS (Rossi et al. 2013), TRIGRS-P, and SLIDE-P (Chen et al. 2019), explicitly integrating uncertainty quantification to address inherent variability in input parameters. These probabilistic frameworks provided robust predictions by transparently managing and communicating uncertainties. More recently, significant advancements have emerged through the integration of advanced technologies, including ML and artificial intelligence (Huang 2023; Al-Najjar et al. 2024).

Hybrid models incorporating machine learning methods enhance predictive performance by combining physical realism with sophisticated data-driven techniques. Additionally, integration of Internet of Things (IoT) technology and real-time monitoring systems has transformed data collection and analysis, enabling timely and accurate early warnings (Oguz et al. 2022). The future success of landslide susceptibility assessment depends on achieving an optimal balance between technical sophistication and practical applicability. While model development has progressed substantially, Wei et al. (2021) demonstrate how integrated approaches combining physical principles with advanced statistical and machine learning techniques can enhance model reliability while maintaining practical utility. These developments, along with improved accessibility of assessment tools, are crucial for advancing effective landslide risk management strategies in an increasingly complex environmental context.

Climate change adaptation has become a crucial focus, prompting model developments to handle evolving climate scenarios and extreme weather events explicitly. Oguz et al. (2024) emphasized methodologies that can cope with non-stationary climatic conditions, enhancing the resilience of landslide prediction frameworks. Zhang et al. (2022) and Feng et al. (2023) emphasize the need for enhanced methods in handling climate change impacts and uncertainty quantification. The integration of socio-economic factors into risk assessment frameworks, as highlighted by recent studies, has become increasingly important for comprehensive landslide management.

Furthermore, spatial resolution and data coverage have substantially improved through the integration of high-resolution datasets from remote sensing and LiDAR (Rossi et al. 2013). This advancement provides detailed spatial analysis capabilities, significantly refining predictive accuracy across broader geographical areas. Multi-hazard integration has also gained prominence, as demonstrated by Vandromme et al. (2020). Models are now considering cascading effects and interactions between different natural hazards, facilitating comprehensive and integrated risk management strategies. Concurrently, advanced data integration and management practices, such as standardized data formats and improved spatial–temporal data handling techniques Ji and Cui (2023) have strengthened models' interoperability. Accessibility and user interface improvements have also emerged as a priority. Recent developments include user-friendly visualization tools, web-based platforms, and simplified implementation methods (Ji and Cui 2023). These improvements enhance stakeholder engagement, making complex models more practical and broadly applicable. Abdollahi et al. (2024) incorporate root reinforcement effects and post-wildfire conditions into a physically-based landslide model, demonstrating how changes in vegetation cover and soil cohesion influence slope stability. Their model accounts for the reduction in root cohesion due to wildfire damage, providing a more realistic assessment of landslide susceptibility in fire-affected catchments.

Overall, the transition from basic deterministic methods toward advanced, interdisciplinary, and technology-driven approaches positions physically-based landslide susceptibility modelling as a critical component of effective disaster risk management and mitigation strategies. The field of physically-based rainfall-induced landslide modelling demonstrates significant advancements and promising trends.

6 Conclusion

Based on the comprehensive review of 70 studies incorporating more than twenty landslide prediction models, several key findings emerge regarding the current state of rainfall-induced landslide modelling. The analysis reveals a progressive evolution in modelling approaches, from simplified infinite slope methods to more complex three-dimensional ones. While infinite slope models remain dominant due to their computational efficiency and applicability to shallow landslides, advanced approaches like SCOOP 3D demonstrate the growing recognition that complex landslide mechanisms often require three-dimensional analysis.

The widespread use of Richards' Equation in models such as TRIGRS, SUSHI, Iverson, and HISSM underscores its role as the standard in simulating transient rainfall infiltration for landslide susceptibility assessment. This reflects a growing emphasis on accurately modelling pore pressure dynamics, which significantly influence slope stability during rainfall events. In contrast, models like SINMAP, SLIP, and ALICE, which rely on steady-state or simplified hydrological assumptions, are limited in capturing the temporal variability of subsurface flow. Meanwhile, the integration of uncertainty quantification represents a critical advancement. Probabilistic models such as TRIGRS-P, SLIDE-P, and HIRESSS address natural variability in both soil parameters and rainfall inputs, offering more robust predictions. This shift acknowledges the limitations of purely deterministic frameworks, which may present an illusion of precision in contexts where input variability is significant.

Model coupling and integration are emerging as important developments, particularly for multi-hazard assessment. The iCRESTRIGRS approach demonstrates how linking hydrological and stability models can simulate cascading disaster chains involving both floods and landslides from the same rainfall event. The incorporation of ML approaches signals a paradigm shift toward data-driven methods that can identify complex patterns without explicitly modelling physical processes. These approaches show promise for complementing traditional physics-based models, especially in regions with extensive monitoring data. Despite these advancements, significant limitations persist across all models. Data scarcity remains the most universal challenge, with all models requiring detailed soil properties, rainfall data, and landslide inventories that are rarely available across large regions. Computational demands create implementation barriers for sophisticated models, while scale issues complicate application across different spatial extents. The literature reveals insufficient attention to climate change adaptation, with few models explicitly addressing non-stationary conditions. These findings suggest that future research should focus on developing multi-scale modelling approaches, improving uncertainty quantification, enhancing model coupling for multi-hazard assessment, and creating frameworks adaptable to changing climate conditions. The ideal approach likely involves strategic combinations of models with complementary strengths rather than reliance on any single prediction method.

While this study provides a comprehensive evaluation of PBDM for rainfall-induced LSM, certain limitations remain. The study relies only on the Scopus database, which may exclude relevant approaches included in studies indexed in other databases. Furthermore, while emerging trends such as ML integration are discussed, their direct implementation within physically-based frameworks has not been investigated as falling outside the study's scope. In response to the limitations identified throughout this review, Table 3 provides a structured summary of key methodological gaps, implementation challenges, and corresponding recommendations across the examined models. This synthesis highlights pressing needs for improved data availability, integrated hydrological-soil frameworks, and scalable, user-accessible tools. Moreover, the limited incorporation of non-stationary climate data, socio-economic drivers, and real-time monitoring underscores the need for future research that bridges deterministic modelling with adaptive, interdisciplinary approaches. Addressing these gaps is critical to advancing physically-based landslide susceptibility frameworks that are not only technically rigorous but also contextually and operationally relevant in diverse geographies.

Practitioners aiming to apply deterministic physically-based models for rainfall-induced LSM should carefully align model selection with the quality and availability of geotechnical, hydrological, and topographic data, as well as the specific characteristics of the target region. Simpler models with steady-state assumptions (e.g., SINMAP, SLIP) may be suitable for preliminary regional assessments, while more complex models incorporating Richards' equation and transient hydrological responses (e.g., TRIGRS, HISSM) are better suited for detailed site-scale analyses where sufficient input data exist.

For reliability, costs, and time optimisation, a tiered modelling strategy is recommended, starting with low-complexity models and gradually integrating more advanced frameworks as data resolution, field calibration, and computational capacity allow. Sensitivity analysis should be prioritised to identify parameters that most influence model outcomes and validation against historical events or field data are essential where possible. Effective implementation also depends on robust data management, including standardised data collection protocols, quality assurance checks, and thorough documentation of sources and assumptions.

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Data availability No new data has been generated in this study.

Declarations

Ethical approval Since the research was not a clinical trial of investigational medicinal products and did not include human subjects. Therefore, an ethics statement is not applicable and does not require human research ethics approval. The study is based exclusively on published literature, measured field data/maps, and statistical analysis and mapping.

Competing interests The authors declare that they have no competing interests.

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