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Review Article: Rainfall-Induced Landslide Prediction Models, Part I: Empirical-Statistical and Physically Based Causative Thresholds

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ABSTRACT.

Landslides rank among the most devastating hazards, leading to loss of life and destruction of infrastructure, with rainfall being a primary triggering factor. Global climate change has increased landslide occurrence; accordingly, accurate landslide prediction is crucial to reduce damage and losses. Since landslides account for 17% of all natural hazard fatalities, several studies have been done across the globe to predict these events better. Despite the considerable number of review articles, a comprehensive comparison between empirically, physically, deterministically, and phenomenologically based prediction models is still missing. Moreover, they lack adopting mixed methodology. Accordingly, a mixed review that comprised scientometric, systematic, and bibliometric analysis was employed. This study (Part I of a two-part review) examines two approaches for analyzing local-scale landslides: empirical-statistical methods and physically based causative threshold models. Deterministic and phenomenologically based prediction models are discussed in part ii and have been published (Ebrahim et al., 2024a). This study explores the practicality and constraints associated with the aforementioned methodologies. As a result, critical insights into rainfall-induced landslides are examined. Macroscopically, antecedent rainfall surpasses the intensity-duration thresholds. Physically based causative thresholds can be utilized when geotechnical or hydrological data are limited. Microscopely, hybrid artificial intelligence models provide higher prediction accuracies. Finally, research suggestions are highlighted, as modeling artificial intelligence models with extensive datasets to achieve high prediction accuracy is still needed for further development.

Keywords: Landslides; Prediction; Rainfall-induced landslides; Empirical models; Physically-based models.

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INTRODUCTION.

"A landslide is the movement of a mass of rock, earth, or debris down a slope (Cruden, 1991)." These events naturally occur in hilly regions and play an essential role in shaping mountainous landscapes. Landslides happen when the strength of rock or soil is insufficient to resist the stresses induced by triggering factors. They are a prevalent hazard in sloped terrains, leading to loss of life, infrastructure destruction, and economic damages (Chae et al., 2020). As illustrated in Figure 1, between January 2004 and December 2016, non-seismic landslides caused the deaths of nearly 55,997 individuals in 4,862 incidents (Froude & Petley, 2018). Additionally, the World Health Organization reported that landslides claimed over 18,000 lives between 1998 and 2017 (Online: Landslides (who. int), accessed October 19, 2024)

Landslides can be triggered by various factors, including earthquakes, volcanic activity, floods, and intense rainfall, with rainfall being the most common cause of slope instability. Increasingly severe rainstorms, driven by climate change, are contributing to the occurrence of catastrophic landslides (Zhao et al., 2019a; Wu et al., 2020; Harsa et al., 2023). Hungr et al. (2014) classified landslides into 32 distinct types based on material composition (such as rock, debris, or soil) and movement mechanisms (such as falls, topples, slides, and flows). This classification, an extension of the earlier Varnes system, offers a more comprehensive framework for analyzing landslide processes. By categorizing landslides according to their triggers and dynamics, the classification provides a valuable tool for understanding their complexity. However, this study focuses specifically on rainfall-induced landslides, as they are among the most frequent and destructive types in certain regions.

Rain-induced landslides are typically shallow, with slip surfaces running parallel to the slope surface (Saadatkhah et al., 2015; Das et al., 2022; Thang et al., 2022). According to Caine (1980), the depth of shallow landslides is generally less than 2 to 3 meters. Similarly, studies by Zhang et al. (2011) and Huang et al. (2015) reported shallow landslides with a thickness of

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less than 3 to 5 meters. A ground survey conducted by the Geotechnical Engineering Office (GEO) in Hong Kong identified several shallow landslide scars with vertical depths of under 3 meters (Liu et al., 2022). Shallow landslides are particularly hazardous due to their rapid onset and intensity (Formetta & Capparelli, 2019). They involve the movement of soil or debris near the surface, typically extending to depths of only a few meters. In contrast, deep-seated landslides affect larger masses of material, including bedrock, and occur at much greater depths. Figure 2 provides a visual comparison of shallow and deep-seated landslides, highlighting differences in failure depth and material displacement, which are essential to this study's focus (Dou et al., 2015).

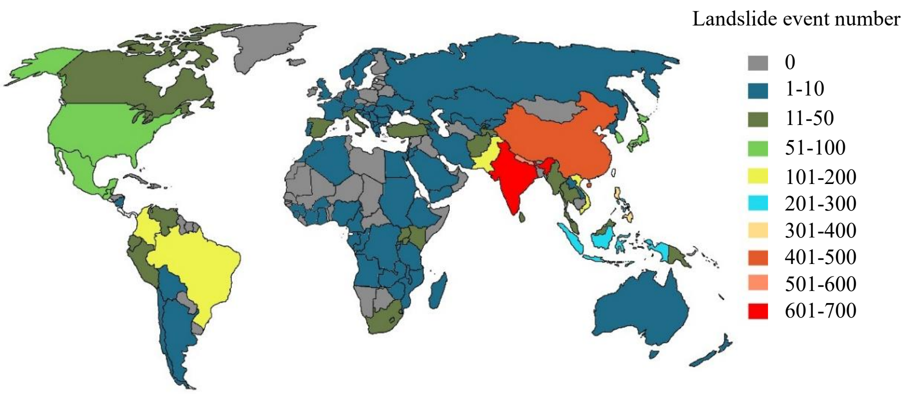

Figure 1. Fatal non-seismic landslides by nation from 2004 to 2016: Figure reproduced with permission (Froude & Petley, 2018).

According to Terzaghi, when a slope experiences movement, any intervention aimed at preventing further sliding must be tailored to the specific mechanisms that initiated the event. Mitigation techniques such as stabilizing piles, soil nailing, drainage systems, and other strategies are crucial, particularly when the slope is exposed to unforeseen triggers like heavy rainfall, earthquakes, or degradation of geotechnical properties (Huang & He, 2023). In recent years, there has been an increased focus on leveraging landslide prediction models to reduce the risks associated with these disasters. These models play a key role in minimizing the

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impacts of rainfall-induced landslides and facilitating the development of early warning systems (Liang & Uchida, 2022). Landslide prediction models are vital for several reasons. First, they help identify areas prone to landslides, enabling proactive risk mitigation strategies such as constructing retaining walls or planting vegetation. Second, they provide timely alerts of potential landslides, allowing authorities to secure structures and evacuate residents, which can significantly reduce the risk of casualties and property damage. The prediction of landslides has garnered significant attention as a practical approach to forecasting both the spatial (location) and temporal (timing) aspects of landslide events (Valentino et al., 2014; Ma et al., 2017). Therefore, this paper aims to explore the key factors that influence rainfall-triggered landslides, highlighting the importance of each factor in achieving accurate predictions of these events.

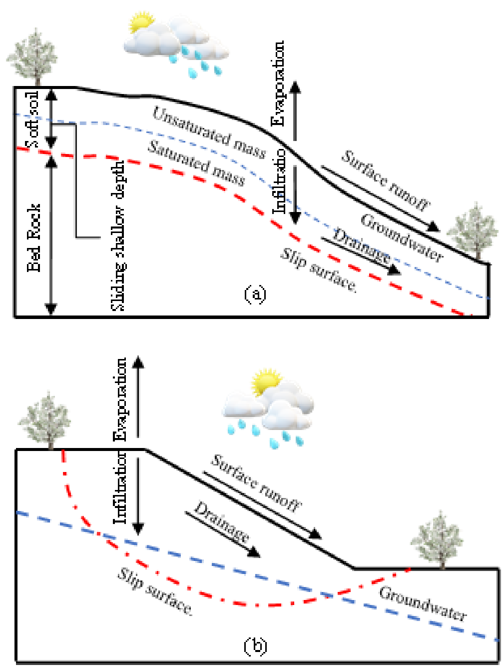

Figure 2. a) Shallow landslides; b) Deep-seated landslides. (Refer to Hungr et al. (2014) for more information regarding different classifications of landslides)

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This study will utilize both quantitative (scientometric) and qualitative (systematic) approaches to analyze the existing literature. It will present a range of methods for landslide prediction, including empirical-statistical thresholds, physically based causative models, physical analytical and numerical models, and landslide susceptibility analysis, organized into two distinct sections. This review paper represents the first of two parts, concentrating on rainfall-induced landslide prediction models. This review paper is the first of two parts focused on rainfall-induced landslide prediction models. In this first part, we comprehensively review empirical and physically-based models used to predict rainfall-triggered landslides. The second part of the review has already been published (Ebrahim et al., 2024a) and addresses deterministic models and landslide susceptibility assessments. Together, these two parts offer a complete overview of the different approaches for predicting rainfall-induced landslides, bridging the gap between empirical studies and advanced deterministic modeling techniques.

This study integrates various statistical methods, such as statistical regression, artificial intelligence, probabilistic models, and mathematical analytical models, into landslide prediction. It uses bibliometric analysis to assess and evaluate the accuracy of these statistical models. Part II of the study provides a detailed theoretical framework for rainfall-induced landslides and their initial conditions, as outlined in Ebrahim et al. (2024a). Table 1 summarizes several review studies that have explored landslide prediction approaches, many of which focus on a single methodology. Notably, scientometric analysis has been infrequently applied in this context. The novelty of this study lies in several key contributions: it presents a combined scientometric and systematic review, utilizing bibliometric analysis to compare the accuracy of different models; offers a comprehensive explanation of the initial conditions and theoretical geotechnical and hydrological concepts underlying rainfall-induced landslides; and includes both empirical statistical thresholds and physically based causative models, along with

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deterministic physical models and landslide susceptibility maps in Parts I and II. Furthermore, this study highlights the latest advancements in the field.

This two-part review explores the evolution of different approaches, starting with a macroscopic perspective based on input parameters and initial conditions, followed by a microscopic examination of alternative analysis models for the same method. The structure of this research is as follows: Section 2 outlines the research methodology; Section 3 highlights the scientometric analysis; Section 4 focuses on the systematic analysis, which is divided into two subsections: 1) empirical-statistical thresholds, and 2) physically based causative thresholds; Section 5 provides the discussion; Section 6 presents the conclusion and future work; Section 7 summarizes the notations and abbreviations; and Section 8 lists the references.

Table 1. Available review articles for landslide prediction techniques.

Study	Content
Zhang et al. (2011)*	Geotechnical and hydrological concepts related to rainfall-triggered landslides
Chae et al. (2017)*	Landslide susceptibility, modeling of runout, monitoring, and early warning systems
Segoni et al. (2018)*	Rainfall-based landslide thresholds
Merghadi et al. (2020)*	Application of machine learning algorithms for assessing landslide susceptibility
Shano et al. (2020)*	Overview of various prediction methods, emphasizing statistical models
Yanbin et al. (2022)*	Use of machine learning techniques in landslide susceptibility analysis
Zou & Zheng (2022)**	Scientometric review, limited physical prediction models, and case studies
Huang et al. (2022)***	Landslide susceptibility models based on Geographic Information System (GIS) data
Petrucci (2022)*	Analysis of the main causes behind landslide-related fatalities
Vung et al. (2023)*	Exploration of challenges, opportunities, and future research directions for rainfall-induced landslides
Ebrahim et al. (2024a)*	Deterministic and susceptibility-based landslide prediction models
Ebrahim et al. (2024b)*	Time series-based prediction models for landslides
*Refers to systematic reviews; **Scientometric analysis; ***Bibliometric approach	

METHODOLOGY OF THE STUDY.

This study employs a mixed review approach, combining both quantitative (scientometric) and qualitative (systematic) methods. The aforementioned technique is offered to assist researchers

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in improving systematic review reporting using scientometric analysis. In addition, it sheds light on the difficulty of performing manual searches on database engines. This approach integrates the strengths of both strategies, which have been widely used in other fields (Yin et al., 2019; Wuni & Shen, 2020; Ebrahim et al., 2024c). As a result, a mixed review strategy was used to meet the study's primary objective in the field of landslide prediction. Figure 3 illustrates the methodical flow for a systematic review, which consists primarily of three processes: identification, screening, and eligibility. Regarding scientometric analysis, Figure 4 demonstrates the steps of the aforementioned analysis, which mainly consist of gathering bibliometric data, exporting bibliometric data to an appropriate program, evaluating data, and discussing results.

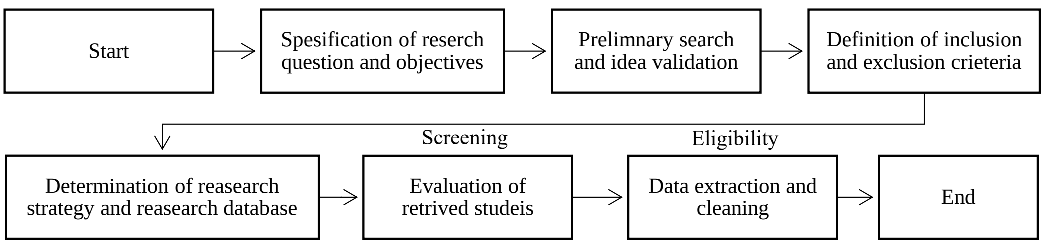

Figure 3. Methodological flow for a systematic review

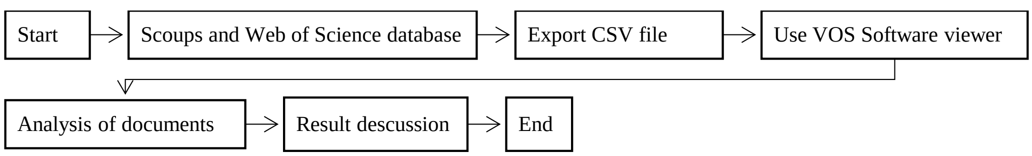

Figure 4. Methodological flow for scientometric analysis.

Identification Process.

Landslides can be classified based on various factors, such as geology, engineering, environmental science, ecology, meteorology, atmospheric science, geochemistry, geophysics, physical science, and water resources (Zou & Zheng, 2022). Additionally, as highlighted in the keyword mapping by Zou and Zheng and Ebrahim et al. (Zou & Zheng, 2022; Ebrahim et al., 2024c), landslides are associated with a wide range of keywords. Therefore, the research process begins with the identification of relevant studies on landslides, guided by the authors' perspectives. This section outlines the use of keywords, search databases, and inclusion and exclusion criteria to filter the collected papers. A standard review methodology for screening the selected studies is detailed in Section 5.

Database and Keyword Selection

To ensure a comprehensive retrieval of relevant articles, it is recommended to use multiple databases in a systematic review. The three most commonly utilized databases in engineering research are Scopus, Web of Science, and Google Scholar. Scopus and Web of Science are also compatible with advanced scientific mapping tools like VOS Viewer. This study focuses primarily on Scopus and Web of Science as the main sources for searching landslide prediction literature. Additionally, Google Scholar is employed in the snowballing strategy. Once the search databases are selected, key terms such as "landslide prediction" are identified to cover all available datasets and prediction techniques.

Criteria for Inclusion and Exclusion.

In any systematic review, inclusion and exclusion criteria play a vital role in filtering search results and prioritizing the most relevant studies to the research question. This study applied the following inclusion criteria: 1) studies focused on landslide prediction, aligned with the aim outlined in the INTRODUCTION section; 2) studies published up to 2024; 3) articles published in peer-reviewed journals; 4) studies published as research articles or review papers; and 5) studies published as final versions. The exclusion criteria were: 1) papers published in languages other than English; 2) studies lacking available full text; 3) manuscripts from subject areas outside of engineering; and 4) articles published in non-journal sources. The search strategy in Scopus and Web of Science with inclusion and exclusion criteria was as follows:

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Scopus: TITLE-ABS-KEY("landslide prediction") AND PUBYEAR > 1999 AND PUBYEAR < 2025 AND (LIMIT-TO(SUBJAREA, "ENGI")) AND (LIMIT-TO(DOCTYPE, "ar") OR LIMIT-TO(DOCTYPE, "re")) AND (LIMIT-TO(PUBSTAGE, "final")) AND (LIMIT-TO(LANGUAGE, "English")).

Web of Science: https://www.webofscience.com/wos/woscc/summary/94fee090-b6a4-4ecf-a951-5b904e6fb3a8-01155ef62f/recently-added/1

Screening and Assessment of Collected Articles.

The Scopus and Web of Science databases provided 88 and 99 articles, respectively. Initially, 8 duplicate articles were removed. The low number of duplicates can be attributed to the differing criteria between the Web of Science and Scopus databases, as well as the broad range of related keywords. The systematic review and meta-analysis (PRISMA) procedure (Moher et al., 2009) was then applied to evaluate and assess the collected articles (see Figure 5). As a result, 47 papers were excluded due to irrelevance or unavailability of the full text. After evaluating the full texts of the remaining articles, 132 articles met the inclusion criteria.

The backward and forward snowballing approach was then employed to identify additional studies that were not retrieved through the Scopus and Web of Science searches (Wohlin, 2014). The 132 included papers were used as the starting point for the backward and forward snowballing search strategy's pertinent investigations. Unlike "forward snowballing," which involves locating new publications based on those that cite the paper under investigation, "backward snowballing" involves searching the reference lists of each paper in the start set for pertinent papers. The new set is made up of the newly discovered articles from this procedure. The cycle was repeated until no further documents were discovered. Sixty-eight relevant new articles were discovered because of this search approach. It should be noted that 29 papers were included during the manual search for articles that were conducted during the full-text review,

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making a total of 229 articles acceptable for inclusion. The whole screening and evaluation process are summarised in Figure 5.

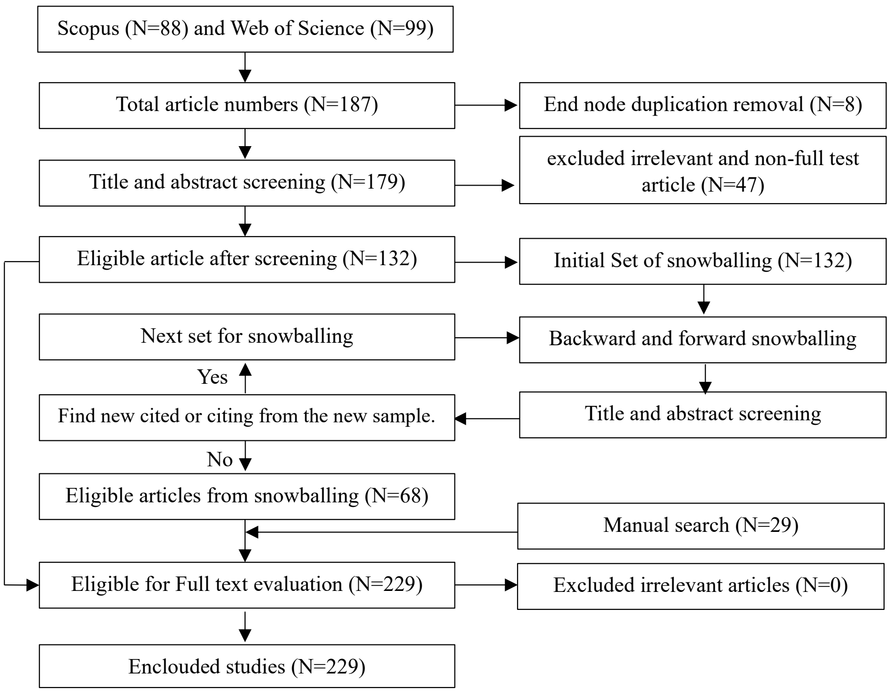

Figure 5. Screening and selecting flow diagram: PRISMA.

In this section, we listed the number of papers included in the study as part of the methodological process, specifically, the selection criteria and scope of the literature review. This is intended to provide context for the analysis that follows. It should be emphasized that the number of manuscripts illustrated above in Figure 5 are reviewed in two parts: this study (part i) and the study of Ebrahim et al. (2024a) which has been published. The actual analysis and interpretation of the selected papers begin in the SCIENTOMETRIC ANALYSIS Section.

SCIENTOMETRIC ANALYSIS

In this section, we provide a detailed analysis of the selected studies. The scientometric analysis commenced after completing the screening process to examine the relationships among authors, keywords, publications, and countries within specific research areas. This analysis was

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conducted using the open-source VOSviewer software tool (van Eck & Waltman, 2010), a widely recognized visualization tool employed in this study to analyze the results. The primary goal of the scientometric analysis is to ensure that the findings are meaningful and relevant for inclusion in the systematic review. A total of 229 manuscripts, identified through snowballing and manual searches, were analyzed using VOSviewer software.

The Trend In Annual Publications For Landslide Prediction.

Figure 6 illustrates the annual publication trend of landslide prediction-related studies. From 2000 to 2014, the average number of articles published per year was approximately three. The publishing rate thereafter experienced a significant jump from 8 to 28 publications between 2015 and 2023 in which the researcher's primary area of interest is landslide prediction for the past nine years. This trend is not unexpected, considering the increasing global focus on reducing the loss of human life, property, and economic assets due to landslides. Then, it becomes apparent that the previously indicated rate abruptly dropped to only 8 manuscripts in 2024. The decline is because this study (part ii) was completed in May 2023 (Ebrahim et al., 2024a) while part i was before the mid-end of 2024 as more research is expected to be published.

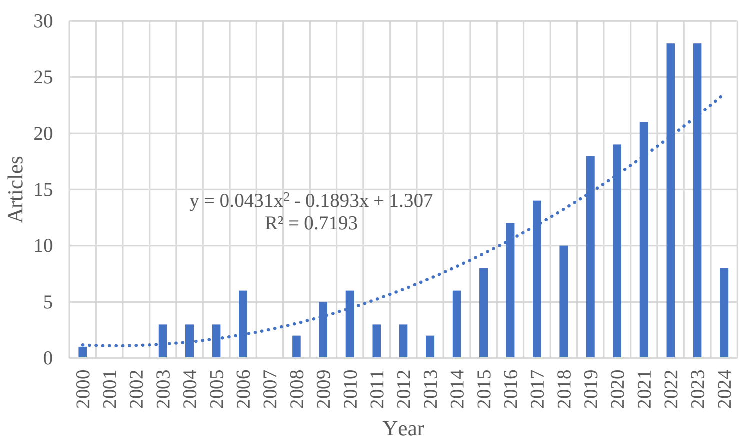

Figure 6. The total number of articles per year related to landslide prediction.

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Leading Journals in Landslide Prediction Contributions

The VOSviewer software has been used to identify the leading journals in landslide prediction, as shown in Table 2. This analysis helps guide researchers in selecting reputable journals in this field. Two thresholds were applied during the VOSviewer analysis: 1) a minimum of five papers per journal, and 2) a minimum of ten citations per journal. The unit of analysis was "sources," and the analysis type employed was "bibliographic coupling." As a result, 10 journals out of 86 met these criteria (Figure 7). It's important to note that there are no universally established thresholds for the number of manuscripts or citations per journal (Zou & Zheng, 2022). Node size in Figure 7 highlights the journals' influence as weighted by publications. The number of linkages between a journal and other journals is represented by its total link strength (van Eck & Waltman, 2009). Table 2 presents the 10 journals where the highest publishing and topmost cited journal is “Landslides”, with 32 articles and 4195 citations.

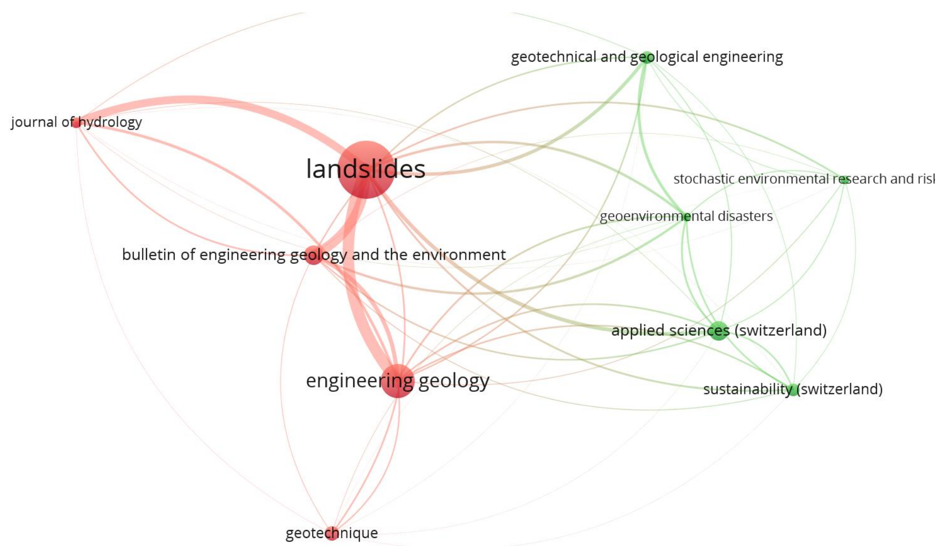

Figure 7. The top journals contributing to the field of landslide prediction.

Table 2. The top journals contributing to landslide prediction research.

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No	Source	Documents	Citations	Total strength link
1	Landslides	32	4195	1190
2	Engineering Geology	19	1414	733
3	Bulletin of Engineering Geology and the Environment	11	317	625
4	Applied Sciences (Switzerland)	11	178	354
5	Géotechnique	8	6117	142
6	Geotechnical and Geological engineering	7	173	330
7	Sustainability (Switzerland)	7	76	253
8	Journal of Hydrology	6	1456	396
9	Geoenvironmental disaster	5	404	405
10	stochastic environmental research and risk assessment	5	290	172

Active Nations in Landslide Prediction.

The identification of top scientists, laboratories, organizations, authors, and nations is made easier with an understanding of the scientific collaboration network in any subject of study. This can greatly facilitate academic collaboration. The thresholds mentioned above were applied, with "countries" as the unit of analysis and "bibliographic coupling" as the analysis type. Out of a total of 44 countries, only 15 met the criteria. The size of the node in Figure 8 represents the influence of each country in the field, weighted by the number of publications. To give two examples, China and Italy have the most publications worldwide, recording 77 and 31 articles, respectively. Ethiopia has 5 publications and poor connections to other nations. Additionally, Table 3 presents information on the top five countries contributing to landslide prediction research. Moreover, both academic and industrial practitioners seeking innovative solutions for landslides can benefit from understanding the collaborative network of countries that are investing more in this field.

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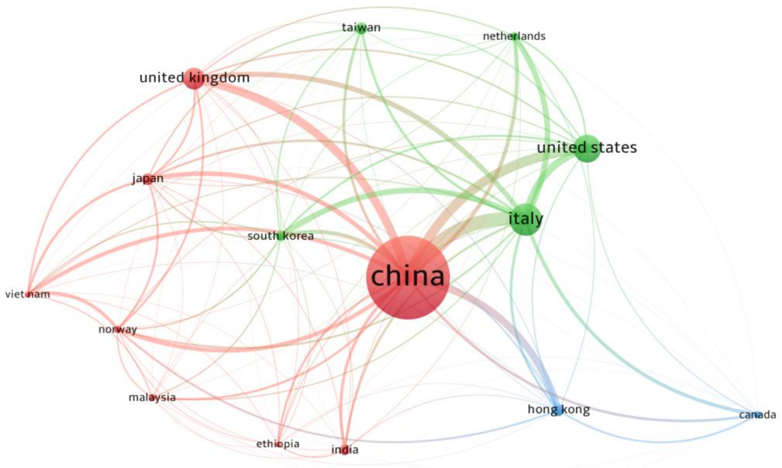

Figure 8. Top countries publishing in landslide prediction.

Table 3. Top five prominent and publishing countries relevant to landslide prediction.

Country	Documents	Citations	Total link strength
China	77	3896	7348
Italy	30	5007	5622
United States	26	5146	2963
United Kingdom	20	6299	2623
Japan	11	2351	2098

Article Co-Citation Analysis in Landslide Prediction.

The total number of citations for any publication indicates its contribution to the field. Thus, this section includes citations of the most cited publications in landslide prediction research. Since there is no strong correlation between these publications, the top 10 cited articles were selected directly from the Scopus and Web of Science databases. These articles span from 2000 to 2024. To mitigate the issue of older research receiving more citations than more recent work, a normalized citation measure was employed in this study. The citation count for each article was normalized by dividing the number of citations by the average number of citations for all articles published in that year (van Eck & Waltman, 2009). Consequently, the top five papers

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based on normalized citation (NS) are: (Merghadi et al., 2020; Soga et al., 2016; Froude & Petley, 2018; Ebrahim et al., 2024c; Hungr et al., 2014), as presented in Table 5.

Table 5. Top 10 cited articles according to normalized citations (NS).

Author	Article	Journal	Citation	NS
Merghadi et al. (2020)	Machine learning methods for landslide susceptibility studies: A comparative overview of algorithm performance	Earth-Science Reviews	603	8.20
Soga et al. (2016)	Trends in large-deformation analysis of landslide mass movements with particular emphasis on the material point method	Géotechnique	383	5.80
Froude & Petley (2018)	Global fatal landslide occurrence from 2004 to 2016	Natural Hazards and Earth System Sciences	1164	5.62
Ebrahim et al. (2024c)	Recent Phenomenal and Investigational Subsurface Landslide Monitoring Techniques: A Mixed Review	Remote Sensing	7	4.90
Hungr et al. (2014)	The Varnes classification of landslide types, an update	Landslides	2274	4.32
Ikram et al. (2023)	A novel swarm intelligence: cuckoo optimization algorithm (COA) and SailFish optimizer (SFO) in landslide susceptibility assessment	Stochastic Environmental Research and Risk Assessment	37	4.16
Zhang et al. (2021a)	Application of an enhanced BP neural network model with water cycle algorithm on landslide prediction	Stochastic Environmental Research and Risk Assessment	140	3.50
Mondini et al. (2023)	Deep learning forecast of rainfall-induced shallow landslides	Nature communications	31	3.49
Chae et al. (2017)	Landslide prediction, monitoring and early warning: a concise review of state-of-the-art	Geosciences Journal	267	3.03
Long et al. (2022)	A multi-feature fusion transfer learning method for displacement prediction of rainfall reservoir-induced landslide with step-like deformation characteristics	Engineering Geology	47	2.94

Keyword Co-occurrence Mapping in Landslide Prediction.

The VOSviewer software is capable of identifying the most frequently used keywords by selecting "co-occurrence" as the analysis type and "all keywords" as the unit of analysis. For this study, the minimum number of occurrences for a keyword was set to ten. As a result, only 45 keywords out of 1785 met this criterion, as shown in Figure 9. The size of each keyword node is proportional to its frequency of occurrence. Notably, the most commonly used keywords, "landslide" and "landslides," have the largest node size. The analysis reveals three distinct clusters: the blue cluster, which is associated with landslide susceptibility maps; the red cluster, which focuses on physical models; and the green cluster, which pertains to

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physically based thresholds. This analysis will help authors choose keywords that make published work in a specific region easier to identify in the future. VOSviewer's clustering capability was used to understand the mainstreams of any study field. The keyword network enables the researcher to obtain such information without reading the entire document. Furthermore, the subjectivity that permeates this information is not present in the conclusions reached from the narrative and systematic evaluations (Hussein & Zayed, 2021).

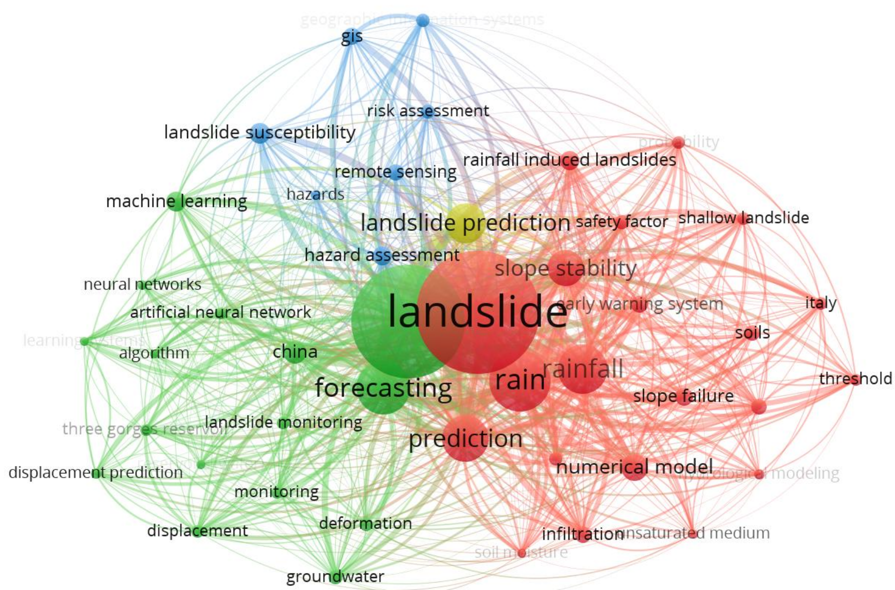

Figure 9. Keyword mapping in landslide prediction weighted by occurrence.

SYSTEMATIC REVIEW.

In this section, landslide prediction techniques are reviewed comprehensively. Landslide prediction techniques can be classified into two categories: 1) the scale of the investigated case and 2) the accessibility of inventory data. To explain this natural event, landslides can be examined from either a local or national perspective. The landslide scale classification is addressed by (Oguz et al., 2022), who categorized the scale into local landslides and national scales. To clarify, Figure 10 presents the national map of Hong Kong and the local 2018

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landslide. For the local scale, empirical-statistical thresholds, triggering-physical thresholds, and physical-deterministic models can be adapted based on the available data and the required accuracy of the prediction. However, landslide susceptibility, landslide risk, and landslide vulnerability maps can be utilized on a national scale. Figure 11 summarises the whole process adopted in this review based on the aforementioned classification. This Figure will be discussed in detail in two parts of this study: part i (this manuscript) and part ii (Ebrahim et al., 2024a) which has been published.

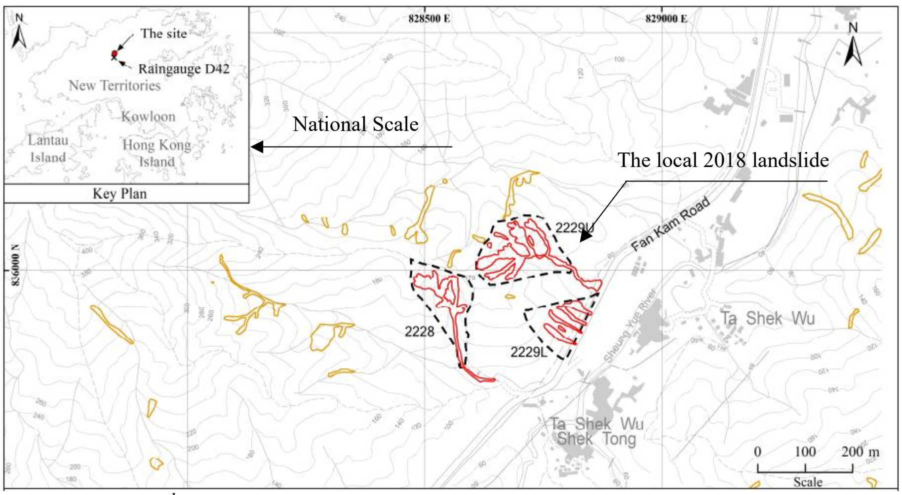

Figure 10. The 29th August 2018 landslides, above Fan Kam Road, Pat Heung, Hong Kong (AECOM, 2019) (By courtesy of Geotechnical Engineering Office HKSAR; used with permission)

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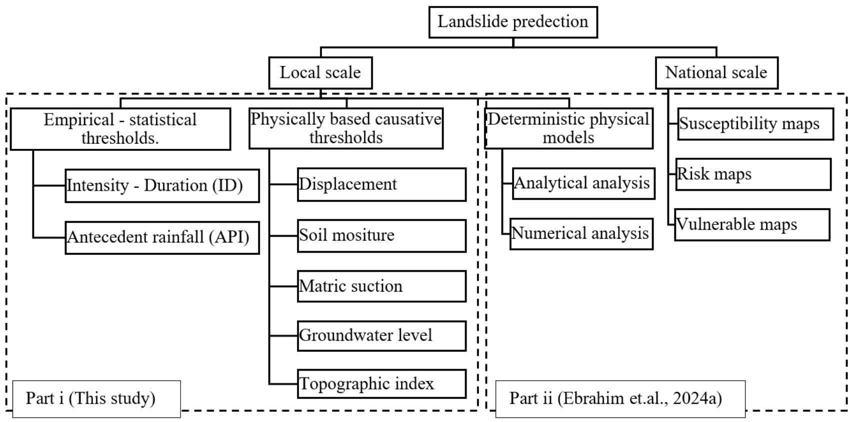

Figure 11. Classifications of landslide prediction models. Part ii has been already published (Ebrahim et al., 2024a).

In this section, we present a comparative analysis based on a comprehensive review of the literature. All figures and comparisons are created by the authors to synthesize and highlight key trends and findings across multiple studies. While the original data and results are from previously published research, each study is cited in the text. Given the large number of studies compared in some of the plots, it is impractical to list all sources directly below each figure. Instead, readers are referred to the relevant citations in the text for detailed references to the original studies.

Empirical-Statistical I-D Thresholds.

Intensity-Duration Thresholds.

Understanding the factors that trigger landslides is essential. Researchers have started predicting landslide occurrences using simple empirical thresholds (Caine, 1980; Hong et al., 2006; Lee et al., 2014; Gariano et al., 2019). Historically, landslides have been linked to rainfall, with landslides often depending on rainfall conditions. By analyzing historical data on rainfall intensity (I) and duration (D) for specific regions, rainfall thresholds can be established

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as a minimum limit beyond which landslides may occur (Wu et al., 2015; Zhao et al., 2019a). As Guzzetti et al. (2024) put it, "Rainfall thresholds are defined by a minimum amount of rainfall that, when exceeded, can trigger landslides. These thresholds are crucial for predicting potential landslides and form a core component of many landslide early warning systems. Using statistical regression, Equation 1 proposed by (Caine, 1980) as well as Equation 2 presented by (Hong et al., 2006) are examples of these thresholds. These equations apply only to a certain scenario. Furthermore, the general equation is presented by Equation 3 proposed by (Peruccacci et al., 2017). Equation 3 was developed for an area that suffers from landslides using a new technique called CTRL-T (Gariano et al., 2019). CTRL-T is a recent model that can automatically extract rainfall (Melillo et al., 2018).

1) $I = 14.82D^{-0.39}$ ***2)*** $I = 15.58D^{-0.52}$ ***3)*** $E = (\varepsilon \pm \Delta\varepsilon)D^{(\xi \pm \Delta\xi)}$

Where E represents the rainfall event, ϵ is the scaling parameter, and ζ is the shape parameter, which defines the intercept and slope of the power law curve, respectively. Additionally, Δϵ and Δζ denote the uncertainties associated with these two parameters

Furthermore, Ering and Babu (2020) developed Intensity-Duration (I-D) thresholds through the Forecasting of Landslides Induced by Rainfall (FLaIR) model. FLaIR can deal with varied rainfall inputs using the gamma-type transfer function *Ξ*(t) (Equation 4). Figure 12 illustrates that while these thresholds may offer high accuracy, the occurrence of false positive alarms limits their predictive effectiveness (Hong et al., 2018; Zhao et al., 2019a; Uwihirwe et al., 2020). To clarify, the intensity-duration (I-D) concept involves determining a critical intensity threshold, which, when exceeded, triggers landslides. These critical intensity values are fixed for a specific duration.

4) $\Xi(t) = t^{\nu-1}\exp\left(-\frac{t}{\mathrm{T}}\right) / T^{\nu}\Gamma(\nu)$,

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where υ denotes the dimensionless parameter, and T denotes the temporal scale.

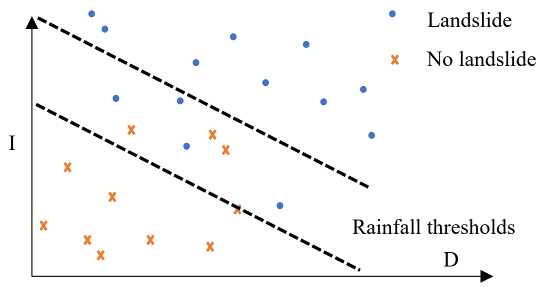

Figure 12. Uncertainties of rainfall thresholds.

Antecedent Rainfall Thresholds.

To address the limitations of I-D thresholds, causal thresholds have been proposed. Rainfall influences several interconnected factors, such as increasing ground saturation, soil weight, groundwater levels, soil erosion, and the effective stress of the soil, which in turn reduces the safety factor for slope stability (Chhorn et al., 2016). When analyzing rainfall-induced landslides, it is important to consider the significant role of antecedent rainfall, as it can also have a substantial impact on landslide occurrence (Hong et al., 2018). This factor helps account for other causative elements that contribute to landslide events (Lee et al., 2014; Chhorn et al., 2016; Hong et al., 2018; Uwihirwe et al., 2020). This can be illustrated by the infiltration, storage, and evaporation process, which mainly relies on the timing of the porewater pressure change in the subsurface soils (Uwihirwe et al., 2020). However, the specific duration of antecedent rainfall that is most critical for landslide prediction remains unknown (Chhorn et al., 2016). Lee et al. (2014) proposed the antecedent precipitation index (API), as shown in Equations 5, 6, and 7. Meanwhile, Huang et al. (2015) incorporated both the maximum hourly rainfall intensity along with the accumulated current rainfall, as well as the rainfall from the past six days.

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5) $API_{30} = 115 + 1.2x10^{-12} N^{10.6}$ **6)** $E_3 = -0.726 API_{30} + 295.0$ **7)** $E_3 = -0.726 API_{30} + 194.3$

Where API_{30} is the 30-day antecedent precipitation index, N is the number of rainy days within the 30 days concerned, and E_3 is the commutative 3-day rainfall. Equation 6 is for a major landslide, and Equation 7 is for a medium landslide.

Hong et al. (2018) applied inter-event time definitions (IETDs) and found that the highest accuracy was achieved with an IETD of 12 hours. IETD can be defined as the interval of time between two distinct rainfall occurrences. IETDs offer a viable way of analyzing antecedent rainfall, as shown in Figure 13. Chhorn et al. (2016) proposed various durations rather than a single crucial time to increase forecast accuracy. The best combination that gave a probability of 58.5% was found to be antecedent 1 hour, 15 hours, and 19 days. Uwihirwe et al. (2020) used the Bayesian probabilistic approach, maximum true skill statistic, and minimum radial distance to determine that rainfall on the occurrence day, along with antecedent rainfall from the previous 10 days, provided the best accuracy, achieving an AUC of 0.669 (see Figure 14-a). Unlike previous studies, Zhao et al. (2019b) developed a modified API to consider the variation in the evaporation process and the maximum soil moisture capacity. The modified API threshold surpasses the general form of I-D thresholds adopted by (Brunetti et al., 2010) (Figure 14-b). Aryastana et al. (2024) concluded that considering a cumulative rainfall of 30 days (i.e., antecedent effect) could improve the accuracy of the traditional thresholds achieving an accuracy of over 90%. Ebrahim and Zayed (2024) found that considering Hong Kong as a case study, the recovery time can vary between two weeks to approximately five weeks.

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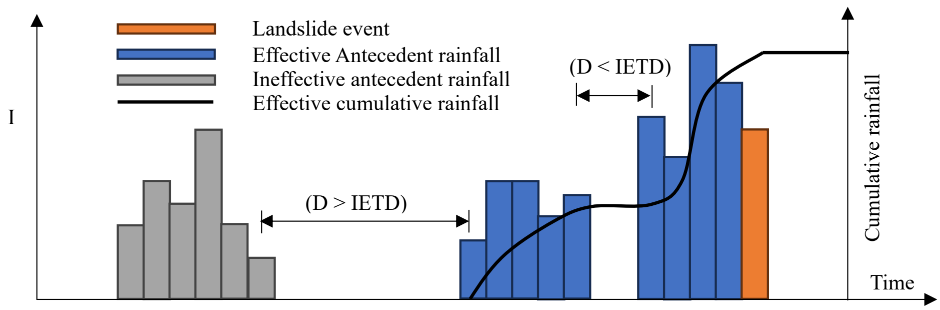

Figure 13. Rainfall pattern with effective cumulative rainfall for different non-rainfall periods (D).

I-D Thresholds Prediction Accuracy.

The accuracy of any model depends on several factors, including the availability of data, rainfall parameters, and the specific characteristics of each case study. In a recent study, Uwihirwe et al. (2020) utilized the Bayesian probabilistic approach, maximum true skill statistic, and minimum radial distance to assess the accuracy of various rainfall-triggering thresholds. As presented in Figure 14-a, the best accuracy (AUC) is achieved using rainfall events. On the other hand, this method suffers from a high false positive rate (FPR). In contrast, adopting simple causative antecedent rainfall (API_{10}) reduced the FPR. Similarly, Zhao et al. (2019b) proved that the modified API can achieve better results than I-D models (see Figure 14-b).

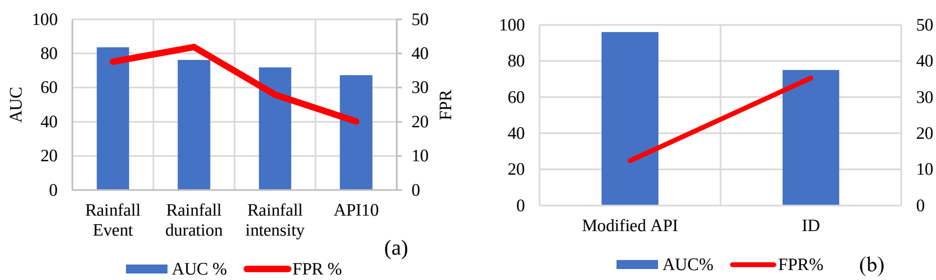

Figure 14. Accuracy (AUC) and true false positive rate (FPR) for different rainfall variables.

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As illustrated above, considering the slope response in terms of antecedent effect (i.e., moisture dynamics) helped the model to achieve better accuracy than relying only on rainfall. These trigger thresholds for landslide causation have been recently proposed by several studies (Lee et al., 2014; Huang et al., 2015; Chhorn et al., 2016; Bogaard & Greco, 2018; Hong et al., 2018). These methods are simple and consider only antecedent rainfall as a causative trigger of landslides. Therefore, different causative features are required for further improving the prediction accuracy and will be discussed in section (5.2) “Physically Based Causative Thresholds”.

Physically Based Causative Thresholds and Prediction.

If a landslide occurs during a rainfall period where the total precipitation reaches its peak, this period is considered the critical duration. However, if the landslide happened while the cumulative antecedent rainfall was not at its highest, then the landslide was caused by factors other than rainfall (Chhorn et al., 2016). The connection between rainfall-induced landslides and the reduction in soil strength is affected by several factors, such as slope infiltration, vegetation cover, topography, and hydraulic properties. The amount of rainfall cannot solely determine the occurrence of landslides, as other factors may influence their likelihood. Therefore, relying solely on a rainfall threshold is insufficient in explaining the occurrence of landslides. Furthermore, once established, the threshold is the same regardless of the soil conditions (Hong et al., 2018; Zhao et al., 2019a). Integrating rainfall as an external trigger with the causative factors of landslides provides reasonable accuracy with a low false positive rate. These causative features (i.e., instability indicators) can be as follows: antecedent rainfall (discussed earlier) (Hong et al., 2018); moisture content (De Luca & Versace, 2017; Bezak et al., 2019; Zhao et al., 2019b); topographic thresholds (Ho et al., 2012); displacement (Bednarczyk, 2018); suction of the soil (Davar et al., 2022); and groundwater level (Cao et al., 2020). Therefore, this section is arranged as shown in Figure 15 to list such applications.

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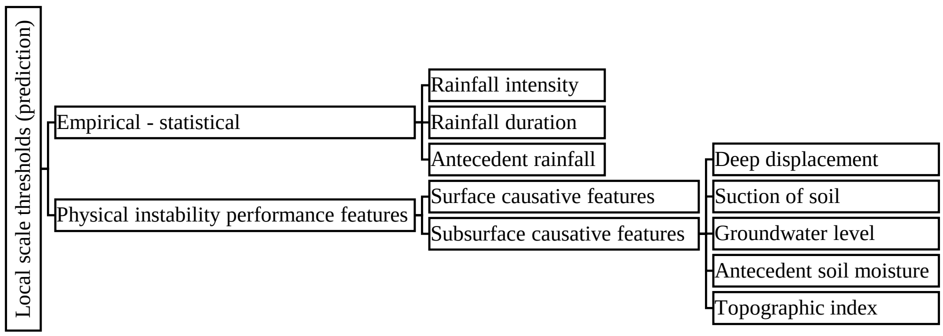

Figure 15. A schematic view for regional thresholds (prediction).

It should be emphasized that the term physically-based causative refers to an approach that combines rainfall, as the main triggering factor, with additional indicators of instability to enhance model accuracy. While rainfall remains a critical trigger, other factors—such as moisture content, topographic thresholds, displacement, soil suction, and groundwater level—are integrated to improve the robustness of landslide predictions. In this section, we examine these secondary indicators of instability, emphasizing how they complement primary causative factors such as rainfall, thereby offering a more holistic understanding of landslide dynamics.

Displacement Instability Performance and Prediction.

Landslide displacement prediction can be categorized into four key processes: data inventory and input parameters, model selection, data preparation (including sampling and decomposition), and model evaluation, as presented in Figure 16. Each process will be discussed in detail as follows.

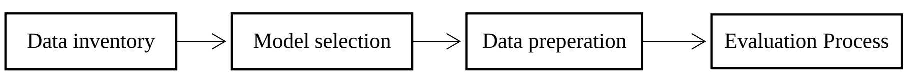

Figure 16. Landslide displacement prediction process.

1. Data inventory and input model parameters.

When enough monitoring data are collected, numerous mathematical approaches can be utilized to predict landslides with reasonable accuracy. Full-site investigations, real-time

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monitoring, and laboratory tests can be used as quick warning signs. For example, the occurrence of significant pore-pressure variations could serve as an early warning indicator before substantial movements take place. However, this mainly depends on the precision of the geotechnical data interpretation and the selection of monitoring locations. Since the geotechnical and hydrological properties require massive work to provide accurate datasets and have a limited generalization ability (Niu et al., 2021), the monitoring of landslide movements offers a viable way to overcome the aforementioned drawbacks (Lian et al., 2014). Various researchers have based their studies on continuously monitored displacement data using GPS data (Lian et al., 2014; Yao et al., 2015; Li et al., 2021; Niu et al., 2021; Zhang et al., 2021a; Zhang et al., 2021b; Wang et al., 2023b), GNSS (Krkač et al., 2017), optical fiber (Han et al., 2021), and fiber Bragg grating technology (Shentu et al., 2022). One of the most studied areas is the Three Gorges region near the Yangtze River in China, which experiences landslides due to rainfall and fluctuations in reservoir levels (Lian et al., 2014; Yao et al., 2015; Cao et al., 2016; Lian et al., 2016; Liu et al., 2016; Xing et al., 2019; Gao et al., 2020; Han et al., 2021; Li et al., 2021; Zhang et al., 2021a; Zhang et al., 2021b; Long et al., 2022; Wang & Zhao, 2023; Wang et al., 2023a; Wang et al., 2023b). In addition to historical displacement data, the model inputs also include other causative factors as outlined in Table 6. These factors are as follows: rainfall data factor that can reach up to 75 features (Krkač et al., 2017); antecedent and rolling rainfall, rainfall intensity, and effective rainfall (Liu et al., 2016); groundwater level that can count 10 variables (Krkač et al., 2017); climate features (Krkač et al., 2020); reservoir water level parameters (current value, antecedent change rate, average value, etc.) (Zhang et al., 2021a; Wang et al., 2023b); and porewater pressure (Sasahara, 2017; Bednarczyk, 2018). A schematic view can summarize the aforementioned variables presented in Figure 17.

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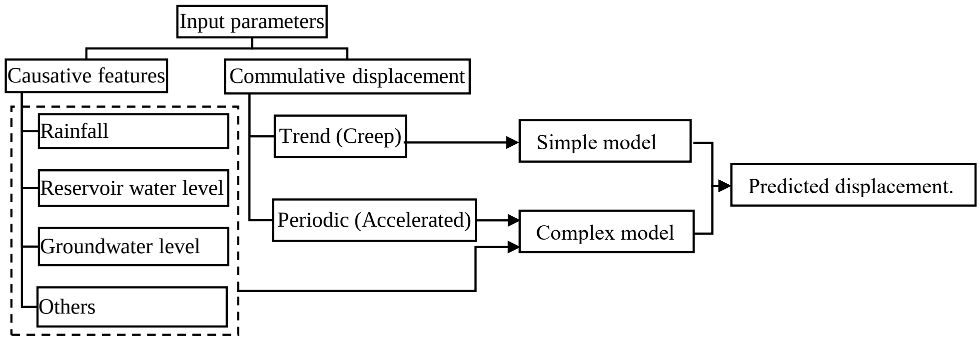

Figure 17. Schematic view of the input parameters.

2. Model selection.

First, researchers have adopted regression analysis due to its advantages, including the fact that it does not require prior information to create the function, is simple to understand, and can estimate the contributions of the input variables (Zhang et al., 2016). Bednarczyk (2018) correlated the relationship between the magnitude of displacement (S) with cumulative rainfall (R) and cumulative pore pressure difference using linear regression. However, geotechnical monitoring data (i.e., pore pressure) are lacking. Similarly, Chen et al. (2018) used linear correlation to examine the relationship between rainfall, reservoir level fluctuations, and surface displacement. On the other hand, the relation between the aforementioned variables is complex and needs to be investigated with nonlinear relationships. The reason for such complex behavior is the time lag between the peak external triggering and peak displacement of the slope. This lag is variant, with the case study ranging from approximately 6 months to 6 days (Chen et al., 2018) (Figure 18). Abolmasov et al. (2015) tried to correlate the displacement with the river level, which exhibited a low correlation (R^2 = 0.145) considering the time lag effect and the accelerated displacement concept (refer to Figure 19), Sasahara (2017) concluded that regression analysis using hyperbolic relationships provides reasonable prediction accuracy for temporal variation of the shear strain and surface displacement using pore water pressure and groundwater level, respectively. However, this study was based on a laboratory physical

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uniform soil model. However, Natural slopes are made up of more complicated, non-uniform soil layers. Li et al. (2021) adopted a new mathematical short-term forecasting of landslides (STFL) to predict the failure time. This method achieved accurate prediction ($R^2 > 0.99$) (refer to Equation 8 and Figure 19). In the tertiary stage, when the tangential angle exceeds 79°, the displacement parameters can be employed to obtain the equation unknowns using the Levenberg–Marquardt (LM) algorithm.

8) $S = P_1(P_2^{P_3 t} - 1)/(P_0 - t)$, where P_0, P_1, P_2, and P_3 are the simulated parameters, t denotes time, and S denotes displacement.

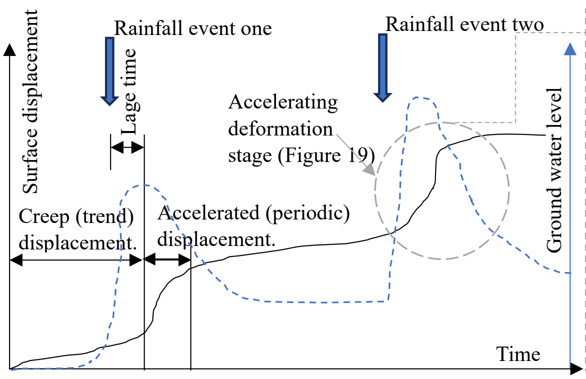

Figure 18. The relationship among rainfall events, surface displacement, and groundwater level with time.

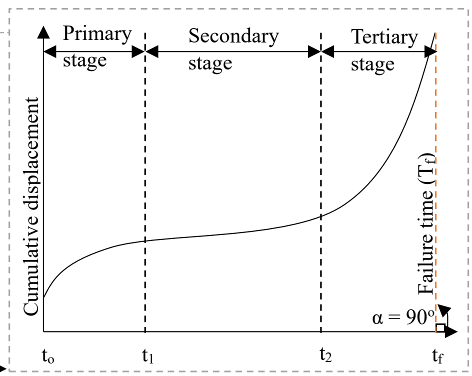

Figure 19. Accelerated deformation stage.

The thresholds for landslide deformation vary from one landslide to another. Displacement thresholds are thus not recommended. Shentu et al. (2022) proposed alert limits based on the direction angle of the displacement rather than its value. However, the tangential angle of the curve changes when the scales of either the displacement or time coordinates are adjusted. Consequently, Li et al. (2021) suggest using the displacement rate. However, researchers have tried to predict the displacement before the real failure time for early warning purposes and to create a displacement threshold.

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With the advancement of intelligent algorithms, an increasing number of nonlinear models have been employed in landslide displacement prediction. Additionally, investigating the affecting triggering factor improves the quality of the dataset, reduces the randomness, and decreases the computational effort (Han et al., 2021). Consequently, it is impractical to use linear or empirical equations to simulate or predict dynamic, non-linear, and unsymmetrical data (Lian et al., 2014; Yao et al., 2015). Intelligence models offer a viable way to manage such dynamic relationships. Artificial intelligence models can be regression (Niu et al., 2021), classification (supervised) (Tengtrairat et al., 2021), and clustering (unsupervised) (de Souza & Ebecken, 2012; Lian et al., 2016). The application of supervised learning techniques is the most prevalent in recent research articles (Ebrahim et al., 2024c). Intelligence regression models can be used to predict displacement (Lian et al., 2014), groundwater level, and matric suction (Davar et al., 2022). It can be combined with physical models to improve the model performance (Marrapu et al., 2021), reduce uncertainty (Xing et al., 2019), and overcome missing data issues (de Souza & Ebecken, 2012). Classification models were utilized to provide landslide susceptibility maps (Tengtrairat et al., 2021). Artificial regression models were mainly adopted for regional areas, such as physical models and empirical-statistical thresholds. At the same time, classifications and landslide susceptibility (LSM) were mainly used for large catchments to plan land usage (Oh & Lee, 2017). The regression intelligence model is discussed first in this study (part i), and LSM is discussed afterward in part ii which has been published (refer to (Ebrahim et al., 2024a). Figure 20 highlights the different recently adopted methods regarding displacement prediction.

Thus, single artificial models have been adopted, such as ANN (BPNN) (de Souza & Ebecken, 2012; Liu et al., 2016; Neaupane & Achet, 2004), RNN (Yao et al., 2015), ELM (Yao et al., 2015; Cao et al., 2016), GM(1,1) (Yao et al., 2015), SVM (Cao et al., 2016), RF (Krkac et al., 2017; Krkač et al., 2020), and MLR (Krkač et al., 2020). However, these single models

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may be improved due to the dynamic nature of landslides and their influencing factors (Lian et al., 2014; Yao et al., 2015; Gao et al., 2020; Li et al., 2021). For example, landslide displacement can be classified into trend and periodic behavior, as shown in Figure 21. The former mainly depends on the creep effect of landslides, such as lithology, structure, and stress state, while the latter is pertinent to random factors such as rainfall, reservoir level fluctuation, and groundwater change. Predicting sudden changes in displacement has received much interest due to its significant effect (Lian et al., 2016). Traditional models such as ANN and SVM have low accuracy in predicting such behavior because the volume of such displacement points (mutational points) is much lower than the trend point. Moreover, the periodic points are always delayed with the triggering factor (Figure 22). Therefore, Gao et al. (2020) and Li et al. (2021) recommended using multi-data-driven models to manage such complex behavior.

EEMD–ELM (Lian et al., 2014), LSTM-DMA (Xing et al., 2019), GM-ENN (Gao et al., 2020), KGM, MKGW, and WMKGM (Li et al., 2021), WCA-BPNN (Zhang et al., 2021a), SSA-LSTM (Yang et al., 2022), EEMD-RNN, EEMD-GRU, EEMD-LSTM, EEMD-SVM, EMD-LSTM, and EEMD-ELM (Niu et al., 2021), ELM-RS-SVR (Wang et al., 2023a), SVM-(MSI, BA, GWO, DA, WOA, GOA, SSA)-CEEMD (Zhang et al., 2021b), SVC-PSO-SVR (Han et al., 2021), DES-VMD-(BLSTM, BGRU, BRNN), DES-(BLSTM, BGRU, BRNN) (Wang et al., 2023b), and (GOA-GA-VMD)-GRA-(TempoVar-Transformer) (Ye et al., 2024) were utilized to overcome the shortening of the single models. Hybrid models refer to a model that combines the advantages of more than one model to surpass the drawbacks of a single model.

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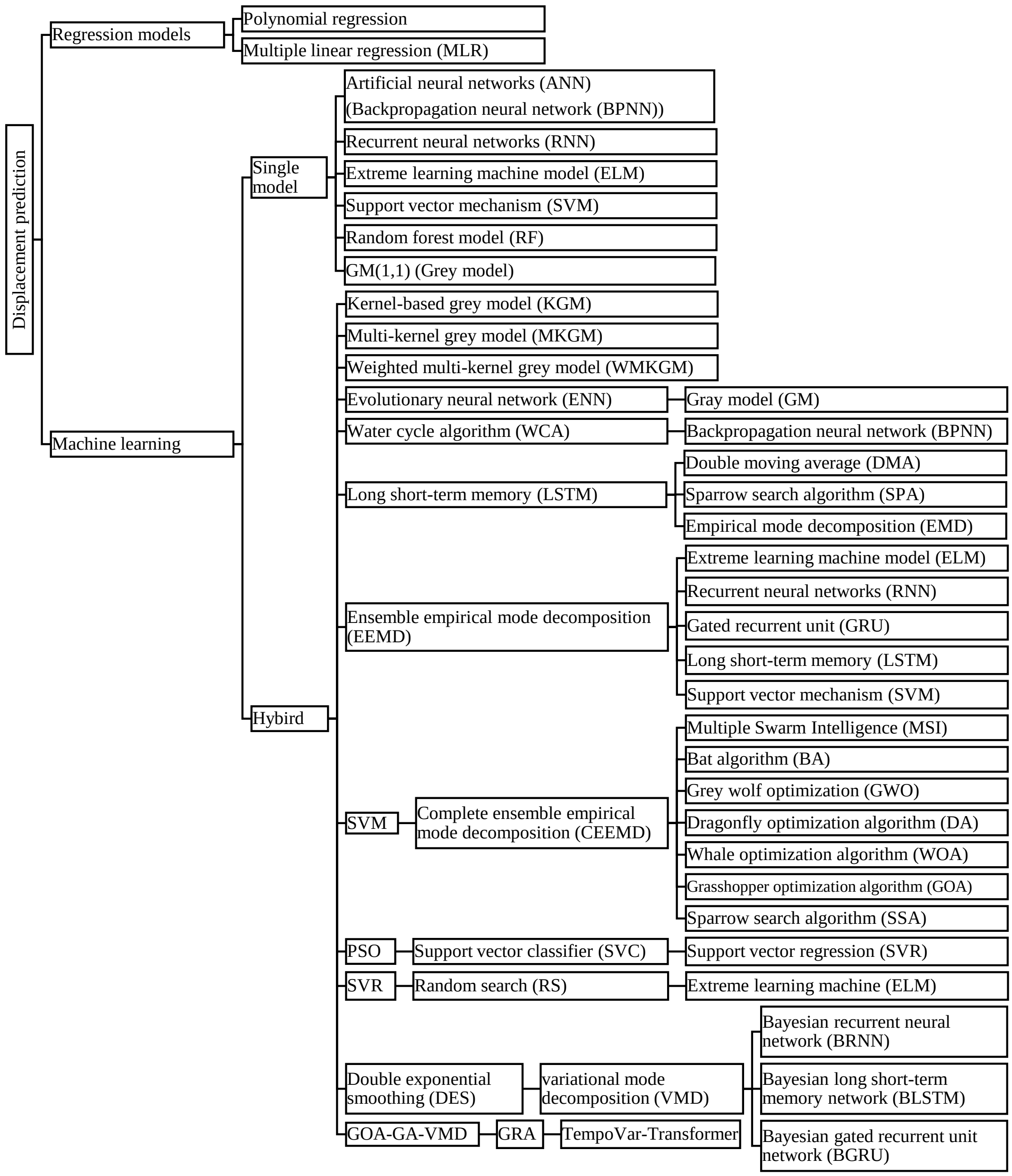

Figure 20. Model selection of landslide displacement.

3. Model decomposition and data preparation.

As shown in Figure 22, the cumulative displacement can be separated into creep and accelerated displacement using various analysis techniques, including high-pass (HP) filter analysis (Zhang et al., 2021a), double moving average (DMA), and single moving average (SMA) models (Xing et al., 2019). Other methods include empirical mode decomposition (EMD) (Niu et al., 2021), ensemble empirical mode decomposition (EEMD) (Lian et al., 2014), EEMD with kurtosis criterion (Niu et al., 2021), and complete ensemble empirical mode decomposition (CEEMD) (Zhang et al., 2021b). The CEEMD mode has an advantage over EMD and EEMD that can consider the residual term of first decreasing and then increasing. A support vector classifier (SVC) can be used to classify the creep and acceleration state (Han et al., 2021). DES-BDNN (Wang et al., 2023b) and K-means clustering (Lian et al., 2016) were also adopted to divide the total displacement into stationary and mutational points. Variational mode decomposition (VMD) can be employed to isolate each displacement component, with optimization achieved through the GroupWise coupling algorithm (Ye et al., 2024). Following this, the cumulative predicted displacement is calculated by superimposing the results from both models. It is important to note that periodic displacement is predicted using factors such as rainfall, reservoir level, groundwater level, and periodic displacement itself. In contrast, trend displacement is forecasted using historical cumulative displacement data (Niu et al., 2021).

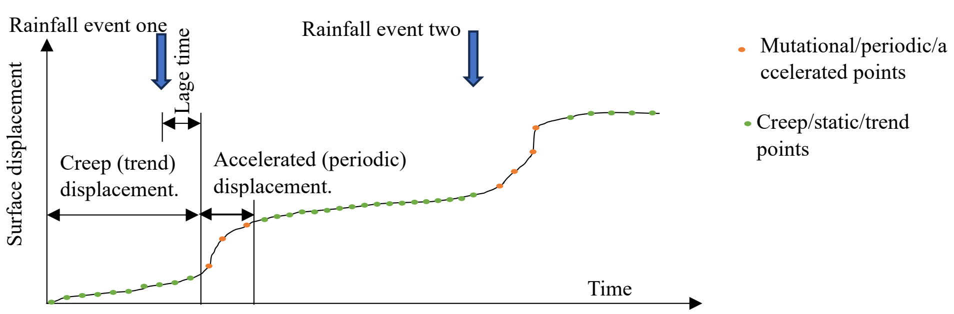

Figure 21. Accelerated and creep displacement points.

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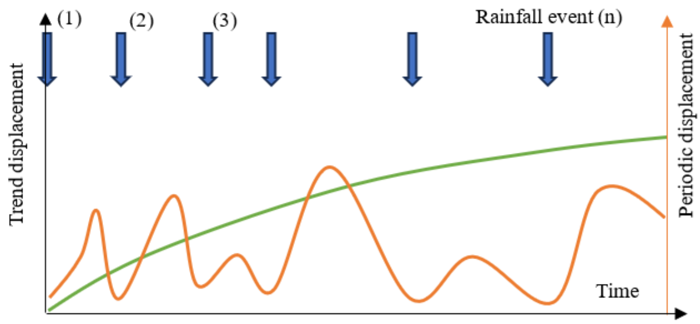

Figure 22. Trend and periodic displacement change according to a rainfall event.

4. Training and testing data split ratio.

Generally, the ratio of the training and testing datasets is a factor affecting the accuracy of the prediction. Krkac et al. (2017) adopted different ratios and suggested that a testing ratio of up to 4% is acceptable, as shown in Figure 23. Krkač et al. (2020) adopted 49 Folds with a training ratio of 98% and a testing ratio of 2%. Wang et al. (2023b) utilized a new technique to reduce the complexity of nonlinear displacement and expand the quantity of training data using VMD and interpolation, respectively. Most of the mentioned studies in Table 6 divided the monitoring data based on a specific period or number of fixed measurements. For comparison purposes, it is suggested to calculate the ratio and round it up to ± 5% if the ratio is not mentioned in the article. Training to testing sampling ratios of 70%:30% (Yao et al., 2015; Liu et al., 2016; Gao et al., 2020; Zhang et al., 2021a; Zhang et al., 2021b; Davar et al., 2022; Ye et al., 2024) and 80%:20% (Lian et al., 2014; Cao et al., 2016; Lian et al., 2016; Xing et al., 2019; Marrapu et al., 2021; Yang et al., 2022) are mostly employed. This was followed by a sampling ratio of 85%:15% (Han et al., 2021; Niu et al., 2021), 90%:10% (Li et al., 2021; Wang et al., 2023a), 60%:40% (Sasahara, 2017), and 50%:50% (Neaupane & Achet, 2004).

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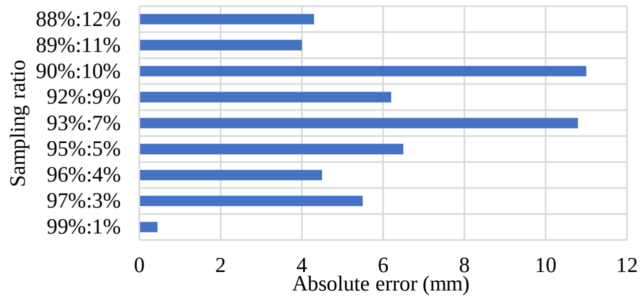

Figure 23. Absolute error values versus different sampling ratios.

5. Missing data and training data shortage.

Monitoring surface displacement encounters complicated circumstances such as monitoring device failure, data noise, and loss, resulting in low forecast accuracy (Shentu et al., 2022). Additionally, computerized monitoring equipment is continuously exposed to the outdoor environment, leading to inevitable issues such as deterioration, aging, power loss, and other factors, all of which can result in missing monitoring data (Wang & Zhao, 2023). Some researchers have attempted to remove these missing data to create a complex intelligence model (de Souza & Ebecken, 2012), use a small dataset (Shentu et al., 2022), adopt statistical filling for missing data series (Li et al., 2021; Wang & Zhao, 2023), and utilize fusion transfer learning (Long et al., 2022).

de Souza and Ebecken (2012) utilized artificial neural networks ANN combined with statistical means (correlation and principal component analysis PCA) and clustering (K-means and Dendrogram approaches) to predict rainfall missing data where PCA and correlation combined with ANN achieved the best results. Shentu et al. (2022) adopted a small sampling dataset using a new multivariate grey model (Feedback Optimizing Background Grey Model FOBGM (1, N)) to predict the deep displacement. The proposed model achieved the best accuracy compared with GM (1,1), GM (1, N), OGM (1, N), and BPNN. However, this study neglects the actual complex conditions, as it is based on laboratory tests. Moreover, using a

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small-sample dataset is not an ideal solution (Wang & Zhao, 2023). They propose a time series prediction model for landslide displacement based on mean-based low-rank autoregressive tensor completion (MLATC), which addresses the issue of missing data during the landslide monitoring process. Li et al. (2021) applied cubic spline interpolation to handle data gaps, used Savitzky-Golay filters to smooth noisy data, and employed the t-test to remove misfits. A novel technique for handling missing data is proposed by Long et al. (2022), which assumes that landslides in similar geographical and geological settings share similar deformation properties, though they vary in magnitude. In this context, multi-feature fusion transfer learning (MFTL) is used to incorporate data from neighboring locations with similar displacement behavior as a training dataset. This approach provides a viable solution when a sufficient training dataset is lacking. The dataset considered factors such as rainfall and reservoir level fluctuations to predict mutation and creep displacements. Additionally, for mutation displacement, the non-uniform weight error (NWE) was combined with MFTL to improve prediction accuracy.

6. Regression performance implementation.

To evaluate model accuracy, the most commonly used methods for displacement prediction models include the coefficient of determination (R^2) and root mean squared error (RMSE). Additionally, various other evaluation metrics, such as mean absolute error (MAE) and mean squared error (MSE), are also employed. These parameters can be calculated using equations 9, 10, 11, and 12 (Willmott & Matsuura, 2005). Higher values of these parameters indicate poorer model predictions, whereas values closer to 0 indicate higher accuracy. Moreover, the standard deviation ratio (SDR) can be used to evaluate the model where the closest SDR to 0 highlights high accuracy (Bland & Altman, 1996). Pearson-R Correlation (PRC) assumes that the values should fall between -1 and +1, where +1 denotes the strongest possible positive agreement (Cohen, 1998).

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9) $R^2 = 1 - \left(\sum_{i=1}^{N} (X_i - Y_i)^2 / \sum_{i=1}^{N} (Y_i - \overline{Y})^2 \right)$

10) $RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (X_i - Y_i)^2}$

11) $MAE = \frac{1}{N} \sum_{i=1}^{N} |X_i - Y_i|$

12) $MSE = (RMSE)^2$

Where Y_i is the specific value of the i^{th} real data; $\overline{Y}$ is the average value of the real data; X_i is the specific value of the i^{th} predicted data.

7. Displacement models prediction accuracy.

The performance of a prediction model is influenced not only by the intelligence of the model itself but also by the underlying controlling factors. Landslide issues, for instance, have been extensively studied through physical models, where the theoretical relationship between input and output parameters is already established. Thus, if the input parameters in an intelligent model correspond to the physical features, the output should ideally align with that of the physical model (i.e., analytical models). The effectiveness of statistical or intelligent models is largely determined by controlling factors, such as the strong dependence between the model and these factors, the quality of the dataset, the sampling ratio, and the accuracy of the inventory data. Table 6 provides a detailed comparison of these models, considering both their final accuracy and performance. Additionally, Figures 24, 25, and 26 present a comparison focused solely on the accuracy and performance of the models, emphasizing those with the best results. The structure of this discussion is designed to offer insights into the controlling factors and initial conditions influencing the models.

In general, there is no universally superior model; rather, the best prediction depends on the investigation of the influencing features and the consideration of the actual initial conditions, which can significantly enhance model accuracy (refer to Figure 21) (Han et al., 2021; Dal Seno et al., 2024). Consequently, outdated or irrelevant features can negatively impact the model, making it beneficial to remove these factors (Cao et al., 2016). Studies have

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indicated that BPNN (Liu et al., 2016) and MLR (Krkač et al., 2020) offer reasonable accuracy; however, these models are relatively simple and fail to capture dynamic and non-linear relationships. This limitation arises because the well-established datasets often closely represent the physical mechanisms (Krkač et al., 2020; Liu et al., 2016). Marrapu et al. (2021) found that ANNs trained on large datasets tend to deliver higher accuracy compared to those trained on smaller datasets. However, when the dataset lacks critical information, the model needs to be refined to better understand these complex relationships (Zhang et al., 2021a). A solid understanding of the physical behavior and initial conditions is essential for selecting the most appropriate model. For instance, Wang et al. (2023a) categorized displacement into trend and periodic datasets, which helps in selecting a more suitable model.

Disregarding the influence of the dataset, sampling ratio, and model assumptions, Figures 24, 25, and 26 emphasize the accuracy of various models, specifically in terms of root mean square error (RMSE) and coefficient of determination (R^2). All data are provided in Table 6 for further information. GM (1,1) achieved the minimum RMSE among all single models for total displacement. At the same time, PSO-SVR-SVC hit the minimum RMSE among all hybrid models. The maximum R^2 can be achieved for creep displacement by adopting simple polynomial regression, while the minimum RMSE is recorded using the LSTM-DMA hybrid model. Regarding periodic displacement, RS-SVR records the maximum R^2 and hits the minimum RMSE. Generally, trend displacement can be predicted using a simple polynomial regression (Zhang et al., 2021a; Wang et al., 2023a), a grey model (Gao et al., 2020), or a single artificial intelligence model such as ELM (Wang et al., 2023a) and DES (Wang et al., 2023b). These models provide high accuracy for trend displacement. However, the problem is a periodic displacement that exhibits complex and non-linear behavior (Gao et al., 2020; Li et al., 2021). The short-term acceleration effect displacement (Periodic) requires hybrid model analysis such as RS-SVR.

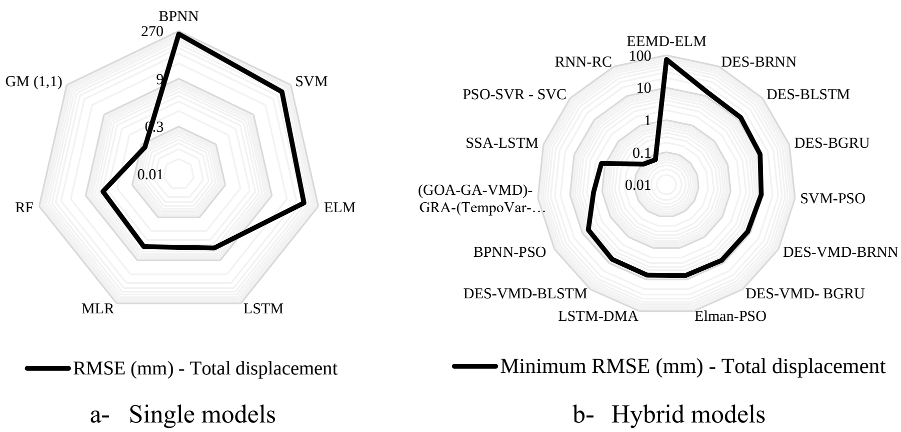

Figure 24. Comparison between different models' accuracy according to RMSE.

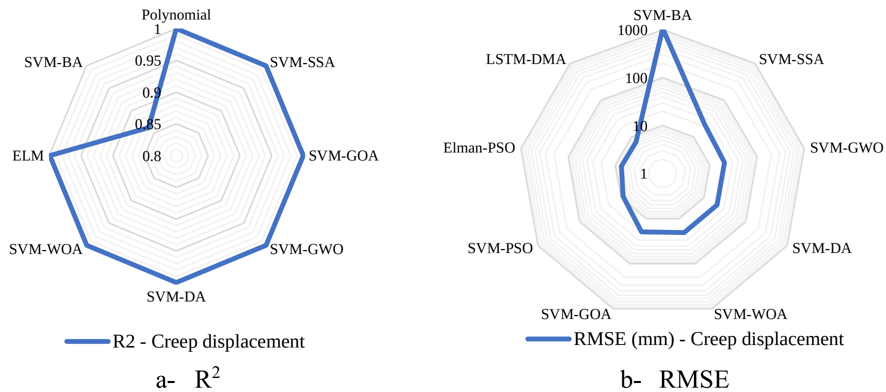

Figure 25. Comparison between different creep models' accuracy.

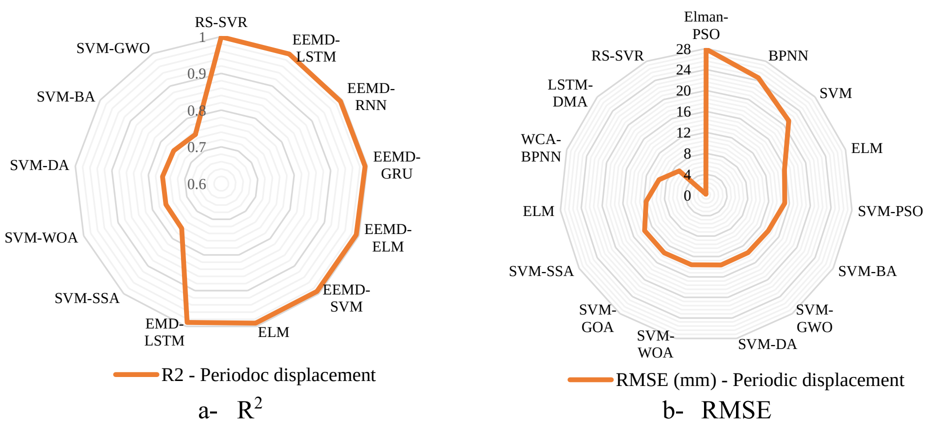

Figure 26. Comparison between different periodic models' accuracy.

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Table 6. Recent artificial intelligence models predict landslide displacement.

Study	Key features	Model with the best accuracy			Sampling ratio (Training: Testing)	Model performance: (R^2)[1], RMSE (mm)[2], MAPE%[3], MSE (mm^2)[4], Minimum error%[5], Maximum error %[6], MAE (mm)[7], MAPE (mm)[8]	
		Creep	Periodic	Decomposition		Creep displacement	Periodic displacement
(Neaupane & Achet, 2004; Yao et al., 2015; Cao et al., 2016; Liu et al., 2016; Krkač et al., 2017; Krkač et al., 2020; Li et al., 2021; Yang et al., 2022)	- Trend features: Time series cumulative displacement. - Periodic features: Antecedent, rolling, and current data for rainfall, reservoir level, and groundwater level. - Infiltration and evaporation data to estimate effective rainfall*.	BPNN		-	- Varied sampling ratio (refer to Section 4.2.1.4) - 70%:30% and 80%:20% are widely adopted	0.891[1]	
		ELM		-		0.984[1]	
		RF		-		0.998[1] 2.56[2]	
		MLR		-		3.06[2]	
		KGM		-		0.9998[1]	
		RNN-RC				0.07[2] 0.04[3]	
		BPNN-PSO		-		38.4[4]	
		SSA-LSTM		-		0.965[1] 1.307[2]	
(Lian et al., 2014; Gao et al., 2020; Xing et al., 2019; Niu et al., 2021; Zhang et al., 2021a; Zhang et al., 2021b; Han et al., 2021; Wang et al., 2023a; Wang et al., 2023b; Ye et al., 2024)		PSO-SVR		SVC		0.08827[2] 0.02105[8]	
		DES	VMD-BLSTM	DES-BDNN		0.983[1] 7.224[2]	
		GM (1,1)	ENN	-		0.2[5]	9.73[6]
		ELM	RS-SVR	-		0.9991[1]	0.9991[1] 0.1993[2]
		Polynomial	WCA-BPNN	High Pass (HP) filter		> 0.99[1]	40.60[3] 9.47[2]
		LSTM-DMA		DMA		7.28[2] 6.02[7]	6.92[2] 5.7[3]
		EEMD-ELM		EEMD		74.00[2]	2.3944[3]
		Polynomial	EEMD-LSTM	EEMD and kurtosis criterion		1[1]	0.998[1] 0.25[3]
		SVM-SSA		CEEMD		0.9998[1] 22.766[4]	0.762[1] 13.589[2]
		GRA-TempoVar-Transformer		GOA-GA-VMD		1.86[2] 4.85[7]	

Matric Suction and Groundwater Prediction.

Artificial intelligence models can also be employed to predict internal causative factors, such as soil matric suction (SMS) and groundwater levels, due to their non-linear and complex nature. In this context, SMS, which can represent soil shear strength, was predicted using a hybrid intelligence model developed by Davar et al. (2022). This hybrid model not only incorporates extensive datasets of physical soil properties but also evaluates the effects of three different algorithms: Bayesian Regularization Backpropagation (BR-BP), Particle Swarm Optimization (PSO), and Butterfly ANN Optimization Algorithm (BOA). The proposed hybrid model addresses the slow learning rate and generalization issues often associated with ANN models. The study utilized comprehensive field monitoring and laboratory data, including soil depth, VSMC, air

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temperature, rainfall, soil temperature, and suction. Among the various models, PSO-ANN demonstrated the best performance.

Similarly, groundwater level fluctuations are closely linked to landslide occurrences, with the behavior of groundwater being influenced by rainfall and reservoir level fluctuations, albeit with a time lag. Cao et al. (2020) applied a hybrid model known as the Genetic Algorithm-Support Vector Machine (GA-SVM) to address the nonlinearity between intrinsic and extrinsic factors. The model incorporated multiple features, including antecedent and current rainfall and reservoir levels. The results showed that the accuracy of the GA-SVM model exceeded that of the BPNN model. However, both the GA-SVM and BPNN models with multi-features outperformed the GA-SVM model with a single feature. Liu et al. (2021) employed a regression tree model to predict groundwater level changes, using rainfall, soil moisture content, and water level as input parameters. The soil moisture content takes into account various factors such as surface runoff, vegetation, climate conditions, and soil structure. The proposed model outperformed ANN, SVM, ELM, and Gaussian Process Regression (GPR), achieving an RMSE of 0.0812. Ng et al. (2023) introduced a novel multivariate long short-term memory (M-LSTM) model to predict pore water pressure (PWP) responses by simultaneously utilizing spatial and temporal PWP data from multiple measurement locations. However, such models are limited by the lack of geotechnical data, whereas displacement prediction is more widely adopted due to the availability of monitoring data for surface displacement.

Moisture Content and Topographic Thresholds.

Zhao et al. (2019b) incorporated the effect of antecedent soil moisture content along with recent rainfall using a Bayesian probabilistic approach. The soil moisture content was calculated using the SHETRAN (Système Hydrologique Européen TRANsport) model. The rainfall event,

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antecedent soil wetness, rainfall duration, cumulative rainfall (mm), and landslide were examples of the datasets used in the Bayesian analysis. Thus, probabilistic thresholds can provide better accuracy than I-D thresholds. De Luca and Versace (2017) utilized the new GFM (Generalized FLaIR Model), which can be used for both shallow and deep-seated landslides. The GFM considers the initial soil moisture that depends on antecedent rainfall. Additionally, several configurations can be defined to choose the most suitable threshold, as illustrated in Equations 13 and 14. A lumped conceptual hydrological model is used to develop a threshold (Equation 15). The production storage level (PSL) is calibrated using evaporation and discharge data, accounting for the wetness increase throughout the entire event (WI) (Bezak et al., 2019). This model was developed based on the GR4J model, as adapted from Perrin et al. (2003) (refer to Figure 27). The *R - PSL* threshold produces meaningful results compared to *I-D* thresholds for long-duration rainfall, while for events with different characteristics, such as short duration, other definitions, such as hourly rainfall data, are used instead of daily rainfall (Bezak et al., 2019).

13) $Y(t) = \int_{t-M}^{t} I(\mathrm{T})\Xi(t-\mathrm{T})d\mathrm{T}$

14) $Y_{cr}(t) = \left(R^{*}{}_{D}(t-d)/D\right) + \left(f\left[R^{*}{}_{D}(t-d)\right]/d\right)$

15) $R = a * PSL + b$

where Y is a mobility function, I is rainfall intensity, Ξ represents a filter function that can take different mathematical expressions, t is time, T is defined on the interval [t-M; t], M is the process's temporal memory, and $R^{*}{}_{D}$ is cumulative rainfall filtered on D and d durations and evaluated at the instants (t-d) and t, respectively.

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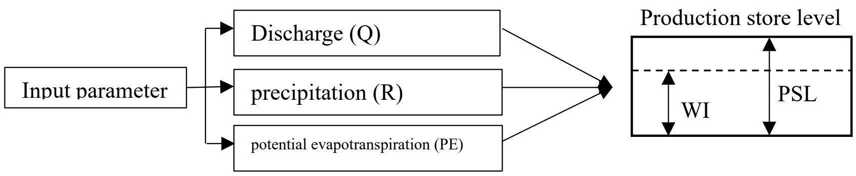

Figure 27. GR4J model.

The saturation storage of the soil, as described by Lee and Ho (2009), is illustrated in Figure 28. The soil thickness above the bedrock (H) is divided into the unsaturated zone (z) and the saturated zone (h). When the cumulative rainfall exceeds the water storage capacity of the unsaturated zone, the depth of the saturated zone increases. Full saturation of the soil layer occurs when the rainfall reaches from the ground level to the bedrock level (Cho, 2017). As a result, the saturated thickness can be calculated using Equation 16 (Ho & Lee, 2017). Additionally, topography plays a crucial role, and a wetness index proposed by Kirkby (1975) is used to describe the spatial distribution of the surface soil, as shown in Equation 17. Therefore, thresholds can be concluded based on these assumptions illustrated in Equations 18 and 19 (Ho et al., 2012).

16) $h(t) = H - Z(t) - FRC\left[ATI - \ln\left(\frac{W}{\tan\beta}\right)\right]$

Where *h(t)* denotes the saturated water height at time *t*, *H* represents the soil thickness, *W* is the unit width collecting area, *tanβ* is the surface slope, and *ATI* refers to the average topographic index in the catchment. *FRC* is a model coefficient obtained through the flow recession records.

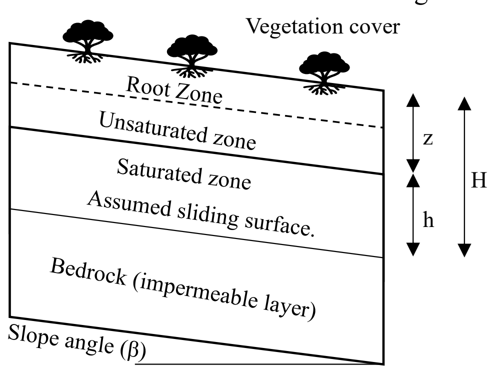

Figure 28. The coupled hydrological-slope instability model.

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17) $TWI = \ln(W / \tan\beta)$

18) $\tan\beta \geq \left[\frac{C}{\gamma_t g H \cos^2\beta} + \tan\phi\right]$ lower thresholds

19) $\tan\beta < \left[\frac{C}{\gamma_t g H \cos^2\beta} + \left(1 - \frac{\gamma_w}{\gamma_t}\right)\tan\phi\right]$ upper thresholds

Since C denotes the cohesion, g represents the gravitational acceleration, γ_t is the bulk density of the soil, γ_w is the density of water, H is the soil thickness measured vertically, β is the gradient of the hill slope, and φ is the angle of the soil's effective friction.

It is assumed that soil moisture content can be correlated with the topographic wetness index (TWI) during wet conditions (Wang et al., 2020). The TWI is used to represent the spatial distribution of surface soil using digital elevation models (DEMs) (Lee & Ho, 2009; Ho et al., 2012; Ho & Lee, 2017). A high-resolution DEM helps reduce uncertainties in slope geometry (Valentino et al., 2014). Consequently, soil thickness is essential for performing instability analysis (Lee & Ho, 2009; Ho et al., 2012; Wang et al., 2016; Cho, 2017; Ho & Lee, 2017; Wang et al., 2020). In contrast to the TWI, the soil wetness index (SWI) is influenced by rainfall conditions (Rodrigues Neto et al., 2023). This factor accounts for soil moisture conditions, which are crucial in determining the occurrence of landslides (Zhao et al., 2020). Using hydrological models, the Soil Wetness Index (SWI) can be estimated, allowing for the development of SWI thresholds. Additionally, SHETRAN is a finite difference hydrological model based on partial differential equations for flow and transport, solved in a three-dimensional grid (Birkinshaw & Ewen, 2000). This model is particularly effective in simulating soil moisture responses to rainfall. SHETRAN considers meteorological conditions such as potential evapotranspiration and precipitation and topographic properties such as TWI. Additionally, land cover and soil type were considered. This method counts for antecedent conditions, not only for current conditions. The Soil Wetness Index

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(SWI) is calculated using the rainfall data from the previous day of a rainfall event, with average values taken from all meteorological stations. The SWI for the last day of the rainfall event in a warning zone is calculated for each grid cell within that zone. This value is then compared to a predefined soil wetness threshold. If the SWI exceeds the threshold, the corresponding grid cell is classified as being wet (Zhao et al., 2020).

DISCUSSION

Empirical-statistical thresholds were built, assuming that rainfall is the most critical causative feature for landslide occurrence (Hong et al., 2018). This assumption can be advantageous if topographic, geotechnical, and hydraulic elements are lacking. These models do not need slope-mounted measurement equipment (Ering & Babu, 2020). Due to their simplicity, empirical models are preferred for early warning systems (EWS) (De Luca & Versace, 2017). These thresholds provide a simpler alternative to the complex procedures involved in physically based models, which require extensive data monitoring, collection, and model calibration. As a result, physically based models are seldom used in operational Early Warning Systems (EWS) (Bezak et al., 2019). However, a notable constraint of these thresholds is the limited usage for a specific case study (Huang et al., 2015). With limited data on rainfall and landslide occurrences, empirically based models struggle to provide accurate rainfall thresholds (Pagano et al., 2010; Wu et al., 2015). While these thresholds can achieve high accuracy, their forecasting capability is often limited by a significant proportion of false positive alarms (Hong et al., 2018; Uwihirwe et al., 2020).

Physically based causative thresholds are constructed based on certain assumptions, assuming that the relationship between landslides and the controlling feature factors will remain relatively constant in the future (Krkač et al., 2017). In essence, these models operate under the assumption that past events will recur in the future without notable changes and that sudden

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failures, such as strain softening along the sliding surface, will not take place. As sudden failures are seldom included in training datasets, these models lack the ability to predict such events. As a result, any factors absent from the training data remain beyond the scope of prediction (Xing et al., 2019; Zhang et al., 2021b). These models neglect random events due to the lack of monitoring data and rarely available data, such as wind and vehicle loads (Wang et al., 2023a). Additionally, these models have some limitations: The prediction accuracy depends on the prediction step, whereas better accuracy comes from the small-step prediction (Gao et al., 2020). Regression models, unlike landslide susceptibility maps, are generally more suited for smaller areas due to their dependency on field monitoring data. Causative thresholds often concentrate on a single parameter, such as displacement or groundwater levels, while overlooking essential factors like spatial variations in land cover, soil composition, topography, and geotechnical or hydrological attributes. Moreover, most of these models are limited to historical data for training, restricting their ability to provide real-time predictions or adapt to sudden changes (Liu et al., 2021). Despite these limitations, these models have notable advantages. Artificial intelligence models, for instance, can analyze multiple causative factors using existing monitoring data, delivering extended warning periods compared to theoretical models and greater accuracy than empirical-statistical thresholds. Furthermore, they are a cost-effective alternative for landslide prediction, as they require minimal geotechnical investigation.

Figure 29 presents a comprehensive framework for modeling landslides across local and national scales. The flowchart delineates a clear, structured progression from macroscopic models focused on a national-scale landslide to more localized models, offering fine-tuned, detailed insights on a regional basis. These modeling approaches reflect a hierarchical decision-making

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process where different input parameters, ranging from geological factors to rainfall intensity, guide the selection of the most appropriate model type.

At the national scale (refer to part ii (Ebrahim et al., 2024a)), the framework demonstrates how factors like geology, geomorphology, soil, and hydraulic properties, along with triggering factors such as rainfall, lead to the generation of landslide susceptibility maps. These maps serve as the foundation for risk assessments using multivariate models, AI techniques, and hybrid approaches. These elements allow for the precise identification of areas with high risk and the corresponding impacts on infrastructure and human life (refer to Ebrahim et al. (2024a) for more insights).

Transitioning to the local scale, the framework shifts to more detailed models that account for complex geometrical, hydrological, and soil conditions. Here, the integration of physical, mathematical, and AI models becomes essential. Deterministic physical models take the lead, simulating intricate landslide processes by considering site-specific conditions (refer to part ii (Ebrahim et al., 2024a)). Statistical regression, AI, and probabilistic models complement these physical responses, offering insights into landslide initiation based on landslide response such as displacement, groundwater levels, matric suction, or moisture content. These models, in combination with I-D thresholds (rainfall intensity-duration), help forecast landslide initiation with increasing accuracy. One of the most innovative aspects of Figure 29 is its representation of hybrid modeling approaches, where the strengths of different methods, such as statistical regression, AI, and physical models, are combined. This integrated approach is essential for improving predictive accuracy in complex scenarios, especially in rainfall-induced landslide studies. The API threshold analysis, for example, stands out as a novel way of incorporating antecedent rainfall information to refine early warning systems. Accuracy assessment, represented through color codes

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(reasonable, good, better, perfect), reflects the refinement and calibration of models. This visual representation is essential for researchers as it offers a quick assessment of model reliability based on specific input conditions. This multi-tiered approach is fundamental for developing more robust predictive frameworks that can be tailored to different geographic scales, from national susceptibility mapping to site-specific, highly accurate risk assessments.

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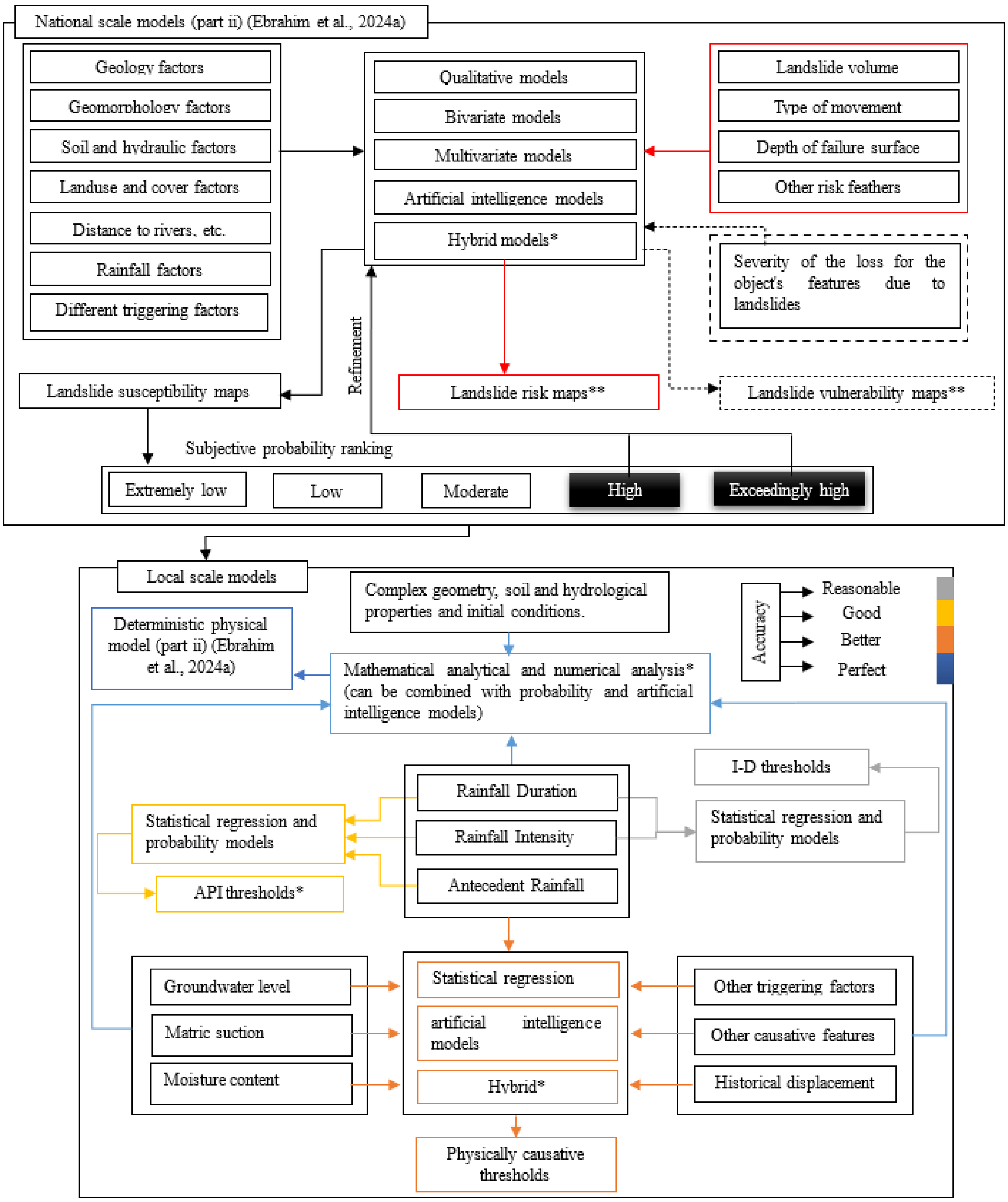

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884 **Figure 29.** Various prediction models with their respective accuracy, input parameters, and
885 analysis techniques (Ebrahim et al., 2024a). * denotes the model with the best accuracy, and **
886 indicates out-of-scope models.

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CONCLUSIONS AND FUTURE WORK.

This study combined both quantitative (scientometric) and qualitative (systematic) analyses. The scientometric approach is an effective method for addressing the challenges of manual searches by highlighting the most significant contributions from keywords, authors, institutions, and countries. The main finding is that landslide prediction models have evolved significantly over the past decade, reflecting the growing global concern for reducing the loss of lives and financial resources. The journal "Landslides" stands out as the most frequently published and cited. China leads in terms of publications, citations, and international collaboration. The most-cited article, based on both total and normalized citations, is by Merghadi et al. (2020). The most common keywords include "Landslides," "Landslide," "rain," "forecasting," and "rainfall.

This study showcased the latest advancements and cutting-edge landslide prediction models, including both empirical statistical thresholds and physically based causative thresholds. When only rainfall data are available, empirical thresholds (I-D thresholds) can give good accuracy while having a significant false positive rate. Recently, because antecedent rainfall can effectively imitate the initial moisture content of the soil, API thresholds are more accurate than I-D thresholds. API criteria not only improve accuracy but also lower the number of incorrect predictions. Statistical regression or probability analysis approaches can be used to create these criteria. However, these thresholds are far from the physical mechanism of the slope itself. It can be adopted when the physical input parameters are lacking.

Consequently, physically based causative thresholds correlate external rainfall-triggering factors with any internal slope feature, such as displacement, soil moisture, suction stress, and groundwater level. Displacement thresholds have been widely investigated due to the availability of their input data, while other causative features are lacking due to their dependency on the

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geotechnical and hydrological parameters. Statistical regression models can be used to predict displacement. These models, however, failed to predict the sudden increased displacement. Single artificial intelligence models have recently been adopted for complicated issues. These models have acceptable accuracy but are unable to anticipate periodic displacement. As a result, recent studies have divided displacement into trend and periodic terms. Polynomial or basic artificial intelligence models can be used to forecast trend displacement. On the other hand, periodic displacement can be precisely anticipated by utilizing hybrid artificial intelligence models. Furthermore, hybrid models can deal with missing data and a lack of training data. Nonetheless, these models cannot predict any variable outside the training dataset, lack sophisticated initial conditions, and ignore slope geometry.

Future Directions and Recommendations.

High-accuracy models can be achieved by considering two key factors: 1) choosing the appropriate features based on a deeper understanding of the case study's initial conditions, and 2) selecting a suitable model to capture the relationship between these features. Despite advancements in statistical modeling, such as hybrid AI models, there are still some gaps that need to be addressed, as outlined in Table 7.

Table 7. Research gaps in landslide prediction models (I-D thresholds and physically based causative thresholds)

Gap	Recommendations
I-D thresholds suffer from a high false prediction rate. This can be illuminated because of two reasons: 1) I-D thresholds neglect the vegetation cover that affects the rate of the infiltration and the subsurface water content; and 2) I-D thresholds	Field tests shall be performed to build the relationship between rainfall, evaporation, infiltration, and surface runoff. Sensitivity analysis shall be performed to select the optimum physical properties that achieve better accuracy. This may reduce the false prediction rate

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neglect the slope properties (geometry, geotechnical properties, etc.)	and keep the advantages of the I-D thresholds as a simple technique.
Physically based causative thresholds rely mainly on surface characteristics (i.e., surface displacement) neglecting the sudden failure scenario. This can be explained by the issue of the available data. In other words, the prediction models that consider the actual subsurface mechanism of landslide (i.e., tilting, suction stresses, groundwater variation, deep displacement, etc.) are lacking.	Monitoring of subsurface characteristics provides a well-established dataset to be used afterward to predict the complex mechanism of the landslide using hybrid AI models. This may overcome the limitation of the available models and may help better understand landslide non-linear complex mechanisms.
Most studies neglect the effect of the harsh environment such as data loss. Additionally neglects the effect of the communication issue such as the data rate.	A sensitivity analysis shall be developed to investigate and optimize the data rate and model selection considering the issue of data loss.

DECLARATIONS

Availability of Data and Materials

The data presented in this article were either provided in tables as examples or can be found in the cited references.

Competing Interests

The authors declare no competing interests.

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Authors' Contributions

Conceptualization, K.M.P.E., and T.Z.; methodology, K.M.P.E., and T.Z.; formal analysis, K.M.P.E., S.M.M.H.G., T.Z., and G.A.; investigation, K.M.P.E., and T.Z.; resources, T.Z.; data curation, K.M.P.E., S.M.M.H.G., T.Z., and G.A.; writing— original draft preparation, K.M.P.E.; writing—review and editing, S.M.M.H.G., T.Z., and G.A.; supervision, T.Z. All authors have read and agreed to the published version of the manuscript.

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Declaration of generative AI and AI-Assisted Technologies in The Writing Process

During the preparation of this work, the author(s) used [GPT 3.5] to [rephrase, check grammar and spelling]. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

NOTATION AND ABBREVIATIONS

Table 8. Notation

D	Rainfall duration	ε	Scaling parameter
I	Rainfall intensity	ζ	Shape parameter
E_N	Rainfall event,	υ	Dimensionless parameter
API_N	Antecedent precipitation index	Y_i	Value of real data
N	Number of rainy days	X_i	Value of predicted data
R_a	Antecedent rainfall	C	Cohesion
Ro	Rolling rainfall	ϕ	Internal friction angle
R	Cumulative rainfall	Q	Discharge
PE	Potential evaporation	g	Gravitational acceleration
S	Displacement	γ_w	The unit weight of water
$\Xi\ (t)$	Gamma-type transfer function	γ_t	Wet unit weight
t	time	H	Thickness above the bedrock layer
T	Temporal scale/Time intervals	z	Unsaturated thickness
M	Temporal memory	h	Saturated thickness

Table 9. Abbreviation

EWS	Early warning systems	*GRU*	Gated recurrent unite
FLaIR	Forecasting of Landslides Induced by Rainfall	*BRNN*	Bayesian recurrent neural network
GFM	Generalized FLaIR model	*BLSTM*	Bayesian long short-term memory network
IETDs	Inter-event time definitions	*BGRU*	Bayesian gated recurrent unit network
SMS	Soil matric suction	*BDNN*	Bayesian deep neural networks
VSMC	Volumetric soil moisture content	*EMD*	Empirical mode decomposition
PSL	Production storage level	*EEMD*	Ensemble empirical mode decomposition
WI	Wetness increase	*CEEMD*	Complete ensemble empirical mode decomposition

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TWI	Topographic witness Index	*DMA*	Double moving average
SWI	Soil wetness index	*SMA*	Single moving average
SHETRAN	Système Hydrologique Européen TRANsport	*DES*	Double exponential smoothing
AUC	The area under the ROC curve	*VMD*	Variational mode decomposition
ROC	Receiver operating characteristic	*KGM*	Kernel-based grey model
FPR	False positive rate	*MKGM*	Multi-kernel grey model
R^2	Coefficient of determination	*WMKGM*	Weighted multi-kernel grey model
RMSE	Root mean square error	*WCA*	Water cycle algorithm
MSE	Mean square error	*MSI*	Multiple Swarm intelligence
MAE	Mean absolute error	*BA*	Bat algorithm
SDR	Standard deviation ratio	*GWO*	Grey wolf optimization
PRC	Pearson-R correlation	*DA*	Dragonfly optimization algorithm
GM	Grey model	*WOA*	Whale optimization algorithm
MLR	Multilinear regression	*GOA*	Grasshopper optimization algorithm
ANN	Artificial neural networks	*SSA*	Sparrow search algorithm
BPNN	Backpropagation neural networks	*PCA*	Principal component analysis
SVM	Support vector mechanism	*FOBGM*	Feedback optimization background grey model
RF	Random forest model	*MLATC*	Mean-based low-rank autoregressive tensor completion
SVC	Support vector classifier	*MFTL*	Multi-fusion transfer learning
SVR	Support vector regression	*NWE*	Non-uniform weight error
RS	Random Search	*BR-BP*	Bayesian regularization backpropagation
RNN	Recurrent neural networks	*BOA*	Butterfly optimization Algorism
ENN	Evolutionary neural network	*GA*	Genetic algorism
ELM	Extreme learning machine	*GPR*	Gaussian process regression
LSTM	Long short-term memory	*GRA*	Grey correlation analysis
VMD	Variational Mode Decomposition	*GA*	Genetic algorithm

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