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Review article: From spatial to spatial-temporal rainfall representation and beyond in landslide susceptibility modelling

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Abstract. Rainfall is increasingly incorporated as a time-dependent predictor in landslide susceptibility modelling, yet its temporal evolution is rarely preserved. Instead, rainfall is commonly condensed into scalar statistical descriptors, limiting how rainfall-triggering processes are represented and learned. This review synthesizes 211 studies published between 2000 and 2025 that explicitly incorporate time-varying rainfall information into landslide susceptibility modelling. The review reveals that the apparent importance of rainfall often depends on how spatial heterogeneity and temporal variability are represented within susceptibility models. At regional scales, broad terrain–climate heterogeneity can amplify the statistical importance attributed to rainfall. Beyond the temporal attribution uncertainty introduced by spatial presence–absence sampling, rainfall evolution is predominantly reduced to scalar descriptors that provide a lossy representation of rainfall processes: selected characteristics are retained, while temporal organization and potentially triggering-relevant rainfall patterns are discarded before entering the model. Looking forward, intensifying hydroclimate volatility under climate change makes the temporal organization of rainfall increasingly critical for understanding rainfall-triggered landslides. At the same time, advances in high-resolution data and sequence learning make it feasible to move beyond scalar rainfall descriptors and learn complete rainfall patterns from their temporal evolution, paving the way towards more process-informed prediction of rainfall-triggered landslides.

1 Introduction

Landslides are natural hazards involving the downslope movement of rock, soil, or debris under the influence of gravity (Cruden and Varnes, 1996), and they represent one of the most destructive types of geological disasters worldwide. Due to their sudden onset, high destructive potential, and widespread distribution, landslides have caused severe human casualties and economic losses, particularly in mountainous and densely populated regions (Froude and Petley, 2018). Global statistics further indicate that, over recent decades, non-seismic landslides have resulted in a large number of deaths and have affected millions of people around the world (World Health Organization). With ongoing population growth and rapid urban expansion, the impacts of landslide hazards are expected to intensify further, especially in developing and transitional economies (Kjekstad and Highland, 2009; Turner, 2018). Against this background, landslide susceptibility analysis has become a key component of disaster risk management, providing science- and evidence-based support for hazard mitigation, and early warning systems.

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Landslide occurrence is controlled by the combined effects of predisposing and triggering factors (Reichenbach et al., 2018). Predisposing factors – such as slope geometry, lithology, soil properties, and geomorphological conditions – primarily determine the spatial distribution of landslide-prone areas, whereas triggering factors, including rainfall (Kirschbaum and Stanley, 2018; Cui et al., 2024), earthquakes (Guo et al., 2023) and human activities (He et al., 2025) can disrupt slope stability and initiate landslide events. Among these triggers, rainfall plays a particularly prominent role (Huang et al., 2025). As the most widespread and frequent landslide trigger at individual to regional scales, rainfall affects slope stability through multiple mechanisms, including the reduction of strength due to loss of suction, the increase of pore water pressure, and the modification of shallow hydrological processes in soil–water system (Cui et al., 2024). At the slope scale, physically based models have provided detailed insights into the hydrological processes governing the stability of individual landslides. However, landslide occurrence is not confined to individual slopes but can affect entire regions that are typically characterized by heterogeneous environmental and geological conditions. As a result, focusing exclusively on single-slope stability cannot adequately capture the spatial patterns of landslide occurrence. Consequently, analyzing landslide susceptibility at the regional scale, while explicitly accounting for rainfall as a key triggering factor, has become a central research direction in landslide susceptibility assessment.

In addition to heterogeneous environmental and geological conditions, regional-scale studies are also confronted with spatially heterogeneous rainfall patterns. More importantly, rainfall exhibits pronounced temporal variability, which introduces a critical time dimension into landslide analysis and shifts the research focus from identifying where landslides are more likely to occur toward understanding when landslide occurrence becomes more probable under dynamically changing hydrological conditions. Although numerous modelling approaches have been developed to assess rainfall-induced landslides, regional-scale susceptibility studies commonly rely on idealized representations of rainfall, such as intensity–duration thresholds (Godt et al., 2008; Segoni et al., 2018), cumulative rainfall (Huang et al., 2023), rainfall intensity (Xiao et al., 2018) or rainfall-related indices (Shou and Lin, 2020), used as direct model inputs. Most regional susceptibility models do not explicitly represent rainfall evolution as a dynamic pattern. Instead, rainfall dynamics are typically reduced to static or aggregated descriptors or metrics that discard much of the temporal information governing slope failure, thus neglecting historical rainfall information, antecedent rainfall effects, and the inherent rainfall memory or temporal structure that governs the hydrological evolution of the soil. Moreover, at regional scales, presence/absence data often leaves the temporal attribution of rainfall forcing ambiguous: presence samples are linked to known landslide occurrence dates, whereas absence samples frequently lack clearly defined reference dates (Edrich et al., 2024). This requires additional assumptions in defining rainfall accumulation periods and temporal reference frames. As a result, key temporal characteristics embedded in the temporal structure of rainfall, including rainfall sequencing, persistence, dry–wet transitions, and lagged rainfall–landslide responses, are often not explicitly captured, all of which contribute to the triggering of landslides at varying extents. Consequently, despite the recognized importance of rainfall as a triggering factor, the role of its temporal variability in regional landslide susceptibility analysis remains insufficiently resolved. Nevertheless, the integration of temporal rainfall information into landslide susceptibility modelling has received increasing attention in recent years (Steger et al., 2026; Moreno et al., 2025).

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To address rainfall-induced landslides, a wide range of modelling approaches have been proposed, spanning physically based and data-driven frameworks (Lee et al., 2008; Park et al., 2019; Huang et al., 2022; Collini et al., 2022; Ma et al., 2025b). Existing review studies have examined rainfall-induced landslides from perspectives such as triggering mechanisms (Ebrahim et al., 2024), topographic controls on rainfall spatial variability (Mafigiri et al., 2025), and modelling methodologies (Tyagi et al., 2022), often with an emphasis on specific processes or application contexts. However, beyond these process-oriented and spatially focused perspectives, a systematic synthesis of how rainfall-induced landslide research has evolved from purely spatial susceptibility mapping toward explicitly or implicitly spatio-temporal frameworks remains largely lacking. A central unresolved question is therefore not whether rainfall should be incorporated into susceptibility models, but how its temporal structure should be represented, such as the consideration of antecedent conditions and the implicit or explicit encoding of temporal constraints. As a result, the transition from static, space-only susceptibility zonation to susceptibility frameworks constrained in both space and time has not yet been comprehensively reviewed.

This review article provides a combined bibliometric and conceptual synthesis of 211 publications (between 2000 and 2025) on rainfall-driven landslide susceptibility assessments. The review demonstrates how rainfall information has been incorporated into landslide modelling frameworks from both spatial and temporal perspectives. Specifically, we analyse how spatial scales and study-area delineation strategies are reflected in modelling practices and rainfall–terrain–landslide relationships, with particular emphasis on how temporal sampling frameworks and rainfall representations capture the dynamic nature of landslide triggering. This review aims to clarify how rainfall processes are represented in current landslide susceptibility studies and to provide a perspective for advancing spatio-temporal landslide modelling.

2 Materials and methods

2.1 Article selection and inclusion criteria

This study conducted a systematic review of publications assessing the influence of time-dependent factors on landslide susceptibility, using the Web of Science (WoS) Core Collection as the primary data source. WoS was selected due to its wide disciplinary coverage, standardized indexing system, and its suitability for bibliometric analyses with high reproducibility.

The literature search strategy consisted of two groups of keywords. The first group was used to define the research object and included “landslide susceptibility” OR “mass movement susceptibility”; The second group was designed to capture studies explicitly addressing temporal or dynamic aspects and included: “time-dependent” OR “time dependent” OR “time-varying” OR “temporal” OR “temporal variation” OR “dynamic” OR “spatio-temporal” OR “time series”. While susceptibility has traditionally been regarded as a spatial concept without explicit temporal prediction, recent studies increasingly incorporate dynamic triggering factors without necessarily changing the original susceptibility terminology (Reichenbach et al., 2018), leading to the emergence of spatial-temporal susceptibility modelling frameworks. To reduce the risk of missing conceptually relevant studies due to terminology inconsistencies across the literature, a small number of additional influential studies were identified through citation tracking and expert-guided screening.

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Table 1. Dynamic factors classification and the number of its related papers

Factors	Keywords	Number of papers
Rainfall	rainfall; precipitation; antecedent rainfall; rainfall intensity; rainfall accumulation; rainfall duration; storm duration; I–D; intensity–duration; cumulative rainfall	341
Earthquake	earthquake; seismic; PGA; peak ground acceleration; PGV; seismic shaking; aftershock	142
Vegetation	NDVI; LAI; leaf area index; vegetation cover; vegetation greenness; vegetation phenology	91
Soil moisture	soil moisture; soil water content; volumetric water content; VWC; groundwater; water table; pore-water pressure; pore water pressure; matric suction; soil saturation	58
River level	river level; river discharge; streamflow; water level; flood; flooding	48
Temperature	temperature; heatwave	31
Human activity	deforestation; land use change; urban expansion; construction activity; mining activity	28
Snow and freeze-thaw	snowmelt; freeze-thaw; frost thaw; snow cover; snowfall	14
Evapotranspiration	evaporation; evapotranspiration	5

The initial search was conducted in November 2025, updated in January 2026, yielding a total of 703 publications. In the second stage, the retrieved studies were classified according to the type of time-dependent factors considered, such as rainfall, earthquakes, vegetation dynamics, soil moisture, and other dynamic environmental variables. This classification was primarily based on article title, keywords and abstracts. Among these studies, 341 publications explicitly involved rainfall-related factors (Table 1). To ensure consistency and avoid double counting of synthesized evidence, review articles were excluded from further analysis. In addition, only studies that incorporated rainfall variables as covariates or explicit inputs in landslide modelling or analysis were retained. Studies in which rainfall was mentioned only qualitatively or as a general background condition were excluded. After applying these inclusion and exclusion criteria, a final dataset of 211 articles published between 2000 and 2025 was obtained for subsequent bibliometric and conceptual analyses.

2.2 Bibliometric analysis framework

Each selected publication was examined by collecting technical and scientific information across four complementary categories, designed to jointly characterize the impact of research, thematic focus, spatial organization, and the treatment of temporal information in rainfall-driven landslide susceptibility studies. For each category, a set of descriptive attributes and classification criteria was defined. In a limited number of cases, not all relevant details could be retrieved from the original publications.

- **Category I – Publication productivity and scientific impact:** The first category evaluates research productivity and scientific impact based on publication counts and citation metrics. This analysis focuses on temporal trends in scientific output, considering both publication year and citation frequency in order to identify major development phases and shifts

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in research attention. Although a small number of publications were dated prior to 2000 or after 2025 (with only one record in 1998 and one in 2026), the analysis was restricted to the period from 2000 to 2025 to avoid statistical dispersion and to ensure temporal consistency across the dataset.

- **Category II – Research themes and keyword-based topic distribution** characterizes the dominant research themes by analyzing the most frequently used terms in the abstract and author keywords. Based on the collected literature, high-frequency terms were extracted and subsequently harmonized through a normalization process to ensure semantic consistency while preserving the original meaning of the descriptors. For keywords, singular and plural forms (e.g., landslide vs. landslides, hazard vs. hazards) were merged, and different expressions referring to the same concept were consolidated. For example, terms related to landslide early warning (e.g., early warning, early warning system, landslide early warning, regional landslide early warning system) were grouped under a unified category "landslide early warning". Similarly, multiple expressions describing landslide susceptibility (e.g., susceptibility analysis, susceptibility mapping, susceptibility evaluation, integrated susceptibility) were aggregated into the category "landslide susceptibility". Method-related terms belonging to the same methodological family – such as InSAR, SBAS-InSAR, MT-InSAR, PS-InSAR, and interferometric synthetic aperture radar – were grouped under a single InSAR category.

- **Category III – Study area characteristics, spatial scale and definition** records study-area location, spatial scale, delineation strategy, and modelling approach. The 211 studies were classified as individual, regional, or global scale, and their modelling approaches were compared across these scales. Regional studies were further categorized as using administrative, physiographic, or hybrid delineation based on whether the reported boundaries followed administrative units (e.g., provinces, states, or cities), physiographic units (e.g., basins, watersheds, or mountain regions), or both. Study-area size was reported in 136 publications and used for quantitative comparisons across regions and countries.

- **Category IV – Time-dependent variables and modelling-chain configurations** examines how time-dependent information is incorporated into landslide susceptibility studies and propagated through the modelling chain, thereby outlining a typical workflow from temporal sampling and input construction to model application. Particular attention is given to rainfall representation, including the temporal assignment of rainfall information to presence and absence samples and the quantification of rainfall characteristics. The analysis further identifies the types and temporal scales of dynamic variables and summarizes common combinations of temporal inputs, modelling approaches, and evaluation strategies.

3 Results

3.1 Publication trends

By January 2026, a total of 211 publications related to rainfall-induced landslide susceptibility were identified for the period 2000–2025. No relevant studies were found between 2000 and 2003. Based on the temporal variations in annual publication

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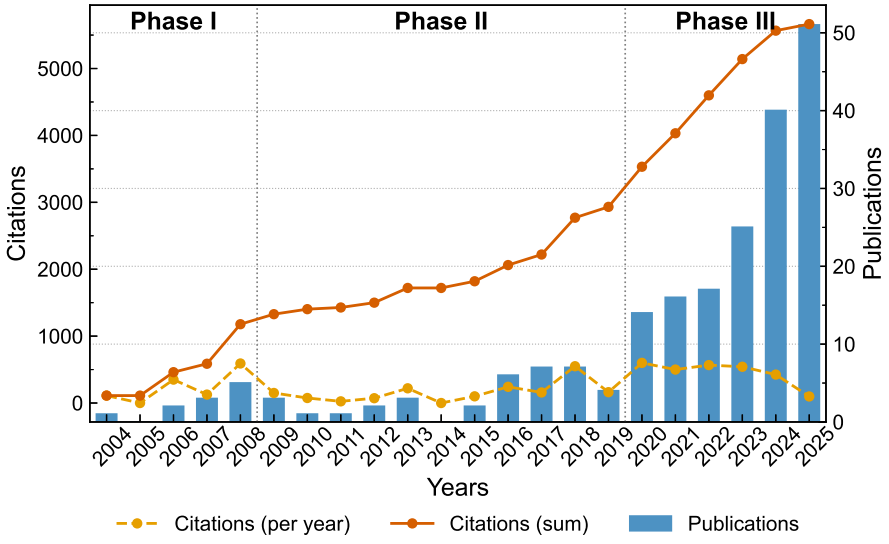

Figure 1. Temporal evolution of publications and citations in spatio-temporal landslide susceptibility studies incorporating rainfall representations. Publication and citation trends reveal three distinct developmental phases, with Phase III characterized not only by rapid publication growth but also by a conceptual transition toward explicitly modelling rainfall-triggered susceptibility.

output and cumulative citation counts, the development of this research field can be divided into three distinct stages (Fig. 1): the Emergence stage (2004–2008), the Transition stage (2009–2019), and the Rapid expansion stage (2020–2025).

Phase I (2004–2008) represents the emergence stage, during which rainfall was first systematically incorporated into spatio-temporal landslide susceptibility analysis. Although the number of publications was limited, several seminal studies established the fundamental theoretical and methodological framework of the field. In particular, Zêzere et al. (2004) proposed a spatio-temporal landslide susceptibility framework that explicitly coupled rainfall as the temporal component with susceptibility as the spatial component, introducing rainfall amount–duration characteristics to describe triggering conditions. Subsequent studies began to emphasize the role of time-varying rainfall (Salciarini et al., 2006) and integrated physically based models to analyse slope stability controlled by rainfall (Gorsevski et al., 2006; Mateos et al., 2007), leading to the development of representative tools such as TRIGRS (Godt et al., 2008).

Phase II (2009–2019) corresponds to a transitional and consolidation period. During this stage, annual publication output remained relatively low but stable, while cumulative citations continued to increase, indicating growing academic attention without large-scale expansion. Research efforts were primarily directed towards the integration of spatio-temporal probability concepts and the evaluation of the applicability of different models for rainfall-induced landslides (Apip et al., 2010; Lanni et al., 2012; Wu and Chen, 2013). For example, Bui et al. (2013) introduced machine learning (ML) approaches into spatio-temporal landslide susceptibility analysis, comparing support vector machines (SVM) and logistic regression (LR) models

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while accounting for antecedent rainfall accumulation and rainfall thresholds. This study received relatively high attention within this phase.

Phase III (2020–2025) is characterized by rapid expansion. During the phase III period, publication output has increased continuously, with a pronounced acceleration after 2020. Concurrently, both annual and cumulative citation counts have remained high, indicating that rainfall-induced landslide susceptibility has become an important and mainstream research direction. This rapid growth is likely driven by the convergence of several technological and societal developments rather than by methodological advances alone. The increasing availability of open-access databases (Gulla et al., 2021) and satellite-derived precipitation products (Ma et al., 2025a; O'Leary et al., 2025; Du et al., 2025) has substantially lowered the barriers to large-scale susceptibility modelling. In addition, the rapid expansion also coincides with growing scientific concern over the impacts of climate change on hydroclimatic variability. Increasing evidence suggests that climate warming is intensifying *hydroclimate whiplash* and other precipitation extremes, thereby amplifying rainfall-triggered hazards such as flash floods and landslides (Swain et al., 2025). More importantly than the increase in publication numbers, Phase III marks a conceptual transition from treating rainfall as an environmental covariate toward explicitly modelling rainfall-triggered susceptibility.

3.2 Disciplinary distribution and keywords

Based on the frequency analysis of terms extracted from the abstracts of the 211 studies, the most frequently occurring words include landslide, susceptibility, rainfall, spatial, hazard, map, slope, factors, and prediction. Based on their semantic attributes, these high-frequency terms can be grouped into four categories:

- Terms related to objects and events, such as landslide, disaster, events, and inventory
- Terms related to environmental factors and conditions, including rainfall, precipitation, river, soil, and vegetation
- Terms related to methods and modelling, such as machine learning, modelling, regression, and algorithm
- Terms related to outcomes and applications, including prediction, performance, hazard, management, and future

In addition, terms such as spatial, temporal, dynamic and spatio-temporal co-occur in a subset of abstracts, indicating that both spatial and temporal dimensions are explicitly mentioned in these studies, for example, in analyses involving multi-temporal factor evolution or time-varying variables (Ran et al., 2012; Qu and Jin, 2024; Qu and He, 2025).

The distribution of author keywords is shown in Fig. 2. "landslide susceptibility" appears 108 times, making it the most frequently used keyword. Among the top 15 keywords, terms related to objects or processes include landslide, rainfall-induced landslide, hazard, shallow landslide, slope stability, and dynamic landslide susceptibility. The keyword "rainfall-induced landslide" is commonly used in studies focusing on rainfall-triggered events, such as Liu et al. (2024) and Li et al. (2022). Method-related keywords mainly include machine learning, random forest, and logistic regression, which are applied in multiple landslide susceptibility studies (Hua et al., 2021; Yao et al., 2023). In addition, "dynamic landslide susceptibility" appears as a keyword in a subset of publications, including Wang et al. (2024a) and Jiang et al. (2025), describing frameworks that incorporate time-varying information into susceptibility analysis.

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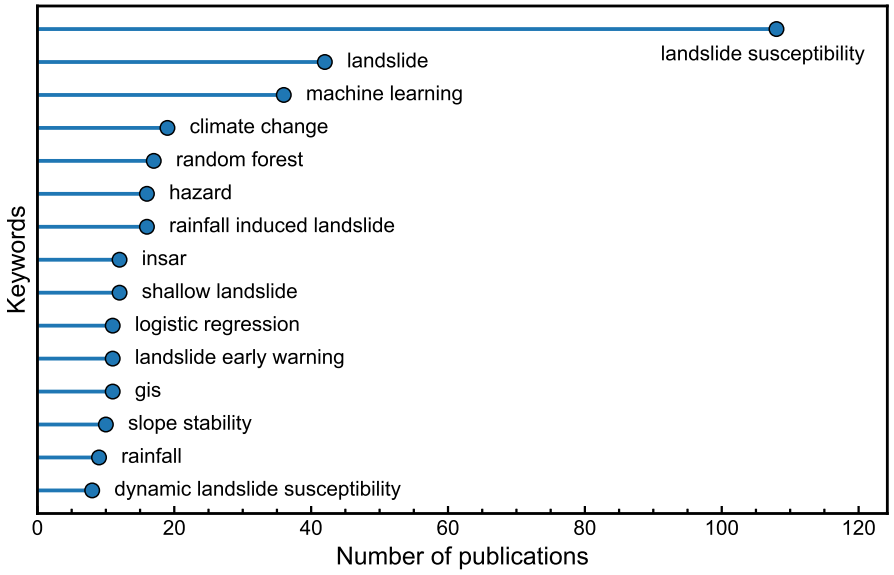

Figure 2. Frequency ranking of the top 15 author keywords. The dominance of "landslide susceptibility" highlights the primary focus of the literature, while the high frequency of "machine learning" reflects its widespread adoption in susceptibility modelling. In contrast, keywords related to dynamic landslide susceptibility remain comparatively infrequent, indicating that temporally explicit susceptibility modelling is still relatively underrepresented.

3.3 Spatial scale and study-area characteristics

Spatial scale represents a fundamental dimension of landslide susceptibility assessment, influencing not only the spatial representation of landslide processes but also the selection of modelling strategies and data sources. To better understand how rainfall-informed spatio-temporal landslide susceptibility studies have been implemented, the spatial characteristics of the studies were analysed from two perspectives. First, the geographic distribution and spatial extent of study areas were examined to identify the regions where rainfall-informed spatio-temporal landslide susceptibility studies have been conducted and to quantify the range of study-area sizes. Second, studies were classified according to spatial scale to compare study designs and modelling practices adopted at individual, regional, and global levels.

3.3.1 Geographic distribution and spatial extent of studies

An analysis of spatial scale and geographic distribution of the works is presented here. Figure 3 and 4 illustrate the spatial characteristics of spatio-temporal landslide susceptibility studies incorporating rainfall information from two perspectives: the continental distribution of study areas represented in the literature and the variation in the size of study area between countries.

Overall, research activity exhibits a pronounced global concentration pattern, with a limited number of countries dominating both publication output and the spatial distribution of study areas. This general pattern is consistent with previously reported

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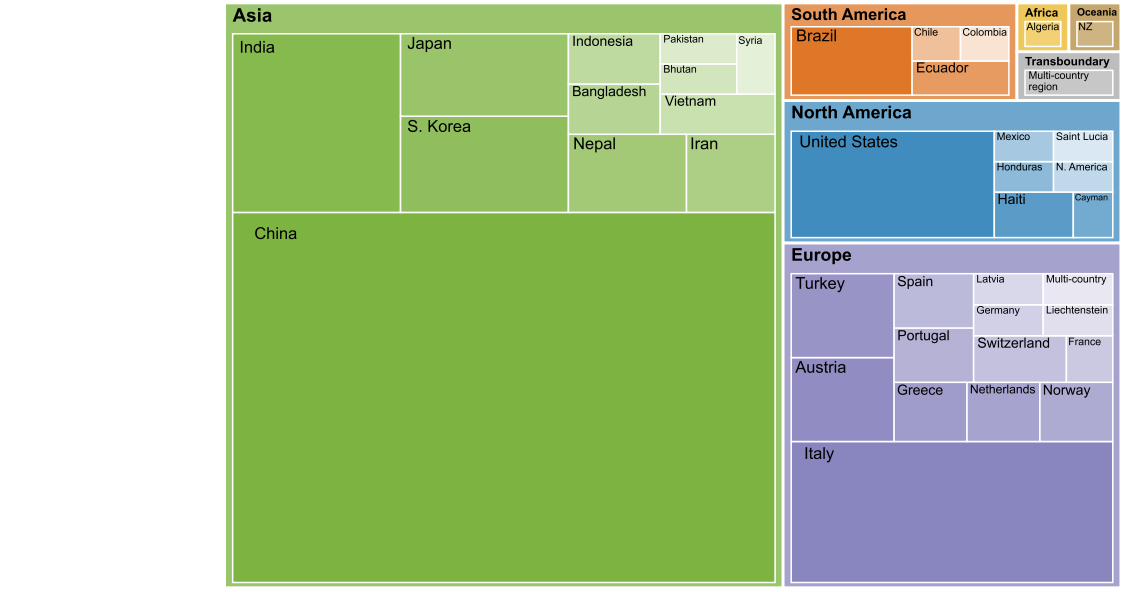

Figure 3. Continental distribution of landslide susceptibility studies incorporating rainfall representations. Different colours indicate the continent in which each study was conducted, and the size of each marker represents the number of studies from that country. The geographical concentration of studies highlights a strong regional bias, with research primarily clustered in landslide-prone regions.

global bibliometric analyses of landslide research (Wu et al., 2015). As shown in Fig. 3, the studies are unevenly distributed across continents according to the locations of their study areas. Asia represents the most prominent region in terms of research output, followed by Europe and North America, whereas South America, Africa, and Oceania contribute comparatively fewer studies. At the national level, study areas located in China, Italy, India, and the United States account for a substantial proportion of the literature. This distribution indicates that rainfall-informed landslide susceptibility research has been concentrated in regions where landslide hazards are widespread and where sustained scientific efforts have supported the development of long-term research programmes. The strong geographic concentration also implies that many methodological conclusions have been established within a relatively small set of environmental settings, raising questions about the transferability of rainfall representations to different climatic and geomorphological regimes, which needs to be further explored.

A total of 136 studies explicitly reported study area sizes; Figure 4 shows the general distribution of the size of the study area reported. When displayed on a logarithmic scale ($\log_{10}$ km^2), the study areas span several orders of magnitude. Most studies are concentrated within the range of $\log_{10}(\text{area}) \approx 2-4$, corresponding to spatial extents of approximately 10^2–10^4 km^2. Notably, a small number of studies fall within the range of $\log_{10}(\text{area}) < 1$. These investigations typically focus on individual landslides or very small spatial domains and often rely on high-resolution data to conduct detailed analyses of individual landslide bodies or localized unstable slopes (Lizárraga and Buscarnera, 2020; Marotti et al., 2023). Although such small-scale studies represent only a minor proportion of the overall literature, they form a distinct category characterized by fine-scale investigation and process-oriented analysis (Ran et al., 2012; Oguz et al., 2022). Clear regional patterns can also

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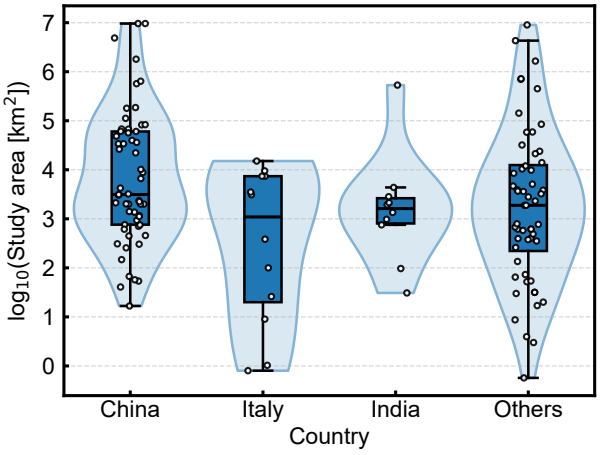

Figure 4. Study-area scale of spatio-temporal landslide susceptibility studies considering rainfall representation across different countries. Violin plots show the distribution of study area sizes ($\log_{10}$ km^2), boxes summarize the median and interquartile range, and individual points represent single studies. The figure illustrates the broad range of spatial extents adopted in rainfall-induced landslide susceptibility studies.

be observed in the spatial scales of the reported study areas. China and India appear frequently in the literature, reflecting repeated investigations in well-known landslide-prone regions such as the mountainous areas of southwest China (e.g., the Sichuan–Tibet region) (Huang et al., 2023) and parts of eastern India (Chakrabortty et al., 2020). In Europe and East Asia, countries such as Italy, Spain, Greece, and Japan also constitute important case-study regions that have been widely used in landslide susceptibility modelling research. Representative examples include studies conducted in Italy (Collini et al., 2022), Spain (Rodriguez-Caballero et al., 2021), Greece (Nefros et al., 2023), and Japan (Ishibashi, 2024).

Overall, rainfall-induced landslide susceptibility research is strongly concentrated in a limited number of well-investigated landslide-prone regions (Park et al., 2019). Meanwhile, the spatial extent of study areas varies considerably across investigations, ranging from individual landslides and slope-scale analyses (Ye et al., 2024; Ding et al., 2025) to large regional assessments covering extensive mountainous regions (Huang et al., 2022, 2025). Such variability reflects potential differences in study objectives, modelling strategies, and the definition of analysis areas. To better understand these scale-dependent characteristics, the studies were further classified into individual, regional, and global categories, and the corresponding study-area delineation approaches and modelling practices were subsequently examined.

3.3.2 Study designs and modelling practices across spatial scales

Building upon the analysis of study area size, the spatial organization of rainfall-induced landslide susceptibility studies is further examined from the perspectives of study scope, modelling approaches and regional delineation strategies (Fig. 5, Fig. 6 and Fig. 7).

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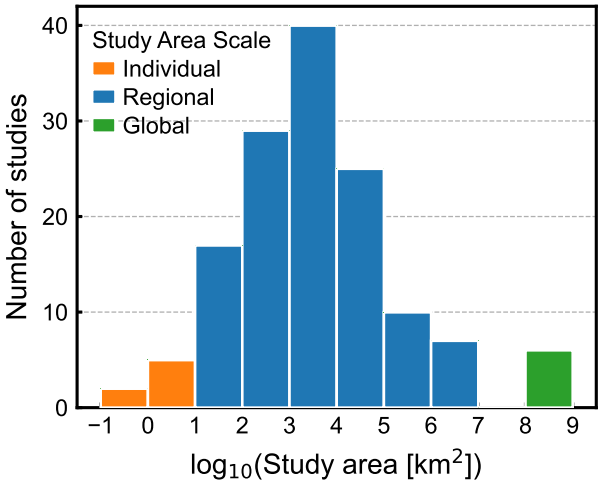

Figure 5. Frequency distribution of study-area sizes in landslide susceptibility studies incorporating rainfall representations. Bar colours distinguish individual, regional, and global study scales. Most studies are concentrated at regional scales, whereas individual landslide and global-scale assessments remain comparatively uncommon.

To facilitate comparisons across studies, the studies were classified into three categories: individual, regional, and global, based on study-area extent and research focus (Fig. 5). The distribution of study areas shows a clear concentration within the range of 10^2–10^4 km^2 ($\log_{10}(\text{area}) \approx 2-4$). Correspondingly, most studies adopt a regional-scale framework, accounting for 90.8% of the literature. In comparison, individual-scale studies represent 5.0%, while global-scale assessments account for only a very small proportion.

Further examination of modelling paradigms reveals notable differences between spatial scales. At the regional scale (Fig. 6a), data-driven approaches dominate the literature, accounting for 80.0% of studies, with ML representing the most widely adopted modelling framework. physically based models account for 15.4% of studies, while hybrid frameworks combining process-based and data-driven components represent a smaller proportion (2.1%). A small fraction of studies do not explicitly report model details. Within the data-driven category, commonly adopted machine-learning algorithms include random forest (RF) (Ren et al., 2024; Nocentini et al., 2024), support vector machines (SVM) (She et al., 2024), and artificial neural networks (ANN) (Tyagi et al., 2023, 2025). These approaches are widely used for modelling the complex and nonlinear relationships between environmental conditioning factors and landslide occurrence. In contrast, studies focusing on individual landslide bodies exhibit a markedly different methodological pattern (Fig. 6b). Compared with regional-scale studies, the use of physically based models increases substantially, accounting for a proportion comparable to that of data-driven approaches (44.4% each). This shift reflects the greater feasibility of process-based analyses at smaller spatial scales, where detailed geotechnical, hydrological, and topographic information is often available (Oguz et al., 2022; Marotti et al., 2023). modelling strategy is fundamentally scale dependent. Regional susceptibility studies rely predominantly on data-driven methods and statistical inference, whereas physically based models become increasingly feasible at the individual slope. The increasing use of phys-

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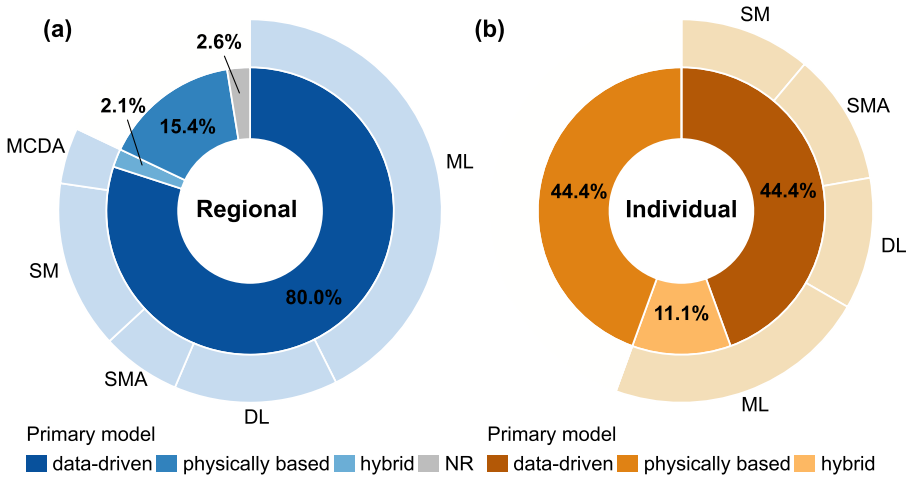

Figure 6. Composition of modelling approaches in spatio-temporal landslide susceptibility studies at regional (a) and individual slope (b) scale. The inner ring summarizes the primary modelling categories, and the outer ring shows the corresponding modelling methods. The distribution indicates clear differences in modelling preferences across spatial scales, with data-driven approaches dominating regional studies, whereas physically based models are comparatively more common at the individual-slope scale.
Model abbreviations: ML, Machine Learning; SM, Statistical Methods; SMA, Statistical Model Analysis; MCDA, Multi-criteria Decision Analysis; DL, Deep Learning; NR, Not Reported

ically based models at smaller spatial scales likely reflects the greater availability of detailed geotechnical, hydrological, and topographic information, enabling process-oriented simulations of slope instability and rainfall-triggering failure mechanisms (Oguz et al., 2022; Ding et al., 2025).

Regarding regional delineation strategies, administrative regions are the most frequently adopted spatial framework (Fig. 7a). Mixed approaches that combine administrative and physiographic regions represent 34.2%, while purely physiographic delimitation account for 20.4%. These results indicate that region-scale analyses are most commonly organized according to administrative units, while natural landscape structures are increasingly incorporated as complementary spatial constraints. Further classification by administrative and physiographic hierarchy reveals that four delineation categories dominate regional-scale landslide susceptibility studies, all exceeding the average frequency across categories. Provinces are the most frequently adopted (58 studies), followed by national-scale analyses (53 studies), drainage basins (47 studies), and mountain regions (37 studies). Together, these categories account for the majority of regional study designs, indicating a preference for study-area frameworks that either align with administrative decision-making structures or correspond to major geomorphological and hydrological systems. Other delineation categories are considerably less common. Local administrative delineations, including cities, states, districts, and counties, are used less frequently, while coastal zones (12 studies), plateaus (9 studies), and reservoir- or lake-controlled areas represent only a small proportion of physiographic delineations. Overall, these patterns sug-

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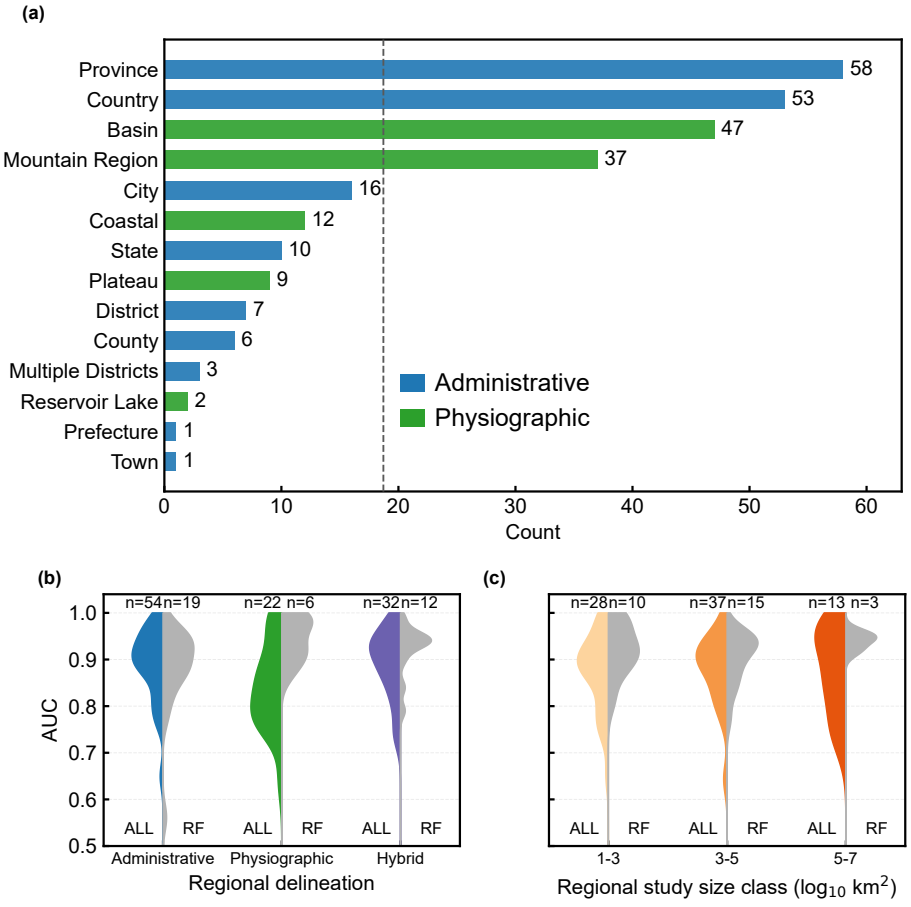

Figure 7. Regional delineation strategies (a) and model performance across regional delineation strategies (b) and regional study-area size classes (c). Panel (a) summarizes the frequency of administrative and physiographic delineation strategies adopted in regional studies. Panels (b) and (c) compare AUC distributions across delineation strategies and study-area size classes, respectively; coloured and grey violin plots represent all models and Random Forest (RF) models. Administrative delineations, particularly province- and country-based studies, are more frequently adopted than physiographic delineations. Overall AUC distributions are broadly comparable across delineation strategies and study-area size classes, although RF models show slightly higher AUC values for physiographic delineations.

gest that regional-scale landslide susceptibility assessments are primarily conducted within study-area frameworks that provide coherent administrative governance or strong topographic and hydrological organization.

Reported AUC values provide an overall comparison of model performance across regional delineation types. To reduce the influence of algorithmic heterogeneity, AUC distributions are presented for all models and RF-only models separately (Fig. 7b and Fig. 7c). For regional delineation types (Fig. 7b), AUC values from all models are mainly distributed between 0.8 and 0.95, with noticeable differences in variability among region types. Physiographic regions exhibit a broader distribution and lower median values compared to administrative and hybrid regions, indicating greater dispersion in reported performance.

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When restricting the comparison to RF-based studies, the influence of model heterogeneity is reduced, allowing a more direct comparison among delineation types. Both physiographic and hybrid regions are associated with relatively higher AUC values compared to administrative regions, with physiographic regions appear to slightly higher median performance. At the same time, the distributions become more compact, indicating more consistent model behaviour across studies. For regional study size classes (Fig. 7c), AUC values remain within a similar range across all size classes in both datasets, and no clear monotonic relationship with study size is observed. The distributions largely overlap, although minor differences in spread can be observed. Compared to all-model results, the RF-only subset shows more concentrated distributions across all size classes, with reduced variability.

Taken together, the results indicate a strong spatial concentration of rainfall-induced landslide susceptibility research, primarily located in Asia, Europe, and North America and conducted at the regional scale (10^2-10^4 km^2). This pattern is associated with the predominant use of administrative and physiographic delineations and data-driven models, while physically based approaches are more common at the individual-landslide. Across these settings, AUC values remain broadly comparable, although differences between all-model and RF-only results suggest an influence of model selection on reported performance.

3.4 Temporal representation and quantification of rainfall features

In rainfall-induced landslide susceptibility research, rainfall is widely regarded as one of the most important external controlling factors. A large body of work shows that rainfall is not only a direct trigger of landslides but also influences susceptibility patterns by regulating surface deformation, soil water conditions, and shallow hydrological processes. With increasing rainfall intensity or cumulative amount, areas classified as highly susceptible tend to expand, whereas low-susceptibility zones generally contract (She et al., 2024).

At the regional scale, rainfall information is often used to enhance model responsiveness under anomalous or extreme climatic conditions. For instance, rainfall temporal trends, spatial distributions, and intensity scenarios were incorporated to construct and compare susceptibility patterns in the Chingshui River watershed (Shou and Yang, 2015). Similarly, in the Maipo basin in the Central Andes, susceptibility changes under different precipitation-threshold scenarios were evaluated by combining geomorphological settings with rainfall precursors (Maragano-Carmoña et al., 2023). Other studies have also highlighted the close linkage between precipitation characteristics and historical shallow landslides, supporting rainfall as a key triggering factor in susceptibility mapping (Arab Amiri and Conoscenti, 2017). Overall, although rainfall has been widely incorporated and its importance has been demonstrated from multiple perspectives, most studies emphasize variable inclusion and model performance, while comparatively few systematically examine why rainfall becomes dominant at specific spatial scales or how it reshapes regional susceptibility patterns.

A typical workflow is performed to summarize the details in publications, with a focus on the temporal information in the works, linking the temporal framing of landslide inventories, sampling strategies, rainfall representations and modelling approaches. Via the Sankey diagram in Fig. 8 the literature reveals a remarkably consistent modelling paradigm. Most studies follow a typical workflow, beginning with multi-year landslide inventories, followed by spatial presence–absence sampling as defined in Table 2, the derivation of statistical rainfall metrics without a temporal component, and finally the application

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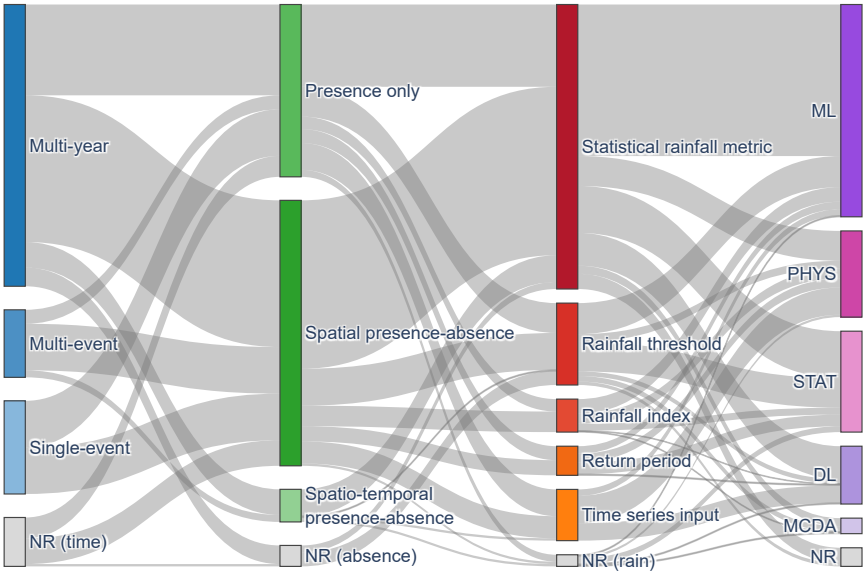

Figure 8. Rainfall information construction in spatio-temporal landslide susceptibility studies. The figure highlights a dominant information flow in the literature. Most studies combine multi-year landslide inventories with spatial presence–absence sampling, derive rainfall information using statistical rainfall descriptors, and subsequently apply machine-learning models. The dominant information flow indicates that rainfall is most commonly represented using statistical descriptors before being incorporated into predictive models.
Model abbreviations: ML, Machine Learning; STAT, Statistical Methods and Statistical Model Analysis; MCDA, Multi-criteria Decision Analysis; DL, Deep Learning; PHYS, physically based Models; NR, Not Reported

of machine learning models. This dominant workflow effectively transforms rainfall from a dynamic triggering process into a static conditioning variable. In contrast to this dominant pathway, rainfall representations that explicitly capture triggering dynamics, such as rainfall thresholds (Segoni et al., 2018; Huang et al., 2022), event-based rainfall metrics (Xing et al., 2021; Cui et al., 2024), or direct rainfall time-series inputs (Yuan and Chen, 2023; Fang et al., 2023), are comparatively less common in the literature. The predominance of this workflow explains why many susceptibility models successfully identify where landslides occur while remaining considerably less effective at representing when landslides become likely.

Taken together, these observations suggest that the incorporation of rainfall information in landslide studies involves several methodological steps, each of which may influence how rainfall–landslide relationships are interpreted. Accordingly, the following subsections examine three key aspects of this process: the temporal representation of rainfall, the assignment of rainfall information to presence and absence samples, and the quantification of rainfall metrics and their incorporation into landslide modelling.

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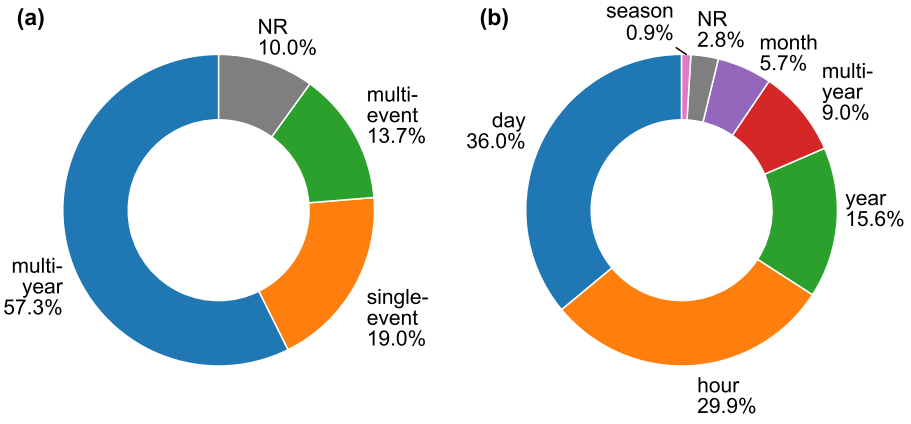

Figure 9. Temporal characteristics underlying rainfall representation in spatio-temporal landslide susceptibility studies. (a) Temporal extent of landslide inventories, indicating the time span over which landslide records are compiled. (b) Minimum temporal aggregation unit used for rainfall feature calculation, indicating the finest temporal unit adopted to derive rainfall representations. Multi-year inventories are the predominant source of landslide records, whereas daily and hourly rainfall data constitute the most commonly adopted temporal resolutions for rainfall representation.

Abbreviation: NR, not reported

3.4.1 Temporal representation of rainfall

The temporal framing of rainfall is characterized by both the temporal coverage of the landslide inventory and the minimum temporal unit used to calculate rainfall features. Figure 9 summarizes these two complementary aspects in the studies. The former reflects the temporal extent of landslide inventories, whereas the latter represents the finest temporal aggregation unit used to derive rainfall features, such as hourly intensity, daily accumulation, or monthly mean rainfall.

As shown in Fig. 9a, the multi-year scale is most frequently conducted in calculations of spatio-temporal landslide susceptibility studies, accounting for 57.3% of the studies. In contrast, temporal scale based on rainfall events, such as single-event and multi-event analyses, are considerably less common. This pattern indicates that rainfall is often aggregated over relatively long temporal periods and incorporated into landslide models as a background climatic variable (Cao et al., 2022), being less explicitly used to characterize individual rainfall-triggered events (Tiranti et al., 2019; Vega-Ruiz et al., 2025). Figure 9b further illustrates the finest temporal scale considered in rainfall feature calculation across the studies. It should be noted that a single study may employ rainfall features at multiple temporal scales (e.g., both daily (Collini et al., 2022) and yearly metrics (Abdo, 2022)); in such cases, only the finest temporal scale used in the study is recorded in the statistics. The results show that daily rainfall (36.0%) represents the most common finest temporal scale, followed by hourly rainfall (29.9%), whereas monthly (Dong et al., 2023), yearly (Zhou et al., 2025), or multi-year (Li et al., 2020) scales are used less frequently. This distribution suggests that most studies construct rainfall features starting from relatively fine temporal scales and subsequently aggregate them using different time windows to capture antecedent rainfall accumulation and potential lag effects. In contrast,

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Table 2. Sampling strategies used in landslide susceptibility studies

Sampling strategy	Description	Typical application
Presence-only sampling	Only landslide occurrences are used as observations, without defining absence samples	Rainfall threshold models
Spatial presence–absence sampling	Both presence and absence samples are represented only by their spatial locations (x, y)	Landslide susceptibility modelling
Spatio-temporal presence–absence sampling	Both presence and absence samples are represented by spatial locations and a specific time (x, y, t)	Spatio-temporal landslide hazard modelling

coarser temporal scales are more commonly associated with the representation of long-term background or periodic rainfall conditions. Although rainfall features are often derived from relatively fine temporal scales (e.g., hourly (Cui et al., 2024) or daily rainfall (Segoni et al., 2018)), they are typically aggregated over longer windows during model construction to represent the cumulative influence of rainfall on landslide occurrence (Tyagi et al., 2023). Such temporal aggregation may influence how rainfall–landslide relationships are represented in landslide models.

Therefore, the selection of rainfall temporal characteristics reflects not only technical decisions in data processing but also the objectives of the study and the adopted modelling framework. Rainfall features at different temporal scales may play distinct roles in describing rainfall-triggering mechanisms and in regional-scale landslide susceptibility analysis.

3.4.2 Assignment of rainfall information to presence and absence samples

In landslide modelling studies, the way rainfall information is associated with absence/presence samples and incorporated into models largely depends on the sampling strategy used to construct the modelling dataset. As summarized in Table 2, three main sampling frameworks can be identified in the existing literature: presence-only, spatial presence–absence sampling, and spatio-temporal presence–absence sampling. These three frameworks differ fundamentally in whether rainfall conditions need to be defined for absence samples, which in turn affects how rainfall features are represented in landslide models.

In contrast, spatial presence–absence sampling is more commonly adopted in regional-scale landslide susceptibility studies. In this approach, absence locations are randomly selected within the study area as negative samples, but these samples usually lack explicit temporal information (Abraham et al., 2023). Consequently, while rainfall conditions at landslide locations can be determined from the timing of events, rainfall conditions for absence samples cannot be directly determined and therefore must be inferred through additional assignment procedures. To address this issue, various assignment strategies have been proposed (Table 3), including statistical sampling based on rainfall distributions (Ye et al., 2024; Alatza et al., 2025), nearest-station assignment (Wang et al., 2020), random temporal assignment (Ahmed et al., 2018; Chakrabortty et al., 2020), and uniform rainfall assumptions (Yang et al., 2024; Gómez-Miranda et al., 2025). These approaches avoid the need to assign a specific observation time to each absence sample while preserving, to varying degrees, the temporal variability of rainfall information. Nevertheless, different assignment strategies may introduce uncertainties in terms of spatial consistency and physical realism.

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Table 3. Strategies for assigning rainfall conditions to absence samples in spatial presence–absence sampling

Method	Description
Statistical attribution	Rainfall conditions are assigned using statistical summaries or probability distributions derived from historical rainfall records
Nearest-station attribution	Rainfall conditions are assigned using observations from the nearest available rain gauge station
Random temporal attribution	Rainfall conditions are assigned by randomly sampling observations from historical time series
Uniform rainfall assumption	A uniform rainfall condition is assigned to all absence samples regardless of location or time

For example, statistical sampling may weaken the spatial heterogeneity of rainfall, nearest-station assignment may introduce biases when station density is low or rainfall gradients are strong, and random or uniform assignment may generate unrealistic rainfall-sample combinations. These limitations indicate that the assignment of rainfall conditions to absence samples remains a fundamental source of uncertainty in spatial presence–absence modelling when dynamic rainfall information is incorporated.

To reduce the uncertainty associated with assigning rainfall information to absence samples, recent studies have begun to adopt a a spatio-temporal presence–absence sampling framework, in which each combination of a spatial unit and a temporal sampling unit is treated as an independent observation (Steger et al., 2026). Under this framework, each sample is represented as (x, y, t), allowing rainfall conditions to be assigned consistently to both presence and absence samples while accounting for their spatio-temporal variability. Different studies, however, implement the temporal component in different ways. While most studies explicitly sample temporal units from the observation period, Edrich et al. (2026) introduced a probabilistic strategy in which rainfall predictors for absence samples are probabilistically inferred from historical rainfall records and incorporated directly into the machine-learning training dataset, allowing temporally representative rainfall information to be assigned without relying on a single sampled observation time. These differences reflect diverse implementations of the spatio-temporal presence–absence framework. According to the literature surveyed in this study, the number of studies adopting the spatio-temporal presence–absence framework remains relatively limited (13 in total), and their key methodological settings are summarized in Table 4. In terms of spatial representation, spatio-temporal presence–absence studies mainly employ grid cells or slope units as spatial discretization units, while a smaller number of studies use catchments as modelling units. Regarding temporal sampling units, existing studies include both short-term rainfall analyses at daily or event scales and long-term modelling approaches at annual scales. Meanwhile, temporal sampling strategies vary across studies and can generally be grouped into three patterns: exhaustive sampling of all time steps (covering both landslide-event time steps and the full time series), random sampling of time steps from the time series, and hybrid strategies combining continuous and random sampling. These differences reflect the diverse implementations of the spatio-temporal presence–absence framework in practice. Overall, the variability observed in spatial units, temporal sampling units, and temporal sampling strategies indicates that the spatio-temporal presence–absence framework remains in an early stage of methodological development, and no consensus has yet emerged regarding its optimal implementation.

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Table 4. Summary of studies adopting the spatio-temporal presence–absence sampling framework

Reference	Sampling period	Spatial unit type	Temporal sampling unit	Temporal sampling strategy
Edrich et al. (2026)	1950 – 2022	grid cell	event-based	probabilistic
Steger et al. (2026)	2005 – 2020	catchment	daily	random sampling
Du et al. (2025)	2011 – 2020	grid cell	yearly	all time steps
Wang et al. (2025)	2013 – 2021	slope unit	multi-scale	all time steps
Wang et al. (2024a)	2013 – 2021	slope unit	yearly	all time steps
Nocentini et al. (2023)	2000 – 2019	grid cell	event-based	mixed
Fang et al. (2023)	2008 – 2020	grid cell	time window	random sampling
Ahmed et al. (2023)	2017 – 2018	slope unit	event-based	all time steps
Wang et al. (2022)	1985 – 2015	catchment	yearly	all time steps
Wu and Lin (2022)	1996 – 2015	slope unit	event-based	all time steps
Collini et al. (2022)	2013 – 2019	grid cell	daily	all time steps
Knevels et al. (2020)	2009 and 2014	points	daily	random sampling
Tseng et al. (2020)	2005 and 2009	grid cell	event-based	random sampling

Notes: Sampling period refers to the time span used to construct landslide inventories and corresponding sample labels. In the Temporal sampling unit column, multi-scale indicates that rainfall features were represented at multiple temporal scales (yearly, seasonal, monthly, and daily). Spatio-temporal presence–absence samples are generated by combining each spatial unit with rainfall conditions at specific time steps.

3.4.3 Representation of rainfall information in landslide modelling

Besides sampling strategies, the representation of rainfall information is another key element in landslide modelling. Since rainfall is the primary triggering factor for many landslides, the way precipitation is quantified and incorporated into models deserves particular attention. As illustrated in Fig. 8, rainfall inputs can be broadly categorized into several quantification strategies, including statistical rainfall metrics (Abdo, 2022; Dahal et al., 2024), rainfall thresholds (Segoni et al., 2018; Lee et al., 2021), rainfall indices (Pereira et al., 2020; Shou and Lin, 2020), and time-series rainfall inputs (Gao et al., 2023; Yuan and Chen, 2023). Among these, statistical rainfall metrics represent the most widely adopted approach, serving as a bridge between raw precipitation observations and model-ready features. To better understand how these rainfall representations are used in modelling, we analysed the attributes of statistical rainfall metrics and their relationships with modelling approaches and temporal scales.

Because statistical rainfall metrics represent the most widely adopted rainfall representation, the following analysis focuses on their individual attributes and their relationships with modelling approaches and temporal scales. Figure 10 summarizes these patterns. Cumulative rainfall is the most frequently used attribute, particularly in machine learning models, where it appears in 53 of the studies. This dominance reflects the widespread assumption that antecedent rainfall accumulation plays a critical role in controlling landslide initiation. Mean rainfall (Tyagi et al., 2023) and maximum rainfall (Ullah et al., 2024) also

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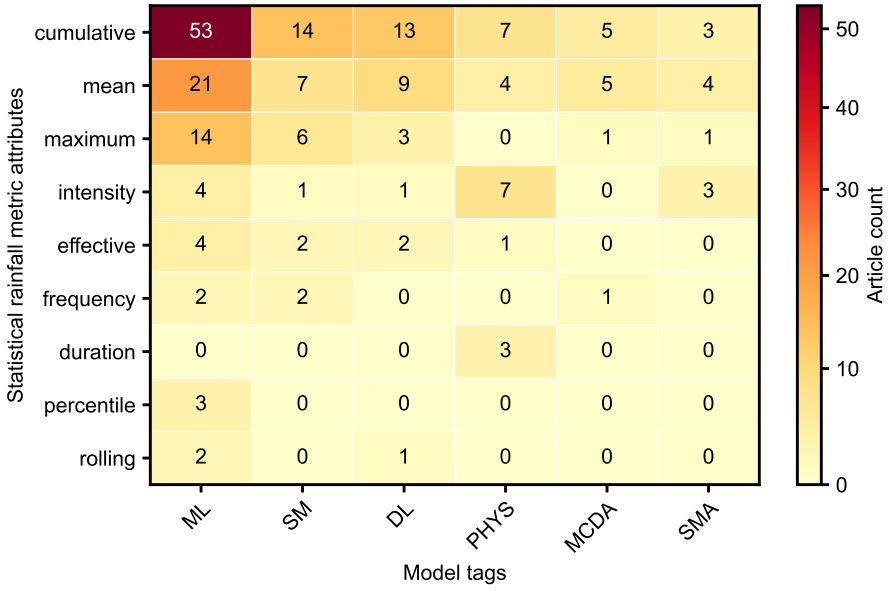

Figure 10. Distribution of statistical rainfall metric attributes across modelling approaches. Cell colours indicate the number of studies using each rainfall metric attribute within each modelling approach. Cumulative rainfall metrics dominate across all modelling approaches, while physically based models rely comparatively more on rainfall intensity than other approaches.

Model abbreviations: ML, Machine Learning; SM, Statistical Methods; DL, Deep Learning; PHYS, physically based Models; MCDA, Multi-criteria Decision Analysis; SMA, Statistical Model Analysis

appear frequently, again primarily in ML-based models. In contrast, rainfall intensity (Li et al., 2021) is relatively more common in physically based models, reflecting their emphasis on short-duration triggering mechanisms and infiltration dynamics. Overall, the results indicate that data-driven models tend to rely on aggregated rainfall descriptors, whereas physically based approaches more frequently consider process-oriented features such as rainfall intensity or duration.

Figure 11 further examines how rainfall quantification strategies relate to temporal scales. The results reveal a clear dependence between rainfall representation and rainfall temporal scale. Cumulative rainfall is the most widely used rainfall metric across all temporal scales (Xing et al., 2021). Its frequent application at hourly and daily scales reflects the importance of antecedent rainfall accumulation for landslide triggering, whereas its widespread use at annual scales indicates that cumulative rainfall is also commonly employed to characterize long-term hydroclimatic background conditions. In contrast, mean rainfall becomes the most common metric at multi-year scales, where rainfall features are often used to characterize long-term climatic conditions rather than triggering processes (Wang et al., 2024b). Rainfall threshold approaches are primarily associated with event-based or daily analyses, reflecting their role in defining critical rainfall conditions for landslide occurrence (Nefros et al., 2023). Time-series rainfall inputs appear mainly at short temporal scales, where sequential rainfall observations are directly used as model inputs (Kim et al., 2013; Gatto et al., 2023).

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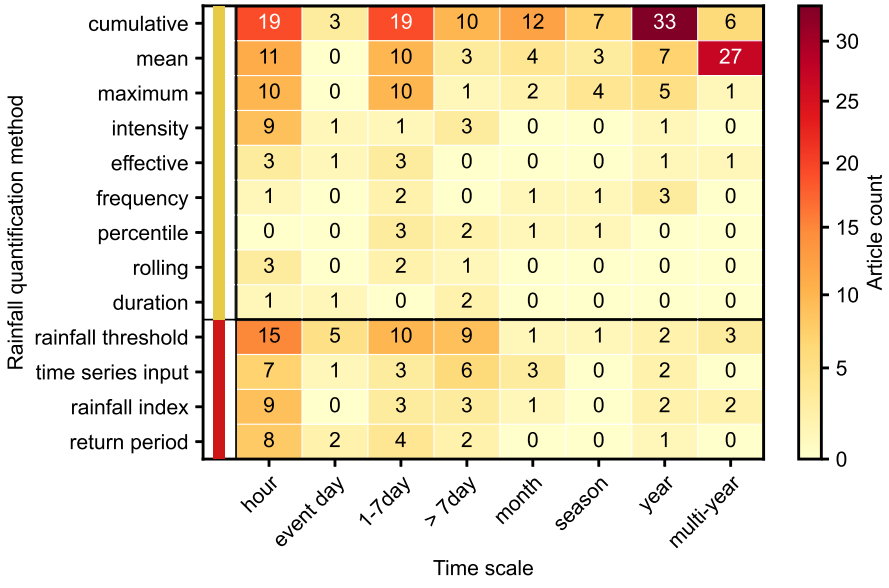

Figure 11. Distribution of rainfall quantification methods across temporal scales, including subclasses of statistical rainfall metrics. The upper part summarizes statistical rainfall descriptors (e.g., cumulative, mean, maximum, and intensity), whereas the lower part presents other rainfall representations, including rainfall thresholds, time series inputs, rainfall indices, and return periods. Cell colours and values indicate the number of studies in each category. Statistical rainfall descriptors are the predominant approach, with cumulative rainfall representing the predominant quantification method, whereas other rainfall representations are adopted considerably less frequently.

Taken together, these results suggest that the choice of rainfall metric is strongly linked to the temporal perspective of the study. Short-term landslide analyses typically rely on event-based cumulative rainfall or rainfall time series, while long-term susceptibility studies more commonly employ aggregated rainfall statistics such as mean annual rainfall. This pattern highlights a fundamental distinction between triggering-oriented analyses and long-term susceptibility assessments, which rely on different representations of rainfall information. Notably, the same rainfall metric may serve different purposes depending on the temporal scale considered.

4 Discussion

Interpreting the role of rainfall in landslide models requires considering not only the physical triggering mechanisms but also the methodological choices embedded in study design. As shown in Table 1, rainfall is frequently identified as the most influential predictor in spatial-temporal landslide susceptibility models. However, this apparent dominance does not arise solely from the intrinsic physical role of rainfall. Rather, it is shaped by a chain of methodological decisions regarding how landslide studies are spatially organized, how presence and absence samples are constructed, and how rainfall features are represented in the models. Therefore, the interpretation of the importance of rainfall is closely linked to three interconnected aspects of

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modelling design: (i) spatial scale and study-area delineation, (ii) sampling strategies used to construct landslide datasets, and (iii) the representation of rainfall processes in model features. Examining these aspects together provides a clearer perspective on how rainfall information is incorporated into landslide modelling frameworks and why rainfall features often emerge as dominant predictors in the literature.

4.1 Spatial scale and study-area delineation

The prominence of rainfall features in regional landslide susceptibility models reflects not only their physical role as triggering factors but also the way spatial heterogeneity is represented through study-area delineation. Most rainfall-driven susceptibility studies adopt regional modelling frameworks based on administrative or hybrid delineations, which facilitate hazard management and data integration but simultaneously influence model interpretation.

Administrative regions often encompass diverse climatic and geomorphological settings. Within such heterogeneous domains, rainfall captures not only triggering conditions but also broad terrain–climate gradients, allowing it to act as an integrated indicator of spatial heterogeneity. Consequently, rainfall features may emerge as highly influential predictors because they statistically explain multiple sources of spatial variation in addition to their physical triggering role. In contrast, physiographic delineations, such as watersheds or mountain systems (Chan et al., 2018; Ahmed et al., 2023), partially account for this heterogeneity through the delineation itself, allowing rainfall features to more directly reflect triggering processes.

This interpretation is supported by the findings of this review. After reducing the influence of model heterogeneity, physiographic and hybrid delineations consistently achieved higher AUC values than administrative regions, suggesting that part of the observed variation in model performance originates from differences in how spatial heterogeneity is represented rather than from model choice alone. More broadly, the widespread identification of rainfall as the dominant predictor should therefore be interpreted partly as a consequence of modelling design rather than solely as a reflection of physical triggering mechanisms. The apparent dominance of rainfall in susceptibility modelling therefore reflects an interaction between physical triggering processes and modelling design, reinforcing the need to interpret rainfall importance in the context of spatial representation rather than as a purely physical signal.

4.2 Presence–absence sampling and temporal uncertainty

Sampling strategy is another critical yet often overlooked factor shaping how rainfall information enters landslide susceptibility models. Although both presence-only and presence–absence approaches are used, the latter has become the dominant framework in data-driven modelling because it provides explicit classification information for statistical and machine-learning algorithms (Shou and Chen, 2021). However, incorporating rainfall into a presence–absence framework introduces a fundamental challenge: absence samples have no associated failure time (Edrich et al., 2024). While rainfall conditions can be directly extracted for landslide samples with known occurrence times (Du et al., 2025), rainfall for absence samples must be assigned indirectly, typically through randomly selected reference dates or probabilistic approaches (Rabby et al., 2023). Consequently, rainfall conditions associated with absence samples are approximations rather than observations, introducing temporal attribution uncertainty into rainfall representation.

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Two strategies have recently emerged to address this limitation. The first extends conventional spatial datasets into spatio-temporal presence–absence frameworks, in which each sample is defined by a location–time pair and rainfall features are directly linked to specific environmental conditions (Knevels et al., 2020). This framework reduces temporal attribution uncertainty and enables repeated observations at the same location, making it particularly suitable for modelling reactivated landslides. Alternatively, probabilistic approaches infer rainfall conditions for absence samples from historical rainfall distributions and incorporate these probabilistic estimates directly into model training (Edrich et al., 2026).

Introducing the temporal dimension fundamentally changes the statistical structure of modelling datasets. Because landslide events are rare relative to the number of location–time combinations, spatio-temporal datasets are characterized by severe class imbalance (Collini et al., 2022). Denser temporal sampling further increases the number of non-landslide samples while leaving the number of landslide events essentially unchanged, potentially biasing models towards the dominant non-landslide class. More importantly, these developments highlight that improving rainfall-driven susceptibility modelling requires advances not only in rainfall representation, but also in how temporal information is incorporated into the sampling framework itself.

4.3 Representation of rainfall and its temporal dependency

Current landslide susceptibility models rarely learn rainfall processes directly. Instead, rainfall is predominantly represented through handcrafted statistical descriptors, such as cumulative rainfall, mean or maximum intensity (Moreno et al., 2025). While these descriptors retain selected characteristics of rainfall events, they inevitably compress dynamic rainfall processes into single scalar variables, discarding much of their temporal organization. This simplification is fundamentally inconsistent with the hydrological controls of rainfall-induced landslides, including soil-moisture accumulation (Gorsevski et al., 2006), pore-water pressure development (An et al., 2016), and transient infiltration dynamics, all of which evolve continuously through time. Consequently, rainfall sequences with identical cumulative totals may produce markedly different hydrological responses and slope stability conditions because they differ in their temporal organization rather than their rainfall amount alone.

Antecedent rainfall indices illustrate this limitation well. Although they introduce rainfall history through predefined temporal windows and weighting schemes such as exponential decay (Lee et al., 2022), the rainfall sequence is ultimately condensed into a single value. Consequently, they remain scalar descriptors that preserve only selected characteristics of rainfall history while discarding its full temporal organization.

With the increasing availability of high-resolution rainfall observations and advances in machine-learning techniques, recent studies have begun to incorporate rainfall time series directly into landslide models or to extract rainfall features from rainfall sequences. In this context, landslide occurrence depends not only on rainfall amount within a given period but also on the temporal structure of antecedent rainfall, a characteristic referred to here as rainfall temporal dependency (Ng et al., 2021; Ren et al., 2024). Rainfall temporal structure therefore provides a time-aware representation of rainfall, preserving persistence, sequence patterns, and temporal dependencies that are largely discarded by scalar descriptors.

This review suggests that rainfall representation is undergoing a conceptual transition from handcrafted statistical descriptors towards time-aware representations that preserve rainfall temporal structure. Enabled by advances in high-resolution precipitation observations and sequence-learning techniques, future landslide susceptibility models will increasingly be able to learn

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directly from rainfall sequences rather than from predefined rainfall metrics. Such a transition has the potential to improve both predictive performance and the physical interpretability of rainfall-triggering processes.

4.4 Challenges and future directions

Despite substantial progress in rainfall-induced landslide susceptibility modelling, several methodological challenges remain and provide important directions for future research. Interpretation of rainfall effects is strongly influenced by modelling design, including spatial scale, study-area delimitation, and sampling strategies (Reichenbach et al., 2018; Merghadi et al., 2020). Building upon the findings of this review, three priorities deserve particular attention:

1. Current spatial presence–absence frameworks introduce temporal uncertainty when assigning rainfall conditions to absence samples (Xiong et al., 2024). The increasing availability of high-resolution rainfall datasets provides new opportunities for developing genuinely spatio-temporal susceptibility frameworks, including temporally explicit presence–absence sampling strategies. However, these approaches also introduce challenges associated with increasing data volume and severe class imbalance, requiring more effective sampling strategies and modelling techniques (Lombardo et al., 2018).

2. Process-oriented rainfall characterization deserves greater attention in future landslide susceptibility modelling. Existing studies predominantly select rainfall descriptors for their statistical convenience or predictive performance, while their links to hydrological and slope-failure processes are often insufficiently established (Lee et al., 2021). Future research should develop physically interpretable rainfall representations that distinguish antecedent wetting, event-scale triggering, rainfall persistence, and dry–wet transitions, and evaluate their contributions across different geomorphological and climatic settings.

3. Climate change is expected to intensify hydroclimate volatility, increasing the frequency of rapid transitions between wet and dry conditions and amplifying rainfall-triggered hazards, including landslides (Swain et al., 2025). These changing rainfall regimes highlight the need for susceptibility models that explicitly represent rainfall temporal dynamics rather than relying solely on traditional statistical descriptors, to improve model robustness under non-stationary climatic conditions. As hydroclimate variability continues to increase, representing complete rainfall patterns rather than isolated rainfall statistics may become essential for capturing increasingly complex rainfall–landslide relationships.

5 Conclusions

Rainfall is widely recognized as the primary trigger of many landslides, yet its predictive role in landslide susceptibility modelling depends fundamentally on how rainfall is represented within the modelling framework rather than on rainfall alone. The apparent importance of rainfall therefore reflects not only physical triggering processes but also methodological choices embedded in study design. At regional scales, administratively defined modelling domains often encompass broad terrain–climate gradients, allowing rainfall features to capture large-scale environmental variability beyond their direct triggering role.

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More fundamentally, however, most current modelling frameworks do not directly represent rainfall processes. Instead, the temporal evolution of rainfall is first condensed into handcrafted statistical descriptors before being introduced into predictive models. Although these descriptors retain selected characteristics of rainfall events, much of their temporal organization and sequential structure is inevitably discarded. Consequently, models infer rainfall–landslide relationships from simplified rainfall proxies rather than from the evolution of rainfall itself, potentially overlooking informative rainfall patterns relevant to slope failure.

These findings suggest that the central challenge in rainfall-driven landslide susceptibility modelling lies not only in identifying effective rainfall predictors, but in fundamentally rethinking how rainfall is represented. The next generation of susceptibility models should therefore move beyond handcrafted statistical descriptors towards directly learning complete rainfall sequences and their temporal organization, enabling rainfall processes themselves to become the basis of prediction rather than their statistical summaries.

Code availability. This review article does not use or generate any original software code.

Data availability. This review article does not use or generate any original research data.

Author contributions. **FZ:** Methodology, Formal analysis, Data curation, Writing - Original Draft, Writing - Review & Editing, Visualization **AE:** Conceptualization, Writing - Review & Editing **AY:** Conceptualization, Methodology, Writing - Review & Editing, Supervision **JK:** Conceptualization, Writing - Review & Editing, Supervision

Competing interests. The authors declare that they have no conflict of interest.

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