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UPDATE

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Recent advancements of landslide hydrology

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Abstract

Occurrence of rainfall-induced landslides is increasing worldwide, owing to land use and climate changes. Although the connection between hydrology and rainfall-induced landslides might seem obvious, hydrological processes have been only marginally considered in landslide research for decades. In 2016, an advanced review paper published in WIREs Water [Bogaard and Greco (2016), *WIREs Water*, 3(3), 439–459] pointed out several challenging issues for landslide hydrology research: considering large-scale hydrological processes in the assessment of slope water balance; including antecedent hydrological information in landslide hazard assessment; understanding and quantifying the feedbacks between deformation and infiltration/drainage processes; overcoming the conceptual mismatch of soil mechanics models and hydrological models. While little progress has been made on the latter two issues, a variety of studies have been published, focusing on the role of hydrological processes in landslide initiation and prediction. The importance of the identification of the origin of water to understand the processes leading to landslide activation is largely acknowledged. Techniques and methodologies for the definition of landslide catchments and for the assessment of landslide water balance are progressing fast, often considering the hydraulic effect of vegetation. The use of hydrological information in landslide prediction models has also progressed enormously. Empirical predictive tools, to be implemented in early warning systems for shallow landslides, benefit from the inclusion of antecedent soil moisture, extracted from different sources depending on the scale of the prediction, leading to significant improvement of their predictive skill. However, this kind of information is generally still missing in operational LEWS.

This article is categorized under:
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KEYWORDS

hydrology, lab and field experiments, landslide, landslide early warning systems, machine learning

1 | INTRODUCTION

Landslides occur worldwide, they cause thousands of deaths in urbanized areas and substantial direct or indirect damages to infrastructures and private properties with billions in monetary losses per year (Bhardwaj et al., 2019; Cui et al., 2019; Froude & Petley, 2018; Haque et al., 2016; Ma et al., 2020). Besides, landslide occurrence is increasing as a consequence of climate and land use changes (Alvioli et al., 2018; Camici et al., 2015; Ciabatta et al., 2016; Gariano & Guzzetti, 2016; Wei et al., 2018).

The research on landslide hazard assessment involves a broad range of science fields from earth science to engineering science due to its multidisciplinary nature, and consequently, it is discussed in a range of specialized scientific journals around the world. Generally, the term "landslide" indicates a movement of slope-forming materials like rock, debris, soil, or a combination of these, and the kind of material and the mode of movement can differentiate the various types of landslides (Hungr et al., 2014). Among dangerous landslides, rainfall-induced are by far the most frequent, which are triggered during or following periods of intense and persistent rainfall. Deep-seated landslides are often related to attenuated hydrological effects following rainfall periods, for example, time-lagged groundwater level fluctuations. In contrast, the most common landslides are shallow, that is, those affecting the uppermost part (up to 3 m) of the slopes, and these typically have a more direct link to rainfall (e.g., Sidle & Bogaard, 2016). They often evolve in the form of debris flows, mobilizing loose soil or rocks along steep slopes, and running channelized through the gullies (Hungr et al., 2001).

Although the connection between hydrology and rainfall-induced landslides might seem obvious, hydrological processes have been only marginally considered in landslide research for decades, and *landslide hydrology* is still an emerging field of research. The way any shallow or deep hydrological process develops along hillslopes (i.e., rainwater infiltration, evapotranspiration, overland runoff, subsurface runoff, groundwater recharge, percolation, etc.) depends on the complex interplay of meteorological forcing (precipitation characteristics, such as duration, peak, and mean intensity; evapotranspiration demand) and geo-hydrological characteristics of the slope and the surrounding area. While slope failure mechanisms are quite well established, as they are related to pore water pressure increase or gradients (either in saturated or unsaturated soil conditions), the complex hydrological processes eventually leading to landslide triggering are often neglected or poorly defined. In recent years, increasing attention has been given to improve the understanding driving hydrological processes and quantifying their magnitude in landslide research. Focus here is frequently on a wider, broader, inclusion of hydrological processes, and their nonlinear nature.

In 2016, an advanced review paper was published in WIREs Water (Bogaard & Greco, 2016), devoted to landslide hydrology, in which several challenging research issues were pointed out, that is:

- *Hydrological perspective*: the inclusion of large-scale (in time and space) hydrological processes in the assessment of the water balance of a potentially unstable soil mass.
- *Process dependencies*: the mutual effect of deformation and infiltration/drainage processes at pedon and slope scale.
- *Model representation inconsistency*: the mismatch of soil mechanics models and hydrological models, in terms of scale and process conceptualization.
- *Missing hydrological state in forecasting*: the inclusion of catchment hydrological information in regional landslide hazard assessment.

The focus of this update is to report on the progress made in the landslide hydrology field, addressing both the identified open research questions and emerging topics but also discussing where the research progress is modest. With this, we aim to stimulate and encourage scientists and practitioners making next steps in landslide hydrology and help bridging gaps between theory and practical application. This update is centered around the link between hydrology and slope deformation/failure, while studies about mobilized mass propagation and impact were excluded. It is organized into the following sections:

- Section 2 expands on the importance of a hydrological perspective in landslide research with special focus on the boundary conditions.

- The third section explores how laboratory and field experiments, as well as field monitoring, can help to identify the major hydrological processes developing on hillslopes affected by landslides.
- In the fourth section, the focus moves to new modeling approaches of machine learning (ML) techniques which seem to offer novel operational tools for landslide hydrology.
- Finally, in the fifth section, we take a closer look at novel operational landslide warning and forecasting systems and the use of hydrological information for improving regional hazard assessment and landslide early warning systems.

2 | THE HYDROLOGY PERSPECTIVE IN LANDSLIDE RESEARCH

Landslide hydrology has been framed as "filling-storing-draining" (Bogaard & Greco, 2016). An increase in water storage in a soil mass will lead to an increase in pore pressure and lower effective stress which is the underlying fundamental physical mechanism of slope failure (Terzaghi, 1943).

As such, the increase of water storage (and pore pressure) is a consequence of water infiltration, but it also requires that the drainage mechanisms of the slope, concurrently developing but typically with different timescales, are not able to drain out much of the infiltrated water (Box 1, Figure 1). These hydrological processes are influenced by the boundary conditions around the slope, which are inherently site-specific and often dynamically changing in response to seasonal (eco)hydrological processes: evaporation and transpiration to the atmosphere, and drainage both vertically via leakage through soil bedrock interface and laterally through subsurface flow (e.g., Marino, Comegna, et al., 2020; Pirone et al., 2015; Scherer & Malík, 2018). Field monitoring and experiments, supported by modeling, can help identify the major hydrological processes affecting the slopes through their boundaries, thus allowing more reliable prediction of landslide occurrence. Dynamically changing behavior of slopes may also be the result of hydromechanical coupling, as hydrological processes affect slope equilibrium, and deformations may affect slope hydrology as well, owing to soil swelling (e.g., Schulz et al., 2018), cracking (e.g., Liang, 2020; Luo et al., 2023), or to previous landslide activity (e.g., Mirus et al., 2017).

In recent years, a strong increase in awareness about the importance of vegetation has led numerous researchers to also investigate its multiple effects on slope stability, and to establish approaches suitable for its quantification. Nevertheless, the multiple processes which lead vegetation to enhancing the stability of hillslopes are still unclear and need to be investigated, due to the complexity of hydrological and mechanical interactions between root system and soil cover, which depend on the climate, vegetation, soil type, depth of failure surface, and, so, on the type of landslide studied (Kim et al., 2017; Sidle & Bogaard, 2016). Apart from the well-established beneficial effect of root water uptake, which contributes to lowering pore pressure (e.g., Ng et al., 2021; Zhu & Zhang, 2019), contradictory results have been obtained regarding the effects of the presence of roots on the infiltration process. For instance, Balzano et al. (2019) analyzed shallow landslides in Scotland, where the rhizosphere, that is, the portion of soil directly affected by plant roots, was characterized by hydraulic conductivity higher than the underlying soil, thus promoting the lateral diversion of water with beneficial effects for slope stability. Differently, Qin et al. (2022) analyzed the hydrological effect of root distribution in lab and field measurements and showed that the higher permeability in the rooted topsoil compared to underlying, nonrooted zone, can have the opposite effect, promoting high infiltration rates and building up critical pore pressures in case of high-intensity rain events. Masi et al. (2021) published a recent review on the multiple hydrological (e.g., suction, canopy interception, infiltration-subsurface flows) and mechanical (soil reinforcement, surcharge, buttressing, deep anchoring, rock fracturing) effects of vegetation on slope stability, also providing an inventory of papers published worldwide between 2015 and 2020. A still unexplored aspect is the mutual interaction of landslides and vegetation in the development and evolution of slope ecosystems (Gonzalez-Ollauri & Mickovski, 2017b), as mostly the focus has been limited to the effect of changing roots on slope strength (e.g., McGuire et al., 2016).

Initial or antecedent wetness state of the soil due to previous precipitation, evaporation, and transpiration has received ample attention. However, the influence of the lower bedrock boundary condition was mostly neglected or assumed static. In Box 1, an illustrative example of the controlling role of dynamic boundary conditions in the case of pyroclastic deposits

BOX 1 Slope water balance.

Considering the hydrological boundary conditions is a minimum prerequisite to assess the dynamic water balance of a slope, depending not only on how much it is raining and how much water is infiltrating, but also on exploring how the slope is dynamically draining out the infiltrated water.

Figure 1 shows a hydrological system (i.e., a slope schematized as a bucket) filling over a rain event and contemporarily draining. Depending on infiltration and drainage rates, water storage in the bucket may significantly increase (a) or not (b). Pore water pressure build-up occurs only if water storage significantly increases. Drainage through the boundaries of a slope is typically three-dimensional (3D), hence depending on large-scale processes, that is, related to the hydrology of an area wider than the mere landslide scarp, thus evolving over a long time scale. Rainfall infiltration is instead a one-dimensional (1D) local mechanism evolving over a relatively short time interval during and after a rainfall event. These typically different time scales and spatial features allow splitting between causes and triggers of landslides, as suggested by Bogaard and Greco (2016). Draining processes at the boundaries of slopes often exhibit seasonal changes, in response to all the processes of the water cycle affecting the slope as a part of a larger hydrological system.

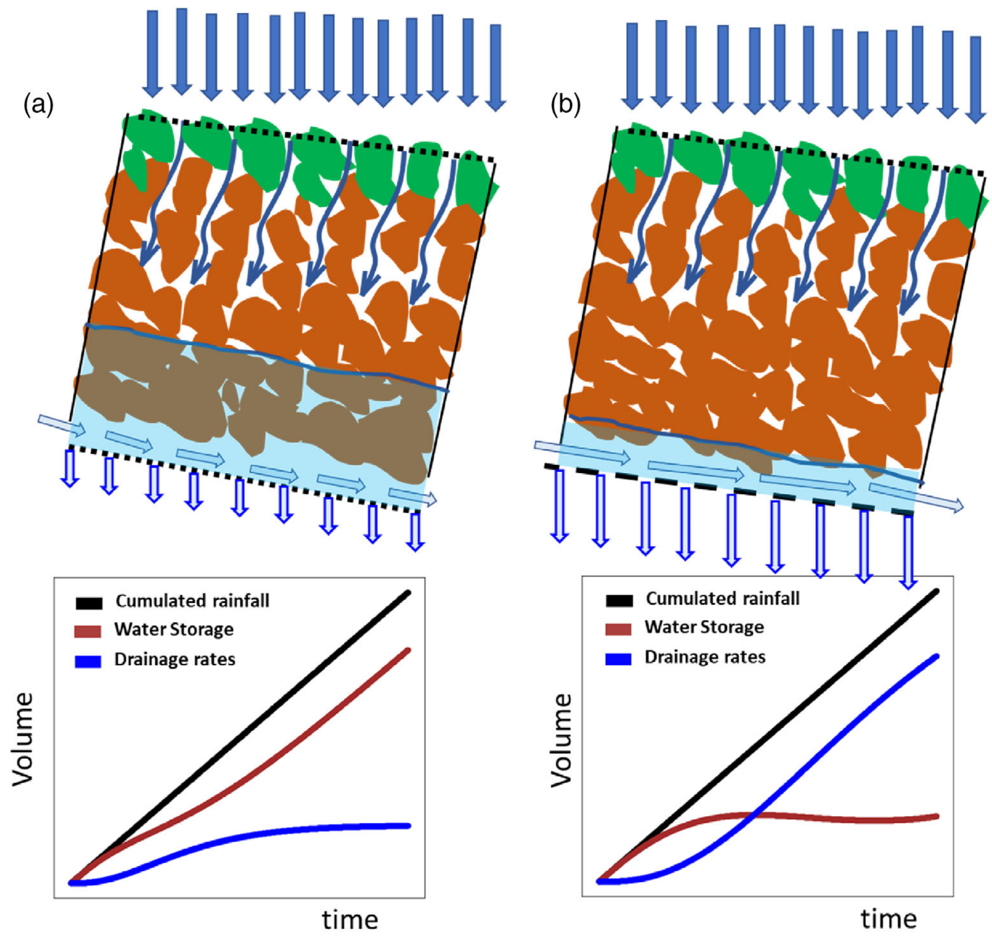

FIGURE 1 Example of the interplay between filling and draining processes.

Of course, the water balance gives information about the wetness state of the slope, which is useful to assess the global conditions potentially predisposing to landslides. The exact location where landslides may occur depends on slope-specific singularities, the knowledge of which is usually far beyond the available information. However, awareness of the increased probability of landslide occurrence is enough for regional hazard assessment.

An example of how dynamically changing lowermost boundary condition affects the hydrological response of shallow unsaturated pyroclastic soil deposits in southern Italy is given in (Greco et al., 2018, 2021; Marino et al., 2021). They show how high or low hydraulic conductivity and connectivity, respectively corresponding to wet or dry conditions, control the leakage of water through the interface between the soil and the underlying fractured limestone bedrock. Specifically, the delayed dynamics of the moisture content at the base of the soil cover, related to temporary accumulation of water in a perched aquifer in the upper part of the fractured limestone, offer a possible interpretation of the seasonal hydraulic behavior of the soil–bedrock interface, through which leakage is usually allowed in late winter and spring, but not during autumn and early winter. In these two seasons, different duration and intensity of landslide-triggering rainfall have been identified, offering a possible explanation for why most landslides in the area occur in late autumn and early winter (Marino et al., 2021).

overlaying limestone bedrock is given (Greco et al., 2021; Marino et al., 2021). Similar behavior was observed in a Himalayan catchment, in India (Illien et al., 2021). The temporary storage of water in perched aquifers developing in the fractured bedrock caused the delayed activation of drainage processes compared to rainfall, which controlled the seasonal occurrence of floods and might also affect other kinds of geohazards. In fact, the infiltrated rainwater first flows through the unsaturated superficial zone of the soil (vadose zone), before reaching the groundwater and then the streams, since the response of groundwater to precipitations is delayed, showing a reaction at a weekly or even monthly scale.

Several examples indicate that the assessment of the water balance of a hillslope, besides the definition of the hydraulic boundary conditions, requires the identification of landslide catchment. The latter being the upslope area collecting precipitation and snow melt, which converge through subsurface water flow in a smaller area, leading to critically high pore water pressures. In 2016, Bogaard and Greco wrote "The hydrological research to integrate all water fluxes and stocks in mountain systems, mountain bedrock, hillslope, valley aquifers, and surface water streams, is getting started in recent years. The insight we gain in the quantitative disentangling of origin of water fluxes contributing to the base flow in mountainous areas can also show to be beneficial for better understanding and quantifying landslide water balances."

In their review on groundwater in mountainous regions, Somers and McKenzie (2020) write that catchment streamflow in high mountainous regions gets its discharge for a large part from the regolith (mainly from interface weathered soil and bedrock), through deep fracture flow but also from water exfiltrating in mountain valleys. The infiltrating water does not only originate from rain, but also from snow and glacier melt. Climate changes are accelerated in mountain regions due to the elevation effect compared to the global average and lower parts of the globe. Besides, changes in precipitation from snow to rainfall, the effect of rain-on-snow, and changes in spatial and temporal distribution of snow cover due to climate change, can have profound effects on the mountain hydrology, especially on subsurface hydrology. This influences the dynamics of the slope water balance and consequently deformations in mountainous regions and therefore should be an important focus in mitigation works of, for example, deep-seated landslides.

Wayllace et al. (2019) showed how estimating rainfall and snowmelt infiltration over a large upstream catchment helped to explain the seasonally varying stability conditions of a landslide in an embankment of Interstate-70 (Colorado, USA), highlighted by piezometer and inclinometer measurements. di Lernia et al. (2022) modeled the stability conditions of the Fontana Monte landslide (Italy). They found that the piezometric regime at large depths was influenced by the contact with an underground aquifer fed by a large upstream recharge area, a recurrent feature of several slopes in the South-Eastern Apennines. The resulting high piezometric head values predispose the slopes to failure.

The definition of landslide catchment can also be made using water chemistry and isotopic analysis, a well-established approach in hillslope hydrology, but still rarely applied to landslide studies. Recently, Pfeiffer et al. (2021) introduced a method linking isotope time series to estimate elevation origin of the retrieved groundwater with a topographical analysis of potential flow paths. Including the uncertainty of elevation and location origin, this was merged into a map of recharge probability. The results showed two upslope recharge areas, most likely responsible for the recharge of the landslide area, that were found to be in good agreement with previous interpretations by local experts. It shows how powerful detailed isotopic analysis can be for the hydrological understanding of deep-seated landslides.

Adding to complexity, landslide catchments are not necessarily static. Specifically, large groundwater systems can be affected by earthquake events. Changes in hydrological flow paths in response to earthquakes have been reported, leading to changes in stream flow, ground water level and flow direction changes, geyser eruption frequency, and groundwater temperatures (Ingebritsen & Manga, 2019; G. Zhang et al., 2021). This hydrological shift has been also identified as the reason for changes in slope stability or slope deformation rate (Mikoš et al., 2004).

3 | UNDERSTANDING LANDSLIDE HYDROLOGICAL PROCESSES THROUGH EXPERIMENTS AND FIELD MONITORING

Several studies demonstrate and investigate how the complex hillslope hydrological processes in response to precipitation can affect the triggering of landslides (Marc et al., 2017; Sousa et al., 2020). Most of them focus on rainwater infiltration and overland runoff processes, as widely reported by Chiu et al. (2019), Chen et al. (2020), Sidle and Bogaard (2016), and Morbidelli et al. (2018). Basically, several studies have been conducted from different conditions of investigation, carried out through flume experiments in the laboratory at relatively small-scale, field large-scale experiments, and monitoring on real slopes.

In the first case, the laboratory experiments are performed in an artificial environment under controlled conditions, which are aimed at investigating the deformation and triggering mechanism of landslides (e.g., Darban et al., 2019; Lora et al., 2016; Weng et al., 2018) and debris flows (Hu et al., 2016, 2018). Other experiments focused on the infiltration process in layered sloping deposits, focusing on the possible formation of capillary barriers and flow diversion, which may affect the triggering mechanism of shallow landslides (Capparelli et al., 2020; Damiano, 2019; Damiano et al., 2017; Reder et al., 2017). van Asch et al. (2018) investigated how the hydraulic conductivity of the soil, together with the slope inclination angle, controls the type of triggering mechanism of debris flows in cohesionless deposits with varying grain sizes. Other authors conducted laboratory tests in order to understand the role of hydrologic initial and boundary conditions on the triggering of landslides and debris flows. Hu et al. (2015) showed that the occurrence of the prevailing triggering processes (i.e., erosion and transport by overland runoff or decrease of soil strength due to infiltrating water) is controlled by the initial soil moisture content. Schilirò et al. (2019) integrated flume experiments with physically based modeling. They observed two potential triggering mechanisms in a sand deposit, that is, the uprise of a temporary water table and downward advance of the wetting front, in case of relatively low and high initial soil water content, respectively. The increase in the initial water content can significantly influence the triggering time.

Laboratory tests have also been conducted to study the effects of vegetation on the hydrology of slope stability. For example, Chen et al. (2021) and Qin et al. (2022) discussed how the vegetation type can induce different hydrological effects on the permeability and water storage capacity of slope soil, improving the erosion resistance and so playing a suitable and not negligible role in slope stability response. Yildiz et al. (2019), based on the results of experiments on root-permeated specimens in an inclinable large-scale direct shear apparatus, studied the contribution of plant-induced suction to shear strength for root-permeated soils, planted with combinations of different species. The results suggested that longer plant growth duration and more species yielded higher matric suction and shear stress. Controlled laboratory tests allow understanding the effects of single factors on slope stability, which may be hidden by the complexity of real field case studies. However, the results may sometimes diverge from the real field behavior due to scale limitations, making the application of the results of such experiments cumbersome. In this respect, field monitoring, carried out in a real-site setting, observing natural phenomena without controlling the variables affecting slope response to the meteorological forcing, allows quantifying the major hydrological processes on real scale. In such real situations, heterogeneities are common, and it is possible to observe how surface cracks, fissures, irregular topography, and macrospores may affect preferential flow paths. The specific features such as vegetation cover, plant roots, and variability of soil geotechnical and hydraulic properties often require short- or long-term monitoring to understand their effect on slope hydrologic behavior. Specifically, continuous field monitoring is indispensable to identify the major hydrological processes controlling the slope water balance and, consequently, to investigate the causal preparatory conditions for landslide triggering.

At slope scale, the influence of hydrological processes on the triggering of landslides, typically deep-seated, can be investigated by field measurements of pore water pressure in response to precipitations through piezometers (Di Maio et al., 2020; Xu et al., 2016). Good correlation between the recharge of landslide aquifer and piezometric level rise after intense rainfall periods was often observed, which can help to predict accelerations of sliding movements (e.g., Belle et al., 2018). For shallow landslides, several studies show how the hydrological monitoring of the regolith moisture regime can allow the understanding of the complex hydrological processes leading to slope failure. Rianna et al. (2014) carried out measurements of meteorological variables and soil suction, water content, and heat, over 2 years at a steep slope covered with unsaturated pyroclastic deposits in Campania (Italy). They recognized that actual evaporation and infiltration flows, both controlled by initial soil moisture, are particularly suitable to interpret the landslides caused by rainfall infiltration. Bordoni et al. (2015) investigated the effect of topsoil hydrological properties on shallow landslides, calculating the safety factor based on hydraulic and geotechnical models, the parameters of which were calibrated based on continuous field observations at a test slope for about 2 years. Fusco et al. (2017) found that antecedent hydrological conditions due to seasonal climate variability play an important role in ash-fall pyroclastic soil mantle in shallow landslide initiation during rainfall events. Few studies, based on field measurements at slopes, showed how plant roots provide an increase in shear strength, as they absorb water from the soil for their biological activity, and release it into the atmosphere, leading to an increase in soil suction and, so, to a positive effect against rainfall-induced landslides (e.g., Gonzalez-Ollauri & Mickovski, 2017a). Marino, Comegna, et al. (2020) investigated through field monitoring the interaction between soil cover, vegetation, and atmosphere in a slope covered with pyroclastic deposits laying upon a densely fractured limestone bedrock. Their study shows how extending the monitoring outside the specific slope, that is, by measuring water level and discharge in streams running at slope foot, allows to assess of the seasonality of infiltration and drainage processes, which controls the conditions that may predispose the slopes to shallow landslides. In fact, the hydrological control of the response of slopes to precipitations, represented by antecedent moisture condition, can be assessed at catchment scale (Uber et al., 2018; Zhuo & Han, 2017). Hürlimann et al. (2014) described a monitoring system installed in the Rebaixader catchment (Central Pyrenees, Spain) for debris flows initiation and flow dynamics. Discharge measurements were carried out with sensors placed inside the channel. Furthermore, sensors were installed throughout the catchment to measure meteorological variables and soil wetness conditions. The monitoring system was able to detect six debris flows and 11 debris floods between summer 2009 and autumn 2012. In situ field measurements in a limited set of locations can indeed be representative for an unexpected large region, and for this reason, soil moisture network design studies for hydrological applications is changing in order to define the minimal required number of sensors for capturing accurately the catchment-scale soil moisture information, as reported by Zhuo et al. (2020). Obviously, the monitoring system should be customized (i.e., relevant variables, installed sensors, frequency of acquisition, etc.) to the features of the specific case and based on the expected major processes. Hürlimann et al. (2019) published a noteworthy review paper showing the most recent techniques for developing monitoring systems for debris-flow triggering. They highlighted different strategies of design, depending on the purpose of monitoring (research or early-warning purposes) and site characteristics (i.e., sediment concentration and grain size). A mismatch in the reported monitoring situations arises, owing to the adoption of different guidelines for the choice of the sensors adopted in each site. They also provided a list of sensors suitable for the different mechanisms of initiation of debris flows.

Recent research has been focusing on experiments designed ad hoc directly in the field. Sitarenios et al. (2021) analyzed numerically the results of a field experiment carried out on a steep forested slope in Reutlingen (Switzerland), where a landslide was triggered after 15 h intense artificial rainfall (Askarinejad et al., 2018). The experiment highlighted the role played by a system of interconnected fissures in the bedrock, that redirected infiltrating water from the upper part of the slope towards lower altitudes, where local exfiltration from the bedrock occurred, accelerating saturation of the soil cover and the increase of pore water pressure. The field-scale experiment, conducted by Oorthuis et al. (2018, 2020) in a full-scale embankment, helped in understanding how the interaction between soil, vegetation, and atmosphere can affect rainwater infiltration during winter/spring and dry periods. In particular, the experiments were carried out measuring meteorological variables (i.e., rainfall, soil and air temperature data, relative humidity, barometric pressure, solar radiation, and wind speed) and evaluating the slope hydrologic response in terms of soil volumetric water content and pore water pressure. The authors described the slope thermo-hydraulic response considering four plots with both north and south aspects and vegetation covers (bare or vegetated). The monitoring results showed high soil moisture during winter and spring and a dry period during summer and autumn. Most of the short rainfall events did not lead to significant variations in terms of volumetric water content and pore water pressure at all depths. Only after high rainfall did the deepest soil layer reach saturation. During rainfall, vegetation enhanced infiltration and decreased runoff, reducing surface erosion, and slope stability. In dry periods, instead, plant transpiration induced higher soil suction through root water uptake and, hence, improved slope stability.

From the above examples, it becomes clear the different potential of lab and field experiments, compared to field monitoring (Figure 2). The first focus on improved understanding of the effect of single local factors on slope hydrology and slope stability (e.g., morphology, vegetation cover, initial conditions), while field monitoring aims at identifying and understanding the major hydrological processes occurring in a slope. The specific focus of many studies on the effects of vegetation is understandable, especially in view of the increased societal demand to have nature-based solutions to slope stability problems, which also fulfill technical design standards, the application of which is still limited to very shallow soil stabilization, owing to the still scarce knowledge of their effectiveness, as pointed out in the recent review by de Jesùs Arce-Mojica et al. (2019).

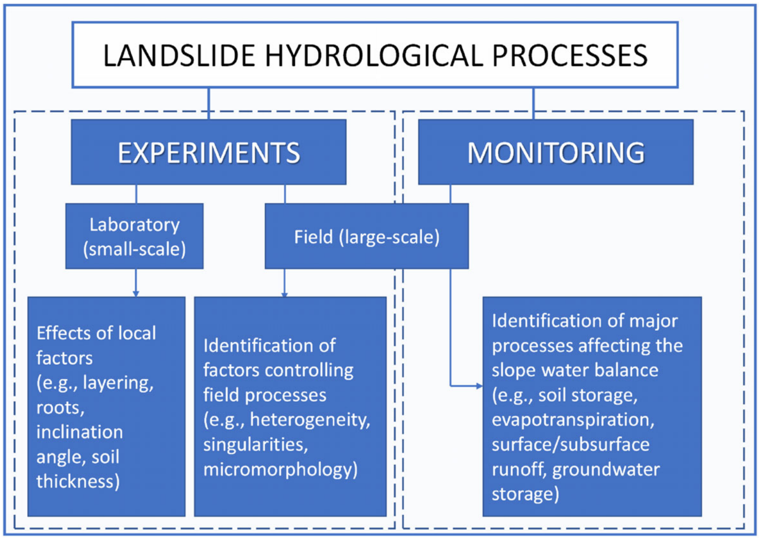

FIGURE 2 Progress in the understanding of landslide hydrology favored by experimental and monitoring activities.

4 | ML APPLICATIONS IN HYDROLOGY AND LANDSLIDE STUDIES

The recent rapid development of information technology has pushed the entire scientific community into the new age of Artificial Intelligence (AI), leading to a new research challenge in data exploitation strategies also in hydrology and landslide applications. In fact, in the last two decades, the increasing amount of available data provided by sensor networks and satellite remote sensing has led to the exponential growth of the use of new data-driven methodologies, like ML (Box 2).

BOX 2 Machine learning.

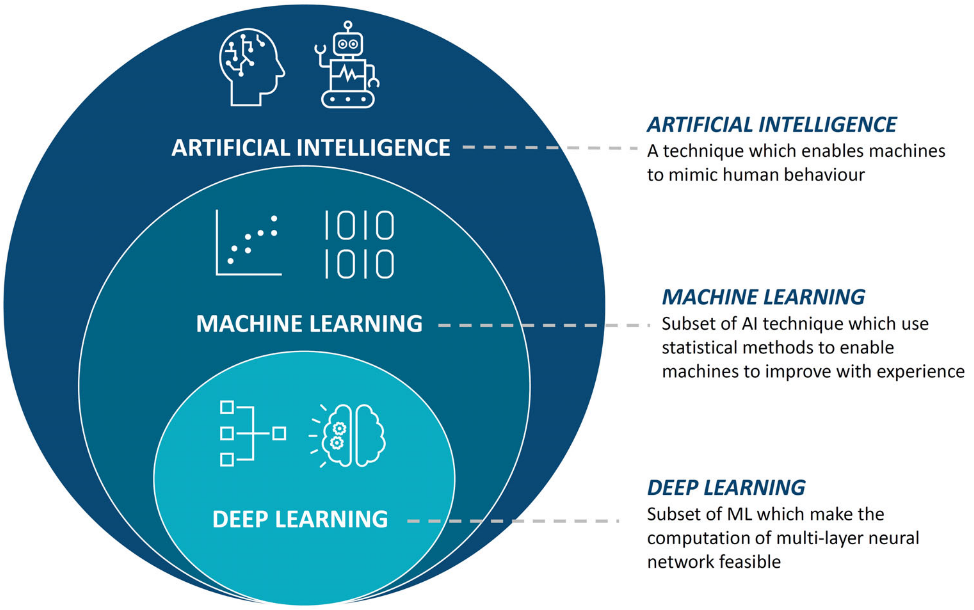

FIGURE 3 Credits: Edureka.com

The classic ML, a branch of Artificial Intelligence (see Figure 3), follows the scientific paradigm of induction-deduction: in the inductive step, the model learns from raw data (training set) while in the deductive step, the model is applied to predict the behavior of new data (predicted output). Typical machine-learning problems are pattern recognition, classification, regression, clustering, dimension reduction, and representation learning. ML can be classified into three learning types: supervised, un-supervised, and semi-supervised methods. In the first one, the classes for training are already known (the training set is labeled) and the typical applications can be classification, regression, and some dimension reduction techniques; instead, in the second one, the classes of patterns used for training are unknown (the training set is not labeled), and it is typically used for data clustering; in the last one, semi-supervised method, the training set is only partially labeled, and the distribution of unlabeled patterns could help optimize the classification rules. Several ML algorithms are widely in use, such as linear classifier, logistic regression, Naïve Bayes (NB), Bayesian Network, support vector machines (SVM), decision tree, random forest, Adaboost, bootstrapped aggregation (Bagging), k-nearest neighbor (k-NN), and artificial neural network (ANN). The latter has given rise to a subfield of ML, known as deep learning (DL; Goodfellow et al., 2016). DL is based on neural networks with many hidden (deep) layers, allowing analyzing huge amounts of data from different sources. Popular deep learning algorithms for classification are convolutional neural networks (CNNs). Although ML approaches are commonly described in the literature as "sophisticated techniques" (McAfee & Brynjolfsson, 2017), they do not consider the physics of the simulated phenomena. This aspect could be considered a weak point for hydrological applications, as process understanding is not the primary target of ML, so its use may lead to misleading interpretations. In fact, owing to the continuously increasing computational power of available computers, it is possible to train ML models with many parameters, capable of adapting their output to any specific feature (even to errors) of the available experimental data (i.e., overtraining, limiting the generalizability of models).

However, while large hydrological and meteorological data series are nowadays commonly available, data on landslide occurrence are still relatively scarce. A possible approach to overcome this limitation may be represented by the generation of rich synthetic data series (e.g., Peres et al., 2018; Roman Quintero et al., 2023). Likely for this reason, applications of ML to landslide research have been mostly devoted to landslide susceptibility mapping (i.e., assessment of static spatial probability of landslides over large areas, where numerous landslides had been recorded), rather than to time-dependent landslide hazard assessment or prediction. In this, the most commonly used predisposing factors are morphological (slope, elevation, aspect), hydrological (drainage network, wetness index), geological, as well as related to rainfall characteristics (Prakash et al., 2020). Linking combination of these factors to observed landslide occurrences are the basis of landslide susceptibility maps. The statistical analysis can be done very well using ML. Merghadi et al. (2020) and Prakash et al. (2020) provide exhaustive reviews of ML models used worldwide. Their reviews show that the Random Forest method is one of the most widely used methods hereto.

However, there are some examples of applications of ML to the simulation or prediction of hydrological processes and variables that can be potentially exploited for landslide studies. In fact, uncertainty in parameter estimation of physically-based hydrological models and in mechanistic modeling of complex environmental systems has led numerous researchers to look forward to data-driven forecasting tools, like artificial neural networks (ANNs), an expansion of which are the recurrent neural networks (RNN; Rumelhart et al., 1986), and the long-short-term memory (LSTM; Hochreiter & Schmidhuber, 1997), as an effective alternative to physically based models. Moreover, another well-known type of ML technique used by many researchers is support vector machine (SVM), usually applied in classification (SVC), and regression (SVR) problems (Huang et al., 2010).

Concerning the processes of rainfall infiltration, surface runoff generation, and drainage, the hydraulic conductivity of the soil K_s is an important variable that should be evaluated. Numerous ML algorithms have been indeed applied to predict the permeability of the soil (e.g., Singh et al., 2021). In particular, Araya and Ghezzehei (2019) compared four different ML techniques (K-Nearest Neighbors, Support Vector Regression, Random Forest, Boosted Regression Trees), in order to predict the hydraulic conductivity K_s.

Moreover, as it is commonly known, soil moisture content has a vast range of applications and it is a crucial variable for hillslope hydrology, which controls many processes involving the slopes, including runoff generation, rainwater infiltration, evapotranspiration, and subsurface flow (Uber et al., 2018). Specifically, many scientific papers show and discuss applications of ML to soil moisture estimation for hydrological modeling purposes. Moreover, accurate estimates of moisture conditions within the potentially unstable soil mass can be very useful also for landslide prediction, even if they have not been originally developed for such purpose.

In this context, many ML techniques are useful to *learn* the behavior of soil moisture content from training data sets, that is, from remote sensing measurements of existing satellite missions or from field monitoring (Greifeneder & Notarnicola, 2021; Marini et al., 2020; Pasolli et al., 2015).

Currently, ANN- and SVM-based models are the most popular and used methods to estimate the soil moisture content, because they can reproduce non-linear relationships between input and output with high level of accuracy (Ahmad et al., 2010; Gill et al., 2006; Wu et al., 2008). More recently, it has been demonstrated that the use of specific ML-based algorithms (e.g., LSTM) can yield an accurate forecast of hydrological conditions in response to rainfall in terms of pore water pressure (Orland et al., 2020). Fang et al. (2017) used LSTM to predict soil moisture data remotely sensed from satellite. Ahmad et al., 2010 predicted near-surface soil moisture content (i.e., uppermost 5 cm soil layer) of a study area in Iran, with 30 m resolution, by optical and thermal sensors of Landsat 8 Satellite Data and by knowledge of land-use, with random forest (RF), SVR, ANN, and elastic net regression (EN). The obtained results are in close agreement with field measurements of available soil moisture. Zhang et al. (2017) proposed a machine-learning method to address and deepen the question of soil moisture estimation on a national scale for cropland in China. In their study, a ML model (namely, H_2O model), based on a deep feedforward neural network (Learning, 2016; Thathachar & Sastry, 2004), is compared to the soil moisture data provided by the Soil Moisture Active Passive (SMAP; Entekhabi et al., 2010) and the Global Land data assimilation system (GLDAS; Rui & Beaudoing, 2020). The results show that soil moisture estimated by the H_2O model performed better than SMAP and GLDAS products, compared to field measurements of soil moisture.

Xu and Liang (2021) wrote an introductory review on ML in hydrology, and Lange and Sippel (2020) published a nearly exhaustive list of hydrologic applications of ML, mainly for the prediction of streamflow, runoff from a catchment, water transport through the soil and groundwater flow.

An important application of ML is given by LSTM frameworks for filling spatial–temporal data gaps in hydrological series, as reported by Ren et al. (2019) and Orland et al. (2020). In fact, field hydrological monitoring data series from numerous sites of landslide-prone hillslopes are sometimes discontinuous, owing to the failure of monitoring or transmission devices or to poor quality of the measurements. They showed that 6 months of representative observations can be sufficient for doing good predictions of soil suction. This confirmed that the model was able to catch the nonlinear hydrologic hillslope response, even for high-intensity rainfall events, although these exceptional events were excluded from model training.

Another application of ML is monitoring and nowcasting of deep-seated landslides, as reported in the recent review by van Natijne et al. (2020). Besides, more recently, Stanley et al. (2021) outlined a new data-driven nowcasting approach for global rainfall-triggered landslide hazard assessment. Different applications of ML models are also available in landslide displacement prediction. For instance, in Yang et al. (2019), the LSTM model is applied, providing improved prediction of landslide displacements in the Three Gorges Reservoir Area, China, compared to the SVM model.

However, the proliferation of hydrological applications of ML algorithms, favored by the increasing availability of data and powerful computers, seems often not supported by the required understanding of the modeled physical processes, leading to very case-specific results, lacking generality. In this respect, the preliminary assessment of the water balance directly from the experimental data may represent a useful guidance for building sound models based on ML.

5 | THE ROLE OF HYDROLOGICAL INFORMATION IN LANDSLIDE EARLY WARNING APPLICATIONS

As widely reported in the scientific literature, the most used tools for forecasting landslide occurrence, aimed at hazard assessment and related risk mitigation, can be roughly divided into physically based mathematical models and empirical (statistical) models. The first category requires detailed information about the spatial features of environmental, hydrological, geological, and geotechnical parameters of a given study area (Aristizábal et al., 2016; Fan et al., 2016; Greco et al., 2018), and, for this reason, its application is still limited mostly to local/slope or small catchments, and only in a few cases to operational landslide forecasting in local early warning systems applications (e.g., Canli et al., 2018). The second type, usually at a larger scale, that is, national/regional and global, mostly uses empirical thresholds linking precipitation, hydrology, and other dynamic variables with landslides occurrence. However, this binary classification has become fuzzy over the last two decades as more data and large-scale hydrometeorological model results have become available.

Traditionally, the adopted tools for landslide prediction at large scale rely on precipitation information alone, although the use of hydro-meteorological approaches is fast growing (Bogaard & Greco, 2018). This is partly due to the availability of relevant datasets that can relatively easily be implemented for operational purposes. The empirical rainfall threshold is still the most used, typically in the form of precipitation duration (*D*) and average intensity (*I*) or total rainfall depth (*H*; Garcia-Urquia & Axelsson, 2015; Gioia et al., 2015; Guzzetti et al., 2020; Monsieurs et al., 2019; Peruccacci et al., 2017; Piciullo et al., 2020; Rosi et al., 2015, 2019; Segoni et al., 2014). Overall, *ID* thresholds are more used than *HD* ones, as they provide a convenient way to compare the rainfall intensity to the hydraulic conductivity of the soil. This allows us to predict the possible occurrence of overland runoff. Nevertheless, the *ID* and *HD* formulations can be considered practically equivalent.

Undeniably, when considering large areas, the definition of rainfall thresholds remains the most used approach, as it requires relatively few and easily available data, that is, the time and location of landslides, and rainfall data recorded by rain gauge associated with the closest landslide event. Several authors (Guzzetti et al., 2020; Piciullo et al., 2018; Segoni, Piciullo, et al., 2018) thoroughly reviewed the early warning systems at regional, national, and global scales, based on different threshold types for forecasting rainfall-induced landslides. Major attention goes to the optimization methods that are used to define thresholds for landslide occurrence searching for the best predictive performance and evaluated with various metrics. Several authors used the true skill statistic (TSS; e.g., Leonarduzzi et al., 2017; Uwihirwe et al., 2020), or the probability of detection (POD) skill scores and ROC analysis (e.g., Abraham et al., 2021; Gariano et al., 2015), or with a frequentist statistical method (Peres & Cancelliere, 2021; Peruccacci et al., 2017). Other probabilistic techniques also have been proposed such as the application of the Bayes theorem for defining the thresholds (e.g., Berti et al., 2012; Jiang et al., 2021).

It is worth noting that empirical rainfall thresholds for landslide initiation strongly depend on the separation criteria adopted for the definition of rainfall events (Gariano et al., 2020; Leonarduzzi et al., 2017; Peres et al., 2018), as periods of continuous precipitation separated from each other by dry intervals with no (or little) rain. This choice is constrained by the temporal resolution of the available rainfall record (hourly, daily, weekly, or monthly). In fact, as argued by Marra (2019), when only daily or even coarser resolution data are available, obtained thresholds are lower than those with hourly or finer resolution, mostly due to imprecision in the definition of event duration. Regarding this uncertainty, Jordanova et al. (2020) and Melillo et al. (2015) suggest using seasonally different interevent periods for warm/dry and cold/rainy seasons, according to the different climate conditions which occur during the year in the specific area. Melillo et al. (2018) developed an algorithm called CTRL-L to define empirical rainfall thresholds at different exceedance probabilities. This algorithm considers local morphological, seasonal, and climatic conditions to separate consecutive rainfall events. Hereto, it identifies the most representative rain gauge available and assigns a weight to each landslide depending both on geographical and rainfall features. More recently, Rosi et al. (2021) have added a third parameter, that is, the mean cumulated rainfall depending on the different time intervals of 7, 10, 15, and 30 days over a given area (MeAR, Mean Area Rainfall), for defining a rainfall threshold as a surface in a 3D space for LEWS, to consider the effects of antecedent precipitation on the potentially unstable soil mass.

Nonetheless, the definition of events within a continuous rainfall record, carried out with the aim of identifying events that produced effects in a hydrologic system (i.e., triggering landslides on a slope), should be considered from a hydrological point of view. In fact, the separation between two consecutive events should be made based on the time needed for the effects on the system of the first event to disappear (or to significantly decrease). The application of this approach is relatively easy when dealing with the events triggered by overland runoff (i.e., floods or debris flows), by identifying the end of flood runoff on the recession limb of the hydrograph observed at catchment outlet. Instead, for shallow landslide triggering, the process leading to the trigger is in most cases rainwater infiltration into the soil cover. This may last long after the end of the rainfall event, depending on the thickness of the soil cover and on the hydraulic characteristics of the soil. However, infiltration is controlled by soil moisture near the ground surface, and so, if antecedent conditions are to be distinguished from the direct effects of the current rainfall event, the time required for the topsoil to be drained by gravity after the previous rainfall event (i.e., topsoil moisture approaching field capacity) should be assumed as separation time between rainfall events (e.g., Roman Quintero et al., 2023).

Despite the importance of slope conditions at the onset of potentially triggering rainfall events, as described by Bogaard and Greco (2016), the empirical thresholds based only on rainfall intensity and duration neglect the importance of the hydrological processes occurring within the slope during the precipitation. This often leads to a decreased performance, with a high number of false alarms in early warning applications. The false warning messages are unwanted in disaster management and should be prevented when possible. With the use of hydrological information, landslide hazard assessment can become more robust as the role that antecedent soil wetness is incorporated and as such helps improving the prediction of landslide hazards in early warning systems. Recently, many papers have been published analyzing and confirming the added value of hydrological information for the definition of empirical landslide initiation thresholds (i.e., identification of hydrometeorological thresholds). To this aim, various sources of hydrological information can be used. Ciavolella et al. (2016) and Marino et al. (2022) identified hydrometeorological

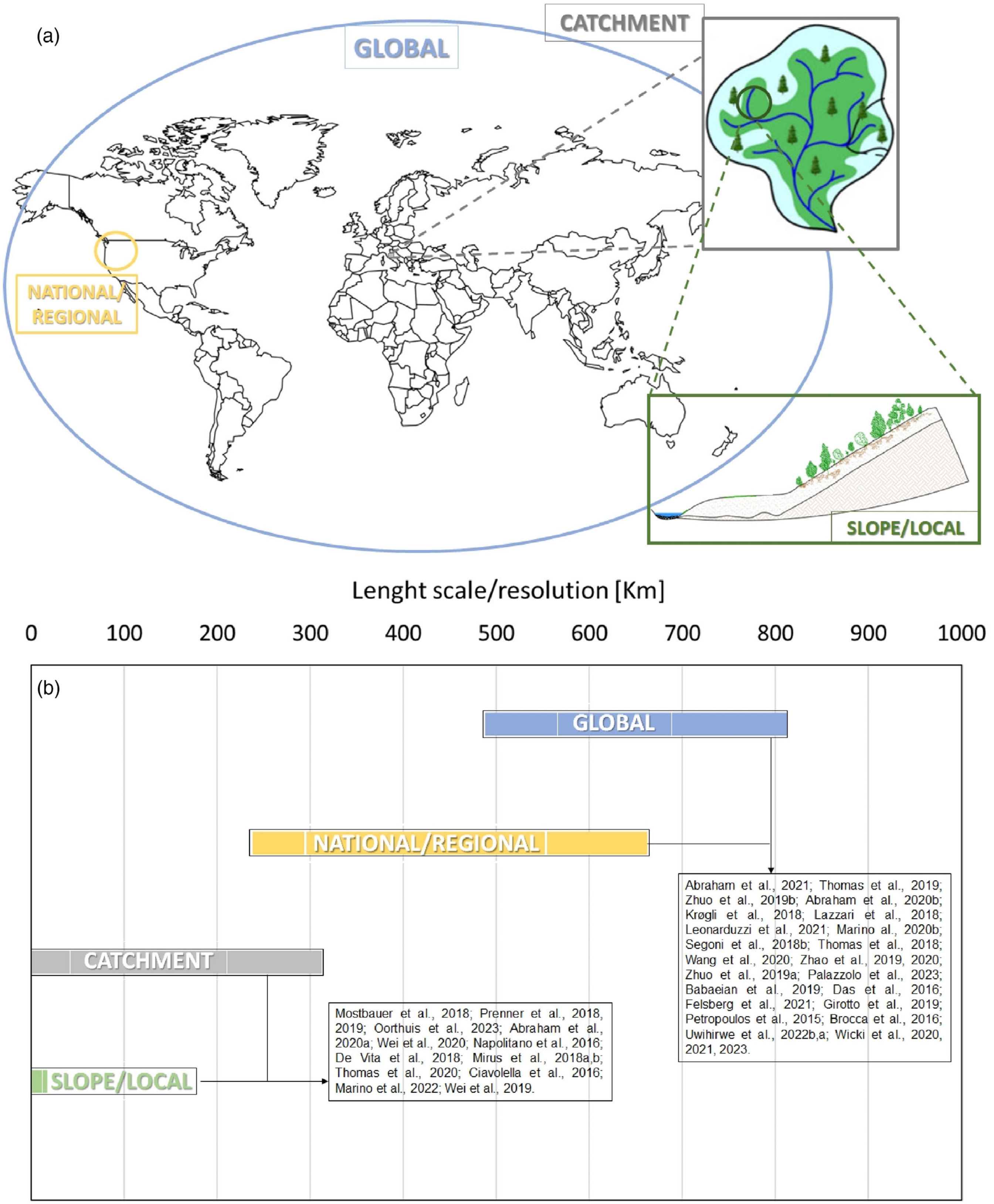

FIGURE 4 Examples of the scale classes of the early warning systems considered for this review are blue, global; orange, national/regional; gray, catchment; green, slope/local (a). References of papers based on hydrological information for the different scales of analysis (b).

TABLE 1 Remote sensing instruments and satellite platforms (past and current) for global soil moisture observation (Mohanty et al., 2017).

Instrument	Satellite	Frequency (GHz)	Band	Spatial resolution (d)	Temporal resolution	Sensor type
AMSR-2	GCOM-W1	6.9–89	S, X	25–50 km	2	Passive
AMSR-E	Aqua	6.9–89	C, X	25–50 km	2	Passive
Aquarius	Aquarius	1.26	L (active)	76–156 km	7	Active/passive
		1.41	L (passive)			
ASAR	ENVISAT	5.33	C	30–1000 m	5	Active
ASCAT	MetOp	5.25	C	25–50 km	2	Active
MIRAS	SMOS	1.4	L	35–60 km	3	Passive
NISAR	NISAR		L and S	0.1–50 km	12–60	Active
PALSAR	ALOS	1.27	L	10–100 m	46	Active
RADARSAT-1 and Sentinel-2		5.40	C	10 m	24	Active
Tandem-L	Tandem-L	1.2	L	3–20 m	8	Active
Sentinel-1A and Sentinel-1B			C	5–20 m	6–12	Active
SMAP	SMAP	1.41	L (passive)	40 km (passive)	2–3	Active/passive
		1.26	L (active)	3 km (active)	2–3	
SSM/I	SSM/I	19.35	K	13–69 km	0.5	Passive
WindSAT	Coriolis 6.8–37		C, X, and K	8–71 km	8	Passive

thresholds based on antecedent catchment water storage, estimated with a simplified lumped model, and total event precipitation depth, obtaining predictive performance comparable to those of traditional precipitation intensity-duration thresholds.

However, in most LEWS applications, antecedent soil moisture is usually considered as proxy of landslide predisposing conditions. As illustrated in Figure 4, the most suitable source of information about soil moisture depends on the scale of the prediction (i.e., from global to regional to catchment or event to single slope).

Basically, at a very large scale (i.e., global or national/regional), there are mostly two different sources of soil moisture information: (1) satellite-based remote sensing techniques (Abraham et al., 2021; Thomas et al., 2019; Zhuo, Dai, Han, Chen, Zhao, & Berti, 2019) and (2) hydrological modeling (Abraham, Satyam, Pradhan, et al., 2020; Krøgli et al., 2018; Lazzari et al., 2018; Leonarduzzi et al., 2021; Marino, Peres, et al., 2020; Segoni, Rosi, et al., 2018; Thomas et al., 2018; Wang et al., 2020; Zhao et al., 2019, 2020; Zhuo, Dai, Han, Chen, & Zhao, 2019), although recently also meteorological reanalysis data of soil moisture are available (e.g., Palazzolo et al., 2023). Insights on soil moisture retrieval from satellite data, focusing on many practical aspects, such as frequency, sensor type, and spatial and temporal resolution, can be found in Mohanty et al. (2017) and Beck et al. (2021), from which Tables 1 and 2 have been adopted.

Soil moisture satellite products have been largely used for regional/national to global landslide prediction applications (Babaeian et al., 2019; Das et al., 2016; Felsberg et al., 2021; Girotto et al., 2019; Petropoulos et al., 2015). Given the relatively coarse spatial and temporal resolution (see Tables 1 and 2), downscaling techniques are often applied to generating soil moisture datasets with finer spatial and temporal resolution (Park et al., 2017; Sabaghy et al., 2018). Moreover, as satellites provide information on the moisture of the very top soil (i.e., between 2 and 5 cm below ground surface, depending on the frequency of the electromagnetic signal), several attempts have been made to obtain root-zone soil moisture estimates (i.e., up to 100 cm below the ground surface) from satellite products, using soil hydrological information and data-driven models (Kornelsen & Coulibaly, 2014; Manfreda et al., 2014; Pan et al., 2017).

Besides direct satellite information and products derived from these, increasing use is made of soil moisture information coming from global and regional hydrological models. Most models used for landslide hazard prediction are calibrated, when possible, with in situ measurements (for national/regional scale as well as for smaller scale). With synthetic data, Marino, Peres, et al. (2020) showed a significant improvement in landslide predictive performance in two subregion-areas in southern Italy by adopting hydrometeorological thresholds based on total event rainfall depth coupled with modeled top 5 cm soil moisture prior to the onset of rainfall (i.e., near-surface moisture content). In the

TABLE 2 The 18 soil moisture products evaluated by Beck et al. (2021).

Acronym	Spatial sampling	Temporal sampling	Temporal coverage	Latency
AMSR2	∼47 km	1–3 days	2012–present	∼1.5 days
ASCAT	∼30 km	1–2 days	2007–present	2–4 months
SMAPL3E	∼30 km	1–3 days	2015–present	∼2 days
SMOS	∼40 km	1–3 days	2010–present	∼12 h
ESA-CCI	0.25°	Daily	1978–2018	∼1 year
MeMo	0.1°	3 hourly	2015–present	∼12 h
ERA5-Land	0.1°	Hourly	1979–2020	2–3 months
GLDAS-Noah	0.25°	3 hourly	1948–2020	∼4 months
HBV-ERA5	0.28°	3 hourly	1979–2020	∼6 days
HBV-IMERG	0.1°	3 hourly	2000–present	∼3 h
HBV-MSWEP	0.1°	3 hourly	2000–present	∼3 h
VIC-PGF	0.25°	Daily	1950–2016	Several years
ERA5	0.28°	Hourly	1979–2020	∼6 days
GLEAM	0.25°	Daily	1980–2018	6–12 months
HBV-ERA5 + SMAPL3E	0.1°	3 hourly	2015–2020	∼6 days
HBV-IMERG + SMAPL3E	0.1°	3 hourly	2015–present	∼2 days
HBV-MSWEP + SMAPL3E	0.1°	3 hourly	2015–present	∼2 days
SMAPL4	9 km	3 hourly	2015–present	∼2 days

same study, the authors showed that an even larger improvement could be obtained by considering modeled soil moisture of the uppermost meter of soil (i.e., root-zone moisture content). Leonarduzzi et al., 2021 explored two approaches of soil moisture estimate for rainfall-induced shallow landslide prediction applied to a regional-scale study in Switzerland. Specifically, they considered two alternative approaches to combine the antecedent saturation at different resolutions with the rainfall characteristics. In the first one, they coupled a coarse resolution (12.5 km × 12.5 km) physically based model (TerrSysMP) with slope stability assessment with the infinite slope hypothesis. In the second one, a threshold, based on rainfall duration and soil saturation from a finer spatial resolution (500 m × 500 m) conceptual model (PREVAH), has been defined. The obtained results indicate the importance of the spatial resolution of antecedent soil saturation conditions for the improvement of landslide prediction. Satellite products have been also mixed with hydrological modeling for improving the performance of LEWS (Brocca et al., 2016). Uwihirwe, Riveros, et al. (2022) explored the potential of incorporating downscaled satellite-derived near-surface soil moisture product provided by Planet, formerly VanderSat (VdS) and model-derived water content from Wflow_sbm (van Verseveld et al., 2022) to reproduce in situ soil moisture trends, for landslide forecasting in Rwanda. They clearly showed the good performance of hydrometeorological thresholds with the incorporation of the satellite-based antecedent soil moisture for the 5 cm, 50 cm, and 2 m depths.

Besides satellite and model results, the potential of in situ measured soil moisture for regional LEWS has been studied. The innovative integration of model data and field measurements allowed for improving operational landslide forecasting (Uwihirwe, Hrachowitz, et al., 2022; Wicki et al., 2020). For example, Wicki et al. (2020) show that the density of sensor networks for soil moisture measurements highly impacts the performance of a regional LEWS in Switzerland, depending on the distance between the measurement location and the area of landslide activity. The added value of soil moisture information does not seem to be limited by the difficulties of installation and management of soil moisture sensors on steep terrain, as measurements collected in flat areas allow distinguishing critical from noncritical conditions for landslide triggering in the Swiss Alps (Wicki et al., 2023). Wicki et al. (2021) tried also to investigate which information on soil moisture is more useful, between simulated with physically based model or measured in situ. They wrote: "The advantage of soil moisture simulations over in situ measurements is the better representation of triggering event conditions, probably due to the homogenization of the hydrological processes and the site representation (number and depths of sensors included). On the other hand, the simulation-based forecast model performed worse than the measurement-based model at reproducing critical antecedent saturation conditions, possibly due to the inadequate representation of the long-term water storage".

At a smaller scale of analysis (i.e., catchment or local/slope), the incorporation of antecedent hydrological information, either by field measurements or by hydrological modeling (Mostbauer et al., 2018; Prenner et al., 2018, 2019) is useful for landslide prediction. Inclusion of hydrometeorological information helps in understanding the different triggering processes of debris flows in alpine catchments in Austria (Mostbauer et al., 2018; Prenner et al., 2018, 2019) and in the Pyrenees (Oorthuis et al., 2023). Measurements of antecedent soil wetness, coupled with physically based modeling, allow identifying reliable rainfall thresholds for landslide triggering (e.g., Abraham, Satyam, Bulzinetti, et al., 2020; Wei et al., 2020), in some cases leading to the definition of different thresholds for wet and dry soil conditions (e.g., De Vita et al., 2018; Napolitano et al., 2016). Mirus, Becker, et al. (2018); Mirus, Morphew, and Smith (2018) derived hydrometeorological thresholds based on monitoring of the antecedent soil water content, measured with probes installed in the shallow subsurface, obtaining a significant improvement of the performance of landslide early warning systems for single slopes in the US. Thomas et al. (2020) showed how hydrometeorological thresholds, based on soil wetness and rainfall, outperformed thresholds based only on rainfall intensity and duration for the prediction of instability of slopes covered with coarse-grained soil in Puerto Rico.

The illustrated examples show that, so far, the hydrological information considered for landslide early warning applications has been nearly in all cases soil moisture. However, this does not seem the only possible choice, as deep-seated landslides are known to be affected by groundwater level fluctuations (e.g., Wei et al., 2019), the measurement of which may be in some cases useful even for shallow landslide prediction (Roman Quintero et al., 2023). In general, the choice of the most suitable hydrological variable to be monitored or modeled to effectively improve landslide early warning systems is not trivial, and it should be made based on the understanding of the major hydrological processes controlling the accumulation of water in a slope (e.g., Marino et al., 2021).

6 | CONCLUSIONS

The hydrology of fast and slowly deforming slopes is a societal very relevant research field, at the same time very challenging. The fact that deforming slopes are unique in space and time does not refrain researchers to search for the underlying universal principles and mechanisms. These are required to come up with an appropriate mitigation design. Besides structural interventions, which will remain required to protect society from economic and human losses, improved understanding of drivers can lead to more reliable landslide early warning systems.

In this update of the 2016 advanced review paper (Bogaard & Greco, 2016), we addressed the progress made in several challenging research issues that were pointed out before. In the last 7 years, studies on landslide hydrology have shown great creativity, resulting in monitoring campaigns and models able to assess the slope water balance, and in techniques to better delineate the landslide hydrological catchments. Like in many natural science fields, we have seen skyrocketing in ML empirical modeling, basically in all aspects of landslide hydrology. Lastly, the search for adding hydrological information in landslide early warning systems has been boosted. At various scales, research groups have been creative in looking for hydrological information or proxy information. This has paid off in the form of LEWS with reduced false alarms but also in surprising discoveries about the value of in situ soil water content information. Similarly, the regional soil moisture products which are based on remotely sensed information are astonishing. Although promising, the operational inclusion of this information in LEWS is still to be done.

What still seems to be lacking behind is a more detailed understanding of the process dependencies, that is, the feedback between soil deformation and its hydraulic behavior. The mismatch between hydrological and geotechnical modeling seems not to attract much attention, reflecting the different perspectives of local slope stability analyses (i.e., looking for the surface, within a slope, where the factor of safety drops below one) and large-scale hydrological modeling (i.e., looking for processes, outside the slope, that may affect its equilibrium). However, this scale mismatch is something that should be addressed, especially if LEWS are going to be based on near real-time regional hydrological modeling.

AUTHOR CONTRIBUTIONS

Roberto Greco: Conceptualization (equal); investigation (equal); supervision (equal); writing – original draft (equal); writing – review and editing (equal). **Pasquale Marino:** Investigation (equal); visualization (equal); writing – original

draft (equal); writing – review and editing (equal). **Thom Bogaard:** Conceptualization (equal); investigation (equal); supervision (equal); writing – original draft (equal); writing – review and editing (equal).

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

No data have been used for this review.

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