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Modeling shallow landslides and root reinforcement: A review

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ABSTRACT

Slope Stability Models (SSMs) are valuable tools used as decision support in land management to mitigate catastrophic effects caused by rainfall-induced shallow landslides. In particular, SSMs incorporating the presence and influence of vegetation allow for the evaluation of how trees influence relative slope stability and how forest management could ensure the root reinforcement effect in space and time. By implementing empirical knowledge about complex mechanical and hydrological processes, SSMs have been realized by employing different modeling approaches and methods, becoming suitable for different contexts and scales of analysis. Recent SSMs increasingly consider vegetation both as a mechanism to counteract the triggering process of shallow landslides and as a manageable and modifiable tool for mitigating hazards.

This review aims to analyze the state-of-the-art of SSMs applicable to vegetated slope areas, investigating those that consider root reinforcement and some of the most cited SSMs in the literature that neglect this effect instead. After classification and exposition on the spatial and temporal dimension of the analysis, modeling approaches, and complexity, we discuss the identification of the most suitable Slope Stability Model (SSM) for individual applications considering four fundamental aspects: modeling approaches, the analysis scale, and purpose, and the output data. Although all SSMs allow for risk analysis by quantifying the factor of safety, only a few allow for an accurate assessment of how changes in vegetation structure, due to the occurrence of natural and human disturbances, also affect the stability of a studied area. Such information is critical to identifying land management criteria to preserve and enhance the protection effect.

The improvement of data collection and measurement techniques to obtain parameters for stability analysis required the development of new SSMs able to exploit the improved detail of information, thus allowing for increasingly accurate analyses.

1. Introduction

Rainfall-induced Shallow Landslides (SLs) are among the most common gravitational mass movements on natural and artificial slopes, acting as landscape agents of sediment transfer and erosion. However, SLs are also potential hazards with well-known consequences that affect both the human environment, causing loss of life and damage to structures and infrastructures (Schwarz et al., 2010; Askarinejad, 2013; Dorren and Schwarz, 2016; Ran et al., 2018), and the natural environment, shaping many landscapes worldwide (Istanbulluoglu, 2005) and

Abbreviations: BRR, Basal Root Reinforcement; DEM, Discrete Element Method; FAIR, Findability, Accessibility, Interoperability, and Reuse; FBM, Fiber Bundle Model; FDEM, combined Finite-Discrete Element Method; FEM, Finite Element Method; FoS, Factor of Safety; GIS, Geographic Information System; ISM, Infinite Slope Method; LA, Limit Analysis; LEM, Limit Equilibrium Method; LEMs, Limit Equilibrium Methods; LRR, Lateral Root Reinforcement; MS, Method of Slices; NMs, Numerical analysis Methods; PMs, Physically-based Models; RR, Root Reinforcement; RBMw, Root Bundle Model Weibull; SL, Shallow Landslide; SLs, Shallow Landslides; SSDMs, Slope Stability Physically-based Deterministic Models; SSPMs, Slope Stability Physically-based Probabilistic Models; SSM, Slope Stability Model; SSMs, Slope Stability Models; TWI, Topographic Wetness Index; WWM, Wu-or-Waldron Method.

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affecting the agroforestry production in general (Jones et al., 2008). Since the frequency and intensity of critical rainfall events are expected to increase in the future due to more unstable air masses and greater magnitude storms associated with climate change (Gariano et al., 2017), the escalation of previously mentioned SLs-induced consequences is also expected (Crozier, 2010). As such, mitigation strategies must be identified to protect natural and man-made environments.

Shallow Landslide (SL) susceptibility depends on several environmental factors such as terrain and soil physical properties, hydrological regimes, and land use. Among these factors, land use dramatically influences landslide susceptibility, showing a crucial stabilizing effect due to the root reinforcement activation in case of vegetation presence (Glade, 2003; Sidle and Ochiai, 2006; Persichillo et al., 2017). In the specific case of forested areas, several studies confirm this effect, i.e., as forested surface increases, the presence of unstable areas decreases and, consequently, the number of SL events (Montgomery et al., 2000; Reichenbach et al., 2014). However, considering that vegetation conditions may change rapidly in space and time, it is difficult to assess this positive effect over large areas and adequately consider its contribution in predicting potential SLs. Knowing and assessing land-use changes, specifically in vegetation cover, is critical when using SSMs.

There is worldwide interest in developing reliable SSMs capable of localizing areas most susceptible to landslides in the context of urban, environmental, and landscape planning activities (Moos et al., 2018). The accessibility and detail of data required for slope stability assessment have improved significantly in recent decades, consequently refining the quality of SSMs results based on appropriate assumptions and modeling approaches. One example is implementing detailed information of above-ground forest structure obtained by remote sensing techniques, for example, through aerial and terrestrial laser scanning or structure for motion (Camarretta et al., 2020; Neuville et al., 2021).

The application of SSMs has proven valuable and necessary in various contexts. One application is the development of hazard maps of SL susceptibility and quantifying the frequency with which they occur (scenario-based). A fundamental requirement for use of such maps in the planning process is their constant updating in case of significant landscape changes, for example, topography modifications due to human activities (construction of infrastructure, mining, etc.). However, the stability assessment in this type of analysis often neglects the vegetation presence and contribution. SSMs are also valuable in the protective forest definition identifying areas where direct protection for structures and infrastructure is evident (e.g., Silva-Protect Project, 2016 for the identification and management of direct protection forests). Additionally, combining the SL risk analysis and estimated root reinforcement values is possible to evaluate which silvicultural measures are appropriate to improve and ensure the stabilizing effect of forests. The use of SSMs allows for detailed silviculture management on critical areas requiring priority action, e.g., on steep slopes or channels subject to detention and transport of large woody debris, or in forests subject to alteration caused by disturbance factors, e.g., forest fires, storms, pathogens (Vergani et al., 2016). At local scales, SSMs support the design and sizing of technical protection measures, as well as the cost-benefit analysis of soil bio-engineering measures (Bischetti et al., 2021).

All these applications demonstrate the central role of forests, and vegetation in general, in the mitigation of SL events (Stokes et al., 2014), defining SSMs as valuable tools for the management and, eventually, improvement of soil protection. Forests mitigation effects are central in slope stability, as well as to riparian ecosystems (Pollen and Simon, 2005; Hubble et al., 2010) and urban environments (Stokes et al., 2014; Mickovski, 2021), degraded lands (Ji et al., 2020; Zhu et al., 2017), and agricultural systems (Loades et al., 2010).

Considering the opportunity of using SSMs as decision support in forest and land management against SLs, this review aims to analyze the SSMs state-of-the-art applied in vegetated areas, investigating those that explicitly consider roots effect. In this paper, the mechanical effect of roots in slope stability was mainly considered, while their hydrological effect in the soil is briefly mentioned. Other aspects related to the effects of above-ground vegetation are neglected, such as tree mass increasing driving forces on steep slopes or rainfall interception affecting the delivery rate and amount of water to the soil.

In order to give a complete picture about the assessment of rainfall-induced shallow landslides, some central definitions and empirical knowledge on hydrological and mechanical processes will first be introduced, followed by a description and comparison of approaches used for slope stability calculation and modeling, and discussions of the appropriate SSM identification for analysis in each specific context. This review highlights how SSMs need to be improved to achieve more accurate analyses.

2. Definition of shallow landslides, slope stability, and root reinforcement mechanisms

Landslide processes involve the downslope movement of soil or rock under the effect of gravity (USGS, 2004). Shallow landslides (SLs) are a subset of these processes that usually involve soil masses less than 2 m thick (Phillips et al., 2021), generally sliding translationally over the failure surface at or near discontinuities in the soil profile or the bedrock contact. SLs are of interest to several fields research related to soil science (Tofani et al., 2017) and this multidisciplinarity involves observing the same process from different perspectives.

Generally, slope stability is defined as an equilibrium condition of the soil mass able to resist its gravity-driven downslope movement that should be maintained despite changes in hydrologic and mechanical conditions (e.g., increased soil weight due to rainwater infiltration). The loss of stability describes the situation in which the equilibrium condition failed, favoring the SL triggering. However, also the slope stability definition takes on different meanings depending on the scope of study and the user's main aims (McColl, 2015). Generally speaking, it considers i) the disposition factors that determine the stability conditions of the slope; ii) how a triggering event (e.g., rainfall) changes initial stability conditions; and iii) how changes in soil properties promote the exceeding of the critical failure threshold and SL triggering. In slope stability analysis, boundary conditions are defined by considering environmental characteristics (i.e., morphology, lithology, pedology, and vegetation cover) and evaluating their influence on the triggering hydrological and mechanical processes (Sidle and Bogaard, 2016).

The most common indicator used to quantify slope stability is the Factor of Safety (FoS) obtained by the ratio of stabilizing forces (i.e., soil shear strength and root reinforcement) to destabilizing forces (i.e., the gravitational driving force of the soil mass). Slopes are typically considered stable when FoS is ≥ 1; slope failure occurs at FoS < 1. Temporal changes in the FoS are mainly influenced by factors acting over shorter or longer periods such as i) soil suction and pore water pressure during rainfall events that result in short-term changes in, ii) water content varying due to seasonal conditions, specifically considering subsurface fluxes and water loss by evapotranspiration, iii) vegetation altering soil physicochemical characteristics through root growth and decay, and iv) soil depth influenced by the intensity of the pedogenesis process (Ziemer, 1981; Liang et al., 2007; Ghestem et al., 2011). Roots introduce complexity in evaluating vegetated slope stability and FoS calculations, affecting the accuracy of the analysis.

Root Reinforcement (RR) is defined as the additional force provided by roots opposing the soil mass deformation and displacement under gravity. RR can be distinguished according to the root stress experienced by orientation of the shear plane (i.e. horizontal or vertical). Field observations validated by field and laboratory tests have shown the activation of root stress in tension, compression, bending, and shear mechanisms (Zhou et al., 1998; Docker and Hubble, 2008; Schwarz et al., 2011; Cohen and Schwarz, 2017; Schwarz et al., 2015). These three types of stresses assume fundamental importance in the distribution of forces activated during SL initiation (Schwarz et al., 2015). The RR mechanism can distinguished in i) basal RR provided by roots growing through an horizontal shear plane (i.e. approximately parallel tot he soil surface) and ii) lateral RR, provided by roots growing through a vertical shear plane. It is relevant to highlight that the basal RR, if present, is the most efficient reinforcement mechanism (Cohen and Schwarz, 2017) since it guarantees a root anchoring effect to the deeper and stable soil layers. However, the activation and intensity triggered by the basal RR depend on both the root system morphology and the thickness of the rooted zone.

3. Empirical Knowledge

Critical information on understanding shallow landslide (SL) processes is briefly reviewed, developing the context to discuss their implementation in modeling approaches. The goal is to discuss the principal hydrologic processes that promote the initiation of SLs and the mechanical processes resulting from changes in soil water conditions.

3.1. Hydrological processes

In rainfall-induced SLs, hydrological processes are generally recognized as the leading causes of soil shear strength loss by increasing soil water content and pore water pressure (Lehmann et al., 2013). Hydrological effects depend strongly on the water content antecedent the triggering rainfall event and on seasonal evapotranspiration processes, thus are time-dependent (Chirico et al., 2013; Arnone et al., 2016a). For this reason, it is necessary to consider these dynamics in slope stability models for the factor of safety quantification.

It is well-known that the increase of soil water content can promote i) the development of subsurface water movement, e.g., infiltration and flows, which influence both soil characteristics and hydrological behavior; and ii) the development of positive pore water pressures under saturated conditions (Bishop, 1955; Morgenstern and Price, 1965), and iii) decrease the negative pore water pressure (toward zero, or reduce the matric suction) under unsaturated conditions.

Rainwater infiltration causes changes in soil moisture conditions, which is strongly influenced by environmental variables such as soil porosity or transmissivity. Changes in soil moisture affect infiltration rate, generally fast at the onset of rainfall reducing as soil moisture increases, and the water movement through the soil. Water flow always in the negative pressure gradient, both in unsaturated and saturated conditions (i.e. Darcy's law), but in the particular case of saturated soils, water movement occurs mainly driven by the forces of gravity (Nimmo, 2009).

Reaching soil saturation occurs through subsurface flows, generally distinguished into the matric and preferential flows path. The unsaturated diffuse flow consists of water movement between pores, resulting in a uniform moisture condition throughout the soil. Gravity force and matric pressure gradients are the driving factors, and their effects depend on soil characteristics, such as soil permeability, porosity, etc. Additional water supply promotes water movement by overland flow or through preferential flows, developed in the macropores and spaces created by the pedofauna and plant roots. Nimmo (2009) pointed out the existence of three basic modes of preferential flow i) flow through macropores; ii) funneled flow, also called deflected or focused flow, consisting of flow deviation caused by the presence of obstacles that promotes water accumulation in adjacent areas; and iii) unsteady conductive flow. However, in some cases, preferential flow promotes soil drainage by limiting pore pressure development during storms (Penna et al., 2015; Bogaard and Greco, 2016).

Preferential flow development is crucial in SL initiation processes. For example, several studies have shown a central role for flows developed in the presence of shallow bedrock fractures (Reneau and Dietrich, 1987; Montgomery and Buffington, 1997). Exfiltration is the process in which the development of high pressures at the soil-bedrock interface is caused by the connection of some bedrock fractures to areas of hydraulic recharge (Montgomery et al., 2002; Askarinejad and Springman, 2021). This process is strongly influenced by rainfall duration and intensity, as well as by the morphological and geological characteristics of the area, promoting the occurrence of SLs on planar and convex slopes, as well as differences in the timing and mode of SL initiation in topographically similar areas (Montgomery et al., 2002).

As a result of water infiltration, the increase in soil weight, which is considered as mechanical loading (Lehmann et al., 2013), occurs. This new condition could be critical in very steep areas where the destabilizing loads promote the unstable mass sliding driven by the gravity force (Lepore et al., 2013; Shao et al., 2016).

Pore water develops a positive pressure, recognized as the main effect of rainfall-induced SLs. The main consequence of the positive pore pressures development is reducing the effective stresses in the soil resulting in a shear strength reduction. Lehmann et al. (2013) observed that also hydrological connectivity is a critical process that can promote SLs triggering in large interconnected areas.

Roots influence infiltration processes by pores formed by plant roots and creating preferential drainage pathways (Beven and Germann, 1982). In addition, roots reduce soil moisture through evapotranspiration depending on the time scale of analysis (Arnone et al., 2016a). In the short term, when considering the influence of this process at the slope scale, it assumes less influence if compared to the magnitude of the root mechanical contribution to ensuring stability (Sidle and Bogaard, 2016). Roots hydrological effects are more influential in the hydrologic balance of an entire basin, draining and regulating flows over large areas (Cohen and Schwarz, 2017).

All hydrologic processes are influenced by soil depth, considered a critical control parameter for assessing how a saturated condition can be achieved. The combination with soil physico-chemical characteristics and the groundwater table height determine the water storage capacity. However, the measurement of soil depth still presents some difficulties, particularly in knowing its variability in space. To overcome this problem, some of the most popular hydrological models calculate flows considering surface topography and developing terrain indices based on the digital terrain model (Borga et al., 2004; Lanni et al., 2011), computed with algorithms in GIS environment (e.g., Montgomery and Dietrich (1994); Pack et al. (1998); Baum et al. (2005)). Among these indices, the most widely used in slope stability modeling is the topographic wetness index introduced by Kirkby and Weyman (1972).

The evaluation of hydrological processes, mainly predicting through models how pore water pressure varies in response to precipitation events, is fundamental to evaluate their influence on mechanical processes and calculate the probability of SLs event.

3.2. Mechanical processes

The relationship between driving forces, such as gravity, soil particle friction, and pore water pressure, result in the local loss of shear strength and thus the initiation of SL. This central concept can be incorporated into the Mohr-Coulomb rupture criterion that defines the shear strength of saturated soils. Terzaghi (1943), with his theory of effective stress, identifies the difference between total stress and positive pore water pressure as the leading cause of changes in soil mechanical behavior and the consequent movement of the unstable mass on the slip plane.

Through root reinforcement (RR), vegetation provides greater resistance to soil movement due to root-soil friction, greater cohesion, and stiffness of the soil mantle. The contribution of RR in increasing soil cohesion was highlighted since the 1970s (Gray, 1974). This effect was analyzed in both laboratory tests, using standard Casagrande shear box (Giadrossich et al., 2010), large machines reproducing the same principle (Yildiz et al., 2018), and field experiments (O'Loughlin, 1972; Ekanayake et al., 1997). Giadrossich et al. (2017) reviewed methods for evaluating and quantifying RR, where the discriminant is the consideration of soil-root interaction and the behavior of the root itself in the final output. A key aspect discussed concerns the better accuracy of data measured in the field than those obtained in the laboratory. Field tests preserve the complexity of the soil-root system, which is partly lost in laboratory reconstructions.

The geometry and conceptual representation of SL have led to a distinction between Basal Root Reinforcement (BRR) and Lateral Root Reinforcement (LRR). BRR acts on the basal shear surface of the SL and would be the most effective reinforcement mechanism if uniformly distributed along with the profile (Cohen and Schwarz, 2017). However, the progressive reduction in root number, with increasing soil depth, affects the intensity of RR (Swanson and Swanston, 1977; Schmidt, 2001; Rickli and Graf, 2009; Giadrossich et al., 2019). Some studies (Schmidt, 2001; Montgomery et al., 2009; Schwarz et al., 2010) highlighted the need to also consider LRR as a stabilizing mechanism that can be activated in the lateral sides of potential the SL and able to influence their size (Reneau and Dietrich, 1987; Schmidt et al., 2001; Roering et al., 2003; Schwarz et al., 2010). The magnitude of the LRR depends on the spatial distribution of the roots (Cohen and Schwarz, 2017; Giadrossich et al., 2020) and the sliding mass deformation (Zhou et al., 1998; Giadrossich et al., 2019), activating simultaneously along all sides in case of the soil mass rigid behavior (Zhou et al., 1998; Giadrossich et al., 2019), or progressively in case of differential deformation.

Schwarz et al. (2015) have schematically reconstructed the progressive triggering of rainfall-induced SLs and the corresponding activation of the RR. Due to the increase in pore water pressure and subsequent reduction in soil suction, a local loss of shear strength occurs, resulting in downslope movement of the sliding mass. This condition is evident in the field with the development of a tension crack at the top and sides, where tension-activated roots can be observed to counteract the failure. Simultaneously, lateral compressive stresses develop in the downslope zone due to root compression and passive earth pressure. If the cumulative lateral stress exceeds the critical value, the soil gives way by developing a failure surface. This condition is similar to the passive soil pressure conditions (Kramer, 1996). Considering the root compression, this study observed that it does not affect overall soil strength but increases stiffness and acts as a delay factor in the initiation of SLs (Schwarz et al., 2015).

Passive soil pressure is still poorly considered in stability assessment. Most geotechnical parameter studies in the literature focus on soil shear strength, while few consider passive wedge of shearing soil. Field observations have shown that the triggering mechanisms of SLs are characterized by differential deformations that show localized activation of zones in tension, shear, and compression (Schwarz et al., 2015; Cohen and Schwarz, 2017; Cislaghi et al., 2019). In our knowledge, the study of Burroughs (1985) is the first effort to integrate ground water response, soil shear strength, and root strength in slope stability modeling.

Assessing how soil mechanical processes, and in particular RR, change over space and time is still complex and nowadays done based on a limited number of samples which are averaged according to the reference scale of the analysis (Montrasio et al., 2011; Baum and Godt, 2010).

4. Modeling approaches: The physically-based models

Slope stability models (SSMs) are based on three main approaches for quantifying stability conditions: conceptual, statistical, and Physically-based models (PMs), which can be more specifically divided into Slope Stability Physically-based Deterministic Models (SSDMs) and Slope Stability Physically-based Probabilistic Models (SSPMs). Studies on shallow landslide (SLs) triggering based on conceptual and statistical

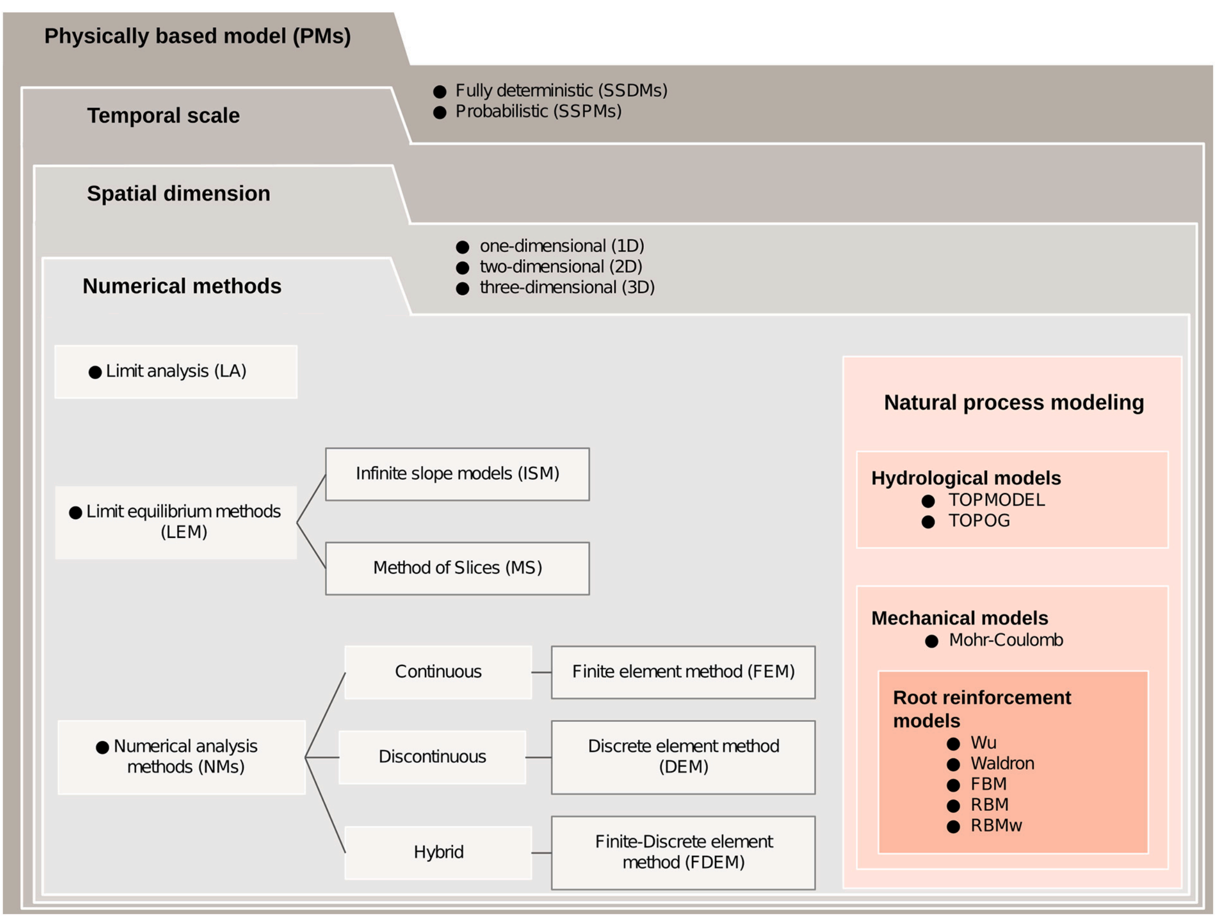

Fig. 1. Modeling scheme. Physically-based models, both fully deterministic and probabilistic, can implement temporal scale combined with different spatial dimensions and numerical methods to simulate main hydrological and mechanical processes, including the root reinforcement.

approaches are still few, according to a review by Reichenbach et al. (2018). The analysis of stability in vegetated slopes, thus considering root reinforcement (RR), is generally performed through the physically-based approach (Fig. 1).

However, to provide a complete picture of the current state of SSMs, the conceptual and statistical approaches will also be briefly described in Appendix A and Appendix B.

Physically-based models PMs generally combine a hydrological module to quantify the pore soil water pressure varying over space and time and a mechanical module to evaluate soil mechanical parameters changing due to hydrological response (Capparelli and Versace, 2011). The combined analysis of the processes provides numerical values indicative of the slope stability condition and its failure probability.

PMs analyze morphological, hydro-mechanical, and meteorological information that influence SLs triggering (Kim et al., 2014). For example, these models evaluate the susceptibility of SLs by extrapolating the following data from the digital terrain model: i) slope and altitude (Kim et al., 2014); ii) soil properties, depth, and soil water flows.

PMs mainly consist of i) fully deterministic models, entirely based on measured or estimated parameters, and ii) probabilistic models, which consider a probability distribution, both in terms of spatial distribution and uncertainty of the parameters considered.

The reliability of the analysis performed with PMs depends strongly on the type of input parameters measured or estimated, but also on the degree of complexity implemented in PMs for the simulation and modeling of the interactions of underlying processes. In particular, in the stability analysis on vegetated slopes, adding a fixed value of root cohesion to soil cohesion is potentially less plausible than an analysis based on estimating the variability of diameter and number of root-bundles in the soil. However, another aspect of evaluating the accuracy is the objective of the analysis.

PMs are based on numerical models for the reconstruction and evaluation of the investigated slope, considering a spatial and, in some cases, temporal dimension for stability assessment.

4.1. Numerical methods for slope modeling

The factor of safety (FoS) calculation can be made by models based on different analysis methods, from limit analysis to the widely used limit equilibrium methods, and finally, more complex numerical or analytical approaches (finite element method; discrete element method).

Limit analysis. Limit Analysis (LA) assumes that the soil mass has a perfectly plastic stress-strain relationship (Drucker and Prager, 1952) and can be represented empirically by two theorems: upper bound or lower bound plasticity (Chen, 2007). These theorems are shown to be helpful when both lower and upper solutions can be estimated, considering the collapse load enclosed between edges from below and above (Yu et al., 1998).

The lower bound plasticity theorem assumes that the external loads are not more significant than the collapse loads and that the material failure criterion is not exceeded at any point in the soil mass. The equilibrium is satisfied by the stresses on the entire soil mass. This theorem does not consider deformations and displacements, and the stress state is not necessarily the actual state at collapse (Leshchinsky and Ambauen, 2015).

The upper bound plasticity theorem considers a set of external loads acting on a failure mechanism, and their work on a displacement increment is equal to that from the internal stresses (Yu et al., 1998). When the work rate along a kinematically allowable collapse surface due to the external loads is greater than or equal to the work done by the internal stresses, the external load cannot exceed the effective collapse load.

Lower bound and upper bound analyses support the exact solution (Leshchinsky and Ambauen, 2015; Yu et al., 1998), a necessary consideration when applying these approaches to slope stability.

The LA fundamentals applied to rigid-perfectly plastic material are i) the soil mass reaches the breaking point though without yielding if in the lower limit the stress is at equilibrium; and ii) the soil mass moves past internal dissipation if plastic deformation develops in the upper limit. Liu et al. (1995) pointed out some problems in the formulas used in the LA, such as the complexity of the computational formulation, low efficiency for problem-solving, and limited scope. The applications of LA are mainly with plane stress-strain and asymmetric plate/shell analyses and assumes the effect of pore water pressure by reducing soil strength (Camargo et al., 2016). Recently updated versions of LA-based methods are emerging as effective slope stability assessment techniques, e.g., the 3D numerical limit analysis of Camargo et al. (2016).

Limit Equilibrium Methods. Limit Equilibrium Methods (LEMs) are among the most widely used solutions for slope stability assessment, the spread of which has been aided by the ability to analyze complex soil profiles and different loading conditions (Yu et al., 1998; Lepore et al., 2013; Arnone et al., 2016a). For these reasons, LEMs are used to evaluate both two- and three-dimensional systems. In addition, simple analyses of two-dimensional systems can be used to preliminary assess the slope stability conditions. Space discretization assumptions allow for more or less complex solutions. The simplest leads in the Infinite Slope Method (ISM), while more complex is the Method of Slices (MS). For example, ISM assumes the slope as a rigid block, homogeneous in its mechanical and hydrological characteristics, and calculates the FoS required to reach a state of limiting equilibrium.

ISM is the oldest, simplest, and most widely used among LEMs (Selby, 1993; Pack et al., 1998; Montgomery and Dietrich, 1994; Burton and Bathurst, 1998; Borga et al., 2002; Arnone et al., 2011; Lepore et al., 2013). Its main feature is modeling the slope failure considering it as planar and parallel to the slope surface. This approach allows verifying the equilibrium either by considering a single point on the slope or assessing the stability of a soil block by knowing width and length dimensions and the fixed profile thickness of soil. The latter assumption is considered reasonable because SLs are generally characterized by shallow depths relative to the length of the failure surface. The ISM assumes homogeneous or average soil properties along the soil profile to make the model statically determinate, analytically tractable, and computationally effective. Both of the former assumptions favor the application of ISM at a large scale even when the model domain is finely discretized. However, researchers aimed to establish a threshold value of approximate length-to-depth ratio to avoid significant errors due to oversimplification. Griffiths et al. (2011) proposed a threshold value of sixteen, based on a series of numerical experiments using a continuum mechanics model. Milledge et al. (2012) extended these experiments using the same model to examine thousands of slope scenarios covering the range of conditions expected for natural and found that the FoS was in error by less than 5% when length/depth ratios exceeded twenty-five.

The ISM root reinforcement is usually implemented as additional values of fixed cohesion representing the combined soil-root combination in the Mohr-Coulomb equation, both for deterministic and probabilistic approaches. This is the simplest assumption considering that most studies do not have spatially explicit controls on root reinforcement's spatial density or depths. Variable value of root cohesion in ISM is implemented by using the Root Bundle Model Weibull (RBMw) (Schwarz et al., 2013; Dazio et al., 2018; Gehring et al., 2019), or the Fiber Bundle Model (FBM) (Pollen and Simon, 2005).

The MS discretizes the slope into vertical slices, and calculates the forces and/or moments acting on each slice. Several methods were proposed, differing on how the interaction between the various slices is considered (Chen et al., 2017), and whether equilibrium is calculated for forces and/or moments. As a result, the value of the obtained FoS may be different. Considering that the number of available equilibrium equations is less than the number of unknowns in slope stability problems, MS relies on assumptions to make the problem controlled (Duncan, 1996). Some of these assume i) the absence of deformation on the boundaries between the slices (Morrison and Greenwood, 1989), ii) the influence of different inter-slice forces (Chen and Shao, 1988; Zheng et al., 2014) or pore water pressures acting on the inter-slice boundaries (Morrison and Greenwood, 1989). Duncan (1996) observed that when all equilibrium conditions are satisfied (the equilibrium of forces and moments), no effect of these assumptions was observed in the FoS calculation, while when only the equilibrium of forces is satisfied, the FoS is significantly affected by the slope set for the lateral forces between slices. For this reason, they stated that force equilibrium methods offer a reduced degree of accuracy compared to methods that satisfy all equilibrium conditions. In the MS approach the RR is implemented as fix value (Greenwood, 2006) calculated by using the Wu-or-Waldron Method (WWM) (Wu et al., 1979; Waldron and Dakessian, 1981).

LEMs are still widely used and generally preferred to complex numerical models because of their simplicity (Chen et al., 2003).

Numerical analysis methods. Numerical analysis Methods (NMs) were implemented to simulate the spatial complexity of geotechnical and hydrological parameters considered in slope stability analysis. NMs consider deformation, subsidence, pore pressure, and soil suction changes after an intense rainfall event. For this reason, NMs are more descriptive and accurate, but they need high computational costs and detailed input data (Rossi et al., 2013; Milledge et al., 2014). The most currently used NMs modeling can be divided into three main groups: i) continuous, ii) discontinuous, and iii) hybrid.

The Finite Element Method (FEM) belongs to continuous NMs and is commonly used to evaluate condition changes of elements subjected to stress and deformation arising from resisting and driving forces. FEM was adopted to solve oversimplification in modeling through ISM, where variations in soil mechanical behavior caused by the heterogeneity of physical characteristics and lateral interactions/deformations are neglected. The basic FEM approach is partitioning complex structures, characterized by infinite degrees of freedom, into a set of simpler elements connected to form a single mesh at specific points called *nodes* (Rajapakse, 2016). In the case of slope modeling, parameters related to displacements, velocities, and balance of forces are attributed to each node while material properties defining the stress-strain behavior are attributed to elements consisting of polygons composed of nodes. This discretization approach allows the calculation of active forces through simple algebraic equations (Rapp, 2017), providing more realistic modeling of progressive soil deformations.

Applications of FEM consider several approaches. Some are based on the Mohr-Coulomb concept of elastic-plastic soil, to which a value of apparent cohesion representing root reinforcement is added. These applications involve meshing the root model and soil matrix by nodes and considering contact near the soil-root interface using kinematic conditions (Dupuy et al., 2005). Other applications of FEM consider the development of new material models for rooted soil. The study of Świtała et al. (2018, 2019) proposed a coupled hydro-mechanical model to assess the root effect on soil's mechanical and hydrological behavior. Root reinforcement, considered as uniform parameter which change depending on vegetation type (Świtała, 2016), is combined with the Cam-clay model for unsaturated soils (Tamagnini, 2004) and implemented through a finite element code (Sanavia et al., 2006, 2008). Further FEM applications consider root as geogrid discrete element into the soil mesh (Mickovski et al., 2011; Mao et al., 2014b). These recent studies assume that all roots have same properties: their basic constitutive material is isotropic and strength and modulus of elasticity are equal in case of compression and tension loadings.

Despite the significant advances in slope stability modeling made by FEM, there are some significant limitations. For example, difficulties in modeling the development of soil cracks consequent to the SLs initiation can be addressed by applying the material point method of Sulsky et al. (1994), able to deal with large material deformation. The material point method involves i) a continuum discretized into a finite number of material points, representing the volume of an element (Abe et al., 2014) and characterized by mass, velocity, acceleration, stress, strain, and other properties (Lagrangian description of the material) (Andersen and Andersen, 2010), and ii) an empty computational mesh in which the stability equations are solved and iteratively updated during the analysis (Eulerian grid) (Conte et al., 2020). From the combination of these two methods, the model was implemented simulating the reaction of an elasto-plastic material when subjected to significant deformations (Andersen and Andersen, 2010). However, to the best of our knowledge, there are no applications of this modeling approach in rooted soils.

As alternative solutions to continuous approaches, discontinuous methods have been developed for slope stability assessment. The Discrete Element Method (DEM) is the most widely used, developed to address engineering problems in granular, discontinuous, heterogeneous, anisotropic, and nonelastic materials. The DEM, like the FEM, is used to evaluate the effect of roots on different analysis scales. For example, Cundall and Strack (1979) and Bourrier et al. (2013) applied this method to study roots influence on the shear resistance, while Cohen and Schwarz (2017) implemented the DEM in the development of a new SSM, SOSlope.

The studies of Cundall and Strack (1979) and Bourrier et al. (2013) propose a modeling approach that discretizes the soil into locally deformable individual spherical elements and the roots as flexible cylinders embedded in the soil matrix. This model considers the root tensile loading until breakage, the root bending loading, the root-soil adhesive links until adhesion breakage, the root slippage associated with a frictional resistance at the root-soil interface (Bourrier et al., 2013). Under the influence of loading forces, elements move through space and interact with neighboring elements. At each time step, the contact forces between the particles are calculated for each displacement and recursively summed before the next time step.

The study of Cohen and Schwarz (2017) proposes the use of DEM for slope modeling and analysis using SOSlope. In this model, the DEM is combined with the spring-block model of Olami et al. (1992) (a subset of the self-organized criticality approach of Bak et al. (1988)) to consider forces redistribution on the slope and recursive computation of equilibrium. Starting from raster information of the digital terrain model, the slope is discretized into a series of blocks connected by links that simulate the mechanical forces of roots and soil (Cohen et al., 2009). In this way, in quantifying the factor of safety, derived from the ratio between resistive and active forces, the effect of the basal root reinforcement is considered a resistive force, while the lateral root reinforcement as an active force. Like the previous method, the loss of block stability caused by the increase of the soil water content causes its movement, affecting lateral bonds and positions of the adjacent blocks. Depending on the movement direction of the block, the bonds simulate tension or compression forces.

Finally, hybrid NMs modeling was also developed combining FEM and DEM and obtaining the Finite-Discrete Element Methods (FDEM). FDEM allows simulating a solid region as a set of deformable finite elements, by FEM, that may be subjected to progressive fracturing, by DEM (Munjiza et al., 1995).

4.2. Dimensional systems of slope stability analysis

Currently available SSMs have been realized in one, two, and three dimensional systems (1D, 2D, and 3D), providing different solutions depending on the final analysis purpose, data, and tools availability. Implementing a complex multidimensional system requires detailed data availability regarding the starting stability condition with a certain degree of precision and variability (uncertainty and spatial distribution). With the increase of spatial dimension, also the computational time increases due to a large number of freedom degrees necessary to solve.

The most commonly used models are those in 2D, generally based on ISM, which allow making assessments either in planimetric terms, as in the case of most SSMs, or considering the vertical section of the slope, such as SLIP4EX (Greenwood, 2006). The advantage of 2D SSMs is the low number of data inputs required, and lower computational time, allowing wider use in both engineering and scientific research (Pollen-

Bankhead and Simon, 2010; Greenwood, 2006; Genet et al., 2010; Thomas and Pollen-Bankhead, 2010). More complex FEM- and DEM-based SSMs implemented in 3D require more input data, associated with greater inherent uncertainty, and a deeper understanding of processes, thus requiring more computational time.

Root reinforcement does not usually have the same spatial dimension as the respective SSM in which RR is implemented. In most PMs, the root contribution is considered in the force balance as a constant (static) value of uniformly distributed cohesion (Fig. 2a), and accounted for as basal cohesion. However, in both SSDMs and SSPMs, some models calculate the root reinforcement considering the spatial variability of RR. Among these, we can mention Mao et al. (2014a) which uses a homogeneous root cohesion for each soil layer, while it is set to zero in the case of non-vegetated areas. On the other hand, Arnone et al. (2016b) instead considers variations in basal root reinforcement (Fig. 2b) based on the distribution of trees. More complex models consider the RR variability across multiple dimensions (Fig. 2c), considering spatial variability of both lateral and basal RR. Among the SSPMs, van Zadelhoff et al. (2021) and Cislaghi et al. (2017) consider both basal and lateral RR. While among the SSDMs, Milledge et al. (2014) consider both lateral and basal root cohesion which decrease exponentially with increasing depth, identifying the critical depth and position of water table (Liucci et al., 2017). Cohen and Schwarz (2017) consider basal and lateral RR spatially distributed based on the tree position and dimensions, including root -tensile and -compressive forces on the slope.

Regarding the time dimension, only a few SSMs consider the progressive slope failure caused by the variation in the short time of the parameter values and thus the equilibrium conditions of the slope (Montgomery and Dietrich, 1994; Baum et al., 2002; Rossi et al., 2013; Cohen and Schwarz, 2017). For example, Bordoni et al. (2015) reported some studies where the TRIGRS model (Baum et al., 2002) was used to analyze timing and location of SL triggering considering local (Salciarini et al., 2008) and regional (Salciarini et al., 2006; Godt et al., 2008) scales.

Aiming to obtain a more complete analysis, parameters variability should be considered changing over time. Particular attention is focused on factors that, changing over short time periods, significantly influence in the triggering process, such as the increase of pore pressure (Montgomery and Dietrich, 1994; Baum et al., 2002; Rossi et al., 2013) and soil saturation (Montrasio and Valentino, 2008), or the activation of roots resistance forces (Schwarz et al., 2013). However, also changes over longer periods, such as soil depth (D'Odorico and Fagherazzi, 2003) or root decay (Vergani et al., 2016, 2017b), should be considered allowing the stability assessment over years or decades (D'Odorico and Fagherazzi, 2003; Ciervo et al., 2017).

5. Comparison of physically-based models

Twenty-one slope stability models (SSMs) are analyzed in this paper (Tables 1 and 2). Tables 1 shows the probabilistic model approaches, while Table 2 shows the deterministic model approaches. The selection of models was made with objective criteria based on those models that consider the contribution of roots in the FoS calculation. In addition, some models among SSMs were selected with a subjective criterion, considering which, in our opinion, are the most used in the literature but which do not consider the RR. Models in both tables are sorted by date of publication. The main objective of each model is to meet the operational needs of stability analysis and assessment in specific applications. For this reason, it is difficult identifying the strengths and weaknesses of a SSM. However, it is more functional understanding in which environments and analysis scale the use of the SSM is most effective by considering methods and approaches implemented.

Starting from the evaluation of the modeling approach used to develop the SSM, it is evident from the Table 1 that all SSPMs are based on the ISM and consider a 2D dimensional space. Assuming its easy applicability and the request of few input data, often efficiently obtainable, the ISM allows to optimize the computational time for obtaining information about the stability conditions of the area. However, it especially encourages the application of SSPMs in analysis over extensive areas. Differently, SSDMs aim to provide more detailed information about the processes promoting the SLs initiation. To do this, some SSDMs apply more complex modeling methods that allow for better implementation of soil-root interactions. Table 2 shows that the most recent SSDMs consider the slope through multidimensional systems based on the FEM and DEM. The complexity of these models requires more significant detail in the input data, resulting in longer modeling times that require consideration of smaller areas of extent.

The modeling approach generally influences the choice of the analysis scale, another essential criterion to evaluate the appropriate SSM. Their application ranges from regional scale to slope scale of analysis (Table 3). In particular, regional scales analyses aim to identify susceptible and more landslide-prone areas by investigating catchments, while slope scales analyses aim to understand in detail how variations in water content can determine the instability of sloping soils.

In large areas, the accuracy of the analysis depends on the SSM

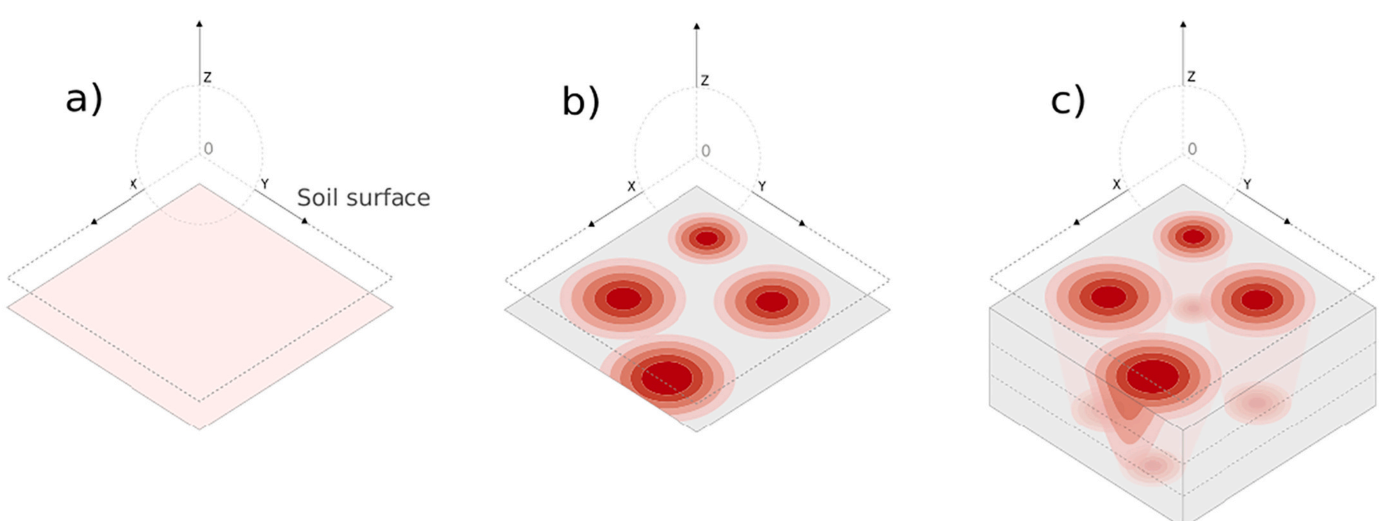

Fig. 2. Root reinforcement a) uniformly distributed on horizontal layers, b) two dimension spatially variable on horizontal layers, and c) spatially variable both for horizontal and vertical surfaces.

Table 1
Characteristics of slope stability physically-based probabilistic models.

Model approach	Model name	Authors	Root reinforcement parameter	Root reinforcement model	Geothecnical model	Hydrological model	Dimension of calculations (mathematical spatial dimension)	Dimension of discretization (physical spatial dimension)	Type of output	note
Physically-based models Probabilistic approaches (SSPMs)	**LISA** (Level I, II, III Stability Analysis)	Hammond, 1992	Costant value of root cohesion	–	LISA II: LEM - ISM LISA III: LEM-MS	–	LISA II: 1D LISA III: 2D	2D	P(Fos) Map	Monte Carlo Regarding RR, the user can change the roots distribution considering timber stand
	SINMAP (Stability Index Mapping)	Pack et al., 1998	Costant value of root cohesion	–	LEM - ISM	TOPOG (O'Loughlin, 1972)	1D	2D	SI maps	Definition of SI classes Recommended for regional scales
	The coupled hillslope model **STARWARS - PROBSTAB**	van Beek, 2002	Costant value of root cohesion	WWM (Wu et al., 1979) *	LEM - ISM	STARWARS based on Richards eq	1D	2D	FoS P(FoS) Map Critical depth Map (+ Sensitivity maps of each input parameter)	Regional scale Root cohesion parameter introduced at the original version of the model by Kuriakose et al., 2006* Schmidt et al., 2001 approach
	GEOtop-FS	Simoni et al., 2008	Costant value of root cohesion	–	LEM - ISM	GEOtop (Rigon et al., 2006), 3D richard's equations	1D	2D	P(Fos) Map	
	Park model	Park et al., 2013	–	–	LEM - ISM	TOPMODEL (Beven and Germann, 1982)	1D	2D	FOS and P (FoS) maps	Monte Carlo
	HIRESSS (HIgh Resolution Slope Stability Simulator)	Rossi et al., 2013	–	–	LEM - ISM	Richard's equation	1D	2D	P(FoS) Map varying over time	Monte Carlo Real time monitoring
	tRIBS-VEGGIE (Triangulated Irregular Network (TIN)-based Real-time Integrated Basin Simulator-VEGetation Generator for Interactive Evolution)-Landslide model	Arnone et al., 2016a (Lepore et al., 2013)	Variable value of root cohesion*	RBMw (Schwarz et al., 2013) + Topological model (Arnone et al., 2016a)	LEM - ISM	Richard's equation	1D	2D	P(FoS) map	*Basal root tensile force
	PRIMULA (PRobabilistIc MUltidimentional shallow Landslide Analysis)	Cislaghi et al., 2017	Variable value of root cohesion*	FBM (Pollen and Simon, 2005)	LEM - ISM	TOPMODEL (Beven and Germann, 1982)	1D	3D	P(FoS) map	*Basal and Lateral root tensile force
	SlideforMAP	van Zadelhoff et al., 2021	Variable value of root cohesion*	RBMw (Schwarz et al., 2013)	LEM - ISM	TOPMODEL (Beven and Germann, 1982)	1D	3D	P(FoS) map and several others maps about estimated parameters	Normal distribution of soil parameters *Basal and Lateral root tensile force

Table 2
Characteristics of slope stability physically-based deterministic models.

Model approach	Model name	Authors	Root reinforcement parameter	Root reinforcement model	Geothecnical model	Hydrological model	Dimension of calculations (mathematical spatial dimension)	Dimension of discretization (physical spatial dimension)	Type of output	Note
Physically-based models Deterministic approaches (SSDMs)	**SHALSTAB** (Shallow Landsliding Stability Model)	Montgomery and Dietrich, 1994 (version of Reginatto et al., 2012)	–	–	LEM - ISM	TOPOG (O'Loughlin, 1972)	1D	2D	Coefficient of instability degree map	Definition of coeff instabilIty classes High dependence on scale and resolution considered Using SHALSTAB with scale equalor smaller than 1:50.000 are suitable only for preliminary studies
	dSLAM	Wu and Sidle, 1995	Costant value of root cohesion	–	LEM - ISM	The combined sub/ surface kinematic modeling approach by Takasao and Shiiba (1988)	1D	2D	Maps of FOS distributions, landslide locations, debris flow paths, failure potential distributions, and other stability-related parameters	
	SHETRAN	Ewen et al., 2000	Costant value of root cohesion	–	LEM - ISM	Boussinesq equation for vertically averaged lateral flow and Richards equation for vertical flow	1D (2D)	2D	Singular value of FoS	Dual resolution: GISLIP and SHESLIP Two coefficient are considered to simulate the soil erosion due by both raindrop impact and surface water flow.
	TRIGRS (Transient Rainfall Infiltration and Grid-based Regional Slope-stability analysis)	Baum et al., 2002	Costant value of root cohesion	–	LEM - ISM	Version of Richard's eq. proposed by Iverson (2000) and extended by Baum et al. (2002)	1D	2D	FoS map Pore Water Pressure Map	Regional scale Root cohesion in the revised models of Kim et al., 2014; Saadatkhah et al. (2016)
	TRIGRS unsatured	Savage et al., 2004	Costant value of root cohesion	–	LEM - ISM	Srivastava and Yeh (1991)	1D	2D	FoS map Pore Water Pressure Map	Regional scale
	Kokutse model	Kokutse et al., 2006	Costant value of root cohesion	WWM (Wu et al., 1979)	FEM	–	3D	3D	Singular value of FoS	3D model of root systems
	SLIP4EX	Greenwood, 2006	Costant value of root cohesion	WWM (Wu et al., 1979)	LEM - MS	–	2D	1D	Singular value of FoS	Preliminary analysis Fine roots are assumed to have no influence on cohesion
	Lu and Godt model	Lu and Godt, 2008	–	–	LEM - ISM	Steady unsaturated seepage conditions	1D	1D	Singular value of FoS	
	SUSHI (Saturated Unsaturated Simulation for Hillslope Instability)	Capparelli and Versace, 2011	–	–	LEM	Hydro-SUSHI module base on Richard equation	2D	1D	Soil suction variability along soil profile	SUSHI uses the FDM for mathematical solution.
	MD-STAB	Milledge et al., 2014	Variable value of root cohesion	Dunne, 1991; Benda and Dunne, 1997	LEM - ISM	Hydrostatic conditions	2D	3D	FoS map and SL size	Identification of critical depth and position of water table (Liucci_2017). Lateral and basal root cohesion

(*continued on next page*)

Table 2 (*continued*)

Model approach	Model name	Authors	Root reinforcement parameter	Root reinforcement model	Geotechnical model	Hydrological model	Dimension of calculations (mathematical spatial dimension)	Dimension of discretization (physical spatial dimension)	Type of output	Note
										decrease exponentialy with increasing depth
	Ecosfix 1.0	Mao et al., 2014a	Variable value of root cohesion	WWM (Wu et al., 1979)	FEM	–	2D	3D	FoS maps	FoS is determine by defining an upper threshold of nodal displacement. Root cohesion spatially variable; values don't consider the stiffness of the roots.
	SOSlope (Self-Organized Slope)	Cohen and Schwarz, 2017	Variable value of root cohesion*	RBMw (Schwarz et al., 2013)	DEM (Lu and Godt approach)	TOPMODEL (Beven and Germann, 1982)	3D	2D	FoS and several others maps about estimated parameters	RR is 3D-spatialiy distributed based on the tree position and dimentions Self-organized Critically approach *Basal and lateral reinforcement; tensile and compressive force

ability to simulate the spatial variability and uncertainty of environmental characteristics and physical parameters (e.g., soil depth and porosity, root cohesion), aiming at obtaining more realistic and plausible values through the probabilistic distribution of input parameters.

In the analysis of smaller areas, it is relatively easier to have detailed information, which can also be obtained by measuring required parameters in the field. In this context, parameters variability is reduced, consequently reducing the degree of uncertainty and allowing the assumption of uniform distribution relative, for example, to hydrological and mechanical soil properties or the rainfall distribution over the investigated area.

Based on this reasoning, SSPMs are preferred in regional analysis scales, as they better implement physical parameters and landscape variability. In contrast, SSDMs are generally preferred in local scales, providing detailed information about hydro-mechanical processes that favor SL triggering on a slope. However, the Table 3 shows that SSPMs can be used also for slope-scale analysis but obtaining less detailed results, while some SSDMs are valuable also for regional scale analysis, for example SHETRAN model can be applied to a single hillslope or to all subbasins in a large (e.g., 5000 km^2) river basin (Ewen et al., 2000).

Modeling approach and analysis scale influence the analysis purpose of appropriate SSM application. The Table 3 shows that all SSMs allow for risk analysis, some even identifying SL trigger locations, sizes, and flow paths. Only a few have proven useful for assessing the effect of vegetation, and in particular, how the stability of the area changes as forest structure changes (Mao et al., 2014b; Arnone et al., 2016a; Cohen and Schwarz, 2017; Cislaghi et al., 2017; van Zadelhoff et al., 2021). In these cases, evaluating the actual vegetation's conditions and its influence on soil protection is necessary to identify appropriate management criteria aimed at preserving and improving the mitigation effect. Furthermore, considering changes to which ecosystems and landscapes are and will be subjected in the future due to natural and human disturbances, assessing consequent changes in root reinforcement (Preti, 2013; Vergani et al., 2016, 2017a) and landslide susceptibility is critical for accurate and effective land-use planning.

For this reason, it is crucial to focus on analyzing how SSMs consider the effect of vegetation in stability assessment. From both Tables 1 and 2, it is evident the use of different methods to quantify and implement the root reinforcement effect. In particular, in addition to SSPMs and SSDMs that neglect the effect of vegetation, other SSMs consider vegetation using either a spatially uniform value or a variable value of root reinforcement added to soil cohesion. Observing the temporal order used to illustrate the SSMs considered in the Tables 1 and 2, it is evident that in both cases, the most recent ones incorporate more carefully the root reinforcement, preserving its characteristic of spatial and temporal variability. This aspect is justified by the possibility of developing SSMs implemented with more complex modeling approaches, thanks to the improvement of technology and techniques for data collection and measurement. Focusing on the purpose of this article, the root reinforcement model and how SSMs consider this factor as input parameter is analyzed.

In the specific case of SSPMs, only two of the investigated models neglect the effect of vegetation, i.e., the method proposed by Park et al. (2013), for stability analysis in a GIS environment, and the HIRESSS model of Rossi et al. (2013), which analyze SL triggering conditions in real-time and on large areas. The decision to neglect vegetation effects could be justified by choice to find a simple and accessible method, as in the case of Park's method, or by the analysis purpose, as in the case of the HIRESSS model that aims to limit the processing complexity and get the result in the shortest possible time.

The remaining SSPMs that consider the root reinforcement contribution allow for more realistic evaluations of vegetated slopes. LISA (Hammond, 1992), SINMAP (Pack et al., 1998), STARWARS-PROBSTAB (van Beek, 2002), and GEOtop-FS (Simoni et al., 2008) consider root reinforcement an additional uniform value of apparent cohesion calculated using the static model proposed by Wu et al. (1979) and Waldron

Table 3
Applicability of slope stability models which consider root reinforcement. Models highlighted in orange consider the contribution of roots in calculating slope stability.

MODEL APPROACH	MODEL NAME	APPLICABILITY								Note
		Modeling		Analysis scale		Analysis purpose		Output data		
		Complex numerical method	Multidimentional space	Regional	Slope	Risk assesment	Vegetation effect	Stability factor	Additional information	
SSPMs	LISA									
	SINMAP							*3		
	STARWARS - PROBSTAB									*1: All SSPMs are implemented with LEM-ISM
	GEOtop-FS									
	Park model	*1			*2					*2: All SSPMs can be used for slope-scale analysis, although they generally use and provide less detailed output data than SSDMs.
	HIRESSS									
	tRIBS-VEGGIE									*3: Stability Index
	PRIMULA									
	SlideforMAP									
SSDMs	SHALSTAB							*4		
	dSLAM									
	SHETRAN									
	TRIGRS									
	TRIGRS-unsatured									
	Kokutse model									*4: Definition of coeff instabillty classes
	SLIP4EX									
	Lu and Godt model									
	SUSHI									
	MD-STAB									
	Ecosfix 1.0									
	SOSlope									

and Dakessian (1981). In contrast, tRIBS-VEGGIE (Arnone et al., 2016a), PRIMULA (Cislaghi et al., 2017), and SlideforMAP (van Zadelhoff et al., 2021) consider root reinforcement variability over space. These consider variable or dynamic root cohesion are based on the fiber bundle model of Pollen and Simon (2005) (PRIMULA) and the RBMw of Schwarz et al. (2013) (tRIBS-VEGGIE and SlideforMAP). Another important aspect to highlight is that while tRIBS-VEGGIE considers only basal reinforcement, PRIMULA and SlideforMAP consider both basal and lateral reinforcement, improving the broad applicability of these models. These SSPMs are also appropriate for forest planning purposes, automatically reconstructing the hypothetical vegetation cover using probabilistic approaches applied to accessible information layers (e.g., comparisons between digital terrain and surface models, applications of allometric equations to determine trees size) (Murgia et al., 2021).

Considering SSDMs, also in this case there are models which neglect the effect of vegetation, such as the SHALSTAB model (Montgomery and Dietrich, 1994; Reginatto et al., 2012), the Lu and Godt model (Lu and Godt, 2008), and the SUSHI model (Capparelli and Versace, 2011). This choice may depend on their primary purpose, evaluating hydrological processes that promote SL initiation focusing on the analysis of pore pressure and suction variation in the investigated slope profile. Empirical knowledge regarding hydrological processes (Section 3.1) has shown that, at the local scale, the effect of roots in developing conditions predisposing SL initiation, such as increased pore pressure, is limited. In contrast, it assumes importance in subsurface water drainage at the basin level.

Most of the SSDMs presented in Table 2 show the use of constant values of root cohesion, generally calculated through the method Wu et al. (1979) and Waldron and Dakessian (1981). These SSDMs are dSLAM (Wu and Sidle, 1995), TRIGRS (Baum et al., 2002), TRIGRS-unsaturated (Savage et al., 2004) and Kokutse et al. (2006) model. In addition to the factor of safety quantification, TRIGRS and TRIGRS-unsaturated allow analyzing the spatial distribution of pore water pressure for a more complete understanding of the SL triggering process, while Kokutse et al. (2006) model consider a 3D model of root system.

The SSDMs that alternatively consider variable values of root cohesion are MD-STAB (Milledge et al., 2014), Ecosfix 1.0 (Mao et al., 2014a), and SOSlope (Cohen and Schwarz, 2017). These three SSDMs show different methods of estimating the root reinforcement, which thus affect the final result obtained. In particular, MD-STAB considers root cohesion as an exponential function of soil depth from Dunne (1991) and Benda and Dunne (1997) models, Ecosfix 1.0 considers Wu (1976) and Waldron (1977) models, and SOSlope considers the root bundle model Schwarz et al. (2013). The focus on considering the effect of root reinforcement more plausibly encourages their use in instability assessment analyses, in detailed forest management, and in identification of bio-engineering interventions, e.g., based on tree planting.

This final aspect is also connected with another critical aspect of assessing the applicability of an SSMs is the output data it is capable of producing. All SSMs considered providing information about stability by estimating the factor of safety or failure probability. Some SSMs produce additional information related, for example, to hydrological processes (pore water pressure, saturation, topographic index of humidity), or, as mentioned above discussing the analysis purpose, some produce information on the root reinforcement viewable on GIS environment. In particular, SOSlope for SSDMs and SlideforMAP for SSPMs produce output data related to basal and lateral root reinforcement over the investigated area, allowing to reason focusing on the actual mitigation effect of the forest, as well as the identification of silvicultural practices to improve this effect protection effect where ineffective. In this way, it will be possible to plan more accurately how to manage the forest to reduce the risk of triggering SLs.

Finally, it is worth commenting on computation time. More complex models require geomorphological, geotechnical, and vegetational input data that sometimes may be difficult to access, either due to lack of instrumentation or measurement difficulties. Physically-based probabilistic models are a clear example of this, implementing statistical methods to reproduce parameter variability and proposing a reasonable alternative to conducting time-consuming and expensive parameter measurement campaigns in the field. In general, computational time depends on the level of detail in the spatial discretization and the input data required for models based on complex equations. This aspect is also related to the time required to obtain the result, which strongly depends on the availability of powerful computer tools, showing a critical limitation in using some models.

6. Conclusions

Slope stability models are fundamental tools for understanding and quantifying the susceptibility to landslides of areas with critical environmental characteristics. As a mitigation factor in the shallow landslide initiation process, the focus on the protective role of vegetation has increased in slope stability models since the 2010s, considering the complexity represented by variability in root reinforcement.

The analyzed SSMs show various solutions applicable to different environments and scales, using hydro-mechanical soil and vegetation information to complete the stability analysis. However, it is difficult to make a rank of the most suitable models. The SSM choice depends on the context for which it has been realized, considering different aspects of the model such as dimensional space, computational scale, the purpose of the analysis, and output data. More recent SSM such as tRIBS-VEGGIE, PRIMULA, and SlideforMAP for SSPMs, and MD-STAB, Ecosfix 1.0, and SOSlope for SSDMs, highlight an increasing attention in considering root reinforcement as a variable factor in space and time. This type of model offers a more detailed output concerning the static ones. Moreover, all physically-based probabilistic models are more suitable than deterministic ones to perform regional-scale analysis.

Stability models may improve simultaneously as the techniques for data collection and measurement. The improvement of survey techniques, e.g., aerial and terrestrial laser scanning, is evident to obtain digital terrain and surface models used to estimate forest structure in spatial and dimensional terms. This improvement is not the same for techniques for acquiring data on root reinforcement. SSMs that consider root reinforcement need field measurements for their characterization and quantification. However, there are no shared standards in the specific case of root measurements, and hence aggregation of different sources is relatively ineffective. The proposal of standardized surveying methods and techniques will allow more systematic data collection implementation and improve the quality of root distribution and tensile strength data, particularly in the Findability, Accessibility, Interoperability, and Reuse (FAIR) perspective of Open-Science. The study of equations and models for reconstructing hydrological and mechanical processes will also need to evolve, accommodating this increased detail and then be implemented in increasingly advanced slope stability models.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Conceptual approaches on slope stability analysis

Conceptual models aim to provide a simplified methodology for estimating the FoS changes in space and time (Piegari et al., 2006), identifying ad hoc empirical combinations of factors determining instability dynamics (Segre and di Cosmogeofisica, 1995), and using simplified mathematical equations adapted to real data that cannot always be measured (D'Ambrosio et al., 2003). Studies have demonstrated the ability of some models to reproduce complex dynamics that occur in large and medium-sized SLs, for example, through the cellular automaton model. The original cellular automaton model (Segre and di Cosmogeofisica, 1995) aimed to solve the overestimating problems of the frequency of large SLs events highlighted by the use of power-law statistics. This approach does not consider the temporal resolution and hence different timing of triggering small events, tending instead to merge them into a single large event. A solution has been proposed by the model of Bak et al. (1988), better known as the sandpile model, by developing cellular automatons based on the self-organized criticality approach. This simple method considers progressive slope failure, with scalable results for more realistic analysis. The main features of the sandpile model are the discretization of the system into elements identified by two- or three-dimensional cells, and the application for each cell of specific evolution rules (i.e., triggering, movement, and stopping). Hergarten (2003) identified some critical issues of this model related to the scalability of the obtained results, proposing a solution through the use of the spring-block model of Olami et al. (1992) (Hergarten, 2013). The spring-block model discretizes the slope into blocks based on the digital terrain model grid (Bak et al., 1988). Each block represents the unit of FoS estimation and is connected to neighboring blocks and a rigid guide plate through elastic bonds that simulate the activated forces on the slope. When a block loses stability, it is displaced, causing the neighboring blocks to move. This model implies dissipation, i.e., the potential energy stored gradually in the elastic bonds is partly transferred to the guide plate and partly lost by the system (Liucci et al., 2017). The development of new cellular automatons has continued over the years: Pelletier et al. (1997) and Piegari et al. (2006) have produced a model that considers topography and soil water content; Segre and di Cosmogeofisica (1995), Avolio et al. (2000), and D'Ambrosio et al. (2003) have developed alternatives to cellular automaton models with self-organized criticality approach.

Appendix B. Statistical approaches on slope stability analysis

The statistical models are based on two key assumptions i) future SLs may occur in the same areas susceptible to landslides in the past, and ii) the parameters needed for stability analysis, i.e., mechanical and hydrological information, are derived from the digital terrain model (Guzzetti et al., 2000; von Ruette et al., 2011). Environmental variables considered include slope gradient and curvature, contributing area and curvature, soil and bedrock types, and, only in a few cases, the effect of vegetation. von Ruette et al. (2011) consider four explanatory variables of which the vegetation type is a binary choice between grassland and forest. In statistical models, vegetation is considered a variable that includes all direct and indirect effects on slope stability.

In order to quantify the correlation between precipitation duration-intensity and the probability of SLs occurrence, inventories (Malamud et al., 2004; von Ruette et al., 2013), and global case studies (Guzzetti et al., 2008) are considered. The statistical coefficient representing this correlation is estimated by different methods, the best known of which are: i) bivariate and multivariate analysis (Carrara, 1983; Süzen and Doyuran, 2004b), also called logical regression (Hosmer and Lemeshow, 2000; Süzen and Doyuran, 2004a), through the consideration of explanatory variables classified in some discrete classes (e.g., classes of soil types, ranges of slope angles, etc.), ii) classification and regression trees (Nefeslioglu et al., 2009; Yeon et al., 2010) and random forests (Breiman et al., 1984), recursively analyze information through the graphical realization of a decision tree that allows the identification of values that best represent a given attribute (Nefeslioglu et al., 2009; Felicísimo et al., 2013); iii) support vector machines (Vapnik, 2013) proceeds through nonlinear transformations of variables and binary identification of the probability SLs occur (Brenning, 2005); iv) artificial neural networks (Brenning, 2005; Falaschi et al., 2009; Arnone et al., 2014; Koopialipoor et al., 2019) based on complex interactions between units, also called neurons, through rules that simulate SLs dynamics. Some studies have demonstrated good accuracy of logistic regression (Süzen and Doyuran, 2004b; Ayalew and Yamagishi, 2005; Nandi and Shakoor, 2010), comparable to more complex neural network methods (Nefeslioglu et al., 2008; Yilmaz, 2009; Rossi et al., 2010). In conclusion, von Ruette et al. (2011) argued for the possibility, through statistical methods, of identifying key factors controlling the triggering of SLs to be considered in more detailed analyses with physically-based models.

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