International Journal of Geosciences, 2022, 13, 174-198
https://www.scirp.org/journal/ijg
ISSN Online: 2156-8367
ISSN Print: 2156-8359

Advanced Models Applied for the Elaboration of Landslide-Prone Maps, a Review

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How to cite this paper: König, T., Kux, H.J.H. and Corsi, A.C. (2022) Advanced Models Applied for the Elaboration of Landslide-Prone Maps, a Review. *International Journal of Geosciences*, **13**, 174-198.
https://doi.org/10.4236/ijg.2022.133010

Received: January 27, 2022
Accepted: March 13, 2022
Published: March 16, 2022

Abstract

Landslides are a natural phenomenon that happens all around the world. When happening in urban areas they become a disaster, disrupting the lifestyle of a community or society. Human losses, social impacts, and structural damage are some of the landslide's effects. The current climate variability shows an increase in extreme weather conditions, either with long periods of drought or heavy and long-term rainfall. In Brazil, landslides are one of the deadliest disasters; they are usually preceded and triggered by heavy rainfall and already have affected more than 4 million people. Moreover, with the population growth, areas with high declivities have been occupied and turned into urban areas. Those people living there are vulnerable to suffering from landslides, losing their homes, and in extreme cases, losing their life. The identification and monitoring of landslide-prone areas are crucial to avoid disasters. Several advanced models, with different approaches, were developed to identify the landslide-prone areas. Aiming to decide the model that provides more satisfactory results, this paper presents a literature review of the applicability and limitations of three advanced models. The three models are Sinmap, Shalstab and TRIGRS. The analysis determined that all three models are adequate for stability management in slope areas. Moreover, TRIGRS results are more accurate than Shalstab, and the Sinmap model provides an over-estimation of landslide-prone areas.

Keywords

Disaster, Shalstab, TRIGRS, Sinmap, Landslide Susceptibility

1. Introduction

Natural disasters happen worldwide, and an increase in their occurrences has been observed during the last few decades. The population has grown, changing the society's vulnerability, and the global climate changes might have some influence [1] [2] [3] [4]. With the current climate variability, there is an increase in extreme weather conditions, either with long periods of drought or heavy and long-term rainfall [5].

The landslides are usually preceded and triggered by heavy rainfalls. When a landslide happens in urban areas, they affect community, causing damages to structures, destroying houses, and sometimes killing people [6]-[16]. For instance, since the 1980s in the Loess Plateau of China, 53 landslides have occurred, causing 717 deaths [17]. In Brazil, from 1991 to 2012, 699 landslides were registered. The most deadly landslide happened in January 2011, in the mountainous area of Rio de Janeiro state, resulting in more than 1500 deaths and millions of injuries [13] [16]. According to World Health Organization (WHO), 18 million deaths by landslides were registered from 1998 to 2017 [18]. These scenarios show the importance of identifying and monitoring the landslide-prone areas.

The identification of these areas can be performed using machine learning and statistical methods, such as bivariate-statistical methods, Weight of Evidence, Fuzzy Logic, Logistic Regression, Neural Networks, and even fractal analysis [10] [19]-[30]. Another approach is through physically-based models such as the Shallow Slope Stability Model (SHALSTAB) [31] [32] [33], Stability Index Mapping (SINMAP) [34] [35], Transient Rainfall Infiltration and Grid-based Regional Slope-Stability Model (TRIGRS) [36], TRIGRS-unsaturated [37], physically-based Slope Stability Model (dSLAM) [38], SLOPE/W and SEEP/W [39].

Each of these models has a different approach and level of complexity. The results are also strongly dependent on the quality of input data. Considering that shallow landslides are mostly triggered during extreme precipitation events, the models are coupled with hydraulic models [31] [35] [38] [40] [41] [42]. They attempt to simulate the soil and rainfall conditions to calculate slope stability [42]. However, these models have limited applicability due to their simplifying assumptions. During the slope stability analysis, some models, such as Shalstab and Sinmap, use a unique value across the whole area for rainfall and geotechnical data. It creates an unrealistic scenario due to soil heterogeneity. Furthermore, TRIGRS model considers the transient effects of the rainfall infiltration in different soil layers for the stability calculation. However, there are more input data, and the parameters rely on the uncertainty of vertical and horizontal distribution [43].

The combined use of different models improves each method's quality and reliability, highlighting and identifying the most critical geotechnical parameters (soil cohesion, internal friction angle, specific weight), which caused the landslides [12]. The choice of the best model to mapping landslide-prone areas is determined by the geological, geomorphological, and geotechnical data available since each model needs different input.

This paper compares three different advanced models: Shalstab, Sinmap, and

TRIGRS, highlighting the applicability and limitations of each model. They were chosen for being free of charge when compared with Geoslope. Moreover, the model dSLAM will not be further discussed because it exclusively identifies landslides in forested areas, and in Brazil, the landslides that become disasters happen in urban areas.

2. Model's Analysis and Applicability

This section presents a brief explanation of each model's approach and its applicability. The study cases presented above were chosen considering the different geological contexts of study areas. They were used to determine slope stability in several countries. Furthermore, a few studies acquired the soil properties by literature and others by collecting soil samples, which provide a deeper analysis of the model's applicability. A more detailed explanation of mathematical formulations are presented in [32] [34], and [36] for Shalstab, TRIGRS, and Sinmap respectively.

2.1. Shalstab Model

Reference [31] identifies the landslide-prone areas calculating the critical threshold of rainfall that induce surface rupture [31] [32] [44]. As presented in Equation (1), Shalstab is a deterministic model that associates the Mohr-Coulomb law with the steady-state hydrological model developed by [45].

$$\log\left(\frac{q}{t}\right)=\frac{\sin\theta}{\frac{a}{b}}*\left[\left(\frac{c'}{\rho_w*g*z*\cos^2\theta*\tan\varphi^1}\right)+\frac{\rho_s}{\rho_w}*\left(1-\frac{\tan\theta}{\tan\varphi^1}\right)\right] \tag{1}$$

In Equation (1): q is the rain recharge, t is the soil transmissivity, θ is the inclination (degrees), a is the contribution area (m^2), b is the contour size (m), c' is the soil cohesion (kPa), φ is the internal soil angle (degrees), ρ_s is the soil density (kg·m^{-3}), g is the gravitational acceleration, z is the soil thickness (m), and ρ_w is the water density (kg·m^{-3}).

A digital elevation model (DEM) and, soil physical and mechanical properties (cohesion, soil density, internal friction angle) are required by Shalstab as input data. The result is a seven-class classification map, based on a logarithmic value for q/t, as presented in **Table 1** [8] [46] [47].

Shalstab have been applied in different study areas [15] [44] [47] [48] [49] and presents satisfactory results.

The slope stability in Cunha River watershed—SC, Brazil was analyzed using Shalstab model by [47]. With declivities ranging from 15˚ to over 30˚, this area is predominantly covered by forest. The soil is characterized as Cambisols (poorly developed shallow soils related to the original bedrock). The input data includes a DEM with 15 meters of spatial resolution, and geotechnical parameters acquired in situ and tested in the laboratory. The results validation was performed by using landslides scars inventories and land-cover maps. This study shows that landslides might occur in forested areas with declivities higher than 20˚.

Table 1. Shalstab stability classes.

log q/t
Chronic instability
log $q/t < -3.1$
$-3.1 <$ log $q/t < -2.8$
$-2.8 <$ log $q/t < -2.5$
$-2.5 <$ log $q/t < -2.2$
log $q/t > -2.2$
Stable

Source: Adapted from [32].

Sometimes, the acquisition of geotechnical parameters is difficult due to the location of the study area, time, and resources. Reference [48] evaluates the parameterization of the soil properties due to the limited availability of field or laboratory measurements. The study area is in Rio de Janeiro—RJ, Brazil, the input data were a 2-meter DEM, and a landslide inventory prepared based on previous studies. Geotechnical parameters were acquired from the literature and laboratory tests. To evaluate the parameterization of the soil properties, the authors made several combinations of the geotechnical parameters and performed simulations using Shalstab. The best-fit scenario uses a high value for the internal friction angle and a low value for cohesion. As a result, the landslide scars were located within the two most unstable classes: the chronically unstable and log $q/t < -3.1$. They concluded that Shalstab correctly identified the most unstable areas, and the high-resolution and high-quality topographic data are more important than the precise soil properties data.

A similar approach was applied by [15] in Campos do Jordão—SP, Brazil. This study compares how the input parameters change slope susceptibility. Therefore, three scenarios were modeled, changing the input values of soil depth, cohesion, and internal friction angle. The area, located in the Mantiqueira Mountains, is known for its high hills and erosive depressions. It presents steep slope areas, colluvial soil layer, and declivity ranging from 20˚ to 50˚. Moreover, there are unauthorized human settlements in declivities higher than 30˚, and even some above 50˚. The geotechnical parameters were acquired from the literature, and a DEM with 4 meters of spatial resolution was used. The validation method includes landslide scars inventory and a susceptible map. As a result, the authors identified that soil depth is an essential parameter for stability analysis, and Shalstab correctly identified the most susceptible areas.

Reference [44] also applied the Shalstab model using geotechnical parameters acquired from the literature. The study area is the Guaxinduba River watershed, in the municipality of Caraguatatuba—SP, Brazil. It is a mountainous area of Serra do Mar, with steep slope declivities higher than 40˚ [44]. The validation method consisted in landslide scars inventory and statistical analysis (quantitative indexes). As a result, 50% of the landslide scars are at chronic instability class, while the rest were distributed among other unstable classes. In this study, the authors conclude that Shalstab provides excellent results for identifying landslide-prone areas and is a useful tool for urban planning.

The geotechnical parameters have significant importance for the quality of Shalstab's result, however, [49] evaluate how the quality of DEMs influences the performance of Shalstab. Two different approaches were used for the DEM data: flooding and the Physical Erosion Model for PIT removal (PEM4PIT). The first approach assigns the downstream flow direction by changing the pit elevation. And the PEM4PIT uses an equilibrium equation to adjust the pit and flat points. Two study areas were selected: Sardinia, and an area between Basilicata and Calabria regions, in Italy. The areas, formed by soil layers of silt and sand-clay, are very erodible. The landslides are usually triggered by rainfall and tectonics movements. As a result, the PEM4PIT approach provides better performance in conjunction with Shalstab. The model is a useful tool for mapping landslide-prone areas, but the quality of input data, especially the DEM, has a considerable influence on the results.

2.2. TRIGRS Model

Reference [36] developed the mathematical model TRIGRS (Transient Rainfall Infiltration and Grid-based Regional Slope-Stability Model) to calculate the variation of the Factor of Safety (FS), due to changes in the transient pore-pressure and soil moisture, during a rainfall infiltration.

This model, written in FORTRAN, associates the hydrological model based on [40], which linearized the one-dimensional analytical solutions of Richards Equation (Equation (2)), and a stability model based on the equilibrium limit principle, giving rise to its final formulation (Equation (3)). It represents the vertical rainfall infiltration in homogeneous isotropic materials [50].

$$\frac{\partial\theta}{\partial t}=\frac{\partial}{\partial z}\left[K(\psi)\left(\frac{1}{\cos^{2}\delta}\frac{\partial\Psi}{\partial z}-1\right)\right] \tag{2}$$

where θ is the soil volumetric moisture content (dimensionless), t is the time (s), z is the soil depth (m), $K(\psi)$ is the hydraulic conductivity (m/sKPa) in the z-direction, and Ψ is the groundwater pressure head (kPa).

$$FS=\frac{\tan\phi}{\tan\alpha}+\frac{c-\Psi(Z,t)\gamma_{w}\tan\phi}{\gamma_{s}Z\sin\alpha\cos\alpha} \tag{3}$$

where c is the cohesion (kPa), ϕ is the internal friction angle (deg.), γ_w is the unit weight of groundwater (kN/m^3), γ_s is the soil specific weight (kN/m^3), Z is the layer depth (m), α is the slope angle ($0 < \alpha < 90^{\circ}$), and t is the time (s).

TRIGRS input data are the geotechnical parameters (cohesion, soil specific weight, hydraulic conductivity, and internal friction angle), as well as hydrological data (initial infiltration rate and initial depth of water table), and rainfall duration and intensity. The model allows the changing of input values cell by cell, because it considers the horizontal heterogeneity.

According to [36], the initial depth of water table has a significant impact in TRIGRS accuracy. **Figure 1** represents how TRIGRS calculates the FS. During a rainfall event, infiltration and surface run-off happen simultaneously. There is an increase in the groundwater table and consequently, an increase in water pore-pressure, which precede soil rupture.

TRIGRS has been widely used to identify slope stability and predict unstable areas. Reference [41] applied the TRIGRS model in the steep coastal bluff of Puget Lowland, north of Seattle—Washington, USA. The hillslope process, fluvial, and wave erosion formed the deposit materials that cover the studied area. Long-duration storms usually trigger low-intensity landslides in Puget Lowland. The rainy season of the area occurs during winter, from November to April, and it partially melts the snow, increasing the soil moisture. The landslides occurred in the thin (up to 3 meters) colluvium soil layer, and in steep slope areas with declivity higher than 30˚. The input data consists of a 1.86-meter DEM, elaborated using LiDAR elevation data. The hydraulic and geotechnical data were collected in situ and tested in a laboratory, and the landslide inventory was prepared from aerial photography. Due to its geological heterogeneity, the study area was divided into three different geological units. TRIGRS shows better results compared with static models, however, to this study area the model tends to underpredict the spatial extent of landslides. To improve results, the authors recommended a refined geotechnical and hydrological parameter.

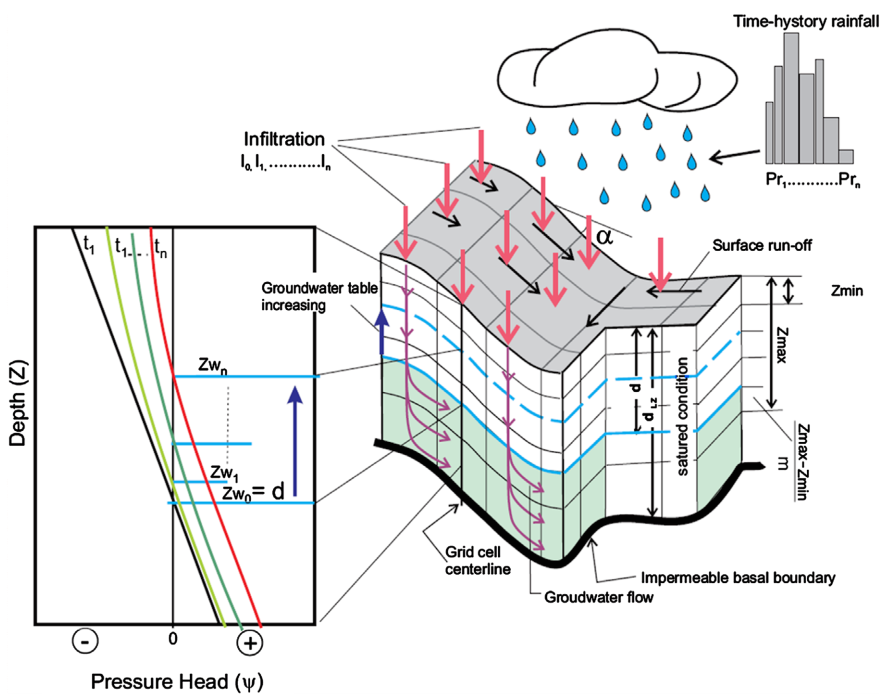

Figure 1. Representation of how TRIGRS model calculates the variation of the Factor of safety, based on the rainfall infiltration in soil layer and groundwater table variation [50].

The authors [51] applied the TRIGRS model in Tenliao Mountain, the northern part of Taipei County, Taiwan area. The area has declivities ranging from 20˚ to 50˚, with soil characterized as a colluvial deposit. In situ measurements to collect soil samples were performed, and further analyzed in the laboratory to provide geotechnical and hydrological data. The authors used a DEM with 10 meters of spatial resolution and a time series of rainfall intensity. The initial condition of the analysis consists of saturated soil, due to the accumulation of more than 500 mm of rain in the previous days. As a result, the unstable areas classified by TRIGRS correspond to those unstable areas identified during the field survey. The rainfall infiltration during the analyzed period had a significant impact on triggering landslides and debris flow. Moreover, an expressway tunnel was under construction only 167 meters far from the soil rupture. This fact, associated with the rainfall infiltration and increase of soil moisture, probably was the trigger mechanism that caused the landslides.

Reference [52] investigates the landslide-prone areas in the Ta-Chia River watershed, Taiwan. The area's declivity ranges from 40˚ to 80˚, with annual average rainfall above 2000 mm. During the summer (June to August), this region is frequently hit by typhoons, and the daily accumulated rainfall can exceed 500 mm. The authors assumed that the geotechnical properties of the soil are strongly related to geological units and use these values as input to the TRIGRS model. They used a DEM with 40 meters of spatial resolution, the daily rainfall intensity from local rain gauges, and satellite images to prepare the landslide inventory. As a result, the model underestimated the unstable zone compared with the landslides occurrences, but this might be related to the initial conditions: differences in the initial groundwater table and shear strength of the soil layer. Despite the results, the authors agree that TRIGRS is useful for identifying landslide-prone areas.

Reference [53] uses the TRIGRS model to identify the landslide-prone area, during the hurricane Ivan (2004). The study area is Macon County in North Carolina, USA, with soil characterized as sandy loam. The input was a DEM with 30 meters of spatial resolution, and hourly rainfall data from hurricane Ivan, provided by the River Forecast Center. Geotechnical parameters were extracted from the State Soil Geographic, which mapped the soil over the USA, and the landslide inventory was acquired from the North Carolina Geological Survey. The initial conditions of analysis consisted of a saturated soil layer due to Hurricane Frances striking the area a week before Hurricane Ivan. As a result, the model was able to predict almost 98% of the landslides, proving to be a useful tool for Early Warning System of landslides events.

Reference [54] applied TRIGRS in Woomyeon Mountain—Seoul, South Korea. The area is covered by forest (mostly oak trees), have declivities higher than 25˚, and buildings and roads surround it. The soil is characterized by a colluvial layer of 3 meters of depth, and underneath it, there is a clay layer of 0.5 meters of thickness. A DEM with 10 meters of spatial resolution and hydrological parameters obtained from laboratory tests was used as input. The geotechnical parameters were acquired from the National Forestry Cooperative Federation, Korean Society of Civil Engineers, and Korean Geotechnical Society, which have conducted geological investigations in this region. The results generated by the model show that 3% of the area has a Factor of Safety < 1, meaning that it is highly unstable, and 33% of the landslides happened within these unstable areas. This study shows satisfactory results in the prediction of unstable areas using the TRIGRS model.

2.3. Sinmap Model

The Sinmap—Stability Index Mapping, developed by [34], has a similar approach to Shalstab. It bases upon the steady-state hydrologic concepts with the infinite slope stability model. Despite the similar approach, Sinmap is a probabilistic model that obtains the input information, such as slope and specific catchment area, from a DEM. This model considers the real uncertainties about the estimation of the other input parameters. It accepts values for upper and lower bounds, using a uniform distribution. Therefore, the model requires the calibration regions, which are sub-samples of the study area based upon the difference between soil, vegetation, or geological data [12] [34] [35] [46] [55] [56] [57].

The input parameters are the lower and upper bound of T/R (Transmissivity ratio to effective Recharge), cohesion, and internal friction angle. The output of Sinmap is a Stability Index (SI) defined as the probability of the area stability, ranging from 0, most unstable, to 1, stable, as presented in **Table 2**.

According to the Sinmap approach, the Factor of Safety (*FS*) is calculated when the most conservative set of parameters still results in stable areas. They

Table 2. Sinmap stability index. Source: Adapted from [34].

Condition	Predicted state	Parameter range	A possible influence of factors not modeled
SI > 1.5	Stable slope zone	Range cannot model instability	Significant destabilizing factors are required for instability
1.5 > SI > 1.25	Moderately stable zone	Range cannot model instability	Moderate destabilizing factors are required for instability
1.25 > SI > 1.0	Quasi-stable slope zone	Range cannot model instability	Minor destabilizing factors could lead to instability
1.0 > SI > 0.5	Lower threshold slope zone	Pessimistic half of range required for instability	Destabilizing factors are not required for instability
0.5 > SI > 0.0	Upper threshold slope zone	Optimistic half of range required for stability	Stabilizing factors may be responsible for stability
0.0 > SI	Defended slope zone	Range cannot model stability	Stabilizing factors are required for stability

are usually represented by values greater than 1. Equation (4) presents the *FS* formula,

$$FS = \frac{C_r + C_s + \cos 2\theta\left[\rho_s g\left(D - D_w\right) + \left(\rho_s g - \rho_w g\right) D_w\right]\tan\phi}{D\rho_s g \sin\theta\cos\theta} \tag{4}$$

where C_r is root cohesion [N/m^2]; C_s is soil cohesion [N/m^2]; θ is slope angle; ρ_s is wet soil density [kg/m^3]; ρ_w is the density of water [kg/m^3]; g is gravitational acceleration [9.81 m/s^2]; D the vertical soil depth [m]; D_w the vertical depth of the water table within the soil layer [m] and ϕ the internal friction angle of the soil [degrees]. The slope angle θ is the arctangent of the slope; S expressed as a decimal drop per unit of horizontal distance.

Several studies have used the advanced model Sinmap in different study areas. Reference [57] used the Sinmap to study the municipality of Nova Friburgo–RJ, Brazil, located in the mountainous area of Serra do Mar. It is a steep slope area with a declivity ranging from 15˚ to more than 35˚ degrees. Colluvial deposits characterize the soil. The colluvial layer is a gravitational deposit of weathered soil, where the physical and geotechnical characteristics are strongly related to bedrock.

The Sinmap input data were a 10 meters DEM, a landslide scars inventory produced based on GeoEye-1 satellite data, and soil parameters acquired from the literature. Considering the geotechnical parameters' uncertainty, the authors simulated three scenarios, changing the range of the cohesion and internal friction angle. As a result, the model provides excellent results and successfully identified 90% of the landslides (55% within the unstable zones, and 35% in areas with critical conditions for soil rupture). However, the authors claim that geotechnical and hydraulic parameters performed in situ and tested in laboratories would provide more accurate results.

Reference [58] studied landslide-prone areas in the Córrego Matirumbide watershed, Juiz de For-MG, Brazil. The area has clayish soils, an annual average rainfall of 1300 mm, and unauthorized human settlement on steep slope areas. The researchers used a DEM with 1 meter of spatial resolution, extracted from LiDAR images, as input data. Geotechnical data were acquired from the literature, and a landslide scars inventory was made during the field survey. As a result, the instability area identified by Sinmap was validated with the presence of landslide scars. The authors verified a correlation between most of the unstable areas and their location in the steepest slope areas, with human settlement. The model proved its efficacy in the identification of landslide-prone areas.

The researchers [59] used the Sinmap model to identify the unstable areas in the Ultrafertil watershed, Cubatão-SP, Brazil. The area, located in the Serra do Mar Mountains, has declivities ranging from 30˚ to 50˚ degrees. Input data were geotechnical and hydrological parameters acquired from the literature. A Digital Terrain Model, with 2 meters of spatial resolution was used. The landslide inventory was elaborated based on aerial orthophotos from 1985, the year when more than a thousand landslides were registered. Three scenarios were proposed to analyze the sensitivity of each parameter in slope stability. The model correctly identified 90% of the landslides in unstable areas. The authors concluded that hydraulic parameters are the most sensitive ones.

Reference [56] applied the Sinmap model in two different study areas: Swabian Alb, Germany, and Wudu County, China. The lithology of the area in Germany is characterized by clay soil underlying marl and limestone. The slopes are covered by debris from previous landslides, usually triggered by rainfall, snow melting, and earthquakes. A small town, named Eningen, is in the study area. The input data were a DEM with 1 meter of spatial resolution, geotechnical parameters acquired from the literature, a landslide inventory extracted from LiDAR images, and field mapping. As a result, 8% of the study areas were classified as unstable, and the model correctly identified 80% of the landslides. The high quality of topographic data provided excellent results.

The Chinese study area lithology is characterized by slates, schist, loess deposits, and is predominantly used for agriculture. The landslides are usually triggered by rainfall, especially during summer, and by tectonic activity. The input data used was a DEM with 30 meters of spatial resolution, geotechnical parameters acquired from laboratory tests, and a landslide inventory prepared from optical remote sensing data. As a result, 22.6% of the area was classified as unstable, and 67.5% of landslides were correctly mapped. The low resolution of topographic data justified the relatively poor results for Wudu.

Reference [60] applied the Sinmap model in Oahu, Hawaii, USA. The geology of the study area is the result of volcanism. It has steep slope areas with declivities higher than 80˚ and a colluvial layer on the slopes formed from weathered basalt. The annual precipitation ranges from 650 mm to 700 mm [60]. The topographic characteristics of the study area might generate flash floods. A landslide inventory was prepared using aerial photography, hydrological and geotechnical parameters were acquired from the Soil Survey Geographic (SSURGO) database and literature. A 10 meters DEM was used as input data. Four calibration regions were chosen, according to geological, geomorphological, and land-cover characteristics. As a result, the Sinmap correctly identified all the landslides within the most unstable classes. The model identified 18% of the study area as very high susceptibility, and 21% as high susceptibility. The authors also compare the Sinmap results with the debris-flow-hazards maps and realize that the model can be used as a tool to identify both hazards.

3. Discussion

The previous analyzed papers show the applicability of the three advanced models Shalstab, Sinmap, and TRIGRS, in different study areas. Each studied area had different geological and geomorphological aspects, proving that the application of these models is not limited to specifics conditions. Notwithstanding, there are similarities: the soil layer where the landslides occurred is colluvial. The most unstable areas identified by the models are in steep slope areas, with declivities higher than 25˚. The models were tested in both natural and forested slope areas [41] [44] [47] [52] [53] [54] [60] [61] and areas with unauthorized human settlements [15] [57] [59].

Some geotechnical data were acquired from the literature, and others were measured in situ. The authors agreed that the models are sensitive to the quality of input data, especially those related to the spatial resolution of DEM, depth to the water table, and the initial soil moisture content. It is essential to highlight that most of the studied areas presented in the papers reviewed have landslides triggered by rainfall. In some cases, earthquakes, volcanism, and hurricanes/typhoons contribute to triggering the landslides. Then, to correctly simulate the initial soil moisture conditions, known accumulated rainfall values are required.

The landslide inventories are critical to validate the results. Therefore, the correct localization of initial soil rupture will provide a better analysis of model's efficiency. Moreover, from the fifteen types of research presented, ten used a landslide inventory to validate the results. Statistical analysis, such as the Receiver Operating Curve (ROC) analysis, quantitative indexes (Scar Concentration—SC and Landslides Potential—LP; Probability of Detection—POD, False Alarm Ratio—FAR, Critical Success Index—CSI), and Success-Error index (SI and EI) also help to assess the performance and reliability of each model [12] [41] [43] [46] [54] [60] [62] [63] [64]. **Table 3** presents a summary of the model's main characteristics based on the literature review.

The three advanced models prove their efficiency for identifying the most unstable areas and are a useful tool to elaborate susceptibility maps. Despite the different validation methods, the mentioned studies' results were satisfactory. Some researchers used a landslide inventory to validate the results, calculating the percentage of landslides in unstable classes [41] [44] [48] [49] [54] [57] [58] [59] [60] [61]. Others verified how the spatial distribution of unstable areas agree with Typhoon trajectory [52] or compare the soil rupture with the variation of pore-water pressure [51]. Risk maps and PEM4PIT methods were also used to analyze the model's performance [15] [49]. Therefore, the models were applied in distinguished regions, with different objectives, and the outcomes were excellent and in agreement with reality.

Each model assumes a different hydrological approach and, consequently, the input parameters vary. The Shalstab and Sinmap input parameters are a DEM and geotechnical parameters (soil cohesion, internal friction angle, specific weight, and depth). The TRIGRS inputs are the geotechnical parameters (cohesion, internal friction angle, specific weight, and depth), a DEM, the hydrological parameters (hydraulic conductivity and diffusivity), the initial depth of water table, and rainfall data. TRIGRS allows the use of different geotechnical parameters cell by cell, considering the soil horizontal heterogeneity. Sinmap also allows the user to make improvements in small areas, due to the multi-calibration process, while Shalstab's parameters are constant and uniformly distributed over the study area.

Table 3. Summary of literature review.

Model	Study Area	Triggered Mechanism	Acquisition data	Validation	Results
Sinmap	Nova Friburgo, RJ, Brazil	Rainfall	Literature	Landslide's inventory	55% landslides in unstable areas
	Juiz de Fora, MG, Brazil	Rainfall	Literature	Landslide's inventory and Susceptibility maps	78.5%landslides in unstable areas
	Cubatão, SP, Brazil	Rainfall	Literature	Landslide's inventory	90% landslides in unstable areas
	Swabian Alb, Germany	Rainfall, Snow melting, Earthquakes	Literature	Sensitivity analysis	80% landslides in unstable areas
	Wudu county, China	Rainfall and Earthquakes	Laboratory tests	Sensitivity analysis	67,5% landslides in unstable areas
	Oahu, Hawaii, USA	Rainfall and Volcanism	Literature	Landslide's inventory and Susceptibility maps	92% landslides in unstable areas
Shalstab	Rio dos Cedros, SC, Brazil	Rainfall	Laboratory tests	Landslide's inventory and land-cover maps	21% of total area are unconditionally unstable
	Caraguatatuba, SP, Brazil	Rainfall	Literature	Landslide's inventory and Sensitivity analysis	55% landslides in unstable areas
	Campos do Jordão, SP, Brazil	Rainfall	Literature	Landslide's inventory and Susceptibility maps	Shalstab unstable areas corroborate with risk maps
	Rio de Janeiro, RJ, Brazil	Rainfall	Literature and Laboratory tests	Landslide's inventory and quantitative analysis	80% landslides in unstable areas
	Sardinia, Italy	Rainfall and Earthquakes	Calculate during PEM4PIT procedure	ROC analysis	Shalstab had better performance using PEM4PIT method
TRIGRS	Seattle, USA	Rainfall	Laboratory tests	ROC analysis	80% landslides in unstable areas
	Taipei county, Taiwan area	Rainfall	Laboratory tests	Landslide's inventory and Variation of pore-water pressure	Variation of pore-water pressure change the soil rupture mechanism
	Tai Chi, Taiwan area	Rainfall and Typhoon	Literature	Landslide's inventory and Typhoon data	Landslides and unstable areas agreeing with typhoon trajectory
	Macon County, North Carolina, USA	Rainfall and Hurricane	Literature	POD/FAR/CSI	98% landslides in unstable areas
	Woomyeon Mountain, Seoul, South Korea	Rainfall	Literature and Laboratory tests	ROC analysis, SI/EI, SC/LP, POD/FAR/CSI	33% landslides in unstable areas

As a result, Shalstab generates a seven-class classification map, based on a logarithmic value for q/t, ranging from chronic instability class to stable. The Sinmap model generates a Stability Index (SI), defined as the probability of a location to be stable, and TRIGRS calculates the variation of the Factor of Safety (FS) due to changes in the transient pore-pressure and soil moisture.

The program interfaces of these three models also differ from each other. Shalstab and Sinmap are performed as an extension of ArcView 3.3, and the output can be saved as a shapefile. TRIGRS is executed with a command-line interface with limited user interactivity [36] and generates an ASCII file. Regardless of most input data and output results, these three models must be prepared and analyzed using GIS (Geographic Information System) programs. The differences and similarities of the models are summarized in **Table 4**.

Literature shows that Shalstab and Sinmap provided quite similar results and that both models correctly predicted unstable areas. The results of a comparative study between Shalstab and Sinmap for the identification of landslide-prone areas [55] show that Sinmap correctly identified 78% of the 44 registered landslides, whereas Shalstab identified 88%. Nevertheless, regarding the classification of the most unstable areas, the models present a disagreeing behavior: 53% of the study area is classified by Sinmap as having a SI lower than 1, meaning that those areas are highly unstable. Furthermore, Shalstab classified as chronic unstable only 24% of the area. Similar results were found in [12] [46] [55] [65], presented in **Table 5**.

The study performed by [63] corroborates the results presented in **Table 5**. Using the ROC analyses, the authors compare the results obtained from Sinmap

Table 4. Characteristics of Sinmap, Shalstab, and TRIGRS models.

	Sinmap	Shalstab	TRIGRS
Input parameters	Cohesion	Cohesion	Cohesion
	Internal friction angle	Internal friction angle	Internal friction angle
	R/T	Soil depth	Soil depth
	DEM	DEM	DEM
	-	-	Hydraulic Conductivity
			Hydraulic Diffusivity
			Initial depth of water table
Data over the study area	Multi-resolution calibration	Uniformly spatially distributed	Cell by cell parameters
Output results	Stability Index (SI)	Log q/t	Factor of Safety (FS)
Output file format	Shapefile	Shapefile	ASCII
Interface	ArcView 3.3	ArcView 3.3	Command Line

Table 5. Comparison of model results.

		Sinmap	Shalstab	TRIGRS
S. Giuletta, Northern Apennines, Italy [55]	Landslides	78%	88%	-
	Unstable areas	53%	24%	
Rio dos Cedros, SC, Brazil [46]	Landslides	71%	100%	-
	Unstable areas	30%	13%	
Oltrepo Pavese, Italy [12]	Unstable areas	18.70%	11%	6.90%
Pizzo D'Alvano, Campania, Italy [65]	Landslides	-	60%	70%
	Unstable areas	-	12%	7.30%

and Shalstab in Northeastern of Korea. The probabilistic model correctly identified 62.58% of the unstable areas, whereas Shalstab identified 82.4%.

The Sinmap probabilistic approach and the range of input values increased the uncertainty of the results, due to the overestimation of unstable classes. Additionally, the model could not predict the failure-size of landslides or even the volume of mobilized material. However, the multi-calibration regions allow the improvement of small areas according to the soil's different physical properties. Shalstab input parameters are constant and uniformly distributed over the study area while still providing more realistic results [12] [46] [55] [60].

Reference [12] compared the performance of different models TRIGRS, Shalstab, and Sinmap in Oltrepo Pavese-Italy, and the results are presented in **Figure 2**.

The author's further analysis of the results shows that Sinmap produced the least realistic scenario. Shalstab generated the spatial distribution of critical rainfall, allowing the identification of soil rupture, and TRIGRS correctly identified the areas that experienced landslides.

The best model for identifying unstable areas is those where the most unstable class coincides with the landslide scars, which accounts for the minor area of the study basin [12] [33] [46] [54] [59] [66].

The TRIGRS model has been providing the most realistic scenarios compared to both Shalstab and Sinmap, due to its capability to evaluate the transient porewater pressure during rainfall events. The steady-state hydrology approach from Sinmap and Shalstab leads to widespread landslide-prone areas [43] [64] [65]. To compare the efficiency between TRIGRS and Shalstab in the identification of the landslide-prone area in Pizzo d'Alvano massif, [43] defined two indexes: Success Index (SI), which correspond to the percentage of correctly classified unstable classes, and the Error Index (EI), which indicates when the computed unstable class does not correspond with verified landslide scars. As a result, the steady-state model generates high values of SI and higher values of EI. TRIGRS, on the other hand, generates for the same values of SI, a lower value of EI, and this result agrees with the reality. **Figure 3** presents the instability results from the comparative analysis between Shalstab and TRIGRS. The results show an

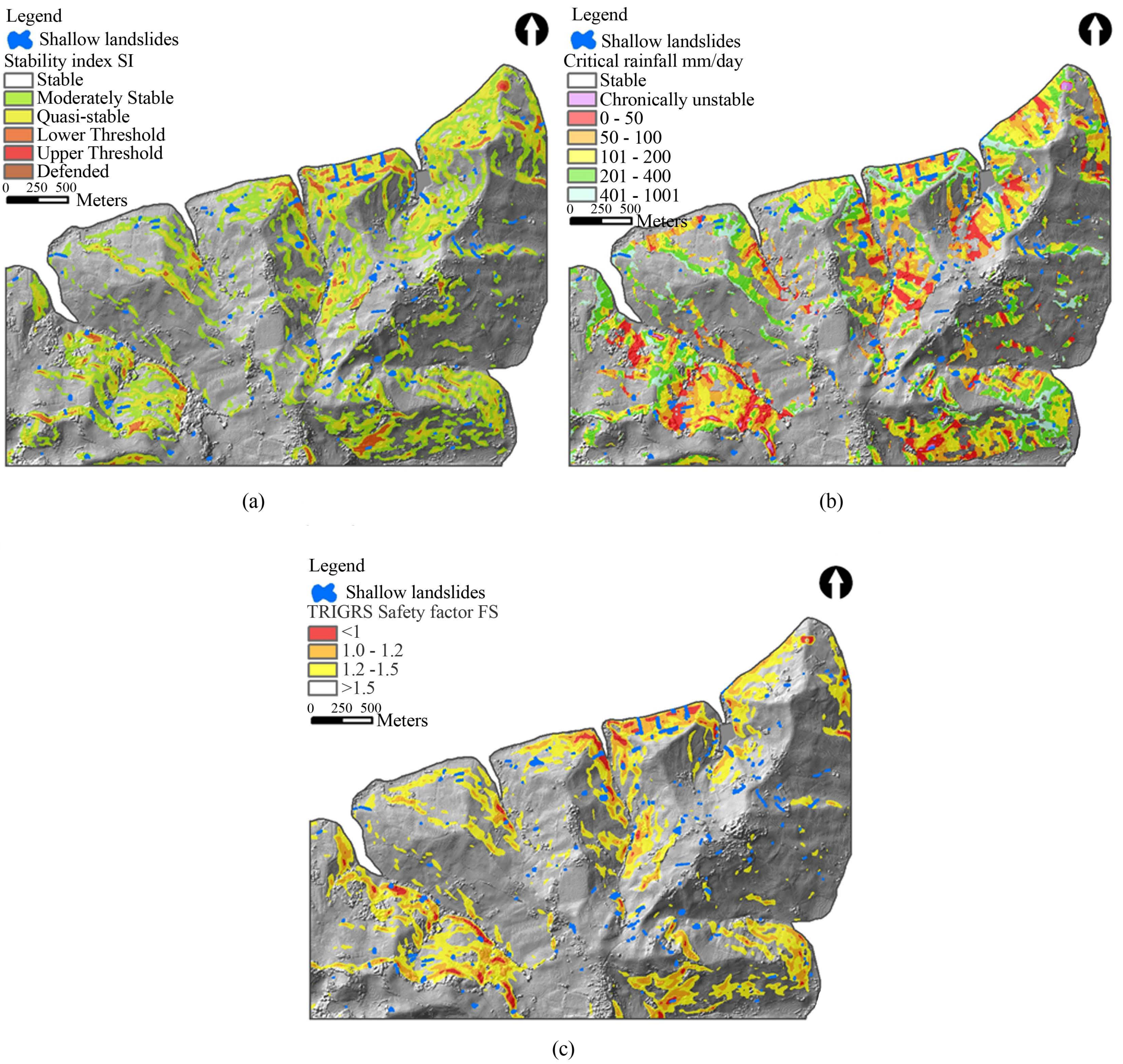

Figure 2. Susceptibility map of Oltrepo Pavese, Italy from: (a) Sinmap, (b) Shalstab, and (c) TRIGRS. Adapted from [12].

overestimation of the unstable classes by Shalstab leading to higher values of EI, while TRIGRS identified just the small areas where landslides occurred.

Other studies presented similar results. According to [53], the TRIGRS model has correctly predicted 98% of the landslides in Macon County, North Carolina, USA, with a low false rate (18%). Reference [67] found similar results applying the model on Oltrepò Pavese, Northwestern of the Italian Apennines: The True Positives (TP) were 73.3%, and False Positives were only 10%. The research conducted by Zhuang *et al.* (2017) analyzed the TRIGRS performance during a 24-hour rainfall, and generated four maps of instability, corresponding to 6:00, 12:00, 18:00, and 24:00 hrs. As a result, the model predicted how the total amount of unstable areas (FS < 1) scaled with the increase of the rainfall duration

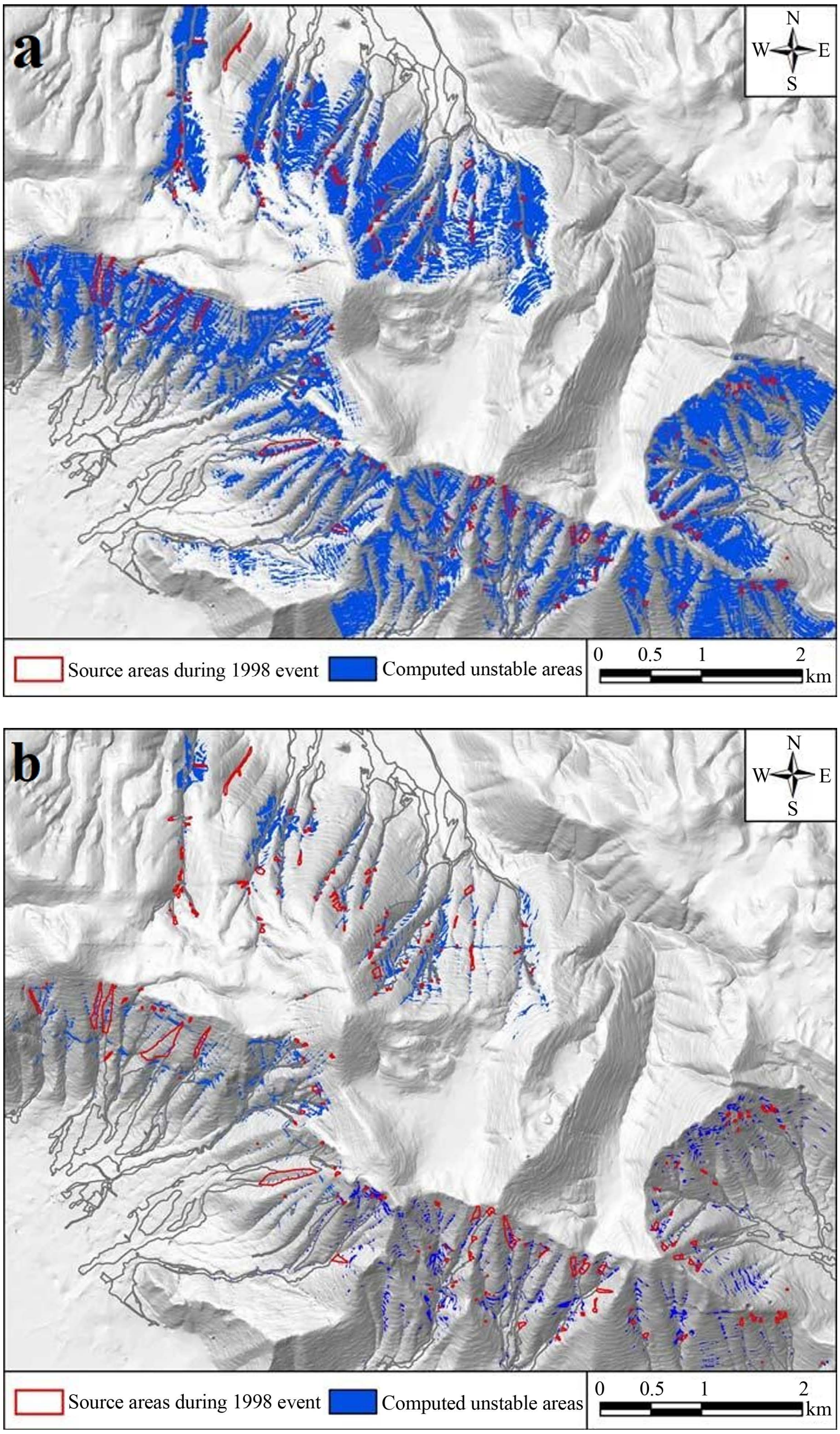

Figure 3. Instability results of Pizzo d'Alvano area from (a) Shalstab and (b) TRIGRS. Source: [43].

(**Figure 4**). At the beginning of rainfall (6:00), the areas with FS < 1 represented just 0.2% of the total area. As time passed, the area increased to 3.3%, 3.8%, and 5.1%, respectively.

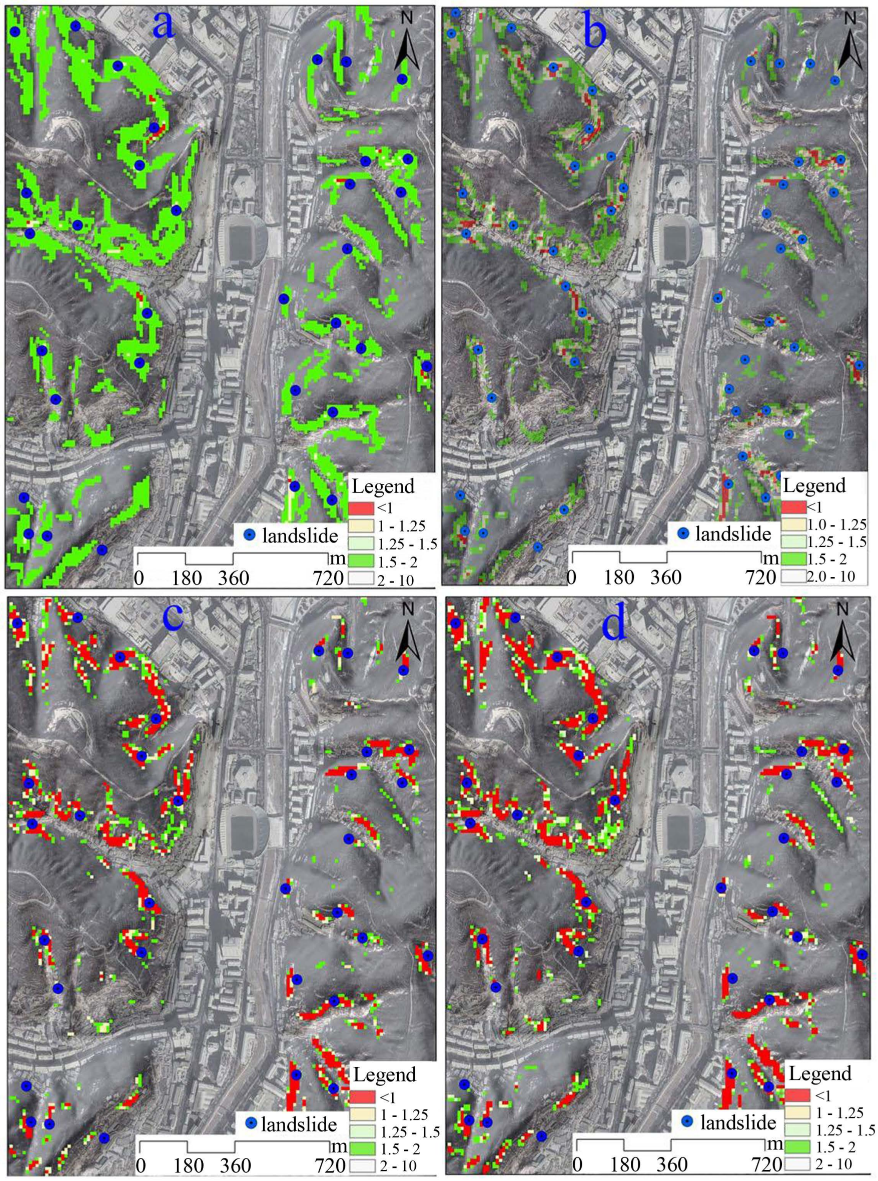

Figure 4. Unstable classes of Yan'an, China during (a) 6:00, (b) 12:00, (c) 18:00 and (d) 24:00 hours. Source: [64].

The TRIGRS model has proven efficient in predicting the landslide-prone areas, primarily due to its dynamic approach, which allows a time-varying analysis. Furthermore, the model can become a useful tool for Early Warning Systems. Another advantage is the input parameters that vary from cell to cell, taking into account the soil heterogeneity [36] [41] [43] [51] [52] [53] [54] [62] [64] [65] [67] [68].

The literature review shows that the three advanced models TRIGRS, Sinmap, and Shalstab, are useful for identifying landslide-prone areas. Both steady-state models correctly identified the areas with landslide scars, and those with a high probability of soil rupture. However, the probabilistic approach from Sinmap overestimates the unstable areas, whereas the deterministic approach from Shalstab generates a more realistic scenario. Moreover, Shalstab is recommended to provide the assessment of initial steady-state groundwater conditions. The transient approach from TRIGRS, which allows the calculation of the variation in pore-pressure and soil moisture during a rainfall infiltration, has proved to be more accurate in identifying unstable areas than the steady-state models. Despite the need for more specific input data (initial depth to the water table, hydraulic conductivity, and diffusivity), which are not always simple to acquire, the model is more precise in the classification of the unstable areas and allows for a time-varying analysis. Such analysis is useful in determining how the Factor of Safety decreases during a rainfall event. Future studies can associate the weather forecast with TRIGRS, to predict the unstable areas and develop an Early Warning System. This type of system could avoid disasters and deaths.

Therefore, each model has its advantages and its limitations. Both Shalstab and Sinmap produce excellent results in identified landslide-prone areas. Besides, the geotechnical input data are similar and easy to acquire. Soil cohesion and internal friction angle can be estimated from the geology and type of soil in the study area. Even though they correctly identify the most unstable areas, these two models tend to overestimate the results. It is a useful tool to enhance the quality of risk maps and verify the slope stability of large areas. As previously mentioned, Shalstab is recommended to provide the assessment of initial steady-state groundwater conditions. TRIGRS results are more accurate, and its use is recommended for small areas. Furthermore, they can be used for temporal analysis of rainfall events and might become a useful tool for Early Warning Systems. The disadvantage is that input data are more specific and not always easy to acquire.

Determining which model should be used to analyze slope stability will depend on the study objective and data availability. In areas where soil samples can be collected, providing the hydraulic conductivity and diffusivity, cohesion and internal friction angle, the model TRIGRS are recommended. Moreover, TRIGRS is recommended to predict instability areas, using weather forecast and time-varying analysis.

However, some slope areas have difficult access, and collecting soil samples is not an option. Therefore, the models Shalstab and Sinmap are the best choice. Both models provide good results identifying landslide-prone areas.

Landslides are usually triggered by rainfall. Notwithstanding, it is essential to highlight that the critical threshold of rain that causes the soil ruptures changes from place to place, depending on soil properties, geological, geomorphological aspects, and climate properties. Such information is necessary for Early Warning Systems.

In Brazil, the Serra do Mar critical threshold for landslides is an accumulated rainfall of 80 mm in 72 hours [16] [69]. An incident of heavy rainfall that triggered several landslides happened in Baixada Santista-SP, located on the Southeastern coast of Brazil, on March 3rd of 2020. During 24 hours, an accumulated rainfall of 320 mm was recorded, whereas 263 mm of rainfall was expected for the entire month [70]. The use of TRIGRS and weather forecast to predict the unstable area could avoid many disasters, such as this one.

Another critical aspect that needs attention is the fact that there is an inverse correlation between declivity and slope stability. The higher the declivity, the less stable the slope. Nonetheless, the literature reveals the presence of human settlements in those steep slope areas. According to [15] [16], areas with declivity above 25˚ are inappropriate for anthropic land uses, either in urban or rural areas. In Brazil's particular case, it is very common to have human settlements (usually unauthorized) in steep slope areas. Additionally, the anthropic changes such as inappropriate discharge wastewater, leakages, inefficient garbage collection, and vertical cuts in slopes, contribute to decreasing the slope stability [8] [14] [15] [16] [71].

4. Conclusions

The present paper evaluates the applicability of three advanced models: the probabilistic steady-state model Sinmap, the deterministic steady-state model Shalstab, and the transient model TRIGRS. Each model has a different approach and distinct mathematical formulas to calculate and identify the landslide-prone areas. Consequently, the input data differ from each other. The steady-state models need a DEM, geotechnical parameters, and landslide inventory. The transient model inputs include those mentioned above and additional hydrological parameters, such as the initial depth to the water table and rainfall data. Moreover, TRIGRS runs using a command line, while Sinmap and Shalstab are executed as an extension of ArcView 3.3. Despite the differences, the models result in susceptible maps. Shalstab susceptible maps are classified based on a logarithmic relation between rain recharge and soil transmissivity (q/t). Sinmap output is a Stability Index (SI) defined as the probability of the area stability, ranging from 0, most unstable, to 1, stable. TRIGRS results classified the area due to variation in Factor of Safety.

A literature review was proposed to analyze and compare each model's applicability, showing its applicability and limitations. The studies presented applied the models in areas with diverse geological and geomorphological characteristics. It emphasizes that the three models are not developed only for a specific condition. In some cases, the landslides were triggered by intense rainfall, others by earthquakes, typhoons, and hurricanes. Moreover, a few similarities were found in the landslide-prone areas: colluvial layers and declivities higher than 25˚. Human settlement, roads, and tunnels might decrease slope stability, becoming landslide-inducing factors. To validate the model's results, researchers used landslides inventory to calculate the percentage of landslides that occurred in the most unstable classes. Some studies used statistical analysis, such as the Successful and Error index, ROC analysis, among others.

The three advanced models proved to be a useful tool for the identification of landslide-prone areas. Results presented in the literature show that the regions classified by these models as unstable have suffered from landslides. Additionally, some of the unstable areas have human settlements, and other constructions, which might become a disaster when a landslide occurs. Researchers and government institutions should use Shalstab, Sinmap, and TRIGRS to improve the quality of susceptible maps and enhance their monitoring.

However, the steady-state models, due to their mathematical approach, overestimate the unstable areas, whereas TRIGRS generates a more realistic and precise result. Although TRIGRS inputs are more specific (*i.e.*, hydrological parameters, initial depth of water table), the calculation of the transient effects of the rainfall infiltration allows a time-varying analysis, serving as a proper tool for Early Warning Systems. Moreover, Shalstab and Sinmap can be used for the primary knowledge of susceptible areas, while TRIGRS should be used for specific events and Early Warning systems.

The authors recommend the use of a steady-state model to identify the unstable areas and prepared landslide-susceptible maps. Furthermore, TRIGRS should be used to analyze small areas due to the complexity of input data. Additionally, this model should be developed to improve the risk analysis of small areas and become a useful Early Warning tool to avoid disasters.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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