Shalstab and TRIGRS: Comparison of Two Models for the Identification of Landslide-prone Areas

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Abstract: *Landslides are natural phenomena occurring worldwide. In Brazil, such events are recurrent and usually preceded and triggered by heavy rainfall. When occurring in urban areas, these events became a disaster, due to economic damage, social impacts, and fatalities. The identification and monitoring of the landslide-prone areas are extremely important, aiming to predict and prevent landslides disasters. Mathematical models have been proving to be an excellent tool in landslide risk preventive measures. Therefore, the objective of this study is to compare and analyze the performance of two different physically-based models: Shalstab and TRIGRS for the identification of landslide-prone areas.*

1. Introduction

A natural phenomenon can become a disaster when it affects urban areas, disrupting a society life-style [Wisner et al., 2003]. Landslides, for example, is characterized as a surface rupture with soil and rock sliding through the slope [Cruden; Varnes, 1996]. They usually happen in hilly areas, and are triggered by rainfall. When it occurs in urbanized areas, they cause significant damage to structures and infrastructures, social impact and, sometimes human losses [Montgomery; Dietrich, 1994; Larsen; Torres-Sanchez, 1998; Zêzere; Trigo; Trigo, 2005; Zizioli et al., 2013; Mendes; Filho, 2015; Mendes et al., 2018a, 2018b; König; et. al., 2019].

During the last decade, there was an increase of extreme weather conditions, such as heavy rainfall for hours or days, floods and drought [Houghton, 2003]. The intensity and duration of rainfall increase soil´s pore-water pressure, triggering several landslides. In Brazil they frequently occur during the rainy season, which corresponds to December until March. From 1991 to 2012, 699 landslides were registered in Brazil, and 79,8% of them happened at the southeast region of the country [Brasil, 2013]. Therefore, the identification and monitoring of landslide-prone areas are essential to disaster risk reduction measures.

The identification of landslide-prone areas can be performed using statistical methods [Carrara et al., 1991; Bai et al., 2009; Cervi et al., 2010; Li et al., 2012] and physically based models such as the Shallow Slope Stability Model (SHALSTAB) [Montgomery and Dietrich 1994; Dietrich and Montgomery 1998], Stability Index Mapping (SINMAP) [Pack et al. 1998], Transient Rainfall Infiltration and Grid-based Regional Slope-Stability Model (TRIGRS) [Baum et al. 2008], TRGIRS-unsaturated [Savage et al. 2004], physically-based Slope Stability Model (dSLAM) [Wu and Sidle 1995], SLOPE/W and SEEP/W [Geostudio, 2005].

Each model has a different approach and a comparison of their results improves the quality and reliability in the identification of landslide-prone areas [Zizioli et al. 2013]. In this frame, the objective of this paper is to compare the performance of two physically based models SHALSTAB and TRIGRS, in determining the landslide-prone areas.

2. Materials and Methods

2.1. Study Area

Placed in the Mantiqueira Moutains, Campos do Jordão municipality was choose as study area. Located on a crystalline plateau, with altitudes above 2000 m and annual precipitations varying from 1205 to 2800 mm [Modenesi-Gauttieri; Hiruma, 2004], this area has recorded recurrent landslide events. One of the most catastrophic landslides documented, occurred in August 1972, resulting in 17 fatalities and 60 houses buried by the mudflow [Amaral; Fuck, 1973]. In January 2000, another landslide event caused 10 fatalities, over 100 injured and 423 strongly damaged houses [Mendes; Filho, 2015; Mendes et al., 2018a, 2018b].
Geologically this area is delimited by two rifts namely: Jandiuvira and São Bento do Sapucaí, from Pre-Cambrian to Paleozoic age, presenting high mountains and erosive depressions [Hiruma; Riccomini, 1999; König; et. al., 2019].

Areas with declivities higher than 30% are inappropriate for constructions and anthropic changes, either in urban or rural areas [Prieto et al., 2017]. In Vila Albertina neighborhood, the steep slope areas are irregularly occupied and has several houses, most of which in precarious building standards. The result of these anthropic changes are the environmental degradation, weight overload and recurrent leakages which changes the slope stability, inducing landslides. Several landslides were documented in Vila Albertina, and more events might happen. Therefore, this area was chosen as study site to modelling slope stability using Shalstab and TRIGRS and prevent future disasters. Figure 1 present the location of both Campos do Jordão and Vila Albertina.

2.2. Shalstab model

The Shallow Landsliding Stability Model – Shalstab, developed by Dietrich and Montgomery (1998), identify the landslide-prone areas calculating the critical threshold of rainfall that induce surface rupture [Montgomery and Dietrich 1994; Dietrich and Montgomery 1998; Vieira and Ramos 2015]. As presented in Equation 1, Shalstab is a deterministic model that associates the Mohr-Coulomb law with the steady-state hydrological model developed by O'Loughlin (1986).

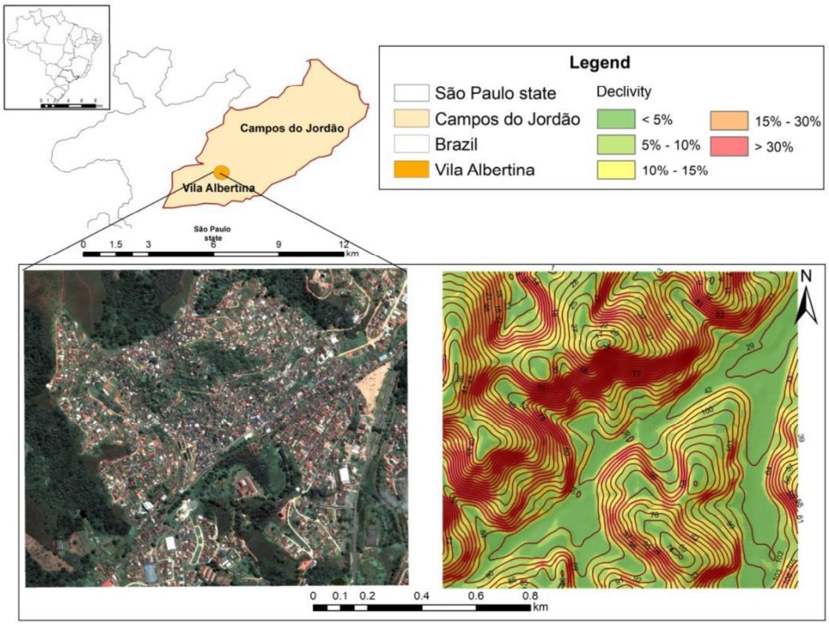

Figure 1. Study area.

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

In Equation 1: q is the rain recharge, t is the soil transmissivity, θ is the inclination (degrees), a is the contribution area (m²), b is the contour size (m), c' is the soil cohesion (kPa), φ is the internal soil angle (degrees), ρs is the soil density (kg*m-3), g is the gravitational acceleration, z is the soil thickness (m), and ρw 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 [Montgomery et. al., 1998; Reginatto et al., 2012; Michel; et. al., 2014; König; et. al., 2019].

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 Dietrich and Montgomery (1998).

Shalstab have been applied in different study areas [Guimaraes et al., 2003; Santini et al., 2009; Reginatto et al., 2012; Vieira; Ramos, 2015; Prieto et al., 2017] and presents satisfactory results.

2.3. TRIGRS model

Baum et al. (2008) 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 Iverson [Iverson, 2000], which linearized the one-dimensional analytical solutions of Richards Equation (Eq. 2), and a stability model based on the equilibrium limit principle, giving rise to its final formulation (Eq. 3). It represents the vertical rainfall infiltration in homogeneous isotropic materials (Baum; et. al., 2008).

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

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

$$\mathrm{FS} = \left(\frac{\tan\phi}{\tan\alpha}\right) + \left[\left(\frac{c - \Psi(Z,t)\Upsilon_w \tan\emptyset}{\Upsilon_s Z \sin\alpha\cos\alpha}\right)\right] \tag{3}$$

Where c is the cohesion (kPa), ϕ is the internal friction angle (deg.), γw is the unit weight of groundwater (kN/m³), γs is the soil specific weight (kN / m³), Z is the layer depth (m), α is the slope angle (0 < α < 90º), 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 Baum et al. (2008), the initial depth of water table has a significant impact in TRIGRS accuracy. Figure 2 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.

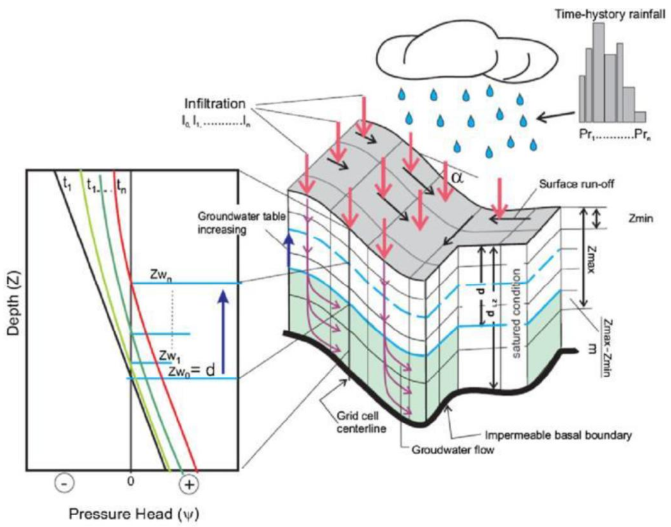

Figure 2. TRIGRS components. Source: Grelle, et al. 2014.

TRIGRS have been widely used to identify slope stability, and predict the unstable areas, as presented in Godt et al. (2008), Chien-Yuan et al. (2005), Tan et al. (2008), Liao et al. (2011), Park et al. (2013), among others.

2.4. Input data

The modeling of landslide-prone areas using Shalstab and TRIGRS requires geotechnical parameters such as cohesion, soil specific weight, hydraulic conductivity, internal friction angle, and the rainfall duration and intensity. These input data were acquired from Mendes et al. (2018a), who collect soil samples, and sent to be analyzed in the laboratory. Table 1 present the geotechnical parameters used as input in Shalstab and TRIGRS models.

Table 1. TRIGRS and Shalstab input parameters.

Input parameters					
Depth (m)	Cohesion (kPa)	Angle of Friction (°)	Hydraulic Conduct. (m s-1)	Hydraulic Diffus. (m s-1)	Specific weight (kNm-3)
1,6	22	43	5,25x10-6	6,45x10-6	18,1
1,6-2,6	19	34	1,18x10-6	6,45x10-6	21,4
2,6-4,6	14	42	3,76x10-6	6,45x10-6	17,5

Source: Mendes et al. (2018a)

The analyzed period in January 1^{th} to 4^{th} of 2000, whereas a heavy rainfall resulted in 10 death, more than 100 injured and 423 houses damaged [Mendes; Filho, 2015; Mendes et al., 2018a, 2018b]. The daily rainfall values are presented in Table 2.

Landslides scars, acquired from König; et. al., (2019), were used to validate the models results.

Table 2. Daily accumulated rainfall.

Date	01/01/00	02/01/00	03/01/00	04/01/00	Total
Daily rainfall	101,0 mm	120,0 mm	60,0 mm	144,5 mm	425,5 mm

Source: Mendes et al. (2018a)

3. Results and Discussion

3.1. Analyzing the results of TRIGRS and Shalstab

Figure 3 presents the landslide susceptibility maps created using the two mathematical models Shalstab and TRIGRS.

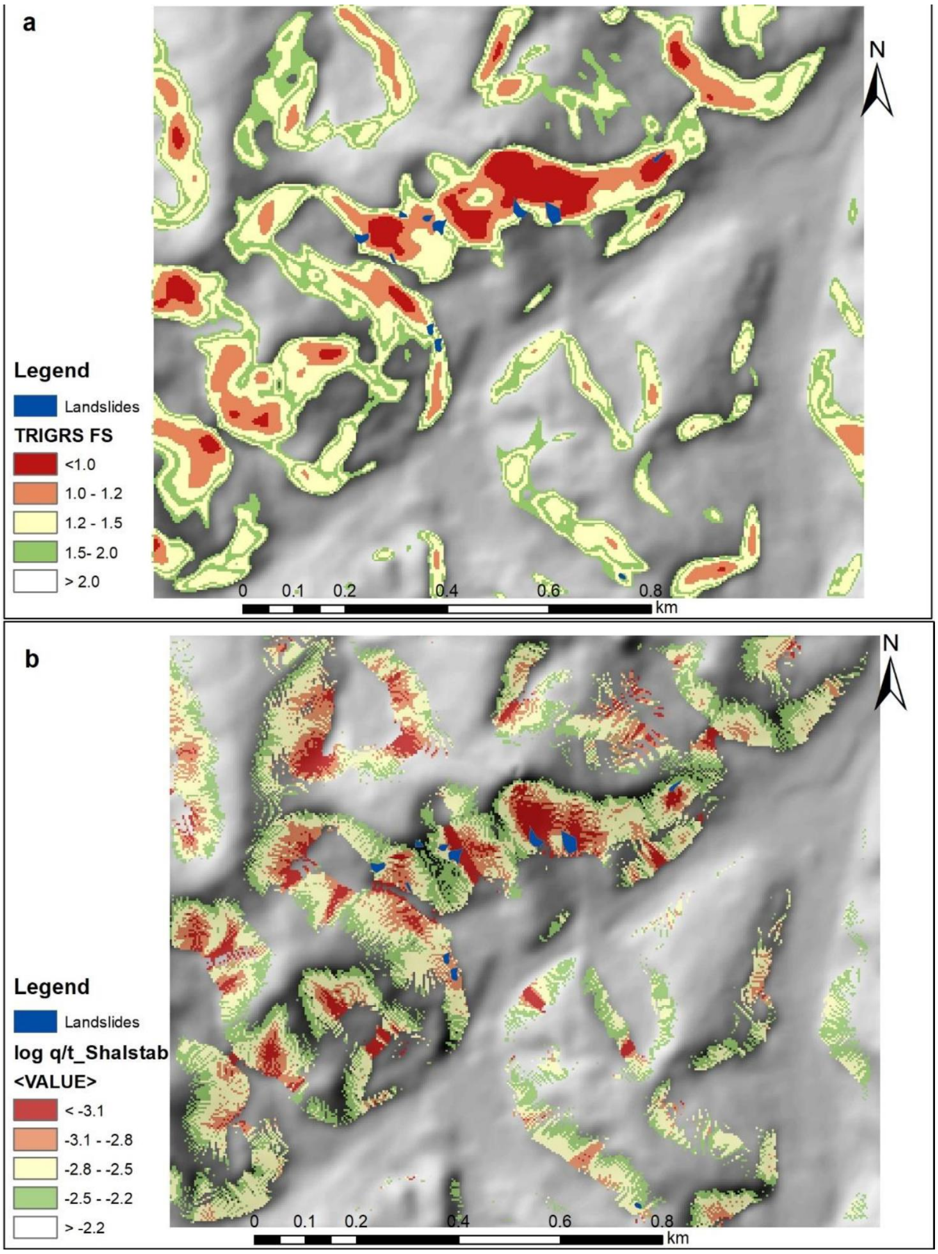

Figure 3. Landslide susceptible areas: a) TRIGRS results. b) Shalstab results.

Analyzing Figure 3, it is possible to assume that both models had quite similar and satisfactory results in identifying landslide-prone areas.

To compare the efficiency between TRIGRS and Shalstab in the identification of the landslide-prone area, two index was defined: Success Index - SI (Eq. 1), which correspond to the percentage of correctly classified unstable classes, and the Error Index – EI ($EI = (\frac{A_{out}}{A_{stb}}) * 100$ Eq. 2), which indicates when the computed unstable class does not correspond with verified landslide scars [Sorbino; et. al., 2010]. Table 3 presents the models efficiency.

$$SI = \left(\frac{A_{in}}{A_{uns}}\right) * 100 \quad \text{Eq. 1.}$$

The variable A_{in} is the computed unstable areas within the triggering areas, and A_{uns} is the triggering areas.

$$EI = \left(\frac{A_{out}}{A_{stb}}\right) * 100 \quad \text{Eq. 2.}$$

The variable A_{out} is the computed unstable areas outside the triggering areas, and A_{stb} is the stable areas.

Table 3. Analysis of Shalstab and TRIGRS Success and Error indexes.

Model	Success Index (SI)	Error Index (EI)
Shalstab	30%	65%
TRIGRS	20%	60%

Shalstab had an SI of 30%, meaning that 30% of the unstable areas (log q/t < -3,1) were triggered zones for landslides. A few landslides were computed in different classes: 60% in areas with medium susceptibility (-3,1 > log q/t > -2,5) and 10% in stable class (-2,5 > log q/t > -2,2). As a result, Shalstab had an EI of 65%. The TRIGRS SI is 20%, a lower value compared with Shalstab´s, but this model has the lowest EI.

A further analysis indicates that TRIGRS model compute 14.96% of instability classes with FS < 1,0, while Shalstab identified 0,57 % (log q/t < -3,1). Table 4 present the percentage of computed areas by both models.

Table 4. Unstable areas identified by both models.

Shalstab		TRIGRS	
Instability Class	% of area	Factor of Safety	% of area
< -3,1	0.57	< 1.0	14.96
-3,1 - -2,8	1.84	1.0 -1.2	6.39
-2,8 - 2,5	7.77	1.2 - 1.5	9.09
-2,5- -2,2	15.13	1.5 - 2.0	5.70
> -2,2	74.69	> 2.0	63.86

For the 96 hours of heavy rainfall, TRIGRS identified that 14,96 % of steep slope areas has FS <1, while Shalstab classified 0,57% as unstable (q/t < -3,1). Despite the higher SI value, Shalstab computed only a few areas as unstable, which agrees with the a EI of 65%. Nevertheless, TRIGRS classified more areas as unstable, reducing the Error Index.

TRIGRS mathematical approach considers the soil heterogeneity, meaning that each soil layers have different geotechnical parameters. According to the soil type, layers change in the quantity of clay, sand, and organic compounds, which results in how the infiltration process affects the soil layer. The model analyzes how the rainfall infiltration might affect the soil layer's behavior, triggering (or not) a landslide. Therefore, the model was able to identify several critical slope areas, differently from Shalstab, that calculated the slope stability using the same geotechnical parameter over the study area. As a result, this model identified fewer landslide-prone areas, underestimating the slope stability.

It is important to highlight the anthropic changes that occurs in these steep slope areas, such as constructions without retaining wall, leakages which increase the soil moisture, environmental degradation, among others. These processes might have modified the soil´s geotechnical properties and induce landslides [Prieto et al., 2017; Mendes et al., 2018a, 2018b; König; et. al., 2019].

The results prove the both models correctly identified the landslide-prone areas, and the statistical analysis shows a similar efficiency between then. Shalstab input parameters are constant and uniformly distributed over the study area while still providing a realistic result. It is a very useful in

the assessment of the initial groundwater conditions. (Meisina; Scarabelli, 2007; Deb; El-KadI, 2009; Zizioli et al., 2013; Michel; et. al., 2014).
TRIGRS is very sensitive to the initial conditions, especially those related to the depth of the water table. Then, the result´s accuracy is related to data reliability, but due to the capability of analyses the changes in transient pore-pressure, it provides good results identifying landslide-prone areas.

4. Conclusion

Landslides triggered by heavy rainfall are recurrent in Brazil, and most of them happen in urbanized steep slopes, causing severe damages and deaths. To avoid disasters, the identification and monitoring of landslide-prone areas are essential. Preventive risk measures include modeling slope stability using mathematical models, such as Shalstab and TRIGRS. Both models were tested in Campos do Jordão municipality, and their performance was compared to determine which model provides a better result in identifying susceptible areas.
Despite the different approaches of each model, their results were satisfactory, and the most susceptible areas were correctly determined. To validate the results, landslides scars were used, and a ROC analysis was performed. The statistical analysis shows a similar efficiency between them. Shalstab had a higher Successful Index than TRIGRS; however, the Error Index was also the highest. Notwithstanding, Shalstab still provides realistic scenarios and is very useful in assessing the initial groundwater conditions. TRIGRS classified more areas as unstable, reducing the Error Index. The capability to analyze the changes in transient pore pressure provides good results in identifying landslide-prone areas.
The authors recommend using both models as a tool for monitoring and mapping landslide-prone areas, enhancing the preventive risk measures.

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