Physically based modelling techniques for landslide susceptibility analysis: A comparison

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Abstract. In mountainous areas, landslides are the most common natural catastrophic event, due to these events thousands of people are killed each year, and millions of dollars are lost in property damage. Landslides are mainly induced by earthquakes, rainfall, or manmade activities. Several GIS techniques, such as synthetic aperture radar, ranging data from spaceborne, airborne, and ground-based platforms, optical, and light detection and various physically based models such as SINMAP, TRIGRS, SHALSTAB etc. have been widely used to study slope failures in recent years. Each of these techniques has advantages and limitations for susceptibility analysis of landslides. The current research focuses on landslide susceptibility models that are physically based, their parameterization and working principle. The study infers that TRIGRS is the most commonly used model for slope stability analysis, whereas GEO top model is the only 3D slope stability model which considers the spatial variation of soil parameters hence it can be considered as the most advanced physically based slope stability model.

1. Introduction

Landslides are by far the most serious environmental threats, with widespread social, economic, and environmental consequences [1]. Landslides are caused by the interaction of a number of complicated components including geology, geomorphology, topography, and seismic variables [2]. Geological factors include weak and soft ground material, jointed and fractured materials, rainfall, snowfall, earthquake, and many more while the geomorphological factors include slope, erosion, vegetation change, tectonic and volcanic uplift etc. Although natural hazards such as landslides are unavoidable, a firm grasp of the tendency and a scientific approach to anticipate the behavior of such events can be effective tools in reducing natural risk and susceptibility [1]. In recent years, GIS-based landslide susceptibility mapping has become increasingly common [3]. The development of GIS based technologies such as satellite imagery and DEM improved the landslide susceptibility as it would be very difficult to analyze the slope stability over a large area with field observations and it would be very difficult to determine parameters such as slope elevation and aspect, drainage network, catchment area, slope convexity with field observations but these parameters can be very easily determined using DEM.
and satellite data [1]. Landslide hazard mapping has been done in a number of locations worldwide, particularly in the last few decades. Some of the strategies for landslide mapping that are available include mapping based on past data, evaluation of landslide occurrence probability, deterministic and statistical analysis, numerical modelling etc. [4].

Statistical approaches are data-driven ways for eliminating subjectivity in weightage assignment and creating more predictable outcomes [5]. Statistical methods include techniques like Fuzzy logic, ANN analysis, LR analysis etc. To reduce subjectivity in the weight assignment technique, probabilistic approaches have also been applied in landslide hazard mapping research. Within a probabilistic framework, the spatial distribution of landslides in response to diverse cause factors is compared using this method [5]. Conditional probability model, WoE technique under Bayesian probability model, SHETRAN physically based model etc. are some of the techniques based on this approach [5]. Mass, energy, and momentum conservation are the core of deterministic models. Distributed hydrological and slope instability methods be situated in deterministic landslide hazard zonation to determine the global variance of level of groundwater, pore pressures, and safety factor [6]. Physically based models like SHALSTAB, Rainfall threshold models etc. follows deterministic approach. Numerical modelling is also very commonly practiced technology to determine factor of safety in slope instability analysis. Generally numerical modelling technologies are based on Limit equilibrium method, Finite difference method, Finite element method etc. GeoStudio-Slope/W, Plaxis-2D/3D, CHASM, SLIDE etc. are some software packages that follow numerical modelling approach.

Physical models for slope failure are based on simple mechanical rules and describe the physical processes that contribute to the landslide event [4], some of these models follow deterministic approach while others follow probabilistic approach. These models considers the spatial variation of ground water-rainfall response throughout the slope, and they don't require landslide data from long past, so they are commonly used in places with incomplete landslide inventory [4]. The present study aims to compare the various physical models such as SLIP, SHETRAN, GEOtop-FS, SUSHI, SINMAP, SHALSTAB, TRIGRS that have been used in studies worldwide over the last decade (2010-2020).

2. Methodology
The study shows the comparison of physically based models for landslide susceptibility analysis. To conduct this study, we collected articles from reputed journals on physically based models for slope instability analysis from the period 2010-2020. The detailed methodology used in the study is shown in the flow chart below.

![Flow chart of the methodology](image_url)
2.1. Working principles of physically based models considered for the study

2.1.1. Stability index mapping (SINMAP). The stability model for infinite slope, used in the SINMAP technique, balances gravity’s destabilizing components with friction and cohesion's restorative components sideways a probable plane of failure parallel to the earth's surface. To calculate the ground stability index (SI), SINMAP examines information such as geographic slope, watershed region, strength, climate etc. [7]. The possibility of any place to remain stable over the uncertainty ranges with considering uniform distribution of the parameters is defined as its SI. SI equals to 0 is considered as least stable whereas SI equals to 1 is the most stable [8–11].

The FoS of the model is simplified considering the wet and dry densities as equal (Eqn. 1).

\[ SI = c' + \frac{\cos^2 \theta [\rho_s g (z - D_W) + (\rho_s g - \rho_w g)D_W] \tan \varphi}{z \rho_s g \sin \theta \cos \theta} \]  

(1)

c' = c_r + c_s

TOPMODEL is the hydrological model used by the SINMAP technique [12]. Analysis done by SINMAP is based on some assumptions as follows:

- Topographical gradients were followed by subsurface flow at shallow depth. This suggests that the surface topography defines the area \(a\) making a contribution something to the flow at any point.
- Each point's lateral discharge \(q\) has a steady-state recharge \(R\) (m/h)
- Lateral flux’s measurements at each point is given by \(T \cdot \sinh\), where \(T = K \cdot z\)

\[ w = \min \left( \frac{Ra}{T \sin \theta}, 1 \right) \]  

(2)

Eq. (2) is included into the dimensionless FoS to define the SI, which becomes:

\[ SI = c + \frac{\cos \theta [1 - \min \left( \frac{Ra}{T \sin \theta}, 1 \right) \gamma \tan \varphi]}{\sin \theta} \]  

(3)

Where, \(c = c_r + c_s / (h \rho_s g)\), \(\gamma = \rho_w / \rho_s\).

The DEM is used to determine the variables \(a\) and \(h\), while the user provides the values for \(C\), \(\tan\), \(\gamma\), and \(R/T\). SINMAP distinguishes between six different types of SI. SI >1.5 and SI >1.0 define the classes with normal stability, moderate stability, and quasi-stable classes; with the most cautious parameters in the indicated range, they illustrate locations that should not fail. FS<1.0 is found in the lower- and upper-threshold classes, with failure probabilities of lower than and more than 50%, respectively. These two classes, denoted by 1.0<SI<1.5 and 0<SI<1.0 respectively, indicates the minimum and maximum ground failure limits. The unconditionally unstable class has the highest chance of failure (>90 percent) within the stated range of parameters.

2.1.2. Shallow Landslide Stability Model (SHALSTAB). SHALSTAB is developed by [13] and is a very common physically based model. This model conducts infinite-slope failure analysis when in steady-state circumstances. For slope analysis it incorporates a hill slope instability model with a hydrological model and Darcy's law to forecast 3-D variance of pore pressures [14–17]. SHALSTAB characterizes steady-state soil saturation depending on upslope impact region assessments using rainfall and topographical data, local slope and soil transmissivity, as well as hydrological model TOPOG.
established by O’Loughlin is used by SHALSTAB [18], [19]. Based on a saturated water flow parallel
to the slope plane in a constant state, this model determines relative wetness (w):

\[ w = \frac{Q}{T \cdot b \cdot \sin \theta} \]  

(4)

Where,
The drainage area and the width of the outflow barrier are represented by a and b, respectively, Q rainfall
necessary to trigger landslides.

The SHALSTAB model forecasts the crucial rainfall needed to cause slope failure across a study
area [13]. The model's design is a balance of hydrological in addition geo-mechanical elements. The
SHALSTAB model solves the following equation to compute the essential precipitation for slope failure
at each grid cell:

\[ \log \left( \frac{Q}{T} \right) = \frac{c'}{a} + \frac{c'}{b} \cdot \frac{\rho_s - \rho_w}{\rho_w} \cdot \frac{1}{\tan \varphi} \]  

(5)

This model's output is measured in mm/day of crucial rainfall, lower the values of output lower will
be the intensity of rainfall required to trigger the slope failure and higher values indicate requirement of
high intensity of rainfall for slope failure.

2.1.3. Transient Rainfall Infiltration and Grid-based Slope-Stability (TRIGRS). A well-known model is
TRIGRS with a physical foundation for shallow landslide investigation. Various applications, such as
landslide hazard mapping, have been tested using TRIGRS [20]. TRIGRS uses the input parameters:
soil depth, slope, sub surface water table depth, saturated hydraulic conductivity (Ks) and steady (initial)
surface flow to forecast in saturated conditions, the pore water pressure regime [21]. The sliding mass's
depth is substantially lower than its length in TRIGRS 1-D infinite-slope instability model. The soil
depth and physical attributes are uniform for every grid cell, and between grid cells, lateral stresses are
neglected [22]. When calculating a safety factor with an infinite slope, the Taylor equation is utilised.

\[ F_s(Z, t) = \frac{\tan \varphi'}{\tan \theta} + c' - \frac{\psi(Z, t) \cdot \gamma w \cdot \tan \varphi'}{\gamma_s Z \cdot \sin \theta \cdot \cos \theta} \]  

(6)

Where, \( \psi(Z, t) \) is the ground water pressure head (\( \psi = u/\gamma w \)), depending on Z is vertical direction
coordinate and t is the time;
To get the safety factor above the saturated zone, the matric suction, \( \psi(Z, t) \cdot \gamma w \), is multiplied by \( \chi \), which
can be approximated as:

\[ \chi = \frac{\theta_v - \theta_r}{\theta_s - \theta_r} \]  

(7)

2.1.4. Systeme Hydrologique Europeen Transport (SHETRAN). SHETRAN is a system having
capability of modelling basin hydrology, sediment transport, and pollutant transport that is physically
based and geographically dispersed [23]. Water flow, sediment transport, and pollutant transport are the
three fundamental components of SHETRAN [24]. Using the 1-D FoS equation for infinite slope, to
determine the frequency of landslides with a shallow depth, to mimic time-space changing soil saturation conditions, the hydrological model was utilised. This takes into account the influence of root cohesion and vegetation.

SHETRAN can model the hydrological response by accounting for spatial variations in land cover and soil parameters. SHETRAN is a hydrological model that now includes a landslide component. Root cohesion is taken into account, but it is usually time invariant. Despite the fact that the model can explain topographic convergence zones in theory but in practical, it is more likely to be used on unconfined debris flows and planar hillslope slides [24]. The SHETRAN model is being used to figure out where the crucial drenched soil depth is expected for a terrain failure to happen. If the time-varying drenched depth surpasses the limitation value during the simulation, the model predicts a landslide. The critical saturated soil depth spatial distribution efficiently offers a map of the failure chances distribution; areas with a higher critical depth have higher failure chances, according to the map, and a high slope angle is thought to be associated with a higher chance of failure [23].

2.1.5. GEOtop-FS. The GEOtop model is a spatially distributed and physically based three-dimensional (3-D) model that calculates the water, energy budgets [24-25]. It simulates unsaturated and saturated subsurface flows, channel flow, surface runoff and stormy fluctuations at the soil-atmosphere interface (e.g., temperature changes, earth temperature, etc.). The inputs of the model comprise maps (DEM, aspect, slope, landcover, soil form), rain, air temperature, and other climatological data are stored in meteorological files (such as relative humidity, wind velocity, shortwave radiation) if available, last but not least, other variables including parameters from Van Genuchten soil water retention curve, residual and saturated water content, numerical parameters for convergence criteria. Key output of the models includes soil suction and ground moisture map, sub-surface water depth maps at different levels, the infinite slope hypothesis is used to compute the FoS component.

The model is designed to work in a distributed environment and it calculates the Safety Factor for each pixel in the watershed, as well as each layer where the soil has been discretized [26].

\[
F = \frac{\tan \varphi'}{\tan \beta} + \frac{2c'}{\gamma z \sin(2\theta)} - \sigma_s \cdot \frac{\tan \theta + \cot \theta}{\gamma z} \cdot \tan \varphi' \tag{8}
\]

Where, \(\sigma_s\) [kPa] is suction stress characteristic curve of the soil defined in eq. (9)

\[
\sigma_s = \begin{cases} 
-(u_a - u_w) & \text{if } (u_a - u_w) \leq 0 \\
\theta_v - \theta_r & \text{if } (u_a - u_w) > 0
\end{cases}
\tag{9}
\]

Soil wetness and pore water pressure multilayer calculation is provided using GEOtop and generates multilayer FoS maps.

2.1.6. Probabilistic Infinite Slope Analysis model (PISA-m). A DEM, maps of forest cover units, geotechnical soil units and data on geotechnical qualities and distributions for each map unit are all inputs into this model. [27]. Using \(\beta\)-PERT, triangular, uniform, and normal distributions [28]. Maps depicting the likelihood that the computed feature of static landslide safety is lower than the threshold value [Prob (FS<1)].

The infinite slope approximation is at the core of PISA-m, and is hence best suited to modelling the incidence of thin landslides in terms of length and width. For a forested infinite slope, the equation for the safety factor (FS) is used to govern the static function of the probabilistic model against sliding [27]

\[
FS = \frac{c_r + c_s + [q_t + \gamma_{mz} + (\gamma_{sat} - \gamma_w - \gamma_m)H_w z] \cos 2\theta \tan \varphi}{[q_t + \gamma_{mz} + (\gamma_{sat} - \gamma_m)H_w z] \sin \theta \cos \theta} \tag{10}
\]
Where, \( q_t \) is tree surcharge, \( \gamma_m, \gamma_{sat} \) are the soil moist and saturated unit weight respectively, \( H_w \) is the pore pressure coefficient.

2.1.7. Saturated Unsaturated Simulation for Hillslope Instability (SUSHI). The SUSHI model features two modules: a geotechnical component (Geo_SUSHI) for assessing slope instability and a hydrological component (Hydro_SUSHI) for investigating sub-soil water movement, with a focus on percolation processes and spatiotemporal changes in porewater pressure [29]–[31]. The Hydro_SUSHI module follows the Richards equation [29], stated as a function of the suction (\( \psi \)). The equation we get:

\[
\frac{\partial}{\partial x} \left[ K(\psi) \frac{\partial \psi}{\partial x} \right] + \frac{\partial}{\partial z} \left[ K(\psi) \frac{\partial \psi}{\partial z} - 1 \right] = C_{SU}(\psi) \frac{\partial \psi}{\partial t} \tag{11}
\]

Where, \( C_{SU}(\psi) \) is a simulation of water flow in both unsaturated and saturated zones, for unsaturated terrain, \( K(\psi) \) is the hydraulic conductivity based on suction.

\[
C_{SU}(\psi) = \frac{\theta}{\eta} S_s + C(\psi) \tag{12}
\]

Where The slope of a soil–water characteristic curve is denoted by \( C(\psi) \).

For unsaturated soils, the Geo SUSHI module employs the Fredlund and Rahardjo slope letdown equation, which is based on well-known General Limit Equilibrium methods.

\[
\tau = c' + (\sigma - u_a)tan \phi' + (u_a - u_w)tan \phi_b \tag{13}
\]

\[
tan \phi_b = \left\{ tan \phi' \left[ \frac{\theta(\psi) - \theta_r}{\theta_s - \theta_r} \right] \right\} \tag{14}
\]

where \( \tau \) is shear strength, \( \phi_b \) denotes the angle expressing the rate of increase in strength due to matric suction, \( \sigma \) is total normal stress and \( \theta(\psi) \) is the water content shown by the suction level (\( \psi \)) retention curve.

The FoS is calculated using the GLE approach, which uses the summation of forces in two directions and moments around a generic point [30]. The FoS is the shear strength parameter reduction required to bring the soil mass into confined equilibrium along the anticipated slip surface.

\[
S_m = \frac{\alpha \tau}{FS} \tag{15}
\]

Where \( S_m \) is the shear force mobilized at the base of the slice, \( \alpha \) is the sloping distance across the base of a slice.

2.1.8. Shallow Landslides Instability Prediction (SLIP). Developed by Montrasio and Valentino [32]. The factor of safety is calculated using a basic physically based model that takes into account the key factors that cause soil slip, such as the quantity of rain, slope geometry, and the condition, soil's mechanical and hydraulic properties. The model's hypotheses were created based on field observations; thus, it can forecast soil slipping in real-world situations. The hypothesis are as follows:

- The top layer of soil is partially saturated, but as you go deeper, the water content increases.
- The sliding surface is displaced in the soil's superficial layer and does not correspond to the soil-bedrock contact.
• The medium grade of slope is substantially bigger than the angle of shear strength of soil and the soil is generally consolidated, according to geometrical medium features. The FoS derived using the limit equilibrium approach, is employed to assess the slope instability [33]. The Mohr-Coulomb strength criteria is used to analyze, stabilizing forces, it addresses the impact of surface saturation on soil cohesiveness, which is a key aspect in the triggering process [33], [34]. The factor of safety can be calculated as:

\[
F_s = \frac{\cot \theta \cdot \tan \varphi' \cdot [\gamma + m \cdot (\eta_w - 1)] + C' \cdot \Omega}{\gamma + m \cdot \eta_w}
\]  

(16)

Where:

\[
y = G_s \cdot (1 - \eta) + \eta \cdot S_r
\]  

(17)

\[
\eta_w = \eta \cdot (1 - S_r)
\]  

(18)

\[
\Omega = \frac{2 \cdot \sin 2 \theta \cdot H \cdot \eta_w}{\gamma + m \cdot \eta_w}
\]  

(19)

\[
C' = [c' + c_\psi] \cdot L = [c' + A \cdot S_r \cdot (1 - S_r) \cdot (1 - m) \cdot \alpha] \cdot L
\]  

(20)

\[
m = \frac{\xi}{\eta H (1 - S_r) \sum_{i=1}^{\omega} h_i \exp[-K_r (t - t_i)]}
\]  

(21)

Symbols in Eqs. (16-21) have following meanings:
The length of the soil slice is L, the saturated proportion of the soil layer in terms of its depth is m, H is the thickness of the potentially unstable layer, S_r is the degree of saturation of the terrain, G_s is the specific weight of the soil, c_\psi is the apparent cohesion given by the unfinished saturation of the surface; A, \alpha and \lambda are limits for numerical calibration, K_r slope’s discharge capacity, \xi is a runoff coefficient, t_i is the time in days to which the rainfall depth h_i resembles; and t is the time.

3. Comparison of models

Paulin et al. [12] used SINMAP model with 30-m, 10-m, 5-m and 1-m DEM and found that 1-m and 5-m maps gave better results than 10-m map and the 30-m map was considered as very less suitable for the prediction of landslide susceptibility analysis. From all the above studies [7-12] it was found that the ability of SINMAP for correctly predicting the unstable slopes depends on the quality of DEM used as input because in case of low resolutions more than 30-m the model fails to mark the unstable locations which shows very small failure and are very shallow.

TRIGRS models is used for numerous slope stability studies throughout the past decade and different researchers used the model under different input parameters. Sarma et al. [21] used input elevation maps with resolution of 1 and 1/3 arc-sec, Tran et al. [20] used a DEM of 1-m resolution and Ciurleo et al. [22] used the DEM with 5-m resolution. So, in the first study all the landslides were mapped correctly and efficiency reaching near to 90% in the second study also all the landslides were mapped good except few small one and it attained an efficiency of almost 85% but in the third study the efficiency dropped below 80% because in a 5-m DEM many shallow landslides were hard to map. It was found that the ability of TRIGRS to correctly model the landslide to be subject to the quality of the input map and the preciseness of the calculated input parameters [19-21].

SHALSTAB is among the oldest physically based slope instability models, Vieira et al. [19] compared the prediction ability of SHALSTAB and TRIGRS under same conditions and it was found that with a 4-m DEM as input both models showed good results but TRIGRS performed comparatively better, this could be due to proper consideration of soil water characteristics and also the effect of water table in slope stability was considered by TRIGRS. Pradhan and Kim [8], Michel et al. [18] compared the landslide susceptibility mapping software SHALSTAB and SINMAP, the result showed that both the models matched the landslide scars but SHALSTAB showed better results than SINMAP. [13-18] used SHALSTAB for slope instability analysis and found that the property of the model to consider uniform spreading of the soil constraints throughout the area of study limits its ability to correctly map
the unstable locations in case of locations with non-uniform variation of geotechnical and hydrological parameters.

Formetta et al. [26] used GEOtop model for slope stability analysis and claimed that this model considers the spatial variation of soil parameters, they studied that this model is based on 3-D Richard equations for stratified soils. They in their study found that the uncertainty of the soil parameters and quality of input maps mainly effects the efficiency of the model.

Two modules make up the SUSHI model for slope stability analysis. Hydro SUSHI is a model for investigating subterranean water circulation based on Richard's equation and Geo SUSHI is based on GLE methods and analyses slope stability using the Fredlund and Rahardjo equation [29]. This model can calculate actual evapotranspiration and its implications on summertime suction levels. [30-31].

Naidu et al. [27] performed slope stability analysis at 3 different locations using the PISA model. In the study they used 3 input maps namely the DEM, NDVI map and the soil map, with NDVI maps as input the effect of root cohesion and tree surcharge can be determined more efficiently with PISA model. Along with these maps this model also required the geotechnical and hydrological parameters of the area like any other slope stability model.

Montrasio et al. [27] used SLIP and TRIGRS model for slope stability analysis and the study area was located in Italy. They studied that SLIP model uses Mohr-Coulomb strength criterion for the calculation of FoS whereas TRIGRS was based on Iverson model and extended Richard’s equation. TRIGRS model was found to be more efficient because TRIGRS considers the pressure due to groundwater head as a function of both vertical and temporal dimensions. Zizzioli et al. [34] compared the model performance of SHALSTAB, SINMAP, TRIGRS and SLIP model. They concluded that SHALSTAB outputs effective rainfall whereas others output stability index and the FoS. The efficiencies of the models were nearly same SINMAP (79%), SHALSTAB (78%), TRIGRS (78%), SLIP (79%).

Zhao et al. [24] studied landslide susceptibility of Darjeeling Himalayas with the help of SHETRAN model. They concluded that SHETRAN model follows a probabilistic approach, the restricted possibility of a landslide occurring was calculated via Bayes' Theorem. The SHETRAN model was shown to be capable of accounting for the effect of foliage on slope instability in terms of evapotranspiration and canopy cover in the study. Abraham et al. [35] used SHETRAN model for slope stability analysis and discussed its limitations, which are, First, all upslope, downslope, and lateral barriers are ignored in the 1-D infinite-slope analysis. Second, a lack of data could hinder the model's capacity to capture local spatial inconsistency in soil characteristics and other factors that cause soil instability; additionally, the DEM's quality and resolution may limit the model's ability to interpretation for topographic controls on land sliding.

4. Discussion

4.1. Models used in landslide susceptibility analysis

Throughout the time span considered for the study (2010-2020) there were various technologies used to determine the susceptibility of a landslide. But as the study is only focused on physically based models there were total 8 models used to fulfil the objective of study, among which TRIGRS was most used model with 54% of studies using TRIGRS, followed by SINMAP (25%), SHALSTAB (14%) and SUSHI, SHETRAN, PISA-m, GEOtop, SLIP combinedly contributing to almost 7% of the studies.
4.2. Input data required
The variety of methodologies and models utilised to assess landslide susceptibility need a large number of data inputs. The cause and kind of landslide, as well as the characteristics of the investigated area, magnitude of the research, availability of data, and the technique utilised, all influence the factor selection [1]. Landslide susceptibility evaluation parameters are classified into four categories: geological, topographical, geotechnical, and ecological aspects [1].

| Model/Input Parameters | SHALSTAB | SINMAP | TRIGRS | SUSHI | GEOtop | PISA | SHETRAN | SLIP |
|------------------------|----------|--------|--------|-------|--------|------|---------|------|
| Soil Depth             | ✔️       | ✔️     | ✔️     | ✔️    | ✔️     | ✔️   | ✔️      | ✔️   |
| Hydraulic Conductivity | ✔️       | ✔️     | ✔️     | ✔️    | ✔️     | ✔️   | ✔️      | ✔️   |
| Transmissivity         | ✔️       | ✔️     | ✔️     | ✔️    | ✔️     | ✔️   | ✔️      | ✔️   |
| Recharge/Rainfall      | ✔️       | ✔️     | ✔️     | ✔️    | ✔️     | ✔️   | ✔️      | ✔️   |
| Effective Cohesion     | ✔️       | ✔️     | ✔️     | ✔️    | ✔️     | ✔️   | ✔️      | ✔️   |
| Internal friction angle| ✔️       | ✔️     | ✔️     | ✔️    | ✔️     | ✔️   | ✔️      | ✔️   |
| Soil Density           | ✔️       | ✔️     | ✔️     | ✔️    | ✔️     | ✔️   | ✔️      | ✔️   |
| Unit weight of soil    | ✔️       | ✔️     | ✔️     | ✔️    | ✔️     | ✔️   | ✔️      | ✔️   |
| Soil Diffusivity       | ✔️       | ✔️     | ✔️     | ✔️    | ✔️     | ✔️   | ✔️      | ✔️   |
| Saturated volumetric water content | ✔️ | ✔️ | ✔️ | ✔️ | ✔️ | ✔️ | ✔️ | ✔️ |

Figure 2. Studies with respect to model used.
Recent studies on landslide susceptibility analysis have considered a total of 25 factors (excluding the DEM) out of which cohesion and internal friction were the most considered limitations with 7 out of 8 models considering, soil depth and hydraulic conductivity were considered by 6 of the 8 models and NDVI index, Evapotranspiration and water table depth were the least considered parameters with only 1 of the 8 models considering each of them (Table 1).

5. Conclusion

The study presents a comparative analysis of various physically based slope stability models used for landslide susceptibility analysis. The study infers that TRIGRS, SHALSTAB and SINMAP contribute to almost 93% of the studies in the past decade, this can be due to their efficiency along with opensource nature and simplicity in implementation as compared to the more advanced GEOtop model. The efficiencies of all these models be contingent on the correctness of input data used for the study (most precisely the quality of DEM), PISA-m and SNE TRAN models are complex to use and have less efficiencies in varying soil conditions as compared to SINMAP, SHALSTAB and TRIGRS. Among all these models GEOtop was the only 3-D model so this model considers the spatial variation of the soil parameters and PISA model is the only model having NDVI map and soil map as input so this model can better explain the effect of tree surcharge and vegetation on slope instability.

Also, among the considered physically based models, internal friction angle and cohesiveness were the maximum considered limits for landslide susceptibility analysis and NDVI, water table depth and evapotranspiration were the least considered parameters. This could be because cohesion and inner
friction are the first parameters affecting the soil strength most and NDVI, water table depth and evaporation being the least used parameters could be because of the complexity in determining these factors for a large area.

Symbols used and their meanings

c_r - Root cohesion

\(c_s\) - Soil cohesion

\(c'\) - Effective cohesion

\(\theta\) - Slope angle

\(\rho_r\) - Wet soil density

\(\rho_w\) - Density of water

\(D_w\) - Vertical height of water table within soil layer

\(\phi\) - Internal friction angle of the soil

\(T\) - Soil Transmissivity

\(w\) - Relative wetness

\(z\) - Soil thickness

\(g\) - Acceleration due to gravity

\(\gamma_w\) - the unit weight of groundwater

\(\gamma_s\) - the soil unit weight

\(\chi\) - Bishop’s effective stress parameter

\(\theta_v\) - Volumetric water content

\(\theta_r\) - Residual water content

\(\theta_s\) - Water content at saturation

\(u_a\) - Pore air pressure

\(u_w\) - Pore water pressure

\(\eta\) - Porosity of soil

FS - Factor of safety

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