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Comparative Studies on Spatial Prediction Models of Rainfall Induced Landslide

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Abstract. Landslide in Kerala are often rainfall triggered, which is not only by high rainfalls over a short period but also by much longer rainfalls that elevate the pore pressure. Commonly, landslide susceptibility maps at district/state level scale are developed using statistical methods failing to take the geotechnical aspects into account. The efficacy of such models is less reliable in Kerala. However, deterministic geotechnical models restrain from addressing the randomness associated with soil properties over an area which is crucial when mapping at large scale. Hence the current study relies on probabilistic approaches to override the limitation. The study, also focuses in considering pore pressure variations by developing a geotechnical landslide model, coded in MATLAB to combine TRIGRS for evaluating the influence of rainfall events with an infinite slope stability model, along with FOSM approach to account for the uncertainties associated with the input geotechnical properties in the soil of the considered regolith thickness. For the validation of the developed method/model, Kottayam district of Kerala is considered as a case study. A comparison between the developed model with existing probabilistic geotechnical landslide models like GIS-TISSA, and a statistically developed model using the Frequency Ratio method is carried out for Koottickal village in Kottayam district.

Keywords: Landslide, FOSM, TRIGRS, Rainfall, Infiltration;

1 Introduction

Significant numbers of studies have been carried out that focus on preparing landslide zones, which indicates areas that are susceptible to landslides. This helps in effective planning of the mitigation activities and resilience improvement measures. In India, Himalayan belts and the Western Ghats are the most landslide prone areas. Comparatively, numerous studies have been conducted in the former than the latter, unfortunately the susceptibility maps that were prepared in several studies could not give reliable estimates of the occurrence of landslides. The existing landslide susceptibility mapping was not found adequate enough to make hazard assessment and mitigation purposes as the models were developed only based on statistical regression methods like Frequency ratio method, logistic regression method etc., without considering the geotechnical properties of the overlying soil. From previous studies, the significance of soil characteristics and slope stability analysis has been proved to be crucial even in the analysis of failure mechanisms of landslides [1]. Most of the rainfall induced landslides are often triggered by building up of pore water pressures in the overlying soil. Hence, it is not wise to neglect the soil properties while preparing a hazard assessment system for landslides.

Under these circumstances, it is necessary to develop a better solution for the problem, wherein more reliable landslide susceptibility maps could be generated. This study focuses on developing a geotechnical landslide susceptibility model which considers the geotechnical properties of the overlying soil addressing the limitation of deterministic slope stability models in accounting for the randomness associated with soil properties over an area using a probabilistic approach. However, the evaluation of transient effects of increased pore water pressure is also crucial in landslide assessment, especially in rainfall-induced slope failure. The developed framework overrides the limitation of existing models by computing the transient pore pressure variation as well as the corresponding changes reflected in the FOS. Kerala State faced the worst flood and landslides after 1924 during the month of August in 2018 and 2019. Almost all parts of the state, except the north and south ends has got affected by this natural calamity. 4728 landslides were triggered in the state, killing over 45 people in the year 2018 and the Puthumala and Kavalappara landslides in 2019 killed over 75 people. In the year 2020, the state witnessed the most catastrophic landslide in Pettimudi taking 70 lives [2]. The most recent landslide was the one happened near Koottickal in Kottayam district in 2021 October. Hence the applicability of the model is tested in Kottayam district of Kerala based on the landslides occurred in Koottickal village in 2021.

2 Methodology

Initially, based on the location of the landslide events acquired from several landslide assessment reports of Kerala till the year 2020 from the database of the Geological Survey of India, a landslide inventory was prepared for Kottayam district. The inventory is used as the training data set for the statistical landslide susceptibility map using a bivariate regression method called Frequency Ratio (FR) method. To have a thorough comparison between the statistical landslide susceptibility model and the geotechnical slope susceptibility model, the recent landslides in Koottickal village of Kottayam district, was taken as a case study. A total of 5 different susceptibility models are developed in this study, out of which 2 models are deterministic and other 2 are probabilistic, both with and without considering the effect of rainfall. The schematic diagram of the work flow is given in figure 1.

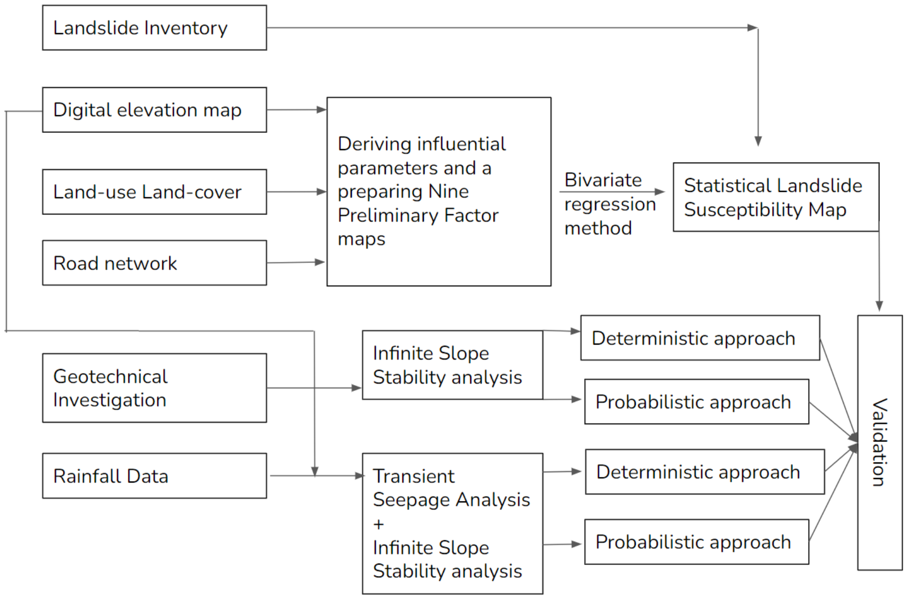

Fig. 1. Work flow of the study

3 Susceptibility Models

3.1 Statistical Landslide Susceptibility Model

For the statistical model, the extracted Digital Elevation Map (DEM) parameters include the slope of the terrain, aspect of the slope, hill shade, and distance to the water drain path. Other considered parameters which include road distance proximity, and land use land cover data. A total of 9 parameters were used to formulate the preliminary landslide susceptibility map. The dependency of landslide occurrence area upon the landslide influencing parameters was established by estimating a ratio of the areas where landslides had and had not occurred with respect to total areas of each sub-class landslide influencing parameter. To identify the influence of the input parameters, a bivariate regression method called frequency ratio (FR) method was adopted across the entire district of Kottayam. The FR model categorized input parameters into different classes and assigns weightages to it on the basis of the influence of each class of input parameters in predicting the occurrence of the landslide. The weightages are calculated as a ratio between the percentage of landslide occurrence pixels of a specific class of a particular influence parameter divided by the percentage of total pixels in a specific class of the particular influence parameter. The ratio is termed as frequency ratio and gives a level of dependency of the parameter to the occurrence of the landslide. ArcGIS tools were used to count the number of pixels in each class of an influence parameter and the number of landslide pixels were counted by overlapping the past landslide points over the factor maps. A larger value closer to unity suggests a stronger correlation between landslide points in the past and each parameter than a lower value. FR is calculated as follows:

$$FR = \frac{(ij)/_{\sum PixL}}{P(ij)/_{\sum Pix}} \tag{1}$$

where,

(ij) number of pixels with landslide within class i of j parameter,
P(ij) Number of pixels in class i of j parameter,
∑PixL total pixel of j parameter with landslide, and
∑Pix total pixel of the area

The landslide susceptibility map for the entire state is developed in terms of Landslide Susceptibility Indexes (LSI). LSI denotes the extends to which an area is susceptible for the occurrence of a landslide. For formulating the map based on LSI, the FR of each landslide influence parameter map were added up as:

$$\text{LSI} = FR_1 + FR_2 + \ldots FR_n \tag{2}$$

where,

FR_1, FR_2, FR_3… FR_n are the frequency ratios of landslide influence parameter maps.

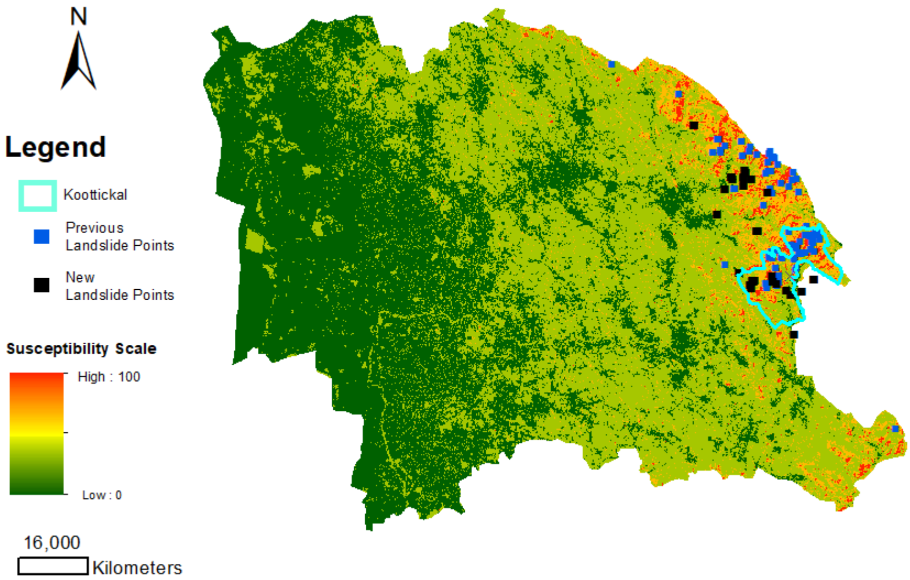

Fig. 2. Kottayam District landslide susceptibility map using FR method

The developed summation map with the index values was then reclassified to be expressed in percentage (0 to 100%) to get the susceptibility map of Kottayam district shown in figure 2. The LSI values closer to 100% denote maximum susceptible regions and lower values represents regions less or not prone to landslides. The map was clipped into the region of interest in the Koottickal village of Kottayam, for further comparison studies.

3.2 Infinite Slope Stability Analyses

The landslide susceptibility map developed running several infinite slope stability analyses implicitly takes into account the soil properties of the region. Several tools and software like ArcGIS, MATLAB, Probabilistic Infinite Slope Analysis Model (PISA-m) [3], GIS-TISSA (GIS-Tool for Infinite Slope Stability Analysis) [4] were explored for developing a methodology by which deterministic and probabilistic slope stability analysis could be carried out on such large DEM data. In infinite slope stability analyses the stability is estimated in terms of a ratio between the resisting force upon the force destabilizing the slope. This ratio is called the factor of safety (FOS). A value of FOS greater than unity represents a stable slope and that less than unity is an unstable slope. When FOS is equal to unity it indicates that the slope is at the limit of equilibrium. The main input parameters considered for the infinite slope stabilities are the geotechnical, hydraulic and slope terrain characteristics. These includes cohesion and angle of internal friction, saturated and unsaturated weights of the soil, depth of water table, slope inclination and soil depth. Moreover, the PISA-m model includes root cohesion as a factor to consider the effect of additional overburden stress and resisting strength provided by the roots of vegetative cover [4]. The model is defined as follows:

$$FOS = \frac{C_r + C_s + [qt + \Upsilon_m D + (\Upsilon_{sat} - \Upsilon_w - \Upsilon_m) H_w D] cos2\beta tan\Phi}{[qt + \Upsilon_m D + (\Upsilon_{sat} - \Upsilon_w - \Upsilon_m) H_w D] sin\beta cos\beta} \tag{3}$$

where,

C_r is the contribution to the soil cohesive strength from the roots when vegetation is present
C_s is the soil cohesive strength qt is the vegetation weight added to the slope (the surcharge)
γ_m is the unsaturated (moist, above the phreatic surface) soil unit weight
γ_{sat} is the saturated (under the phreatic surface) soil unit weight
γ_w is the water unit weight, a constant equal to 9810 N/m^3 in SI units,
D is the depth of the slip surface
H_w is the height of the phreatic surface above slip surface,
normalized relative to soil thickness (dimensionless varies from 0 to 1)
β is the terrain slope
ϕ is the internal friction angle of the soil

The infinite slope model in Eq. (3) examines the conditions under which a slope is prone to be unstable. The conditions are evaluated in terms of the geotechnical characteristics, ground water and soil depth levels, slope inclination, and vegetations. This forms the basic equation of the deterministic infinite slope stability model. As the area of interest is relatively large, the estimation of uncertainty within the considered parameters are also significant, hence a probabilistic approach is found necessary. In this regards, First Order Second Moment (FOSM) method was used in the infinite model to account for the uncertainties. FOSM is based on the Taylor series expansion [3] and the uncertainties in soil properties are fed in terms of their mean value and corresponding standard deviations. The mean and variance of the output FOS is computed using Eq. (4) and Eq. (5) respectively.

$$\overline{FOS} = FOS(\overline{\mathrm{x}}) \tag{4}$$

where,

$\overline{FOS}$ is the mean estimation of the factor of safety

FOS is the factor of safety calculation function as defined by Eq. (3)

$\overline{\mathrm{x}}$ is the set of mean values for the input variables in Eq. (3)

$$(\sigma_{FOS})^2 = \sum_i (\frac{\delta(FOS)}{\delta(x_i)})\,(\sigma_{xi})^2 \quad (5)$$

where,

σ_{FOS} is the standard deviation of FOS

$\partial(FOS)/\partial(x_i)$ are the partial derivative of FOS, given by Eq. (3), with respect to any of the input variables x_i

σ_{xi} are the estimates of the standard deviation for all the input variables x_i

The GIS-TISSA allows manual input of the parameters as factor maps. For the probabilistic model, the factor maps for all the parameters listed in Eq. (3) were generated for different probability distributions. The factor maps represent the variations in the values within an input parameter spread over the spatial area. However, these levels of detail are in general more accurate than assuming the geotechnical characteristics as on value in a deterministic manner. The soil properties were approximated with the help of the results from field visits, various literature and soil map data available in the Department of Soil Survey and Soil Conservation, Kerala. The soil properties considered are tabulated in Table 1. From the basis of various probabilistic studies, all the random parameters were assumed to follow normal distribution [5]. The cohesion was varied from 0 kPa to 10 kPa, and the angle of internal friction was varied from 28 to 33 degrees. The cohesion contributed by vegetation roots was computed by Huang et al. (2006) [4] model. Soil and water table depth were assumed based on previous literatures of corresponding areas. Geo-statistic interpolation methods like IDW were used to assign values at areas with no data across the spatial domain.

Table 1. Input Parameters of landslide models used for case study

Parameters	Value ranges	Units
α	10.2	
Initial infiltration rate	9.5e-08	m/s
Cohesion	0 to 10	kPa
Diffusivity	8e-07	m^2/s
Friction angle	28 to 32	degrees
Minimum slope	5	degrees
Residual water content	0.05	
Saturated conductivity	1.55e-06	m/s
Saturated water content	0.225	
Soil thickness	0 to 5	m
Unit weight	17	kN/m^3
Water table depth	>1.0	m

One of the main limitations in the PISA-m algorithm is that it does not explicitly consider the transient effect of increase in pore water pressure due to rainfall. However, explicit consideration of static effect of shallow water table is included. The latter is made possible by the incorporation of infiltration models, for instance the Transient

Rainfall Infiltration and Grid-Based Regional Slope Stability (TRIGRS) [7] which is explored as another case study in Koottickal village, detailed in the next section.

3.3 Infinite Slope Stability Analysis coupled with Transient Seepage Analysis

The study uses a Fortran program, TRIGRS to model the distribution of increase in pore pressure due to a series of different intervals/intensities of rainfalls. This study put forwards a generic improved framework for slope stability assessment over a large topographical area using DEM, considering the influence of rainfall infiltration and the uncertainties associated with soil properties. TRIGRS uses the analytical solutions for Richards' one-dimensional (1D) partial differential equation representing the vertical subsurface flow in vertically isotropic and homogeneous material [7].

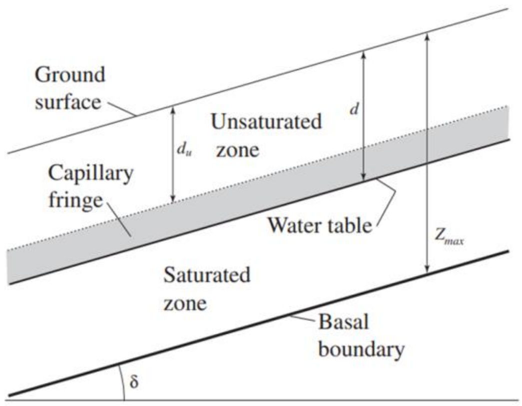

Fig. 3. Schematic representation of an infinite slope in TRIGRS [7]

The one-dimensional Richards equation that is applied for the simulation of the vertically rainfall infiltration through an unsaturated layer from the ground level is:

$$\frac{\partial\theta}{\partial t} = \frac{\partial}{\partial Z}\left[K(\psi)\left(\frac{1}{cos^2\delta}\frac{\partial\psi}{\partial Z} - 1\right)\right] \tag{7}$$

where,
Z is the vertical downward coordinate
t is the time
θ(Z, t) is the soil water content
ψ(Z, t) is the pore pressure
K(ψ) is the hydraulic conductivity and
∂ is the ground slope surface

For the Infiltration, Runoff and Flow Routing calculations, the infiltration at each cell of the domain, Infiltration (I) can be calculated from the precipitation rate (P) and runoff from the adjacent cells in the upslopes (Ru), till I is within the value of hydraulic conductivity (Ks)

$$I = P + R_u \ if \ \ P + R_u \leq \ K_s \tag{8}$$
$$I = K_s \qquad if \quad P + R_u \geq \ K_s \tag{9}$$

If the rainfall and the given runoff values of the neighboring cells is greater than the infiltrability, the runoff, Rd is diverted to neighboring cells in the downslopes.

$$R_d = P + R_u - K_s \qquad if \ \ P + R_u - \ K_s \geq 0 \tag{10}$$
$$R_d = 0 \qquad if \ \ P + R_u - \ K_s < 0 \tag{11}$$

For the case study, the rainfall data from August 2018 was used, acquired from IMD database. From estimating the pressure head, the infinite slope stability analysis was done by making use of the equation proposed by Iverson (2000). The properties of soil were taken similar to that of the previous model, listed in Table 1. The factor of safety FOS is deterministically calculated on cell-by-cell basis at an arbitrary depth Z using following formula:

$$S(Z,t) = \frac{tan\varphi'}{tan\delta} + \frac{c' - \psi(Z,t)\gamma_w tan\varphi'}{\gamma_s Z sin\delta cos\delta} \tag{12}$$

where,

ϕ' is the soil friction angle for effective stress;
c' is the soil cohesion for effective stress;
γ_s and γ_w are the soil unit weight and the unit weight of groundwater, respectively;
ψ(Z, t) is the pressure head as a function of time t and of depth Z; and
δ is the slope angle

MATLAB coding has been done to get the S(Z,t) values. The code was extended beyond the existing capability of TRIGRS to account for the uncertainties in soil properties, making use of FOSM probabilistic approach. The mean and the variance of the FOS was estimated using eq. (3) and eq. (4) in section 3.2. Thus, the probability of failure of slope was calculated as follows:

$$P_f = Prob(FS \leq 1) \tag{13}$$

The developed model, hence combines TRIGRS for evaluating the influence of rainfall events with an infinite slope stability model coupled with FOSM on accounting for the uncertainties associated with the input geotechnical properties in the soil of the considered regolith thickness. Thus, the analysis output fetched by the developed geotechnical landslide susceptibility model includes:

- Transient pore water pressure variation
- Mean value and variance estimate of the FOS;
- Probability of failure (pf) termed as the probability of FOS < 1

The developed geotechnical landslide susceptibility is be validated and compared against and already developed statistical landslide susceptibility model, to quantify its efficacy.

4 Results and Discussion

In 2021 monsoon, numerous landslides occurred in Koottickal village of Kottayam district which cover an area of 32.1 km^2. These landslide points were identified and plotted by a series of field visit. Figure 4 shows the Koottickal village, the darkened region is the area of village and the red polygons are the identified landslide points in 2020 and the blue points are the recent 2021 landslide points. The recently located landslide points are used as the testing database for the validation of different landslide susceptibility models developed for the area of concern.

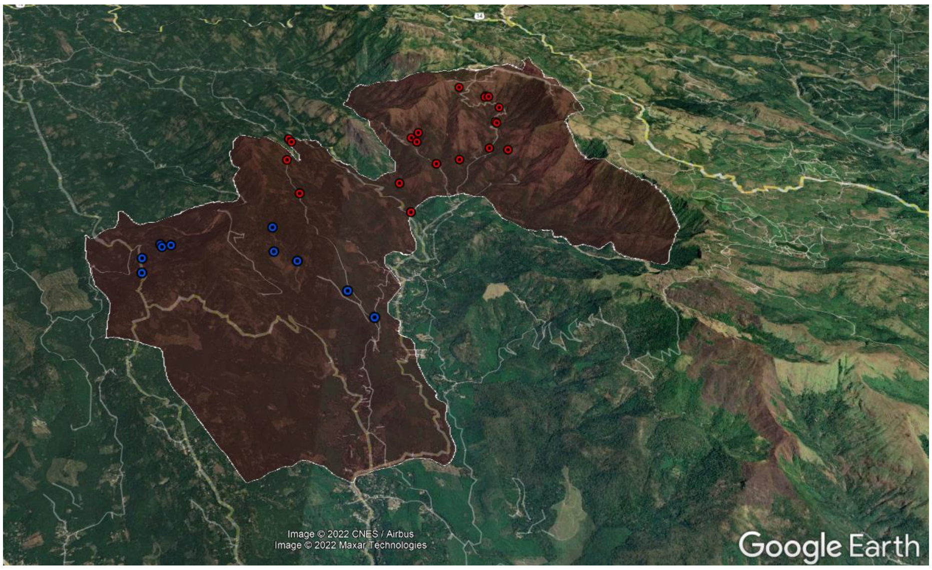

Fig. 4. Koottickal village in Kottayam, Kerala with past and recent landslide points

All the five landslide susceptibility models developed using different approaches are illustrated below in fig. 5. For the comparison of the generated models, a statistical technique used for validation of results, Receiver Operating Characteristic curve (ROC) is used. The generated Area Under Curve (AUC) of the ROC, shows the reliability of the model used. Accordingly, values ranging from 0.5 to 1 indicate that the model is correct; values < 0.5 indicate a random fit [8]. For the study the ROC was generated and AUC was calculated using a python coded ArcGIS tool [9], which used 10000 Monte Carlo iterations. The results of the susceptibility maps are shown in figure 6 and 7.

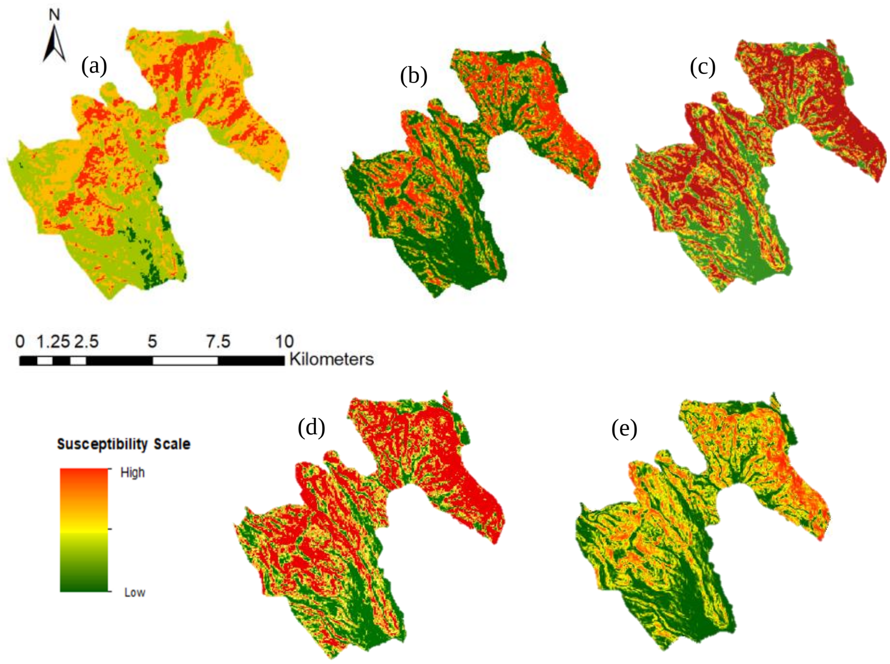

Fig. 5. (a) Statistical landslide susceptibility map; (b) FOS Map using deterministic approach of GIS-TISSA (c) FOS Map using TRIGRS (d) pf Map using probabilistic approach of GIS-TISSA (e) pf Map using TRIGRS coupled with FOSM method

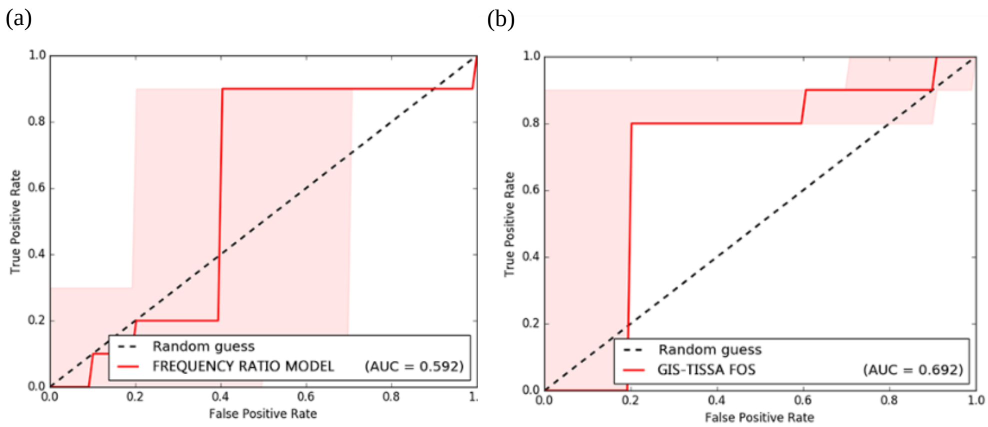

Fig. 6. ROC - AUC of (a) Statistical landslide susceptibility map; (b) Factor of Safety Map using deterministic approach of GIS-TISSA

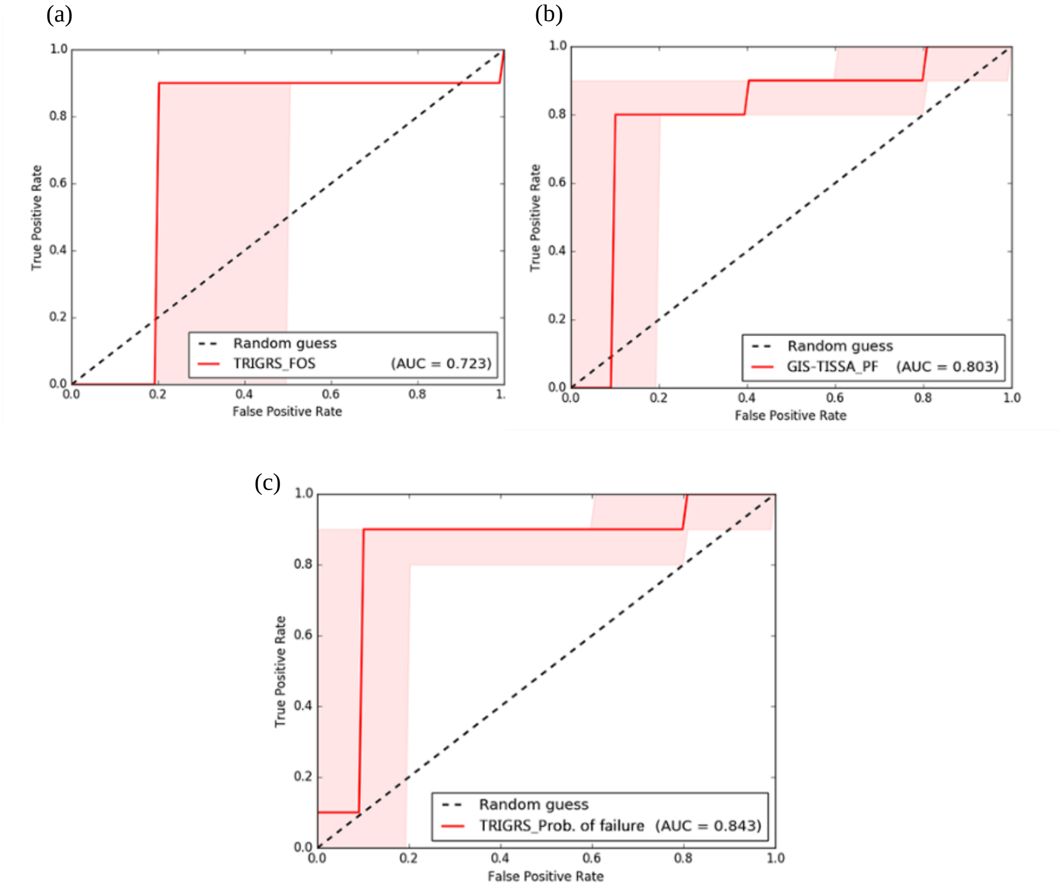

Fig. 7. ROC - AUC of (a) Factor of Safety Map using TRIGRS (b) Probability of Failure Map using probabilistic approach of GIS-TISSA (c) Probability of Failure Map using TRIGRS coupled with FOSM probabilistic approach

5 Conclusions

In this paper, a thorough comparison between the statistical model and the geotechnical models was made possible by considering the same DEM data. The geotechnical model used included mainly 2 tools, GIS-TISSA and TRIGRS. The results highlighted the fact that the statistical models are less accurate than the geotechnical landslide susceptibility model. As per the finding, the prediction capacity of geotechnical models showed improvement over the statistical model by a minimum of 17% in the Koottickal village region. Also, the frequency ratio-based model resulted in non-conservative results which is not a viable option to be considered for hazard risk and mitigation purposes. All the geotechnical models gave conservative results compared to the statistical model.

However, on comparison between the two geotechnical models, the transient seepage analysis could refine the infinite slope stability prediction value at least by 4% in both deterministic and probabilistic models. The probabilistic models gave AUC values greater than its deterministic counterpart models, by about 14-16%. These high improvements in accuracy underlines the need to account for uncertainty in such regional level slope stability models. Moreover, the results collectively suggest the probabilistic approach of the TRIGRS model as the best model for rainfall induced susceptible landslide regions, like Kerala. However, as the model was only been validated in a small region, it will be extended over larger domains, like an entire district or a state to give conclusive findings and performance results.

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