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ORIGINAL ARTICLE

Estimation of Rainfall-Induced Landslides Using the TRIGRS Model

Abhirup Dikshit[1,2] · Neelima Satyam[1] · Biswajeet Pradhan[2]

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Abstract

Rainfall-induced landslides have become the biggest threat in the Indian Himalayas and their increasing frequency has led to serious calamities. Several models have been built using various rainfall characteristics to determine the minimum rainfall amount for landslide occurrences. The utilisation of such models depends on the quality of available landslide and rainfall data. However, these models do not consider the effect of local soil, geology, hydrology and topography, which varies spatially. This study is to analyse the triggering process for shallow landslides using physical-based models for the Indian Himalayan region. This research focuses on the utilisation and dependability of physical models in the Kalimpong area of Darjeeling Himalayas, India. The approach utilised the transient rainfall infiltration and grid-based regional slope-stability (TRIGRS) model, which is a widely used model in assessing the variations in pore water pressure and determining the change in the factor of safety. TRIGRS uses an infinite slope model to calculate the change in the factor of safety for every pixel. Moreover, TRIGRS is used to compare historical rainfall scenarios with available landslide database. This study selected the rainfall event from 30th June to 1st July 2015 as input for calibration because the amount of rainfall in this period was higher than the monthly average and caused 18 landslides. TRIGRS depicted variations in the factor of safety with duration before, during and after the heavy rainfall event in 2015. This study further analysed the landslide event and evaluated the predictive capability using receiver operating characteristics. The model was able to successfully predict 71.65% of stable pixels after the landslide event, however, the availability of more datasets such as hourly rainfall, accurate time of landslide event would further improve the results. The results from this study could be replicated and used in other unstable Indian Himalayan regions to establish an operational landslide early warning system.

Keywords Shallow landslides · Physical models · GIS · Rainfall threshold · Kalimpong

1 Introduction

Precipitation is the main triggering factor behind the majority of landslides in India. Indian Himalayan locales have been generally affected because of the increasing recurrence of landslides. Approximately 30% of landslide occurrences worldwide happen in the Himalayan area, whilst 42% of India's landslide region is located in the north-west Himalayas including Darjeeling–Sikkim Himalayas (Dikshit and Satyam 2018). The immense economic and human life damage caused by landslides necessitates the development of methods that will minimise the effects of this type of disaster. The Kalimpong region, which is part of Darjeeling Himalayas, receives approximately 85% of the annual rainfall during the monsoon season. Ghosh et al. (2016) indicated that approximately 76% of landslide incidents have been triggered by rainfall. Therefore, the relations between landslide occurrences and rainfall conditions, primarily in the Kalimpong area, should be understood. The physical (Baum et al. 2002, 2008) and empirical (Guzzetti et al. 2007, 2008; Althuwaynee et al. 2015) methods are mainly used to understand this relationship. The physical-based methods are based on numerical models and are used to study the relationship among rainfall, pore water pressure, soil type and volumetric water content that can lead to slope instability. By contrast, empirical methods are used to study

✉ Biswajeet Pradhan
biswajeet.pradhan@uts.edu.au; biswajeet24@gmail.com

[1] Discipline of Civil Engineering, Indian Institute of Technology Indore, Indore 453552, India

[2] Centre for Advanced Modelling and Geospatial Information Systems (CAMGIS), Faculty of Engineering and Information Technology, University of Technology Sydney, Sydney, NSW 2007, Australia

landslides caused by rainfall events, particularly heavy downpour that triggers instantaneous landslides and low but continuous antecedent rain that destabilises the slope and triggers landslide. Empirical methods are used to calculate thresholds that, when exceeded, trigger landslides (Segoni et al. 2018; Dikshit et al. 2019). The calculation of several type of thresholds has been successfully achieved for several Indian Himalayan regions (e.g., Sengupta et al. 2010 for North Sikkim; Kanungo and Sharma 2014 for Chamoli, Uttarakhand; Dikshit and Satyam 2018, 2019; Teja et al. 2019 for Kalimpong). However, the accuracy of these thresholds substantially decreases owing to spatial variations in the soil, hydrological and topographic parameters and the availability of data, thereby eventually affecting slope failure (Schilirò et al. 2015).

The problems associated with the empirical rainfall threshold method led to the development of physical (process-based) models (Baum et al. 2002, 2008). Physical process-based models depend on physical laws, which control slope stability and spatially extend using the widely accepted stability models. The models use spatial-related factor attributes, such as slope gradient, soil depth and shear resistance, to predict the amount of rainfall that will cause landslides in a particular area and the time of triggering (Baum et al. 2002; Schilirò et al. 2015). Stability conditions are assessed using the static stability model, which considers the local equilibrium conditions along the potential slip surface. Although several physical models have been developed and used globally, the current study analyses the transient rainfall infiltration and grid-based regional slope-stability (TRIGRS) model because of its robustness and consistent accuracy (Kim et al. 2010). Only a few physical process-based studies have been conducted for major landslide zones in the Indian region. Kuriakose et al. (2009) determined the feasibility of a physical model using the coupled hydrologic and stability model (STAR WARS, PROBSTAB) in Kerala, India. Weidner et al. (2018) studied the relation between critical rainfall and antecedent pore pressure using TRIGRS for the hazard assessment of regions with limited data availability.

In the context of the Indian Himalayan region, the study on rainfall-induced landslides has primarily been on threshold estimation. Few studies have also been conducted to understand landslide risk and developing hazard map using GIS techniques (Surendranath et al. 2008; Ghosh et al. 2012). However, the applicability of physical-based models is yet to be tested in this region. This study is an attempt to understand and test a physical-based approach using TRIGRS model for Kalimpong situated in Darjeeling Himalayas. The results show that the model could be used as a preliminary technique for a warning system and can be further improved upon the availability of more extensive data.

2 Study Area and Data

The study area is Kalimpong (87.47–89.47N, 26.07–28.07E), which is situated in Darjeeling Himalayas, India (see Fig. 1). This area is surrounded by the Relli and Teesta rivers in the east and west, respectively. The elevation of the region ranges from 400 to 1665 m, with 70% of the area having an elevation of over 1000 m. Geologically, Darjeeling–Sikkim Himalayas comprises intra-thrusted rock slices of the fold-thrust belt (FTB) of the eastern Himalayas. This area represents convoluted geological and tectonic milieu, in which rocks from the Precambrian to the Quaternary ages are compared along a specific EW trending tertiary provincial thrust (Mukherjee and Mitra 2001; Ghoshal et al. 2008). Along the Himalayan foothills in the south, coarse to extremely coarse-grained clastics (i.e. conglomerate–sandstone–siltstone) of the Siwalik group are exposed and separated by a frontal thrust (Himalayan foothill or frontal thrust) from the adjoining Quaternary sediments of the foredeep region in the further south. The considerably coarse clastics of the Siwalik group towards the north are thrusted over by the sandstone–shale sequence of the Gondwana along the main boundary thrust (Dikshit and Satyam 2018). The rocks are fluidly adjusted and generally secured by thin to thick heterogeneous debris. The study area has rock types comprising banded gneisses, schist, sandstone with shale, valley fill sediments and younger alluvium of age varying from the Archaean to the Quaternary (West Bengal Water Resource Investigation and Development Department) (see Fig. 3).

A comprehensive field study was conducted in October 2016 to understand the effects of landslide damage on the region. The investigation included measuring the changes in distance between crack walls using tapes and wire devices and collection of disturbed soil samples. This field study showed that apart from receiving a huge amount of rainfall, the area is severely drained by numerous natural mountain streams (kholas) and their tributaries (jhoras), thereby further escalating the existing landslide problem. The water in mountain rivulets is fed from an ample number of perennial outflows present around the crest of the hill (Rao 2009). These streams have increased the sinking areas and played an important part in landslide occurrence in the region. Apart from the aforementioned factors, lithology, erosion of the Teesta River and its tributaries also contribute to landslides.

Figure 2 represents the rainfall data from 2010 to 2016 in a box and whisker plot. The top and bottom of the rectangular boxes are the 75th and 25th percentiles, respectively, whilst the red horizontal lines inside the boxes are the 50th percentiles. The whiskers depict 1.5 times the

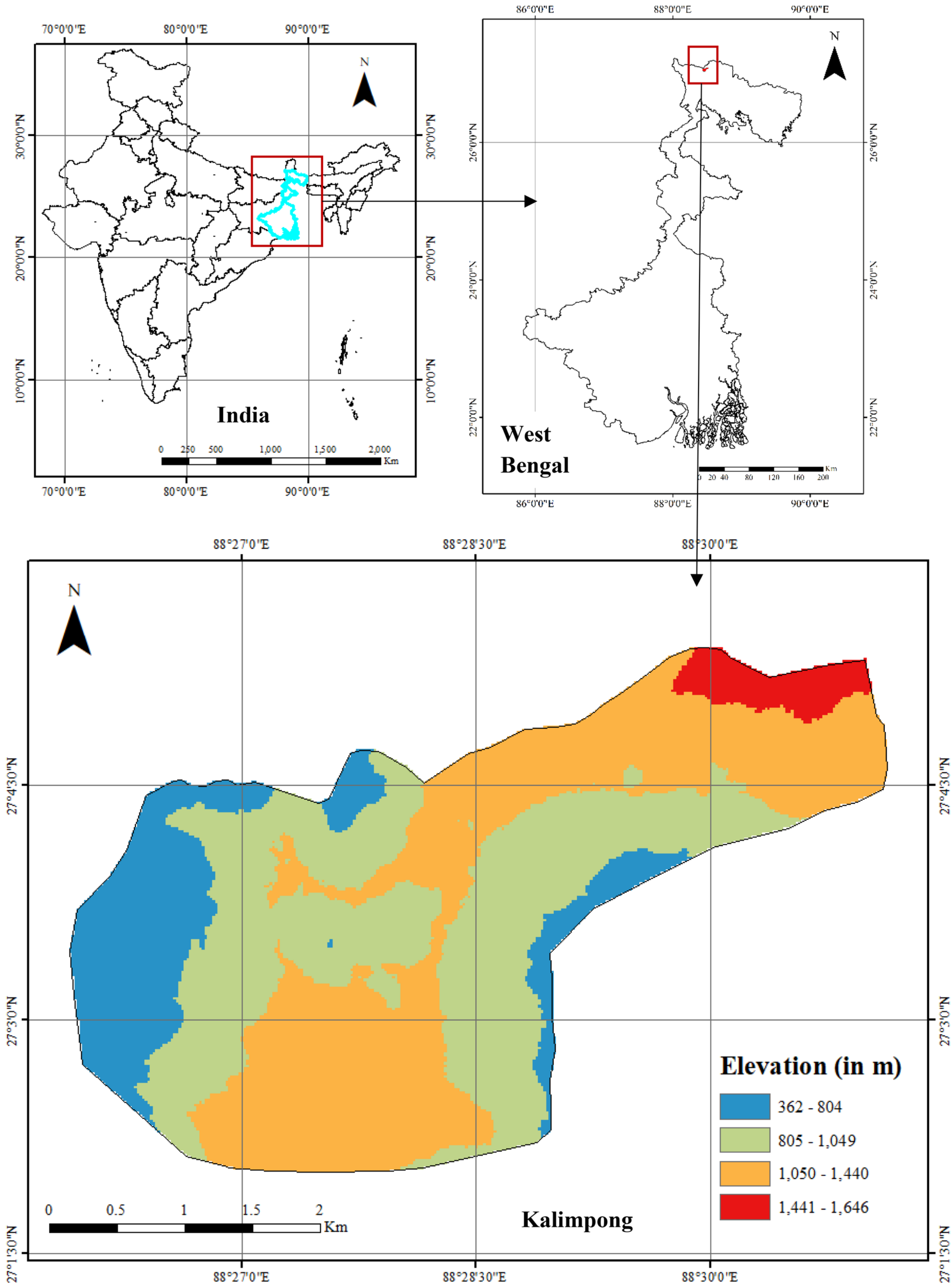


Fig. 1 Location map of the study region

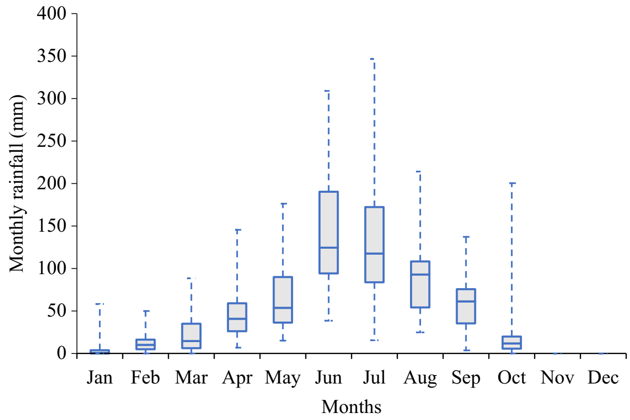


Fig. 2 Box and whisker plots showing the annual variation of monthly rainfall measures in Kalimpong (2010–2016)

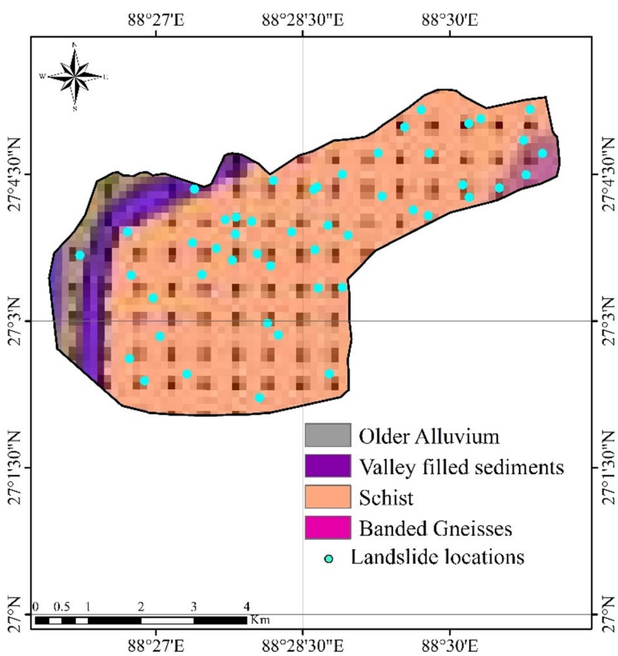


Fig. 3 Hydrogeological map of the Kalimpong region overlayered with the landslide locations

interquartile range (IQR). Monsoon rainfall contributed 85% of the annual rainfall, with the most rainfall occurring in 2015. The majority of the landslides in the area are triggered between June and September, with some prominent and major landslide events in between, because of the high monsoonal precipitation. The occurrence of such a rainfall pattern emphasises that rainfall plays an important role in triggering landslides in Kalimpong. The rainfall pattern is primarily for a short duration with intermittent intense bursts of rain, thereby making the soil loose, which leads to particle disintegration and slope instability (Chatterjee 2010).

The majority of the landslides in Kalimpong are triggered by intense rainfall and improper drainage system (Dikshit et al. 2018a). The region has suffered from over 100 major landslides from 2006 to 2013, approximately 75% of which have been triggered by rainfall (Dikshit et al. 2018b). Figure 3 shows the hydrogeological map of the region overlayered with landslide occurrences from 2010 to 2016. The landslide points are mapped as a single point for multiple occurrences on the same day. The field survey also suggested that the majority of the landslides are translational which has also been identified by Geological Survey of India, GSI. The slope-forming material mainly comprises phyllites, quartzite or schist. The types of landslides in the region based on the distribution of Cruden and Varnes (1996) and identified by GSI are rock fall, rock slide, debris flow, debris slide and earth slide.

Figure 4a shows the damage alongside the NH-31A road, whilst 4b shows the damage of a culvert, which is primarily caused by the presence of rivulets. The damage is the result of monsoonal rainfall and aggravated thereafter by the jhoras.

3 Description of the TRIGRS Model

The TRIGRS model is used to determine infinite slope stability for pore-pressure changes concerning rainfall infiltration (see Fig. 5). The failure of an infinite slope is defined as the ratio of the resisting friction to the gravitationally triggered downslope stress (Kim et al. 2010). The model computes a variety in pore water weight and compares the distinction in the factor of safety because of infiltration. The factor of safety (F_s) is evaluated by adopting an infinite slope model for every cell. The modelling of infiltration caused by rainfall considers precipitation varying from few hours to days and is carried out by utilising an analytical solution of differential equations considering one-dimensional vertical flow in homogeneous materials (Schilirò et al. 2015). The factor of safety is determined as follows:

$$F_s(Z,t) = \frac{\tan\varphi'}{\tan\delta} + \frac{c' - \psi(Z,t)\gamma_w \tan\varphi'}{\gamma_s Z \sin\delta\cos\delta}, \tag{1}$$

where c' and ψ are the effective cohesion and pore water pressure, respectively, at depth Z; ϕ' is the friction angle of the soil, γ_w is the unit volume weight of water, γ_s is the unit weight of soil and δ is the slope angle.

The infiltration models in TRIGRS are based on the linearised solution in Iverson (2000) and extensions to Richard's equation in Baum et al. (2002). The one-dimensional vertical flow of Richards equation is solved using the most recognised numerical model, namely, HYDRUS-1D (Šimunek et al. 1998):

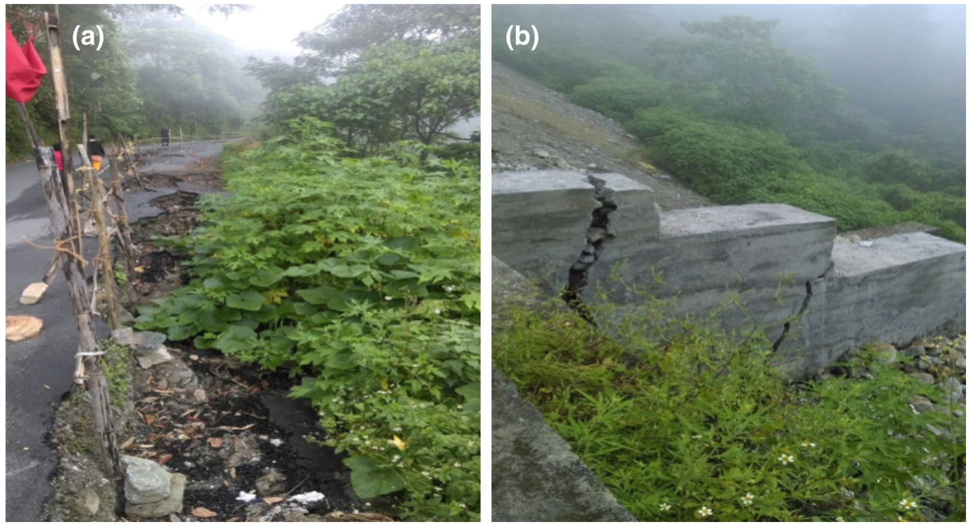


Fig. 4 Landslide damage observed during field study in October 2016

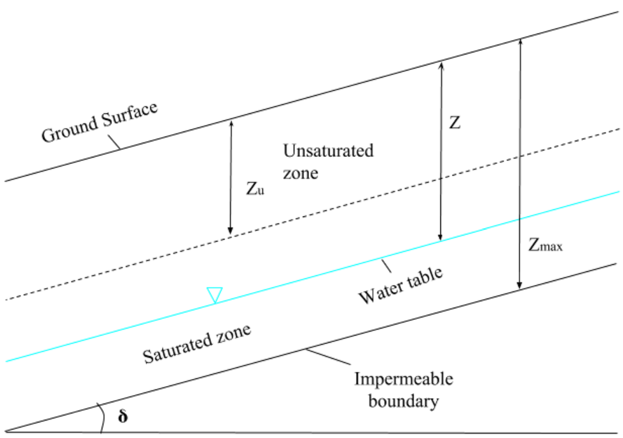


Fig. 5 Conceptual diagram of the TRIGRS model based on infinite slope stability (modified from Baum et al. 2008)

$$\frac{\delta \upsilon}{\delta t} = \frac{\delta}{\delta z}\left[K(\vartheta)\left(\frac{\delta \psi}{\delta z} - \cos \delta\right)\right] - S, \tag{2}$$

where K is the unsaturated hydraulic conductivity, which is provided as follows:

$$K(\psi, Z) = K_s(z) K_r(\Psi, Z), \tag{3}$$

where K_s and K_r are the saturated hydraulic and residual hydraulic conductivities, respectively.

The estimation of soil hydraulic parameters for water flow simulation was conducted using the van Genuchten–Mualem model. This model utilises four different hydrodynamic parameters to linearise Richards' equation in Gardner (1958): saturated (θ_s) and residual (θ_r) water content, saturated hydraulic conductivity (K_s) and a parameter associated with pore size distribution (α_G). The hydrodynamic properties are predicted through ROSETTA Lite module (Schaap et al. 2001) using soil grain size distribution (see Table 1). The module uses daily rainfall data as input and evapotranspiration is determined using the highest and lowest temperature recorded during the study period into the Hargreaves equation (Jensen et al. 1997). Apart from the hydrodynamic parameters, the model input parameters include geotechnical parameters (unit weight γ, cohesion c and friction angle φ), hydraulic diffusivity, initial water table depth and rainfall rate. The model simulates the water table increment when the percolating water surpasses the maximum amount that can be drained by gravity. The infinite slope reaches a limit equilibrium state for the factor of safety equal to 1. Similarly, the infinite slope reaches the unstable and stable state for factors of safety under and over 1, respectively. Thus, the depth of landslide initiation will be the depth where the factor of safety first reaches 1 (Kim et al. 2010). The model utilises a simple surface runoff routing method for pixels with excessive surface water, which can either infiltrate or flow downstream. The summation of precipitation and runoff from the upstream pixels is called infiltration for every pixel. However, infiltration should not exceed the saturated hydraulic conductivity. Excessive water,

Table 1 Hydrodynamic and geotechnical properties considered for the analysis

Parameters	Values
Saturated water content (θ_s)	0.3962
Residual water content (θ_r)	0.0779
Hydraulic parameter (α_G)	2.71 m^{-1}
Saturated hydraulic conductivity (K_s)	1.32×10^{-5} m/s
Cohesion (c)	0.65 kN/m^2
Unit weight (γ)	17.24 kN/m^3
Friction angle (φ)	30°

which could not infiltrate at its pixel, should flow towards the adjacent downstream pixels within a given period. Baum et al. (2002, 2008) described the details of the model.

3.1 Application of TRIGRS

The first part consisted of cataloguing landslides with the location and date of triggering based on the records maintained by GSI, local newspapers and an NGO (Save The Hills). The event on July 1st 2015, which was chosen for calibrating the model, triggered 18 landslides in the region with a rainfall of 226 mm. The landslide resulted in the death of 38 people and the immense destruction of road network, infrastructure, and land. Figure 6 shows the landslide locations and sample of the damage resulting from the landslide.

An extensive survey of the region was conducted in October 2016 and soil samples were collected from the landslide locations (see in Fig. 6). Geotechnical parameters (c, γ, φ) were determined using the collected samples from the field. Table 1 presents the input value of the hydrodynamic and geotechnical parameters considered for this study. The soil thickness of the region is assumed to be 1.5 m (Water Resource Investigation and Development Department, West Bengal). The input parameters were fed into the TRIGRS model and the factor of safety for every pixel was determined.

The results were applied for the 2015 monsoon season, whilst the predictive capability of the model was calculated using the receiver operating characteristic (ROC) method. Back analysis for monsoons between 2010 and 2014, except 2011 (earthquake-induced landslide

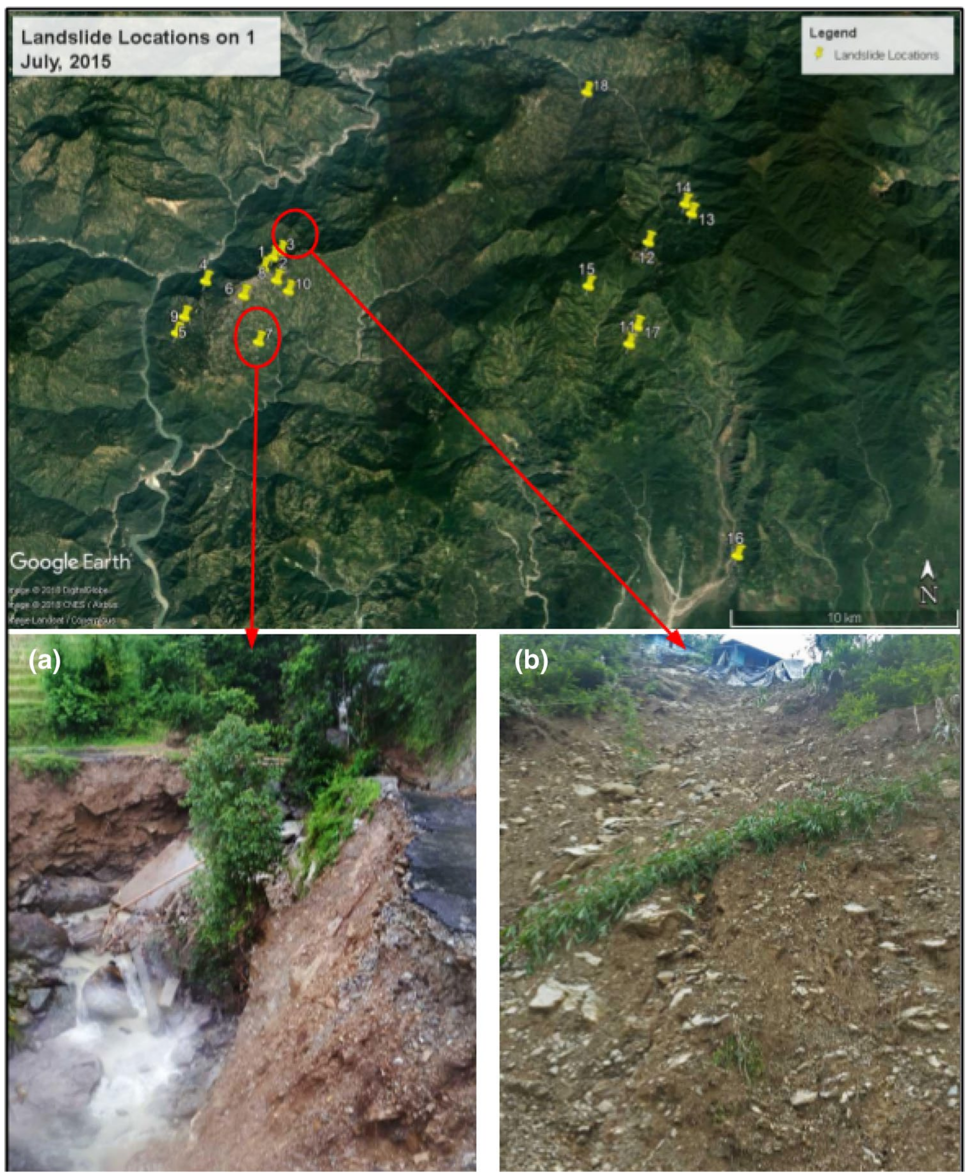


Fig. 6 Landslide locations and the damage pictures for the 1 July 2015 event

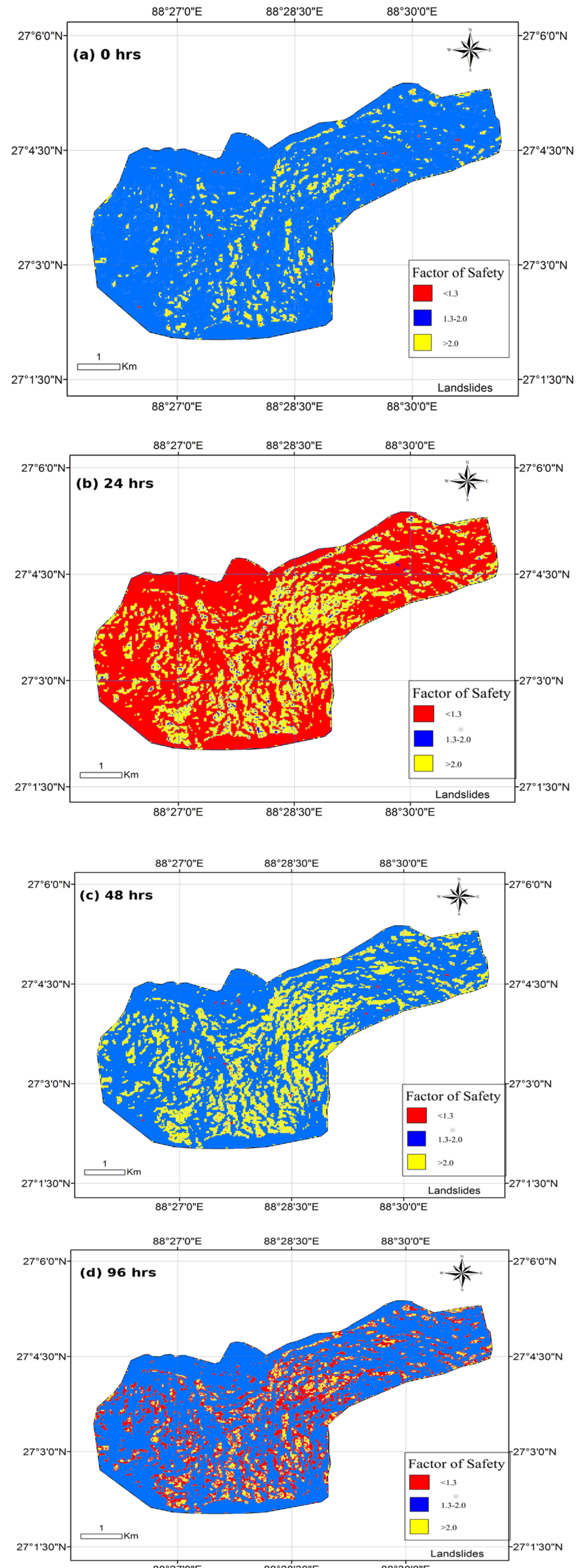


Fig. 7 Slope stability conditions in terms of the factor of safety (F_s) ▶ in the 1 July 2015 event based on the TRIGRS model

occurred), was performed and the results were analysed. The ROC chart demonstrates the outputs of the classification models for binary response (i.e. either unstable or stable). The value of lowest factor of safety was found by running various iterations of the model (Montrasio et al. 2011). The cells with $F_s < 1.3$ were considered unstable, compared to cells with $F_s > 2.0$, which were considered stable for ROC analysis. Therefore, the change of F_s over a period should be understood in developing a trend line for future rainfall events.

4 Results and Discussion

For the 1st July 2015 event, cells recognised with the factor of safety $F_s = 1.3$ steadily expanded as the rainfall intensity increased, thereby implying that the majority of the landslides were triggered by intense rainfall. After 24 h of rainfall, the unstable cells further increased throughout the entire region. For the following 24 h, rainfall ceased and TRIGRS simulated no variation in stability conditions, whilst the Fs values were steady as well. At 96 h after the landslide event, the number of stable cells decreased while the unstable cells started to increase. Figure 7a–d illustrates the variation in a factor of safety at the aforementioned time intervals.

An optimal landslide analysis model accords the known and predicted landslide locations and reduces the prediction of unstable areas to provide complete information about prediction. To overcome the limitations, ROC was used through a confusion matrix to analyse the accuracy of the factor of safety maps (Park et al. 2013). Table 2 presents the relative percentage of the predicted unstable pixels, correctly predicted landslide and stable pixels for the time the model simulation was carried. Before the landslide event (at $t = 0$ h), the correctly predicted landslide pixels were almost nil. For the case of 24 h (i.e. after the landslide event), the correctly predicted pixels were 53.9%, whereas the model predicted 91.2%. Thereafter, the number of correctly predicted landslide pixels started to slowly decrease which was also observed i.e. no occurrence of a major landslide event after the heavy rainfall. After 72 h, there is a significant rise in the landslide pixels (15.8%) which can be attributed to the preceding rainfall. This can be attributed to the already unstable slopes occurred after July 1st rainfall which failed latter. The results signify that the model has potential as a forecasting tool but should be improved with the availability of hourly rainfall data and other attributes, such as time of landslide event and soil depth.

Table 2 Results of the TRIGRS simulation at different times

Time (h)	Predicted as unstable pixels (%)	Correctly predicted landslide pixels (%)	Correctly predicted stable pixels (%)
0	0.50	0.02	99.66
24	91.20	53.90	71.65
48	58.87	41.54	84.61
72	22.70	16.85	89.65
96	38.30	32.65	89.40

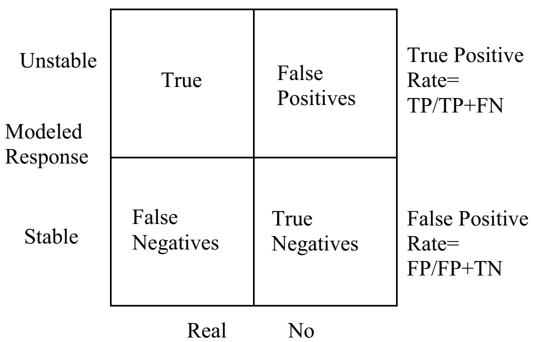


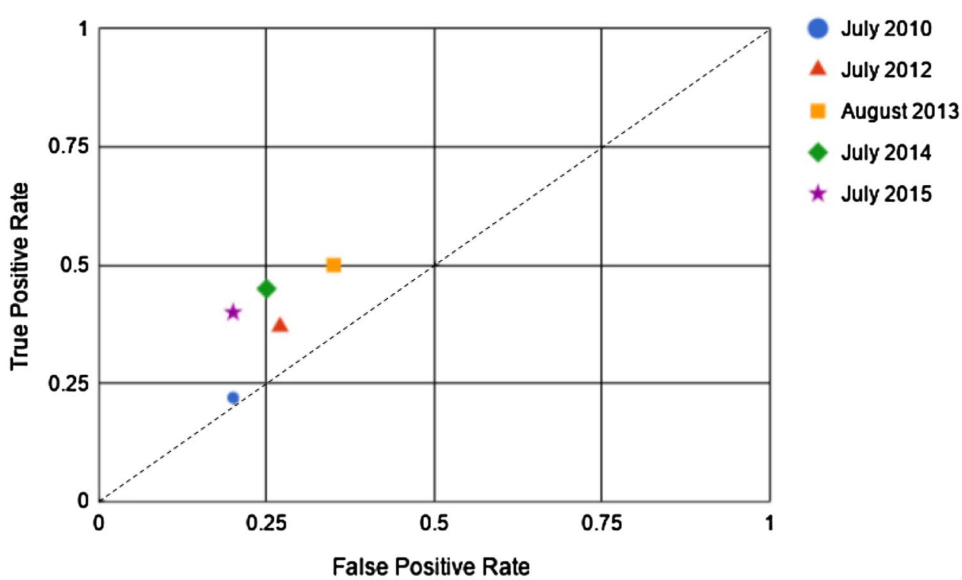
Fig. 8 Contingency table for the binary problem and performance metrics calculated

4.1 ROC Analysis

The ROC analysis is a method that is used to assess the performance of a classification model (Fawcett 2006). ROC is used to analyse the reliability of the factor of safety maps (i.e. a comparison of actual and predicted landslides using software) (Park et al. 2013; Schilirò et al. 2015). The preciseness of the model relies on the quantity of the accurately anticipated positive cells ("landslide presence") or negative cells ("landslide absence") reported as positive (Schilirò et al. 2015). Every cell of the factor of safety map can be categorised into four possibilities (see Fig. 8). (1) True Positive (TP) represents pixels that have a factor of safety below 1 and assessed as unstable and correctly predicts instability. (2) True Negative (TN) gives the correct prediction of stability and determines cells with a factor of safety above 1 and is considered stable. (3) False Positive (FP) represents the pixels with a factor of safety below 1, in which the pixels are assessed as unstable and represents false predictions of instability. (4) False Negative (FN) are cells that missed predictions of instability. Figure 8 depicts the four possible outcomes in a 2 × 2 contingency matrix. Sensitivity is known as true positive ratio (TPR) = TP/(TP + FN) (Zizioli et al. 2013). Specificity is called the true negative rate (TNR) = TN/(TN + FP) (Zizioli et al. 2013). The sensitivity of the model is portrayed as a function of specificity in the ROC graph. Many correct predictions are indicated by high sensitivity, whilst high specificity demonstrates only a few false positives (Montrasio et al. 2011).

The results of ROC show that TPR is consistently greater than FPR and for the event of July 2010, TPR is located near the diagonal (TPR = FPR). The events with the best output of TRIGRS are July 2010, July 2012, August 2013, July 2014 and July 2015. The event of September 2011 was exempted from the analysis because this event was caused by an earthquake. In the analysed cases, TPR ranges between 0.35 and 0.5, whilst FPR was between 0.15 and 0.25. Moreover, additional observations can be done with the ROC curves (see Fig. 9). The value in the lower left part of these figures corresponds to the analysis

Fig. 9 ROC analysis for the different rainfall scenarios



of the TRIGRS run when the instability is considered for $F_s < 1.3$ and the stability is considered for $F_s > 2.0$.

5 Conclusions

The increase in the number of landslide incidents in the Himalayan region has led researchers to evaluate the appropriate models and develop new techniques for landslide disaster mitigation. Several attempts have been made to determine the thresholds using statistical models. However, such models do not consider the spatial variation of soil, geology, hydrology and several physical parameters. The current study attempts to understand the application of a physical-based model (i.e. TRIGRS) for Kalimpong, which is a part of Darjeeling Himalayas and is the first research of its kind to be attempted in the region. Such analysis would help in understanding the variations in factor of safety across the region on the basis of physical parameters. The model uses soil properties, soil depth and hydrodynamic parameters as input. The rainfall event selected for calibration was that of 1 July 2015, which triggered 18 landslides and rainfall was at 226 mm. Thereafter, the quantification between the actual and predicted landslides was evaluated using the ROC technique. The results showed that the model is capable of forecasting landslides from a temporal perspective because of its correct prediction of 54% of the pixels during the day of the landslide. The validation of the model was performed by performing back analysis of the landslide events. The back analysis was carried out for 2010–2015, except 2011, and showed that the modelling results were coherent with the actual incidences with minor errors. This study can be improved with the availability of failure time and hourly rainfall data thereby facilitating the calibration of the parameters. The use of a physical-based approach could further help in understanding the landslide scenario in the Indian Himalayan region with an aim to set up an operational early warning system.

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