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Title: Usage of antecedent soil moisture for improving the performance of rainfall thresholds for landslide early warning

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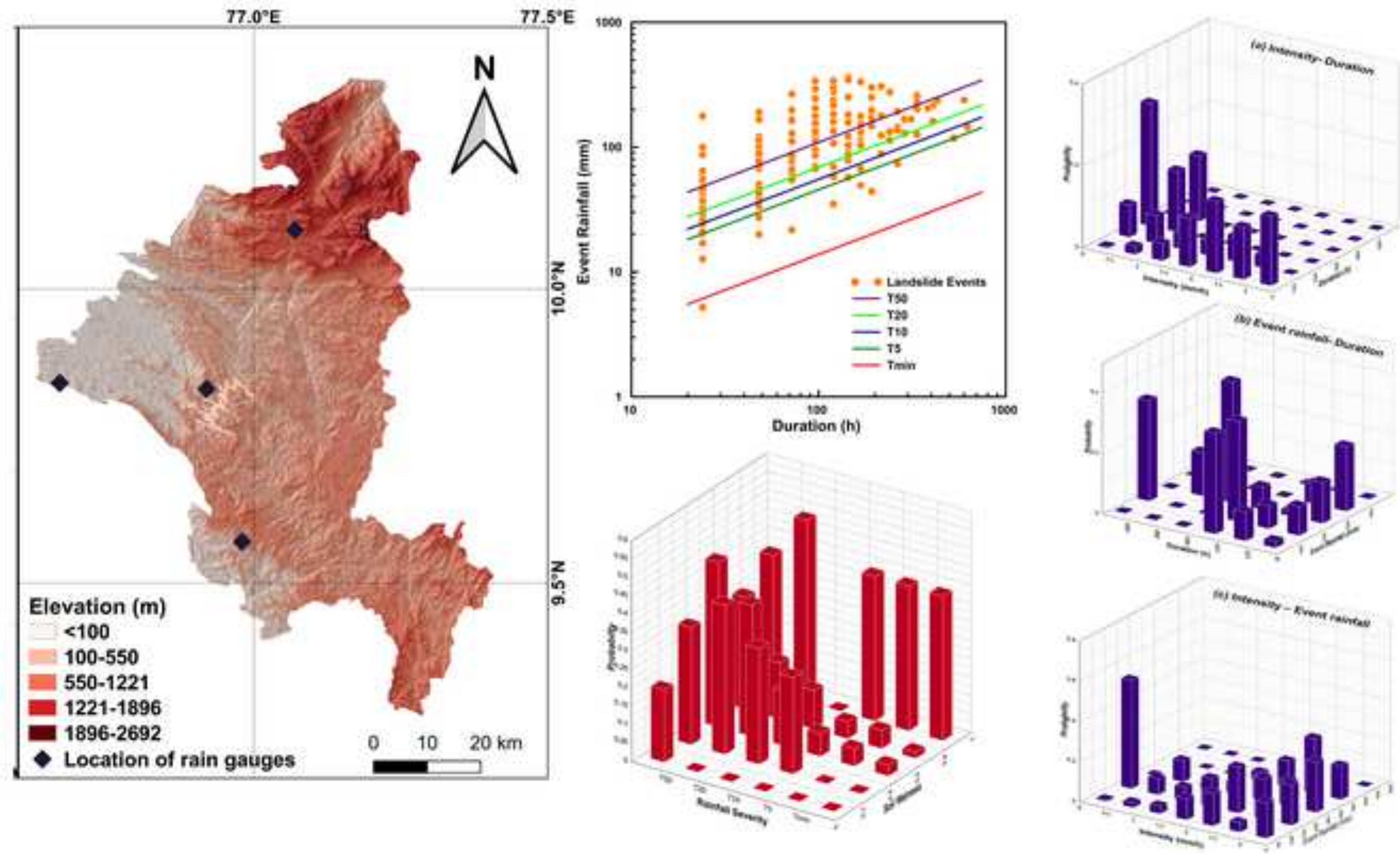
Abstract: Landslides triggered by heavy rains are increasing in number and creating severe losses in hilly regions across the world. Rainfall thresholds on regional and local-scales are being used for forecasting such events, for efficient early warning. Empirical and probabilistic approaches for defining rainfall thresholds are traditional tools which are being used as part of the forecasting system for rainfall induced landslides. Such methods are easy-to-use and are based on statistical analyses. They can be derived without looking into the complex hydro-geological processes involved in slope failures, but are often associated with the disadvantage of higher false alarms, limiting their applications in a regional landslide early warning system (LEWS). This study is an attempt to improve the performance of conventional meteorological thresholds by considering the effect of soil moisture, using a probabilistic approach. Idukki district in southern part of India is highly susceptible to landslides and has witnessed major socio-economical setbacks in the recent disasters happened in 2018 and 2019. This tourist hub is now in need of a landslide forecasting system, which can help in landslide risk reduction. This study attempts to understand the effect of averaged soil moisture estimates derived from passive microwave remote sensing data, for improving the performance of conventional empirical and probabilistic thresholds. For defining empirical thresholds, an algorithm-based approach such as Calculation of Thresholds for Rainfall-induced Landslides Tool (CTRL-T) has been used. Probabilistic thresholds were defined using a Bayesian approach, finding the posterior probability of occurrence using the marginal and conditional probabilities of the control parameters along with the prior probability of occurrence of landslide. The derived rainfall thresholds were quantitatively compared with the Bayesian probabilistic threshold derived using rainfall severity and soil wetness using an area under the curve (AUC) based receiver operating characteristics (ROC) curve method. The results show that when the antecedent moisture content in soil is less, only severe rainfall events can trigger landslides in the study area; while less severe rainfall events can also trigger landslides when the soil is wet. The role of soil wetness in the initiation is used to improve the performance of the conventional methods, and a ROC approach was used for the statistical comparison of different models. Further, the results indicated that the probabilistic threshold using rainfall severity and soil wetness outperformed the conventional approaches with AUC of 0.96, being the most sensitive and specific among the models considered. This result opens new promising perspectives for the development of an operational LEWS in the Idukki district based on a combination of rainfall and soil moisture data. Moreover, this work contributes to strengthen the advancing trend of hydro-meteorological thresholds based on soil moisture, which is gaining a growing attention in landslide studies and that, to date, was lacking evidences in monsoon regions.

Graphical Abstract



Highlights

- Landslides can be predicted using empirical and probabilistic rainfall thresholds.
- Soil moisture is critical in slope stability as it affects the infiltration rate.
- Soil moisture can be used with conventional thresholds for better performance.
- Idukki (India) is highly a highly susceptible landslide zone in the Western Ghats.
- Critical rainfall conditions, considering the soil wetness are derived for Idukki.

Usage of antecedent soil moisture for improving the performance of rainfall thresholds for landslide early warning

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Abstract

Landslides triggered by heavy rains are increasing in number and creating severe losses in hilly regions across the world. Rainfall thresholds on regional and local-scales are being used for forecasting such events, for efficient early warning. Empirical and probabilistic approaches for defining rainfall thresholds are traditional tools which are being used as part of the ~~landslide~~ forecasting system for rainfall induced landslides. Such methods are easy-to-use and are based on statistical analyses. They can be derived without looking into the complex hydro-geological processes involved in slope failures, but are often associated with the disadvantage of higher false alarms, limiting their applications in a regional landslide early warning system (LEWS). This study is an attempt to improve the performance of conventional meteorological thresholds by considering the effect of soil moisture, using a probabilistic approach. Idukki district in southern part of India is highly susceptible to landslides and has witnessed major socio-economical setbacks in the recent disasters happened in 2018 and 2019. This tourist hub is now in need of a landslide forecasting system, which can help in landslide risk reduction. This study attempts to understand the effect of averaged soil moisture estimates derived from passive microwave remote sensing data, for improving the performance of conventional empirical and probabilistic thresholds. For defining empirical thresholds, an algorithm-based approach such as Calculation of Thresholds for Rainfall-induced Landslides Tool (CTRL-T) has been used. Probabilistic thresholds were defined using a Bayesian approach, finding the posterior probability of occurrence using the marginal and conditional probabilities of the control parameters along with the prior probability of occurrence of landslide. The derived rainfall thresholds were quantitatively compared with the Bayesian probabilistic threshold derived using rainfall severity and soil wetness using an area under the curve (AUC) based receiver operating characteristics (ROC) curve method. The results show that when the antecedent moisture content in soil is less, only severe rainfall events can trigger landslides in the study area; while less severe rainfall events can also trigger landslides when the soil is wet. The role of soil wetness in the initiation is used to improve the performance of the conventional methods, and a ROC approach was used for the statistical comparison of different models. Further, the results indicated that the probabilistic threshold using rainfall severity and soil wetness outperformed the conventional approaches with AUC of 0.96, being the most sensitive and specific among the models considered. This result opens new promising perspectives for the development of an operational LEWS in the Idukki district based on a combination of rainfall and soil moisture data. Moreover, this work contributes to strengthen the advancing trend of hydro-meteorological thresholds based on soil moisture, which is gaining a growing attention in landslide studies and that, to date, was lacking evidences in monsoon regions.

Keywords: landslides; rainfall thresholds; LEWS; soil moisture; Idukki

1. Introduction

Forecasting landslides and evacuating people from hazardous zones is an important risk reduction strategy (Althuwaynee and Pradhan, 2017). Considering the climate change and associated extreme rainfall phenomenon, the number of rainfall-induced landslides are expected to rise (Alvioli et al., 2018; Chen et al., 2019; Gariano and Guzzetti, 2016). Being a geomorphological process in the landscape evolution (Iida, 1999), the detailed understanding of slope failure mechanisms involves hydrological studies and forecasting of possible failure planes (Agostini et al., 2014) using relevant geotechnical and meteorological parameters. However, these parameters are highly site specific and often difficult to determine with the desired accuracy (Tofani et al., 2017), except that for single slopes or very small basins (Chae et al., 2017), and sophisticated experimental research is required for understanding the mechanism in detail (Kim et al., 2018). Hence, a more practiced approach is needed to forecast the critical conditions which result in the occurrence of landslides using the primary triggering factor i.e. rainfall – with the aid of rainfall thresholds (Caine, 1980; Keefer et al., 1987; Piciullo et al., 2018). Rainfall thresholds can be empirical, probabilistic, or algorithm based (Althuwaynee et al., 2015; Piciullo et al., 2018; Segoni et al., 2018a). All the approaches exploit historical data to find a mathematical relationship between rainfall and the occurrence of landslides in a region, to identify critical rainfall conditions which can trigger landslides in the future. A rainfall event is most commonly characterised in terms of cumulated rainfall event (E), duration (D), and intensity (I) (which are referred to as "rainfall parameters"). Consequently, the thresholds are often defined as cumulated event rainfall vs. duration (ED thresholds) (Lainas et al., 2016; Melillo et al., 2018, 2016; Peruccacci et al., 2017; Teja et al., 2019) or as rainfall intensity vs. duration (ID thresholds) (Battistini et al., 2017; Brunetti et al., 2010; Guzzetti et al., 2008; Lainas et al., 2016; Wu et al., 2019).

When the definition of thresholds is associated with the generation of many false alarms, their usage in operational Landslide Early Warning System (LEWS) may be inappropriate (Aleotti, 2004; Guzzetti et al., 2008; Kirschbaum et al., 2012; Segoni et al., 2018b). Low performances of rainfall thresholds are traditionally related to the uncertainties associated with the definition of rainfall parameters, the quality and resolution of the historical data and the intrinsic limitations of the statistical models (Gariano et al., 2020; Marra et al., 2017; Nikolopoulos et al., 2014).

Some authors argued that sometimes the statistical correlation between rainfall parameters and landslide initiation is too weak and that hydro-meteorological thresholds accounting for both rainfall and hydrological (e.g. soil moisture) parameters could provide a stronger and more accurate assessment (Bogaard and Greco, 2018; Jakob et al., 2006; Terlien, 1998). Integrating soil moisture with rainfall thresholds has been proven effective in improving the rainfall thresholds (Abraham et al., 2020b; Segoni et al., 2018c; Zhao et al., 2019a), as the antecedent moisture content plays a key role in the shear strength parameters of soil. The soil moisture conditions play a key role in the infiltration process (Song and Wang, 2019) which significantly influences the initiation of landslides (Alimohammadlou et al., 2014; Baum et al., 2008; Bicocchi et al., 2019; Iverson, 2000; Wei et al., 2020; Yang et al., 2019). Weighted indexes (Glade et al., 2000; Ponziani et al., 2012); and satellite data (Zhao et al., 2019b) can be used for estimating soil moisture values when real-time field monitoring (Abraham et al., 2020c; Dikshit et al., 2018; Uchimura et al., 2015, 2010) cannot be conducted. Hydrological models (Abraham et al., 2020b; Zhao et al., 2019a) can also be used for the estimation of soil moisture content. In the published literature, soil moisture combined with rainfall thresholds has been tested mainly in Mediterranean, temperate and alpine climatic settings, whereas in monsoon regions similar types of tests are almost completely missing (Jakob et al., 2006; Mirus et al., 2018a; Valenzuela et al., 2018; Wicki et al., 2020).

The present work attempts to define statistical rainfall thresholds in Idukki district (India) and to improve their effectiveness by coupling rainfall parameters with soil moisture data. First, ED thresholds are defined using an automatic algorithm-based approach (Melillo et al., 2014). The algorithm first identifies the triggering rainfall events using the location of rain gauges and landslides, the time of occurrence of landslides and the time series rainfall data. It recreates multiple rainfall conditions which may result in landslides and identifies the maximum probable rainfall condition based on the location and time. After identifying the triggering rainfall event, the algorithm defines the ED thresholds with multiple exceedance probabilities using frequentist method. Then, by using a probabilistic approach (Berti et al., 2012), the effect of event rainfall, duration and intensity on the occurrence of landslides is evaluated (probabilistic rainfall thresholds). Both empirical (Melillo et al., 2018, 2016; Peruccacci et al., 2017) and probabilistic approaches (Berti et al., 2012; Dikshit and Satyam, 2019) were considered to establish the relationship between primary triggering factor (rainfall) and the result (landslide), and these are simple statistical approaches that are easy to derive by integrating with a rainfall forecasting system. Similar studies have been conducted for Indian Himalayas (Abraham et al., 2020a; Dikshit and Satyam, 2018, 2019; Teja et al., 2019) and the Western Ghats (Abraham et al., 2020e, 2019); however, these methods were not always found to be operational due to a higher number of false alarms or missed alarms, limiting their applications in LEWS. This study aims to overcome these limitations by integrating soil moisture data along with the rainfall thresholds. The objective is to find if the addition of soil moisture data can perform better than the conventional methods based on the rainfall data alone.

2. Description of the study area

The Western Ghats of Indian Peninsula is highly susceptible to rainfall-induced landslides. There is a surge in the number of landslides during monsoon season since 2018, due to very-high intensity rainfalls. The landslides and floods happened in 2018 severely affected the south Indian states of Kerala and Karnataka. Among the 14 districts in the state of Kerala, 13 are part of the Western Ghats and are susceptible to landslides. Nearly 5.3 million people in the state were affected by the disaster in 2018 (United Nations Development Programme, 2018). The Western Ghats scarps, running the whole extent of the mountain range, are highly prone to landslides. Very-high intensity rainfall, along with the anthropogenic activities, has accelerated the geological processes leading to landslides, making the situation alarming (Kuriakose et al., 2009b).

Idukki is a hilly district in the Western Ghats and is the second largest district in the state of Kerala, in terms of area. This district covers an area of 4358 km^2 and derived its name from the word ‘Idukku’ in the vernacular dialect meaning *narrow gorge*. This itself indicates the geography of the area. The district is the major power source of Kerala and houses many hydroelectric projects, including the famous arch dam of Idukki. About 50% of the district is covered by forests and Idukki is drained by three major rivers, two flowing westward and one eastward. The rainfall across the district is varying with the least values recorded in the northern side with a long-term average of 1000 mm while the southern parts record an average rainfall of 5000 mm (Sajeev and Praveen 2014; Department of Mining and Geology 2016). The southwest monsoon season from June to September contributes 60% of the annual rainfall and around 24% is contributed by the North-East monsoon from October to December. Due to varying topography, the climatic conditions in the hill ranges, plateaus and midlands of the district are different from each other.

Fig. 1. Location details of study area. (a) India, and (b) Digital Elevation Model of Idukki (modified using CartoDEM (CartoDEM, 2015)) along with location of rain gauges.

Geologically, Idukki can be divided into three different parts from south to north. The charnockite rocks in the south, migmatitic complex in central portion, and peninsular gneissic complex in the northern part. Granite gneiss is the oldest and predominant group among the peninsular gneissic complex while the charnockite group consists of magnetite quartzite, pyroxene granulite and charnockite (Department of Mining and Geology 2016). Structural cum denudational hills are the predominant geomorphological feature of Idukki. The hills are generally having a thin soil cover overlaid on Precambrian basement rocks. The midlands have a rugged topography with small hills and deep valleys with an average elevation of 50 m. The zone where midlands grades to plateaus are called the foothills, ranging up to 8 km in width. A major portion of the district belongs to the plateau region, with a large landmass of moderate slope. The elevation of the plateau region goes up to 1500 m, and the regions at an elevation greater than 1500 m belong to hilly ranges. More than 50% of the study area is covered by forest loam soils, produced by the weathering of rock under thick forest cover. The midlands are covered by lateritic soil with high permeability and less organic content. The valley portion of the terrain are covered with fine particles of sandy loam to clay type, formed by sedimentation and transportation of hill slopes. The narrow riverbanks consist of fertile alluvial soil and are more common in the midlands.

Because of its topographic variability and heavy rainfall, the district is highly susceptible to rainfall induced landslides. The typology of landslides in the Western Ghats includes earth and debris slides, rock falls, creep, slump and debris flows (Abraham et al., 2020d). Due to the thin regolith layer, shallow landslide (Varnes, 1978) is the most common type during prolonged rainfalls (Kuriakose et al., 2009a). Idukki district in particular is mostly affected by the cut slope failures along the major road corridors, disrupting the transportation network in the district. Recent changes in the land use patterns for infrastructure development and agriculture have affected the stability of slopes of this ecologically sensitive zone (Gadgil et al., 2011) and has aggravated the number of landslide disasters (Kuriakose et al., 2009b). Hence the development of an effective regional scale LEWS is highly needed to forecast the future landslides in the region.

3. Data and Methodology

The study explores the possibility of using soil moisture data in improving the performance of statistical thresholds. The overall methodology flow chart adopted in this study is shown in Fig 2. The methodology involves data collection from multiple sources, the definition of thresholds and their performance evaluation using different skill scores. For the analysis, historical rainfall, landslide, and soil moisture data were collected. For developing empirical and probabilistic rainfall thresholds, only rainfall and landslide data are required, while for developing probabilistic rainfall thresholds based on rainfall severity and soil wetness (RS threshold), the soil moisture data were integrated with empirical ED thresholds using a probabilistic approach. While the empirical threshold considers the effect of rainfall events which resulted in landslides, the probabilistic thresholds consider both triggering and non-triggering rainfall events for the analysis.

Fig. 2. Methodology of study.

3.1 Data collection

The dataset used for this study spans from 2010 to 2018 and the historical data from this period was used to derive the empirical and probabilistic thresholds for occurrence of landslides in Idukki district. The daily rainfall data was collected from the Indian Meteorological Department (India Meteorological Department 2019) for four rain gauges within the district. The landslide data was collected from various government agencies and media reports (Abraham et al., 2019) and only landslides for which the date of occurrence was available were used for the analysis. For each rain gauge a reference area was defined and multiple landslides triggered in the same day in each area were considered as one landslide event and rainfall data were collected from the reference rain gauge. By these criteria, 225 landslide events were identified in the study area which were first used as the input for empirical thresholds. For probabilistic thresholds, a total of 5028 rainfall events recorded by the four rain gauges during the study period were considered.

The average daily soil moisture data was collected from Giovanni's website by National Aeronautics and Space Administration Goddard Earth Sciences Data and Information Services Center (NASA GES DISC) (de Jeu and Owe, 2014, 2012; Giovanni, 2020). The data was derived using land parameter retrieval model (LPRM), which is a multi-parameter retrieval algorithm focused on hydrological and climate studies. It retrieves the soil moisture from the microwave observations from sensors. The observed brightness temperatures were used to derive the soil moisture data, using LPRM (Owe et al., 2008). LPRM is based on a forward radiative transfer model and the output is the volumetric soil moisture content in percentage. The soil moisture on the day before the occurrence of landslide, termed as the 'antecedent soil moisture' was used for the analysis in this research. The spatial resolution of the data is $0.25^{o} \times 0.25^{o}$. The study area (Idukki district) consists of 14 grids of size $0.25^{o} \times 0.25^{o}$ (Figure 1). After calculating the area of Idukki within each grid, the weighted average was calculated for the whole area, for simplified calculation. This value is called the 'averaged moisture content'. Another term, 'soil wetness' is introduced, to represent a range of antecedent soil moisture, on a scale of 0 to 1. The soil wetness values were divided into five equal parts, representing different ranges of moisture content. This classification is used to overcome the limitations associated with using averaged data for a larger area. The value of soil wetness is directly proportional to the moisture content values and indicates the wetness of soil before the landslide.

Thus, by using historical rainfall, landslide and soil moisture data, thresholds were defined using multiple approaches for the study area to find the effect of soil moisture on the forecasting performance of the thresholds.

3.2 Empirical thresholds

The selection of rain gauges and rainfall parameters plays a critical role in the definition of rainfall thresholds (Abraham et al., 2020e). For the study area, rainfall data from the four available rain gauges were considered for the analysis. The intensity-duration thresholds for the study area was earlier derived from using a nearest rain gauge approach (Abraham et al., 2019), considering 225 landslide events occurred from 2010 to 2018. From the pioneering work of Caine (Caine, 1980), ID thresholds were defined for regions across the globe (Abraham et al., 2020c, 2019; Brunetti et al., 2010; Dikshit and Satyam, 2018; Guzzetti et al., 2008, 2007; Segoni et al., 2018a). Even though intensity can easily be converted to event rainfall and vice-versa, recent literature shows a shift towards defining ED thresholds instead of ID thresholds (Melillo et al., 2018, 2014; Peruccacci et al., 2012; Teja et al., 2019; Zhao et al., 2019a). The reason is that E and D are two mutually independent parameters while I is a function of D and E. Hence, for a definition of rainfall thresholds and rainfall severity, the data points on ED plane was considered in this study. In this study, the reconstruction of event- duration thresholds was carried out by using Calculation of Thresholds for Rainfall Induced Landslides - Tool (CTRL-T) (Melillo et al., 2018, 2014). CTRL-T uses an algorithm-based approach, extracting the rainfall events automatically from the daily precipitation data input. From the extracted events, rainfall conditions that have triggered landslides were identified; and –used to derive the rainfall thresholds for the region. The tool considers a buffer zone around each landslide location, to search for the rain gauge and identify the triggering event. In this study, a search radius of 20 km is considered, due to the low rain gauge density in the study area. The algorithm also considers a delay time between the end of rainfall and occurrence of landslide. In this study, the delay time is taken as 48 hours (Melillo et al., 2014). If no rainfall condition is recreated within this delay time before the occurrence of landslide, the event will be discarded by the algorithm. The algorithm first determines the total event rainfall and duration of rainfall for all identified rainfall events and then to minimise the effect of spatial variability of rainfall distribution, single or multiple rainfall conditions (MRC) likely to result in failures and a weight is assigned to each of them. Then for each landslide, the highest weight was used to identify the reference rain gauge and to choose the maximum probable rainfall conditions (MPRC). In this study, five different threshold lines were defined using CTRL-T, at different exceedance probabilities of 1%, 5%, 10%, 20% and 50% (termed as T_1, T_5, T_{10}, T_{20} and T_{50}, respectively). Thresholds and related uncertainties were estimated from MPRCs. The defined thresholds are in the form of a power law, determined using the frequentist approach (Brunetti et al., 2010) and can be expressed as:

$$E = (\alpha \pm \Delta\alpha)\, D^{(\gamma \pm \Delta\gamma)} \qquad (1)$$

where, α is the scaling parameter or the intercept and γ is the shape parameter which denotes the slope of the equation. Δα and Δγ represents the uncertainties associated with α and γ, respectively. The uncertainties are determined using a bootstrap approach.

3.3 Probabilistic approach

The empirical thresholds compare an input value with the defined thresholds and will have a single output (triggering or non-triggering). It is often difficult to decide the exceedance probability to be selected as a threshold beyond which a radical change can be expected in the system (Berti et al., 2012). The discretion between triggering and non- triggering rainfall conditions is not trivial in such cases. To derive the equation, only the triggering rainfall conditions are considered. This increases the chances of false alarms, as numerous rainfall events that cross the threshold line not necessarily trigger landslides.

By considering both triggering and non- triggering rainfalls for analysis, probability-based models are more informative and provide a better option to find extreme events. In this study, a Bayesian approach is used to define probabilistic thresholds (Berti et al., 2012).

3.3.1 One-dimensional analysis

Bayes theorem applies a conditional probability of some event L (landslide) given the occurrence of another event X (rainfall, expressed in terms of E, I or D). This is also called the posterior probability, $P(X|L)$. It can be calculated as follows (Berti et al., 2012):

$$P\ (L|X) = \frac{P(X|L) * P(L)}{P\ (X)} \tag{2}$$

where, $P(X|L)$ is the conditional probability of occurrence of rainfall of magnitude X, when a landslide occurs. This is also called as a likelihood.

$P(L)$ is the prior probability of occurrence of landslide regardless of the occurrence rainfall magnitude.

$P\ (X)$ is the marginal probability of X, which can be defined as the probability of occurrence of rainfall regardless of the occurrence of landslides. The terms can be calculated mathematically using relative frequencies. Let N_R be the total number of rainfall events during study period, N_L be the total number of landslides occurred, N_X be the number of rainfall events with magnitude X and $N_{(X|L)}$ be the number of rainfall events with magnitude X that resulted in landslides. The probabilities can be computed as (Berti et al., 2012):

$$P(L) \approx \frac{N_L}{N_R} \tag{3}$$

$$P(X) \approx \frac{N_X}{N_R} \tag{4}$$

$$P(X|L) \approx \frac{N_{(X|L)}}{N_L} \quad (5)$$

Considering the rainfalls that resulted in landslides only will give us partial information, the likelihood. To understand the influence of rainfall of magnitude X, it is important to compare the prior probability with the posterior probability.

3.3.2 Two-dimensional analysis

Two-dimensional case is the extension of Eq. 2 by considering two conditions X, Y instead of the single condition X in Eq. 2. In the initial analysis, we consider X and Y as magnitude of two rainfall parameters (E,D ; I,D; E,I). The calculation of prior, marginal and conditional probabilities are given below:

$$P\ (L|X,Y) = \frac{P(X,Y|L) * P(L)}{P\ (X,Y)} \quad (6)$$

$$P(L) \approx \frac{N_L}{N_R} \quad (7)$$

$$P(X,Y) \approx \frac{N_{X,Y}}{N_R} \quad (8)$$

$$P(X,Y|L) \approx \frac{N_{(X,Y|L)}}{N_L} \quad (9)$$

The study explores the effect of antecedent soil moisture content using a two-dimensional probabilistic analysis. During the second phase, we considered rainfall severity in ED plane and soil wetness as X and Y, respectively. Based on the values of soil wetness, five different categories were considered for analysis viz, less than 0.2, 0.2 to 0.4, 0.4 to 0.6, 0.6 to 0.8, and 0.8 to 1. The categories based on rainfall severity were less than T_1, T_1 to T_5, T_5 to T_{10}, T_{10} to T_{20}, T_{20} to T_{50} and greater than T_{50}. Thus, the two-dimensional plane was divided into 30 cells as a 6 x 5 matrix as shown in Fig. 6. These values were used for the definition of RS threshold.

4. Results

4.1 Empirical thresholds

CTRL-T tool considered 177 landslide events out of the 225 and the rest were discarded to avoid introduction of relevant spatio-temporal uncertainties in the analysis. The uncertainties are associated with the less rain gauge density in the study area. As described earlier, the landslides for which responsible rainfall conditions were not identified were discarded. This can be due to a distance more than 20 km between the location of rain gauges and landslide or due to a delay time more than 48 hours after the end of any rainfall event. The algorithm forecasted rainfall thresholds with various exceedance probability both in normal and logarithmic plot (Fig. 3). The threshold lines of 1%, 5%, 10%, 20% and 50% exceedance probabilities were used to classify the events into six categories based on the severity of rainfall. These lines are named T_1, T_5, T_{10}, T_{20} and T_{50}, respectively. The slope of threshold lines in logarithmic plot was found to be 0.57±0.03. This value is not in good agreement with the ID thresholds defined for the area in a previous study (Abraham et al., 2019). Though both the studies used frequentist approach for the definition of thresholds, the process of identification of responsible rainfall event was different. In the previous study (Abraham et al., 2019), the responsible rainfalls were identified using a Thiessen polygon approach manually, while in this study, the automatic algorithm, CTLRL-T is used for identifying the responsible rainfall event. The parameters of threshold lines and the uncertainties associated are listed in Table 1.

Fig. 3. Rainfall event – duration thresholds for Idukki district

Table 1. Values of α, γ and the uncertainties associated with different exceedance probabilities

The range of duration of rainfalls considered for analysis vary from 1 to 26 days. For the thresholds to be reliable, the relative uncertainty ($\Delta x/x$ for any variable x) should be less than 10%. Here the relative uncertainty of γ is 5.2%. But with higher exceedance probabilities, the relative uncertainty of α is crossing this limiting value.

With 5% exceedance probability, 20.19mm rainfall can trigger a landslide in the region for a duration of 24 hours and when the duration is 624 hours, a rainfall of 129 mm can trigger landslides in the region. For a better understanding of the effect of each rainfall parameter on the occurrence of landslides, probabilistic rainfall thresholds were defined for the area.

4.2 Probabilistic thresholds

The maximum probable rainfall conditions which were used for the definition of ED thresholds were considered as the triggering rainfall events for the probabilistic analysis. Thus, out of the 5028 rainfall events considered, 177 events were identified as triggering events by CTRL- T algorithm and the rest 4851 events were considered as non-triggering rainfall events. In the one-dimensional case, six categories of rainfall duration, five categories of cumulated rainfall event and seven categories of rainfall intensity were considered. The results are plotted in Fig. 4 (a-f); where Fig. 4a, c and e depict the prior probability, marginal probability and likelihood, and Fig. 4b, d and f depict the prior and posterior probabilities. The variable X in Eq. (2-5) is replaced with D, E and I in the respective graphs. $P(L)$ being a constant parameter (value 0.035 in this study), the ratio of $P(X|L)$ to $P(X)$ determines the variation of posterior probability values. Hence when $P(X|L) > P(L)$, the posterior probability is greater than prior probability and vice versa. The more the variation between prior and posterior probability, the more significant the variable is. It can be seen, that for duration and event rainfall, for the largest values of variables, the values of $P(L|X)$ is less than $P(L)$, while in the case of intensity, high intensity rainfalls are more probable to trigger landslides in the region. The plots of $P(X)$ and $P(X|L)$) are well above the plot of prior probability in all the cases. Intensity was found to be the most significant variable, with the maximum ratio between posterior and prior probabilities.

The maximum posterior probability when the control parameter is D was found to be 0.053 where the value is 0.103 and 0.116 in the case of E and I, respectively. Maximum probability occurs when the duration is between 120 h to 240 h; event rainfall is between 100 mm to 200 mm; and intensity is greater than 3 mm/h.

Fig. 4. Prior, conditional, marginal and posterior probabilities with respect to rainfall parameters. (a, b) Duration; (c, d) Event rainfall; and (e, f) Intensity.

To evaluate the joint occurrence of two parameters, two-dimensional Bayesian analysis were conducted with data on three different planes (Fig. 5). The two-dimensional space for each analysis was divided into small cells based on the categories of parameters used for one-dimensional analysis. Hence the ID plane is a 7 x 6 matrix, ED plane is a 5 x 6 matrix and the EI plane is a 5 x 7 matrix. There are several no data points in all three cases, due to the lower number of landslides considered for the analysis. As identified from the one-dimensional analysis, E and I were found to be more critical parameters than D. This is the reason why this study has considered all three different combinations of the control parameters even though the empirical thresholds are defined on ED plane only. The maximum probability value was obtained on EI plane, when the intensity value is less than 0.5 mm/h and event rainfall is between 100 mm to 200 mm, with a value of 0.54.

Fig. 5. Two-dimensional posterior probabilities of occurrence of landslide on (a) ID plane, (b) ED plane, and (c) EI plane.

It is evident from Fig. 6 that even less severe rainfall events when falling on a moist soil can trigger landslides in the region. Most of the landslides for which rainfall events were less severe happened on days with higher soil wetness. Also, when the rainfall event is severe, even dry soil can be susceptible to landslides. The maximum probability of 0.49 was observed when the rainfall severity was between T_{20} to T_{50} and the soil wetness was between 0.8 to 1. With the available data, when the antecedent soil moisture is less, only extremely severe rainfall conditions can trigger landslides in the area. This affects the performance of the ED thresholds considerably. For different antecedent soil moisture conditions, this makes it easier to decide the threshold line to be used.

Fig. 6. Two-dimensional Bayesian probabilities for occurrence of landslides based on rainfall severity and soil wetness.

5. Discussions

To verify the performance of all models and to understand which model is performing better for the study area, different thresholds should be compared quantitatively (Lagomarsino et al., 2015). In this study, empirical thresholds on ED plane, probabilistic thresholds on all three combinations of control parameters (ED, ID and EI) and also a two-dimensional Bayesian approach by combining empirical ED thresholds with soil moisture have been derived. The maximum probability value obtained in the two-dimensional analysis was in the case of EI thresholds, and the value is 0.54. The value was obtained when the intensity is less than 0.5 mm/h and event rainfall is between 100 to 200 mm. This implies a prolonged duration of 8 days or more. The intensity value is too low in this case, yet the probability value is the maximum. The definition of 2-dimensional Bayesian probability majorly depends upon the relative occurrence of landslides when the rainfall conditions are satisfied and the occurrence of rainfall events with specified conditions. The number of events with the specified EI conditions were less, but more than half of them have resulted in landslides based on the historical data. Thus, the probability of occurrence of landslides is higher in this case. This result points towards the significance of using a physical parameter such as soil moisture for the definition of threshold. The top regolith layer throughout the district consists of forest loam, lateritic soil, alluvial soils etc, with higher fine fraction (Department of Mining and Geology Kerala, 2016). The less permeable soil has a higher water holding capacity and the moisture content increases when the rainfall is continuous. The prolonged rainfall has thus reduced the shear strength of soil and the landslide has happened at a very less intensity value. This complicated process is simplified by using a statistical approach, by considering the effect of soil wetness. To understand the performance of such a model with respect to the meteorological thresholds, a quantitative comparison is required.

An ROC curve approach was used for quantitative comparison. ROC curve is a tool to understand the performance of a model with a binary outcome. Each threshold value can forecast two outcomes for a day; 'landslides' or 'no landslides. If the threshold condition is crossed, the model forecasts 'landslides' and otherwise, 'no landslides. When the forecasting is correct and landslide occurs, it is termed as a true positive (TP). Another possibility of correct outcome is the result 'no landslides' on a day in which landslides do not occur. This can be counted as a true negative (TN) result. When the forecasting goes wrong, it also has two possible outcomes. 'Landslides' forecasted on a non-landslide day, which is a false positive (FP) or simply a false alarm and 'no landslides' forecasted on a day in which landslides occur, termed as false negatives (FN) or missed alarms. A perfect model should only have true outcomes, without any false alarms or missed alarms.

A ROC curve is a plot with a false positive rate of a model on x-axis and a true positive rate on y axis. It evaluates the overall performance of the model. The true positive rate is also called the sensitivity of the model. It provides the proportion of landslide occurrences which are correctly identified ($TP/(TP+FN)$). The specificity of a model is the true negative rate and is the ratio of TN to the sum of TN and FP. The false positive rate can be calculated by subtracting specificity value from 1. An ideal model is expected to have both sensitivity and specificity values as 1. Hence the point (0,1) on ROC curve is called the perfect point. Points which are closer to this perfect point has a better performance. Also, the model with better performance is the one with a maximum area under the curve (AUC) among the different models considered. Threat score and True Skill Statistic (TSS) are two other parameters which were used to understand the performance of a model (Mirus et al., 2018b). Threat score is defined as the ratio of TP to the sum of TP, FP and FN. TSS is the difference between sensitivity and false positive rate. For an ideal model, the value of both these variables should be 1.

ROC curves for all models considered in the study are plotted in Fig. 7 and the statistical attributes are listed in Table 2. From Fig. 7, it can be observed that the RS threshold covers the maximum area in the plane with an AUC of 0.96. The empirical ED threshold has the second highest AUC of 0.86. All the three probabilistic rainfall thresholds have very close AUC values as observed in Fig. 7. EI threshold covers a larger area than the other two, indicating its better performance in comparison with the other two probabilistic rainfall thresholds. The distance from perfect point is minimum in the case of RS thresholds, in the case of critical probabilities 0.1 and 0.15. It can also be observed that the value of threat score and TSS are maximum in the case of RS thresholds. The maximum value of threat score is obtained as 0.24 and TSS as 0.90, both in the case of RS thresholds with critical probability 0.1, which is also the closest one to the perfect point.

Fig. 7. ROC curves for the derived thresholds. Sensitivity is the ability of a model to correctly identify the landslide events and Specificity is the ability to correctly identify the non-landslide events

Looking into the details in Table 2, it confirms with the literature as the empirical thresholds result in many false alarms, making it inadequate to use in an LEWS. The number of false alarms can considerably be reduced by using probabilistic rainfall thresholds, as listed in Table 2. The number of FP in the case of probabilistic ED. ID and EI are much lesser than the other two models considered. But this reduction in false alarms comes with the cost of a higher number of missed alarms (FN). While 171 landslide events out of the 177 events are correctly forecasted by the empirical ED threshold line T_1, and 172 are correctly forecasted by RS threshold when the critical probability is 0.05, the maximum number of correct outcomes for the other probabilistic models are 106, 105 and 117 on ED, ID and EI planes respectively. For improving the performance, we need to balance the number of false alarms and missed alarms, which is achieved by using RS threshold. The RS threshold has FN numbers comparable with that of probabilistic rainfall thresholds, minimising the false alarms and by incorporating an additional filter using soil wetness, it reduces the number of false alarms when compared to the empirical ED threshold.

Table 2. Statistical attributes for quantitative comparison.

The probabilistic rainfall thresholds have high specificity values, pointing to their ability to correctly forecast the days without landslides, but with very less values of sensitivity. The points on ROC curves for probabilistic rainfall thresholds are therefore closer to both the axes, reducing the AUC.

Even though the points have high specificity values, they are located far from the perfect point, due to their inefficiency in correctly forecasting the occurrence of landslides. The RS threshold with a critical probability of 0.1 is the closest one to the perfect point, correctly forecasting 167 landslide occurrences.

From the analysis, the rainfall and soil wetness conditions for which the probability of occurrence is more than 0.1 should be considered critical. This makes it easier to identify the empirical ED threshold line for different values of soil wetness. The critical conditions are mentioned in Table 3.

Table 3. Critical conditions for initiation of landslides in Idukki, based on RS thresholds

From Table 3, it can be understood that when soil wetness is less than 0.2, T_{50} line of empirical ED thresholds should be considered as critical, when the soil wetness is between 0.2 to 0.4, T_5 can be considered as the critical threshold,. for For the next two cases where soil wetness is between 0.4 to 0.8, T_{10} threshold line can be considered as critical if the critical probability is 0.1. In this case, the threshold line for 0.2 to 0.4 is T_5, which is below the threshold line for soil wetness from 0.4 to 0.8. This variation can be due to the smaller number of data points considered in this study. With the available data points, very less cases are reported when the soil wetness is between 0.4 to 0.8, and the rainfall severity is below T_{10}. To avoid any possible missed alarms due to the limitations of the dataset considered, the threshold for soil wetness between 0.4 to 0.8 is considered as T_1, for which the probability of occurrence of landslides is 0.05 in this study. This variation in the critical probability ensures the physical validity and easy export of the model. and wWhen the soil wetness is between 0.8 to 1, even rainfall which are is below T_1 can trigger landslides. Hence, for the last condition, we defined the critical case as T_{min} where T_{min} represents the threshold line with minimum exceedance probability, close to zero. Practically, it represents any possible rainfall condition. The threshold line for 0.2 to 0.4 is T_5, which is below the threshold line for soil wetness from 0.4 to 0.8. This variation can be due to the less number of data points considered in this study. With the available data points, very less cases are reported when the soil wetness is between 0.4 to 0.8, and the rainfall severity is

~~below T_{10}. If the threshold has to be kept as T_5, the critical probability should be 0.05, which will increase the number of false alarms as mentioned in Table 2. Hence based on the available data, the threshold is kept as T_{10}.~~

The soil wetness data can be collected from daily satellite observations as taken in this study, or from real-time field observation using sensors. The severity of rainfall for each day can be estimated from the rainfall forecasts. Using these two inputs, the possibility of occurrence of landslide can be estimated using the conditions mentioned in Table 3. With higher exceedance probabilities, the relative uncertainty of α of ED threshold is crossing this limiting value. Similar results are observed when the rainfall data used is of daily temporal resolution (Teja et al., 2019).

The type of landslides is also an important factor in identifying the associated rainfall. For example, rockfalls may be triggered without any rainfall, debris flows are often triggered by short duration (maybe less than 1 hour) and high intensity (Kean et al., 2011), and shallow landslides are triggered by short-term rainstorms of high-intensity or long-duration rainfall of low to medium intensity (Guzzetti et al., 2008). This is the main reason why the models (ED, and RS) often associated with the disadvantage of higher false alarms. Even though the false alarms are considerably reduced in RS thresholds, it needs further enhancements to be used in an LEWS. There are chances that the model may miss alarms for rock–falls, which can be triggered with no rainfall. In the case of flow like landslides such as debris flows, the failure can be triggered by very short, high intensity rainfalls. Such rainfall events may trigger landslides in relatively dry soils as well. In this case, even if the antecedent soil wetness is less than 0.2, if the rainfall severity is greater than T_{50}, the model will issue a warning. If an event of severity less than T_{50} triggers such an event, the model may miss the alarm. With a higher number of data points and better resolution of rainfall data, this can be improved, and better results can be expected.

6. Conclusions

This study has been conducted to evaluate the effect of antecedent soil moisture content to improving the performance of empirical and probabilistic thresholds for Idukki district in India. The district is suffering from landslides ranging from cut slope failures to debris flows during monsoon seasons. The recent disasters that happened in 2018 and 2019 in the district emphasises the requirement of a landslide early warning system for the region.

In this study, empirical rainfall thresholds on ED plane was derived for the study area using an algorithm-based approach. It was found that with 5% exceedance probability, 20.19 mm rainfall can trigger a landslide in the region for a duration of 24 hours, and when the duration is 624 hours, a rainfall of 129 mm can trigger landslides in the region.

To evaluate the influence of each rainfall parameter on the occurrence of landslides, Bayesian analyses were conducted for both one-dimensional and two-dimensional cases. It was found that both intensity and event rainfall have influence on the occurrence of landslides, and most of the events happened when the rainfall happened in lesser duration. From two-dimensional analysis, the probabilities on EI plane were found to have the maximum values.

To evaluate the effect of soil wetness, another two-dimensional Bayesian approach was conducted, and it was observed that when the soil is relatively dry, severe rainfall events are required to trigger landslides and when the soil is wet, also milder rainfall conditions can trigger landslides in the study area.

A statistical comparison between the considered models was used to find out the best performing model. The comparison was carried out by using a ROC curve approach, where the RS threshold was found to have the maximum AUC of 0.96, among the models considered in this study. The empirical ED threshold generated a relevant number of false alarms, resulting in a low specificity value, while the disadvantage associated with the probabilistic thresholds was the low sensitivity due to a large number of missed alarms. The proposed method, which combines empirical thresholds with soil wetness using a probabilistic approach, performs better than both the root models by optimising the number of false alarms and missed alarms. Based on the comparison, it was found that an RS threshold of probability 0.1 should be considered critical for the study area and critical rainfall severity conditions were identified for each soil wetness condition. The performance could be further enhanced in the future by using hourly rainfall data with more dense rain gauge network for the area. Moreover, real-time monitoring of moisture content data for different locations in the study area can also contribute to better resolution soil moisture data and thereby improving the performance of the model.

The results of the study therefore open new promising perspectives for the development of an operational LEWS in the Idukki district, by combining rainfall and soil moisture data. At the same time, this work provides evidences from a monsoon region about the advances brought by hydro-meteorological thresholds based on soil moisture, which is gaining a growing attention in landslide studies all over the world but before today it was relatively unexplored for the setting of LEWS in the study area. Unfortunately, the use of soil moisture data in operational LEWS with short lead times is technically difficult, consequently another option to be explored is the use of antecedent rainfall conditions as a proxy to the soil moisture, which can be a simpler method to express the soil wetness conditions (Leonarduzzi and Molnar, 2020; Segoni et al., 2018b). More studies must be conducted for this region, to develop an effective LEWS which could obtain a fair compromise between the simplicity of the approach and the quality of the forecasting performance.

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Usage of antecedent soil moisture for improving the performance of rainfall thresholds for landslide early warning

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Abstract

Landslides triggered by heavy rains are increasing in number and creating severe losses in hilly regions across the world. Rainfall thresholds on regional and local-scales are being used for forecasting such events, for efficient early warning. Empirical and probabilistic approaches for defining rainfall thresholds are traditional tools which are being used as part of the forecasting system for rainfall induced landslides. Such methods are easy-to-use and are based on statistical analyses. They can be derived without looking into the complex hydro-geological processes involved in slope failures, but are often associated with the disadvantage of higher false alarms, limiting their applications in a regional landslide early warning system (LEWS). This study is an attempt to improve the performance of conventional meteorological thresholds by considering the effect of soil moisture, using a probabilistic approach. Idukki district in southern part of India is highly susceptible to landslides and has witnessed major socio-economical setbacks in the recent disasters happened in 2018 and 2019. This tourist hub is now in need of a landslide forecasting system, which can help in landslide risk reduction. This study attempts to understand the effect of averaged soil moisture estimates derived from passive microwave remote sensing data, for improving the performance of conventional empirical and probabilistic thresholds. For defining empirical thresholds, an algorithm-based approach such as Calculation of Thresholds for Rainfall-induced Landslides Tool (CTRL-T) has been used. Probabilistic thresholds were defined using a Bayesian approach, finding the posterior probability of occurrence using the marginal and conditional probabilities of the control parameters along with the prior probability of occurrence of landslide. The derived rainfall thresholds were quantitatively compared with the Bayesian probabilistic threshold derived using rainfall severity and soil wetness using an area under the curve (AUC) based receiver operating characteristics (ROC) curve method. The results show that when the antecedent moisture content in soil is less, only severe rainfall events can trigger landslides in the study area; while less severe rainfall events can also trigger landslides when the soil is wet. The role of soil wetness in the initiation is used to improve the performance of the conventional methods, and a ROC approach was used for the statistical comparison of different models. Further, the results indicated that the probabilistic threshold using rainfall severity and soil wetness outperformed the conventional approaches with AUC of 0.96, being the most sensitive and specific among the models considered. This result opens new promising perspectives for the development of an operational LEWS in the Idukki district based on a combination of rainfall and soil moisture data. Moreover, this work contributes to strengthen the advancing trend of hydro-meteorological thresholds based on soil moisture, which is gaining a growing attention in landslide studies and that, to date, was lacking evidences in monsoon regions.

Keywords: landslides; rainfall thresholds; LEWS; soil moisture; Idukki

1. Introduction

Forecasting landslides and evacuating people from hazardous zones is an important risk reduction strategy (Althuwaynee and Pradhan, 2017). Considering the climate change and associated extreme rainfall phenomenon, the number of rainfall-induced landslides are expected to rise (Alvioli et al., 2018; Chen et al., 2019; Gariano and Guzzetti, 2016). Being a geomorphological process in the landscape evolution (Iida, 1999), the detailed understanding of slope failure mechanisms involves hydrological studies and forecasting of possible failure planes (Agostini et al., 2014) using relevant geotechnical and meteorological parameters. However, these parameters are highly site specific and often difficult to determine with the desired accuracy (Tofani et al., 2017), except that for single slopes or very small basins (Chae et al., 2017), and sophisticated experimental research is required for understanding the mechanism in detail (Kim et al., 2018). Hence, a more practiced approach is needed to forecast the critical conditions which result in the occurrence of landslides using the primary triggering factor i.e. rainfall – with the aid of rainfall thresholds (Caine, 1980; Keefer et al., 1987; Piciullo et al., 2018). Rainfall thresholds can be empirical, probabilistic, or algorithm based (Althuwaynee et al., 2015; Piciullo et al., 2018; Segoni et al., 2018a). All the approaches exploit historical data to find a mathematical relationship between rainfall and the occurrence of landslides in a region, to identify critical rainfall conditions which can trigger landslides in the future. A rainfall event is most commonly characterised in terms of cumulated rainfall event (E), duration (D), and intensity (I) (which are referred to as "rainfall parameters"). Consequently, the thresholds are often defined as cumulated event rainfall vs. duration (ED thresholds) (Lainas et al., 2016; Melillo et al., 2018, 2016; Peruccacci et al., 2017; Teja et al., 2019) or as rainfall intensity vs. duration (ID thresholds) (Battistini et al., 2017; Brunetti et al., 2010; Guzzetti et al., 2008; Lainas et al., 2016; Wu et al., 2019).

When the definition of thresholds is associated with the generation of many false alarms, their usage in operational Landslide Early Warning System (LEWS) may be inappropriate (Aleotti, 2004; Guzzetti et al., 2008; Kirschbaum et al., 2012; Segoni et al., 2018b). Low performances of rainfall thresholds are traditionally related to the uncertainties associated with the definition of rainfall parameters, the quality and resolution of the historical data and the intrinsic limitations of the statistical models (Gariano et al., 2020; Marra et al., 2017; Nikolopoulos et al., 2014).

Some authors argued that sometimes the statistical correlation between rainfall parameters and landslide initiation is too weak and that hydro-meteorological thresholds accounting for both rainfall and hydrological (e.g. soil moisture) parameters could provide a stronger and more accurate assessment (Bogaard and Greco, 2018; Jakob et al., 2006; Terlien, 1998). Integrating soil moisture with rainfall thresholds has been proven effective in improving the rainfall thresholds (Abraham et al., 2020b; Segoni et al., 2018c; Zhao et al., 2019a), as the antecedent moisture content plays a key role in the shear strength parameters of soil. The soil moisture conditions play a key role in the infiltration process (Song and Wang, 2019) which significantly influences the initiation of landslides (Alimohammadlou et al., 2014; Baum et al., 2008; Bicocchi et al., 2019; Iverson, 2000; Wei et al., 2020; Yang et al., 2019). Weighted indexes (Glade et al., 2000; Ponziani et al., 2012); and satellite data (Zhao et al., 2019b) can be used for estimating soil moisture values when real-time field monitoring (Abraham et al., 2020c; Dikshit et al., 2018; Uchimura et al., 2015, 2010) cannot be conducted. Hydrological models (Abraham et al., 2020b; Zhao et al., 2019a) can also be used for the estimation of soil moisture content. In the published literature, soil moisture combined with rainfall thresholds has been tested mainly in Mediterranean, temperate and alpine climatic settings, whereas in monsoon regions similar types of tests are almost completely missing (Jakob et al., 2006; Mirus et al., 2018a; Valenzuela et al., 2018; Wicki et al., 2020).

The present work attempts to define statistical rainfall thresholds in Idukki district (India) and to improve their effectiveness by coupling rainfall parameters with soil moisture data. First, ED thresholds are defined using an automatic algorithm-based approach (Melillo et al., 2014). The algorithm first identifies the triggering rainfall events using the location of rain gauges and landslides, the time of occurrence of landslides and the time series rainfall data. It recreates multiple rainfall conditions which may result in landslides and identifies the maximum probable rainfall condition based on the location and time. After identifying the triggering rainfall event, the algorithm defines the ED thresholds with multiple exceedance probabilities using frequentist method. Then, by using a probabilistic approach (Berti et al., 2012), the effect of event rainfall, duration and intensity on the occurrence of landslides is evaluated (probabilistic rainfall thresholds). Both empirical (Melillo et al., 2018, 2016; Peruccacci et al., 2017) and probabilistic approaches (Berti et al., 2012; Dikshit and Satyam, 2019) were considered to establish the relationship between primary triggering factor (rainfall) and the result (landslide), and these are simple statistical approaches that are easy to derive by integrating with a rainfall forecasting system. Similar studies have been conducted for Indian Himalayas (Abraham et al., 2020a; Dikshit and Satyam, 2018, 2019; Teja et al., 2019) and the Western Ghats (Abraham et al., 2020e, 2019); however, these methods were not always found to be operational due to a higher number of false alarms or missed alarms, limiting their applications in LEWS. This study aims to overcome these limitations by integrating soil moisture data along with the rainfall thresholds. The objective is to find if the addition of soil moisture data can perform better than the conventional methods based on the rainfall data alone.

2. Description of the study area

The Western Ghats of Indian Peninsula is highly susceptible to rainfall-induced landslides. There is a surge in the number of landslides during monsoon season since 2018, due to very-high intensity rainfalls. The landslides and floods happened in 2018 severely affected the south Indian states of Kerala and Karnataka. Among the 14 districts in the state of Kerala, 13 are part of the Western Ghats and are susceptible to landslides. Nearly 5.3 million people in the state were affected by the disaster in 2018 (United Nations Development Programme, 2018). The Western Ghats scarps, running the whole extent of the mountain range, are highly prone to landslides. Very-high intensity rainfall, along with the anthropogenic activities, has accelerated the geological processes leading to landslides, making the situation alarming (Kuriakose et al., 2009b).

Idukki is a hilly district in the Western Ghats and is the second largest district in the state of Kerala, in terms of area. This district covers an area of 4358 km^2 and derived its name from the word ‘Idukku’ in the vernacular dialect meaning *narrow gorge*. This itself indicates the geography of the area. The district is the major power source of Kerala and houses many hydroelectric projects, including the famous arch dam of Idukki. About 50% of the district is covered by forests and Idukki is drained by three major rivers, two flowing westward and one eastward. The rainfall across the district is varying with the least values recorded in the northern side with a long-term average of 1000 mm while the southern parts record an average rainfall of 5000 mm (Sajeev and Praveen 2014; Department of Mining and Geology 2016). The southwest monsoon season from June to September contributes 60% of the annual rainfall and around 24% is contributed by the North-East monsoon from October to December. Due to varying topography, the climatic conditions in the hill ranges, plateaus and midlands of the district are different from each other.

Fig. 1. Location details of study area. (a) India, and (b) Digital Elevation Model of Idukki (modified using CartoDEM (CartoDEM, 2015)) along with location of rain gauges.

Geologically, Idukki can be divided into three different parts from south to north. The charnockite rocks in the south, migmatitic complex in central portion, and peninsular gneissic complex in the northern part. Granite gneiss is the oldest and predominant group among the peninsular gneissic complex while the charnockite group consists of magnetite quartzite, pyroxene granulite and charnockite (Department of Mining and Geology 2016). Structural cum denudational hills are the predominant geomorphological feature of Idukki. The hills are generally having a thin soil cover overlaid on Precambrian basement rocks. The midlands have a rugged topography with small hills and deep valleys with an average elevation of 50 m. The zone where midlands grades to plateaus are called the foothills, ranging up to 8 km in width. A major portion of the district belongs to the plateau region, with a large landmass of moderate slope. The elevation of the plateau region goes up to 1500 m, and the regions at an elevation greater than 1500 m belong to hilly ranges. More than 50% of the study area is covered by forest loam soils, produced by the weathering of rock under thick forest cover. The midlands are covered by lateritic soil with high permeability and less organic content. The valley portion of the terrain are covered with fine particles of sandy loam to clay type, formed by sedimentation and transportation of hill slopes. The narrow riverbanks consist of fertile alluvial soil and are more common in the midlands.

Because of its topographic variability and heavy rainfall, the district is highly susceptible to rainfall induced landslides. The typology of landslides in the Western Ghats includes earth and debris slides, rock falls, creep, slump and debris flows (Abraham et al., 2020d). Due to the thin regolith layer, shallow landslide (Varnes, 1978) is the most common type during prolonged rainfalls (Kuriakose et al., 2009a). Idukki district in particular is mostly affected by the cut slope failures along the major road corridors, disrupting the transportation network in the district. Recent changes in the land use patterns for infrastructure development and agriculture have affected the stability of slopes of this ecologically sensitive zone (Gadgil et al., 2011) and has aggravated the number of landslide disasters (Kuriakose et al., 2009b). Hence the development of an effective regional scale LEWS is highly needed to forecast the future landslides in the region.

3. Data and Methodology

The study explores the possibility of using soil moisture data in improving the performance of statistical thresholds. The overall methodology flow chart adopted in this study is shown in Fig 2. The methodology involves data collection from multiple sources, the definition of thresholds and their performance evaluation using different skill scores. For the analysis, historical rainfall, landslide, and soil moisture data were collected. For developing empirical and probabilistic rainfall thresholds, only rainfall and landslide data are required, while for developing probabilistic rainfall thresholds based on rainfall severity and soil wetness (RS threshold), the soil moisture data were integrated with empirical ED thresholds using a probabilistic approach. While the empirical threshold considers the effect of rainfall events which resulted in landslides, the probabilistic thresholds consider both triggering and non-triggering rainfall events for the analysis.

Fig. 2. Methodology of study.

3.1 Data collection

The dataset used for this study spans from 2010 to 2018 and the historical data from this period was used to derive the empirical and probabilistic thresholds for occurrence of landslides in Idukki district.

The daily rainfall data was collected from the Indian Meteorological Department (India Meteorological Department 2019) for four rain gauges within the district. The landslide data was collected from various government agencies and media reports (Abraham et al., 2019) and only landslides for which the date of occurrence was available were used for the analysis. For each rain gauge a reference area was defined and multiple landslides triggered in the same day in each area were considered as one landslide event and rainfall data were collected from the reference rain gauge. By these criteria, 225 landslide events were identified in the study area which were first used as the input for empirical thresholds. For probabilistic thresholds, a total of 5028 rainfall events recorded by the four rain gauges during the study period were considered.

The average daily soil moisture data was collected from Giovanni's website by National Aeronautics and Space Administration Goddard Earth Sciences Data and Information Services Center (NASA GES DISC) (de Jeu and Owe, 2014, 2012; Giovanni, 2020). The data was derived using land parameter retrieval model (LPRM), which is a multi-parameter retrieval algorithm focused on hydrological and climate studies. It retrieves the soil moisture from the microwave observations from sensors. The observed brightness temperatures were used to derive the soil moisture data, using LPRM (Owe et al., 2008). LPRM is based on a forward radiative transfer model and the output is the volumetric soil moisture content in percentage. The soil moisture on the day before the occurrence of landslide, termed as the 'antecedent soil moisture' was used for the analysis in this research. The spatial resolution of the data is $0.25^{o} \times 0.25^{o}$. The study area (Idukki district) consists of 14 grids of size $0.25^{o} \times 0.25^{o}$ (Figure 1). After calculating the area of Idukki within each grid, the weighted average was calculated for the whole area, for simplified calculation. This value is called the 'averaged moisture content'. Another term, 'soil wetness' is introduced, to represent a range of antecedent soil moisture, on a scale of 0 to 1. The soil wetness values were divided into five equal parts, representing different ranges of moisture content. This classification is used to overcome the limitations associated with using averaged data for a larger area. The value of soil wetness is directly proportional to the moisture content values and indicates the wetness of soil before the landslide.

Thus, by using historical rainfall, landslide and soil moisture data, thresholds were defined using multiple approaches for the study area to find the effect of soil moisture on the forecasting performance of the thresholds.

3.2 Empirical thresholds

The selection of rain gauges and rainfall parameters plays a critical role in the definition of rainfall thresholds (Abraham et al., 2020e). For the study area, rainfall data from the four available rain gauges were considered for the analysis. The intensity-duration thresholds for the study area was earlier derived from using a nearest rain gauge approach (Abraham et al., 2019), considering 225 landslide events occurred from 2010 to 2018. From the pioneering work of Caine (Caine, 1980), ID thresholds were defined for regions across the globe (Abraham et al., 2020c, 2019; Brunetti et al., 2010; Dikshit and Satyam, 2018; Guzzetti et al., 2008, 2007; Segoni et al., 2018a). Even though intensity can easily be converted to event rainfall and vice-versa, recent literature shows a shift towards defining ED thresholds instead of ID thresholds (Melillo et al., 2018, 2014; Peruccacci et al., 2012; Teja et al., 2019; Zhao et al., 2019a). The reason is that E and D are two mutually independent parameters while I is a function of D and E. Hence, for a definition of rainfall thresholds and rainfall severity, the data points on ED plane was considered in this study. In this study, the reconstruction of event- duration thresholds was carried out by using Calculation of Thresholds for Rainfall Induced Landslides - Tool (CTRL-T) (Melillo et al., 2018, 2014). CTRL-T uses an algorithm-based approach, extracting the rainfall events automatically from the daily precipitation data input. From the extracted events, rainfall conditions that have triggered landslides were identified; and used to derive the rainfall thresholds for the region. The tool considers a buffer zone around each landslide location, to search for the rain gauge and identify the triggering event. In this study, a search radius of 20 km is considered, due to the low rain gauge density in the study area. The algorithm also considers a delay time between the end of rainfall and occurrence of landslide. In this study, the delay time is taken as 48 hours (Melillo et al., 2014). If no rainfall condition is recreated within this delay time before the occurrence of landslide, the event will be discarded by the algorithm. The algorithm first determines the total event rainfall and duration of rainfall for all identified rainfall events and then to minimise the effect of spatial variability of rainfall distribution, single or multiple rainfall conditions (MRC) likely to result in failures and a weight is assigned to each of them. Then for each landslide, the highest weight was used to identify the reference rain gauge and to choose the maximum probable rainfall conditions (MPRC). In this study, five different threshold lines were defined using CTRL-T, at different exceedance probabilities of 1%, 5%, 10%, 20% and 50% (termed as T_1, T_5, T_{10}, T_{20} and T_{50}, respectively). Thresholds and related uncertainties were estimated from MPRCs. The defined thresholds are in the form of a power law, determined using the frequentist approach (Brunetti et al., 2010) and can be expressed as:

$$E = (\alpha \pm \Delta\alpha)\, D^{(\gamma \pm \Delta\gamma)} \quad (1)$$

where, α is the scaling parameter or the intercept and γ is the shape parameter which denotes the slope of the equation. Δα and Δγ represents the uncertainties associated with α and γ, respectively. The uncertainties are determined using a bootstrap approach.

3.3 Probabilistic approach

The empirical thresholds compare an input value with the defined thresholds and will have a single output (triggering or non-triggering). It is often difficult to decide the exceedance probability to be selected as a threshold beyond which a radical change can be expected in the system (Berti et al., 2012). The discretion between triggering and non- triggering rainfall conditions is not trivial in such cases. To derive the equation, only the triggering rainfall conditions are considered. This increases the chances of false alarms, as numerous rainfall events that cross the threshold line not necessarily trigger landslides.

By considering both triggering and non- triggering rainfalls for analysis, probability-based models are more informative and provide a better option to find extreme events. In this study, a Bayesian approach is used to define probabilistic thresholds (Berti et al., 2012).

3.3.1 One-dimensional analysis

Bayes theorem applies a conditional probability of some event L (landslide) given the occurrence of another event X (rainfall, expressed in terms of E, I or D). This is also called the posterior probability, $P(X|L)$. It can be calculated as follows (Berti et al., 2012):

$$P\ (L|X) = \frac{P(X|L) * P(L)}{P\ (X)} \tag{2}$$

where, $P(X|L)$ is the conditional probability of occurrence of rainfall of magnitude X, when a landslide occurs. This is also called as a likelihood.

$P(L)$ is the prior probability of occurrence of landslide regardless of the occurrence rainfall magnitude.

$P\ (X)$ is the marginal probability of X, which can be defined as the probability of occurrence of rainfall regardless of the occurrence of landslides. The terms can be calculated mathematically using relative frequencies. Let N_R be the total number of rainfall events during study period, N_L be the total number of landslides occurred, N_X be the number of rainfall events with magnitude X and $N_{(X|L)}$ be the number of rainfall events with magnitude X that resulted in landslides. The probabilities can be computed as (Berti et al., 2012):

$$P(L) \approx \frac{N_L}{N_R} \tag{3}$$

$$P(X) \approx \frac{N_X}{N_R} \tag{4}$$

$$P(X|L) \approx \frac{N_{(X|L)}}{N_L} \tag{5}$$

Considering the rainfalls that resulted in landslides only will give us partial information, the likelihood. To understand the influence of rainfall of magnitude X, it is important to compare the prior probability with the posterior probability.

3.3.2 Two-dimensional analysis

Two-dimensional case is the extension of Eq. 2 by considering two conditions X, Y instead of the single condition X in Eq. 2. In the initial analysis, we consider X and Y as magnitude of two rainfall parameters (E,D ; I,D; E,I). The calculation of prior, marginal and conditional probabilities are given below:

$$P\ (L|X,Y) = \frac{P(X,Y|L) * P(L)}{P\ (X,Y)} \tag{6}$$

$$P(L) \approx \frac{N_L}{N_R} \tag{7}$$

$$P(X,Y) \approx \frac{N_{X,Y}}{N_R} \tag{8}$$

$$P(X,Y|L) \approx \frac{N_{(X,Y|L)}}{N_L} \tag{9}$$

The study explores the effect of antecedent soil moisture content using a two-dimensional probabilistic analysis. During the second phase, we considered rainfall severity in ED plane and soil wetness as X and Y, respectively. Based on the values of soil wetness, five different categories were considered for analysis viz, less than 0.2, 0.2 to 0.4, 0.4 to 0.6, 0.6 to 0.8, and 0.8 to 1. The categories based on rainfall severity were less than T_1, T_1 to T_5, T_5 to T_{10}, T_{10} to T_{20}, T_{20} to T_{50} and greater than T_{50}. Thus, the two-dimensional plane was divided into 30 cells as a 6 x 5 matrix as shown in Fig. 6. These values were used for the definition of RS threshold.

4. Results

4.1 Empirical thresholds

CTRL-T tool considered 177 landslide events out of the 225 and the rest were discarded to avoid introduction of relevant spatio-temporal uncertainties in the analysis. The uncertainties are associated with the less rain gauge density in the study area. As described earlier, the landslides for which responsible rainfall conditions were not identified were discarded. This can be due to a distance more than 20 km between the location of rain gauges and landslide or due to a delay time more than 48 hours after the end of any rainfall event. The algorithm forecasted rainfall thresholds with various exceedance probability both in normal and logarithmic plot (Fig. 3). The threshold lines of 1%, 5%, 10%, 20% and 50% exceedance probabilities were used to classify the events into six categories based on the severity of rainfall. These lines are named T_1, T_5, T_{10}, T_{20} and T_{50}, respectively. The slope of threshold lines in logarithmic plot was found to be 0.57±0.03. This value is not in good agreement with the ID thresholds defined for the area in a previous study (Abraham et al., 2019). Though both the studies used frequentist approach for the definition of thresholds, the process of identification of responsible rainfall event was different. In the previous study (Abraham et al., 2019), the responsible rainfalls were identified using a Thiessen polygon approach manually, while in this study, the automatic algorithm, CTLRL-T is used for identifying the responsible rainfall event. The parameters of threshold lines and the uncertainties associated are listed in Table 1.

Fig. 3. Rainfall event – duration thresholds for Idukki district

Table 1. Values of α, γ and the uncertainties associated with different exceedance probabilities

The range of duration of rainfalls considered for analysis vary from 1 to 26 days. For the thresholds to be reliable, the relative uncertainty ($\Delta x/x$ for any variable x) should be less than 10%. Here the relative uncertainty of γ is 5.2%. But with higher exceedance probabilities, the relative uncertainty of α is crossing this limiting value.

With 5% exceedance probability, 20.19mm rainfall can trigger a landslide in the region for a duration of 24 hours and when the duration is 624 hours, a rainfall of 129 mm can trigger landslides in the region. For a better understanding of the effect of each rainfall parameter on the occurrence of landslides, probabilistic rainfall thresholds were defined for the area.

4.2 Probabilistic thresholds

The maximum probable rainfall conditions which were used for the definition of ED thresholds were considered as the triggering rainfall events for the probabilistic analysis. Thus, out of the 5028 rainfall events considered, 177 events were identified as triggering events by CTRL- T algorithm and the rest 4851 events were considered as non-triggering rainfall events. In the one-dimensional case, six categories of rainfall duration, five categories of cumulated rainfall event and seven categories of rainfall intensity were considered. The results are plotted in Fig. 4 (a-f); where Fig. 4a, c and e depict the prior probability, marginal probability and likelihood, and Fig. 4b, d and f depict the prior and posterior probabilities. The variable X in Eq. (2-5) is replaced with D, E and I in the respective graphs. $P(L)$ being a constant parameter (value 0.035 in this study), the ratio of $P(X|L)$ to $P(X)$ determines the variation of posterior probability values. Hence when $P(X|L) > P(L)$, the posterior probability is greater than prior probability and vice versa. The more the variation between prior and posterior probability, the more significant the variable is. It can be seen, that for duration and event rainfall, for the largest values of variables, the values of $P(L|X)$ is less than $P(L)$, while in the case of intensity, high intensity rainfalls are more probable to trigger landslides in the region. The plots of $P(X)$ and $P(X|L)$) are well above the plot of prior probability in all the cases. Intensity was found to be the most significant variable, with the maximum ratio between posterior and prior probabilities. The maximum posterior probability when the control parameter is D was found to be 0.053 where the value is 0.103 and 0.116 in the case of E and I, respectively. Maximum probability occurs when the duration is between 120 h to 240 h; event rainfall is between 100 mm to 200 mm; and intensity is greater than 3 mm/h.

Fig. 4. Prior, conditional, marginal and posterior probabilities with respect to rainfall parameters. (a, b) Duration; (c, d) Event rainfall; and (e, f) Intensity.

To evaluate the joint occurrence of two parameters, two-dimensional Bayesian analysis were conducted with data on three different planes (Fig. 5). The two-dimensional space for each analysis was divided into small cells based on the categories of parameters used for one-dimensional analysis. Hence the ID plane is a 7 x 6 matrix, ED plane is a 5 x 6 matrix and the EI plane is a 5 x 7 matrix. There are several no data points in all three cases, due to the lower number of landslides considered for the analysis. As identified from the one-dimensional analysis, E and I were found to be more critical parameters than D. This is the reason why this study has considered all three different combinations of the control parameters even though the empirical thresholds are defined on ED plane only. The maximum probability value was obtained on EI plane, when the intensity value is less than 0.5 mm/h and event rainfall is between 100 mm to 200 mm, with a value of 0.54.

Fig. 5. Two-dimensional posterior probabilities of occurrence of landslide on (a) ID plane, (b) ED plane, and (c) EI plane.

It is evident from Fig. 6 that even less severe rainfall events when falling on a moist soil can trigger landslides in the region. Most of the landslides for which rainfall events were less severe happened on days with higher soil wetness. Also, when the rainfall event is severe, even dry soil can be susceptible to landslides. The maximum probability of 0.49 was observed when the rainfall severity was between T_{20} to T_{50} and the soil wetness was between 0.8 to 1. With the available data, when the antecedent soil moisture is less, only extremely severe rainfall conditions can trigger landslides in the area. This affects the performance of the ED thresholds considerably. For different antecedent soil moisture conditions, this makes it easier to decide the threshold line to be used.

Fig. 6. Two-dimensional Bayesian probabilities for occurrence of landslides based on rainfall severity and soil wetness.

5. Discussions

To verify the performance of all models and to understand which model is performing better for the study area, different thresholds should be compared quantitatively (Lagomarsino et al., 2015). In this study, empirical thresholds on ED plane, probabilistic thresholds on all three combinations of control parameters (ED, ID and EI) and also a two-dimensional Bayesian approach by combining empirical ED thresholds with soil moisture have been derived. The maximum probability value obtained in the two-dimensional analysis was in the case of EI thresholds, and the value is 0.54. The value was obtained when the intensity is less than 0.5 mm/h and event rainfall is between 100 to 200 mm. This implies a prolonged duration of 8 days or more. The intensity value is too low in this case, yet the probability value is the maximum. The definition of 2-dimensional Bayesian probability majorly depends upon the relative occurrence of landslides when the rainfall conditions are satisfied and the occurrence of rainfall events with specified conditions. The number of events with the specified EI conditions were less, but more than half of them have resulted in landslides based on the historical data. Thus, the probability of occurrence of landslides is higher in this case. This result points towards the significance of using a physical parameter such as soil moisture for the definition of threshold. The top regolith layer throughout the district consists of forest loam, lateritic soil, alluvial soils etc, with higher fine fraction (Department of Mining and Geology Kerala, 2016). The less permeable soil has a higher water holding capacity and the moisture content increases when the rainfall is continuous. The prolonged rainfall has thus reduced the shear strength of soil and the landslide has happened at a very less intensity value. This complicated process is simplified by using a statistical approach, by considering the effect of soil wetness. To understand the performance of such a model with respect to the meteorological thresholds, a quantitative comparison is required.

An ROC curve approach was used for quantitative comparison. ROC curve is a tool to understand the performance of a model with a binary outcome. Each threshold value can forecast two outcomes for a day; ‘landslides’ or ‘no landslides. If the threshold condition is crossed, the model forecasts 'landslides' and otherwise, 'no landslides. When the forecasting is correct and landslide occurs, it is termed as a true positive (TP). Another possibility of correct outcome is the result 'no landslides' on a day in which landslides do not occur. This can be counted as a true negative (TN) result. When the forecasting goes wrong, it also has two possible outcomes. 'Landslides' forecasted on a non-landslide day, which is a false positive (FP) or simply a false alarm and 'no landslides' forecasted on a day in which landslides occur, termed as false negatives (FN) or missed alarms. A perfect model should only have true outcomes, without any false alarms or missed alarms.

A ROC curve is a plot with a false positive rate of a model on x-axis and a true positive rate on y axis. It evaluates the overall performance of the model. The true positive rate is also called the sensitivity of the model. It provides the proportion of landslide occurrences which are correctly identified ($TP/(TP + FN)$). The specificity of a model is the true negative rate and is the ratio of TN to the sum of TN and FP. The false positive rate can be calculated by subtracting specificity value from 1. An ideal model is expected to have both sensitivity and specificity values as 1. Hence the point (0,1) on ROC curve is called the perfect point. Points which are closer to this perfect point has a better performance. Also, the model with better performance is the one with a maximum area under the curve (AUC) among the different models considered. Threat score and True Skill Statistic (TSS) are two other parameters which were used to understand the performance of a model (Mirus et al., 2018b). Threat score is defined as the ratio of TP to the sum of TP, FP and FN. TSS is the difference between sensitivity and false positive rate. For an ideal model, the value of both these variables should be 1.

ROC curves for all models considered in the study are plotted in Fig. 7 and the statistical attributes are listed in Table 2. From Fig. 7, it can be observed that the RS threshold covers the maximum area in the plane with an AUC of 0.96. The empirical ED threshold has the second highest AUC of 0.86. All the three probabilistic rainfall thresholds have very close AUC values as observed in Fig. 7. EI threshold covers a larger area than the other two, indicating its better performance in comparison with the other two probabilistic rainfall thresholds. The distance from perfect point is minimum in the case of RS thresholds, in the case of critical probabilities 0.1 and 0.15. It can also be observed that the value of threat score and TSS are maximum in the case of RS thresholds. The maximum value of threat score is obtained as 0.24 and TSS as 0.90, both in the case of RS thresholds with critical probability 0.1, which is also the closest one to the perfect point.

Fig. 7. ROC curves for the derived thresholds. Sensitivity is the ability of a model to correctly identify the landslide events and Specificity is the ability to correctly identify the non-landslide events

Looking into the details in Table 2, it confirms with the literature as the empirical thresholds result in many false alarms, making it inadequate to use in an LEWS. The number of false alarms can considerably be reduced by using probabilistic rainfall thresholds, as listed in Table 2. The number of FP in the case of probabilistic ED. ID and EI are much lesser than the other two models considered. But this reduction in false alarms comes with the cost of a higher number of missed alarms (FN). While 171 landslide events out of the 177 events are correctly forecasted by the empirical ED threshold line T_1, and 172 are correctly forecasted by RS threshold when the critical probability is 0.05, the maximum number of correct outcomes for the other probabilistic models are 106, 105 and 117 on ED, ID and EI planes respectively. For improving the performance, we need to balance the number of false alarms and missed alarms, which is achieved by using RS threshold. The RS threshold has FN numbers comparable with that of probabilistic rainfall thresholds, minimising the false alarms and by incorporating an additional filter using soil wetness, it reduces the number of false alarms when compared to the empirical ED threshold.

Table 2. Statistical attributes for quantitative comparison.

The probabilistic rainfall thresholds have high specificity values, pointing to their ability to correctly forecast the days without landslides, but with very less values of sensitivity. The points on ROC curves for probabilistic rainfall thresholds are therefore closer to both the axes, reducing the AUC. Even though the points have high specificity values, they are located far from the perfect point, due to their inefficiency in correctly forecasting the occurrence of landslides. The RS threshold with a critical probability of 0.1 is the closest one to the perfect point, correctly forecasting 167 landslide occurrences.

From the analysis, the rainfall and soil wetness conditions for which the probability of occurrence is more than 0.1 should be considered critical. This makes it easier to identify the empirical ED threshold line for different values of soil wetness. The critical conditions are mentioned in Table 3.

Table 3. Critical conditions for initiation of landslides in Idukki, based on RS thresholds

From Table 3, it can be understood that when soil wetness is less than 0.2, T_{50} line of empirical ED thresholds should be considered as critical, when the soil wetness is between 0.2 to 0.4, T_5 can be considered as the critical threshold. For the next two cases where soil wetness is between 0.4 to 0.8, T_{10} threshold line can be considered as critical if the critical probability is 0.1. In this case, the threshold line for 0.2 to 0.4 is T_5, which is below the threshold line for soil wetness from 0.4 to 0.8. This variation can be due to the smaller number of data points considered in this study. With the available data points, very less cases are reported when the soil wetness is between 0.4 to 0.8, and the rainfall severity is below T_{10}. To avoid any possible missed alarms due to the limitations of the dataset considered, the threshold for soil wetness between 0.4 to 0.8 is considered as T_1, for which the probability of occurrence of landslides is 0.05 in this study. This variation in the critical probability ensures the physical validity and easy export of the model. When the soil wetness is between 0.8 to 1, even rainfall which is below T_1 can trigger landslides. Hence, for the last condition, we defined the critical case as T_{min} where T_{min} represents the threshold line with minimum exceedance probability, close to zero. Practically, it represents any possible rainfall condition.

The soil wetness data can be collected from daily satellite observations as taken in this study, or from real-time field observation using sensors. The severity of rainfall for each day can be estimated from the rainfall forecasts. Using these two inputs, the possibility of occurrence of landslide can be estimated using the conditions mentioned in Table 3. With higher exceedance probabilities, the relative uncertainty of α of ED threshold is crossing this limiting value. Similar results are observed when the rainfall data used is of daily temporal resolution (Teja et al., 2019).

The type of landslides is also an important factor in identifying the associated rainfall. For example, rockfalls may be triggered without any rainfall, debris flows are often triggered by short duration (maybe less than 1 hour) and high intensity (Kean et al., 2011), and shallow landslides are triggered by short-term rainstorms of high-intensity or long-duration rainfall of low to medium intensity (Guzzetti et al., 2008). This is the main reason why the models (ED, and RS) often associated with the disadvantage of higher false alarms. Even though the false alarms are considerably reduced in RS thresholds, it needs further enhancements to be used in an LEWS. There are chances that the model may miss alarms for rockfalls, which can be triggered with no rainfall. In the case of flow like landslides such as debris flows, the failure can be triggered by very short, high intensity rainfalls. Such rainfall events may trigger landslides in relatively dry soils as well. In this case, even if the antecedent soil wetness is less than 0.2, if the rainfall severity is greater than T_{50}, the model will issue a warning. If an event of severity less than T_{50} triggers such an event, the model may miss the alarm. With a higher number of data points and better resolution of rainfall data, this can be improved, and better results can be expected.

6. Conclusions

This study has been conducted to evaluate the effect of antecedent soil moisture content to improving the performance of empirical and probabilistic thresholds for Idukki district in India. The district is suffering from landslides ranging from cut slope failures to debris flows during monsoon seasons. The recent disasters that happened in 2018 and 2019 in the district emphasises the requirement of a landslide early warning system for the region.

In this study, empirical rainfall thresholds on ED plane was derived for the study area using an algorithm-based approach. It was found that with 5% exceedance probability, 20.19 mm rainfall can trigger a landslide in the region for a duration of 24 hours, and when the duration is 624 hours, a rainfall of 129 mm can trigger landslides in the region.

To evaluate the influence of each rainfall parameter on the occurrence of landslides, Bayesian analyses were conducted for both one-dimensional and two-dimensional cases. It was found that both intensity and event rainfall have influence on the occurrence of landslides, and most of the events happened when the rainfall happened in lesser duration. From two-dimensional analysis, the probabilities on EI plane were found to have the maximum values.

To evaluate the effect of soil wetness, another two-dimensional Bayesian approach was conducted, and it was observed that when the soil is relatively dry, severe rainfall events are required to trigger landslides and when the soil is wet, also milder rainfall conditions can trigger landslides in the study area.

A statistical comparison between the considered models was used to find out the best performing model. The comparison was carried out by using a ROC curve approach, where the RS threshold was found to have the maximum AUC of 0.96, among the models considered in this study. The empirical ED threshold generated a relevant number of false alarms, resulting in a low specificity value, while the disadvantage associated with the probabilistic thresholds was the low sensitivity due to a large number of missed alarms. The proposed method, which combines empirical thresholds with soil wetness using a probabilistic approach, performs better than both the root models by optimising the number of false alarms and missed alarms. Based on the comparison, it was found that an RS threshold of probability 0.1 should be considered critical for the study area and critical rainfall severity conditions were identified for each soil wetness condition. The performance could be further enhanced in the future by using hourly rainfall data with more dense rain gauge network for the area. Moreover, real-time monitoring of moisture content data for different locations in the study area can also contribute to better resolution soil moisture data and thereby improving the performance of the model.

The results of the study therefore open new promising perspectives for the development of an operational LEWS in the Idukki district, by combining rainfall and soil moisture data. At the same time, this work provides evidences from a monsoon region about the advances brought by hydro-meteorological thresholds based on soil moisture, which is gaining a growing attention in landslide studies all over the world but before today it was relatively unexplored for the setting of LEWS in the study area. Unfortunately, the use of soil moisture data in operational LEWS with short lead times is technically difficult, consequently another option to be explored is the use of antecedent rainfall conditions as a proxy to the soil moisture, which can be a simpler method to express the soil wetness conditions (Leonarduzzi and Molnar, 2020; Segoni et al., 2018b). More studies must be conducted for this region, to develop an effective LEWS which could obtain a fair compromise between the simplicity of the approach and the quality of the forecasting performance.

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Figure

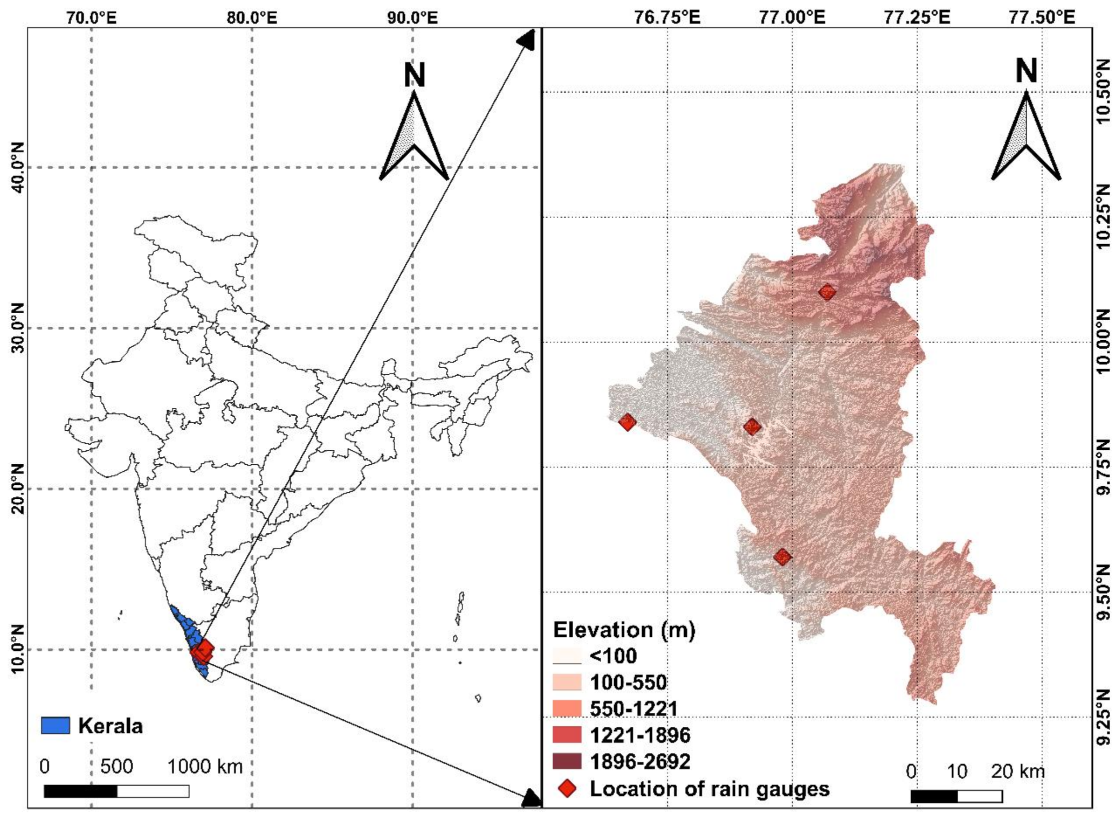

Fig. 1. Location details of study area. (a) India, and (b) Digital Elevation Model of Idukki (modified using CartoDEM (CartoDEM, 2015)) along with location of rain gauges.

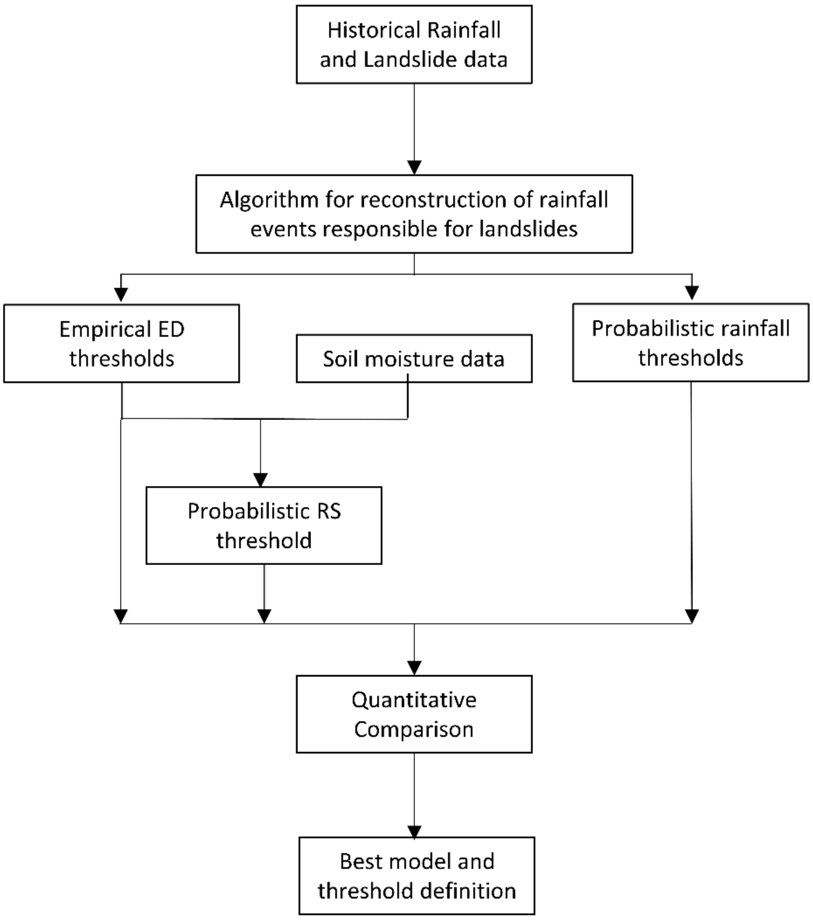

Fig. 2. Methodology of study.

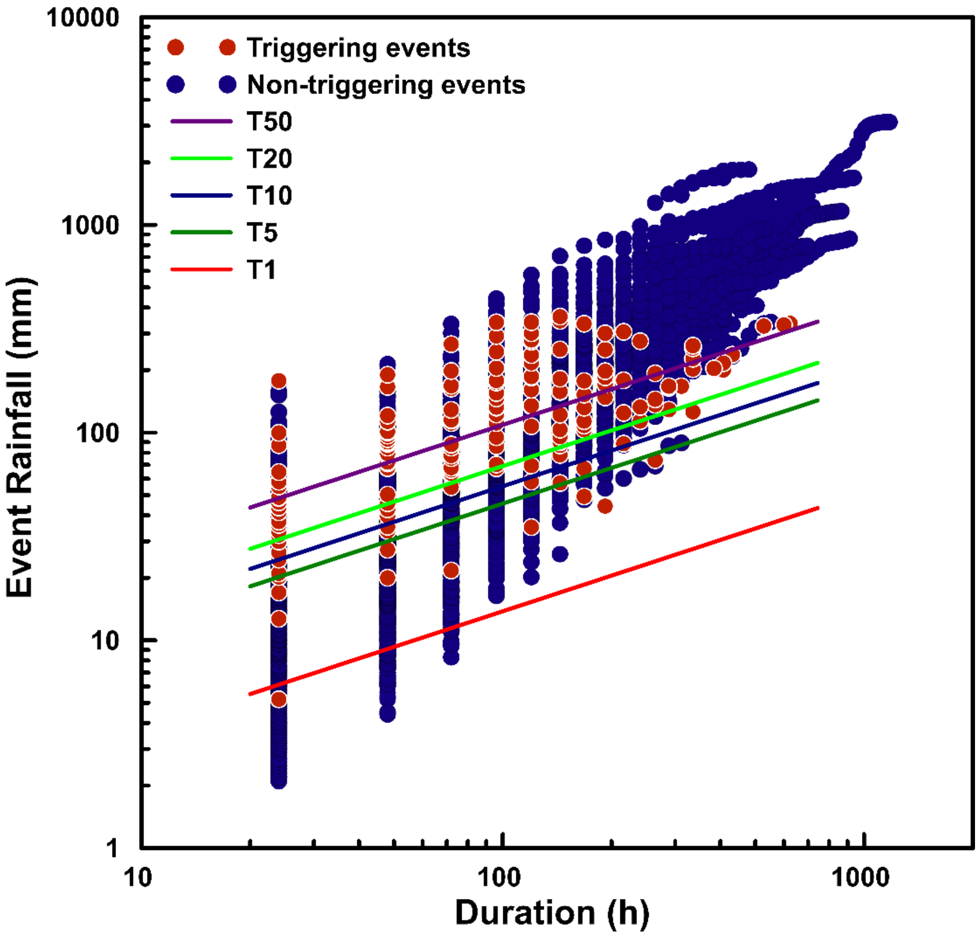

Fig. 3. Rainfall event – duration thresholds for Idukki district.

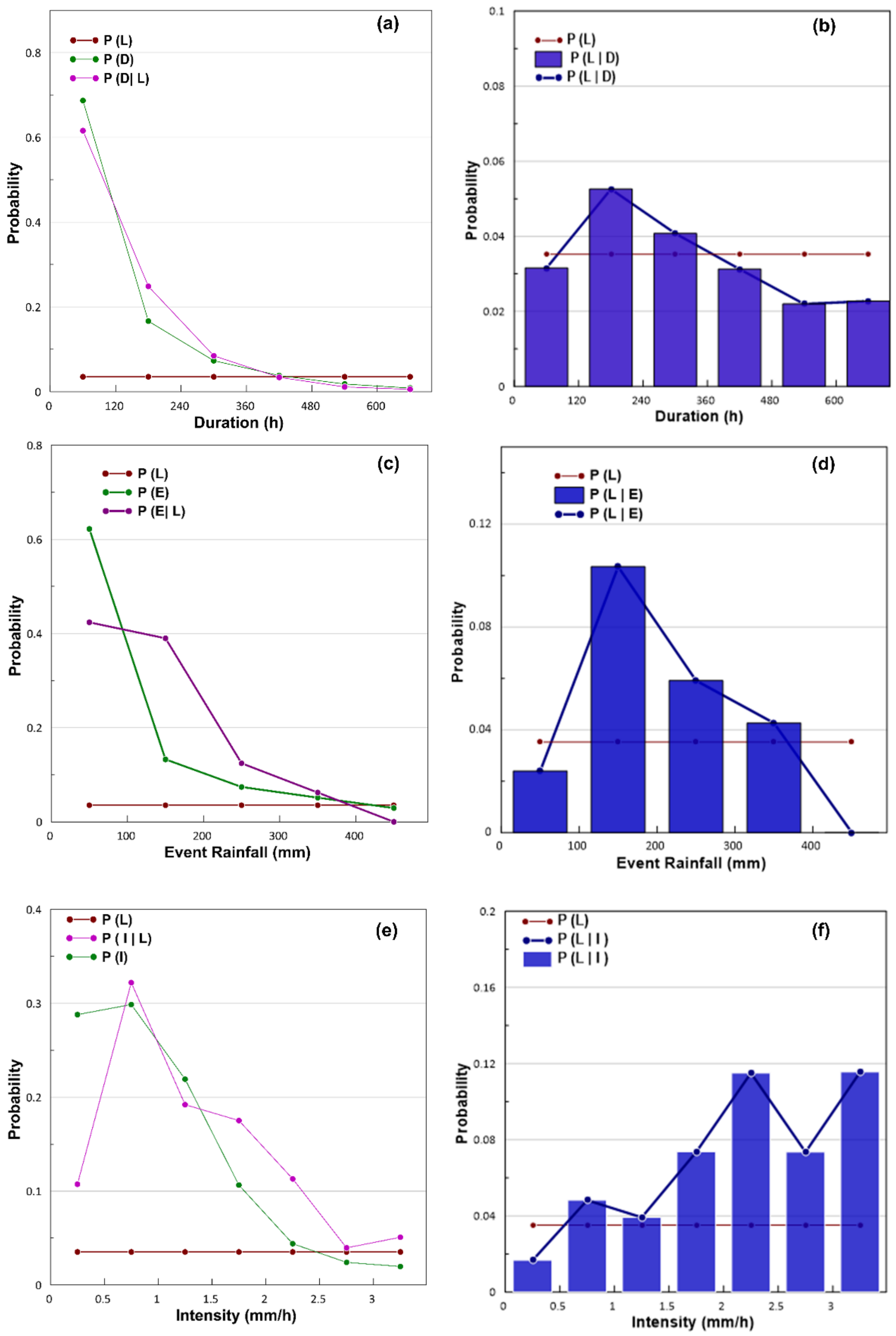

Fig. 4. Prior, conditional, marginal and posterior probabilities with respect to rainfall parameters. (a, b) Duration; (c, d) Event rainfall; and (e, f) Intensity.

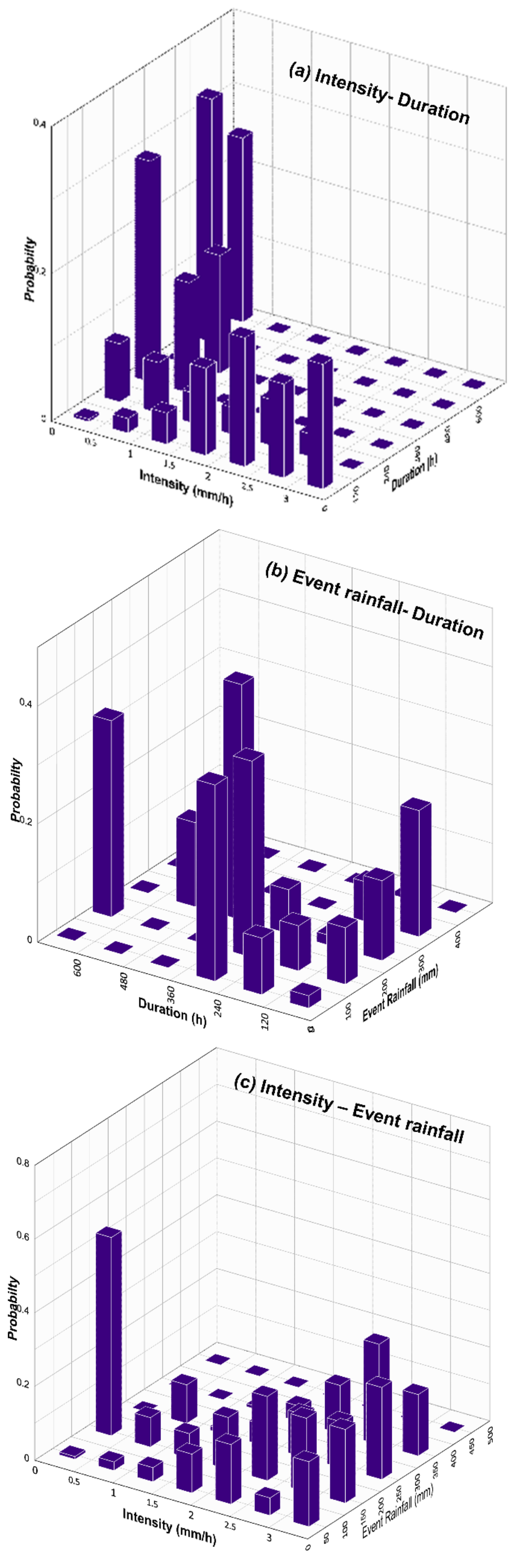

Fig. 5. Two-dimensional posterior probabilities of occurrence of landslide on (a) ID plane, (b) ED plane, and (c) EI plane.

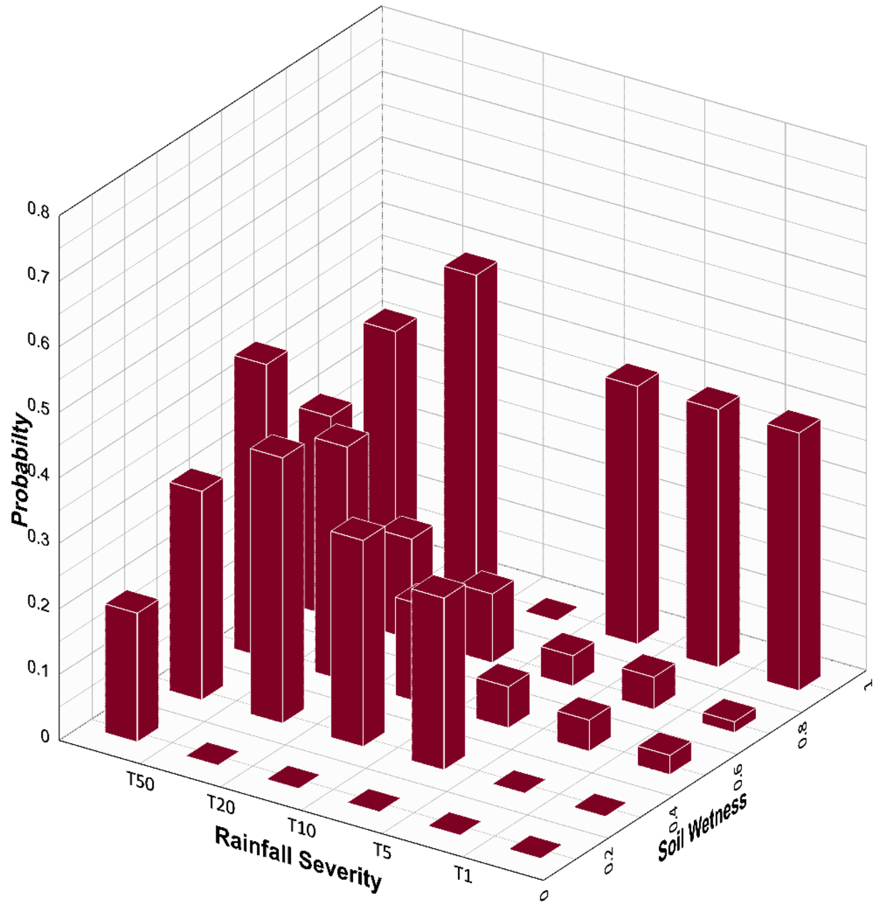

Fig. 6. Two dimensional Bayesian probabilities for occurrence of landslides based on rainfall severity and soil wetness.

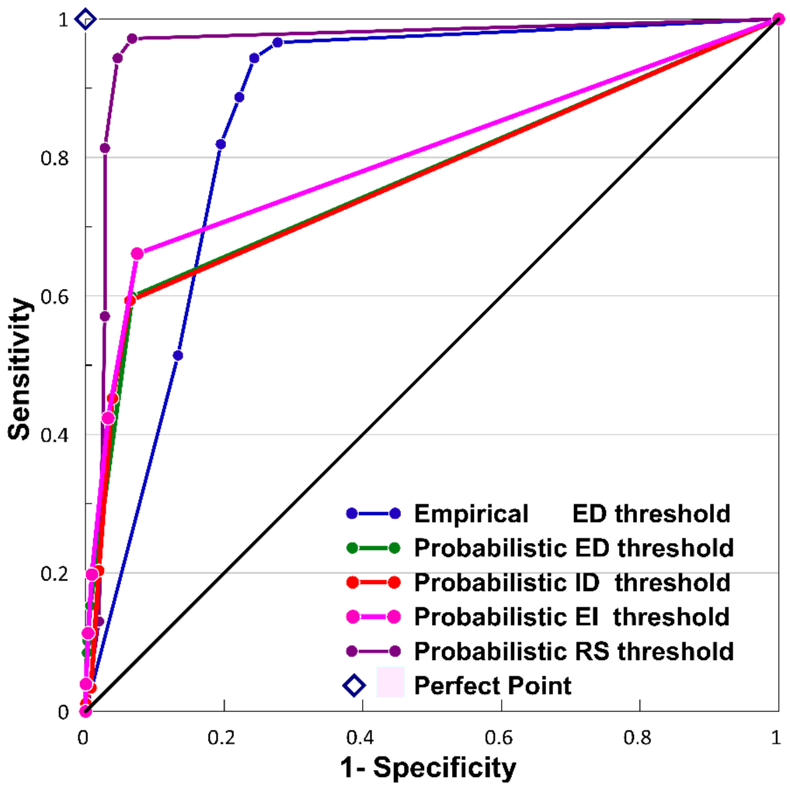

Fig. 7. ROC curves for the derived thresholds. Sensitivity is the ability of a model to correctly identify the landslide events and Specificity is the ability to correctly identify the non-landslide events

Figure captions

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Table 1. Values of α, γ and the uncertainties associated with different exceedance probabilities

Threshold	**α**	**Δα**	**γ**	**Δγ**
T_1	2.3	0.8	0.57	0.03
T_5	3.3	1.1	0.57	0.03
T_{10}	4.0	1.3	0.57	0.03
T_{20}	5.0	1.6	0.57	0.03
T_{50}	7.9	2.4	0.57	0.03

Table 2. Statistical attributes for quantitative comparison.

Threshold model	**Threshold value**	**TP**	**FP**	**FN**	**TN**	**Sensitivity**	**Specificity**	**Distance from perfect point**	**Threat score**	**True skill statistic**	**AUC**
Empirical ED	T1	171	3594	6	9377	0.97	0.72	0.28	0.05	0.69	0.86
	T5	167	3156	10	9815	0.94	0.76	0.25	0.05	0.70	
	T10	157	2878	20	10093	0.89	0.78	0.25	0.05	0.67	
	T20	145	2531	32	10440	0.82	0.80	0.27	0.05	0.62	
	T50	91	1729	86	11242	0.51	0.87	0.50	0.05	0.38	
Probabilistic ED	0.05	106	870	71	12101	0.60	0.93	0.41	0.10	0.53	0.77
	0.1	27	86	150	12885	0.15	0.99	0.85	0.10	0.15	
	0.15	18	36	159	12935	0.10	1.00	0.90	0.08	0.10	
	0.2	18	36	159	12935	0.10	1.00	0.90	0.08	0.10	
	0.3	15	25	162	12946	0.08	1.00	0.92	0.07	0.08	
Probabilistic ID	0.05	105	830	72	12141	0.59	0.94	0.41	0.10	0.53	0.77
	0.1	80	502	97	12469	0.45	0.96	0.55	0.12	0.41	
	0.15	36	247	141	12724	0.20	0.98	0.80	0.08	0.18	
	0.2	6	102	171	12869	0.03	0.99	0.97	0.02	0.03	
	0.3	2	6	175	12965	0.01	1.00	0.99	0.01	0.01	
Probabilistic EI	0.05	117	966	60	12005	0.66	0.93	0.35	0.10	0.59	0.79
	0.1	75	421	102	12550	0.42	0.97	0.58	0.13	0.39	
	0.15	35	117	142	12854	0.20	0.99	0.80	0.12	0.19	
	0.2	20	47	157	12924	0.11	1.00	0.89	0.09	0.11	
	0.3	7	6	170	12965	0.04	1.00	0.96	0.04	0.04	
Probabilistic RS	0.05	172	3133	5	9838	0.97	0.76	0.24	0.05	0.73	0.96
	0.1	167	527	10	12444	0.94	0.96	0.07	0.24	0.90	
	0.15	144	477	33	12494	0.81	0.96	0.19	0.22	0.78	
	0.2	101	470	76	12501	0.57	0.96	0.43	0.16	0.53	
	0.3	23	98	154	12873	0.13	0.99	0.87	0.08	0.12	

Table 3. Critical conditions for initiation of landslides in Idukki, based on RS thresholds.

Soil Wetness	Critical ED threshold line
0.0 – 0.2	T_{50}
0.2 – 0.4	T_{5}
0.4 – 0.6	~~T_{10}~~ T_{1}
0.6 – 0.8	~~T_{10}~~ T_{1}
0.8 – 1.0	T_{min}

***Declaration of Interest Statement**

Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: