Forecasting landslides using mobility functions: a case study from Idukki district, India

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Abstract:

Catastrophic landslides and associated destructions are increasing every year, because of the change in climatic conditions and land use patterns. The ecologically sensitive zones of Western Ghats are highly susceptible to landslides and require scientific attention in developing an efficient early warning system. Definition of empirical rainfall thresholds on local, regional or global scales is the most commonly followed method of forecasting rainfall induced landslides. The limitations associated with such thresholds demands for better forecasting performance, incorporating the effect of physical processes in the initiation of landslides. This study is an attempt to forecast landslides in Idukki district, using mobility functions. The function separates the impossible and certain mobilisation parts and forecasts whether landslides can occur or not. Based on the critical value of mobility function, two different warning levels are proposed for four different reference areas in the district. The study shows that the model is 97 % efficient in smaller areas with uniform topographical and geological conditions, and the performance is reduced as the area becomes larger, with varying topographical and geological properties. The model proves to be an effective landslide forecasting tool that can be integrated with a rainfall forecasting system, to develop an early warning system for the region.

Keywords: rainfall thresholds; early warning; landslides; Idukki

1. Introduction

Landslides are loss of soil or rock mass, denoted by their movement downslope, directly influenced by gravity. It is a major geohazard, which affects the hilly regions all over the world, resulting in severe destruction. Many landslides are part of natural geological evolution [1]. Due to the population rise, more hilly areas are now being inhabited, increasing the risk associated with landslides. In India, most of the landslides occurs during monsoon season, because of severe rainfall events. The rainwater reduces the shear strength of soil, leading to shear failure [2]. Such events occur within a short span of time and result in severe destructions such as loss of properties, lives and disruption of transportation and infrastructure facilities. The socio-economic setbacks caused by landslides demand for a strong scientific intervention to reduce the risk associated with landslides.

Providing early warning for landslides forecasting is an effective risk reduction approach [3,4]. An early warning can provide enough time before the landslide event to take necessary decisions and actions. The authorities and the public should be prepared and well aware of the action plans for the successful implementation of an operational Landslide Early Warning System (LEWS) [5]. The early warning should be issued based on the occurrence of the triggering factor (rainfall) and the in-situ site conditions. The possible slope failure should be foreseen, based on the historical data and physical conditions [6].

Understanding the soil properties and evaluating the stability of slopes is a critical geotechnical problem, and requires sophisticated inputs regarding the physical, hydrological and shear strength properties of soil [7]. Collecting such time dependent information with precision is a challenging task. Such inputs are used in process-based models [8], where infiltration models are used to understand the phreatic lines and the stability of slopes are calculated using infinite slope model [8,9]. Such analysis can be conducted for site-specific studies where precise data can be collected through regular monitoring [7]. When the study area is large, the spatial and topographical variability limits the availability of reliable input data. Hence the most commonly followed method in forecasting landslides is the definition of empirical rainfall thresholds [10].

Empirical thresholds are conventionally defined as a linear relationship between the rainfall parameters on a two-dimensional plane [11–14]. The threshold line defines a critical condition beyond which landslides are expected to happen in a region. The definition of thresholds is subject to the type of landslides and the size of the study area. The information regarding the antecedent rainfall within an interval of a few hours or days is crucial for the initiation of shallow landslides and for deep-seated failures, the duration of antecedent rainfall to be considered can be much longer, up to a few months. Considering the size, the thresholds can be defined for single hill slopes to a global scale. The variations in geology, hydrology, morphology, and climatic conditions can affect the definition of thresholds as the amount of rainfall required to trigger landslides is highly dependent on these factors. Empirical models are simple and can be derived for any region using the historical data [11]. But they are often associated with the limitations due to the simplifying assumptions [15]. Conceptual improvements and timely updates are required for the possible use of empirical thresholds in LEWS [6,16,17].

In this study, mobility functions are used to define a threshold condition which can be considered as a conceptual improvement to the conventional intensity-duration (ID) thresholds [15]. Such functions are used in the development of Forecasting of Landslides Induced by Rainfall (FLaIR) model and have been proven effective in forecasting landslides [18–21].

In India, the Himalayan belt [4,22–24] and the Western Ghats [25,26] are highly prone to landslides. The Western Ghats is located along the Western coast of Indian Peninsular region and is the most prominent orographic feature of the region. 47 % area of the state of Kerala in India is occupied by Western Ghats [27]. The Western Ghats scarps are most susceptible to landslides as compared to the other physiographic units [27]. The retreat of scarps along the weaker planes has formed the current landscape of Western Ghats. Idukki is a hilly district in the Western Ghats and is highly prone to landslides. A very recent landslide event in 2020 has resulted in the death of more than 60 people [28] in the district and it is high time that an operational LEWS should be developed for this economically backward district. This study is an attempt to make use of mobility functions for developing rainfall thresholds for Idukki district.

2. Details of the study area

Idukki district is in the state of Kerala, whose district boundaries coincide with the limits of Western Ghats. A major share of the district is covered by rugged mountains and forests. Low-lying regions are not present in this hilly district whose elevation ranges from midlands to highlands. The highlands are characterised by deep valleys and steep hills. The midland area comprises small hillocks, forming an undulating topography. The hill ranges can be divided into the high ranges, plateau region and the foothills. The midlands grade into the plateau in the narrow foothill zone, with an elevation ranging from 80 m to 500 m. Foothills are narrow strips with width ranging from 2 km to 8 km. The most significant physiographic unit of the district is the plateau region, with an elevation up to 1500 m.

The rocks of Peninsular Gneissic Complex (PGC), charnockite group and the migmatite group constitute a major share of the geology of the region (Figure 1). Regionally folded and well foliated granite gneiss represents the PGC in the northern part of the district. The widespread charnockite group in the southern part is mostly massive, with banded varieties with compositions varying from intermediate to felsic (Figure1). The migmatite complex in the central part is represented by hornblende biotite gneiss and biotite gneiss.

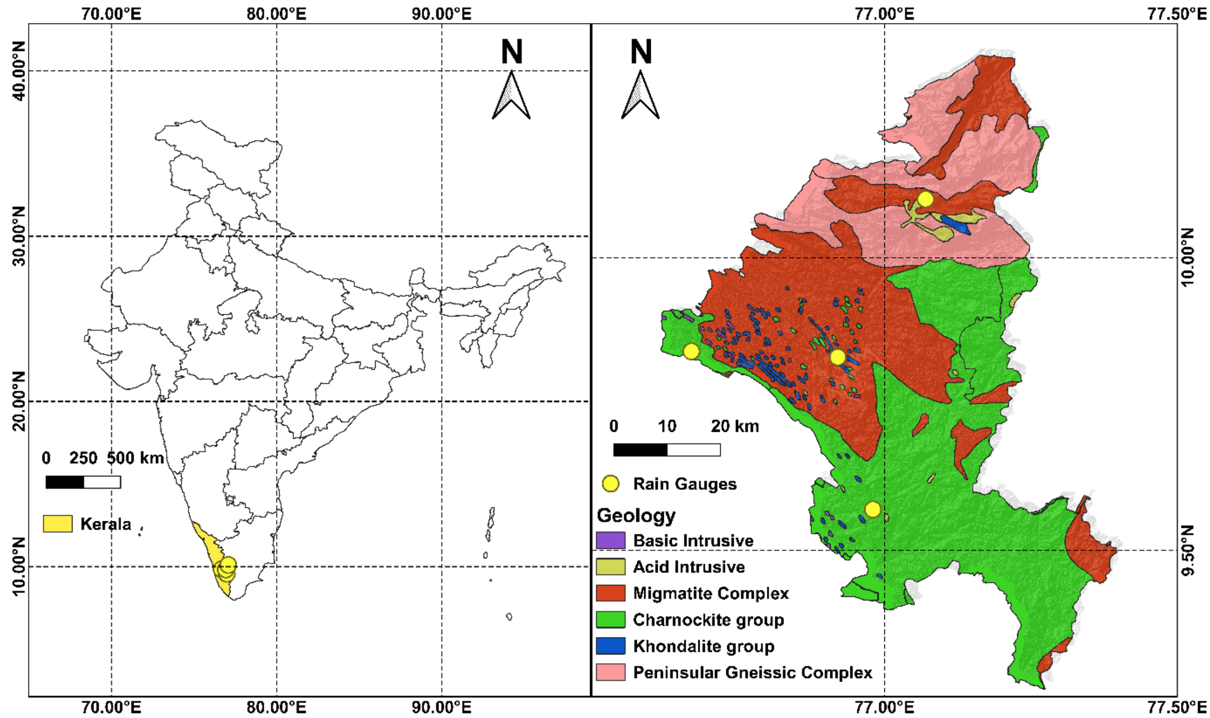

Figure 1. Location details of the study area (a) India, (b) Geology map of Idukki (modified after [29]) and location of rain gauges

The major income source of the district is agriculture and depends highly on the south-west and north-east monsoon for meeting the water requirements for agriculture. Most crops are rain-fed, but the monsoon season also triggers multiple landslides within the district, which results in destruction of lives and properties, including agricultural land. The eastern part of the region belongs to the rain shadow region of Western Ghats and the highest rainfall is recorded in the southern most rain gauge, located at Peerumed.

Most part of the district is drained by Periyar river, one among the major rivers in the state of Kerala. The river originates at the southeastern border of Idukki and flows west. The Idukki dam, one of the highest arch dams in Asia, in located across Periyar river. The district houses many reservoirs and contribute to the power supply and irrigation requirements of the state.

More than 60% of the surface soil is formed by organically rich forest loam soil. Such soil is formed by the weathering of rock under forest cover. The particles are fine grained and are suitable for plant growth, due to their high organic content. Lateritic soil is found in the midlands, which are well drained and have less organic content. The valleys of undulating terrain have a surface layer of hydromorphic soils, formed by the transportation and sedimentation of mass from nearby hill slopes. The particle sizes range from clayey to sandy. Alluvial soils are found along the riverbanks, as narrow strips. The topsoil, in general, consists of clayey particles and have low permeability values. This increases the moisture holding capacity of the soil, making it suitable for agriculture.The highlands have recorded deep seated landslides while the midlands and plateau regions are suffering from cut slope failures and shallow landslides, majorly due to the recent land use changes that had happened in the region.

3. Methodology

3.1 Mobility functions

Mobility functions ($Y(t)$) are generic functions, that can relate to the empirical rainfall thresholds, for forecasting the landslides [15]. The mobility functions depend upon the antecedent rainfall measurements and the definition depends upon historical data. It is assumed that the probability of occurrence of landslides at time t ($P(L_t)$) depends only on the mobility function $Y(t)$ and no modification has been occurred in the hillslope due to human or other factors [30]. Then the probability can be calculated as:

$$P(L_t) = \begin{cases} 0 & if \quad Y(t) < Y_1 \\ g\,[Y(t)] & if \quad Y_1 < Y(t) < Y_2 \\ 1 & if \quad Y(t) > Y_2 \end{cases} \tag{1}$$

Where $g[\,]$ is a generic non-decreasing function which can take values from 0 to 1 as $Y(t)$ varies from Y_1 to Y_2. The mobilisation is possible for values greater than Y_1 and it is certain when $Y(t) > Y_2$. The equation can be further simplified by using a certain value of $Y(t)$ as Y_{cr} where $Y_1 = Y_{cr} = Y_2$. This approximation simplifies the equation by adopting a critical value as threshold, separating impossible and certain mobilisation conditions.

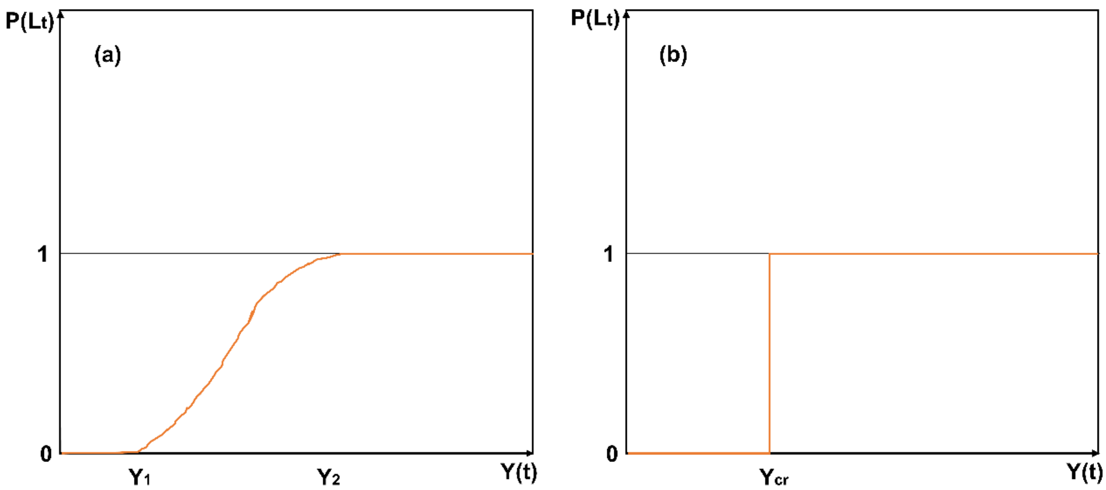

Figure 2. Probability of occurrence of landslides vs mobility function (a) relationship based on Eq. (1), (b) relationship with threshold condition Y_{cr}

For the definition of threshold condition, different criteria can be adopted, depending upon the severity of landslide events. The most common criteria is the occurrence of one or more landslides [31,32]. In the hydrological model FLaIR [15], mobility functions are estimated as a convolution between the infiltration rate $I\,(.)$ and a filter function $\psi\,(.)$. The rate of infiltration is assumed to have a direct relationship with the intensity of rainfall $I_r(.)$ and it depends upon the type of soil. Since the hydrological response is highly site specific, the model is best suited for local scale LEWS, however, it can be successfully extended to regional scales [30] assuming the hydro-geological properties are uniform. In this study, a simple relationship between $I\,(\tau)$ and $I_r(\tau)$ is used [15] as follows:

$$I\,(\tau) = \begin{cases} I_r(\tau) \; when \; I_r(\tau) \leq I_{r0} \\ I_{r0} \quad when \;\; I_r(\tau) > I_{r0} \end{cases} \tag{2}$$

Where τ is the instantaneous time, varying from 0 to t. For simplification, we assume $I_{r0} = +\infty$ and hence the mobility function can be directly related to the intensity of rainfall as :

$$Y(t) = \int_0^t \psi\,(t-\tau)\, I_r(\tau)\, d\tau \tag{3}$$

This formulation assumes a linear behaviour of the model. The choice of filter function is crucial in the definition of mobility function. In this study, a gamma filter function is used to define the mobility function. The filter function is given by the equation:

$$\psi(t) = \frac{\beta^{\alpha}}{\Gamma(\propto)} t^{\propto -1} e^{-\beta t} \qquad t \geq 0, \; \propto > 0, \beta > 0 \tag{4}$$

Where α is the shape parameter β (scale parameter) describes the hydrological response delay of the occurrence of landslides with respect to the rainfall and defines the temporal scale, and $\Gamma(.)$ is the gamma function. The choice of transfer function depends upon the historical rainfall and landslide data. For forecasting the occurrence of landslides, Eq. 4 can be divided into two parts given by:

$$Y(t) = \int_0^{\tau} \psi\,(t-\tau)\, I_r(\tau)\, d\tau + \int_{\tau}^{t} \psi\,(t-\tau)\, I_{r,pred}(\tau)\, d\tau \tag{5}$$

where $I_{r,pred}(\tau)$ is the forecasted rainfall. Thus, the mobility value at a future time t can be computed using the second part of Eq. (6). This value can be compared with the critical value, to understand the probability of occurrence of landslides.

The transfer function has been selected in such a way that the maximum value of mobility is obtained on the day of slope failure. This study uses the rainfall and landslide data for Idukki district from 2010 to 2018. The rainfall data has been collected from India Meteorological Department [33] and the landslide data has been collected from multiple sources including government agencies and media [32]. The data from 2010 to 2017 has been used for selecting the transfer function and the data of 2018 has been used for the validation process, to verify the reliability of the model. Considering the whole year will overestimate the performance of the model, due to high number of days without rainfall. Hence the critical time duration, from June to November is considered for the validation of the model.

3.2 Developing Early Warning

Depending upon the location of rain gauges, the district is divided into for different subzones, called reference areas, and the rainfall is assumed to be uniform within the subzones. The division was done using a proximity analysis by using the Thiessen polygon concept [32,34,35] and was improved further using the administrative boundaries of the district (Figure 3). This division was done due to the variation in meteorological conditions throughout the district. Also, the variations in topography is minimum within each reference area, the area R1 represents the midland region of low elevation, R2 and R3 are parts of hilly region in the eastern and central parts and R4 consists of highly rugged hills and valleys of higher elevation. The rainfall received in the four reference areas is also varying (Figure 4). The cumulative rainfall received during the validation period, from June to November 2018 is shown in Figure 4. It can be observed that the maximum rainfall is recorded in R2, while R1 has recorded the minimum rainfall.

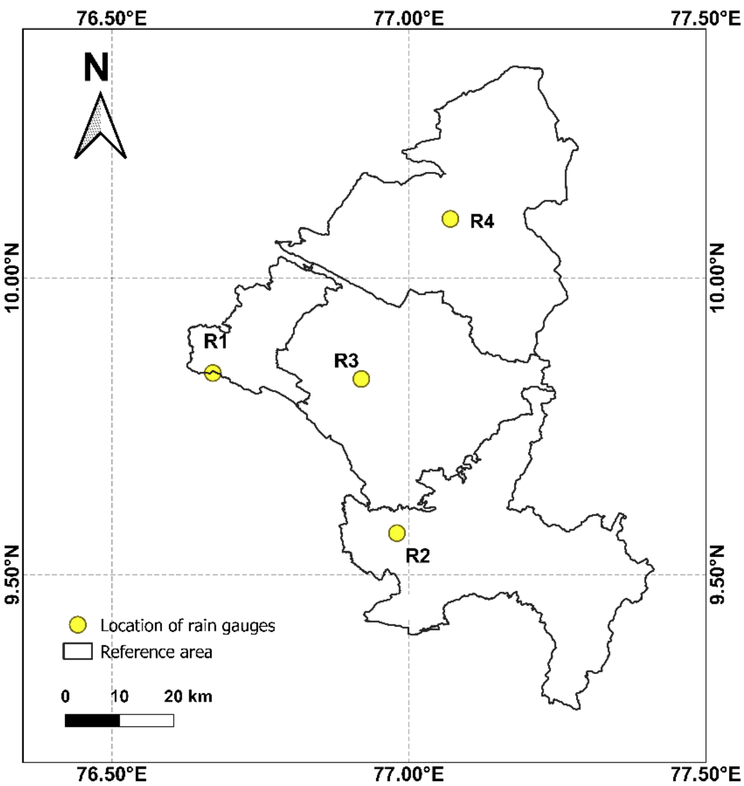

Figure 3. The location of rain gauges and reference areas considered for issuing early warning

The boundaries of reference area are defined in such a way that the rain gauge within the area is the closest one to each point inside and the boundary coincides with the administrative boundary of the local government. This helps in the easy and straightforward operation of the early warning system.

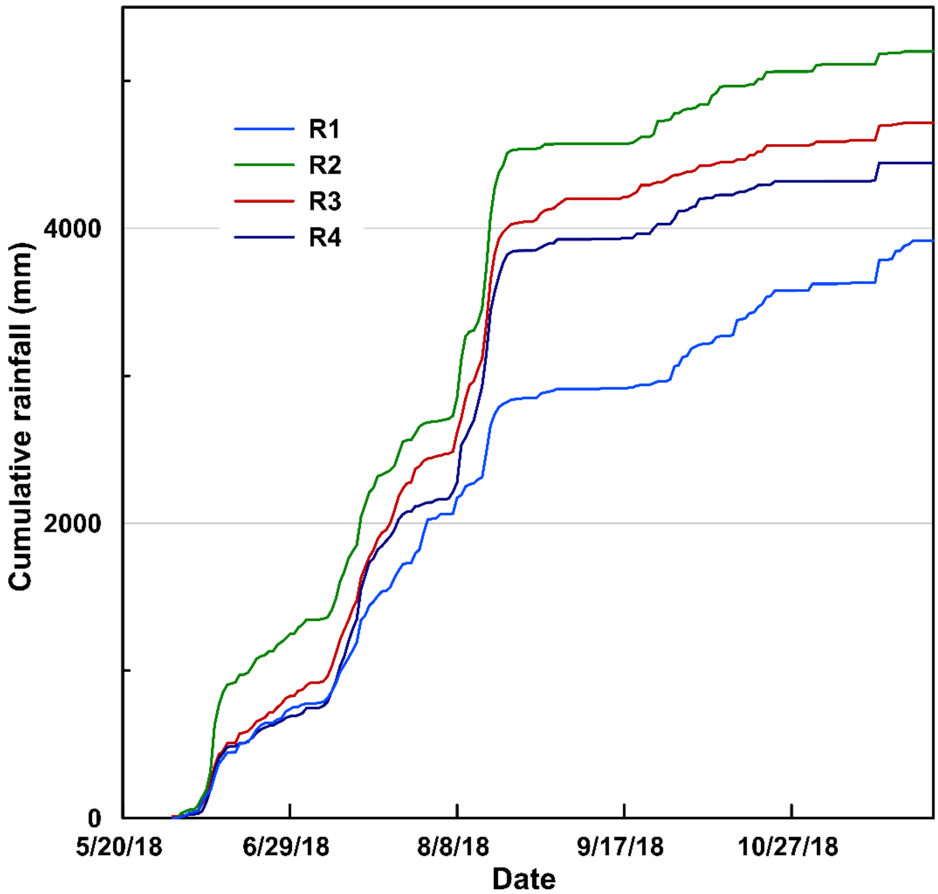

Figure 4. Cumulative rainfall during June to November, 2018

For developing and early warning system, multiple coefficients of the critical value can be used, to provide different levels of warning to the public [25,36–39]. This can be helpful in developing awareness among the public regarding different alert levels and actions to be taken for each level of warning. For defining alert levels, a coefficient is introduced, which is the ratio of mobility function at time t to the critical mobility value Y_{cr} , and can be expressed as:

$$C = \frac{Y(t)}{Y_{cr}} \tag{6}$$

The value of C has to be customised depending upon the history of rainfall and landslides in the region. The variation in climatic and lithological conditions of each reference area will lead to unique values of C for each reference area. In this study, two levels (C_1, C_2) of warning are defined for the study area, "Alert" and "Attention". When "Attention" is issued on a day, landslide events of ordinary criticality can be expected in the region and when "Alert" is issued, severe events can be expected. The forecasting module must be integrated with a rainfall forecasting system for providing sufficient time of intervention, so that necessary actions can be taken prior to the occurrence of landslides.

4. Results

The gamma function was used to define the mobility functions for forecasting landslides in Idukki, India. The critical value of mobility function has been identified using the historical rainfall and landslide data of the region, and customised warning levels were defined for each region. The mobility functions for each reference area are shown in Figure 5. It can be observed that the maximum value of mobility functions has been recorded in all areas during the time of 8^{th} to 10^{th} August 2018, when all areas received a daily rainfall greater than 200 mm. The mobility functions are correlated with the daily intensity of rainfall. The maximum value of mobility function has been recorded in R2, where the district has received maximum rainfall.

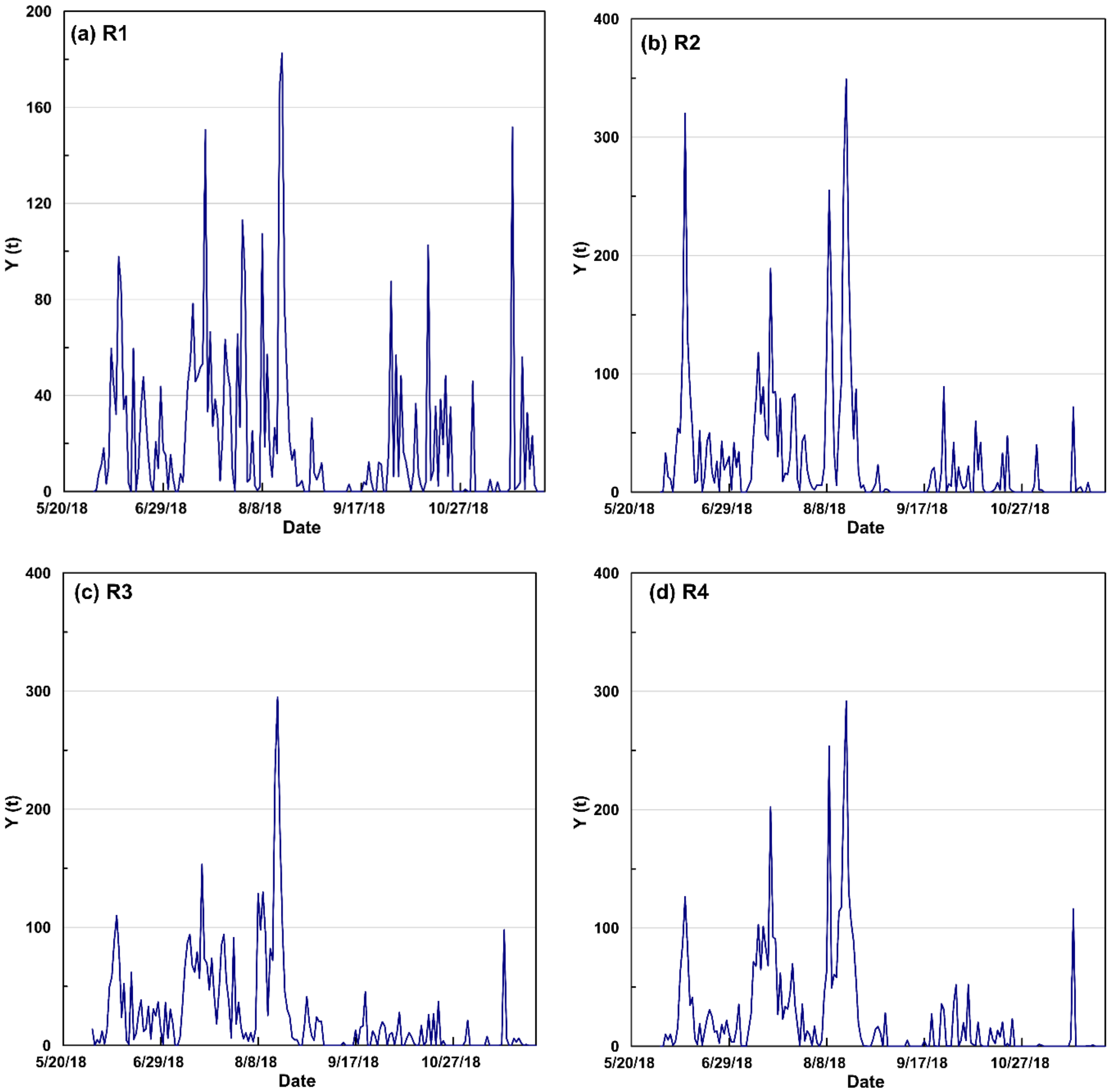

Figure 5. Mobility functions for different reference areas in Idukki district June to November 2018

The multipliers of critical mobility values for each area has been derived by using a trial-and-error procedure, so as to get a maximum number of true warnings and a minimum number of false warnings. Based on the procedure, an algorithm for issuing warning is proposed, as shown in Figure 6. First rainfall intensity in mm/day is calculated from rainfall forecasts and the value is used as an input for the transfer function. These values are compared with the critical mobility value for each area, multiplied with the coefficients (C_1, C_2) to issue warning. The algorithm first check if "Alert" has to be issued or are there chances for critical events. If the condition is not satisfied, it checks for the probability of occurrence of ordinary critical events ("Attention"). If both the conditions are not satisfied, no warning is issued for the day.

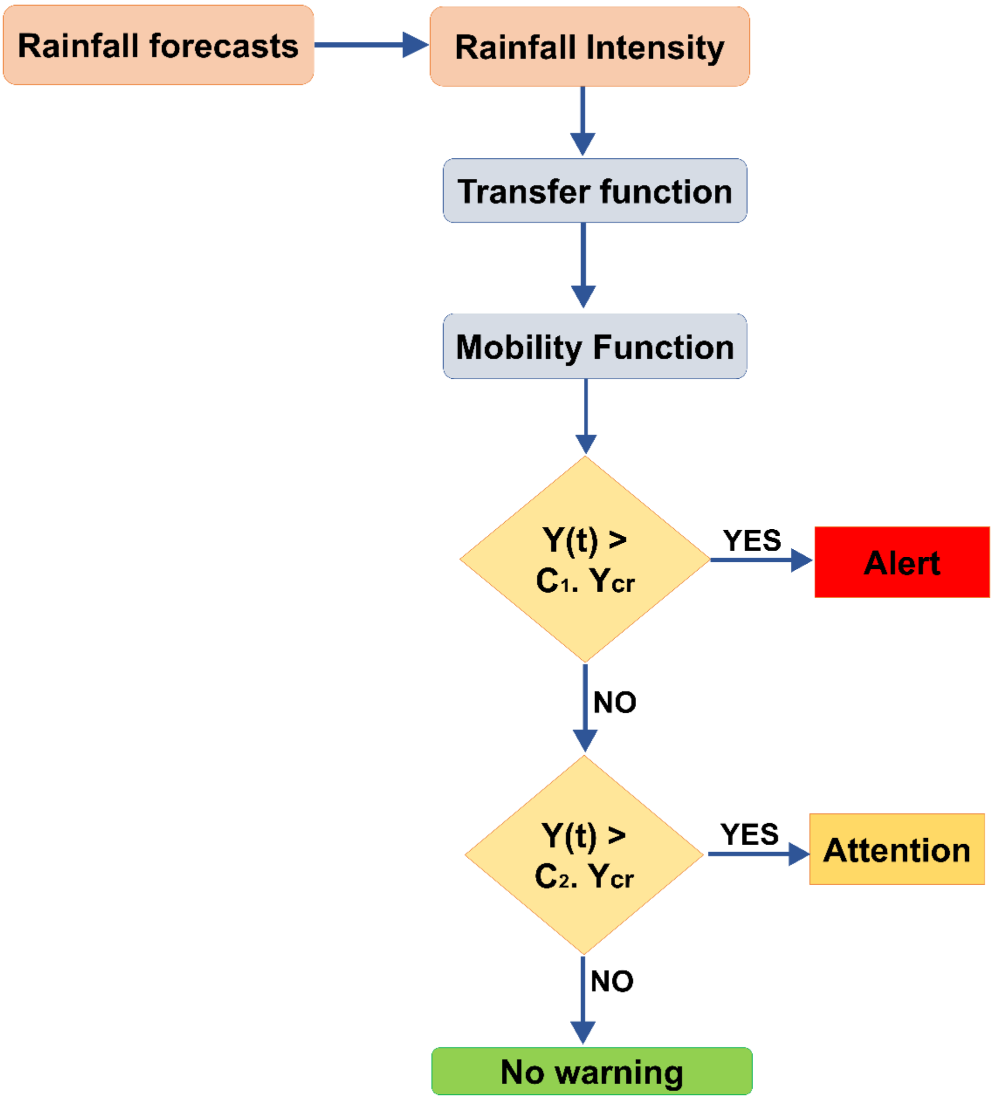

Figure 6. Algorithm proposed for the LEWS for issuing warnings based on mobility function

The performance of the algorithm shown in Figure 6 has been evaluated using a confusion matrix [40]. The warnings issued for 183 days from 1^{st} June to 30^{th} November 2018 has been compared with the observed record of landslides in the study area, to count the number of statistical attributes like True Positives (TP), False Positives (FP), False Negatives (FN) and True Negatives (TN). These values indicate the performance of the model. When warning is issued and landslides have happened, it is counted as TP and if no landslide has happened on a day with warning; it is counted as FP. Landslides can happen on the days without warning also, and such days are counted as FN, while the days on which no warning is issued and no landslide has happened are counted as TN. Both TP and TN are positive outcomes, and FP and FN are negative outcomes. Our objective while customising the coefficients is to maximise the positive outcomes and minimise negative outcomes.

Table 1. Statistical attributes and customised coefficients for the reference areas

Reference area	TP	FP	FN	TN	Efficiency	Threshold	
						Alert C_1	Attention C_2
R1	3	4	0	176	0.97	0.8	0.6
R2	4	4	0	175	0.97	0.8	0.4
R3	6	5	3	169	0.95	0.8	0.4
R4	8	4	6	165	0.95	0.8	0.4

Efficiency is a term which is used to evaluate the performance of the model, which is expressed as the ratio of positive outcomes to the total number of outcomes. The more the efficiency, the better is the model. It can be understood from Table 1 that the efficiency of the model is greater than 95 % in all four reference areas. Also, the value of C_1 is obtained as 0.8 in all the cases. In the case of C_2, the performance is better in R1 when the value is 0.6, but the optimum value is 0.4 in all other areas. For both the larger reference areas (R3 and R4), there are missed warnings, counted as FN, which reduces the performance of the model. Even though the efficiency is high for both R1 and R2, it should be observed that the ration of FP to TP is greater than or equal to 1 in both the cases. This means that out of the total warnings issued, at least 50 % are false alarms. This ratio is lesser in the case of areas R3 and R4. Attempts have to be made to reduce this ratio, without increasing the number of FN, for the LEWS to be efficient.

5. Discussion

From the analysis, it was observed that the performance of the model, even with same coefficients (C_1, C_2) are different for different reference areas considered. The prediction performance of the model depends highly on the uniform meteo-hydrological properties of the region. This is because the hydrological response highly depends upon the properties of soil. When soil properties are varying, the relationship between precipitation and infiltration will also vary. It depends upon a number of factors ranging from slope of terrain to the properties of soil in the unsaturated conditions. But the methodology discussed in this study is only based on the historical data and does not consider the detailed site specific responses for each slope. The method is a conceptual improvement of the conventional empirical thresholds, where the linear threshold is modified using a mobility function. No warnings are missed in R1 and R2, where the topography and the geological conditions are relatively uniform. The efficiency of the model is 97 % in both the regions. All the landslide events in these two regions were correctly forecasted by the model, making it highly sensitive. Sensitivity of a model can be defined by the ratio of TP to the sum of TP and FN. From Table 1, it can be understood that the model is 100 % sensitive in R1 and R2 while the sensitivity is reduced in the case of R3 and R4.

For the days with no landslides, the results show that false warnings are issued by the model multiple times during a monsoon. The term specificity deals with the prediction performance on non-landslide days, and can be defined as the ratio of TN to the sum of TN and FP. In no reference area, the model has given 100 % specific results. The forecast is always associated with false alarms. The rate of false alarms is much lesser than the empirical thresholds, which makes the use of mobility functions a possible tool for use in LEWS. The process of optimisation of coefficients for warning has reduced the number of false alarms considerably. In regions R3 and R4, this came with the cost of many missed alarms.

The use of mobility functions is a conceptual improvement from the conventional statistical thresholds to a hydrological threshold, yet it is not associated with the complex process of evaluating physical processes in detail. Though it overcomes the major limitation of the conventional empirical thresholds, the high number of false alarms, the performance should be further improved for making the model operational in R3 and R4. This can only be done with a higher rain gauge density and more precise rainfall forecasts. The reference areas can be made smaller, so that the properties are uniform throughout. Further research has to be done on this aspect, and the forecasting ability of the model can be improved significantly. For large areas like Idukki district with sophisticated morphology, it is difficult to do detailed physically based analysis and the empirical models are often associated with very high false warnings. Hence the use of mobility functions is a promising approach in forecasting the probability of occurrence of landslides within the study area.

The method can be exported to other parts of the world also, by using the historical landslide and rainfall database for a particular study area. Thresholds can be developed on both local and regional scales. The thresholds, when exported, should be customised for each study region based on its meteo-hydrological properties and landslide histories. The threshold values and the relationship between precipitation and infiltration will be different for each region, and the model has to be calibrated using regional specific data.

6. Conclusions

A tool for forecasting the occurrence of landslides in the South Indian district of Idukki was derived by using mobility functions. Unlike the conventional empirical thresholds, the mobility functions are related to the rate of infiltration and calculates the probability of occurrence of a landslide event using a mobility function. The model thus considers the complex hydrological processes using a generic function and can be used for landslide forecasting, using the historical database.

The study shows that the use of mobility functions results only in a few false alarms for the study region. The region was divided in to four reference areas, based on the location of rain gauges, and the performance of the model was evaluated using the rainfall and landslide data from June to November 2018. The minimum efficiency obtained by the model is 95 % in regions R3 and R4, which have highly varying topography and geology. The major limitations of the model are associated with the assumption that the meteo-hydro-geological properties of the reference area remain the same. The model has very good performance in regions R1 and R2, with an efficiency of 97 % and sensitivity 1.

The proposed model is a promising landslide forecasting tool that can be used in an operational LEWS, along with a precise rainfall forecasting module. The study is significant for the region, which is highly susceptible to landslides as the development of an efficient LEWS is a necessity for the safety of lives and properties n hilly terrains.

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