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Early warning system for shallow landslides using rainfall threshold and slope stability analysis



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ABSTRACT

A combined cluster and regression analysis were performed for the first time to identify rainfall threshold that triggers landslide events in Amboori, Kerala, India. Amboori is a tropical area that is highly vulnerable to landslides. The 2, 3, and 5-day antecedent rainfall data versus daily rainfall was clustered to identify a cluster of critical events that could potentially trigger landslides. Further, the cluster of critical events was utilized for regression analysis to develop the threshold equations. The 5-day antecedent (xvariable) vs. daily rainfall (y-variable) provided the best fit to the data with a threshold equation of y = 80.7 - 0.1981x. The intercept of the equation indicates that if the 5-day antecedent rainfall is zero, the minimum daily rainfall needed to trigger the landslide in the Amboori region would be 80.7 mm. The negative coefficient of the antecedent rainfall indicates that when the cumulative antecedent rainfall increases, the amount of daily rainfall required to trigger monsoon landslide decreases. The coefficient value indicates that the contribution of the 5-day antecedent rainfall is $\sim 20\%$ to the landslide trigger threshold. The slope stability analysis carried out for the area, using Probabilistic Infinite Slope Analysis Model (PISA-m), was utilized to identify the areas vulnerable to landslide in the region. The locations in the area where past landslides have occurred demonstrate lower Factors of Safety (FS) in the slope stability analysis. Thus, rainfall threshold analysis together with the FS values from slope stability can be suitable for developing a simple, cost-effective, and comprehensive early-warning system for shallow landslides in Amboori and similar regions.

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1. Introduction

Analyzing and correlating rainfall threshold with Factor of Safety (FS) for landslides can be valuable to develop an early warning system, especially in tropical regions that is proverbially prone to landslides. The development of a composite model thus can assist in devising a simple, cost-effective, and comprehensible early-warning system for shallow landslides. In such models, it is critical to understand the rainfall threshold and slope stability

E-mail addresses: skochapp@mtu.edu, sajinks@gmail.com (K.S. Sajinkumar). Peer-review under responsibility of China University of Geosciences (Beijing). because the criterion for the shallow landslide to occur is high daily rainfall (Bíl et al., 2015) and the presence of weathered material along a slope (Montrasio and Valentino, 2007; Smith et al., 2015). Such an early warning system can be developed on a site-specific basis and may be generalized for regions that have similar climatological and topographical conditions. An early-warning system is an essential requirement for landslide prone localities as it could reduce the losses and casualties that accompany natural hazards.

Amboori (8°30'28.2"N; 77°11'20.4"E), a small hamlet at the foothills of the Western Ghats in Thiruvananthapuram district, Kerala State, India (Fig. 1) is chosen for this study. Amboori presents a suitable test site to evaluate the applicability of rainfall-induced landslide threshold models in a tropical climate, considering it receives significant amounts of rainfall (~3000 mm per year) and its

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Figure 1. Location map of the study area. (a) Arc Earth map of Kerala with India in inset; (b) slope map, derived from SRTM 30 m resolution DEM, of Amboori highlighting the three landslides; (c) a collage of the then newspaper cutting and photograph.

slopes are covered with a layer of soil (2–3 m thick). Sajinkumar et al. (2011) noted that in tropical regions, a combination of hills capped by overburden and monsoon results in landslide. The casualties, destruction, and damage to property, and other capital losses spawned by such hazards take a heavy toll on everyday life. Hence, predictability and early warning systems have been contemplated (Aleotti and Chodhury, 1999; Glade et al., 2000; Montrasio and Valentino, 2007; Guzetti et al., 2008; Brunetti et al., 2010).

Amboori has witnessed several landslides over the years (Table 1), all to date have occurred during the monsoons and most of them belong to the debris flow category which are shallow in nature. The one which was particularly devastating occurred on November 9th, 2001 that had a death toll of 38 and remains a blot among the landslide events of Kerala, while only a few studies have been carried out in this area. Muthu and Muraleedharan (2005) provided detailed descriptions of the 2001 landslide. Based on several collective reports, Kuriakose et al. (2009) adapted a tabular assignment of landslide type for various regions susceptible to landslides across Kerala since 1984; Amboori was assigned in the shallow landslide category. Sreekumar and Aslam (2010) provided a holistic glimpse on the landslide occurrence in the Western Ghats, where they categorically mention about Amboori. Another work intended for Landslide Hazard Zonation (LHZ) by Muraleedharan and Sajinkumar (2011a,b) brought out critical information on 14 selected facets in the Amboori region, marked as high hazard zones. These facets are based on the 1998 Bureau of Indian Standards (BIS) (IS 14496; Part 2) guidelines modified by the Geological Survey of India known as Landslide Hazard Evaluation Factors (LHEF).

Geologically, Amboori is a part of the Kerala Khondalite Belt (KKB) within the bounds of the Precambrian Southern Granulite Terrain, which is composed of cratonized Archean supracrustal rocks. The KKB is a wedge of khondalite group of granulite grade metasedimentary rocks found between massive charnockite of Cardamon Hills in the north and Nagercoil Block in the south (Chacko et al., 1992; Soman, 2002; Liu et al., 2016). The study region primarily consists of migmatized metapelites of garnetiferous-sillimanite gneiss (Muraleedharan and Sajinkumar, 2011a,b). The Archean rocks are covered by unconsolidated materials such as boulders, colluvium, laterite, and saprolite (Muraleedharan and Sajinkumar, 2011a,b) and are susceptible to movement, especially considering the soil cover is less than 2–3 m.

2. Methods

This study analyzes rainfall threshold and slope stability of Amboori area to identify the possibility of establishing an early warning system, which could minimize the effects of potential landslides. The use of rainfall threshold analysis for determining early warning systems have been established from other studies

Table 1

Landslide inventory of Amboori and adjacent areas. A total of 39 people succumbed and 5 people got injured (Muraleedharan and Sajinkumar, 2011a,b).

Sl. No.	Location/Co-ordinates/ topographic sheet	Type/Mode/ Date of failure	Geology & Land use	^a Dimension (m) & Area (m ²)	Causes & effects
1	Vilangumala 8°29′31.5″N, 77°10′20.8″E TS. No. 58H/3	Debris flow 1965	Overburden above khondalite. Gravelly soil. Rubber plantation	L = 1500 W = 15 T = 1 Affected area: 22 500	Incessant rain
2	Vazhichal 8°29'39.0"N, 77°10'13.7"E TS. No. 58H/3	Debris flow 1965	Overburden above khondalite. Gravelly soil. Rubber plantation	L = 1000 W = 15 T = 1.5 Afford event 15 000	Incessant rain
3**	Pottanthottam 8°31′08.5″N, 77°10′03.9″E TS. No. 58H/2	Debris flow 1988	Overburden above khondalite. Gravelly soil. Rubber plantation, settlement	Affected area: $15,000$ L = 30 W = 25 T = 2 Affected area: 750	Incessant rain. Four people injured and a house destroyed.
4	Chelanthikuzhi 8°30'53.6"N, 77°09'39.74"E TS. No. 58H/2	Debris flow 8 June 1988	Overburden above khondalite. Gravelly soil. Rubber plantation, settlement	L = 500 W = 15 T = 2 Affected area: 7500	Incessant rain
5	Paramukal 8°30'37.9″N, 77°09'28.6″E TS. No. 58H/2	Debris avalanche 1995–1996	Overburden above khondalite. Gravelly soil. Rubber plantation	L = 800 W = 15 T = 1.5 Affected area: 12,000	Incessant rain
6**	Nulliyode 8°29′09.9″N, 77°10′39.4″E TS. No. 58H/3	Debris flow 1965 & 2 October 2000	Overburden above khondalite. Gravelly soil. Rubber plantation	L = 1000 W = 15 T = 1.5 Affected area: 15.000	Incessant rain
7	Pottanchira 8°28'49.8"N, 77°11'20"E TS. No. 58H/3	Rock fall 2000	Khondalite. Rubber plantation and settlement	5 m ³	Incessant rain and removal of the toe material
8**	Amboori 8°30'28.2″N, 77°11'20.4″E TS. No. 58H/2	Debris flow 9 November 2001	Overburden above khondalite. Scree/Gravelly soil. Rubber plantation, settlement	L = 200 W = 35 T = 2 Affected area: 7000	Incessant rain. Destroyed four houses and 38 people died.
9	Kandamthitta 8°30'35.4″N, 77°10'08.9″E TS. No. 58H/2	Subsidence 2007	Gravelly soil. Rubber plantation and agricultural land	L = 15 W = 10 T = 2 Affected area: 150	Incessant rain. One person injured and one house destroyed.
10	Vilangumala 8°29'31.5"N, 77°10'20.8"E TS. No 58H/3	Rock fall 2007	Khondalite. Rubber plantation	$1 \text{ m} \times 1 \text{ m} \times 0.5 \text{ m}$	Incessant rain and removal of the toe material. One person died
11	Kudappanamoodu 8°28'55.8"N, 77°10'56"E TS No 58H/3	Rock fall	Khondalite. Rubber plantation	$5 \text{ m} \times 3 \text{ m} \times 2 \text{ m}$	Incessant rain
12	Kulamakuzhi 8°29'17.5″N, 77°11'47.5″E TS. No. 58H/3	Rock fall	Khondalite. Rubber plantation	1 m ³	Incessant rain
13	Perekonam 8°30'31.9″N, 77°09'27.0″E TS. No. 58H/2	Debris flow 1965 & 2000	Overburden above khondalite. Scree/Gravelly soil. Rubber plantation	$ \begin{array}{l} L = 150 \mbox{ m} \\ W = 10 \mbox{ m} \\ T = 1 \mbox{ m} \\ \mbox{Affected area: } 1500 \end{array} $	Incessant rain

The highlighted landslides are selected for deriving rainfall threshold analysis.

^a L-Length, W-Width, T-Thickness. **Landslides selected for deriving rainfall threshold analysis.

(Glade et al., 2000; Guzetti et al., 2008; Brunetti et al., 2010). For the current study, three landslides that occurred in and around Amboori *viz*, Chellanthikuzhi (No. 4 of Table 1), Nulliyode (No. 6) and Amboori (No. 8) are selected for analysis based on the availability of rainfall data and spatial information. The study utilized cluster analysis, using open source – Waikato Environment for Knowledge Analysis (Weka), for analyzing rainfall threshold. Cluster analysis divides data into clusters that have similar characteristics.

Traditionally, rainfall thresholds are prepared using scatter plots with rainfall duration and intensity or antecedent and daily rainfall combinations (*cf.* Jaiswal and van Westen, 2009; Gariano et al., 2015; Wu et al., 2015; Marra et al., 2016). However, these scatter plots are inadequate to derive rainfall threshold values for the current study area as the rainfall data is widely dispersed due to the erratic monsoons, as it is quite common to any tropical region (*cf.*

Gadgil, 2003; Krishnamurthy and Kinter, 2003). This study attempts to identify the events that are critical to initiate slope instability using cluster analysis.

K-means clustering is the most popular and efficient clustering method which uses prototypes (centroids) to represent clusters by optimizing the squared error function (Kanungo et al., 2002). Given a set of *n* observations ($x_1, x_2, ..., x_n$), which is rainfall in our study, the K-means clustering algorithm aims to partition the '*n*' observations in $K (\leq n)$ sets ($S = \{S_1, S_2, ..., S_K\}$) with each set having maximum variance. The K-means clustering algorithm can be mathematically represented as:

$$\operatorname{argmins} \sum_{i=1}^{k} \sum_{x \in S_i} \|X - \mu_i\|^2 = \operatorname{argmins} \sum_{i=1}^{k} |S_i| \operatorname{Var} S_i \tag{1}$$

where μ_i is the mean rainfall of the values in set I (S_i).

This method of clustering falls into the general category of variance based clustering and uses Euclidean distance (Inaba et al., 1996; Kolliopoulos and Rao, 1999).

The number of clusters (K value) is determined using the Elbow method, which is a basic technique to determine the true number of clusters. The critical clusters are isolated and subsequently scatter plot analysis is conducted for 2, 3, and 5-day antecedent rainfall *vs.* daily rainfall. This process resulted in the derivation of rainfall threshold equation for each condition of antecedent rainfall, from the known data for landslide occurring days, in the form of a linear equation

$$y = mx + c \tag{2}$$

where y is the daily rainfall and x is the antecedent rainfall whereas m and c are constants representing slope and y intercept, respectively. The equation is further used to generate a graphical rainfall threshold exceedance curve. The exceedance of the rainfall threshold value for each antecedent rainfall condition during a given time interval is subsequently plotted. If the values are positive, it indicates possible triggering of a landslide. A graphically derived rainfall threshold exceedance curve can determine whether a landslide is plausible based on the rainfall data recovered over a time interval (Canovas et al., 2016).

Rainfall percolation can cause decrease in resistive strength of slope material (Cho, 2014; Zhang et al., 2015) resulting in landslides. Hence it is critical to evaluate rainfall-induced stability of slopes. The slope stability of the study area is evaluated using the Probabilistic Infinite Slope Analysis (PISA-m) model (cf. Haneberg, 2007) as it is applicable for shallow landslides. PISA-m is a widely used computer program that uses infinite slope equations to calculate the spatially varying Factor of Safety of slopes. The PISAm model requires four input files, three of which are in ASCII inputs, in either Arc or Surfer formats, while the fourth is a parameter file. The output file can be specified by the user in ASCII format shows the Factor of Safety (FS) or probability of failure of the slopes. This study uses the Arc ASCII output format. The three inputs are a Digital Elevation Model (DEM), soil map, and tree root strength. The DEM was obtained from Shuttle Radar Topographic Mission (SRTM) data, which has a spatial resolution of 30 m; soil map is from the National Bureau of Soil Survey and Land Use Planning of the Government of India (NBSS, 1996); and the base map for tree root strength was developed from the Normalized Difference Vegetation Index (NDVI) obtained from Landsat 8 imagery, which also has a spatial resolution of 30 m. This raster was reclassified as per Holben (1986) as a characteristic of certain vegetation types, based on which tree root strength was derived from the studies of Kuriakose and van Beek (2011). All three inputs were prepared in ArcGIS, in ASCII format. The parameter file contains strength criteria of soils (cohesion, friction angle) and trees (surcharge and root cohesive strength) to aid the model in determining the slope stability at a pixel by pixel basis. The PISA-m model also requires the user to specify the unit weight of water (γ_w), which determines the unit of the other variables. In this study, the unit weight of water is assigned the standard value of 9810 N/m³. Additionally, the PISA-m model requires that a minimum slope (minslope) be defined, such that it skips the analysis of any pixels with a slope less than the minimum value; this study uses a minslope value of 15° as slopes less than or equal to 15° is generally considered stable slope (Thomas, 1974; Zwissler et al., 2014). In addition, the PISA-m model requires specifying the error of the DEM (z_err) (Haneberg, 2007). The variables are plugged into Eq. (3) to calculate the FS of the slope in every pixel.

$$FS = \frac{c_r + c_s + [q_t + \gamma_m D + (\gamma_{sat} - \gamma_w - \gamma_m)H_w D]\cos 2\beta \tan \phi}{[q_t + \gamma_m D + (\gamma_{sat} - \gamma_m)H_w D]\sin\beta\cos\beta}$$
(3)

where FS is the factor of safety; c_r is root cohesive strength (pressure); c_s is soil cohesive strength (pressure); q_t is tree surcharge (pressure); γ_m is saturated unit weight of the soil (force/volume); γ_{sat} is moist unit weight of the soil (force/volume); D is soil thickness; H_w is pore pressure coefficient ($0 \le h \le 1$); β is the angle of topographical slope; φ is the angle of internal friction.

In this study, slopes with FS < 1.0 are characterized as highly unstable, FS between 1 and 1.2 as unstable, and FS > 1.2 as stable based on the recommendations of previous slope stability analysis (Aversa et al., 2016). The FS is calculated only for one hypothetical condition *i.e.*, saturated. The saturated condition is chosen to replicate the worst case scenario; it implies that soil pores are filled with water and hence water depth is considered equivalent to soil depth. A schematic of the methodology adopted is presented in Fig. 2.

3. Amboori and other landslides

On the day of the Amboori landslide, the area experienced an exceptionally high amount of rainfall of 82.4 mm, which together with other landslides occurred in this part during monsoons points toward the role of rainfall in triggering landslides. The Amboori landslide initiated from an altitude of 245 m above mean sea level, traveled about 1 km and spread over an area of 0.007 km² (Fig. 3a). The slope of the landslide area ranges between 5° and 42°. Hard rock was exposed in most affected areas, which indicates complete removal of overburden (Fig. 3b and c). A 2 m thick overburden was observed on the flanks of the landslide, giving a rough thickness of the material washed away. A first order stream is found near the toe of the landslide. No trace of this stream is found on the body of the landslide as houses occupy this portion indicating an alteration of the natural stream flow. During the rainy season, water gushes through the landslide body (Fig. 3b). The groundwater is monitored from a well located within the landslide body and shows a depth of 1 m to water level in summer, indicating a voluminous surcharge to the well from the upper slope. After the devastating landslide, the area was terraced and stabilized with rubber plantations (Fig. 3d). The present landscape of the landslide affected area is entirely different, and the landslide scar is unrecognizable due to the dense rubber plantations. The practice of cultivating rubber plantations on slopes susceptible to landslides is not optimal as it allows water percolation and ultimately increasing pore-water pressure and thus lowering effective stress of the soil. Moreover, construction of terraces (Fig. 3d) using random rubbles in the rubber cultivated area results in blockage of free passage of water thus leading to increased infiltration of water (Sajinkumar et al., 2014a,b). Now the area has been stabilized by constructing a retaining wall and improved surface drainage network.

The landslide at Chellanthikuzhi occurred on June 8th, 1988 along with a first order stream course with a length of 500 m and width of 15 m. A 2 m thick soil cover, resting over Precambrian rocks, was displaced creating a prominent topographic hollow. This landslide did not cause much damage as the entire body of the slide was confined within the stream course. Nulliyode has experienced landslides twice, with the first one in 1965 and the second one on October 2nd, 2000. This landslide also occurred along a lower order stream and damaged three houses situated on the



Figure 2. Flow chart depicting the methodology adopted in the present study.

bank of the river. The landslides at both Chellanthikuzhi and Nulliyode occurred in the same fashion exhibiting all characteristics of a shallow slope failure induced by monsoons. These landslides also exhibit terrain and conditioning factors similar to Amboori. Since the morphological features of these two landslides were obliterated by vegetation, the authors were forced to restrict the description.

4. Results

4.1. Rainfall threshold using simple K-means cluster analysis

Rainfall threshold analysis was obtained for this study using data from landslide events at Amboori, Chellanthikuzhi, and Nulliyode. Initially, 21-day rainfall data for each landslide event totaling 63 days is selected viz., ten days before the landslide, on the day of landslide, and ten days after the landslide (Table 2). Additionally, 2, 3, and 5-day antecedent rainfall was obtained for all 63 days. The antecedent rainfall calculation was limited to a maximum of five days, based on previous studies by Sajinkumar et al. (2014b, 2015, 2016) and the authors' field experience on slopes with similar hydraulic conductivity and overburden of ~ 2 m that could saturated the overburden in a short period. Scatter plots were generated for 2, 3, and 5-day antecedent vs. daily rainfall and is shown to be widely dispersed due to the erratic nature of monsoons. Therefore, cluster analysis was performed to identify the group of critical events that facilitate landslides (Fig. 4a-c). The simple Kmeans clustering technique was adopted in this study. The run characteristics of the clustering process are elaborated in Table 3. The number of optimal clusters was selected based on the elbow method (Mooi and Sarstedt, 2011). The cluster favoring landslides is isolated, and a linear trend line is prepared (Fig. 5a-c); the trend line follows the linear equation shown in Eq. (2).

Of the three different trend lines obtained, the 5-day antecedent *vs.* daily rainfall trend line is observed to have all three landslide events above the trend line. Hence this trend line is recommended as the rainfall threshold equation for the study area:

$$y = 80.7 - 0.1981x \tag{4}$$

It is important to note that trend lines from 2, 3, and 5-day antecedent rainfall (Fig. 5a-c) all have intercept values in the range of 78.7–80.7 mm. This indicates that in the absence of antecedent rainfall, a daily rainfall event *i.e.* approximately \geq 78 mm could trigger a landslide in the Amboori region. The negative coefficient of antecedent rainfall, in all three equations (Fig. 5a-c), indicates that an increase in cumulative antecedent rainfall results in a decrease in the amount of daily rainfall required to trigger landslide. The contribution of antecedent rainfall to rainfall threshold varies from approximately 40% for 2-day to 20% for 5-day.

Eq. (4) can be used to predict landslides since, when the antecedent rainfall value is known, daily rainfall predicted based on the equation can be compared with the weather forecast. Using the 63-day rainfall data, a rainfall exceedance graph was prepared, which will assist in recognizing the threshold required for a probable landslide (Fig. 6). During the selected 63 days, the daily rainfall was observed to surpass the threshold 11 times, of which only three resulted in landslides. Therefore, probability of a landslide is observed to be about 27% (3/11). However, as seen from Fig. 6, the probability of landslide significantly increases to 75% (3/4) as the daily rainfall exceeds 100 mm. The authors believe that future work in the region should consider rainfall intensity, to reduce false positives and improve the overall threshold relationship. Considering rainfall intensity measurement is lacking for the Amboori region, it is important to have a conservative threshold equation as presented in Eq. (4).



Figure 3. (a) Detailed site specific map of Amboori landslide prepared on 1:2000 scale (Source: Muraleedharan and Sajinkumar, 2011a); (b) removal of debris resulted in exposing rocky outcrops and water gushing through the landslide affected area. The flow is not confined to a channel; (c) rescue operations immediately after the landslide; (d) the landslide affected area has been stabilized by terrace cultivation.

Table 2

Daily and antecedent rainfall for Amboori region (Source-Daily rainfall: Kerala Irrigation Department; Rain gauge: Neyyar Dam).

Date	Place	Daily rainfall (mm)	Antecedent rainfall: 2-day (mm)	Antecedent rainfall: 3-day (mm)	Antecedent rainfall: 5-day (mm)
28-May-88	Chellanthikuzhi	0	0	0	0
29-May-88		0	0	0	0
30-May-88		0	0	0	0
31-May-88		5.69	0	0	0
01-Jun-88		8.53	5.69	5.69	5.69
02-Jun-88		19.91	14.22	14.22	14.22
03-Jun-88		68.28	28.44	34.13	34.13
04-Jun-88		19.91	88.19	96.72	102.41
05-Jun-88		5.69	88.19	108.1	122.32
06-Jun-88		39.83	25.6	93.88	122.32
07-Jun-88		68.28	45.52	65.43	153.62
08-Jun-88		14.22	108.11	113.8	201.99
10 Jun 88		21.20	82.5	122.33	147.93
10-juli-88		5 50	54.15	65.42	147.55
12_Jun_88		0	36.88	56 79	139.29
13-Jun-88		0	5 5 9	36.88	71 01
14-Jun-88		0	0	5 5 9	56 79
15-Jun-88		5.69	0	0	36.88
16-Jun-88		8.53	5.69	5.69	11.28
17-Jun-88		0	14.22	14.22	14.22
21-Sep-00	Nulliyode	8.2	43	43	43.2
22-Sep-00	5	1.2	50.8	51.2	51.4
23-Sep-00		21	9.4	52	52.4
24-Sep-00		4.6	22.2	30.4	73.4
25-Sep-00		80.2	25.6	26.8	77.6
26-Sep-00		44.8	84.8	105.8	115.2
27-Sep-00		43.4	125	129.6	151.8
28-Sep-00		0	88.2	168.4	194
29-Sep-00		12.4	43.4	88.2	173
30-Sep-00		30	12.4	55.8	180.8
01-Oct-00		58.4	42.4	42.4	130.6
02-Oct-00		11	88.4	100.8	144.2
03-Oct-00		3.2	69.4	99.4	111.8
04-Oct-00		0	14.2	/2.6	115
05-0cl-00		16.9	3.2	14.2	102.0
00-001-00		10.0	17.4	5.0 17.4	75.2
07-0ct-00		0	17.4	17.4	22 A
09-Oct-00		0	10.8	27.6	22.4
10-Oct-00		0	9	10.8	28.2
11-Oct-00		0	0	9	27.6
30-Oct-01	Amboori	0	8.4	8.6	63
31-Oct-01		0	8.4	8.4	59.8
01-Nov-01		0	0	8.4	8.6
02-Nov-01		0	0	0	8.4
03-Nov-01		0	0	0	8.4
04-Nov-01		0	0	0	0
05-Nov-01		9.4	0	0	0
06-Nov-01		26.4	9.4	9.4	9.4
07-Nov-01		11.6	35.8	35.8	35.8
08-Nov-01		0.4	38	47.4	47.4
09-Nov-01		82.4	12	38.4	47.8
10-Nov-01		U	82.8	94.4	130.2
11-Nov-01		U	82.4	82.8	120.8
12-Nov-01		U	U	82.4	94.4
13-INOV-UI		0	0	0	02.0 97.4
14-INUV-UI 15 Nov 01		0.4 11 0	64	64	02. 1 6.4
15-Nov-01		11.2 72.2	176	17.6	176
17-Nov-01		0	834	89.8	89.8
18-Nov-01		2.8	72 2	83.4	89.8
19-Nov-01		0.2	2.8	75	92.6
		- /=			· · · ·

Highlighted are the daily and antecedent rainfall during landslide occurred days.

4.2. Slope stability analysis: map-based probabilistic infinite slope analysis (PISA-m) model

Slope stability analysis was carried out for an area of about \sim 34 km² (a small area in and around Amboori is selected as a pilot work to showcase the possibility of such a study), using the PISA-m.

The slope map, soil map, and NDVI used for slope stability analysis are shown in Fig. 7a–c, respectively. The soil vector map was rasterized. The geotechnical parameters required for the PISA-m (moisture content, specific gravity, void ratio, saturated unit weight, moist unit weight, angle of internal friction, and cohesion) were calculated by geotechnical analysis from the soil samples



Figure 4. Scatter plot showing the different clusters. (a) 2-day antecedent vs. daily rainfall; (b) 3-day antecedent vs. daily rainfall; (c) 5-day antecedent vs. daily rainfall. 'L' indicates landslide incidence.

collected from the field (Table 4). For saturated conditions, pore pressure has a constant value of 1. Sample collection was conducted during the monsoon (June) to understand the extreme field conditions. The mean and standard deviation of the parameters were used for this analysis. The NDVI raster was classified into four classes, which were randomly checked in the field and are found to corroborate with this classification.

Using the PISA-m model, three slope stability sections are identified – the highly unstable slopes (FS < 1) near the banks of the Neyyar reservoir, the unstable slopes (1 < FS < 1.2) on the hill ranges of the Western Ghats, and the stable slopes (FS > 1.2), which are the less-dissected landforms (Fig. 8). The landslide-free zone in Fig. 8 represents either a water body or level-ground. The three landslide events analyzed in this study fall on or near the unstable zone (1 < FS < 1.2). Note that the 30 m spatial resolution of the SRTM data provides a coarse resolution of the spatial extent of the landslide hazard categories. The authors believe that a higher resolution slope map could improve the spatial accuracy of the

landslide hazard classes developed from the PISA-m model (e.g. Greaves et al., 2016; Zhao et al., 2016).

4.3. Implementation of early warning system

The first step in the implementation of an early warning system is to characterize the landslide susceptibility of the area. An earlywarning system may be developed for locations characterized by high topographical slope with the presence of basement crystalline rock overlain by a soil cover with low cohesion that receive seasonal monsoon rains. These locations have a high probability of landslide occurrence since the material cover is loosely placed on the crystalline rock and can induce pore-water pressure build-up. The process of collection of soil and rock properties may be rigorous but is an essential benefit for the prevention of landslide fatalities and economic losses. The topographical slope of areas can be retrieved through GIS software where an estimated slope map can be created using contours from shaded relief. These inputs together with the

Table 3

Run characteristics of cluster analysis (derived from Weka software).

		2-day antecedent vs. Daily rainfall			3-day anteced	lay antecedent vs. Daily rainfall			5-day antecedent vs. Daily rainfall		
Scheme	Simple K-means										
Optimization		Elbow method									
Distance formula		Eucleidan									
Sum of squared errors		1.9207			2.0304			2.5480			
Initial starting point		Cluster 0	Cluster 1	Cluster 2	Cluster 0	Cluster 1	Cluster 2	Cluster 0	Cluster 1	Cluster 2	
		25.6, 39.83	83.4, 0	5.59, 0	93.88, 39.83	89.8, 0	36.88, 0	122.32, 39.83	89.9, 0	71.01, 0	
Final cluster centroid	Antecedant	28.1657	83.0393	10.4834	60.984	94.5983	13.8654	94.5189	129.0727	27.7778	
	Daily	67.0843	11.448	6.0888	58.779	7.0117	5.0557	61.9767	7.4186	5.3109	
Clustered instances		7 (11%)	15 (24%)	41 (65%)	10 (16%)	18 (29%)	35 (56%)	9 (14%)	22 (35%)	32 (51%)	



Figure 5. Linear trend line for isolated cluster favoring landslide. (a) 2-day antecedent vs. daily rainfall; (b) 3-day antecedent vs. daily rainfall; (c) 5-day antecedent vs. daily rainfall. 'L' indicates landslide incidence.

vegetation information obtained from satellite data can be used for the PISA-m model to characterize the landslide susceptibility of the area. Once the landslide susceptibility of the region is characterized, the rainfall data need to be collected for locations that have a FS less than or equal to 1.2.

With the collection of rainfall data for focused locations such as unstable slopes, the antecedent rainfall can be well quantified. The antecedent rainfall information can then be used together with the daily forecast to verify whether these values would exceed the threshold level at the critical slope locations. The proposed approach could provide a 24 h warning for an unstable slope locations which can be critical to reduce human causality and landslide risk. Analyzing and correlating rainfall threshold analysis with FS is a novel approach of study for landslide early warning system, especially in the Western Ghats regions where landslides occur very frequently. Thus this composite model can be a simple, cost-effective and comprehensive early-warning system and may be applicable for all regions that have similar climatological and topographical conditions.

5. Discussion and conclusions

This study is the first to utilize cluster analysis method to obtain rainfall threshold values that trigger landslides. Although the single



Figure 6. Threshold exceedance graph for 5-day antecedent vs. daily rainfall. 'L' indicates landslide incidence.



Figure 7. Thematic maps used in slope stability analysis using PISA-m. (a) DEM derived from 30 m resolution SRTM data; (b) NDVI derived from Landsat 8 imagery; (c) reclassified NDVI.

Table 4	
Geotechnical parameters used	for slope stability analysis.

Sample No. and location	1 Longitude (E) Latitude (N)	Soil type ^a	Moisture content (%)	Specific gravity	Void ratio	Saturated unit weight (gs)	Moist unit weight (gm)	Pore pressure	Angle of internal friction, phi (°)	Soil cohesive strength, cs (N/m ²)
ALH/G5/5	77°11′20.2″	08°29′13.8″	Silty sand	21.02	2.65	0.69	338.62	19.38	1	35	41,187.93
Near Nulliyode			with gravel								
ALH/G19/15	77°11′21.2″	08°30′26.4″	Silty sand	28.44	2.56	0.91	386.97	17.82	1	20	41,129.93
Near Amboori			with gravel								
ALH/G23/20	77°09′36″	08°30′56.5″	Silty gravel	29.31	2.59	1.02	381.13	17.53	1	27	60,801.23
Near Chellanthikuzhi			with sand								

^a USCS classification.

day rainfall is regarded to be the most critical factor for triggering landslides in the Amboori region, the antecedent rainfall is also observed to play a vital role by increasing the pore-water pressure of the soil. It is evident from Fig. 5a–c that an increase in the cumulative antecedent rainfall results in a decrease in the amount of daily rainfall needed to trigger landslides. Note that for the 5-day antecedent rainfall (Fig. 9), a 100% increase in the cumulative antecedent rainfall decreases the daily rainfall required to trigger a landslide by approximately 16%. Therefore, it is a combination of the daily and antecedent rainfall that triggers landslides in tropical regions. Similar research by Jaiswal and vanWesten (2009), studying landslides on cut-slopes of the Nilgiri Hills in southern India, also revealed comparable Rainfall Threshold (RT) with high intercept and low slope that concurs with the present study.

The most important aspect to be noted is the number of days that have exceeded the threshold as positive values. As explained earlier, it is not imperative that a landslide will occur every time the rainfall crosses the threshold value, rather it would be the ideal time to issue an early warning so the community is prepared for a potential landslide event. The positive crossovers of the present study can be categorized as two: (1) before the landslide and (2) after the landslide.

There are six positive crossovers before the landslide, which hadn't resulted in landslide. The main reason for such a number is because of the lack of using rainfall intensity as a parameter. The unavailability of an hourly based monitoring system has resulted in



Figure 8. Slope stability units derived using the PISA-m model.

such positive crossovers. Hence this study also warrants the need for monitoring rainfall intensity for an improved predictive capability (e.g. Staley et al., 2013; Mathew et al., 2014).

The positive crossovers observed after the landslide event, are not expected to trigger additional landslides since it transported all soil down the slope, leaving behind nothing but crystalline Archean rock. Therefore, due to the lack of unconsolidated material at the crown of the hillock, there was no landslide after the landslide occurrence that crossed the RT.

Slope stability analysis conducted using the PISA-m model reveals that in saturated condition landslides have occurred along stable and unstable boundary. According to the results, the areas within the vicinity of FS value between 1 and 1.2 are the landslide vulnerable location. The accuracy of the slope stability assessment can be improved with higher resolution DEM. The use of freely downloadable data like SRTM and Landsat imagery, and the utility of open source software PISA-m for the delineation of slope stability sections is ideal for developing cost-effective ways to establish early warning system that could reduce the effects of a potential landslide.

Rainfall threshold and FS from slope stability analysis can be linked together in a unique composite model (Smith et al., 2015) for developing early warning system. Developing rainfall threshold in areas having FS < 1.2 by the techniques adopted in the study will help in establishing the early warning system. The method of this early warning system is based on the monitoring of daily and antecedent rainfall, in landslide susceptible zones, required to trigger a landslide based on the rainfall threshold equation. Continuous monitoring of daily rainfall or intensity will help in issuing warning when it approaches the threshold and thus monitoring of rainfall data can be also useful in landslide mitigation. The predictability rate of 27% in the present study is generally



Figure 9. 5-day antecedent vs. daily rainfall statistics.

a fair success rate considering the previous studies (Althuwaynee et al., 2015; Gariano et al., 2015).

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