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Estimating rainfall threshold and temporal probability for landslide occurrences in Darjeeling Himalayas

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ABSTRACT: The Indian Himalayan region has been severely affected by landslides causing an immense loss in terms of human lives and economic loss. The landslides are usually induced by rainfall which can be slow and continuous or heavy downpour. The incidences of landslide events in Indian Himalayas have been further aggravated due to the rapid increase in urbanization and thus its increasing impact on socio-economic aspects. There is a dire need for understanding landslide phenomena, estimating its occurrence potential and formulating strategies to minimize the damage caused by them. One of the most affected area is Kalimpong of Darjeeling Himalayas where significant studies have been conducted on zonation, threshold estimation and other related aspects. However, a comprehensive study in terms of temporal prediction for this region remains unattended. The paper deals with assessing landslide hazard using a rainfall threshold model involving daily and cumulative antecedent rainfall values for landslide events. The threshold values were determined using daily rainfall and antecedent rainfall using precipitation and landslide records for 2010–2016. The results show that 20-day antecedent rainfall provides the best fit for landslide occurrences in the region. The rainfall thresholds were further validated using rainfall and landslide data of 2017, which was not considered for threshold estimation. Finally, the results were used to determine the temporal probability for landslide incidence using a Poisson probability model. The validated results suggest that the model has the potential to be used as a preliminary early warning system.

Key words: rainfall threshold, temporal probability, Kalimpong, Darjeeling Himalayas

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1. INTRODUCTION

Globally, landslides are widespread and hazardous phenomena, dangerous to population, infrastructure and agricultural land (Froude and Petley, 2018). A global database of worldwide landslide events from 2004 to 2016 suggests that 75% of landslides occur in Asia with significant incidences in the Himalayan region (Froude and Petley, 2018). The Indian Himalayan region suffers 30% of global landslide incidents. Government records show that landslides in the Himalayan region kill at least one person per 100 km^2 and the average losses in this region is up to 15–20 million USD every year. Estimates indicate that the land loss due to landslides is 120 m/km/yr. leading to annual loss of more than 2000 tons/sq.km (Dikshit et al., 2018a). The increasing incidence of landslide occurrences across the world has led researchers to develop better solutions to effectively address the landslide situation (Gutierrez et al., 2010). This is generally addressed as spatial (where) or temporal (when) landslides may occur (Jaiswal and van Westen, 2009). A review article by Gokceoglu and Sezer (2009) recognised that most of the papers focussed on spatial probability (Pradhan and Lee, 2010; Pradhan et al., 2010; Sezer et al., 2011; Pourghasemi et al., 2012; Sarkar and Dorji, 2019) instead of temporal probability (Jaiswal et al., 2010; Das et al., 2011; Tien Bui et al., 2013; Afungang and Bateira, 2016).

The assessment of temporal probability can be categorised as: (i) Determination of potential slope failure, which evaluates the prevailing slope conditions and assesses instability. Such approach may not be suited for large study regions (Jaiswal and van Westen, 2009) (ii) Analysis of past landslide frequency which can be carried out using either direct or indirect approach. The direct analysis can be considered the ideal way to perform temporal

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probability, however, it requires a large and complete landslide dataset. Such a dataset is usually difficult to collect, especially in the Indian Himalayan region. The indirect approach relies on less data, and a relationship between rainfall and landslide incidence is established (Tien Bui et al., 2013). Subsequently, temporal probability is calculated based on the number of instances precipitation exceeded a threshold value.

The use of thresholds has been extensively used for various regions of the world using several methods (Martelloni et al., 2012; Segoni et al., 2014; Althuwaynee et al., 2015; Gariano et al., 2019). The determination of rainfall thresholds can be achieved using either physical based (Rossi et al., 2013; Dikshit et al., 2019a) or empirically based models (Mercogliano et al., 2013; Segoni et al., 2014; Teja et al., 2019). Physical based models are based on numerical techniques which study relation between precipitation, pore water pressure, soil type and volumetric water content that can lead to slope instability utilises physical terrain properties and geotechnical data based on the characteristics of the study region which are usually site specific and is a challenge to extend to large areas (Wilson and Wieczorek, 1995; Afungang and Bateira, 2016). Also, the use of a physical model is hindered by the computational resources required to perform the model (Segoni et al., 2015; Lee, 2019). On the other hand, empirical methods study the landslides that are caused by rainfall events – both the heavy downpour that triggers instantaneous landslides and the low but continuous antecedent rain that destabilizes the slope and triggers the landslide (Dikshit et al., 2019b). Though this approach is based on a single parameter i.e., precipitation rates, it is significant to note that rainwater is the cause of many changes in soil properties, pressure variations, etc. and hence can be approximated to the changes in rainfall. The empirical models based on rainfall intensity/event rainfall and duration usually require a high quality dataset (hourly data) to determine more accurate results (Jaiswal and van Westen, 2009). These models can also be extended in large areas, unlike physical models. The assessment of temporal probability is carried out by determining the probability of rainfall exceeding threshold values along with the probability of landslide occurrences after threshold exceedance. Similar approach has been carried out by Jaiswal et al. (2010), Tien Bui et al. (2013) for Hoa Binh, Vietnam and Nilgiri region, India, respectively. In another paper, Afungang and Bateira (2016) presented a different approach to determine temporal probability of rainfall triggered landslides for Bamenda Mountain, Cameroon using empirical rainfall and landslide inventory. However, such a study is yet to be conducted for the Indian Himalayan region.

The present study calculates thresholds using antecedent rainfall conditions using empirical methods for rainfall and landslide data from 2010 to 2016. Thereafter, the exceedance threshold probability and temporal probability of the landslide was estimated using the Poisson model. The validation of the thresholds was carried out in two steps: a) using landslide events in 2017 b) analysing the results from a real-time monitoring system installed in the region (Dikshit et al., 2018b). The validation of the thresholds using monitoring data shows that the model can be used as a preliminary step for operational landslide warning system and can also be extended to other landslide prone regions.

2. STUDY AREA AND DATA

2.1. Study Area

The study area is situated in the northeastern part of Indian Himalayas, which covers 42% of India's land area susceptible to landslides (Dikshit et al., 2018b). The focus of the study is Kalimpong, located in West Bengal, India. The landslides in the region can be triggered by both earthquake and rainfall. However, almost three-quarters of the landslides that occurred from 2006 to 2013 were triggered by rainfall (GSI Report, 2016) which makes it imperative to understand rainfall induced landslides. The region falls under Toposheet No. 78A/8 (Survey of India) with elevation ranging from 400 to 1665 m and is girdled by river Teesta and Relli in the west and east (Fig. 1). The slope instability in the area can be attributed to erratic monsoonal rainfall, erosion of Teesta and the improper drainage system (Dikshit and Satyam, 2018). More than 30% of area is characterised by a high elevation of more than 300 m and roughly 50% is part of steep to significantly steep slopes. The study region is a part of the Himalayan region, which constitutes the intra-thrusted rock carves of the Fold-Thrust Belt (FTB) of Eastern Himalaya. The area depicts heterogeneous geology with rocks of Precambrian to Quaternary ages are connected along the E-W direction (Ghoshal et al., 2008).

Geologically, the area comprises of immensely weathered chlorite schist, phyllitic quartzite, which is a part of Gorubathan Formation of Daling Group (Ghoshal et al., 2008). The area comprises several cracks, joints, which leads to an increase in the probability of decomposition and disintegration of rock forming unconsolidated matter. Since a majority of landslides occur during or after the monsoon, debris are saturated or partially saturated. The materials also include quartzite, phyllite, and mica schist. The high number of slope failures in Kalimpong can be related to a high rate of denudation along with a high rate of rainfall leading to activation/reactivation of several unstable slopes.

The region has suffered several landslides with the first major documented landslide in June 1950, which was caused due to

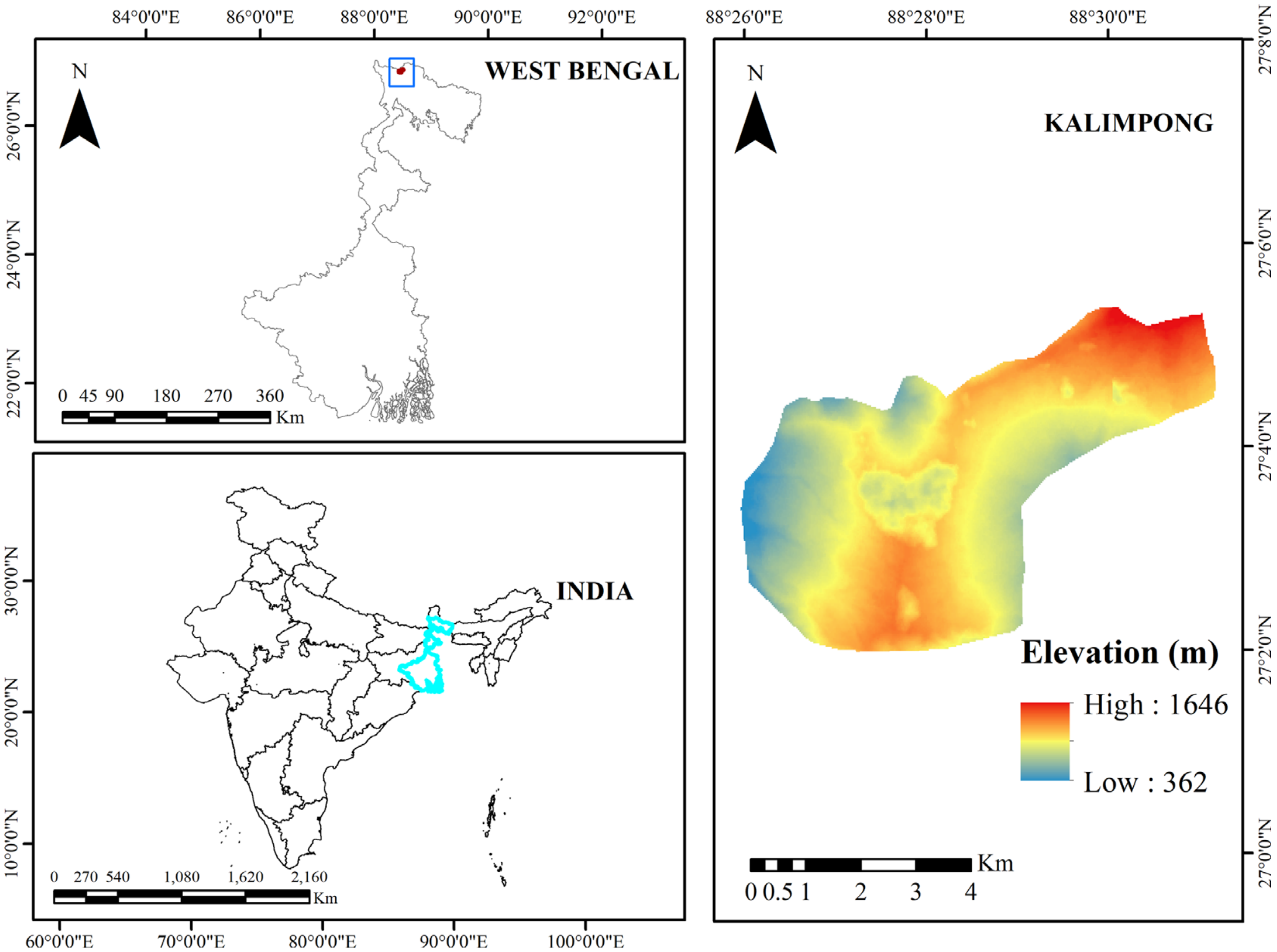

Fig. 1. Location of the study area.

heavy rainfall of over 800 mm. The landslides led to the death of over 100 people with several rendered homeless and causing extensive damage to infrastructure and agricultural land (Dikshit and Satyam, 2019). The event in September 1991 led to massive damage to railway lines, which connected the hills to plains. The landslide events in 2003 due to heavy rainfall led to a loss of 24 lives and similar incidents occurred consecutively for three years (Dikshit and Satyam, 2019). Recent events in June–July 2015 triggered landslides at several locations leading to a loss of 38 people and several missing.

2.2. Rainfall and Landslide Data

The daily rainfall data from 2010 to 2016 was collected from a rain gauge installed at Upper Teesta Catchment, Kalimpong. Rainfall induced landslide events are usually triggered by intense rainfall for a shorter duration or low intensity for longer durations. The monsoon rainfall in Kalimpong can be described as low intensity and long duration with interruptions of intermittent heavy bursts (Dikshit and Satyam, 2018). During the year (2010–2016), which is also the study period, most of the landslides are triggered by incessant and a high amount of monsoon rainfall occurring between June and September with some prominent and major landslide events in between. The average annual and monsoon precipitation during the study period is 1850 mm and 1627 mm, respectively. The contribution of monsoonal rainfall is 85% during the study period. However, the contribution of pre-monsoon and post-monsoon rainfall is 13% and 2% respectively. The occurrence of such a rainfall pattern makes it clear that rainfall plays an important role in triggering landslides in the study area. Figure 2 presents the annual variation in monthly rainfall collected from the rain gauge. The top and bottom of the rectangular boxes are 75th and 25th percentiles, while the horizontal thick lines inside boxes are 50th percentiles. The whiskers depict 1.5 times the interquartile range.

The landslide data was prepared from government reports, online portals and newspapers, and a total of 61 landslide events triggered only due to rainfall were considered for the study. Some landslide events like 18 September 2011 triggered due to earthquake were discarded from the study. The landslide data comprised

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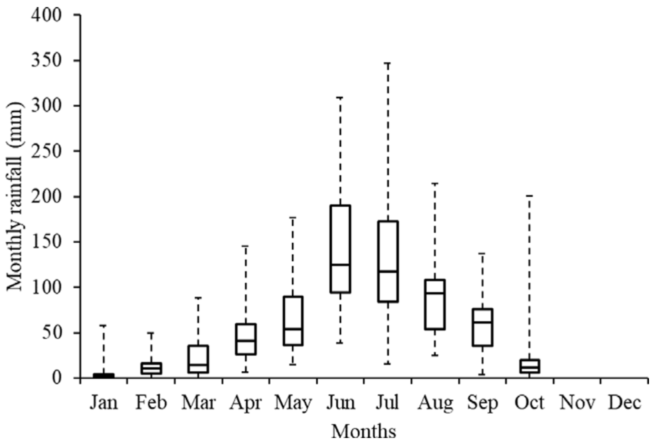

Fig. 2. Box and whisker plots showing annual variation of monthly rainfall measures in Kalimpong (2010–2016).

of occurrence and the approximate coordinates (latitude and longitude, EPSG: 4326). The type of landslide distribution is rock fall, rock slide, debris slide and earth slide, which has been identified by GSI (Cruden and Varnes, 1996). In the present study, shallow translational debris slide and flows associated with cut slopes were considered for temporal probability assessment. Figures 3a and b show some pictures taken during from the field study (October 2016). Figure 3a shows damage to culvert and Figure 3b shows damage on a road along National Highway (NH)-31A. Figures 3c and d show land loss due to slides in the 2015 and 2011 events, respectively.

3. METHODOLOGY

A threshold can be described as a minimum level of some quantity for a process to change (Reichenbach et al., 1998). For rainfall triggered landslides, a minimum rainfall intensity or duration for a landslide to occur is termed as rainfall threshold. Rainfall thresholds have been proposed all over the globe on various scales, and its determination can be considered a preliminary step for landslide hazard assessment. The various threshold types along with their uses and limitations have been described in (Guzzetti et al., 2007, 2008; Segoni et al., 2018). The determination of rainfall threshold revolves around four variables, i.e., daily rainfall, antecedent rainfall, cumulative rainfall and normalised critical rainfall (Tein Bui et al., 2013). The threshold determined utilising rainfall intensity or event rainfall and duration is the most recognised and widely used method (Martelloni et al., 2012; Segoni et al., 2018). The determination of thresholds using any combination of rainfall parameters has been largely determined using a statistical approach (Dikshit and Satyam, 2018; Teja et al., 2019). The thresholds are calculated by drawing the lower-bound curves between rainfall events that led to landslide incidences

Fig. 3. Landslide damages in the region. (a) Damage to culvert, (b) Damaged road section along NH-31A, (c) Land loss during 2015 landslide event, (d) Mudflows and debris (2011 event) (https://savethehills.blogspot.com).

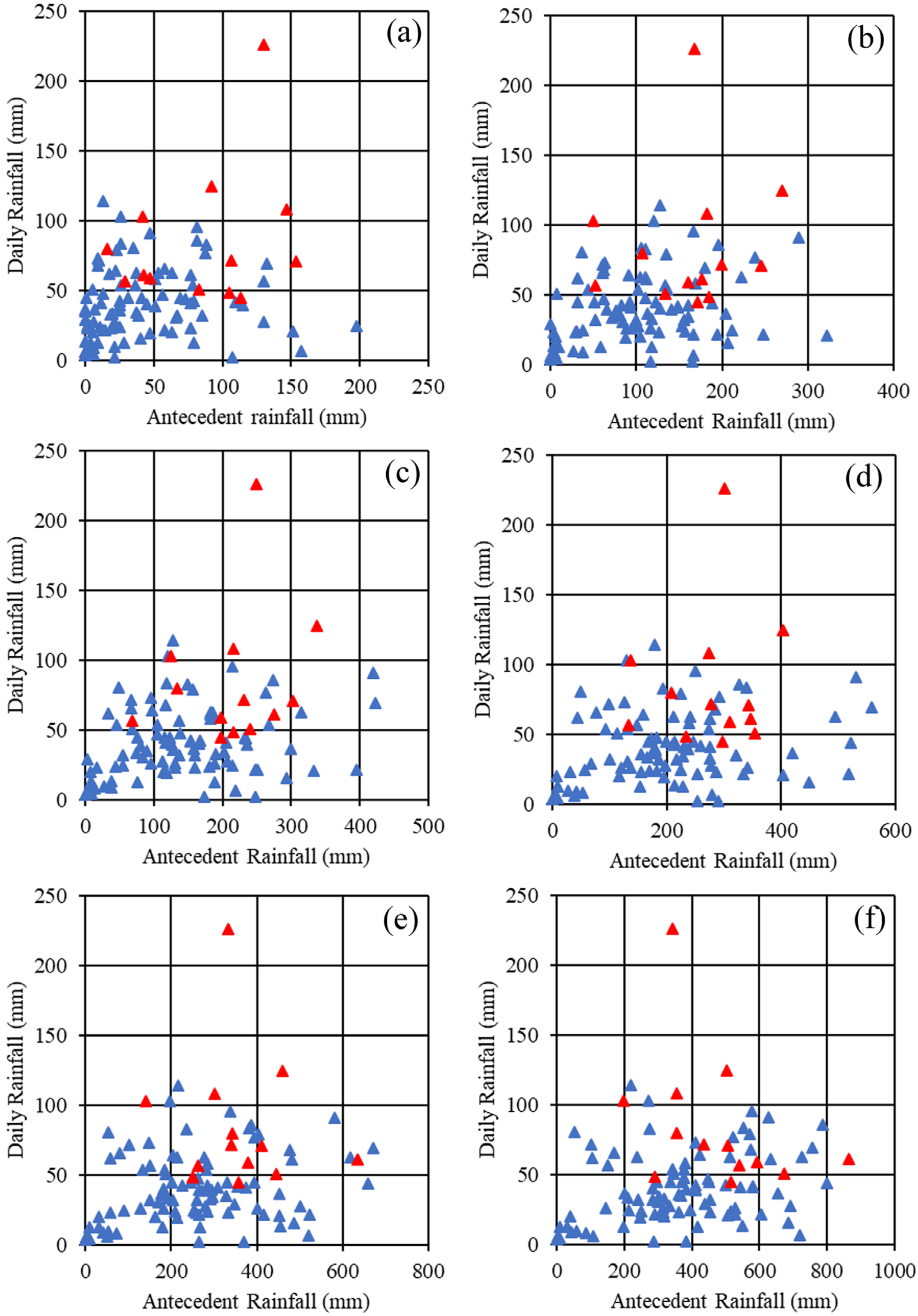

Fig. 4. (a–f) Relationship between daily and antecedent rainfall (3, 5, 7, 10, 20 and 30 days, respectively) for 2010–2016.

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plotted in either Cartesian, semi-logarithmic or logarithmic coordinate system. Apart from the statistical approach, the recent focus has also been on an automatic definition of thresholds for enhancing threshold reproductively and its robustness (Melillo et al., 2018; Gariano et al., 2019). Also, there has been significant advances in the use of machine learning and artificial intelligence techniques to predict landslides (Arabameri et al., 2019; Lee and Oh, 2019). However, the use of any technique for threshold determination is dependent on the choice of parameters conditional to the landslide type along with the quality of data available in the study region.

In terms of rainfall parameters, the effect of antecedent rainfall has been widely accepted to be an important factor for slope instability in the Indian Himalayan region ranging from 15 days to 30 days (Mathew et al., 2014). Similarly, the role of antecedent rainfall plays a crucial role in landslide initiation in Kalimpong (Dikshit and Satyam, 2018; Teja et al., 2019). Antecedent rainfall influences soil suction, leading to an increase in pore water pressure, thereby causing slope instability (Dikshit et al., 2019b). The challenge in forecasting landslides using antecedent rainfall is to ascertain the number of days to be considered for analysis. Various authors have used different time periods to determine the correlation between antecedent rainfall and a number of days for landslide triggering. Kim et al. (1991), Chleborad (2003), Heyerdahl et al. (2003), and Polemio and Sdao (1999) examined for 3, 4, 18 and 180 days respectively. Aleotti (2004) used 7, 10 and 15 days, whereas Terlien (1998) assessed 2, 5, 15 and 25 days.

4. RESULTS AND DISCUSSIONS

4.1. Rainfall Threshold Estimation

The threshold calculation was based on the determination of a number of days of antecedent rainfall necessary for landslide occurrence. To calculate the number of days, a trial and error approach was adopted for six different time periods (3, 7, 10, 15, 20 and 30 days). The results for different time periods are illustrated in Figures 4a–f. The red triangle denotes landslide occurrences, whereas the blue triangle depicts maximum annual precipitation in one day without any landslide event. The distinction between triggering and non-triggering landslide events for various days corresponds to the determination of the best antecedent rainfall period. For the present study, the best discrimination was found for 20-day antecedent rainfall conditions and was adopted for threshold estimation.

The thresholds are determined by a scatterplot with daily rainfall data on the ordinate and the corresponding 20-day antecedent rainfall on the abscissa. The mathematical equation for the threshold is determined using the lower end of plotted points in the graph (Chleboard, 2000). The threshold equation from the analysis came out to be $R_{th} = 66 - 0.07R_{a20}$. R_{th} is the threshold rainfall and Ra_{20} is the 20-day antecedent rainfall (Fig. 5).

The key to employing any thresholds in a region is to validate the results using an independent dataset. A recent review of the global database of 115 rainfall thresholds showed that only 69 works provided a validation of the thresholds (Segoni et al., 2018). Therefore, the thresholds obtained have been validated using the 2017 monsoon rainfall, and the results have been illustrated in Figure 6. In total, there were six times where the threshold is exceeded, 27, 28 and 29 July along with 14, 15 and 17 August. During the monsoon period of 2017, there has been no incidence of a landslide. Further, the results were validated using the results obtained from the installation of a real-time monitoring system located in the south-western part of Kalimpong (Dikshit et al., 2018b). The results from the monitoring systems showed that there were signs of ground displacement during two different incidences, i.e., 28–29 July and 13–17 August. During the monsoon of 2017, there was only one day (27 July) which exceeded the thresholds.

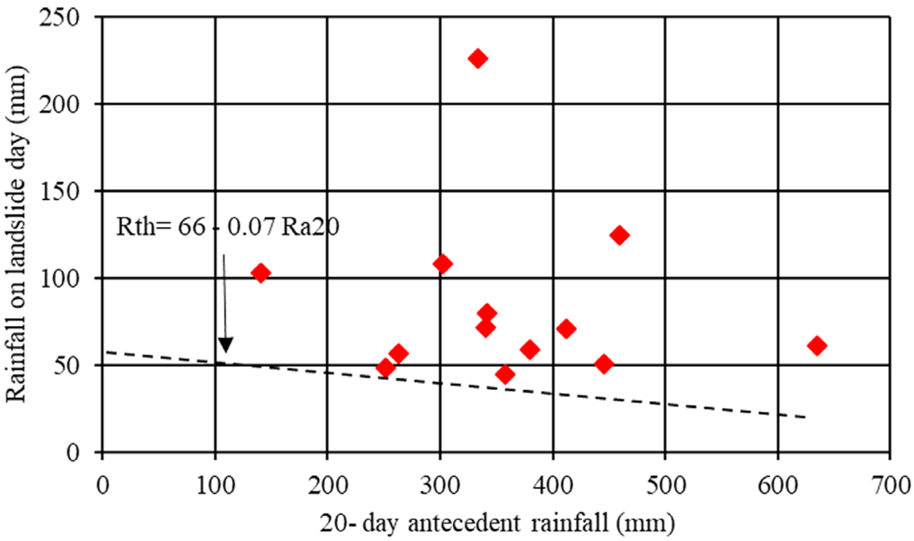

Fig. 5. Rainfall thresholds for Kalimpong region. R_{th} is the threshold rainfall and R_{a20} is the 20-day antecedent rainfall.

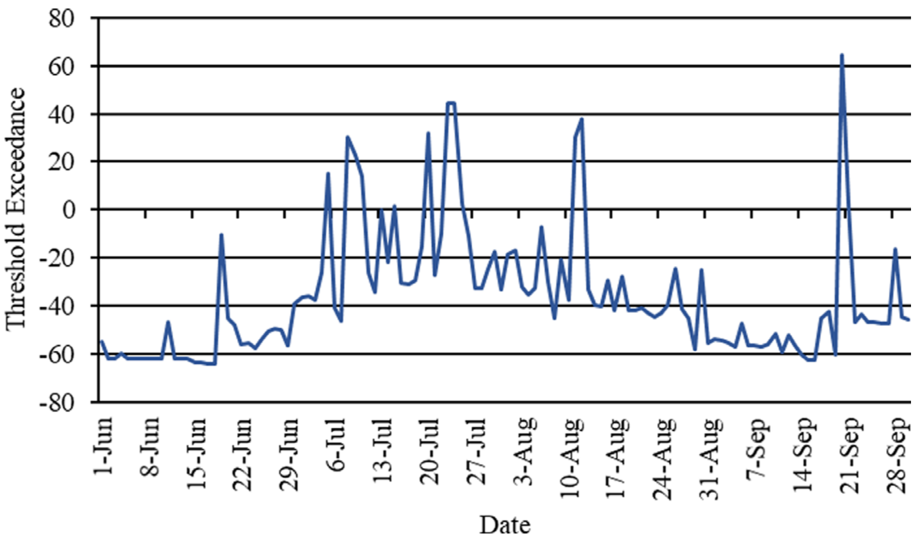

Fig. 6. Validation of the threshold equation using 2017 rainfall for data (June 1–September 30, 2017).

Therefore, it can be observed that the threshold model can be used to foresee landslide incidences.

4.2. Temporal Probability of Landslide Occurrence

There are two assumptions used to determine temporal probability. The first one being the probability of landslide incidence is directly linked to the probability of a rainfall event (Jaiswal and van Westen, 2009). The second being that the occurrence of the landslide has no, or slight possibility is the precipitation is below the threshold. The rainfall records used for determination of thresholds has been used to determine temporal probability of landslides using a Poisson Probability model.

The Poisson distribution for the probability of 'n' landslides for the time 't' can be described as:

$$P(\mathrm{N(t) = n}) = \frac{e^{-t}(\lambda t)^{n}}{n!}. \tag{1}$$

N(t) is the number of landslide incidences in time t, λ is the rate of landslide incidence. Exceedance probability can be defined as the probability of one or more landslides for the time t:

$$P(\mathrm{N(t)} \geq 1) = 1 - \exp(-t/\mu), \tag{2}$$

where $\mu = t^{-1}$; μ and t are the future mean recurrence interval and time period, respectively. μ is estimated using the assumption that landslide incidence in the future will be the same as in the past. The results have obtained from the analysis were shown in Table 1.

5. CONCLUSIONS

The increase in landslide incidences in Indian Himalayan region has led to immense damage to landscape, disrupting human lives and loss of land. One of the most affected regions is Kalimpong in Darjeeling Himalayas, where the majority of the landslides are induced by monsoonal precipitation. The present study determines the rainfall threshold occurrences and estimates the temporal probability of landslides in the region. The conclusions from the study are:

1) The thresholds for the region were determined using antecedent rainfall conditions for rainfall records and landslide incidences from 2010 to 2016. The quantification of antecedent days was carried out for 6 different time periods, out of which 20-day provided the best discrimination and was adopted for threshold estimation.

2) The threshold equation from the analysis came out to be $R_{th} = 66 - 0.07R_{a20}$. The threshold determined were validated using 2017 monsoonal rainfall data along with the results obtained from a real-time monitoring system installed in south-west part of Kalimpong. During the validation period, there were six instances where the threshold is exceeded the calculated value of which only one was false.

3) The temporal probability of landslide incidences were computed using an indirect method based on the mean occurrence rate of the threshold. The return period of the landslide occurrences were determined for various time periods.

The thresholds determined can further be enhanced with the availability of hourly rainfall data along with the time of landslide

Table 1. Temporal probability of landslides

Time	3 months	6 months	1 year	3 years	5 years
Probability	0.675	0.894	0.988	1	1

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occurrence. The work shows that early warning systems can hence be designed based on these rainfall thresholds as a first line of action. The determination of such thresholds can be used for several other parts of Darjeeling Himalayan regions where extensive data is not available.

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