Towards establishing rainfall thresholds for a real-time landslide early warning system in Sikkim, India

Article *in* Landslides · August 2019

DOI: 10.1007/s10346-019-01244-1

Geethu Th
Amrita Vishwa Vidyapeetham

Maneesha Vinodini Ramesh
Amrita Vishwa Vidyapeetham

Divya Pullarkatt
Amrita Vishwa Vidyapeetham

Landslides
DOI 10.1007/s10346-019-01244-1
Received: 26 March 2019
Accepted: 9 July 2019

Geethu Thottungal Harilal · Dhanya Madhu · Maneesha Vinodini Ramesh · Divya Pullarkatt

Towards establishing rainfall thresholds for a real-time landslide early warning system in Sikkim, India

Abstract Sikkim, one of the Northeastern states of India, is a famous tourism spot in the Himalayas with dynamic population density. This mountainous area receives heavy rainfall and is well known for frequent shallow landslides, especially, Chandmari, which is a village, situated in Gangtok area in East Sikkim. Even though it is well known that rainfall and landslides are correlated, Sikkim lacks a well-established landslide early warning system. Such a system is important in this region because it is one of the highest landslide-prone areas in India. The current research attempts to establish rainfall thresholds as part of developing an efficient landslide early warning system for this region. The rainfall thresholds for landslides are derived based on the daily rainfall data available from India Meteorological Department (IMD) for six stations in Sikkim. Analysis of daily rainfall data and landslide events in this area between the year 1990 and 2017 is performed. An intensity–duration (I–D)-based regional rainfall threshold is derived as $I = 43.26\ \mathrm{D}^{-0.78}$ (I = rainfall intensity in mm/day and D = duration in days) for the rainfall-triggered landslides in Sikkim region and a local threshold of $I = 100\ \mathrm{D}^{-.92}$ was developed for the Gangtok area. Furthermore, the influence of antecedent rainfall in landslide initiation is explored by considering the daily, 3-day, 5-day, 7-day, and 20-day cumulative rainfall values associated with landslides. The proposed threshold equations and study of the effect of antecedent rainfall on landslides are intended to aid in enhancing the real-time landslide early warning system (R-LEWS) being developed for Sikkim.

Keywords Antecedent rainfall · Empirical threshold · Landslides · Rainfall thresholds · Real-time landslide early warning system (R-LEWS)

Introduction

Timely warning of landslides can help in evacuating people and thereby reduce the extent of loss of lives which they cause. However, the complex meteo-hydro-geological interactions, which trigger a landslide, are not always exactly understood. This makes the implementation of a landslide early warning system (EWS) difficult. An EWS involves establishment and maintenance of four of its components, namely design, monitoring, forecasting, and education as detailed by Intrieri et al. (2013). In such an EWS, rainfall threshold is a component that is highly significant. The rainfall thresholds depend upon many factors like the climatic, geological, and land use patterns of the region of interest. Accordingly, different categories of rainfall threshold equations exist in literature (Guzzetti et al. 2007; Segoni et al. 2018a).

For landslides that are induced by rain, a threshold is indicated by the quantity of rainfall that most likely results in a landslide. Rainfall thresholds can be categorized into two main broad categories: physical thresholds and empirical thresholds (Guzzetti et al. 2007; Aleotti 2004; Wieczorek and Glade 2005). The initiation of landslides is influenced by the morphological, lithological, hydrological, and soil characteristics of a location and hence the development of a physical threshold requires detailed information on all the above (Guzzetti et al. 2007; Segoni et al. 2018a). To formulate a physical threshold, the impact of rainfall in causing slope instability is majorly established using physically based models integrated with hydrological models (Montgomery and Dietrich 1994; van Westen and Terlien 1996; Crosta 1998; Iverson 2000; Jakob and Weatherly 2003; Godt et al. 2008; Baum et al. 2010). Recently, various approaches have been proposed to develop the physical thresholds for the landslide prediction by linking the rainfall pattern with soil properties, unsaturated conditions of soil, geotechnical, and hydrological factors (Salciarini and Tamagnini 2015; Wu et al. 2015; Arnone et al. 2016; Hsu et al. 2018; Reder et al. 2018; Salvatici et al. 2018). Empirical rainfall thresholds are based on rainfall events, which have caused landslides. Rainfall thresholds are usually defined on an empirical basis (Corominas 2000; Crosta and Frattini 2001; Aleotti 2004; Wieczorek and Glade 2005; Brunetti 2010).

The empirical threshold is the rainfall value which, when reached or exceeded, is likely to trigger landslides (Reichenbach et al. 1998). Based on the available rainfall observations, empirical thresholds are divided into three. They are (1) thresholds that combine rainfall for particular landslides, (2) thresholds that are based on the antecedent rainfall conditions (Aleotti 2004), and (3) other thresholds, incorporating hydrological thresholds (Guzzetti et al. 2007; Kanungo and Sharma 2014; Mathew et al. 2014). The empirical rainfall threshold obtained from individual or multiple rainfall events or various precipitation parameters can be further subcategorized into intensity–duration (I-D) thresholds, rainfall event–duration (E-D) thresholds, and rainfall event–intensity (E-I) thresholds (Guzzetti et al. 2007, http://rainfallthresholds.irpi.cnr.it/threshold_info.htm, accessed 8 May 2019). These threshold types can further be subdivided into global, regional, or local thresholds based on the extent of the geographical area under consideration.

A global threshold explains a general ("worldwide") minimum level below which landslides do not occur, independent of local morphological, lithological, and land-use conditions and of local or regional rainfall pattern and history. The main examples for global thresholds are Caine (1980), Innes (1983), Crosta and Frattini (2001), Clarizia et al. (1996), Cannon and Gartner (2005), Hong and Adler (2008), and Guzzetti et al. (2008). Regional thresholds are established in areas of thousands of square kilometers in area or more. These may be developed for the various regions within a country or for different countries, which have similar geographic and climatic characteristics. A number of regional threshold models exist in literature (Cannon 1985; Ceriani 1992; Larsen and Simon 1993; Aleotti 2004; Lagomarsino et al. 2015; Ma et al. 2015; Rosi et al. 2016; Althuwaynee et al. 2018; Vaz et al. 2018; Pradhan et al. 2018). Local thresholds are based on the local climatic system and geomorphological setting. It is appropriate for one particular landslide or for groups of landslides in an area. The examples for local rainfall thresholds are Cancelli (1985),

Published online: 15 August 2019

Wieczorek (1987), Wieczorek et al. (2000), Aleotti et al. (2002), Giannecchini (2005), Zêzere et al. (2005), Kanungo and Sharma (2014), Chung et al. (2017), Gao et al. (2018), Pradhan (2019), Irawan et al. (2019), and Rosi et al. (2019).

The rainfall thresholds established before 2008 were reviewed by Guzzetti et al. (2007, 2008) on the basis of type of threshold model, extend of threshold defined, and type of landslides. Later, Segoni et al. (2018a) carried out an extensive study on all the rainfall thresholds defined after 2008 all around the world. The review includes the details of different methodologies of threshold definition, application, and various validation techniques used. The work also provided information about the best practices, the most effective solutions used, and the major drawbacks. According to this paper, Hong and Adler (2008) and Guzzetti et al. (2008) published two global scale thresholds in 2008, which is considered as the recent work in the global scale category wherein the former had developed a satellite-based rainfall intensity–duration threshold. Guzzetti et al. (2008) proposed a global rainfall threshold from the rainfall landslide database prepared through a thorough literature search, including international journals, conference proceedings, and event and technical reports. The probability approach was first proposed for defining the threshold by Guzzetti et al. (2008). Among the total rainfall thresholds proposed, majority of the works are at regional and local scales (Segoni et al. 2018a). Lagomarsino et al. (2015), Ma et al. (2015), Rosi et al. (2016), Althuwaynee et al. (2018) Vaz et al. (2018), and Pradhan (2019) are some of the recent established works in regional scale. Lagomarsino et al. (2015), Ma et al. (2015), and Rosi et al. (2016) have partitioned the study area into subzones that have homogeneous geomorphological characteristics and proposed a specific threshold for each of them in order to increase the reliability and performance of these thresholds. The reliability of these rainfall thresholds is evaluated using various statistical indices such as back analyses, contingency tables, and skill scores. Vaz et al. (2018) also used several statistical parameters in order to analyze the effectiveness of the rainfall thresholds proposed for the Lisbon region. Althuwaynee et al. (2018) conducted a study on susceptible regions of northern Turkey and proposed different types of rainfall thresholds such as ED, ID, and antecedent thresholds for selected periods (3, 5, 10, 15, and 30 days) and validated them by calculating the reliability index. Among the different threshold types that they proposed, the ID threshold provided the optimal performance. For the local scale, Kanungo and Sharma (2014) proposed a threshold for Chamoli-Joshimath region in India, using some statistical methods whereas Chung et al. (2017) adopted a deterministic-based model to estimate the local rainfall thresholds for a deep-seated landslide in Taipingshan villa, Taiwan. Gao et al. (2018) proposed the local rainfall intensity–duration thresholds for Hong Kong area, which calibrated three levels of landslide magnitudes for both open hillslope landslides, and channelized debris flows. Recently, Irawan et al. (2019) defined a new empirical rainfall threshold combined with antecedent soil moisture indexes for Banjarmangu district, Indonesia. In addition, Segoni et al. (2018b) highlighted the importance of hydrological bases to empirical rainfall thresholds by integrating mean soil moisture values for improving the landslide EWS in Emilia Romagna Region (Italy).

In India, the impacts of landslides are experienced over at least 15% of its land area (Kanungo and Sharma 2014). The Himalayan region is particularly prone to landslides, which result in significant loss to lives and properties. Sikkim is one of the northeastern states of India, located in the eastern Himalayas and covers around 40% of landslide-prone areas in the country (Dikshit and Satyam 2017). The higher number of landslides occurring over this region coupled with its complex orography and socio-economic conditions makes it a vital region for implementing a landslide EWS. As explained earlier, one of the crucial initial steps in the EWS implementation is the establishment of a rainfall threshold and the development of such a threshold is the focus of the current study.

Over the Himalayan region, a few studies have explored robust relationships between rainfall and landslide initiation. Dahal and Hasegawa (2008) address the rainfall threshold relation for Nepal by fitting the rainfall intensity–duration threshold curve for landsliding as $I = 73.90\ \mathrm{D}^{-0.79}$ by using the rainfall data and landslide events from 1951 to 2006. They establish the normalized rainfall intensity–duration relationships and landslide initiation thresholds from the normalized rainfall intensity data with respect to mean annual precipitation (MAP) as an index. Rainfall thresholds for Garhwal region of Himalayas were explored by Mathew et al. (2014), Kanungo and Sharma (2014), and Ziegler et al. (2017). Mathew et al. (2014) derived the rainfall threshold of Garhwal Himalaya region by establishing the log–log plot of duration and the maximum rainfall intensity that triggered landslides to the duration 1998–2004 and the threshold equation is expressed as $I = 58.7\ \mathrm{D}^{-1.12}$. Similar to Dahal and Hasegawa (2008), Mathew et al. (2014) also derived a normalized intensity–duration relation using the mean annual precipitation. Kanungo and Sharma (2014) attempted to derive the local rainfall thresholds for landslides in and around Chamoli-Joshimath region of the Garhwal Himalayas, based on daily rainfall data. The rainfall data and landslide events of 2009 to 2012 were taken to yield an empirical intensity–duration threshold by fitting lower boundary of the landslide triggering rainfall events and the threshold obtained was $I = 1.82\ \mathrm{D}^{-0.23}$. Kumar et al. (2017) have analyzed landslides due to extreme rainfall events in Jammu and Kashmir region of Himalayas. The rainfall threshold for Kalimpong region is explored by Dikshit et al. (Dikshit and Satyam 2018) by using probabilistic approach. For Sikkim, Sengupta et al. (2010) have related the rainfall and landslide event that occured at Lanta Khola, North Sikkim and derived E-D threshold for the region. However, the exact nature of the relation between rainfall and landslide initiation in the Sikkim region is still not completely understood.

Sikkim is a state, which witnesses heavy inflow of tourists, both from the country as well as from abroad. Landslides result in damaging roads which leads to remote areas being cut-off, which creates difficulties in travel as well as rescue operations. All this indicates that if a reliable early warning is available in Sikkim, it will contribute to better risk mitigation. However, currently, such a system is not in place for Sikkim. In this paper, an attempt is made to establish a regional threshold for Sikkim and a local threshold for Gangtok. The objective of the present study is to arrive at a meaningful rainfall threshold that can be applied in a real-time landslide early warning system (R-LEWS) in Chandmari, Gangtok, Sikkim. A multi-sensor-based system for real-time monitoring and early warning of landslides is implemented in Chandmari with the pilot stage completed in 2015 (Vasudevan et al. 2016; Ramesh et al. 2017). The newly developed thresholds will be integrated into the first level of the multi-level warning model designed for the system deployed in Chandmari.

Study area

Sikkim is considered as one of the major landslide-prone areas with the majority of the population inhabiting hilly terrains that are vulnerable to landslide. This section highlights the geography of our study area in brief which include (i) Sikkim, a state in Northeast India, for which the regional rainfall threshold has been proposed, (ii) Gangtok, a city in the district of East Sikkim, for which the local level rainfall threshold has been developed, and (iii) Chandmari, a locality within Gangtok, where an early warning system based on the Internet of Things (IoT) has been deployed. The state extends approximately 114 km from north to south and 64 km from east to west and has a total geographical area of 7096 km^2. The state has four districts, namely (a) East district, (b) West district, (c) North district, and (d) South district (Fig. 1a) with their headquarters at Gangtok, Gyalshing, Mangan, and Namchi respectively. Sikkim with highly fragile geology and rugged topography is highly affected by various mass movements. From south to north, the Main Frontal Thrust (MFT), Main Boundary Thrust (MBT), and Main Central Thrust (MCT) cross the state running in east-west direction in which MCT is having a very irregular shape. The mountains of Donkya ranges in the east while the Singalila ranges in the west are segregated by Nathu la and Jalepa la, which provides a trade route between Sikkim and China (Tamang et al. 2005). Due to the presence of active thrust zones and heavy rainfall surges, the area experiences many landslides during monsoon. The Sikkim State Disaster Management Authority (SSDMA 2012) provides the landslide susceptibility of the various regions of Sikkim. These data are combined for creating the susceptibility map of Sikkim as depicted in Fig. 1c.

Gangtok in East Sikkim has its terrain highly dissected with steep gorges, broad valleys, and ridges and has an elevation ranging from 350 to about 4630 m covering an area of 945 km^2.The location of Gangtok within Sikkim is shown in Fig. 1a. The main lithological units of the Gangtok region are gneises, Lingse granite gneiss, schistose rocks, and medium to low-grade metasedimentary rocks.

Chandmari location shown in Fig. 1b, in East Gangtok lying at an elevation of 1650 m, had witnessed many landslides in past and is one of the highly susceptible areas. Here the basement rock is of medium- to high-grade gneisses of the Paro formation overlying staurolite and mica/garnet-rich schist. The predominant rock minerals are quartz, feldspar (orthoclase and plagioclase), biotite, muscovite, and chlorite. The mineral lineation of biotite is ranging between 35 and 45° towards southeast. The landslides in the area are mostly rainfall-induced (Vasudevan and Ramanathan 2016). The topsoil is mostly sandy loam to clayey overlying on highly weathered bedrock whose thickness varies up to 20 m. The weathering is predominantly by physical integration as well as chemical decomposition processes (Dubey et al. 2005). The general slope is between 35 and 45° except few areas where slope is more than 60°. The orientation of fracture is parallel to the slope which makes the site prone to landslide (Thambidurai el. al 2017).

Data and methodology

Daily rainfall observations from the India Meteorological Department (IMD) during the period 1990–2017 and the rainfall observations from our R-LEWS in Chandmari from 2015 onwards were utilized for this work. The daily rainfall data from IMD were obtained from six stations of Sikkim, namely Gangtok, Mangan, Namathang, Mazitar, Dentam, and Damthang. The rainfall data availability over these six stations was not uniform in time. For instance, the rainfall observations from Gangtok are available during 1990–2017, whereas data from Mangan is available only for 2001–2017 periods. The location of the rain gauges (from which the rainfall observations for this study were obtained) and landslide events is indicated in Fig. 1d. IMD rainfall observations are available daily at 0830 h Indian Standard Time (0300 UTC). Details of 88 landslide events that had occurred for the duration 1990–2017 have been collected from the reports of the Geological Survey of India (GSI), online sources, and newspapers (Bureau 2016; Froude and Petley 2018; Giri 2018). Some authors have tried to automatically retrieve landslide data from newspapers and to use them in EWS (Battistini et al. 2013, 2017). However, so far, such automatic technique has not been utilized in the current study. Since the landslide events are also collected from the news reports in addition to scientific documents, all details regarding these events including their typology are not always available (Varnes. 1978; Cruden & Varnes. 1996). This might mean that landslides of all typologies may be included in the creation of the threshold. This approach of considering all available landslides of unspecified typologies is followed by many researchers (Bhasin et al. 2002; Anbarasu et al. 2010; Sengupta et al. 2010; Nerella et al. 2019). In the current study, ID thresholds were developed in two stages. At the initial stage, rainfall observations and landslide event details over the whole Sikkim area are used to develop a regional ID threshold for the entire state of Sikkim. Further, the rainfall and landslide events from Gangtok were used to develop a local threshold equation for Gangtok City. Rain observations from our system deployed in Chandmari are available at a very high frequency (every 5 min) for the period 2015–2018 and have been utilized for validation of the threshold equations.

Development of intensity duration rainfall thresholds

Intensity–duration threshold equations connect the mean rainfall intensity (I) with the rainfall event duration (D) in the general form $I = \alpha\ D^{-\beta} + c$ where α, β, and c are empirical parameters. Typically, $c = 0$. Then from the log-log plot of duration and intensity, α is revealed to be the scaling factor (intercept) and β to be the slope of the graph. Therefore, the nature of the intensity–duration threshold equation indicates that while a short burst of intense rainfall can trigger slope failure, a small intensity rainfall event of longer duration also might result in a landslide (Guzzetti et al. 2007). Whether or not mass movement actually occurs due to such a rainfall event depends on other hydrogeological parameters pertaining to slope stability in addition to the amount of rainfall obtained. The majority of the existing rainfall threshold equations encompass 1 to 100 h durations and 1 to 200 mm/h intensities (Guzzetti et al. 2007). Depending on the availability of precipitation observations, either hourly or daily intensities of rainfall are generally considered for producing the equations (Gabet et al. 2004; Glade et al. 2000; Khan et al. 2012; Kanungo and Sharma 2014; Leonarduzzi et al. 2017; Dikshit and Satyam 2018).

Sikkim experiences rainfall throughout the year. The characteristics and variability of rainfall in Sikkim are analyzed in Fig. 2. The temporal variability follows the seasonal variations over the

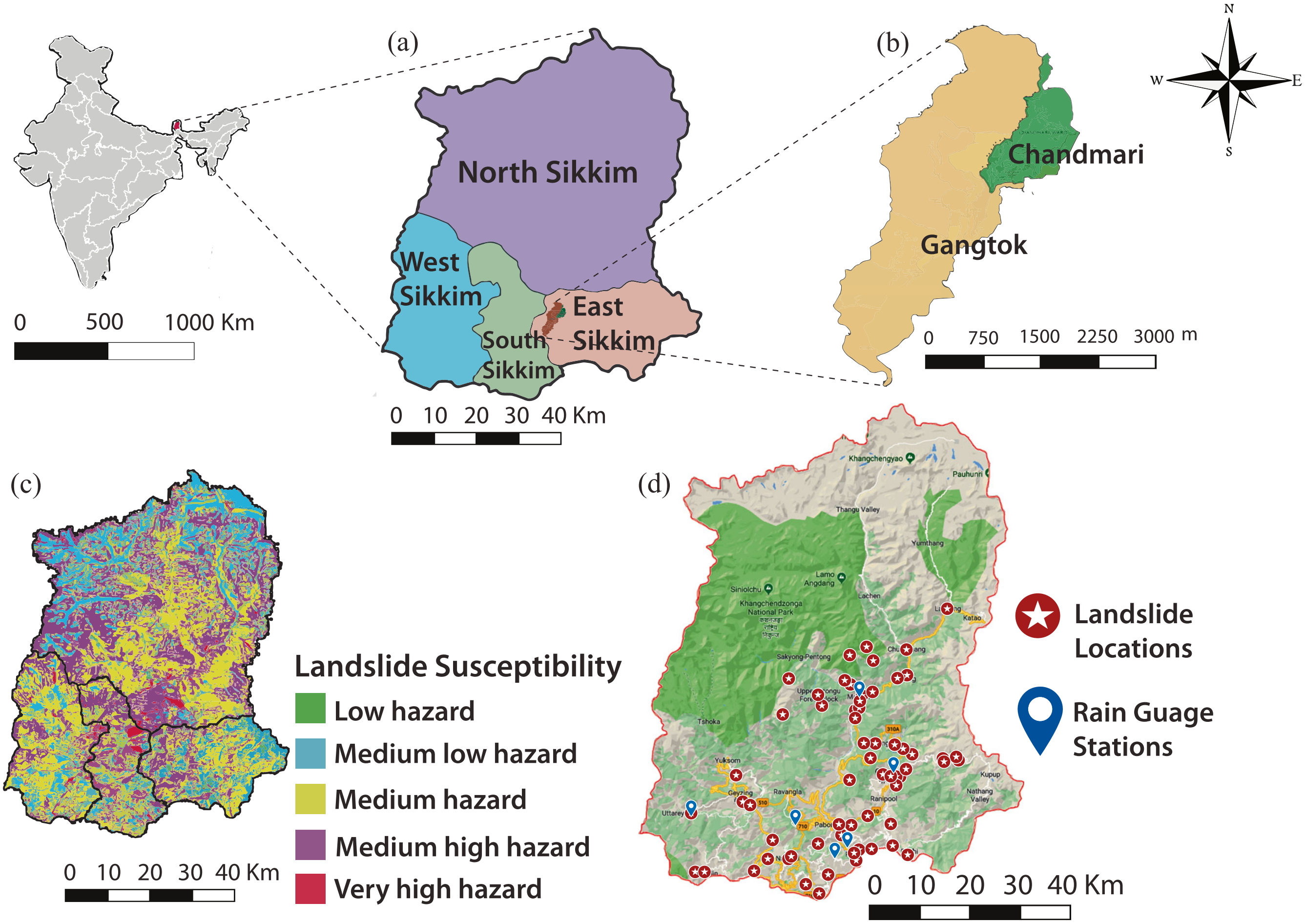


Fig. 1 Maps displaying the study areas Sikkim and Gangtok. **a** Location of Sikkim in India (27.5330° N, 88.5122° E). **b** Location of Chandmari (27.3383° N, 88.6233° E) and Gangtok (27.3389° N, 88.6065° E). **c** The landslide susceptibility map of Sikkim (SSDMA. 2012). **d** Map showing the location of available landslide events during 1990–2018 and the location of rain gauges in Sikkim considered for this study

Indian subcontinent. The daily rainfall observations from the six stations for the period 1990–2017 are utilized to generate long-term average daily rainfall (in mm) over Sikkim. The bar graph in Fig. 2 illustrates the climatic rainfall pattern over Sikkim during 1990–2017. On an average, Sikkim experiences at least a small amount of rainfall almost all months in a year and the peak rain is observed during the monsoon months. It can be seen that the deviation is low during the months of June to September, which is the monsoon season in India. The deviation is largest at the beginning of June and at end of September. Figure 3 shows the rainfall pattern of Gangtok region from 1990 to 2017. The landslide pattern also follows the general trend of rainfall pattern with the number of landslides being larger during monsoon months as compared with other seasons.

The area-wise and monthly distribution of rainfall and available landslide events in Sikkim, which is gathered from GSI reports, online sources, and newspapers during 1990–2017, are depicted in Fig. 4 a and b respectively. From Fig. 4a, it can be inferred that East Sikkim has the highest annual rainfall and it has witnessed more landslides as compared with the other regions of Sikkim. Furthermore, it is evident from Fig. 4b that there is variability in the number of landslide events within a year with respect to the rain. The major rainy season in India is the southwest monsoon or summer monsoon season during June to September, followed by the northeast monsoon or post-monsoon season during October to November. The winter season (December–February) and summer or pre-monsoon season (March–May) are typically seasons during which rainfall received is scanty. The Indian summer monsoon season with an average monthly rainfall of 350 to 500 mm has the maximum number of landslide events. There were no reported landslide events during the months February and March for the period 1990–2017.

Regional rainfall ID threshold for Sikkim

The majority of the rainfall ID thresholds in literature utilize rainfall intensity in millimeter per hour and the duration in hours. However, for the present study, since the available rainfall observations are daily accumulated, we have connected rain intensity in milliliter per day with rainfall event duration also in days. Based on a detailed analysis of rainfall data, a rainfall event is defined as accumulated rainfall over the whole of Sikkim being greater than or equal to 2 mm per day. As depicted in Fig. 1d, 88 landslide events obtained during the period 1990–2017 were used for this

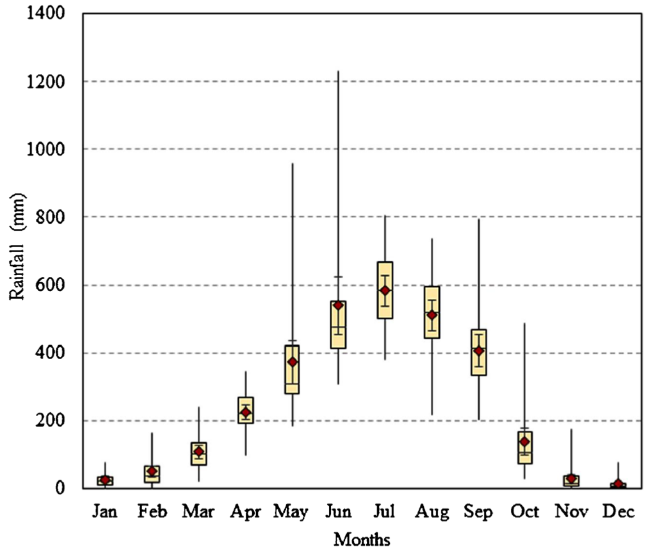


Fig. 2 Boxplot containing the monthly average and 95% confidence interval (1.96 + SD) of rainfall for the period 1990–2017 for Sikkim. The lines above the boxplot indicate the maximum rainfall during each month and the line below the boxplot indicates the minimum rain during each month. The red dot inside the box plot is the mean rainfall for each month

study. The empirical data of rainfall intensity and event duration is fitted using the constrained least square regression.

$$\text{Objective : minimize } \Sigma \left(I_i - \alpha D_i^{-\beta}\right)^2$$

$$\text{Subject to : } \forall (D_i, I_i) : I_i > \alpha D_i^{-\beta}$$

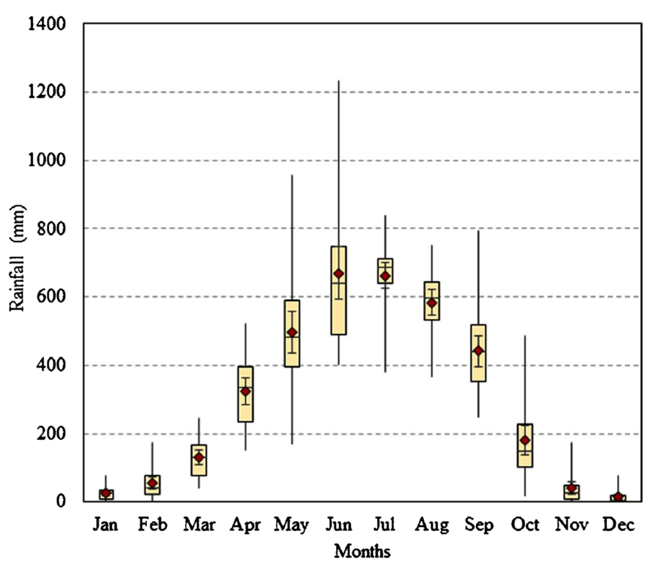


Fig. 3 Boxplot containing the monthly average and 95% confidence interval (1.96 + SD) of rainfall for the period 1990–2017 for Gangtok. The lines above the boxplot indicate the maximum rainfall during each month and the line below the boxplot indicates the minimum rain during each month. The red dot inside the box plot is the mean rainfall for each month

where the (D_i, I_i) represents the duration in days and the intensity in milliliter per day. The threshold equation is obtained by optimizing the coefficients α and β using an efficient multi-objective optimization, non-dominated sorting genetic algorithm II (NSGA-II) (Deb et al. 2002; Liu et al. 2016). The resulting threshold equation obtained for Sikkim is given by,

$$I = 43.26\ \mathrm{D}^{-0.78} \tag{1}$$

The log-log curve for the intensities and durations of rainfall events is shown in Fig. 5. The curve has a minimum duration of 1 day and a maximum of 30 days. The above equation indicates that there is lesser chance of landslide occurrence in Sikkim if the rainfall is below 43.26 mm in a day. For a rainfall event of 30 days duration, the minimum intensity comes down to 3.04 mm/day. This result indicates that even rainfall intensities as low as 3.04 mm/day can contribute to slope instability, provided the rainfall occurs continuously. From the rainfall characteristics of Sikkim, indicated in Fig. 2, such conditions do occur in Sikkim from mid-April through September. Figure 4b shows that the number of landslides over Sikkim also increases from May and peaks in September. The effect of antecedent rainfall on the initiation of a landslide event is thus indicated by this result.

Local ID threshold for Gangtok

The initiation of landslides depends on the geomorphology of the location where it occurs. Hence, the thresholds for slope instability differ from one location to another. This indicates the necessity for identifying rainfall thresholds for specific locations that are landslide prone. The current study, in addition to developing a threshold equation for the entire state of Sikkim, explores the ID threshold for Gangtok. Utilizing a similar methodology as that applied for the entire Sikkim, a threshold equation that is applicable over Gangtok was obtained as follows:

$$I = 100\ \mathrm{D}^{-.92} \tag{2}$$

The above equation indicates a steeper curve than the regional ID threshold equation. According to this equation, slope instability would not occur if the rainfall received in a day is less than 100 mm. However, it also conveys that rainfall of intensity of 4.99 mm/day observed for 26 days could also result in a landslide. Figure 6 shows that the landslide events are more clustered towards the right end of the graph. This indicates that most of the landslides occur in Gangtok are due to comparatively lower intensity rainfall received for longer durations. This shows the influence of soil moisture and antecedent rainfall conditions on landslides in this area. A further in-depth explanation of this result would require more extensive investigation on the hydrological interactions due to rainfall infiltration, which is beyond the scope of the current study.

The threshold for Sikkim, represented by Eq. (1) is compared with some of the existing regional thresholds over the Himalayan region (Fig. 7). Since the proposed equations are defined for 1 to 30 days duration (24 h to 720 h), a comparison is performed with existing equations that are valid for the same time duration. Equation (1) lies within the envelope of existing regional ID

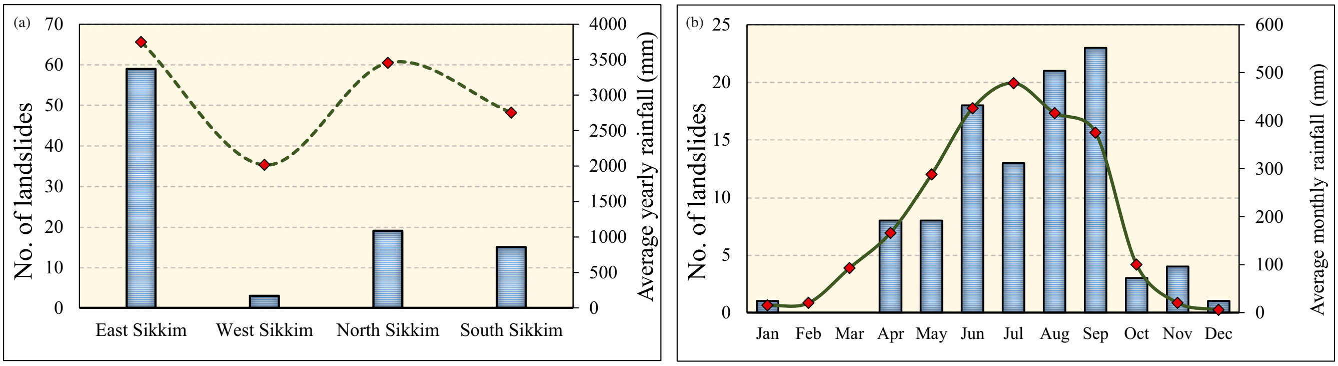


Fig. 4 Distribution of rainfall and major landslides (considered in this study) that occured in Sikkim during 1990–2017 plotted over different regions/districts (**a**) and months (**b**). The bars refer to landslide count and dashed line represent the mean monthly rainfall

thresholds over the Himalayas, as seen from Fig. 7. Since Caine (1980) global threshold equation remains an important benchmark in comparing various threshold equations, it is also included in Fig. 7.

The proposed equation for Sikkim is also validated using the rainfall observations from the R-LEWS in Chandmari. From 2015 onwards, observations are available from the deployed weather station in Chandmari. From these observations, all the rainfall events were identified. In order to check how the proposed threshold equation performs over Chandmari, the rainfall threshold is plotted along with all the rainfall events to identify the ones that exceeded the threshold and ones that did not. These rainfall events were analyzed with the landslide events available during 2015–2018 time period in order to distinguish among them the correctly predicted landslides (true positive, TP), correctly predicted non-landslides (true negative, TN), false alarms (false positive, FP), and missed alarms (false negative, FN) as shown in Fig. 8. The exact number of landslide events that happened remains unknown. The proposed threshold was able to correctly predict (true positive) 9 out of 10 available landslide events, which is indicated by the red dots shown in Fig. 8. During the validation period, only a single missed alarm was identified. The threshold was able to correctly identify the rainfall events, which did not trigger landslides.

To evaluate the proposed threshold, performance evaluation has been carried out between the existing rainfall thresholds and proposed rainfall threshold using available data from 2015 to 2018. The rainfall events are classified into TP (threshold crossed and

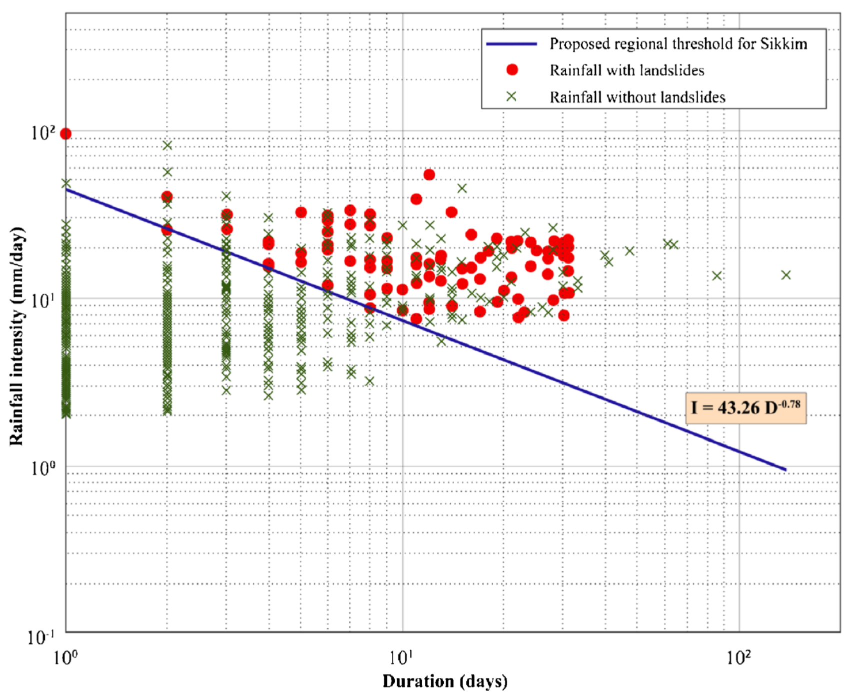


Fig. 5 Regional rainfall intensity–duration threshold for the rainfall events, which led to landslide occurrences in Sikkim for the period 1990–2017. The red dots refer to the rainfall with reported landslides and the green crosses shows the rainfall without reported landslide

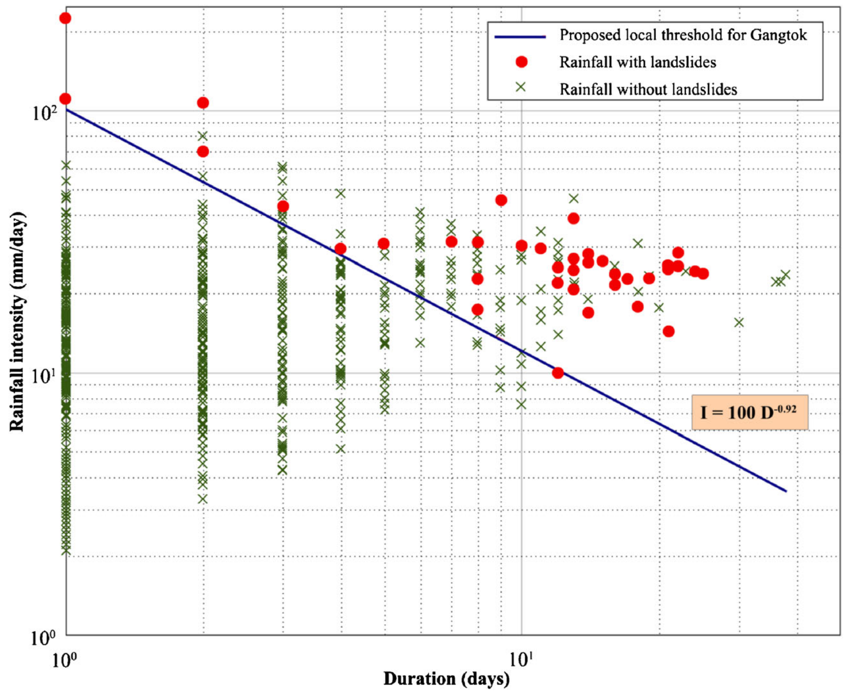


Fig. 6 Local rainfall intensity–duration threshold for the rainfall events, which led to landslide occurrences in Gangtok for the period 1990–2017. The red dots refer to the rainfall with reported landslides and the green crosses shows the rainfall without reported landslide

landslide occurred), TN (threshold not crossed and no landslide), FP (threshold crossed and no landslide), and FN (threshold not crossed and landslide occurred). Along with these, several statistical parameters have been calculated to evaluate the quality of proposed thresholds as shown in Table 1 (Lagomarsino et al. 2015; Rosi et al. 2012; Rosi et al. 2015).

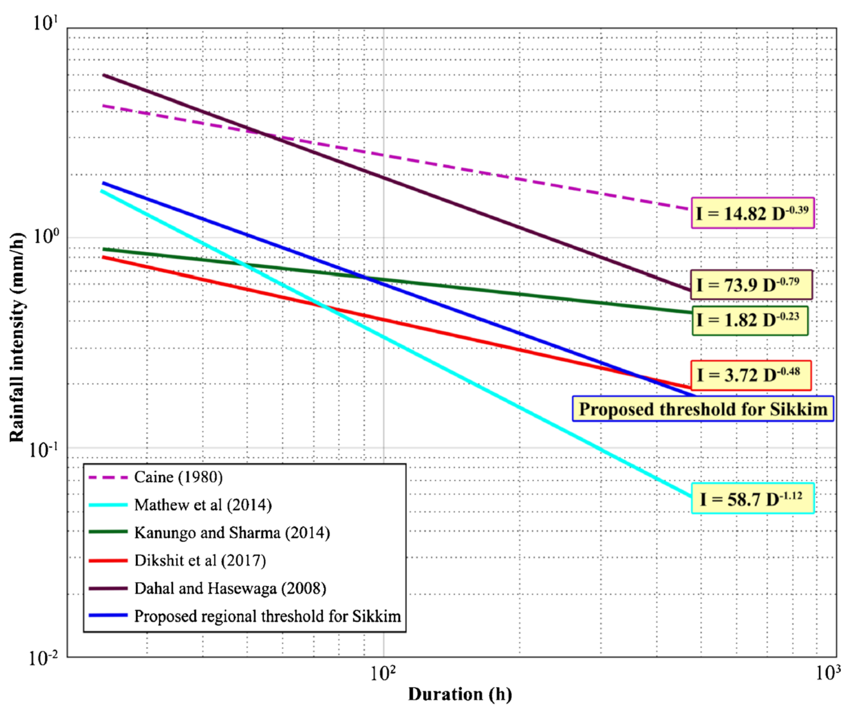


Fig. 7 Comparison of the proposed regional ID threshold for Sikkim with the global threshold defined by Caine (1980) and some of the existing regional thresholds defined for Himalayan region by Mathew (2014), Kanungo and Sharma (2014), Dikshit (2017), and Dahal and Hasewaga (2008)

- Sensitivity (Se): ability to properly classify rainfalls that triggered landslides;
- Specificity (Sp): ability to properly classify rainfalls that did not trigger landslides;
- Positive prediction power (PPP): the probability of correctly classifying a rainfall that triggered landslides;
- Negative prediction power (NPP): the probability of correctly classifying a rainfall that not triggered landslides.
- Likelihood ratio (Lr): the ratio between sensitivity and specificity;
- Efficiency (Ef): Evaluate the overall performance of a model, measuring the proportion of correct predictions with respect to the total
- True skill statistic (TSS): Defined as sensitivity - (1—specificity). It ranges from − 1 to + 1, where + 1 indicates perfect model and values of zero or less indicates a performance no better than random (Ruete and Leynaud 2015).

The comparison between statistical indexes of the study area and other thresholds shows a general improvement of the performance. Performance analysis showed that the regional threshold of Sikkim gave good results since both sensitivity and specificity of every threshold was close to 1. Specificity and NPP result was found to be slightly higher in the current threshold, which means that the new threshold is able to properly classify the rainfall that did not trigger landslides. In particular, the sensitivity of the Sikkim threshold is higher than the sensitivity calculated for the other thresholds, which means that in general, the Sikkim threshold correctly classifies the rainfall that triggered landslides. The specificity of the Sikkim threshold is greater than 0.7, and higher than the other thresholds, which means a good capacity of avoiding FP result. Also, the TSS, integrative measure of landslide prediction performance, of the proposed threshold has higher and positive value compared with other thresholds. It was observed that when compared with the existing threshold equations, the proposed thresholds perform reasonably well.

The current study makes use of daily rainfall observations available over the study region Sikkim. Furthermore, it has a complex orography with many places being difficult to access. Therefore, it is possible that some of the landslides that occur in such places may not get reported. It is possible that our landslide event database has missed such events. It is also probable that some of the reports could have errors with respect to the time of the event. Availability only of daily observations and uncertainties in the time of reported events indicates that determination of triggering vs. non-triggering events will have uncertainties. The proposed thresholds in the current study are based on triggering events alone. The availability of high-frequency rainfall observations will mitigate the uncertainties in the rainfall observations to a great extent, even though the uncertainties in landslide detection remain. The more advanced techniques of determining rainfall thresholds based on triggering and non-triggering events might help in improving the warnings. A more improved version of the threshold equations will be constructed in the future using the real-time observations from the deployed EWS systems, overcoming these limitations.

Effect of antecedent conditions on landslide initiation in Sikkim

The amount and duration of rainfall occurring prior to slope failure is a key factor that influences the triggering of landslides. Previous studies such as Kim et al. (1991), Heyerdahl et al. (2003), Crozier et al. (1999), Glade et al. (2000), Aleotti (2004), Chleborad et al. (2003), Dahal and Hasewaga (Dahal and Hasegawa 2008), and Kanungo and Sharma (2014) have considered the effect of antecedent rainfall in determining rainfall thresholds. According to the area under consideration, antecedent rainfalls of various durations are found to be significant in landslide initiation, in each of these studies. The analysis performed by Kanungo and Sharma (2014), in determining the impact of antecedent rainfall conditions for Garhwal, Himalayas, India, is followed here. Figure 9 shows the plot of daily cumulative rainfall on the day of each event vs. rainfall prior to the landslide, aggregated for 3, 5, 7, 10, 15, and 20 days.

Daily rainfall associated with landslide initiation is compared with the cumulative rainfall for 3, 5, 7, 10, 15, and 20 days prior to the failure in Fig. 9 and in more detail in Fig. 10a–f. The diagonal line in each of the graphs bisects it, with each half indicating the bias towards either x-axis or y-axis. The point that may lie above the diagonal shows failures that are biased towards the daily rainfall. The points falling on the diagonal line indicate landslides with the daily rainfall amount the same as cumulative antecedent rainfall. Majority of the landslide events in Fig. 10 are influenced by the antecedent rainfall condition, as indicated by majority of the points falling below the diagonal line. The relation between daily-accumulated rainfall on the day of slope failure and 3-day accumulated rainfall prior to landslide initiation is shown in Fig. 10a. The straight line bisects the graph. Figure 10a shows that 16% landslides are biased towards daily rainfall, whereas 84% landslides are biased towards 3-days accumulated rainfall. Similarly, Fig. 10b–f show the bias of daily rainfall vs. accumulated rainfall for 5 days, 7 days, 10 days, 15 days, and 20 days. The bias towards antecedent rainfall increases from 5 days (92%). The bias towards the antecedent rainfall is the same for 7 days, 10 days, and 15 days. These results indicate the significance of antecedent rainfall conditions in landslide initiation over Sikkim. Further exploration of this result is required to arrive at a robust relation between the two.

Discussion

Through this section, we would like to discuss and shed some light on (i) how the proposed thresholds are going to form a part of our R-LEWS, (ii) some inferences that were obtained as part of this study, and (iii) some challenges that are faced in this study. Even though rainfall is the main trigger for landslide initiation, a heavy rainfall event in itself may not always cause slope instability. Rainfall ID thresholds provide a lower cut off to the rainfall values below which there is a lower probability of occurrence of landslides. However, if such thresholds alone are used for providing warnings, false alarms may result since soil properties and terrain features also contribute to the initiation and timing of landslide along with rainfall. This demands the incorporation of additional parameters such as soil moisture, pore water pressure, and soil movement for improving the reliability of a landslide-based EWS. Hence, in addition to rain gauges, multiple sensors that capture parameters such as pore pressure, moisture, and movement are

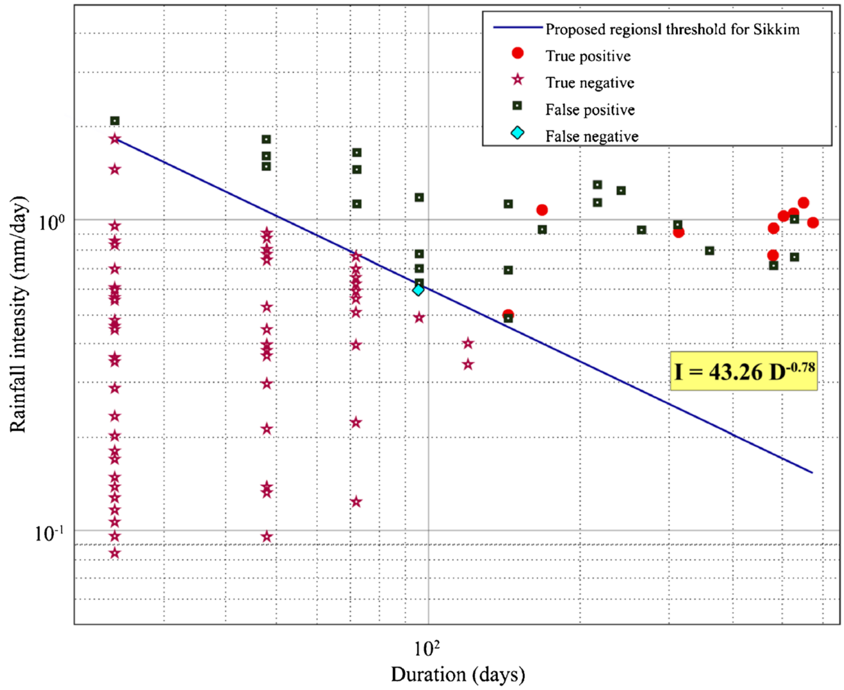


Fig. 8 Validation of the proposed Sikkim rainfall threshold using rainfall events of Chandmari site during 2015–2018

selected for this purpose (Baum et al. 2005; Chleborad et al. 2008; Thiebes 2012; Thiebes et al. 2014; Thiebes and Glade 2016; Piciullo et al. 2018). As part of our R-LEWS, an integrated monitoring module (called as Deep Earth Probes) consisting of several of these heterogeneous sensors is presently deployed in the study area of Gangtok. Based on the detailed geological, geomorphological, and electrical resistivity tomography (ERT) survey of the study region, 11 locations were selected for the deployment of DEPs (Deep Earth Probes) containing sensors which can monitor pore water pressure, soil moisture, movement, etc., (Fig. 11) (Ramesh 2009). The system was designed for continuous monitoring of meteorological, geophysical, and hydrological parameters that may trigger a rainfall-induced landslide. This landslide monitoring system in Sikkim has a total of more than 130 geophysical sensors connected to these 11 DEPs, and collects the real-time data dynamically in the required sampling frequency.

The R-LEWS was piloted at Sikkim in 2015 and the full-scale deployment was completed in 2018. The real-time data from multiple sensors are captured and stored in the database from 2015 onwards. Rainfall data taken from the database of our deployed system were used for the validation of the thresholds developed in this study. The observations from the heterogeneous sensors will be utilized in establishing multi-level landslide warnings as part of the decision support system. The severity of the warnings increases with each level and the concerned authorities can caution the public based on the intensity of the warning level. The rainfall threshold equation analyzed in the current study will form the first level of this multi-level warning framework. The justification of this being the fact that rainfall is the base factor which results in variation in soil moisture and pore pressure. Once the rainfall received exceeds the threshold, observations from other sensors are utilized for determining the succeeding levels of warning so as to enhance the reliability of the whole system. We utilized this methodology so that false alarms that might result from warning based on rainfall threshold alone could be reduced.

Table 1 Results of performance analysis and validation statistics of proposed threshold and existing regional rainfall thresholds in Sikkim using the data during 2015–2018. Se = TP/(TP+FN); Sp = TN/(TN + FP); PPP = (TP)/(FP + TP); NPP = TN/(TN + FN); Lr = Se/(1 - Sp); Ef = (TP+TN)/(TP+TN+FN+FP); TSS = Se − (1 − Sp)

Thresholds	TP	TN	FP	FN	Se	Sp	PPP	NPP	Lr	Ef	TSS
Regional threshold, Sikkim	9	73	26	1	0.9	0.74	0.26	0.99	3.43	0.75	0.64
Mathew et al. (2014)	0	41	58	10	0	0.41	0	0.8	0	0.38	− 0.59
Kanungo and Sharma (2014)	2	33	66	8	0.2	0.33	0.03	0.8	0.3	0.32	− 0.47
Dikshit et al. (2017)	0	45	54	10	0	0.45	0	0.82	0	0.41	− 0.55
Dahal and Hasewaga (2008)	3	9	90	7	0.3	0.09	0.03	0.56	0.33	0.11	− 0.61

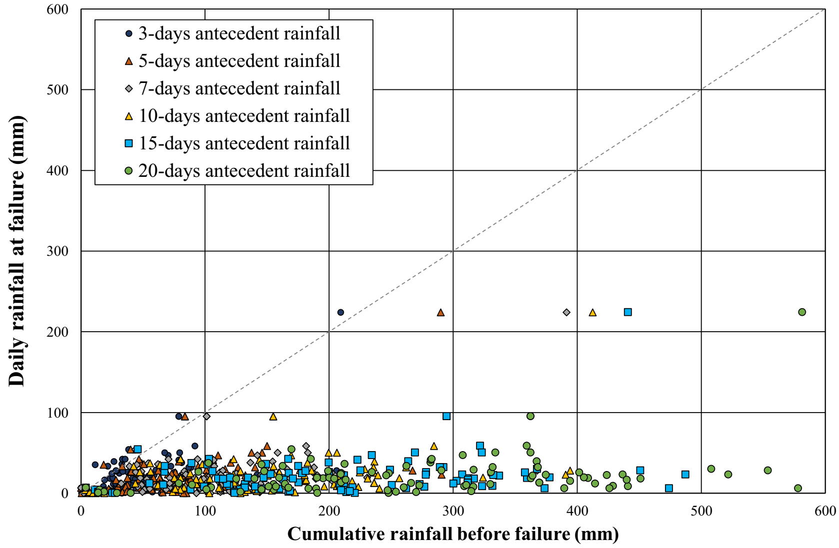


Fig. 9 Daily rainfall on the day of landslide and antecedent rainfall prior to failure (3, 5, 7, 10, 15, and 20 days)

From this study, we could infer that the threshold equation developed for Sikkim has similar characteristics like the other available global and regional models. Validation using rainfall observations from Chandmari indicates that while the proposed regional threshold equation does capture all the landslide events, there are a few rainfall events above the threshold line, which did not result in landslides. This indicates the possibility of false alarms, whose occurrence might be due to the uncertainties in identifying the triggering of landslide events as well as due to the use of daily rainfall observations. The comparison and validation of proposed equations with existing global and regional threshold equations show that using the proposed threshold equation will provide a better detailed threshold value with a possibility of limited number of false alarms. The limited number of false alarms also can be removed by integrating more data from future deployment or deploying denser rain gauge networks and developing site-specific thresholds. This could even be used for building a multi-level rainfall threshold model for the state of Sikkim. This is also pointing to the necessity of establishing a more robust threshold equation for site-specific landslide initiation specifically for Chandmari.

The current study also explores the dynamic behavior of antecedent rainfall condition for landslide initiation in Sikkim by comparing the daily rainfall associated with landslide initiation with the cumulative rainfall for 3, 5, 7, 10, 15, and 20 days before the landslide event. The analysis clearly indicates the influence of antecedent conditions in initiating slope failure. The current study points out the necessity of better understanding the dynamics of the relation between antecedent rainfall, topological terrain parameters, and landslides. The thresholds developed and the technical system deployed in Chandmari currently provide a good performance. In future, the system aims to forewarn landslides, by integrating rainfall forecasts which helps to predict where landslides are likely to occur tomorrow.

Finally, we brief here some of the major challenges in developing this rainfall threshold such as the constrained availability of historic landslide events, rainfall events, and the other connected details. These include uncertainties in both spatial and temporal scale. As we mentioned earlier, the data from GSI website was our primary source of information on landslide events, with additional events collected from other online sources such as web news. But the number of landslide occurrences used for this study may be very limited compared with the actual number of events. This is because only very limited landslide cases are reported by the online media, especially those from the past decades when these online medias were not prevalent, and also consistent and thorough landslide mapping activities would not have been established in those days. Hence, we could restrict using only some landslide events from these study areas, thus adding to spatial uncertainties. Since our R-LEWS was operational only recently, we had to depend on other sources for obtaining the rainfall data and could obtain only daily-cumulated rainfall data in contrary to the minute-wise data from our deployed system. Usually higher frequencies of rainfall measurements are beneficial to threshold determination; however, the present threshold is developed using daily rainfall data, thus adding a limitation on the temporal scale. This limitation can be addressed in future work by fine-tuning the proposed models using the real-time minute-wise data from our R-LEWS. However, the uncertainties due to landslide event data still remain a challenge as complete mapping and recording of landslide occurrences across all regions cannot be guaranteed.

Conclusion and future work

A robust R-LEWS containing heterogeneous sensors for capturing spatio-temporal parameters of landslides is needed for a multi-level warning which is not available in India other than Munnar, Kerala (Ramesh 2009). The overview of such an R-LEWS deployed in Chandmari, Sikkim, is presented in this paper. Even though rainfall is the most common factor among the spatio-temporal parameters of landslides in Sikkim, a reliable rainfall threshold equation for landslide initiation over the region is presently not available in literature. In the current study, a rainfall intensity–duration regional threshold is proposed for Sikkim, India. In

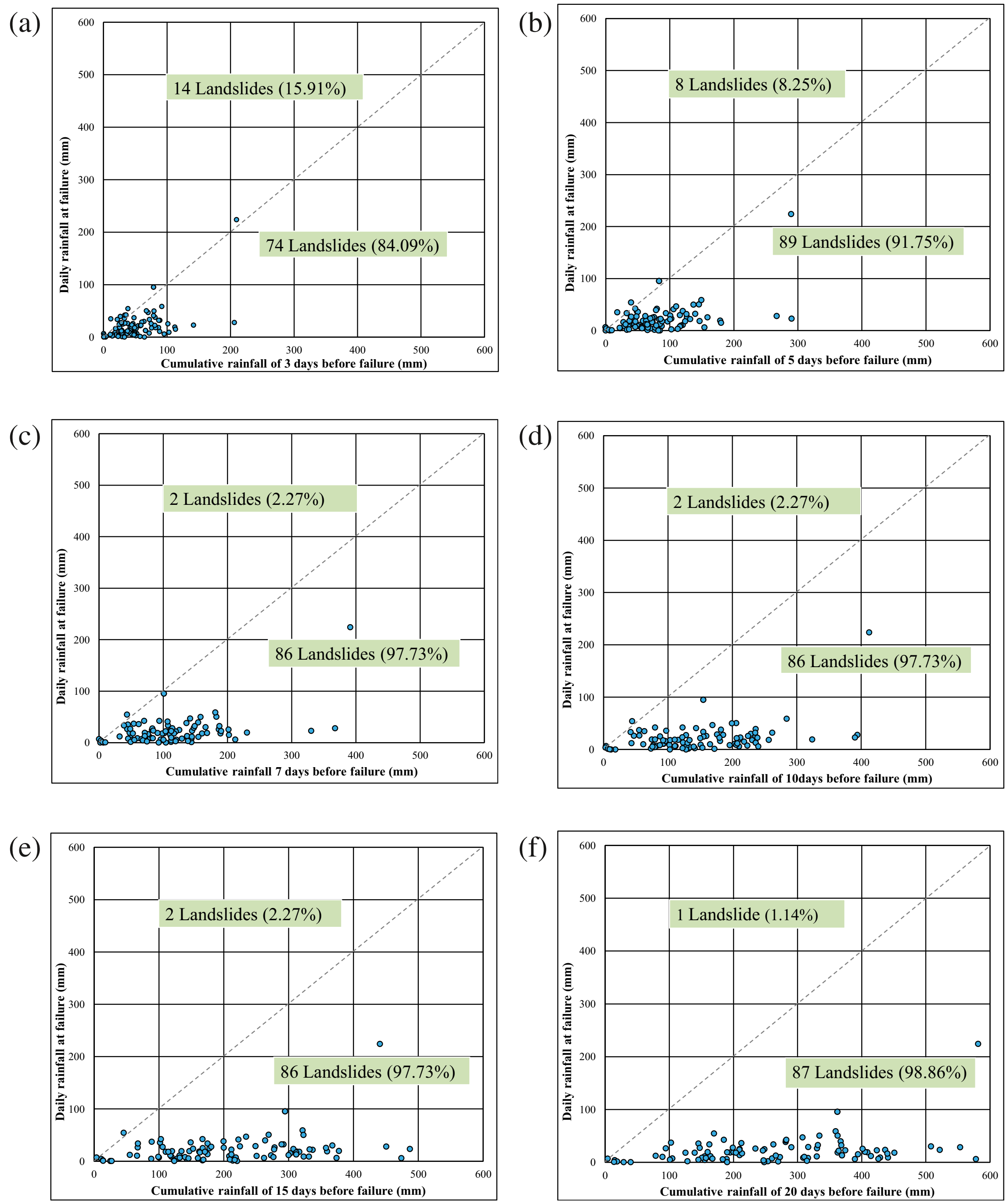
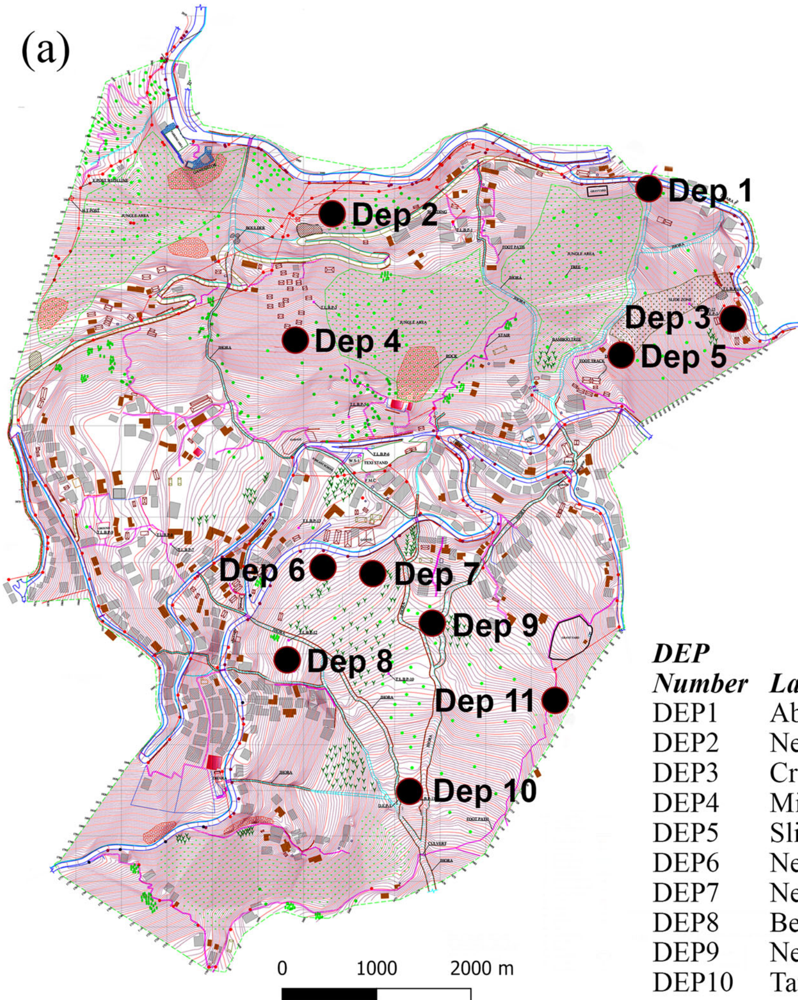


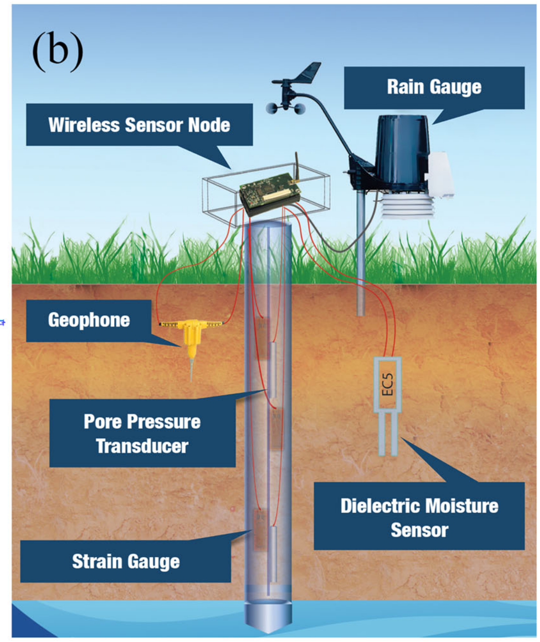
Fig. 10 Daily cumulative rainfall on the day of landslide is plotted with respect to accumulated rainfall during 3 days (**a**), 5 days (**b**), 7 days (**c**), 10 days (**d**), 15 days (**e**), and 20 days (**f**) prior to the landslide event

addition, a local threshold for Gangtok is also developed. The proposed regional and local thresholds are able to give the first level threshold for the initiation of landslides in Gangtok and Sikkim. The above relations are formulated so that they can be utilized in an R-LEWS for Sikkim. The effect of antecedent rainfall on landslide initiation is also investigated. The proposed equations are validated using rainfall observations from the R-LEWS deployed at Chandmari. The proposed equations perform reasonably well over Chandmari. A fully functional R-LEWS will perform better if the physical and dynamic relationships between the various hydro-geological parameters are included. Availability of observations at a high frequency from all heterogeneous sensors of our deployment site will help in reducing the uncertainties in data and to develop a robust real-time site-specific multi-level warning system for Chandmari. This is the objective of a future study.

Acknowledgments

The authors would like to express gratitude for the immense amount of motivation and guidance provided by Dr. Sri. Mata Amritanandamayi Devi, the Chancellor, Amrita Vishwa Vidyapeetham. Special thanks to





DEP Number	*Landmark*
DEP1	Above the crown area
DEP2	Near Ganesh Tok
DEP3	Crown Sliding Area
DEP4	Middle-Inside Forest
DEP5	Sliding Area- Pilit Deployment
DEP6	Near Ganesh Workshop
DEP7	Near Petrol Pump
DEP8	Below the Sliding Road Near Ganesh Workshop
DEP9	Near the house- pathway through numerous steps
DEP10	Tatanchan
DEP11	Tatanchan- near the graveyard

Fig. 11 R-LEWS deployment area in Chandmari. **a** Locations of DEPs in Chandmari (black dots). **b** Design of the Deep Earth Probe containing heterogeneous sensors (Ramesh et al. 2009; Ramesh and Rangan 2014)

Dr. G.C Khanal, Additional Director, Sikkim State Disaster Management Authority and India Meteorological Department for providing the rainfall data. The authors are thankful to Mr. Sangeeth, Mr. Nitin Kumar, Mr. Deepak, Mr. Mukundan, Mr. Arun Kumar, Mr. Balmukund, Mr. Ramesh Guntha, Prof. Balaji Hariharan, Mr. Rayudu, Mr. Ratheesh Kumar and Mr. Audhithiya Vigneswar, Amrita Vishwa Vidyapeetham for their valuable support and hard work during the EWS deployment in Sikkim.

Funding information

This work is partially funded under the project "Advancing Integrated Wireless Sensor Networks for Real-time Monitoring and Detection of Disasters" by the Ministry of Earth Sciences (MoES), Government of India.

References

Aleotti P (2004) A warning system for rainfall-induced shallow failures. Eng Geol 73(3):247–265

Aleotti P, Baldelli P, Bellardone G, Quaranta N, Tresso F, Troisi C, & Zani, A. (2002). Soil slips triggered by October 13–16, 2000 flooding event in the Piedmont Region (Northwest Italy): critical analysis of rainfall data. Geologia Tecnica e Ambientale, 1, 15-25

Althuwaynee OF, Asikoglu O, Eris E (2018) Threshold contour production of rainfall intensity that induces landslides in susceptible regions of northern Turkey. Landslides 15(8):1541–1560

Anbarasu K, Sengupta A, Gupta S, Sharma SP (2010) Mechanism of activation of the Lanta Khola landslide in Sikkim Himalayas. Landslides 7(2):135–147

Arnone E, Dialynas YG, Noto LV, Bras RL (2016) Accounting for soil parameter uncertainty in a physically based and distributed approach for rainfall triggered landslides. Hydrol Process 30(6):927–944

Battistini A, Segoni S, Manzo G, Catani F, Casagli N (2013) Web data mining for automatic inventory of geohazards at national scale. Appl Geogr 43:147–158

Battistini A, Rosi A, Segoni S, Lagomarsino D, Catani F, Casagli N (2017) Validation of landslide hazard models using a semantic engine on online news. Appl Geogr 82:59–65

Baum RL, Godt JW, Harp EL, McKenna JP, & McMullen SR (2005). Early warning of landslides for rail traffic between Seattle and Everett, Washington, USA. In Landslide risk management (pp. 741-750). CRC Press

Baum RL, Godt JW, Savage WZ (2010) Estimating the timing and location of shallow rainfall-induced landslides using a model for transient, unsaturated infiltration. Journal of Geophysical Research 115 (F3)

Bhasin R, Grimstad E, Larsen JO, Dhawan AK, Singh R, Verma SK, Venkatachalam K (2002) Landslide hazards and mitigation measures at Gangtok, Sikkim Himalaya. Eng Geol 64(4):351–368

Brunetti MT, Peruccacci S, Rossi M, Luciani S, Valigi D, Guzzetti F (2010) Rainfall thresholds for the possible occurrence of landslides in Italy. Nat Hazards Earth Syst Sci 10(3):447–458

Bureau. (2016). Landslides shut north sikkim highway. The Telegraph. **Retrieved from:** https://www.telegraphindia.com/states/west-bengal/landslides-shut-north-sikkim-highway/cid/1525234

Caine N (1980) The rainfall intensity-duration control of shallow landslides and debris flows. Geogr Ann: Ser A, Phys Geogr 62(1–2):23–27

Cancelli, A. (1985). Landslides in soil debris cover triggered by rainstorms in Valtellina (Central Alps-Italy). In Proc. IV international conference and field workshop on landslides, Tokyo, August 1985 (pp. 267-272)

Cannon SH (1985) Rainfall conditions for abundant debris avalanches, San Francisco Bay region, California. Calif Geol 38(12):267–272

Cannon, S. H., & Gartner, J. E. (2005). Wildfire-related debris flow from a hazards perspective. In Debris-flow hazards and related phenomena (pp. 363–385). Springer, Berlin, Heidelberg

Ceriani, M. (1992). Rainfall and landslides in the Alpine area of Lombardia Region, Central Alps, Italy. In Proceedings, Interpraevent Int. Symp, Bern (Vol. 2, pp. 9-20)

Chleborad AF (2003). Preliminary evaluation of a precipitation threshold for anticipating the occurrence of landslides in the Seattle, Washington, Area. US Geological Survey open-file report, 3(463), 39

Chleborad AF, Baum RL, Godt JW, Powers PS (2008) A prototype system for forecasting landslides in the Seattle, Washington, area. Rev Eng Geol 20:103–120

Chung MC, Tan CH, Chen CH (2017) Local rainfall thresholds for forecasting landslide occurrence: Taipingshan landslide triggered by typhoon Saola. Landslides 14(1):19–33

Clarizia, M., Gullà, G., & Sorbino, G. (1996). Sui meccanismi di innesco dei soil slip. In International conference Prevention of hydrogeological hazards: the role of scientific research (Vol. 1, pp. 585-597)

Corominas, J. (2000). Landslides and climate. In Keynote lectures from the 8th international symposium on landslides (Vol. 4, pp. 1-33)

Crosta G (1998) Regionalization of rainfall thresholds: an aid to landslide hazard evaluation. Environ Geol 35(2–3):131–145

Crosta, G. B., & Frattini, P. (2001). Rainfall thresholds for triggering soil slips and debris flow. In Proc. of the 2nd EGS Plinius Conference on Mediterranean Storms: Publication CNR GNDCI (Vol. 2547, pp. 463-487)

Cruden, D. M., & Varnes, D. J. (1996). Landslides: investigation and mitigation. Chapter 3-Landslide types and processes. Transportation research board special report, (247)

Dahal RK, Hasegawa S (2008) Representative rainfall thresholds for landslides in the Nepal Himalaya. Geomorphology 100(3–4):429–443

Deb K, Pratap A, Agarwal S, Meyarivan TAMT (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 6(2):182–197

Dikshit, A., & Satyam, N. (2017). Rainfall thresholds for the prediction of landslides using empirical methods in Kalimpong, Darjeeling, India. In Workshop on Advances in Landslide Understanding, JTC1, Barcelona (pp. 255-259)

Dikshit A, Satyam DN (2018) Estimation of rainfall thresholds for landslide occurrences in Kalimpong, India. Innov Infrastructure Solut 3(1):24

Dubey CS, Chaudhry M, Sharma BK, Pandey AC, & Singh B (2005). Visualization of 3-D digital elevation model for landslide assessment and prediction in mountainous terrain: A case study of Chandmari landslide, Sikkim, eastern Himalayas. Geosciences Journal, 9(4), 363

Froude MJ, Petley D (2018) Global fatal landslide occurrence from 2004 to 2016. Nat Hazards Earth Syst Sci 18:2161–2181

Gabet EJ, Burbank DW, Putkonen JK, Pratt-Sitaula BA, Ojha T (2004) Rainfall thresholds for landsliding in the Himalayas of Nepal. Geomorphology 63(3–4):131–143

Gao L, Zhang LM, Cheung RWM (2018) Relationships between natural terrain landslide magnitudes and triggering rainfall based on a large landslide inventory in Hong Kong. Landslides 15(4):727–740

Giannecchini R (2005) Rainfall triggering soil slips in the southern Apuan Alps (Tuscany, Italy). Adv Geosci 2:21–24

Giri, P. (2018). North Sikkim reels under rains, landslides block highways, damage houses. Hindustan times. **Retrieved from:** https://www.hindustantimes.com/india-news/north-sikkim-reels-under-rains-landslides-block-highways-damage-houses/story-YMQYN192owo8NYjbTqtwlI.html

Glade T, Crozier M, Smith P (2000) Applying probability determination to refine landslide-triggering rainfall thresholds using an empirical “antecedent daily rainfall model”. Pure Appl Geophys 157(6–8):1059–1079

Godt JW, Baum RL, Savage WZ, Salciarini D, Schulz WH, Harp EL (2008) Transient deterministic shallow landslide modeling: requirements for susceptibility and hazard assessments in a GIS framework. Eng Geol 102(3–4):214–226

Guzzetti F, Peruccacci S, Rossi M, Stark CP (2007) Rainfall thresholds for the initiation of landslides in central and southern Europe. Meteorog Atmos Phys 98(3–4):239–267

Guzzetti F, Peruccacci S, Rossi M, Stark CP (2008) The rainfall intensity–duration control of shallow landslides and debris flows: an update. Landslides 5(1):3–17

Heyerdahl H, Harbitz CB, Domaas U, Sandersen F, Tronstad K, Nowacki F, ... & Diaz MR (2003, May). Rainfall induced lahars in volcanic debris in Nicaragua and El Salvador: practical mitigation. In Proceedings of international conference on fast slope movements—prediction and prevention for risk mitigation, IC-FSM2003. Patron Pub, Naples (pp. 275-282)

Hong Y, Adler RF (2008) Predicting global landslide spatiotemporal distribution: Integrating landslide susceptibility zoning techniques and real–time satellite rainfall estimates. International Journal of Sediment Research 23 (3):249–257

Hsu YC, Chang YL, Chang CH, Yang JC, Tung YK (2018) Physical-based rainfall-triggered shallow landslide forecasting. Smart Water 3(1):3

Innes JL (1983) Debris flows. Prog Phys Geogr 7(4):469–501

Intrieri, E., Gigli, G., Casagli, N., & Nadim, F. (2013). Brief communication” Landslide early warning system: toolbox and general concepts”

Irawan, A. M., Virgianto, R. H., Safril, A., Gustono, S. T., & Putranto, N. D. (2019). Rainfall threshold and soil moisture indexes for the initiation of landslide in Banjarmangu sub-district, Central Java, Indonesia. In IOP Conference Series: Earth and Environmental Science (Vol. 243, No. 1, p. 012028). IOP Publishing

Iverson RM (2000) Landslide triggering by rain infiltration. Water Resour Res 36(7):1897–1910

Jakob M, Weatherly H (2003) A hydroclimatic threshold for landslide initiation on the North Shore Mountains of Vancouver, British Columbia. Geomorphology 54(3–4):137–156

Kanungo DP, Sharma S (2014) Rainfall thresholds for prediction of shallow landslides around Chamoli-Joshimath region, Garhwal Himalayas, India. Landslides 11(4):629–638

Khan YA, Lateh H, Baten MA, Kamil AA (2012) Critical antecedent rainfall conditions for shallow landslides in Chittagong City of Bangladesh. Environ Earth Sci 67(1):97–106

Kim SK (1991). Prediction of rainfall triggered landslides in Korea. Landslides, 2, 989-994

Kumar A, Asthana AKL, Priyanka RS, Jayangondaperumal R, Gupta AK, Bhakuni SS (2017) Assessment of landslide hazards induced by extreme rainfall event in Jammu and Kashmir Himalaya, northwest India. Geomorphology 284:72–87

Lagomarsino D, Segoni S, Rosi A, Rossi G, Battistini A, Catani F, Casagli N (2015) Quantitative comparison between two different methodologies to define rainfall thresholds for landslide forecasting. Nat Hazards Earth Syst Sci 15(10):2413–2423

Larsen MC, Simon A (1993) A rainfall intensity-duration threshold for landslides in a humid-tropical environment, Puerto Rico. Geogr Ann: SerA, Phys Geogr 75(1–2):13–23

Leonarduzzi E, Molnar P, McArdell BW (2017) Predictive performance of rainfall thresholds for shallow landslides in Switzerland from gridded daily data. Water Resour Res 53(8):6612–6625

Liu Y, Guo J, Sun H, Zhang W, Wang Y, Zhou J (2016) Multiobjective optimal algorithm for automatic calibration of daily streamflow forecasting model. Math Probl Eng 2016

Ma T, Li C, Lu Z, Bao Q (2015) Rainfall intensity–duration thresholds for the initiation of landslides in Zhejiang Province, China. Geomorphology 245:193–206

Mathew J, Babu DG, Kundu S, Kumar KV, Pant CC (2014) Integrating intensity–duration-based rainfall threshold and antecedent rainfall-based probability estimate towards generating early warning for rainfall-induced landslides in parts of the Garhwal Himalaya, India. Landslides 11(4):575–588

Montgomery DR, Dietrich WE (1994) A physically based model for the topographic control on shallow landsliding. Water Resour Res 30(4):1153–1171

Nerella, S. P., Alajangi, S., & Dhakal, D. (2019). Landslide susceptibility mapping using GIS-based likelihood frequency ratio model: a case study of Pakyong—Pacheykhani area, Sikkim Himalaya. In Proceedings of International Conference on Remote Sensing for Disaster Management (pp. 569–586). Springer, Cham

Piciullo L, Calvello M, Cepeda JM (2018) Territorial early warning systems for rainfall-induced landslides. Earth Sci Rev 179:228–247

Pradhan, A. M. S. (2019). Rainfall-induced shallow landslide prediction and development of warning model in Korean Mountain by (Doctoral dissertation)

Pradhan AMS, Lee SR, Kim YT (2018) A shallow slide prediction model combining rainfall threshold warnings and shallow slide susceptibility in Busan, Korea. Landslides 16(3):647–659

Reichenbach P, Cardinali M, De Vita P, & Guzzetti F (1998). Regional hydrological thresholds for landslides and floods in the Tiber River Basin (central Italy). Environmental Geology, 35(2-3), 146-159

Ramesh, M. V. (2009). Real-time wireless sensor network for landslide detection In Sensor technologies and applications, 2009. SENSORCOMM'09. Third International Conference on (pp. 405-409). IEEE

Ramesh, M. V. (2017). Slope stability investigation of Chandmari in Sikkim, northeastern India. In Workshop on world landslide forum (pp. 363-369). Springer, Cham

Ramesh MV, Rangan VP (2014) Data reduction and energy sustenance in multisensor networks for landslide monitoring. IEEE Sensors J 14(5):1555–1563

Ramesh, M. V., Pullarkatt, D., Geethu, T. H., & Rangan, P. V. (2017). Wireless sensor networks for early warning of landslides: experiences from a decade long deployment. In Workshop on world landslide forum (pp. 41-50). Springer, Cham

Reder A, Rianna G, Pagano L (2018) Physically based approaches incorporating evaporation for early warning predictions of rainfall-induced landslides. Nat Hazards Earth Syst Sci 18(2):613–631

Rosi A, Segoni S, Catani F, Casagli N (2012) Statistical and environmental analyses for the definition of a regional rainfall threshold system for landslide triggering in Tuscany (Italy). J Geogr Sci 22(4):617–629

Rosi A, Lagomarsino D, Rossi G, Segoni S, Battistini A, Casagli N (2015) Updating EWS rainfall thresholds for the triggering of landslides. Nat Hazards 78(1):297–308

Rosi A, Peternel T, Jemec-Auflič M, Komac M, Segoni S, Casagli N (2016) Rainfall thresholds for rainfall-induced landslides in Slovenia. Landslides 13(6):1571–1577

Rosi A, Canavesi V, Segoni S, Dias Nery T, Catani F, Casagli N (2019) Landslides in the mountain region of Rio de Janeiro: a proposal for the semi-automated definition of multiple rainfall thresholds. Geosciences 9(5):203

Ruete, A., & Leynaud, G. C. (2015). Goal-oriented evaluation of species distribution models' accuracy and precision: true skill statistic profile and uncertainty maps (No. e1478). PeerJ PrePrints

Salciarini, D., & Tamagnini, C. (2015). Physically based rainfall thresholds for shallow landslide initiation at regional scales. In Engineering geology for society and territory-Volume 2 (pp. 1041–1044). Springer, Cham

Salvatici T, Tofani V, Rossi G, D'Ambrosio M, Stefanelli CT, Masi EB et al (2018) Application of a physically based model to forecast shallow landslides at a regional scale. Nat Hazards Earth Syst Sci 18(7):1919–1935

Segoni S, Piciullo L, Gariano SL (2018a) A review of the recent literature on rainfall thresholds for landslide occurrence. Landslides:1–19

Segoni S, Rosi A, Lagomarsino D, Fanti R, Casagli N (2018b) Brief communication: using averaged soil moisture estimates to improve the performances of a regional-scale landslide early warning system. Nat Hazards Earth Syst Sci 18(3):807–812

Sengupta A, Gupta S, Anbarasu K (2010) Rainfall thresholds for the initiation of landslide at Lanta Khola in North Sikkim, India. Nat Hazards 52(1):31–42

Sikkim State Disaster Management Authority (2012). Multi-hazard risk and vulnerability assessment in north, East, West and South Sikkim

Tamang JP, Thapa MP, Sharma RM, Rai AK, Rai P, Dhakal R (2005) Carrying capacity study of Teesta Basin in Sikkim. Biol Environ Food Resource 8

Thiebes B (2012) Landslide analysis and early warning systems: local and regional case study in the Swabian Alb. Springer Science & Business Media, Germany

Thiebes, B., & Glade, T. (2016). Landslide early warning systems–fundamental concepts and innovative applications. In Landslides and engineered slopes: experience, theory and practice, edited by: Aversa, S., Cascini, L., Picarelli, L., and Scavia, C., Proceedings of the 12th International Symposium on Landslides, Napoli, Italy (pp. 12—19)

Thiebes B, Bell R, Glade T, Jäger S, Mayer J, Anderson M, Holcombe L (2014) Integration of a limit-equilibrium model into a landslide early warning system. Landslides 11(5):859–875

Varnes DJ (1978) Slope movement types and processes. Special Report 176:11–33

Vasudevan, N., & Ramanathan, K. (2016). Geological factors contributing to landslides: case studies of a few landslides in different regions of India. In IOP Conference Series: Earth and Environmental Science (Vol. 30, No. 1, p. 012011). IOP Publishing

Vasudevan, N., Kolathayar, S., Sridharan, A., & Ramanathan, K. (2016). An investigative study of seismic landslide hazards. In Proceedings of the international conference on recent advances in rock engineering (RARE-2016) (pp. 16—18)

Vaz T, Zêzere JL, Pereira S, Oliveira SC, Garcia RA, Quaresma I (2018) Regional rainfall thresholds for landslide occurrence using a centenary database. Nat Hazards Earth Syst Sci 18(4):1037–1054

Westen CV, Terlien MJT (1996) An approach towards deterministic landslide hazard analysis in GIS. A case study from Manizales (Colombia). Earth Surf Process Landf 21(9):853–868

Wieczorek, G. (1987). In central Santa Cruz Mountains, California. Debris flows/avalanches: process, recognition, and mitigation, 7, 93

Wieczorek, G. F., & Glade, T. (2005). Climatic factors influencing occurrence of debris flows. In Debris-flow hazards and related phenomena (pp. 325–362). Springer, Berlin, Heidelberg

Wieczorek GF, Morgan BA, Campbell RH (2000) Debris-flow hazards in the Blue Ridge of central Virginia. Environ Eng Geosci 6(1):3–23

Wu YM, Lan HX, Gao X, Li LP, Yang ZH (2015) A simplified physically based coupled rainfall threshold model for triggering landslides. Eng Geol 195:63–69

Zêzere J, Trigo RM, Trigo IF (2005) Shallow and deep landslides induced by rainfall in the Lisbon region (Portugal): assessment of relationships with the North Atlantic Oscillation. Nat Hazards Earth Syst Sci 5(3):331–344

Ziegler, A. D., Bhardwaj, A., Wasson, R. J., & Chow, W. (2017). Estimating the characteristics of extreme rainfall events using a suitable precipitation product in the Garhwal Himalaya in India. In EGU General Assembly Conference Abstracts (Vol. 19, p. 2028)

G. T. Harilal · D. Madhu · M. V. Ramesh (✉) · D. Pullarkatt
Amrita Center for Wireless Networks & Applications (AmritaWNA),
Amrita School of Engineering, Amritapuri, Amrita Vishwa Vidyapeetham,
Kollam, India
Email: maneesha@amrita.edu

G. T. Harilal
e-mail: t.hgeethu@gmail.com

D. Madhu
Department of Physics,
Amrita School of Arts & Sciences, Amritapuri, Amrita Vishwa Vidyapeetham,
Kollam, India