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Probabilistic rainfall thresholds in Chibo, India: estimation and validation using monitoring system

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Abstract: The Himalayan region has been severely affected by landslides especially during the monsoons. In particular, Kalimpong region in Darjeeling Himalayas has recorded several landslides and has caused significant loss of life, property and agricultural land. The study region, Chibo has experienced several landslides in the past which were mainly debris and earth slide. Globally, several types of rainfall thresholds have been used to determine rainfall-induced landslide incidents. In this paper, probabilistic thresholds have been defined as it would provide a better understanding compared to deterministic thresholds which provide binary results, i.e., either landslide or no landslide for a particular rainfall event. Not much research has been carried out towards validation of rainfall thresholds using an effective and robust monitoring system. The thresholds are then validated using a reliable system utilizing Microelectromechanical Systems (MEMS) tilt sensor and volumetric water content sensor installed in the region. The system measures the tilt of the instrument which is installed at shallow depths and is ideal for an early warning system for shallow landslides. The change in observed tilt angles due to rainfall would give an understanding of the applicability of the probabilistic model. The probabilities determined using Bayes' theorem have been calculated using the rainfall parameters and landslide data in 2010-2016. The rainfall values were collected from an automatic rain gauge setup near the Chibo region. The probabilities were validated using the MEMS based monitoring system setup in Chibo for the monsoon season of 2017. This is the first attempt to determine probabilities and validate it with a robust and effective monitoring system in Darjeeling Himalayas. This study would help in developing an early warning system for regions where the installation of monitoring systems may not be feasible.

Keywords: Early warning; Probabilistic thresholds; Kalimpong; Monitoring

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Introduction

Landslides are widespread and hazardous phenomena which present a severe danger to people, infrastructure, agricultural land (Petley, 2012; Dowling and Santi 2014). Rainfall is the primary triggering factor for most of the landslides and therefore, determining rainfall parameters capable of landslide occurrences is necessary and relevant. Several studies have been carried out across the globe by correlating the rainfall conditions which lead to landslide incidences (Brunetti et al. 2010; Staley et al. 2013; Zêzere et al. 2015). Some attempts have also been made to develop techniques for reproducible representation of the thresholds (Vessia et al. 2016; Melillo et al.

2018). However, most of the work presented in the literature are rarely validated. A recent review of the global database of 115 rainfall thresholds showed that 31 works provided a validation of the thresholds calculated with the same dataset as used for calibration, however only 38 works validated with an independent dataset (Segoni et al. 2018). The most common method for validation is the skill score (usually derived from the contingency matrix) (Staley et al. 2013). In other cases, the validation has been provided by comparing two different threshold models for the same region and determining the most effective model (Lagomarsino et al. 2015).

The Indian Himalayan region covers 0.18 million km² of the 0.42 million km² of India's landmass prone to landslides. The reason for landslide triggering in the region is primarily because of monsoon rainfall and consequent infiltration (Dikshit and Satyam 2018). The physical determinants of the area like geology, topography alongside predominant elements like the seismic activity and heavy rainfall during monsoons cause severe landslide issue in the region. Hence, it is very difficult to setup an early warning system using only rainfall threshold techniques. Regarding rainfall thresholds for Indian Himalayan region, very few studies have been carried out using empirical methods to determine thresholds (Sengupta et al. 2010; Kanungo and Sharma 2014; Dikshit and Satyam 2018). The present study provides a validation of the thresholds determined using a probabilistic approach and validates it using an effective and robust monitoring system for Chibo region which is a part of Darjeeling Himalayas.

Berti et al. (2012) developed the probabilistic technique for determining thresholds using the Bayesian approach and was applied to the Emilia-Romagna region in Italy. The study categorised rainfall events into well-defined, uncertain and undefined events for rainfall data from 1939-2000. The analysis concluded that landslide incidences are dependent on rainfall intensity, duration and total rainfall for an event, however not dependent on antecedent rainfall. Do and Yin (2018), determined probabilistic thresholds for Ha Giang region, Vietnam using Bayesian analysis. They determined one-dimensional Bayesian probability using 26 landslides events occurred between 1989-2009 and two-dimensional probability for 11 landslides for a time period of three months in 2013. González and Caetano (2017) also calculated probabilistic rainfall thresholds for Sierra Norte De Puebla, Mexico and developed a warning system. The use of probabilistic methods in landslide studies is beneficial due to three reasons. i) Such methods include variability and uncertainty into a model which provides a quantitative assessment of threshold reliability. The analysis is more descriptive and is capable of assigning reliability for a particular threshold (Berti et al. 2012). ii) Deterministic thresholds lead to binary results which in most cases the distinction is significant which is not the case with probabilistic thresholds and provides a better estimate for extreme cases. iii) Probability-based techniques are usually used for quantitative risk assessment to ascertain confidence level of forecasting (Refice and Capolongo 2004). Bayesian analysis can also be applied for a rainfall event which led to several landslides by including a component that would calculate the number of landslide events initiated by each precipitation event.

Chang et al. (2008) analysed relation for typhoon triggered landslides for severe precipitation situation which could be used to calculate probabilistic landslide incidences for a real time monitoring system. Marques et al. (2008) analysed severe landslide incidences for severe rainfall events in Portugal using a probabilistic functional form of Gumbel's extreme value distribution. Glade et al. (2000) determined the probability of landslide occurrence using an antecedent daily rainfall for landslide sections of North Island in New Zealand. Chung and Fabbri (1999) presented a joint conditional probability method which represented subsequent landslide risk using five different procedures for the model. Spigelhalter (1986); Agterberg et al. (1990) used Bayesian techniques for geologic prediction models. Rosi et al. (2015) established that a more extensive and updated calibrated dataset improves the capability of thresholds and thereby improving predictability for landslide early warning systems.

The monitoring system used for the study comprises of a microelectromechanical (MEMS) based tilt sensor and a control circuit which is mounted on a box and fit on a steel rod. Besides the tilt sensor, a steel rod is placed whose movement determines the tilt angle rate. The use of MEMS based monitoring system has been successfully conducted on several unstable slopes in Japan and China (Uchimura et al. 2010; Yang et al. 2018). Uchimura et al. (2010) installed the MEMS based system on a real slope in Kobe, Japan and long-term monitoring results depicted that such a technique is feasible, reliable and cost-effective for an early warning system setup. Yang et al. (2018) installed a similar monitoring system in Wenchuan, China and developed a scheme for identifying multivariate hydrological parameters and proposed an intensity probability (I-P) threshold model with the capability of forecasting the possibility of landslides triggered by rainfall. There are various methods to determine the displacement of individual slope sections, extensometer being used the most. However, the use of extensometer is not very useful as it is difficult to ascertain the failure of slopes in the future and the use of such systems is costly. The use of mechanical reinforcements (retaining walls, ground anchors) is also ineffective due to the presence of large numbers of unstable slopes in the region. Yin et al. (2010) proposed the use of GPS and remote sensing with radar technology (InSAR) to monitor the long-term displacement of larger areas. Tessari et al. (2017) used SAR data to determine and monitor the landslide prone zones for Italian Pre-Alps region whereas Fodella et al. (2017) used the GB-InSAR monitoring technique for two years in Vicentine Prealps, Italy to assess the landslide kinematics and risk for deep-seated gravitational slope deformations. Costanzo et al. (2016) developed an integrated system using different sensors spread across the vulnerable landslide sites in Calabria, Italy to monitor the several physical parameters associated with slope failure. The data collected was used to evaluate the associated risk using mathematical models and determining warning levels for mitigation purpose.

1 Methodology

The probabilities are determined using the available rainfall and landslide data using Bayes' theorem. The rainfall values are collected from an automatic rain gauge setup at Tirpai Bazar, Kalimpong. The rainfall parameters used for calculating probability are mean rainfall intensity, rainfall duration and event rainfall. The probabilities are determined using one-dimensional and two-dimensional Bayes' theorem. The methodology for the calculation of probability is as follows:

One-dimensional Bayesian probability determines the conditional probability $P(A|B)$ which relates to the probability of landslide occurrence (A) because of rainfall parameter (B) and the equation is:

$$P(A|B) = \frac{P(B|A).\ P(A)}{P(B)} \tag{1}$$

$P(B|A)$ = probability of rainfall event of degree B when landslide occurs (also known as likelihood)

$P(A)$ = prior probability i.e, landslide incidence whether a rainfall event of degree B occurs or not.

$P(B)$ = marginal probability of rainfall of degree B, even if a landslide occurs or not.

$P(A|B)$ = probability of landslide incidence for a rainfall event of degree B (posterior probability).

Let the count of rainfall events for a time period be N_R; count of landslide incidence during the same time period be N_A, count of rainfall events of degree B be N_B and count of rainfall events leading to landslides be $N_{(B|A)}$, Eq. 1 can be determined as:

$$P(A) \approx N_A/N_R \tag{2}$$

$$P(B) \approx N_B/N_R \tag{3}$$

$$P(B|A) \approx N_{(B|A)}/N_A \tag{4}$$

Usually, probabilities determine the likelihood of landslide for rainfall parameters initiating its occurrence. In this study, the rainfall parameters used to determine probabilities are mean rainfall intensity, rainfall duration and event rainfall.

Two-dimensional Bayesian probability determines the conditional probability of landslide incidents using a combination of any two triggering factors.

$$P(A|B,C) = \frac{P(B,C|A).\ P(A)}{P(B|C)} \tag{5}$$

where B, C denotes the range of values of any two rainfall parameters responsible for landslide incidences. For e.g. if B and C denote rainfall intensity and rainfall duration respectively, the probability of landslide occurrence due to both the factors is expressed using Eq. 5. The conditional probability $P(A|B,C)$ can be determined by interpreting observed data and calculating

$P(B,C|A)$, $P(A)$ and $P(B,C)$. The detailed application of the method along with a worked out example has been explained in detail in Berti et al. (2012). Any set of rainfall parameters can be used to determine probability of landslide event using two-dimensional probability method and its importance can be examined by comparing it with prior probability (Berti et al. 2012). Similarly, this technique can be used for evaluating probability with m-variables such as combined effect of rainfall parameters like duration, intensity and cumulated rainfall.

1.1 Advantages and limitations of probabilistic thresholds

The major drawback of the empirical or deterministic methods is it only considers the rainfall that caused landslides, i.e., triggering rainfall. Bayes' theorem considers all the rainfall events which may or may not have led to landslides. When considering only the triggering rainfall, the probabilities determined represent only a portion of the uncertainty (Berti et al. 2012). Bayesian approach is advantageous as it considers all the rainfall events both triggering and non-triggering which allows it to determine all possible uncertainties regarding probabilities. Bayes' probability method explicitly finds the likelihood of a landslide occurrence for the same rainfall event which depends on numerous factors like hydrological behaviour, a decrease in shear strength, gradual failure, and even human behaviour. Also, probability computed using Bayes' approach can be updated dynamically for with availability of new data by merely shifting posterior probability into likelihood. Finally, this procedure is also suitable for practical decision making in which it is crucial to account for the number of missed alerts and false alarms.

Probability computed using Bayesian approach fails in conditions where the rainfall B never resulted in landslides. This means that the probability of landslide occurrence will be zero as likelihood is also zero which may be surprising. To overcome this limitation, it is essential to evaluate long-term data series to understand the marginal distribution of rainfall and the likelihood function to be determined using a complete landslide inventory for the same long term duration.

Another limitation like traditional methods is its accuracy over long-term use of historical data. There are several factors which affect the recurrence of landslides over a period like the change in slope, land use and cover, precipitation data and human activities. Therefore, the circumstances under which landslides occurred in the past may not be similar for future slide conditions which means that prior probabilities will no longer be significant. In the present study it is assumed that the frequency and spatial distribution of landslides do not change significantly.

1.2 Monitoring system

The study depicts an effective monitoring system equipped with a Micro Electrical Mechanical System (MEMS) technology which measures tilt angles of a steel rod installed in the unstable layer of slope (Dikshit et al. 2018). The system is suited to identify the initial stage of surface failure indicating the bottom layer of the soil to be stable and the top layer to be displacing. The system consists of two steel rods, one tilt sensor encompassed in a box, volumetric water content sensor and a wireless transmission kit. The first steel rod is attached with a MEMS tilt sensor (accuracy = 0.017°, resolution = 0.003°) and volumetric water content sensor (resolution = 0.1%) which is embedded in the soil to 1-1.5 m. Small movements of 0.02° can be determined, which may vary depending on the local conditions. The steel rod moves along the ground displacement and the variation in tilting rate is detected. Another steel rod is placed beside the tilt sensor which has a wireless transmission kit enclosed in a box onto the rod. The sensor unit is powered by four *C* size alkaline batteries which work for a year in the monitoring area. The data collected from the sensors are transferred to the data logger via radio communication. The data logger assembles the data from all the sensors placed over a slope and sends them to a server on the Internet through a cell phone network (Uchimura et al. 2015). The data is processed and an anomalous change in the tilting rate of the sensors can be identified and subsequently, a warning can be generated. The system provides data at an interval of 10 minutes. The monitoring system consists of six tilt sensors along with a rain gauge setup in the Chibo area. The use of such a monitoring system for early warning of landslides is ideal for shallow landslides and may not be suited for deep-seated landslides (Dikshit et al. 2018).

The volumetric water content sensor determines the dielectric soil constant. The moisture content measures at a single point whereas the tilt sensor determines the tilting rate of the soil mass around the sensor (Dikshit et al. 2018). The total displacement is determined from beginning and the rate of displacement is used as a determinant for the warning. The various characteristic tilting rate for early warning system is depicted in Figure 1 (Uchimura et al. 2009):

(1) Tilting rate = 0.01 °/hr. - Attention should be given.

(2) Tilting rate = 0.1 °/hr. - Alarm needs to be generated.

(3) Tilting rate= 1 °/hr. - Failure would occur.

2 Study Area

Kalimpong is situated in Eastern Himalayas in the rugged mountainous terrain in West Bengal state . The area is encompassed by river Teesta in the west and river Reli in the east. The Eastern section of the Himalayan region receives the most rainfall in the entire Himalayan region with an average annual rainfall of 3000-5000 mm (Ghosh 2011) making Kalimpong region highly vulnerable to rainfall-induced landslides. The soil contains a high proportion of sand, gravel and silt and with the increase in elevation, it varies from coarse to rocky stretch (Dikshit and Satyam 2018). The hydrogeological map of Kalimpong overlayered with elevation of Chibo region is depicted in Figure 2. Table 1 depicts the constituents of the hydrological map with the symbol representing the type of rock, its age and lithology along with aquifer details and hydrogeology.

The history of landslides in Kalimpong dates to 11th and 13th June 1950, where a heavy spell of rain of 834.10 mm caused widespread damages to roads, railways, houses and public works. 127 people were killed and several hundred were rendered homeless (Sumantra and Raghunath 2016). The Siliguri-Kalimpong railway line was closed forever, as the hillsides in that region were considered unsafe for railways. A similar event happened between 15th and 16th September 1991 causing numerous landslides in and around Kalimpong affecting human lives and severing the

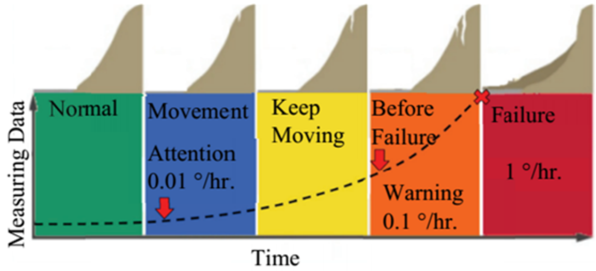


Figure 1 Stages representing the real-time quantification of slope risks using MEMS based monitoring system (precaution, warning and failure).

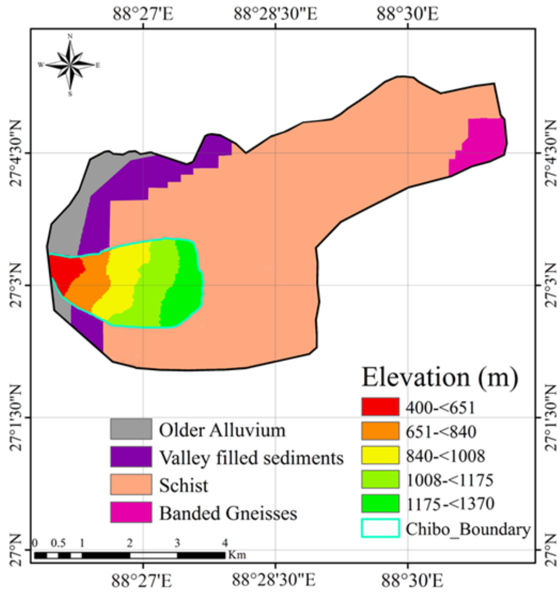


Figure 2 Elevation of the study area (Chibo) along with the hydrogeological map of Kalimpong (Source: Water Resource Investigation and Development Ministry, Govt. of India, 2015) in India.

Table 1 Hydrogeological properties of the study area

Rock type	Banded Gneisses, Schist, Sandstone with shale, Valley fill sediments and Younger Alluvium
Age	Azoic to Quarternary
Lithology	Granular/ fracture zones variably encountered between 20-400 m below ground level
Aquifer description	Thickness of aquifer varies between 5-50 m in consolidated rocks and 50-700 m in alluvium
Hydrogeology	Groundwater yield prospects between 2-2000 m³/day in consolidated rock and 200-1500 m³/day in alluvium

railway connection between hills and plains. In 2003, extreme rainfall caused widespread landsliding leading loss of 24 precious lives. Several landslide disasters happened in the year 2004, 2005, and 2006 (Sumantra and Raghunath 2016). In June 2011, heavy precipitation of 60 mm in 3 hours caused several landslides. Similar incidents occurred in June - July 2015 which triggered landslides at several places leading to loss of 38 people and several missing.

Chibo is in the western slope of Kalimpong (27°03'N, 88°27'30"E) and has suffered several landslides and subsidence. The area experiences heavy monsoonal precipitation (2000-4000mm) (GSI Report 2018). The area experiences the highest and lowest temperature of 25°C and 3°C respectively. The region belongs to Darjeeling Himalayas containing rocks from Precambrian to Quaternary ages (Dikshit et al. 2018). The southern part of the region comprises of coarse to a very coarse grained sedimentary arrangement of siltstone associated with Siwalik group (GSI Report 2018). The type of landslides in the region based on Cruden and Varnes (1996) distribution are rock fall, rock slide, debris flow, debris slide, and earth slide which has been identified by the Geological Survey of India (GSI). Since most of the landslides occur during or after the monsoon, the debris is saturated or partially saturated. The materials also include weathered grey phyllite, phyllitic quartzite, mica schist and sheared quartzo-feldspathic gneiss. The field visit by the authors during October 2016 revealed that the depth of landslides varies from few centimetres to few meters. The Chibo village is situated in Zone-IV which is a high-risk zone as per the seismic zonation map of India (BIS 2002a). The seismic activity in the area is primarily due to the build-up of strain resulting from the collision of the Indian Plate with the Eurasian Plate in the north. With the advent of time after the collision at the E-W trending Indus-Tsangpo Suture Zone, several others E-W trending tectonic features have been developed subsequently. Apart from the E-W trending thrusts, several NE-SW and NW-SE trending transverse faults are also present (GSI Report 2018).

The area comprises of damp sections (33%) and more than 50% is wet. The region is drained by jhoras (mountain rivulets) which occupy 0.5% of the area but drains 10.5% of the region (GSI Report 2018). The land cover is natural in 76% of the study area, agriculture is practised on 12% and the remaining 12% consists of settlement, roads and infrastructure (GSI Report 2018). Majority of the area consists of moderate susceptible landslide zones whereas the area along the path of jhoras is high to very high susceptible zones. The region is primarily drained by Pyarieni and OC jhora. The field study revealed that area to the left of Pyarieni jhora is under massive subsidence and is on the verge of failure. A comparable observation was also found around OC jhora which makes the area around these two jhoras ideal for monitoring purpose. Therefore, a total of six tilt sensors along with a data logger, one tipping bucket rain gauge to collect local rainfall data was installed across the jhoras.

3 Data Collection

The daily rainfall data for determining probability was collected from an automatic rain gauge maintained by the non-governmental organization, Save The Hills (www.savethehills.blogspot.com). The selection of rain gauge is depended on two factors. i) vicinity of rain gauge with the monitoring area to minimise the effect of spatial distribution ii) number of landslides being covered for accurate threshold determination. The monsoon comprises an average of 88.5% of annual rainfall for the study period, with the minimum and maximum rainfall occurring in 2013 and 2011 respectively. Figure 3a describes the yearly daily precipitation for 2010-2016 and Figure 3b illustrates the cumulative rainfall along with average daily precipitation for the study period.

A single rainfall event has been determined by counting the total number of consecutive days of rainfall. The total rainfall during a single event (in mm) is divided by the duration (days) to calculate mean rainfall intensity (mm/day). A total of 189 rainfall events for the monsoon period occurred between 2010-2016. The landslide database was prepared from several sources like the landslide inventory data prepared by GSI, newspaper articles and reports from non-governmental organizations. The database included the dates of landslide occurrences along with their coordinates. The landslide records included the damages caused

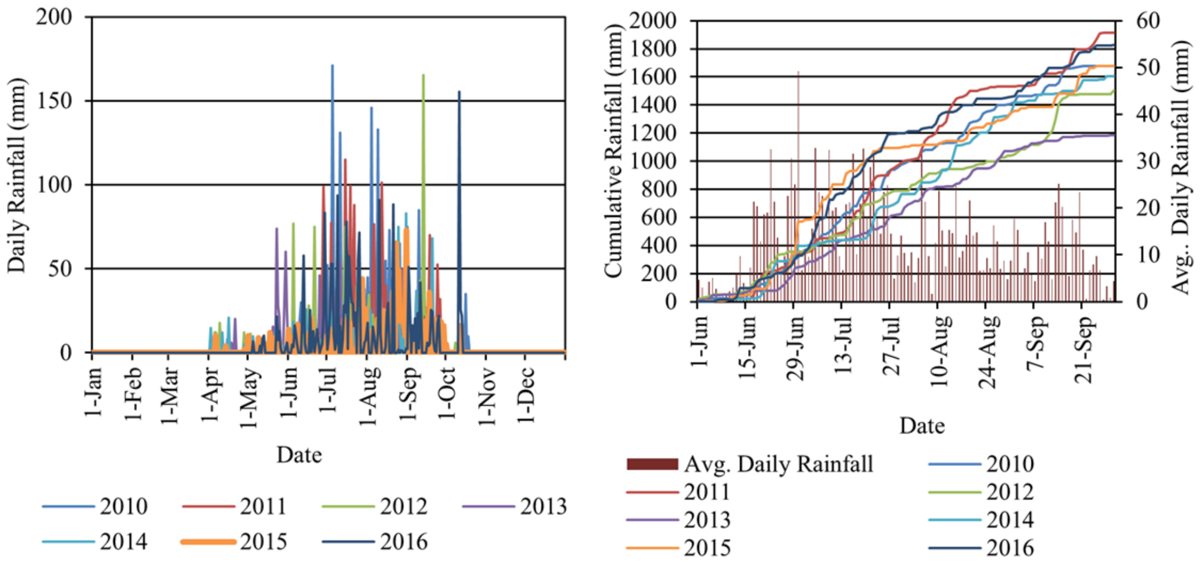


Figure 3 (a) Daily rainfall data (yearly) (b) Cumulative rainfall data for monsoon season (2010-2016).

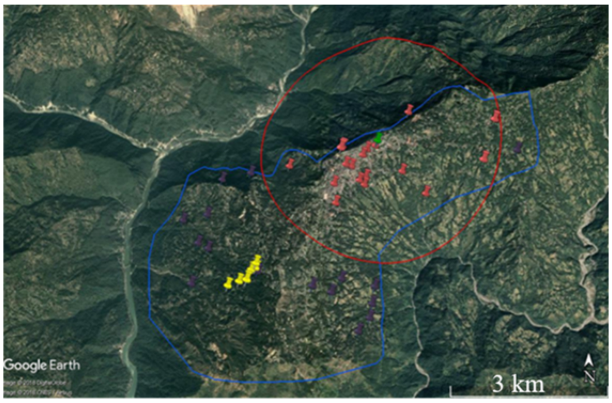


Figure 4 Landslide Inventory map along with the locations of tilt sensor. The rain gauge used for probabilistic modelling is marked in green; Yellow markers represent the tilt sensors; Red and purple markers depict the landslide locations used and discarded from probabilistic modelling respectively.

which varied from casualty to obstruction of highways. Any minor incidence not involving damage to life or property or deterrent to human lives was not considered (e.g., landslide occurrence atop the slope but not damaging human lives in any way). An inventory of 61 landslides was determined. The area has only one rain gauge and to minimise the spatial distribution of landslides, the landslide locations in a buffer radius of 15 km were selected which reduced the number landslide events to 36 (Gariano et al. 2018). Figure 4 represents the landslide locations considered for the study (red), not considered (purple) and the tilt sensors (yellow). On comparing the daily rainfall data for monsoon 2017 from both the sources (Tirpai Bazar, Chibo) the variation was found to be negligible.

The region was monitored for 5 months (15 June - 10 November 2017) and the results imply a significant variation in the tilting rate of the sensor. The use of such sensors should also be encouraged as it is difficult to determine the exact section of slope which would fail in subsequent rainfall events and the problem can be solved by setting up several inexpensive sensors across the area (Dikshit et al. 2018). The results obtained from the tilt sensors are in accordance with the field observations carried out after the monitoring period.

4 Results and Discussion

As mentioned, 189 rainfall events and 36 landslide events were considered for probabilistic threshold determination and the results are depicted in Figure 5 (a-f). The highest number of rainfall events existed in the 0-10 mm/day range of rainfall intensity, whereas most number of landslide events occurred in 20-30 mm/day bracket. Figure 5 (a, c, e) represents the likelihood, prior and marginal probability for event rainfall, rainfall duration and mean rainfall intensity

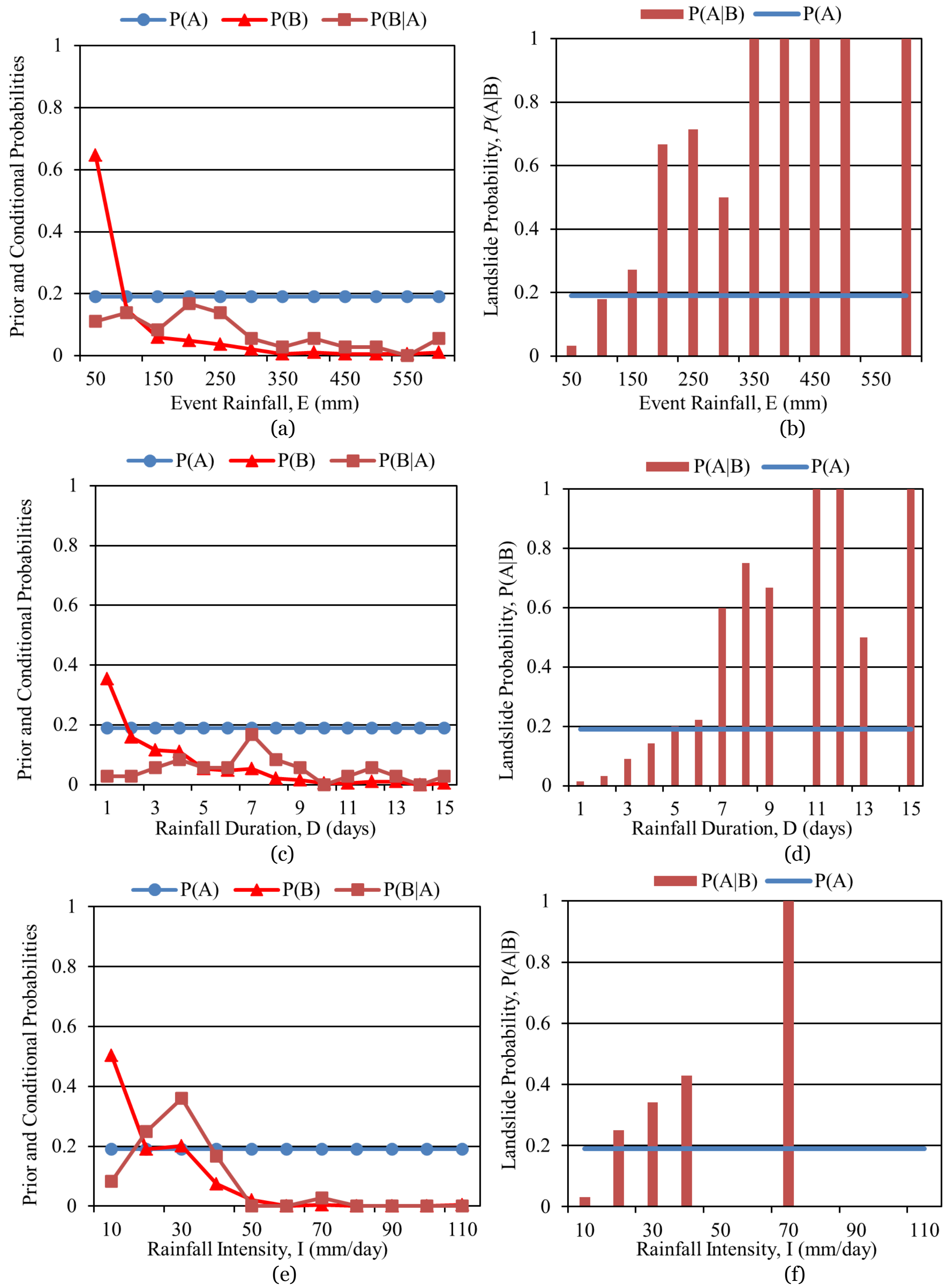


Figure 5 Computed probabilities for one-dimensional Bayesian analysis of Chibo region. Rainfall parameters considered are: (a–b) cumulative rainfall, (c–d) rainfall duration, and (e–f) rainfall intensity.

respectively. Figure 5 (b, d, f) illustrates the marginal probability due to various rainfall parameters. The change in the probabilities for various ranges of rainfall parameter represents that every rainfall factor is significant for landslide occurrence. However, rainfall intensity is the most critical factor compared to other variables with probability reaching 0.43 for mean rainfall intensity greater than 30 mm/day.

The results from 2D Bayesian analysis indicate that landslide probability increases due to both rainfall duration and intensity, but intensity has more effect on landslide probability (Figure 6). The maximum value of probability of 0.667 reaches for rainfall events for 7 days with an intensity higher than 30 mm/day. The probability of landslides computed using Bayesian is comparable with regional rainfall thresholds (Dikshit and Satyam 2018). The significance of the analysis can be comprehended from the fact that even small values of probability cannot be disregarded for vulnerable areas and must be analysed along with the associated risk. To verify the obtained probabilistic results, a sensitivity analysis was performed for 1D and 2D results. The input parameters (mean rainfall intensity, rainfall duration, event rainfall) were varied and the resulting change was observed. The results showed an incline towards variation in rainfall intensity and the landslide probability shifted up to 20% for a few combinations of rainfall parameters which were considered in the study. However, there was very little variety with the change in term of precipitation occasions. Comparative analysis was performed for two-dimensional probability and the results were more sensitive compared to one-dimensional results. The investigation revealed that a combination of rainfall intensity and total rainfall is most sensitive compared to other combinations.

The incidents of extreme rainfall events may lead to an increase in the probability of landslide occurrences which can be related to low sample size of such events. Samples with small data size contain very little information and a small change in the count of landslide event would lead to contrasting results. The effect of low sample size can also be observed in this study especially for higher values of rainfall parameters where probability tends to reach 1.

The analysis of the tilting rates of all the sensors depicted that Tilt Sensor 2 and 3 showed significant variation in tilting rates on two different occasions during the monitoring period One was on 28 July- 29 July 2017 and the other was 13 August-17 August 2017. Tilt sensor 2 and 3 was installed on the left bank of Pyareini and OC jhora respectively and the changes in the tilting rates were substantiated with subsidence around the sensor area (Figures 7 and 8). The results obtained suggest that the movement started from atop the slope which gradually drifted to the centre of the slope with closure towards the end of the slope (Dikshit et al. 2018). The daily and cumulative rainfall data during the monitoring period has been

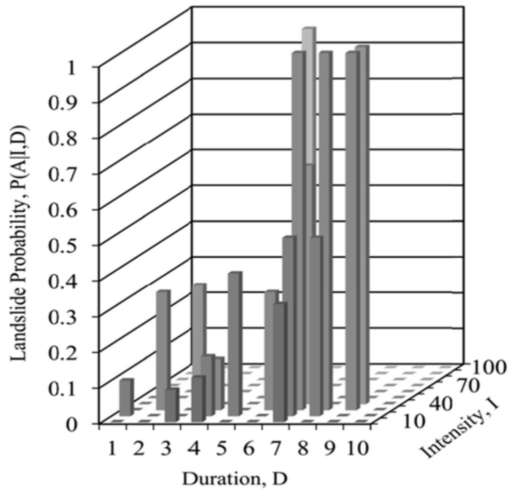


Figure 6 Histogram of landslide probability as a function of rainfall duration and intensity.

Figure 7 Subsidence near **Pyarieni** Jhora (Tilt Sensor 2) and ground (Dikshit et al. 2018).

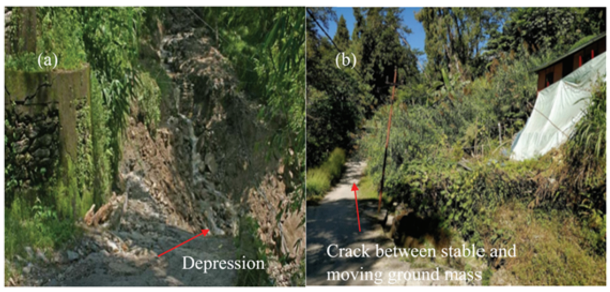


Figure 8 Ground displacement near OC Jhora (Tilt Sensor 3) (Dikshit et al. 2018).

depicted in Figure 9. The maximum daily rainfall of 92.1 mm was collected on 23 July 2017 and the cumulative rainfall during the monsoons (15 June-30 September) was 1770.2 mm. The time histories of the obtained data have been depicted in Figure 10 (a, b, c). The probabilities for various rainfall parameters during both the displacement time periods is verified with the monitoring results.

For the initial displacement period, concerning Tilt Sensor 2 the rainfall event before the displacement period had a rainfall intensity of 36.35 mm/day for 9 days which imply a probability of 0.429 and 0.667 accordingly. The event rainfall during this period was 363.54 mm indicating the probability of 1. The high value of probability is due to the small sample size. On verifying it with the

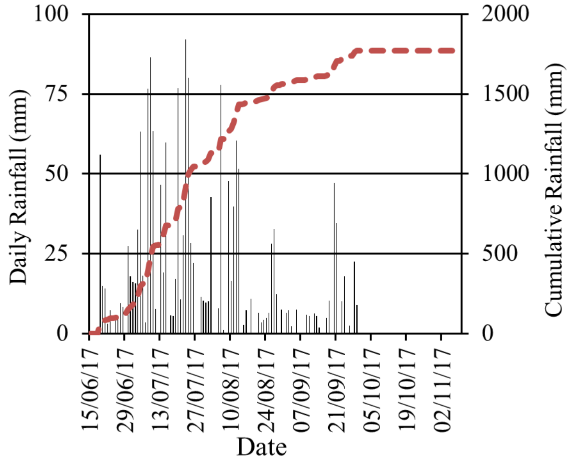
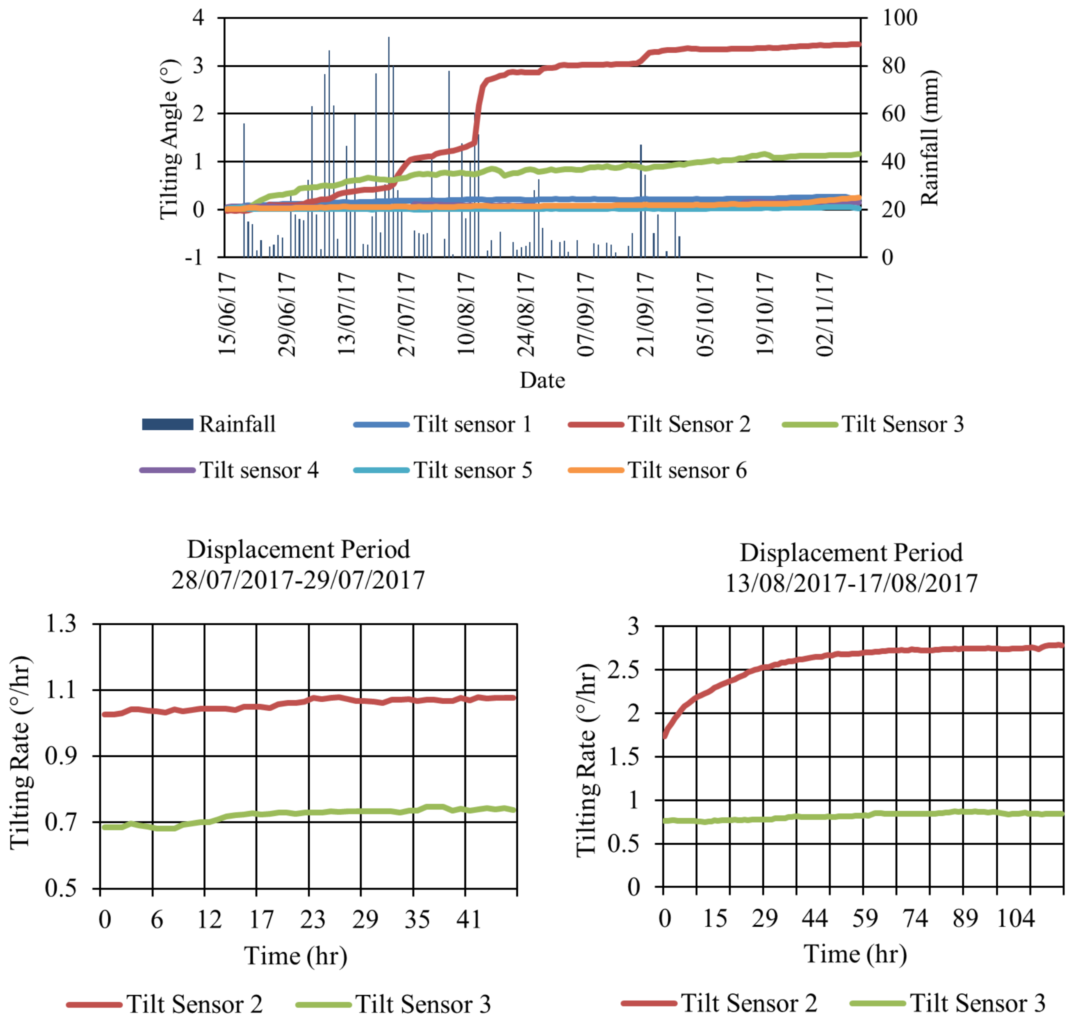


Figure 9 Daily and Cumulative rainfall during the study period.



(a)

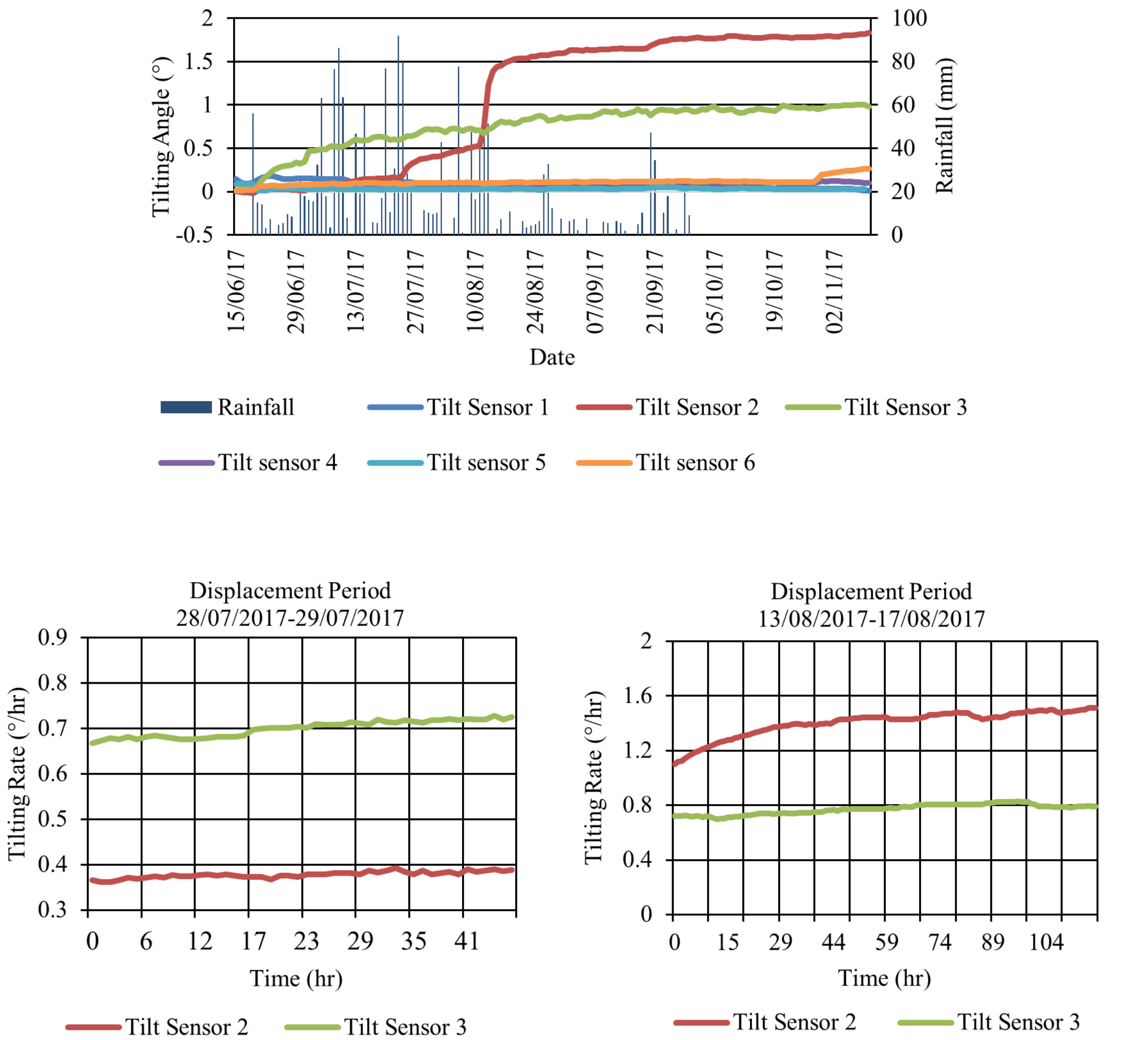
Figure 10 (a) Time history of the tilting angle in X-direction and zoom up of the ground displacement time period.
(-To be continued-)

monitoring data, it was found that the average tilting rate during the period in the parallel direction was 0.005°/hr with the maximum rate being 0.01165°/hr. The tilting rate achieved its highest value initially in the parallel direction on 28 July and later in perpendicular direction on 29 July with a gap of 22 hours. Since these observations are very small, it is difficult to detect by human eyes but can be easily detected by the tilt sensors (Dikshit et al. 2018).

Similarly, the rainfall event preceding the latter displacement period had rainfall intensity of 38.9 mm/day with a duration of 3 days resulting in the probability of 0.429 and 0.091 respectively. The total event rainfall during this period related to a probability of 0.179. The average tilting rate during the period in the parallel and perpendicular directions was 0.019°/hr and 0.01°/hr respectively with the maximum rate being 0.081°/hr and 0.017°/hr.

The maximum tilting rate during the initial displacement period for Tilt Sensor 3 in the parallel and perpendicular direction was 0.016°/hr and 0.0126°/hr. The following displacement period depicted maximum tilting rate of 0.0167°/hr and 0.011°/hr in the parallel and perpendicular direction to the slope. The joint probability of rainfall intensity and duration depicts that in the

(-Continued-)

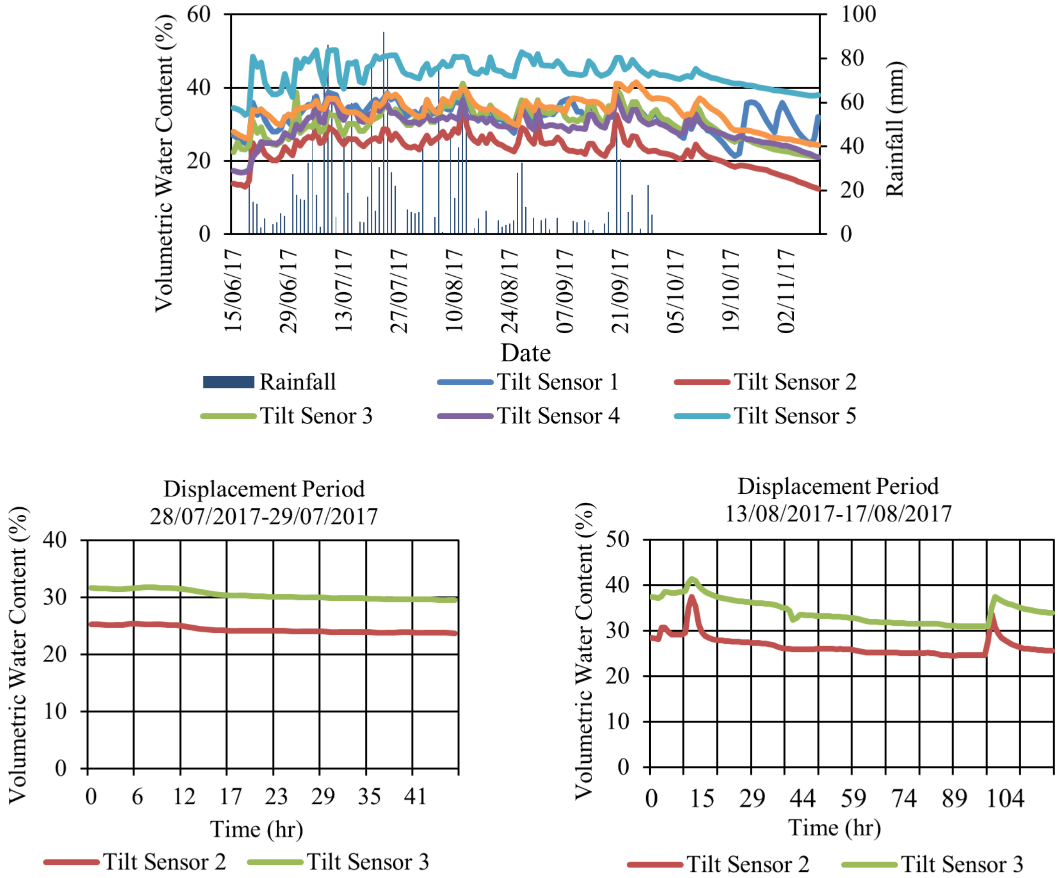


(b)

Figure 10 (b) Time history of the tilting angle in Y-direction and zoom up of the ground displacement time period

(-To be continued-)

(-Continued-)



(c)

Figure 10 (c) Time history of the water content and zoom up of the ground displacement time period.

initial and latter displacement period has a probability of 1 and 0.143 respectively which is exceedingly high. The results verify that the probabilities calculated using historical data are in line with the monitoring results. On both the occasions the probabilities were of significant value and the average tilting rate suggests that attention needed to be given. Since the time scale of the probability calculation and monitoring data were of daily and hourly levels respectively it is difficult to determine the possibility of using a probabilistic model for an early warning system. However, it is safe to say that the probabilistic model can be used as the first line of action for areas in the Indian Himalayan region where monitoring is not available. With the availability of hourly rainfall data, the probabilities can be further enhanced, and the calibration of the thresholds can be carried out with the help of the monitoring setup.

5 Conclusions

This paper determines the probabilistic thresholds and validates it with a robust and simple monitoring system for Chibo, Darjeeling Himalayas. The use of such a monitoring system over traditional instruments like extensometer is a newly proposed technique in the Indian Himalayan region. It should also be borne in mind that the rainfall values used for probability calculation are from a different source compared to the monitoring site. However, when comparing the daily rainfall values from both the sources for monsoon, 2017 the variation is negligible. The following conclusions from the study can be drawn:
(1) The study included the determination of probabilities for landslide incidences using rainfall and landslide data for 7 years (2010-2016). Such type of analysis is different from the traditional

empirical thresholds and involves understanding the importance of various rainfall characteristics for landslide occurrences.

(2) The probabilities were determined using Bayes' theorem as the thresholds are determined for each rainfall parameter along with a combination of rainfall parameters. The benefit of using such a technique is that it emphasizes the importance of every rainfall parameter responsible for landslides. The results depict that a single rainfall parameter may not be effective for the determination of slope failures. Therefore, two dimensional Bayesian probability should be used to determine thresholds. The availability of hourly rainfall data would further enhance the results and give more realistic probability values for landslide incidences.

(3) Six tilt sensors were installed across the unstable slopes in Chibo which is primarily drained by Pyareini and OC jhoras flowing across the area. The monitoring system was tested for 5 months (15 June-10 November 2017). There was a substantial change in the tilting rate in regions near two sensors (Tilt sensor 2 and 3) and ground displacement was evident. Based on the monitoring data, it was observed that there were two time periods (28 July – 29 July 2017) and (13 August – 17 August 2017) which depicted significant tilting rates of the sensors and indicated by ground displacement. When comparing with the probabilistic results, the initial period was affected due to rainfall duration whereas the later period was because of event rainfall.

The usage of the monitoring system and probabilistic thresholds for determination of landslide incidences is a first of a kind attempt in Indian Himalayan scenario which could help in setting up an early warning system.

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References

Agterberg FP, Bonham-Carter GF, Wright DF (1990) Statistical pattern integration for mineral exploration, Computer Applications in Resource Estimation, Prediction and Assessment of Metals and Petroleum (G. Gaal and D.F. Merriam, editors), Pergamon Press, New York. pp 1-21.

Bean, MA (2009) Probability: The Science of Uncertainty with Applications to Investments, Insurance, and Engineering, 448 pp., American Mathematical Society, Providence, R. I.

Bureau of Indian Standards, 2002a. Seismic Zonation Map of India: IS: 1893 (Part - I); Revised.

Berti M, Martina MLV, Franceschini S, et al. (2012) Probabilistic rainfall thresholds for landslide occurrence using a Bayesian approach. Journal of Geophysical Research: Earth Surface 117: F04006. https://doi.org/10.1029/2012JF002367

Chang KT, Chiang SH, Lei F (2008) Analysing the relationship between Typhoon-triggered landslides and critical rainfall conditions. Earth Surface Processes and Landforms 33: 1261-1271. https://doi.org/10.1002/esp.1611

Chung CF, Fabbri AG (1999) Probabilistic prediction models for landslide hazard mapping. Photogrammetric Engineering and Remote Sensing 65-12: 1389-1399.

Costanzo S, Di Massa G, Costanzo A, et al. (2016) Software-defined radar system for landslides monitoring. New Advances in Information Systems and Technologies 445: 325-331. https://doi.org/10.1007/978-3-319-31307-8_34

Cruden DM, Varnes DJ (1996) Landslide types and processes. In: Turner AK, Schuster RL (eds.), Landslides: investigation and mitigation. Transportation Research Board special report 247. National Academy Press, Washington DC. pp 36-75.

Dikshit A, Satyam DN (2018) Estimation of rainfall thresholds for landslide occurrences in Kalimpong, India. Innovative Infrastructure Solutions 3: 24. https://doi.org/10.1007/s41062-018-0132-9

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 N, Towhata I (2018) Early warning system using tilt sensors in Chibo Kalimpong, Darjeeling Himalayas, India. Natural Hazards 94: 727. https://doi.org/10.1007/s11069-018-3417-6

Do H, Yin K (2018) Rainfall Threshold Analysis and Bayesian Probability Method for Landslide Initiation Based on Landslides and Rainfall Events in the Past. Open Journal of Geology 8: 674-696. https://doi.org/10.4236/ojg.2018.87040

Dowling CA, Santi PM (2014) Debris flows and their toll on human life: a global analysis of debis-flow fatalities from 1950 to 2011. Natural Hazards 71: 203. https://doi.org/10.1007/s11069-013-0907-4

Frodella W, Salvatici T, Pazzi V, et al. (2017) GB-InSAR monitoring of slope deformations in a mountainous area affected by debris flow events. Natural Hazards and Earth System Sciences 17: 1779-1793. https://doi.org/10.5194/nhess-17-1779-2017

Gariano SL, Sarkar R, Dikshit A, et al. (2018) Automatic calculation of rainfall thresholds for landslide occurrence in Chukha Dzongkhag, Bhutan. Bulletin of Engineering Geology and the Environment. https://doi.org/10.1007/s10064-018-1415-2

Ghosh S, Carranza EJM, van Westen CJ, et al. (2011) Selecting and weighting spatial predictors for empirical modeling of landslide susceptibility in the Darjeeling Himalayas (India). Geomorphology 131: 35-56. https://doi.org/10.1016/j.geomorph.2011.04.019

Glade T, Crozier M, Smith P (2000) Applying probability determination to refine landslide-triggering rainfall thresholds using an empirical Antecedent Daily Rainfall Model. Pure and Applied Geophysics 157: 1059-1079. https://doi.org/10.1007/s000240050017

González A, Caetano E (2017) Probabilistic rainfall thresholds for landslide episodes in the Sierra Norte De Puebla, Mexico. Natural Resources 8: 254-267. https://doi.org/10.4236/nr.2017.83014

Guzzetti F, Peruccacci S, Rossi M, et al. (2007) Rainfall thresholds for the initiation of landslides in central and southern Europe Meteorology and Atmospheric Physics 98: 239-267. https://doi.org/10.1007/s00703-007-0262-7

Kanungo DP, Sharma S (2014) Rainfall thresholds for prediction of shallow landslides around Chamoli-Joshimath region, Garhwal Himalayas, India. Landslides 11(4): 629-638. https://doi.org/10.1007/s10346-013-0438-9

Lagomarsino D, Segoni S, Rosi A, et al. (2015) Quantitative comparison between two different methodologies to define rainfall thresholds for landslide forecasting. Natural Hazards and Earth System Sciences 15: 2413-2423. https://doi.org/10.5194/nhess-15-2413-2015

Marques R, Zˆezere J, Trigo R, et al. (2008) Rainfall patterns and critical values associated with landslides in Povoa¸c˜ao County (S˜ao Miguel Island, Azores): relationships with the North Atlantic Oscillation. Hydrological Processes 22: 478-494. https://doi.org/10.1002/hyp.6879

Melillo M, Brunetti MT, Peruccacci S, et al. (2018) A tool for the automatic calculation of rainfall thresholds for landslide occurrence. Environmental Modelling and Software 105: 230-243. https://doi.org/10.1016/j.envsoft.2018.03.024

Refice, A, Capolongo D (2004) Probabilistic modeling of uncertainties in earthquake-induced landslide hazard assessment. Computers and Geosciences 28: 735-749. https://doi.org/10.1016/S0098-3004(01)00104-2

Rosi A, Lagomarsino D, Rossi G, et al. (2015) Updating EWS rainfall thresholds for the triggering of landslides. Natural Hazards 78: 297-308. https://doi.org/10.1007/s11069-015-1717-7

Spiegelhalter DJ (1986) A statistical view of uncertainty in expert systems, Artificial Intelligence and Statistics, (W.A. Gale, editor), Addison-Wesley Publ. Co., Reading, Massachusetts. pp 17-55.

Staley DM, Kean JW, Cannon SH, et al. (2013) Objective definition of rainfall intensity–duration thresholds for the initiation of post-fire debris flows in southern California. Landslides 10: 547-562. https://doi.org/10.1007/s10346-012-0341-9

Sumantra SB, Raghunath P (2016) Causes of Landslides in Darjeeling Himalayas during June-July, 2015. Journal of Geography and Natural Disasters 6: 173. https://doi.org/10.4172/2167-0587.1000173

Tessari G, Floris M, Pasquali P (2017) Phase and amplitude analyses of SAR data for landslide detection and monitoring in non-urban areas located in the North-Eastern Italian pre-Alps. Environmental Earth Sciences 76: 85. https://doi.org/10.1007/s12665-017-6403-5

Uchimura T, Towhata I, Wang L, et al. (2009) Development of low-cost early warning system of slope instability for civilian use. In: Proceedings of the 17th ISSMGE, Alexandria. vol. 3, pp 1897-1900.

Uchimura T, Towhata I, Trinh TLA, et al. (2010) Simple monitoring method for precaution of landslides watching tilting and water contents on slopes surface. Landslides 7(3): 351-358. https://doi.org/10.1007/s10346-009-0178-z

Uchimura T, Towhata I, Wang L, et al. (2015) Precaution and early warning of surface failure of slopes using tilt sensors. Soils and Foundations 55(5): 1086-1099. https://doi.org/10.1016/j.sandf.2015.09.010

Vessia G, Pisano L, Vennari C, et al. (2016) Mimic expert judgement through automated procedure for selecting rainfall events responsible for shallow landslide: a statistical approach to validation. Computers and Geosciences 86: 146-153. https://doi.org/10.1016/j.cageo.2015.10.015

Wilson RC, Wieczorek GF (1995), Rainfall thresholds for the initiation of debris flows at La Honda, California. Environmental and Engineering Geoscience 1: 11-2. https://doi.org/10.2113/gseegeosci.I.1.11

Yang Z, Cai H, Shao W, et al. (2018) Clarifying the hydrological mechanisms and thresholds for rainfall-induced landslide: in situ monitoring of big data to unsaturated slope stability analysis. Bulletin of Engineering Geology and the Environment. https://doi.org/10.1007/s10064-018-1295-5

Yin Y, Zheng W, Liu Y, et al. (2010) Integration of GPS with InSAR to monitoring of the Jiaju landslide in Sichuan, China. Landslides 7(3): 359-365. https://doi.org/10.1007/s10346-010-0225-9