# Quantitative Comparison of Rainfall Thresholds: A Case Study from Kalimpong, India

**Minu Treesa Abraham* and Neelima Satyam***

## Abstract

*The increasing frequency of landslides has become a matter of prime concern in the context of Indian Himalayas. Massive losses are reported due to landslides every year, demanding the development of strategies to minimise the impact of such events. Kalimpong in the Darjeeling Himalayas is one among the landslide susceptible towns in India, where rainfall is identified to be the primary triggering factor for the occurrence of landslides. Attempts have been made in the past to develop local-scale rainfall thresholds for the region using different approaches. Among the various methods, empirical methods are observed to be the simplest approach in predicting landslides. The procedure includes finding the relationship between rainfall and landslides happened in the past to predict the possible occurrence of landslides in future. In this work, three different empirical relationships derived for the region are compared to find the best-suited method and to testify their applicability in an operational Landslide Early Warning System(LEWS). The Event Duration thresholds defined using an algorithm based approach is found to be performing better than the other two models considered in the analysis. It is observed that the empirical relationships have to be improved conceptually to be used as a tool for LEWS.*

**Keywords:** Landslides, Rainfall Thresholds, LEWS

## Introduction

Rainfall induced landslides are claiming several lives and causing large scale destructions in Indian Himalayas. The increase in population and urbanisation of hilly areas are making the scenario worse by increasing the fatalities. Kalimpong town is located in the Darjeeling Himalayas, in West Bengal State (India) and is highly affected by landslide hazards. During monsoon seasons every year, landslides are creating havoc in the region

* **Minu Treesa Abraham,** Discipline of Civil Engineering, Indian Institute of Technology Indore, Madhya Pradesh, India. Corresponding Author Email: minunalloor@gmail.com

* **Neelima Satyam,** Discipline of Civil Engineering, Indian Institute of Technology Indore, Madhya Pradesh, India. Email:neelima.satyam@gmail.com

by disrupting communication and transportation facilities and damaging houses and agricultural lands. As the people of the locale are depending on agriculture and tourism as its major income sources, landslides and associated losses are directly affecting the economy of the town. Transportation facilities are often blocked during monsoon causing difficulties to both locals and tourists.

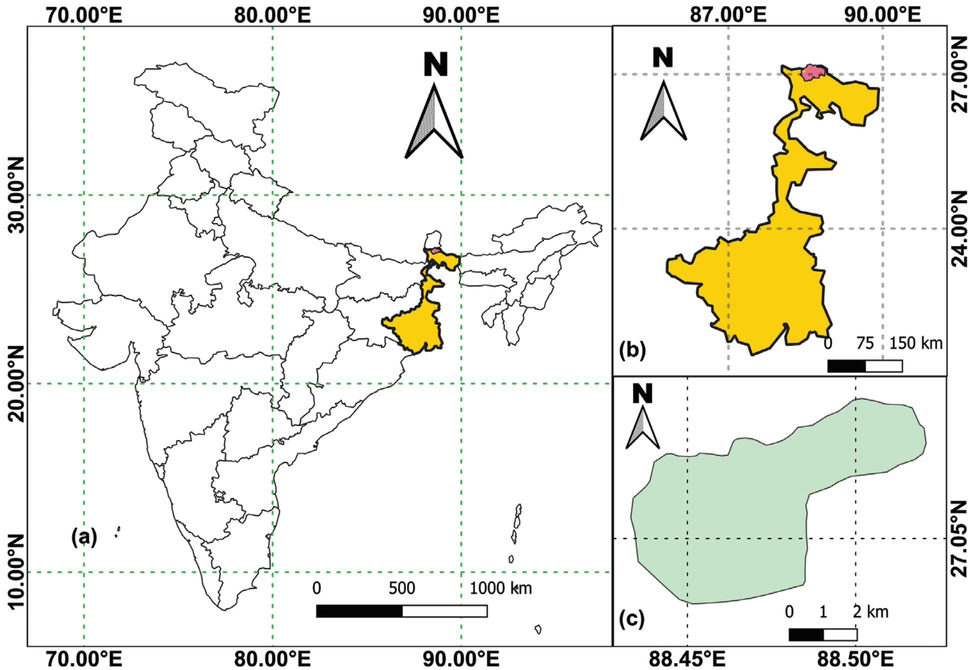
Continuous precipitation and infiltration increase the moisture content of the soil. This in turn increased pore water pressure and decreases the shear strength of soil, which is attributed as the reason for slope failure due to rainfall. But the soil properties and slope conditions are often complicated, as these parameters vary greatly within a short distance and time. The spatial and temporal variation of in situ parameters makes the detailed understanding of physical processes complicated and hence prediction of landslides based on physical parameters is hence suitable for detailed site-specific studies. A widely accepted approach is to obtain the relationship of several rainfall parameters (Event rainfall, Intensity and Duration) which resulted in landslides in the past to predict the future landslides. The thresholds are termed as Empirical thresholds, as it derives an empirical relationship which differentiates the rainfall events which can trigger landslides from those which cannot trigger landslides. In other words, thresholds define a critical condition above which landslides are likely to occur.

In this study, three such thresholds defined for Kalimpong town, one based on Intensity-Duration relationship, one based on intensity-duration relationship, one based on antecedent rainfall conditions and a third one based on the event-duration relationship are being evaluated. The objective is to find the best model among the three, which predicts the possible occurrence of a landslide in the study area.

## Study Area

Kalimpong town is a part of Kalimpong district in the state of West Bengal in India (Fig. 3.1). The town is located between rivers Relli and Teesta and has altitudes as high as 1,247 m (Dikshit and Satyam, 2018). The region is characterised by steep and very steep slopes which become unstable due to high precipitation in the monsoons. Due to poor lithological quality and erosion by river Teesta and its tributaries, most of the western slopes in this region are destabilised (Dikshit and Satyam, 2018). Highly weathered chlorite schist, phyllite and phyllitic quartzite of the Daling group contribute to the geology of the region (Sumantra, 2016). The rocks are usually covered by a thin to thick heterogeneous debris material (GSI Report, 2016). The topsoils are mostly red in colour with occasional dark soils (Dikshit and Satyam, 2018) due to the presence of phyllites and schists. The particle size ranges from coarse to rocky as the elevation increases.

**Fig. 3.1: Location Map of Kalimpong (a) India; (b) West Bengal; (c) Kalimpong Town**




The region is drained by a system of streams which are the tributaries of rivers Relli and Teesta. The smaller order streams join together and become higher-order streams. These untrained rivulets often called as jhoras in the locale have increased the landslides in the area. Regions near to the major jhoras are suffering from continuous sinking during the monsoons(Dikshit and Satyam 2019). The population in this hilly area is increasing and this demands more construction activities and toe modifications of hills. These anthropogenic activities have also contributed to the increased number of landslides in the region.

## Rainfall Thresholds

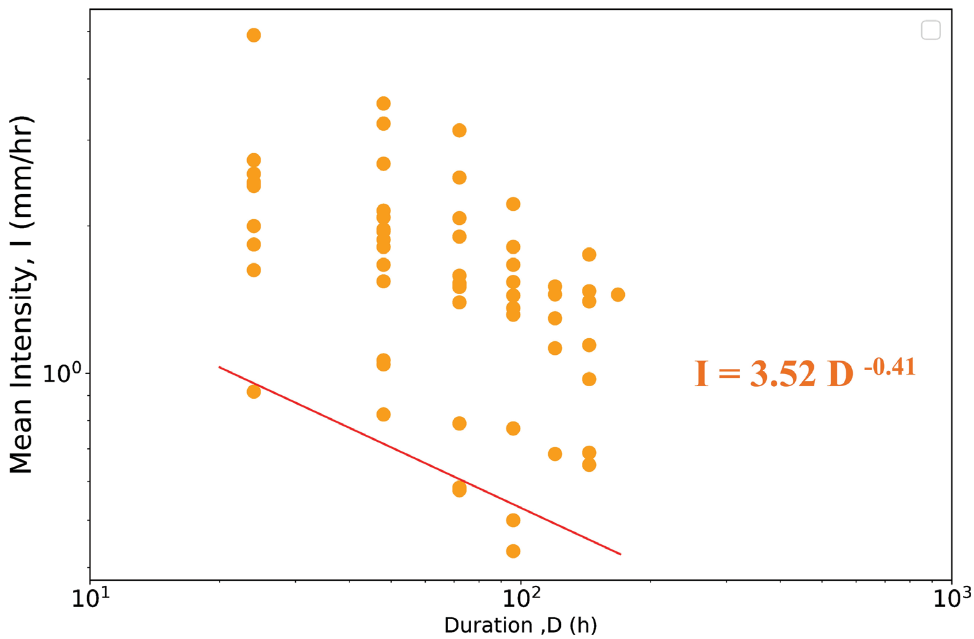
Three different thresholds established for the region is considered in this study for quantitative comparison. The first threshold considered was Intensity-Duration (ID) Thresholds prepared using a catalogue of 61 landslide events that happened in the region from 2010-2016 (Figure 2) (Dikshit and Satyam, 2017). The rainfall associated with each landslide event was found using a frequentist approach and a threshold was defined for the region as

$$I = 3.52D^{-0.41} \quad [1]$$

where I is the average intensity associated with the rainfall event intensity in mm/h

D is the duration of event in hours calculated from the start of rainfall till the occurrence of landslide.

**Fig. 3.2: Intensity- Duration Thresholds (Dikshit and Satyam 2017)**




An analysis based on antecedent rainfall was also conducted for the study are and thresholds were defined as rainfall of 88.37 mm over a period of 10 days and rainfall of 133.5 mm over a period of 20 days are potent enough to trigger landslides in the region.

The use of Intensity (I) as a variable to define the rainfall thresholds is criticized considering the variables measure independent quantities while determining functional relationships. This assumption is violated when searching for a relationship between the rainfall duration *D*, and the rainfall means intensity I because the rainfall means intensity depends on the rainfall duration, through the cumulated rainfall (E). For this reason, Event-Duration (ED) thresholds are widely followed in the recent literature (Teja, Dikshit and Satyam, 2019; Melillo et al., 2018; Zhang and Han, 2017) apart from the classical Intensity-Duration approach. The empirical relationship between cumulated rainfall event and duration was derived for the area using an algorithm based approach, named CTRL-T. The approach is more precise in nature as it considers the location of the rain gauge, its altitude and by comparing the location of landslide events, the algorithm reconstructs the rainfall event associated with it. The events are discarded if the landslide events are not occurring within a user-defined circumference around the locations of available rain gauges. The user can prescribe a lag time also, beyond which a rainfall event is not potent enough to trigger a landslide. 29 landslide events were considered by the algorithm for the analysis, which came within 15 km radius around the rain gauge considered for analysis. Statistical bootstrapping was used to find the uncertainty associated with threshold and with 5 per cent exceedance probability, event-duration threshold for Kalimpong was derived as

$$E = (4.2 \pm 1.3)D^{(0.56 \pm 0.05)} \qquad [2]$$

where E is the cumulated rainfall calculated from the start of rainfall event till the day of the landslide in mm and D is the duration in hours. These three thresholds were considered for the quantitative comparison by using rainfall and landslide data of the years 2016 and 2017.

## Results and Discussions

The results of all three models were simulated using the rainfall data of 2016-2017. The rainfall data was collected from the rain gauge maintained by Save The Hills at Tirpai, Kalimpong ("Save The Hills Blog"). Details of landslides were collected from the Geological Survey of India Reports, print media, field investigations (Dikshit and Satyam 2017) and field monitoring (Dikshit and Satyam, 2019).

Based on the occurrence or non-occurrence of landslides, it is evaluated whether the model predicted correct/incorrect results. The results can be of four types (Table 1). By using the conventional approach of the confusion matrix, the results are classified as True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). TP are assigned for days on which landslides occurred as predicted by the model. True Negatives are assigned to days without landslides as correctly predicted by the model. False Positives are used when model issue an unsafe condition and landslides did not take place. FN condition is used to identify days on which landslides occurred but the model failed to predict the landslide.

**Table 3.1: Classification of Model Predictions**

| Observations | | TP | FP | FN | TN |
|---|---|---|---|---|---|
| ID | (Dikshit and Satyam 2017) | 8 | 98 | 7 | 618 |
| Antecedent | (Dikshit and Satyam 2018) | 15 | 206 | 0 | 510 |
| ED | (Teja, Dikshit, and Satyam 2019) | 8 | 75 | 7 | 641 |

Some statistical attributes were derived using these four outputs, which quantifies the performance of each model as tabulated in Table 3.2.

**Table 3.2: Statistical Comparison of Rainfall Thresholds**

| Statistical Attributes | ID | Antecedent rainfall | ED |
|---|---|---|---|
| | (Dikshit and Satyam 2017) | (Dikshit and Satyam 2018) | (Teja, Dikshit, and Satyam 2019) |
| Sensitivity = TP / (TP + FN) | 0.53 | 1.00 | 0.53 |
| Specificity = TN / (FP + TN) | 0.86 | 0.71 | 0.90 |
| Efficiency = (TP + TN) / (TP + FP + FN + TN) | 0.86 | 0.72 | 0.89 |
| Likelihood ratio = Sensitivity / (1 – Specificity) | 3.90 | 3.48 | 5.09 |

It can be observed that out of the 3 models, only thresholds based on antecedent rainfall was able to predict all the landslide events correctly. ID and ED thresholds predicted 7 out of 8 shallow landslides occurred in 2016, but failed to forecast the slow movements happened in 2017. These models consider the effect of immediate preceding effects only and hence the long term effect of rainfall the resultant pore pressure generation is not considered. While in the case of antecedent rainfall thresholds, it forecasted all the landslide events during the validation time, but the number of false alarms is very high in this case. The term sensitivity measures the ratio of occurrences of landslides which are correctly identified. It is observed that the antecedent rainfall thresholds are having the highest value of sensitivity, i.e. 1. Similarly, the term specificity measures the days without landslides, which are correctly predicted by the model. Specificity is the maximum for the ED threshold and is the minimum for Antecedent rainfall thresholds. For a model to be used as a part of LEWS, it should have both sensitivity and specificity as 1. Hence it is important to analyze the efficiency and likelihood ratio of the models, which count the overall performance. Efficiency quantifies the ratio of correct predictions with respect to the total number of days. The ED thresholds are having a maximum efficiency of 89 Per cent. In case of landslide, predictions accounted for each day, the number of true negatives is usually of a higher order than the other variables. Hence the efficiency values are obtained as values close to one and the different models will have comparable efficiency values. To overcome this disadvantage, we use the term likelihood ratio, which is the ratio of sensitivity and (1-specificity). As this parameter considers the effect of sensitivity and specificity in a single value, this is a more reliable parameter for comparison. In this study, ED threshold is having the highest Likelihood ratio. Antecedent rainfall thresholds can be improvised by methods to limit the number of false alarms and can be used as a part of LEWS along with a rainfall forecasting system.

## Conclusion

A comparative analysis was carried out to determine the suitability of different rainfall thresholds defined for Kalimpong town in West Bengal. For the comparison purpose, a dataset of 2 years was used and three different models were quantitatively analysed and the statistical attributes were compared to obtain the best-suited model among them. The main findings from the study can be summarised as:

- Intensity-Duration and Event-Duration thresholds are useful for the prediction of shallow landslide events but they fail in forecasting the deep-seated movements which are the effect of long term rainfall.
- Antecedent Rainfall thresholds are correctly predicting both rapid and slow movements in the study area, but the model produces a very high number of false alarms, which reduces the overall performance of the model.
- The Event-Duration threshold is giving better performance among the models considered with an efficiency of 89 per cent likelihood ratio of 5.09.
- The performance of the models can be conceptually improved to reduce the number of false alarms to be used as a part of LEWS.

## References

Dikshit, A. and Satyam, N. (2018). "Estimation of Rainfall Thresholds for Landslide Occurrences in Kalimpong, India". Innovative Infrastructure Solutions 3 (1): 1-10. https://doi.org/10.1007/s41062-018-0132-9.

Dikshit, A. and Satyam, N. (2017). "Rainfall Thresholds for the Prediction of Landslides Using Empirical Methods in Kalimpong, Darjeeling, India". In JTC1 Workshop on Advances in Landslide Understanding. Barcelona, Spain.

Dikshit, A. and Satyam, N. (2019). "Probabilistic Rainfall Thresholds in Chibo, India: Estimation and Validation Using Monitoring System". *Journal of Mountain Science*, 16 (4): 870-83. https://doi.org/10.1007/s11629-018-5189-6.

Melillo, M., Brunetti, M.T., Peruccacci, S., Gariano, S.L., Roccati, A. and Guzzetti, F. (2018). "A Tool for the Automatic Calculation of Rainfall Thresholds for Landslide Occurrence". Environmental Modelling and Software 105: 230-43. https://doi.org/10.1016/j.envsoft.2018.03.024.

"Save The Hills Blog". http://savethehills.blogspot.com/. Accessed on August 20, 2019.

Sumantra, S.B. (2016). "Causes of Landslides in Darjeeling Himalayas during June-July, 2015". *Journal of Geography & Natural Disasters*, 6(2). https://doi.org/10.4172/2167-0587.1000173.

Teja, T.S., Dikshit, A. and Satyam, N. (2019). "Determination of Rainfall Thresholds for Landslide Prediction Using an Algorithm-Based Approach: Case Study in the Darjeeling Himalayas, India". *Geosciences* 9(7): 302. https://doi.org/10.3390/geosciences9070302.

Zhang, J. and Han, D. (2017). "Catchment Morphing (CM): A Novel Approach for Runoff Modeling in Ungauged Catchments". Water Resources Research 53(12): 10899-907. https://doi.org/10.1002/2017WR021403.