Abstract: The Himalayan region with its complex geological features, steep slopes, rugged topography, and intense monsoonal rainfall create ideal conditions for landslides. The damage caused due to landslides is immense causing significant loss of life and property initiating a dire need to formulate strategies in minimizing its impact in areas affected by landslides. Several attempts have been presented by various researchers in order to establish rainfall intensity thresholds using various parameters of rainfall conditions. These methods provide deterministic thresholds, i.e., landslide or no landslide; such thresholds are not always suited for landslides. In this paper, rainfall thresholds have been evaluated using a statistical method which results in the probability of landslide occurrence for single or multiple rainfall parameters leading to slide initiation. The results are expressed in terms of probabilities by analyzing two different variants of Bayes theorem, i.e., 1D and 2D. Probabilistic thresholds were calculated for Kalimpong region of Darjeeling Himalayas using available rainfall and landslide data during the year 2010–2016. The probabilities calculated for landslide occurrence were found to be 0.37 for rainfall intensity greater than 10 mm/day. However, the probability for a combination of rainfall intensity of 30 mm/day with duration of 3 days was calculated to be 0.67. The results also depicted that landslides are related to rainfall event parameters especially with rainfall intensity.

Subjects: Civil, Environmental and Geotechnical Engineering; Soil Mechanics; Georisk & Hazards

Keywords: landslides; early warning; rainfall thresholds; Darjeeling Himalayas; probabilistic method

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PUBLIC INTEREST STATEMENT
The increase of landslide incidences in the Himalayan region has led to the development of various kinds of study with an aim to set up an early warning system. The aim of the present work is to understand the effect of rainfall parameter to landslide triggering in terms of probabilities. This would help in determining the most important rainfall parameter and thereby devise strategies with an aim to save human lives. Such a study has rarely been conducted for Indian Himalayan region and hope it would encourage further research on various other regions.
1. Introduction

Landslides triggered by incessant rains have been havoc in Indian Himalayas claiming several lives and displacing thousands of people besides damaging crops, properties, and all means of communication. The number of deaths caused due to landslides stands third among the natural disasters. The Himalayan region accounts for 30% of the worldwide occurrence of landslides. Estimates indicate loss of land due to slides is up to 120 m per km per year leading to yearly soil loss of about 2,500 t per sq. km (NDMA report, 2011). Kalimpong is a hilly region situated in West Bengal state, India, and is heavily affected by landslides. Most of the landslides are triggered during the monsoon season of June and October.

Rainfall-induced landslides originate due to the increase of pore water pressure in soil (Campbell, 1975; Wilson & Wieczorek, 1995). The reasons for an increase in pressure or changes in moisture content in soil are responsible for landslides (Wilson & Wieczorek, 1995). Landslide prediction becomes difficult if the properties of soil parameters and slope conditions change greatly over short distances which make it impossible to forecast the timing, location, and intensity of triggering events. Apart from heterogeneity of soil, the other challenging factor is to analyze the mechanics of groundwater flow and the development of instability along with stability models (Wieczorek & Guzzetti, 2000). The actual failure of a slope is complicated involving numerous causes which influence hydrologic behavior and the shear stresses involved. Therefore, a direct relation between rainfall and slope failure is difficult to formulate. Several studies have been done all over the world to develop relation between rainfall thresholds and landslide incidences using empirical, hydrological, or physical (process-based) models (Capparelli & Versace, 2011; De Luca & Versace, 2017). The physical rainfall threshold models combine slope features, soil characteristics along with a steady or transient groundwater flow model (Baum, Savage, & Godt, 2002; Chen & Zhang, 2014). Physical models integrate hydrological models for a simplified description of the dynamics of infiltration and saturation phenomena, together with geotechnical approaches for the stability analysis. Physical models usually attempt to account for infiltration and vertical movement of water into the ground surface, for modeling the longitudinal trend of groundwater.

Several rainfall thresholds have been devised using empirical models which correlate antecedent rainfall with landslide occurrence. The rainfall threshold relationship is fitted to an empirical equation $I = \alpha D^\beta$ (where $I$ is the rainfall intensity [mm/h], $D$ is the rainfall duration [h], $\alpha$ is a scaling parameter [the intercept], and $\beta$ is the shape parameter that controls the slope of the power law threshold curve). Several rainfall thresholds for Indian Himalayan scenario have been proposed (Dikshit & Satyam, 2018; Kanungo & Sharma, 2014), using the threshold equation for local, regional, and global scales. However, since rainfall is not the only factor which causes slides, a certain extent of uncertainty is inevitable for calculation of rainfall thresholds (González & Caetano, 2017). The accuracy of empirical thresholds is restricted with the availability of rigorous rainfall and landslide data. Lack of data may increase uncertainty in determining thresholds using empirical methods. Moreover, the results using empirical approach can be impacted due to several factors like the rainfall data resolution, rain gauge location including the landslide timing and location. In order to overcome the limitations, Bayesian approach is used to determine the probability of landslide occurrence with respect to rainfall event characteristics. The study area is Kalimpong town in Darjeeling Himalayas in the state of West Bengal which has a history of landslides caused mainly due to rainfall.

2. Methodology adopted

Limit or threshold is characterized as the base or most extreme level of some amount required for a process to happen or a state to change (White, Mottershead, & Harrison, 1996). For precipitation instigated landslides, a threshold represents the minimum intensity, the minimum level of pore water pressure, soil moisture, slope angle, decrease in shear strength, or displacement required for a landslide initiation (Guzzetti, Peruccacci, Rossi, & Stark, 2007; Wilson & Wieczorek, 1995).
Figure 1(a) describes deterministic precipitation thresholds where there is a distinct isolation amongst triggering and non-triggering precipitation for slide initiation. Deterministic thresholds support a binary decision either 0 (no landslides) or 1 (landslides occurred) which in most cases the distinction isn’t inconsequential (Figure 1(b)). The reasons for landslide initiation are complex and are usually controlled by a combination of precipitation parameters and factors such as soil moisture, pore pressure distribution, soil type, and field stress affect landslide occurrence (Berti et al., 2012). Likelihood-based techniques are worthwhile as they coordinate different precipitation parameters and uncertainty giving a quantitative appraisal and better estimating of threshold limit unlike the definitive forecast of deterministic methods (Berti et al., 2012). Therefore, if the output is not limited to either failure or no-failure condition for a given rainfall event, deterministic approach is not relevant and probabilistic model should be used.

While analyzing probability, there may be several cases where a single rainfall event could cause multiple landslides in the same area. Multiple cases of landslide due to single rainfall event can also be considered using Bayesian analysis by adding another variable which counts the number of landslides triggered due to each rainfall event. However, multidimensional analysis is confined due to insufficient data and its pertinence in practical applications is limited. Generally, the landslide probability is directly proportional to the extent of the area, i.e., with increase in the area leads to increase in landslide incidence.

2.1. One-dimensional Bayesian probability

Conditional probabilities are computed using Bayes’ theorem which would determine the probability of landslide occurrence caused due to rainfall expressed in terms of total rainfall, intensity, or duration. Conditional probability is given as $P(A|B)$ which means “probability of landslide occurrence ($A$) due to a particular rainfall parameter ($B$)” and is determined by the Bayes’ theorem as

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

- $P(B|A)$ = conditional probability of $B$ given $A$, i.e., probability of rainfall event of magnitude $B$ when a landslide happens.
- $P(A)$ = probability of landslide occurrence despite the rainfall event of magnitude $B$ occurs or not.
- $P(B)$ = probability of rainfall of magnitude $B$, whether a landslide happens or not.
- $P(A|B)$ = conditional probability of $A$ given $B$, i.e., probability of a landslide occurrence when a rainfall event of magnitude $B$ happens.

Let the number of rainfall events during a time period be $N_R$; number of landslide occurrences during the same time period be $N_A$, number of rainfall events of magnitude $B$ be $N_B$ and the number of rainfall events resulting in landslides be $N_{B|A}$, then the terms in Equation (1) can be expressed as
\[ P(A) = \frac{N_A}{N_R} \]  \hspace{2cm} (2)

\[ P(B) = \frac{N_B}{N_R} \]  \hspace{2cm} (3)

\[ P(B|A) = \frac{N_{B|A}}{N_A} \]  \hspace{2cm} (4)

In general, probabilities would help in determining the likelihood of landslides. The choice of variables in one-dimensional analysis depends on parameters which are the key reasons for slide initiation, for our study variables considered are event rainfall, rainfall duration, and rainfall intensity. A full description of the approach briefly summarized here can be found in Berti et al. (2012).

2.2. Two-dimensional Bayesian probability

Two-dimensional Bayesian probability estimates the conditional probability of event for joint occurrence of two parameters considered.

\[ P(A|B, C) = \frac{P(B|C, A)P(A)}{P(B, C)} \]  \hspace{2cm} (5)

where \( B, C \) denotes combined probability of having a certain or range of value of any two variables. If \( B \) equals rainfall intensity and \( C \) is rainfall duration, the probability of landslide occurrence due to rainfall event of given duration and intensity is expressed using Equation (5). Any pair of precipitation parameters for likelihood of landslide occurrence can be calculated using two-dimensional Bayesian probability (e.g., rainfall intensity, total event rainfall, and rainfall duration), and their significance can be analyzed by comparing landslide probability with prior landslide probability \( P(A) \). Bayes method can likewise be utilized for multidimensional analysis with \( n \)-variables like joined impact of rainfall duration, rainfall intensity and groundwater conditions to evaluate probability of landslide occurrence.

3. About the study area

Darjeeling and Sikkim Himalayas cover more than 40% or 0.18 million sq. km of landslide prone areas in India (Geological Survey of India [GSI]). The focus of study was Kalimpong region in Darjeeling Himalayas situated in West Bengal state with an average elevation of 1,247 m comprising 1,056 km\(^2\) (Figure 2). It is situated on a curved ridge surrounded by Teesta river in the west central and Relli river in the east (Dikshit & Satyam, 2018). About half of the region is covered by moderately steep to steep and very steep slopes (>25\(^\circ\)) and 32% of the study area is represented by high relief (>300 m). Landslides in this region are primarily caused due to poor lithological quality, erosion of river Teesta at the toe and its tributaries and high intensity of rainfall during monsoon (Chatterjee, 2010). The report by GSI, 2016 identified that 75% of the landslide occurrences in this region during 2006–2013 was triggered by rainfall. Geologically, the region comprises moderately to highly weathered chlorite schist, phyllite, phyllitic quartzite belonging to Gorubathan Formation of Daling Group. The rocks are variably altered and are generally covered by a thin to thick heterogeneous debris material (Dikshit & Satyam, 2018). The soils in the region are generally reddish with intermittent presence of dark soils composed mainly of phyllites and schists. The soil comprises a high percentage of gravel, sand, and silt and varies from rock outcrops to coarse loamy to fine loamy. The eastern side of the Teesta river mostly comprises sandy soils with soil characteristics varying from coarse to rocky with the increase in elevation (Dikshit & Satyam, 2018). The region comprises several cracks, joints which increases the probability of decomposing and disintegrating the rock to form unconsolidated matter.

3.1. Landslides in Kalimpong

Majority of landslides in this region is due to heavy rainfall and untrained water streams known as jhoras in the region (Dikshit & Satyam, 2018) which loosens up the soil by breaking of bonds and particle disintegration causing sloped surface area to be fully saturated causing landslides. Due to rainfall, soil absorbs water which increases the burden on soil by rise in pore water pressure thus increasing the probability of landslides. Landslides are triggered by seepage of water in joints and cracks and facilitate the soil/debris to slide downward due to gravity. In addition to rainfall, a
network of small rivers of various orders significantly drains the area. There are majorly five subbasins present in the region which flow down as tributaries of Teesta river. Figure 3 represents the drainage map of the area. The complete basin comprises first order which joins to form second and higher order streams (Dikshit & Satyam, 2018). Oftentimes the first order streams disappear from some location in the hill and then reappear down slope. The major streams are mostly perennial supported by the rainwater which percolates ground water. Heavy rainfall, especially during monsoon, enables these streams to flow with great vigor causing them to carry small pebbles to huge boulders. The increase in the use of concrete and asphalt for construction activities in upper parts of hill forbid rainwater percolation into soil draining out the excess rainwater as surface runoff. The absence of planned drainage system in the new built up areas allows the rainwater to find passage into any of the natural tributaries eventually feeding the major streams. This causes intense lateral and headward erosion resulting into successive bank failures mostly in the form of large landslides (Chakraborty, Ghosh, Bhattacharya, & Bora, 2011).

3.2. Rainfall and landslide data
For the present study, daily rainfall values for 2010–2016 were used for the analysis (Figure 4). The measurement of rainfall for landslide investigations should be site specific to each slope failure but since this area is largely ungauged, the rain gauge at Teesta was taken as reference. Total of 214 rainfall events occurred between 2010 and 2016.

Landslide data were prepared from published literature along with local newspaper reports and reports from nongovernmental organizations. The landslide information included the location and rainfall triggering date. The landslide inventory map showing the locations of the landslides, based
4. Application of Bayesian approach in the present study

One-dimensional analysis is used to compute probability of landslide occurrence when a certain amount of rainfall event occurs. It calculates the relation of a variable $B$ for a certain event $A$. For the present study, $A$ represents landslide occurrences and $B$ represents any parameters which on which the model has been assessed, is depicted in Figure 5. The majority of the landslides are concentrated over $27^\circ 4^\prime 30^\prime\prime$ N and $88^\circ 28^\prime 30^\prime\prime$ E whereas the rest are scattered.
describes rainfall event, such as rainfall duration or intensity. As discussed in Section 2.1, the correlation between landslide probability $P(A|B)$ and prior landslide probability $P(A)$ indicates significance of $B$ for occurrence of event $A$ (Berti et al., 2012).

4.1. With one-dimensional Bayesian probability
The methodology was applied to Kalimpong region with the procedure explained in Section 2.1. Rainfall probability $P(B)$ is calculated for $N_R = 214$ rainfall events occurred between 2010 and 2016, and the conditional probability $P(A|B)$ is calculated for $N_A = 36$ rainfall events that triggered landslides. $P(A) = N_A/N_R = 36/214 = 0.17$. $P(B|A)$ is calculated by considering various rainfall intensity values, for rainfall intensity greater than 50 mm per day, $P(B|A) = P(I > 50|A)$. Similar analysis was conducted for various intensity ranges ($0 \leq I < 50$, $50 \leq I < 100$, $I > 150$ mm/day) and the landslide probability is represented using histogram.

Out of 214 rainfall events occurred in the study period, 58 rainfall events and 23 landslide events occurred for intensity between 0 and 50 mm/day, $P(B) = 58/214 = 0.27$ (Figure 6(e)). Probability of landslides is given as $P(A|B) = P(A|I < 50) = 0.29 \times 0.14/0.27 = 0.145$ (Figure 6(f)). The increase in dissimilarity between $P(B|A)$ and $P(B)$ indicates increase in probability of landslides and high significance of variable used (Berti et al., 2012).

The probabilities calculated considering various rainfall parameters are depicted in Figure 6. The graphs on left compare frequency distributions of triggering rainfall against total rainfall, that is $P(B|A)$ against $P(B)$. The ratio of probabilities multiplied with $P(A)$ provides probability of landslides $P(A|B)$ depicted on right side. The results in Figure 6 indicate that rainfall parameters like cumulative rainfall, duration, and intensity are very important for determining landslide probability. In each case, the probabilities $P(B|A)$ and $P(B)$ are distinct and the computed landslide probability is greater than prior probability $P(A)$. Rainfall intensity among other variables is the most used and significant variable for threshold calculation, having probability as high as 0.37 for intensity greater than 10 mm/day.
Landslide possibility increases with extremity of rainfall parameters like increase in rainfall amount, duration, or intensity even though the increase may be uneven due to irregular distribution of data. However, at the peak values of the parameters considered landslide probability decreases (Figure 6(a–f)). This uncommon trend is generally due to two reasons. First, calculated probabilities of such severe events are affected due to low sample sizes. Samples with little data are less informational and a little variation in the recorded number of landslides would result in very different probability. In order to understand the impact of such uncertainty, the difference between $P(\text{A}|\text{B})$ and $P(\text{A})$ is depicted to understand the significance of the considered variable.

**4.2. With two-dimensional Bayesian probability**

The landslide probability (two-dimensional probability) increases with both rainfall duration and intensity, but intensity affects the landslide probability more as shown in Figure 7. The highest value of probability of 0.67 reaches for rainfall events for duration of 3 days with an intensity of 30 mm/day and also for rainfall of 4 days with intensity of 20 mm/day. The importance of such analysis can be understood from the fact that even a small probability cannot be neglected for vulnerable areas and has to be analyzed with the risk associated for each probability.
The two-dimensional approach is more reliable compared to one-dimensional as it involves a combination and also determines the most important parameter. As the results for one-dimensional signify that the rainfall intensity is the most important parameter, however when considering two dimensional, it shows that apart from rainfall intensity, rainfall duration also plays an important part. The analysis also suggests that the use of two dimensional can be beneficial if the sample size is large as determining probabilities from small sample size can lead to contrasting results with a small change.

5. Results and discussions
Probabilities were calculated for landslide occurrences using various rainfall parameters like rainfall intensity, event rainfall, and rainfall duration. In case of event rainfall, the probability variations are 0.35, 0.45, 0.60, 0.80, 0.70, 0.24 for 50, 100, 150, 200, 250, and 300 mm of event rainfall, respectively (Figure 6(a and b)). Similarly, in case of rainfall duration, the probabilities of landslides are 0.02, 0.025, 0.24, 0.17, 0.18, 0.08, 0.25, 0.175, and 0.98 for 1, 2, 3, 4, 5, 6, 7, 8, and 9 days of rainfall, respectively (Figure 6(c and d)). Figure 6(e and f) depicts that in case of rainfall intensity, probabilities are 0.38, 0.19, 0.12, 0.08, 0.07, 0.16, and 0.02 for 10, 20, 30, 40, 50, 60, and 70 mm rainfall intensity, respectively. In case of two-dimensional probabilities, the probabilities achieved highest value of 0.67 for rainfall of duration 3 days with an intensity more than 30 mm/day whereas lowest value of 0.10 for rainfall duration of 1 day with intensity of 10 mm/day (Figure 7).

6. Conclusions
Though various methods have been proposed in literature of the present paper to relate rainfall threshold with landslide occurrence, such approach may not always be helpful to understand the effect and to forecast landslides as it only considers the rainfall which resulted in landslides. The important question which arises using such methods is the effect of rainfall which did not result in...

Figure 7. Histogram of landslide probability as a function of rainfall duration and intensity.
landsides and its interdependency with various rainfall parameters. In order to overcome this limitation, Bayesian methodology was used which considers all the rainfall aspects and provides more clarity on landslide occurrence. The analysis was carried out for a period of 7 years (2010–2016) using various rainfall parameters including duration, intensity, and event rainfall. The probabilities for landslide occurrences were determined using two approaches (one-dimensional and two-dimensional). The former approach uses a single rainfall parameter whereas the latter uses a combination of two rainfall parameters. The conclusions from the study are as follows:

1. The results signify that probability of landslide occurrence is 0.37 for rainfall intensity greater than 10 mm/day for one-dimensional case and 0.67 for rainfall of duration 3 days with intensity more than 30 mm/day for two-dimensional case.

2. The use of two-dimensional approach provides a better understanding of the landslide incidents compared to one dimensional. However, it would depend on the richness of the data. Samples with little data are less informational and a little variation in the landslide information would depict contradictory probability.

3. The use of probabilistic approach over deterministic methods is a better alternative to set up an early warning system for landslide affected areas and can be used as a first line of action.

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