B.TECH. PROJECT REPORT

ON

Analysis of rainfall induced landslides in parts of Western Ghats, India

By:

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DISCIPLINE OF CIVIL ENGINEERING

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Analysis of rainfall induced landslides in parts of Western Ghats, India

A PROJECT REPORT

Submitted in partial fulfillment of the requirements for the award of the degree of Bachelor of Technology

in the

Discipline of Civil Engineering

Submitted by:
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Declaration of Authorship

I hereby declare that the project entitled **“Analysis of rainfall induced landslides in parts of Western Ghats, India”** submitted in partial fulfillment for the award of the degree of Bachelor of Technology in the Discipline of Civil Engineering and completed under the supervision of **Dr. NEELIMA SATYAM**, Associate Professor, Discipline of Civil Engineering, IIT Indore is an authentic work and I have used the original content from my research paper submitted and published during the period of this project .

Furthermore, I declare that we have not submitted this work for the award of any other degree elsewhere.

Signature:

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Date:

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Certificate

This is to certify that the thesis entitled "**Analysis of rainfall induced landslides in parts of Western Ghats, India**" and submitted by Pothuraju Deekshith, Roll No. 160005024, in partial fulfillment of the requirements for CE 493 B.Tech Project embodies the work done by him under my supervision. It is certified that the declaration made by the student is correct to the best of our knowledge.

Supervisor

Dr. NEELIMA SATYAM

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Date:

"An investment in knowledge pays the best interest."

Nelson Mandela

Abstract

Analysis of rainfall induced landslides in parts of Western Ghats, India

Idukki is a district in the Southern part of India in the state of Kerala, which is extremely susceptible to landslides. It is mostly comprised of hilly areas which is a center for an extensive diversity of flora and fauna, has been badly suffering due to the slope stability issues caused because of heavy precipitation. For this region a properly established landslide early warning system is in the need of the hour, bearing in mind the recent past i.e. the landslide disasters in the years 2018 and 2019. This research is an effort to define a regional scale rainfall threshold with help of various methods like empirical, probabilistic, algorithm-based models for landslide incidences in Idukki district, as the primary step of establishing a landslide early warning system. With the use of the rainfall and landslide data catalogue from 2010 to 2018, an intensity-duration threshold was found as $I = 0.9D^{-0.16}$ for the Idukki region of Kerala state. In activation landslide events the effect of the antecedent precipitation situations was explored in detail with the concept of cumulative rainfalls of 3 days, 10 days, 20 days, 30 days, and 40 days preceding the failure. As there is an increase in the number of days preceding the landslide, the landslide events distribution shifts in the direction of antecedent rainfall conditions.

When the number of days was increased from 3 to 40, the biasness amplified from 72.12% to 99.56%. In probabilistic method, using the Bayes theorem the probabilities (1-D &2D) are expressed after analyzing one or two variants of rainfall parameters namely intensity, rainfall, duration. Probabilistic thresholds are derived for the study region using available rainfall and landslide data during the year 2010–2018. It was established that for an intensity of 45mm/day the probability of the occurrence of a landslide is 0.45 and for an intensity of 30mm/day lasting up to 12 days the probability of the occurrence of a landslide is 0.50. Using the algorithm-based method the E-D threshold was established as $E = (1.7\pm0.4)D^{(0.66\pm0.01)}$. The derived equations and probabilities can be used along with a rainfall forecasting system for landslide early warning in the study region.

Keywords: rainfall thresholds; landslides; Idukki; early warning system

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List of Abbreviations

• **I**	**I**ntensity
• **D**	**D**uration
• **E**	**E**vent Rainfall
• **I-D**	**I**ntensity-**D**uration
• **E-D**	**E**vent Rainfall-**D**uration
• **E-I**	**E**vent Rainfall-**I**ntensity
• **CTRL-T**	**C**alculation of **T**hresholds for **R**ainfall **I**nduced **L**andslides - **T**ool
• **ERT**	**E**lectrical **R**esistivity **T**omography
• **IMD**	**I**ndia **M**eteorological **D**epartment
• **GSI**	**G**eological **S**urvey of **I**ndia
• **KSDMA**	**K**erala **S**tate **D**isaster **M**anagement **A**uthority
• **MRC**	**M**ultiple rainfall Conditions
• **MPRC**	**M**aximum probable rainfall condition

Dedicated to all my teachers and my wonderful parents, for inculcating into me the love for ventures into the scientific unknown, and for placing unwavering belief in me.

Chapter 1

Introduction

1.1 Background

The state of Kerala (India) confronted with the worst disaster in its history in 2018. While 433 lives were lost the disaster affected nearly 54 lakh people [1,48]. Numerous landslides, predominantly debris flows, were related with the adversity. It was observed that 13 out of 14 districts in the state are part of the Western Ghats and are susceptible to to landslide mishaps. The escarpments of the Western Ghats, which are the precipitous parts, are more vulnerable to landslides due to heavy precipitation. Efforts have been made by scholars to study the activating factors of landslides in the Himalayas [2,8,48] and the Western Ghats [9,10,48]. Though, on a regional scale, laying out rainfall thresholds for the incidence of landslides in the region of Western Ghats has not been tried yet. This study is an effort to define a regional threshold for the Idukki district (Kerala) which has a very high probability for landslide incidence in the Western Ghats. A rainfall threshold can be developed or established using empirical, process-based, algorithm-based, probabilistic methods. The process-based tactic takes in to account the physical and hydrological constraints which can lead or result in a landslide event. This has a requirement of highly cultured inputs, as the spatial and temporal scattering of these parameters can be analyzed and examined only through complete site-specific studies [11,48]. Due to the boundaries of defining the process-based thresholds, this research defines the rainfall conditions that when exceeded, are likely to commence landslide events in the Idukki district in the Western Ghats.

1.2 Empirical Approach

Empirical approach predominantly focuses on the happenings of rainfall and landslide events. Empirical thresholds can be categorized into three: (1) thresholds which uses rainfall information for some specific events, (2) thresholds which take into account rainfall conditions prior to failure, and (3) all others which contain hydrological thresholds [12]. In the present research, thresholds for the first two categories are acquired for Idukki using past rainfall and landslide data. A rainfall event is defined by three parameters, namely rainfall intensity, rainfall duration, and rainfall event. Cumulated rainfall is the total amount rainfall from the commencement of the rainfall event to the happening of failure [13,48]; the term duration specifies the precipitation period or the duration of the rainfall event considered; rainfall intensity is the amount of precipitation in a given time span, i.e., the rate of precipitation over the considered period [14,48]. Thus, the term rainfall intensity gives a notion of the average rate of rainfall during an event, not the highest intensities. Another significant factor which plays a vital role in the applicability of the threshold is the area that is considered for the study of the research. Based on the zone, thresholds are classified into local, regional, and global. The consistency of the slopes depends upon the hydro-meteo-geological constraints or parameters of the area and the conditions for the activation of landslides vary from region to region. Global thresholds give a universal minimum, below which probabilities of landslide happening is zero, not taking into account any physical factors. Regional thresholds are concerned with zones of a few to some thousands of square kilometers where physiographic, meteorological and climatic features are alike. Local thresholds can be implemented to one or a small cluster of landslides in areas of sizes up to the series of hundreds of square kilometers. Regional and local thresholds do well for the zone they were established for, but they cannot be transferred to other areas effortlessly [16,48]. These thresholds can be used in regional/local cautionary systems for giving an alert level to the government and community in common.

Empirical thresholds can be categorized again based on the rainfall parameters used as total rainfall event-duration (ED) thresholds, intensity-duration (ID) thresholds, and total rainfall event-intensity (EI) thresholds [12,48]. A common, well-accepted contract which controls the selection of rainfall parameters is that shallow/rapid landslides are commenced by rainfalls of high intensity and short duration and deep-seated landslides happen when it rains constantly over a long time [17,48]. This study emphasis on the commencement of shallow landslides which result in maximum fatalities during the monsoon period in the region and henceforth thresholds established on intensity-duration plane and antecedent rainfall are established for Idukki. The aim is to begin the initial steps towards an effective and actual regional scale alert system for the Idukki district.

1.3 Probabilistic Methods

Many rainfall thresholds are devised with the concept of empirical models which compare antecedent rainfall and landslide occurrence. The threshold is established using rainfall parameters being fitted into an empirical equation of the form $I = \alpha D^{-\beta}$ (where I is the rainfall intensity [mm/h], D is the rainfall duration [h], α is a scaling parameter [the intercept], and β is the shape parameter of the power law threshold curve which controls the slope) [2]. Various rainfall thresholds in many cases have been proposed and established, with the help of the threshold equation for global, regional and local scales [12]. However, since rainfall is not the only driving factor for the occurrence of slides, uncertainty to some extent is inevitable for the calculation of rainfall thresholds. Non-availability of rigorous data of rainfall and landslides will affect the accuracy of empirical thresholds. Deficiency of data can increase the uncertainty in determination of thresholds using empirical methods [3,4,6].

Moreover, the results obtained from the empirical approach may be impacted due to several influences like the rainfall data resolution, rain gauge location along with the time of occurrence of landslide and location. So as to overcome the limitations, Bayesian approach can be used to establish the probability of occurrence of slides with the use of rainfall event characteristics [6,47]. The study area is Idukki district in the state of West Bengal which has a past of landslides triggered primarily due to rainfall.

1.4 Algorithm-based Approach

Relating the rainfall conditions and landslide information is mostly done with the help of statistical analysis. Statistical methods can be used to determine a limiting threshold in 2d planes, namely I-D (Intensity Duration) plane and E-D (Event rainfall Duration) plane [46]. However, there are a few downsides with its use: (i) input data quality and it's availability , which might end up in increasing the uncertainty ; (ii) defining and identifying the corresponding rainfall event, which emphasized a general fault of the outdated rainfall threshold methods is the bias of the investigation, which results in not being able to replicate the investigation, and the valuation of the rainfall event in actual, i.e., the authentic quantity of precipitation accountable for the causing of slide[46,50]. So as to overcome such hurdles, researchers creating and developing methods for a particular and an unbiassed description of empirical rainfall presented numerous novel approaches to come over these glitches by developing and launching thresholds which can be used for early warning system. Researchers developed an automated system or model to reconstruct rainfall conditions which are accountable for the triggering of events and determination of thresholds with the help of rain-gauge as well as satellite data.

Cluster scrutiny practice has been implemented to analyze precipitation thresholds and give the factor for safety to establish or develop a system of early warning [34]. Lately, the usage of machine learning and artificial intelligence methods are likewise being used to predict and forecast landslides. The research based on the concept of threshold estimate in the western Ghats is negligible and is restricted to defining the intensity-duration (ID) thresholds. The estimation of threshold in the Idukki region is short of the use of the neutral or objective definition, which is crucial for thresholds, for better forecasting and predictability of landslides. For the current research, rainfall thresholds are established for the Idukki Region with the help of a semi-automatic empirical approach, which is called the Calculation of Thresholds for Rainfall-Induced Landslides-Tool (CTRL-T) [50], using the catalogue of data of rainfall and landslide records from 2010–2018 [46]. The tool uses an algorithm to reconstruct rainfall triggering conditions and practices statistical approaches to give the cumulated event rainfall-rainfall duration thresholds and quantify the amount and scale of uncertainty.

Chapter 2

Study Area

In the state of Kerala, Idukki district was the worst-hit district during the 2018 calamity, with 143 major landslides in the state government records [1]. As revealed in the slope map of Idukki, the geography of the area consists of slopes as precipitous as 80 degrees and the elevation can range up to 2692 m. A major share of the population of the district Idukki had houses in these unstable slopes, which were damaged and destroyed in the 2018 landslides regardless of the building typology. 97% of the major thoroughfares in the districts cut through the rugged mountains and hills, which are often impassable due to landslides in the monsoons [18]. Sprawling across an area of 4358 km2, Idukki is the supplier for 66% of the electric power requirements of Kerala [19]. This district which is majorly covered by forests is the second largest one in terms of area in the state of Kerala.

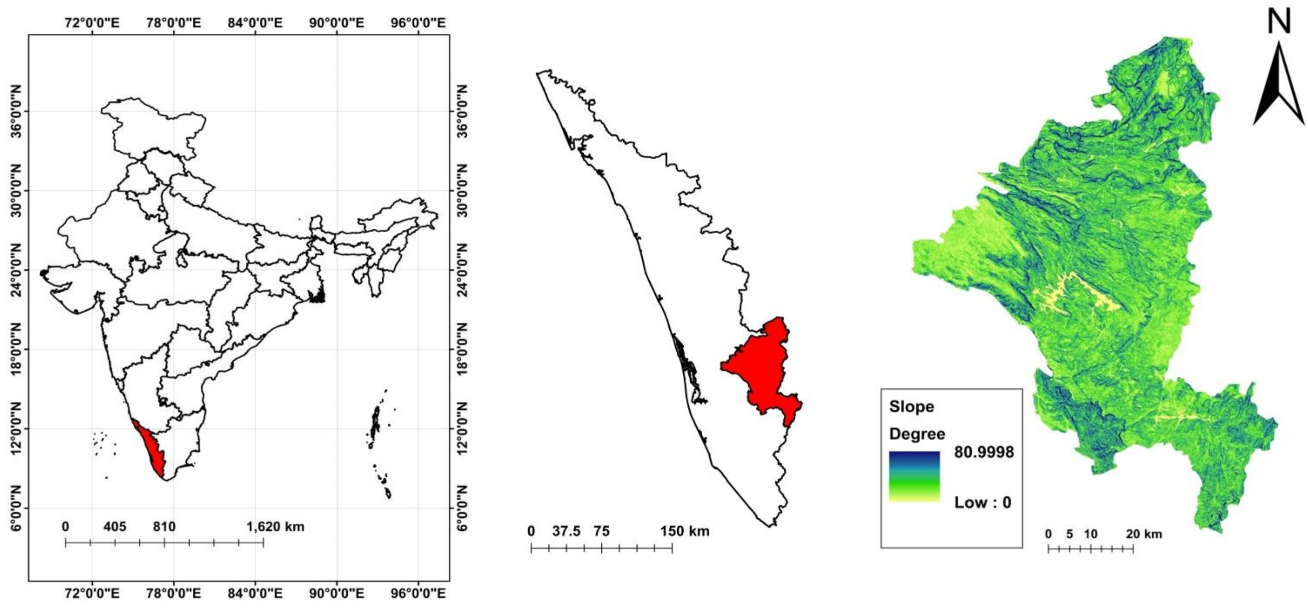


Figure 1 Location and slope map of the Idukki district.

The Western Ghats can be divided into two sections as north and south, which are separated by the Palghat Gap. Deep-seated landslides are recorded in the northern flank and the eastern segment while the southern section mostly experiences shallow landslides. Idukki belongs to the southern part of Kerala, where regolith thickness ranges from 0.25–5 m [21] and is vulnerable to shallow landslides [20]. Geomorphic classification of the terrain divides the area into four namely rugged hills, ridges and valleys, fringe slope, and plateau [22]. Escarpments of the Western Ghats consist of frictional soil which has less cohesion, hence being stable during the dry conditions and losing their strength when the moisture content increases. Plateau regions have a thicker layer of top soil, abundant in clay content due to their morphology and tropical climate. Geologically, rocks of Wayanad, Charnockite, Khondalite, and Migmatite groups play a role in the formation of a part of South Indian Precambrian metamorphic shield [22]. The foremost weathering process is hydrolysis in the area, which is due to the high precipitation [24].

2.1 Triggering Factors

The Escarpments of the Western Ghats encounter a yearly rainfall as high as 5000 mm as a result of the southwest monsoon, northeast monsoon, and pre-monsoon showers [25]. The Western wing of the Western Ghats encounter landslides during the southwest monsoon while the eastern side is influenced mainly during the northeast monsoon.

Figure 2. Damages that happened due to landslides in the Idukki district in 2018. (a) Debris slide at Anachal. (b) Debris flow at Kallimai. (c) Subsidence at Kallarkutty approach road. (d) Earth slide at Cheruthoni [22].

Huge amounts of high-intensity rainfalls increase the water pressure in the pores of the soil masses, which eventually results in the decrease of the shear strength of the soil. This is deemed as the primary factor for the triggering of landslides in the Indian Himalayas [2,4,26] and The Western Ghats [27]. The crevices in the bedrock siphons the surplus rainwater to unstable zones in the slopes during the monsoon [28]. Visuals of some of the landslides which took place during the 2018 monsoon are shown in Figure 2. The population of this region grew rapidly after the 19th century, as the people from the midlands started migrating into the hilly region [29]. The industrially backward district was in search for better infrastructure due to an enlargement in population. As a result, the land usage has changed significantly in a short time period, which supported the occurrence of landslides in the area. Wide reaching hill-toe modifications have been done in the district in recent decades for the motive of infrastructure development, due to which the hill slopes have become precipitous, without the lateral support. The terraced slopes, altered for monoculture plantations with no adequate drainage provisions, aggravated the framework. Due to the drain blockages, water from the intense rainfall collects in the top soil layers, resulting in landslides.

In a complete landslide record of Kerala until 2010, organized by the Geological Survey of India (GSI), 64 major cases were reported in the district of Idukki [30]. The landslide typologies differ from creep and subsidence to wreckage flows and avalanches. Along the major thoroughfare corridors of the district, earth/debris slides have become frequent during monsoon period [18]. The sharp turns and vertical cuts along the thoroughfares are highly vulnerable to cut-slope failures. Unceasing rainfall and the subsequent pore pressure increase adversely affects the steep slopes and outcomes in landslides. To wind up, from the case studies showed by GSI, a major portion of the events in Idukki are of debris flow

2.2 Database for Analysis

Structuring a chronology of landslides established on the historical records is the primary stage of any landslide menace study [33]. A landslide catalogue for the research has been established taking inputs from the Geological Survey of India (GSI) [22], newspapers, state government reports [1,34], and from communications with the people of the zone. The dates of commencement of landslides were gathered with a weekly exactness, and with a spatial accuracy of nearest mentioned site the locations were collected from the reports. The data catalogue consists of the spatial (Figure 3) and temporal distribution of landslides and the typology. From four rain gauge stations in the Idukki district, upheld by the India Meteorological Department (IMD) [36], the rainfall data used for the model is collected every day from the year 2010. The places of rain gauge stations are given in Table 1. The monthly scattering of effective rainfall in the Idukki district from 2010 to 2018 is shown in the box plot shown in Figure 4.

The distribution of rainfall is non-uniform throughout the district of Idukki. In a longstanding rainfall analysis led by GSI, it was marked that the average annual rainfall fluctuates from 1000 mm in the northeast regions of Anamudi peak to nearly 5000 mm near Peermedu [18]. The four rain gauges from where the data was collected are located at Thodupuzha, Peermedu, Idukki, and Munnar (Figure 3).

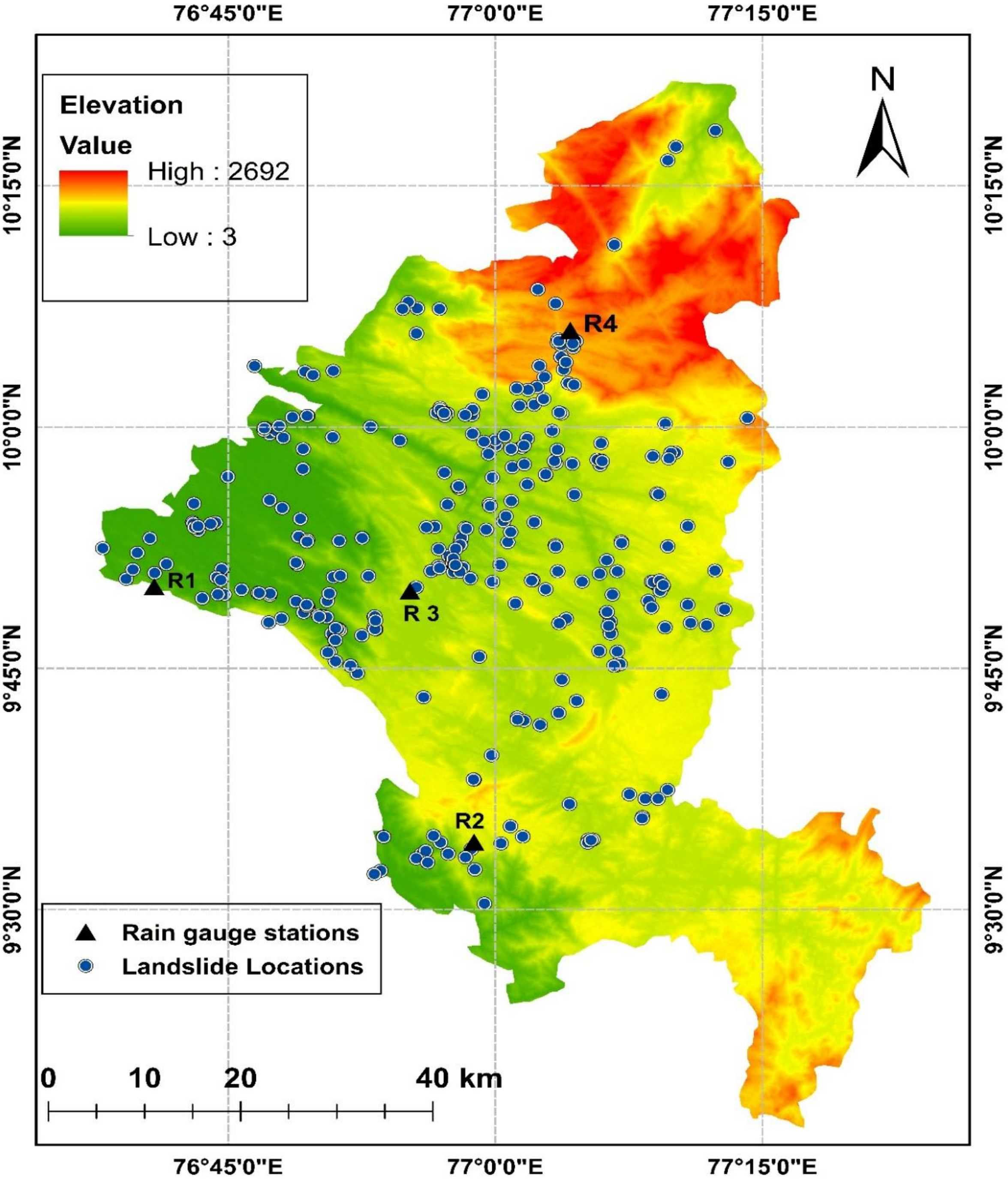


Figure 3 Digital Elevation Model [35] of the Idukki district along with the spatial distribution of landslide locations and rain gauge stations (2010–2018).

The district average and the disparity of annual rainfall from the four rain gauges is plotted in Figure 5.

The variances in rainfall conditions will lead to under -estimation or over-estimation of the strength and duration values if we take in consideration the average rainfall. Hence the rainfall occurrence linked with each landslide was found out grounded on the spatial distribution of the four rain gauges [37].

Rain Gauge Number	Place	Location
R1	Thodupuzha	9.83N, 76.67E
R2	Peermedu	9.57N, 76.98E
R3	Idukki	9.83E, 76.92E
R4	Munnar	10.10N, 77.07E

Table 1 Location of rain gauge stations

Recognizing a reference rain gauge is a challenging task as clarified by many experts, particularly when the number of existing rain gauges is limited. One of the most common ways is to pick the rain gauge based on its closeness to the landslide location [14,38].

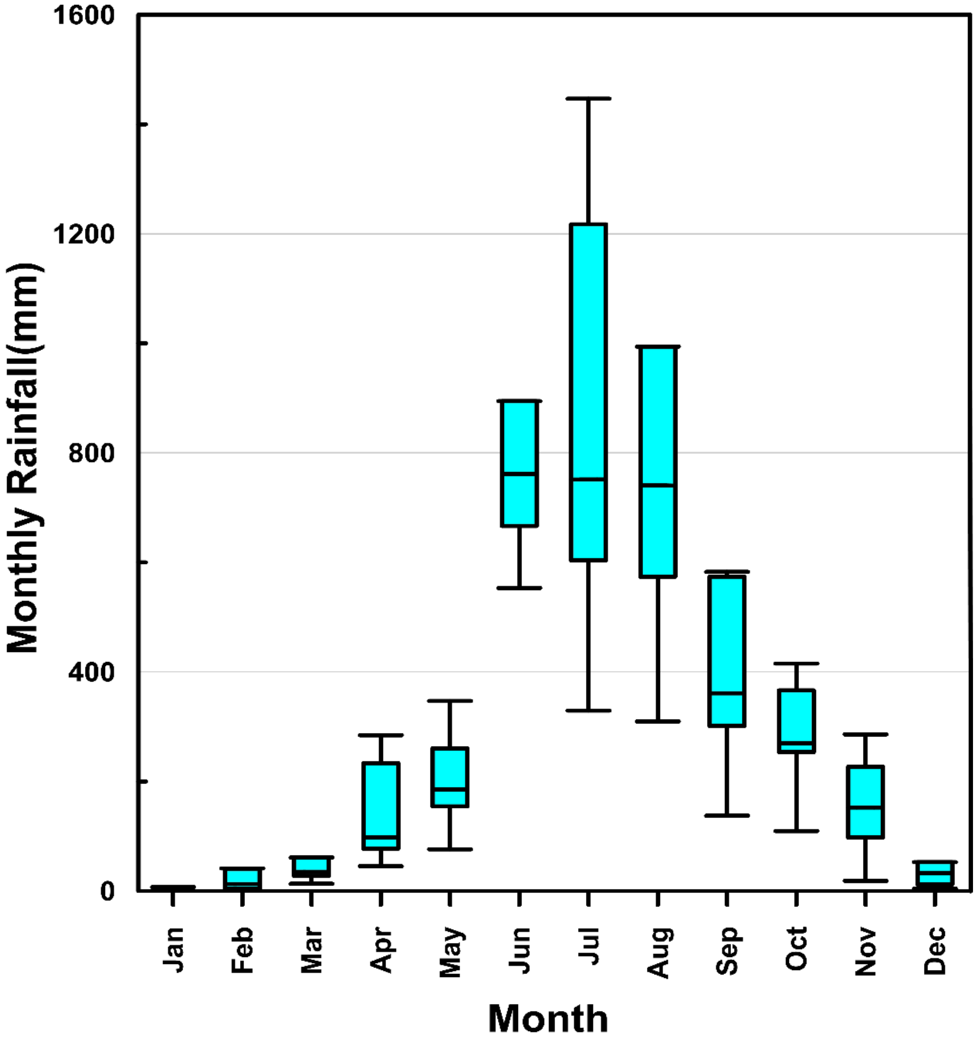


Figure 4 Box and whisker plot with monthly distribution of rainfall in Idukki district (2010-2018). The bottom and top lines indicate minimum and maximum values respectively and the line inside the box represents the median.

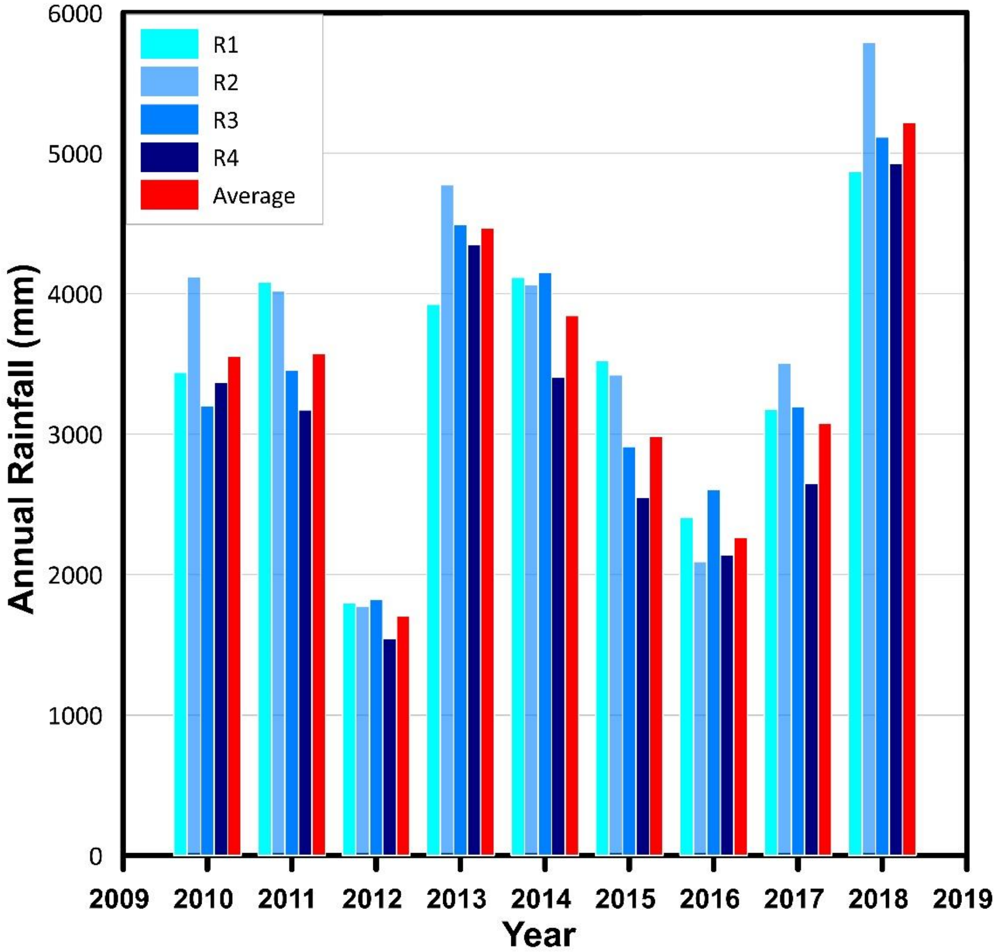
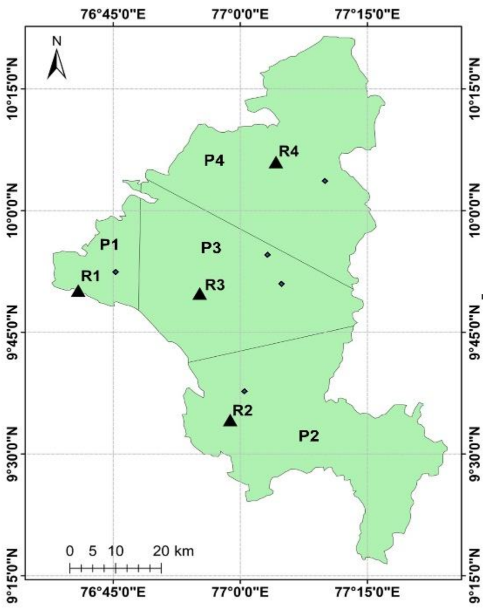


Figure 5 Variation of Annual rainfall measured in four rain gauges during study period.

◆ LANDSLIDE ◇ NO LANDSLIDE ▲ RAIN GAUGE



Polygon No.	Rain Gauge No.	I	D	L
P1	R1	0.2	24	◇
		2	48	◆
		1	24	◇
P2	R2	0.5	72	◇
		3	72	◆
		2	96	◇
P3	R3	0.6	108	◇
		1.5	24	◆
		2.6	48	◆
P4	R4	2.4	72	◆
		0.7	96	◇
		1	120	◇

DATABASE (Rainfall Parameters associated with Landslide Events)

I	D
2	48
3	72
1.5	24
2.6	48
2.4	72

Figure 6 Conceptual sketch showing development of dataset: P1, P2, P3 and P4 represent the four Polygons and R1, R2, R3 and R4 are the reference rain gauges in each polygon. D = Duration of rainfall (hours); I = Intensity of rainfall (mmh^{-1}); L = Occurrence of landslide

Hence in this study, the district was segmented into four Thiessen polygons, based on the position of rain gauges (Figure 6) [37]. P1 Polygon is engaged by a flat and plain region, P2 is found in the eastern hilly area of the study area, P3 denotes the central hilly zone, and P4 holds the sides of the mountain and the hills Close to the foot of the mountainside, thus splitting this zone with unusual physiographic characteristics from the others. As a result, dividing up the area in four areas by means of Thiessen polygons is finer than functioning considering the complete area as one. Each of the polygon expresses a region, which is adjoining to the rain gauge in it (reference gauge). For every point Interior to any polygon is considered to be closer to the referenced gauge, than the other rain gauges. The partition of polygons and the choice of reference gauge is constrained by the spatial scattering only. Each polygon is presumed to be a region of alike rainfall conditions with a reference rain gauge. The technique of developing a data-catalogue is illustrated in Figure 6 by means of a sample dataset, i.e., the values (I, D) and the places of landslides are not from the actual catalogue, but are randomly chosen for demonstrating the methodology. For all landslide occasions that happened in Thiessen polygon P1, the interpretations from R1 are taken. The process was same for all landslide events. The readings analogous to landslide happenings, recorded by separate reference rain gauges,
were then fused to a lone data catalogue. The particular number of triggered landslides and places were not accessible from the reports and hence multiple landslides on a single date inside the same polygon is measured as a single landslide occurrence. A threshold describes the likelihood of happening of at least of one landslide occasion in the area. Thus, a total of 225 landslide events are reflected in the current analysis, which took place during the stretch 2010–2018.

Chapter 3

Literature Survey

This part describes the various research articles and literature that I have referred to during the course of this project.

2.1 Landslides in Kerala

During the floods of 2018 in Kerala, Idukki was the worst and disastrously hit district, with about 143 landslide movements as per official database. Topography of this zone involves slopes as steep as 80^0 and the elevations ranging up to a height of 2692m. A noteworthy portion of population of the region had homes built in these uneven and unstable slopes, which got demolished in the 2018 landslides regardless of the building typology. 97% of the major roads in the Idukki district pass through the rugged highlands and hills, that are repeatedly jammed due to landslides in the monsoons.

2.2 I-D and Antecedent Rainfall Thresholds

Kanungo et al., 2014 [2]; have established the thresholds which can be used in the establishment of landslide warning systems region of the Garhwal Himalayas to lead the traffic flow and deliver safety to the pilgrims and tourists using this route for travelling during the mid-monsoon seasons. Most of slides in the parts of Indian sub-continent are activated by rainfall. Numerous efforts in the global scenario have been thru to develop and establish rainfall thresholds in respect of antecedent rainfall and intensity- duration models on global, regional and local scales for the incidence of landslides. This paper put forward an effort in the direction of establishing local rainfall thresholds for slides on the basis of everyday rainfall data near Chamoli-Joshimath area of the Garhwal Himalayas, India. The rainfall threshold connection which is fitted to the least border of the landslide triggering rainfall events is $I=1.82\ D^{-0.23}$ (I=rainfall intensity in millimeters per hour and D=duration in hours). It was discovered that in case of rainfall events with briefer duration ($\leq$24h) having a rainfall intensity of 0.87mm/h, the danger and risk of landslide incidence in that part of the territory is anticipated to be high. Also, the part of antecedent rainfall in triggering slides was examined by keeping in view of daily rainfall when failure happened and diverse period cumulative rainfall preceding the failure bearing in mind all 128 landslides .It was detected that a minimum of 10-day antecedent rainfall with an amount of 55mm and a 20-day antecedent rainfall with an amount of 185mm are necessary for the instigation of landslides in this area.

2.3 Probabilistic Approach

Abhirup et al. [6], 2018; and Berti et. al,2012; have used the probabilistic approach in their respective study regions to establish the probabilities of occurrence of landslides in various situations. Berti et. al,2012; have applied this approach to the Emilia-Romagna Area of Italy using the benefit of the past landslide catalogue, which comprises of more than 4000 slide events whose date of incidence is identified with daily accurateness. The outcomes display that land sliding in their study area is sturdily linked to rainfall incident parameters (duration, intensity, total rainfall) whereas antecedent rainfall appears to be of lesser importance. The dispersal of the landslide probability in the rainfall duration-intensity in their research showed a rapid increase at particular duration-intensity intervals which directs a radical variation of state and recommends the existence of a real physical threshold.

2.4 Algorithm-Based Approach

Teja et. al, 2019 [46]; used a methodology which involves the usage of an automatic means that determines the summed event rainfall–rainfall span thresholds at numerous probabilities of exceedance and the corresponding cases of not being certain. The study was done for the Kalimpong Region in Sikkim Himalayas with the everyday precipitation and data catalogue of landslides for the time period of 2010–2016. The outcomes indicate that a precipitation of 2days along with an event precipitation of 36.7 mm can root the reason for slides in the study area. This type of investigation study was the initial to be steered for the Himalayas and can be assumed as a primary step in defining further dependable limits of threshold which can be used as in functioning of the system of early warning.

Chapter 4

Objectives

After reading various research articles and new articles it was very clear that a landslide early warning system is in the need of the hour for the state of Kerala. During the time of 2018 floods in Kerala, 5.4 million population was affected and 1.4 million people were displaced and the floods costed the lives of 433 people of Kerala. The statistics say that Idukki district was the district which was worst hit by the floods and has experienced 143 landslides as per official records and there are many more landslides which are unnoticed and not in the records.

So, I planned to do the following things during the course of this research:

- To prepare a catalogue of everyday rainfall data and landslide data of Idukki district of Kerala with most possible accuracy.
- To derive the regional scale rainfall thresholds for the study region using different approaches like Empirical approach (I-D thresholds and Antecedent rainfall thresholds), Probabilistic thresholds, Algorithm-based methods (CTRL-T). As different models work well for different regions depending upon the physical and hydrological properties of the study area, I would be working on a few models and check for the likeliness and efficiency of those models.
- The established thresholds are to be validated using the everyday rainfall data and landslide data of 2019
- Using the validation results the model with high efficiency and high likelihood ratio can be termed as a decent model for the prediction of landslides in this region.

Chapter 5

Discussion on Analysis of Thresholds

The need for establishing and developing rainfall thresholds and then early warning systems for the Idukki district was highlighted in a few site-specific studies led by the GSI. In view of the increased number of fatalities which occurred in the study area recently, rainfall thresholds with the help of intensity-duration relationships, antecedent rainfall conditions, using CTRL-T method and probabilistic approaches have been developed in the current research.

5.1 Intensity-Duration Thresholds

A whole of 225 landslide incidences were noted during the study period (2010–18), which were activated by rainfall. The hourly intensities of all such rainfall events linked with the incidence of landslides were computed and plotted with the duration of episodes in hours on a logarithmic coordinate scale. The spreading of these events is form fitted using an equation which is the power-law distribution in the form of

$$I = \alpha D^{\beta} \qquad (1)$$

$$\text{i.e., } \log(I) = \log(\alpha)+\beta \log(D) \qquad (2)$$

where

β and α are empirical parameters, I is Intensity of rainfall in mmh^{-1}, D is Duration of rainfall event in hours, which is in the form of a straight line of the form y = mx + c.

Usage of this equation generally has two important assumptions. The primary one is that with increase in the intensities of precipitation, the probability of occurrence of landslides increases non-linearly. Under the threshold line value, the likelihood of instigation of slide is less, and directly above the threshold line, the probability of incidence of slides will increase nonlinearly [2]. Another supposition is that the instigation of slides reduces as the duration of precipitation increases. The 'β' term in Equation defines with the rise in duration this rate at which the declination of critical intensity happens increases. The frequentist method of describing intensity-duration thresholds is being used in this research. The empirical rainfall situations that triggered landslides were initially log-transformed and fitted using Equation (2), which is corresponding Equation (1) i.e. the power-law in Using the method Frequentist, a line that best fits for the distribution was derived as $I = 2.54D^{-0.16}$ (Figure 7) having a coefficient of determination (R^2) of 0.04. The data scattering results in a lesser value of R^2 and henceforth the uncertainty or ambiguity related with the fitted line is assessed with a confidence interval of 95%. Bearing in mind the uncertainties, Equation (1) gets modified in to

$$I = (\alpha \pm \Delta\alpha)\ D^{(\beta \pm \Delta\beta)} \qquad (3)$$

The equation of the best fit line was obtained as $I = 2.54D^{-0.16}$, with a confidence interval of $I = (2.54 \pm 0.65)D^{(-0.16 \pm 0.05)}$.

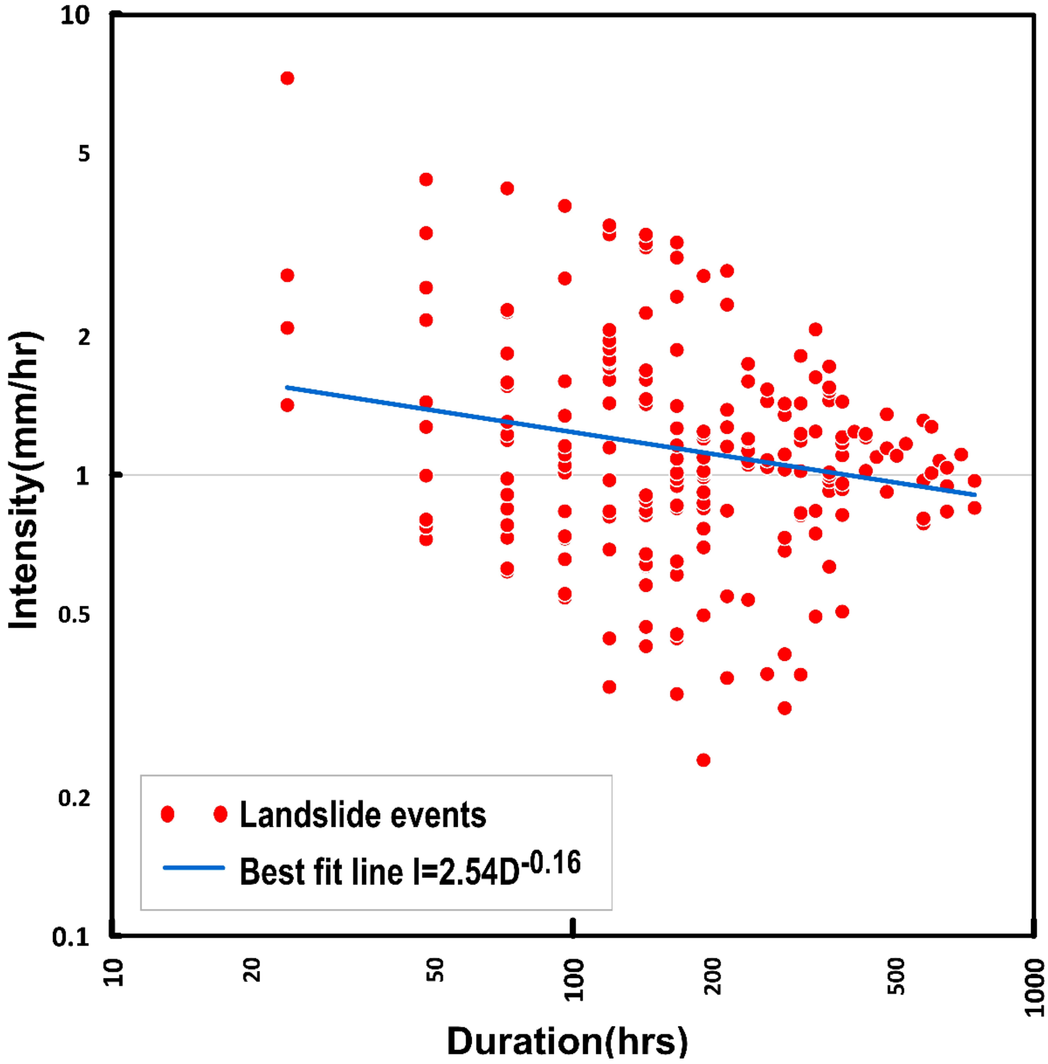


Figure 7 Rainfall Intensity vs Duration (ID) plot on logarithmic scale for Idukki district fitted using power law.

The method is built on the basis of the concept of least square regression and the data is fitted with the help of a power-law. The difference between logarithm of event intensity log (I) and the value on the best fit line log (I_f) for every event is computed. This change is termed as ‘δI’. Kernel density estimation is made use of to govern the probability density function of the distribution of ‘δI’ and the outcome was fitted with a Gaussian function which is of the following form:

$$f(x) = ae^{-\frac{(x-b)^2}{2c^2}} \qquad (4)$$

where c is nonzero, a and b are real constants.

a,b,c, , R, and the thresholds conforming to several exceedance probabilities may be described for the region. For a random variable that is normally distributed, a = $\frac{1}{\sigma\sqrt{2\pi}}$, b=μ and $c^2 = \sigma^2$ where σ and μ are the standard deviation and mean of this distribution, correspondingly. Hereafter the equation becomes

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (5)$$

This equation is then used to fit the 'δI' distribution, to regulate the rainfall threshold as depicted in Figure 8. The data tracks a distribution which is similar to the typical Gaussian distribution. Hence based on the concept of standard Gaussian distribution, a T_5 line was then plotted as in Figure 8, which has an exceedance probability of 5%.

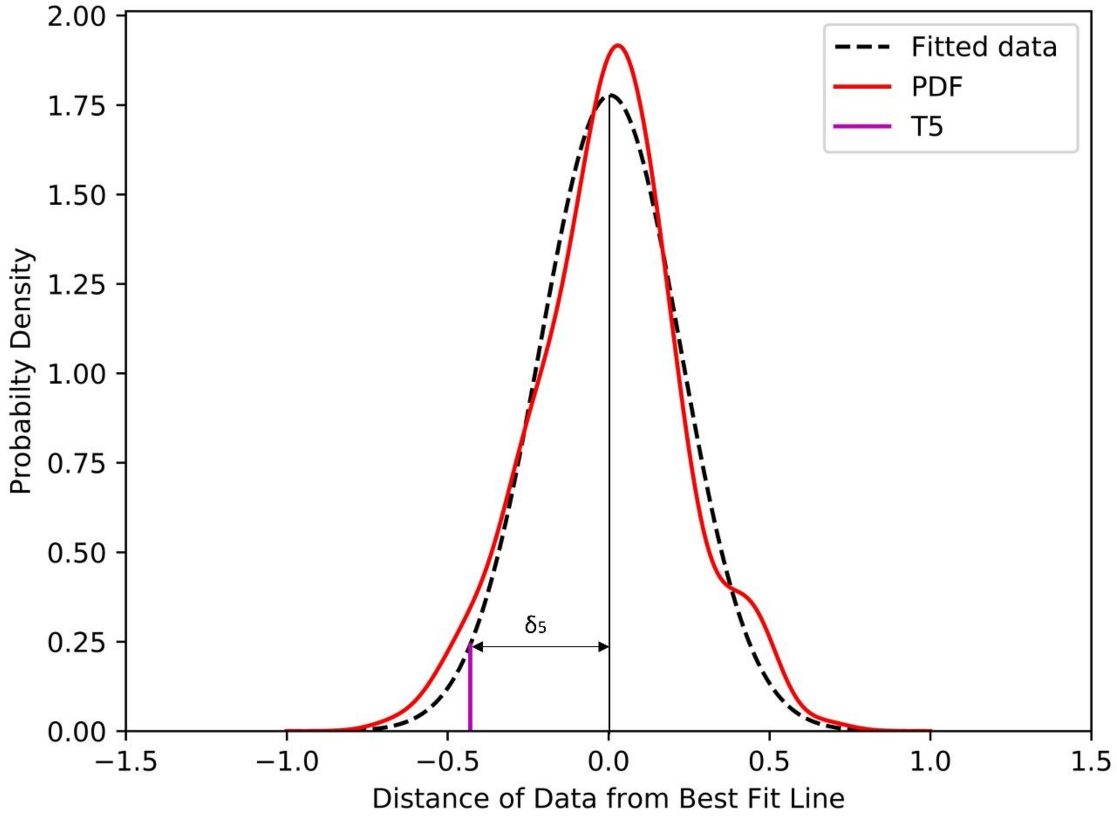


Figure 8 Probability density function of the distribution of δI, fitted using a Gaussian distribution.

The length 'δ_5' designates the aberration of threshold line relative to the best fit line. This deviation was then used to create the intercept of the corresponding threshold line (Figure 9). Seeing the threshold line, we can infer that for a minimum duration (24 hours), a incessant rainfall of 0.54 mmh^{-1} can activate landslides. The extreme duration of a rainfall event which was observed throughout the study period was

31 days. The attained outcomes predict that an intensity of 0.3 mmh^{-1} for a span of 31 days can activate landslides in this region. The confidence interval was attained as $I = (0.9 \pm 0.1)D^{(-0.16 \pm 0.05)}$.

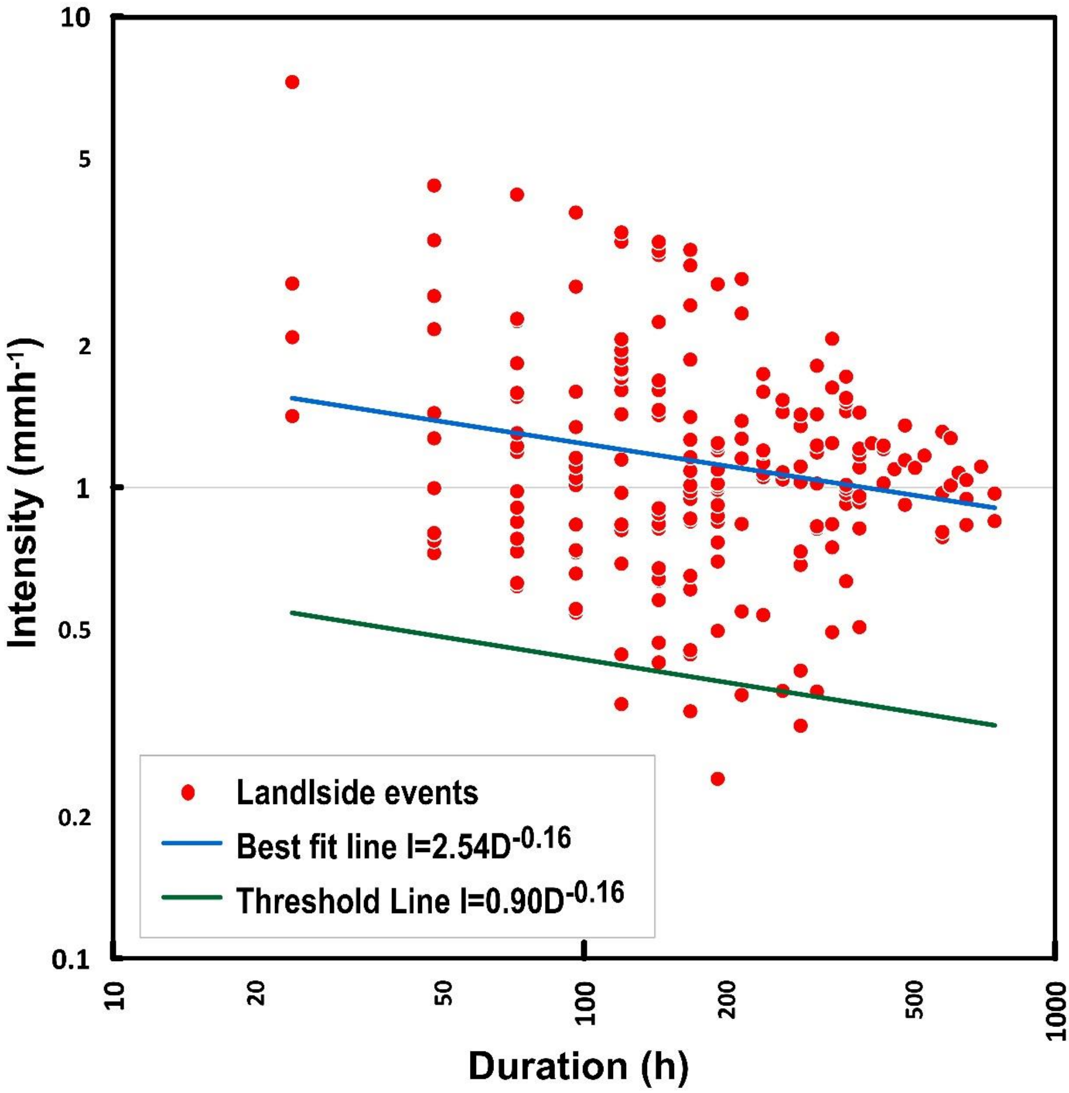


Figure 9 Intensity-Duration Threshold for Idukki district on logarithmic scale.

The greatest number of events happened for a span of 7 days for which the least intensity to initiate a slide occurrence was found to be 0.4 mmh^{-1}. The smaller value of thresholds for brief duration events highlights the necessity for considering antecedent rainfall situations for deriving and establishing thresholds. Hence thresholds on the basis of antecedent rainfall situations are also derived for the region.

5.2 Thresholds Based on Antecedent Rainfall

Intensity-duration thresholds take in to account only the instantly preceding rainfall episode as an activating factor of slides. Landslides may happen as result of moistness content variation due to incessant precipitation also, which is tough to monitor exactly.

Therefore, an easy way is to know the effect of antecedent rainfall and describe a threshold which is based on antecedent precipitation prior to the landslide event. Studies have been led all across the globe, bearing in mind diverse antecedent time spans ranging from 3 days to 120 days [2,4,42].

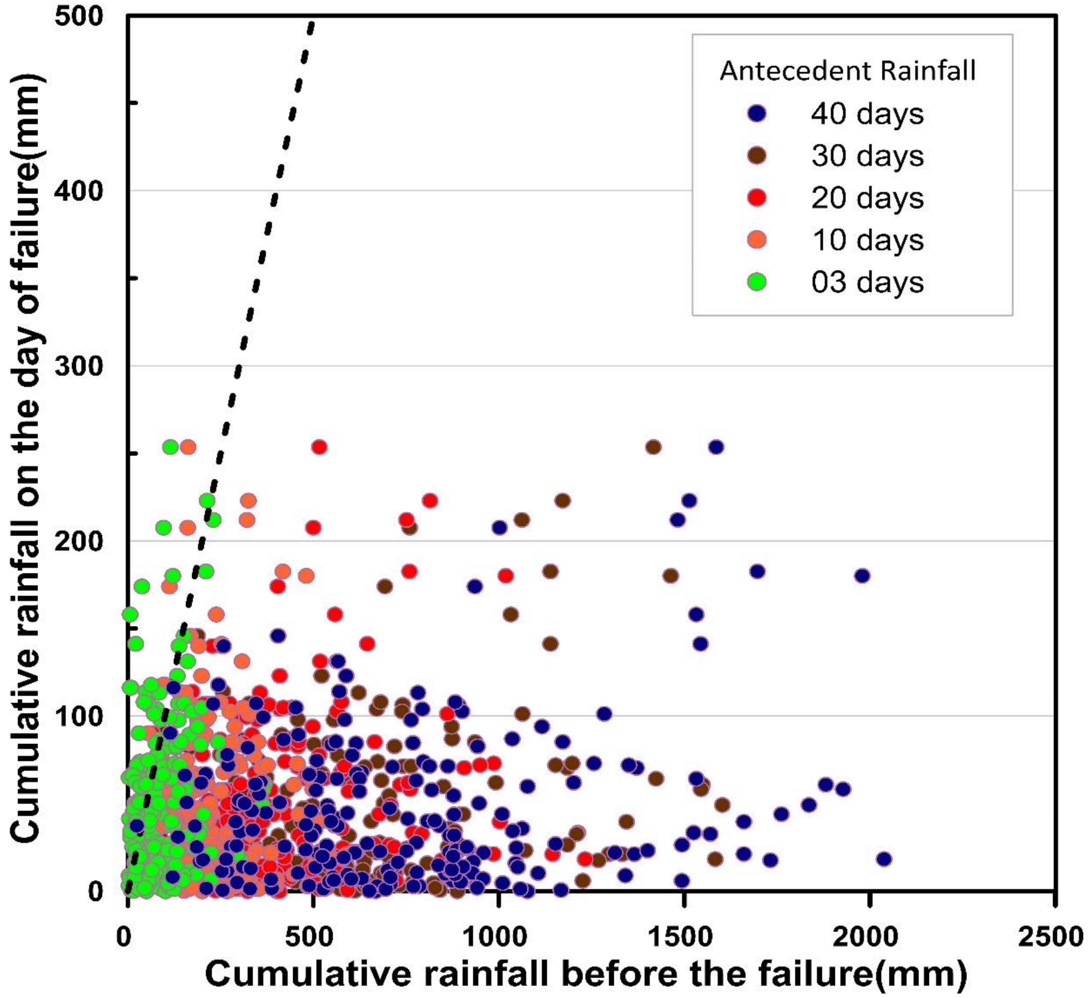


Figure 10. Plot of daily rainfall vs. antecedent rainfall (3, 10, 20, 30 and 40 days).

The database consisting of 225 landslides during the period of nine years was used for our analysis. Daily rainfall archives at failure are related with the antecedent rainfall of 3, 10, 20, 30, and 40 days prior to the failure. The graph is then plotted having antecedent rainfall (mm) and daily rainfall (mm) on the x and y axes correspondingly.

The plot's diagonal line controls the data's scattering bias (Figure 10). A noteworthy part of slide events is influenced in the direction of the antecedent rainfall in almost all the cases. Henceforth a threshold is described for each individual time spans of antecedent rainfall that are considered in this particular study as revealed in Figure 11a–e. In the initial case, three days' antecedent precipitation was considered, 28% of the all the events which are considered are inclined towards daily rainfall, and the residual 163 slides are influenced towards the three days' antecedent precipitation. For further cases, the biasness ratio to daily rainfall and antecedent rainfall were derived and found to be, 1:224 for 40 days',3:222 for 30 days',6:219 for 20 days', and 11:214 for 10 days' antecedent precipitation preceding to the slide incident.

Figure 11 Plot between daily rainfall and antecedent rainfall before failure for (a) 3days, (b) 10 days, (c) 20 days, (d) 30 days , (e) 40 days and (f) Biasness towards antecedent rainfall.

It is obvious from the study that the biasness in the direction of antecedent rainfall, which was 72% in the case of 3 days' antecedent precipitation amplified to 99.56% when the antecedent precipitation of 40 days was taken into account as revealed in Figure 11f. The research can be polished if the time-based resolution of the rainfall data catalogue that was available is enhanced in quality.

5.3 Probabilistic Approach

5.3.1 One-Dimensional Bayesian probability

Baye's theorem is useful for the computation of the conditional probabilities which can be used in the determination or definition the possibility of the slide incidence caused because of precipitation articulated in the terms of entire rainfall, intensity, or duration. Provisional probability is taken as P(A|B) and it tells that "probability of the occurrence of a landslide (A) owing to a detailed rainfall parameter (B)" and can be defined with the use of Bayes' theorem as

$$P(A|B) =(P(B|A)* P(A))/P(B) \qquad (6)$$

- P(B|A) = given event A conditional probability of event B, i.e., probability of rainfall episode of magnitude B when a landslide happens.
- P(A) = when the precipitation episode of magnitude B has occurred or not, probability of landslide incidence

- P(B) = when a landslide happens or not, probability of precipitation episode of extent B.
- P(A|B) = conditional probability of A given B that is possibility of a slide incidence when a precipitation episode of extent B happens.

Let the no. of precipitation episodes through the period of specific time be N_R; no. of incidences of slides thru the same time span be N_A, no. of precipitation episodes of extent B be N_B and the no. of precipitation episodes instigating slides be $N_{(B|A)}$, then Equation (6) can be stated as

$$P(A)=N_A/N_R \tag{7}$$

$$P(B)=N_B/N_R \tag{8}$$

$$P_{(B|A)}=N_{(B|A)}/N_A \tag{9}$$

Commonly, probabilities assist in the estimation and definition of likelihood of slides. Variables can be chosen depending on the parameters in one-dimensional analysis, that are the chief motives for commencement of slide, for my study, considered variables are the event rainfall, rainfall duration, and rainfall intensity. As discussed hitherto, the relation among landslide probability P(A|B) and prior landslide probability P(A) shows the implication of B for prevalence of event with name A.

Figure 12 One dimensional probabilities: prior, conditional and landslide probabilities [for the case of event duration, rainfall event and rainfall intensity]

The procedure was useful to Idukki section with the above elucidated procedure. Rainfall probability that is P(B) is computed for NR = 1416 precipitation episodes between the years 2010 and 2016, and the conditional probability which is P(A|B) is found for NA = 225 rainfall episodes which caused slides. P(A)= NA/NR = 225/1416=0.16, B was considered as intensity, event rainfall and duration in each case (B|A) is found by bearing in mind several range of values, for rainfall intensity, event rainfall and duration.

This investigation was led for numerous intensity ranges ($0 \leq I < 10$, $10 \leq I < 20$, $20 \leq I < 30$ so on up to $70 \leq I < 80$ and $I \geq 80$ in m), duration ranges($0 \leq D < 3$ so on up to $21 \leq D < 24$ and $D \geq 24$ in days) and event rainfall ranges ($0 \leq E < 100$ so on up to $600 \leq E < 700$ and $E \geq 700$ in mm the landslide probability is denoted in the form of histogram. Landslide possibility showed an increasing trend with the extremity for rainfall parameters namely increase in rainfall intensity, amount and duration. The increase seems to be a little uneven because of the fact that data is irregularly distributed. Though, at the highest values of the parameters taken in to consideration landslide possibility decreases. This uncommon trend may be basically because of two reasons. Firstly, due to low sample sizes the possibilities of such extreme events are affected. Samples containing lesser data are less informational and even a slight difference in the noted number of landslides will result in a very diverse probability. So as to comprehend the influence of such ambiguity, the difference of P(A|B) and P(A) has been shown to clearly mark the implication of every used variable.

5.3.2 Two-Dimensional Bayesian Probability

Bayesian probability of two-dimensions can be used for the estimation of the probability with conditional statements of an event in the case of joint occurrence of two parameters that are considered.

$$P(A|B,C)=(P(B|C,A)P(A))/P(B,C) \tag{10}$$

where B, C means combined probability of a case or a certain range of values for any two variables. If B in this case is rainfall intensity and C being rainfall duration, the probability of slide incidence because of rainfall event of given duration and intensity is described using Equation (10). Similarly, any pair of rainfall parameters responsible for likelihood of landslide incidence can be analyzed and calculated with the concept of two-dimensional Bayesian probability (e.g., rainfall intensity, total event rainfall, and

rainfall duration), and their implication can be analyzed by linking landslide probability with prior landslide probability P(A). Bayes method can also be used in the case of multidimensional analysis having n-variables namely joined impact of rainfall intensity and duration and groundwater environments to assess the probability of landslide occurrence.

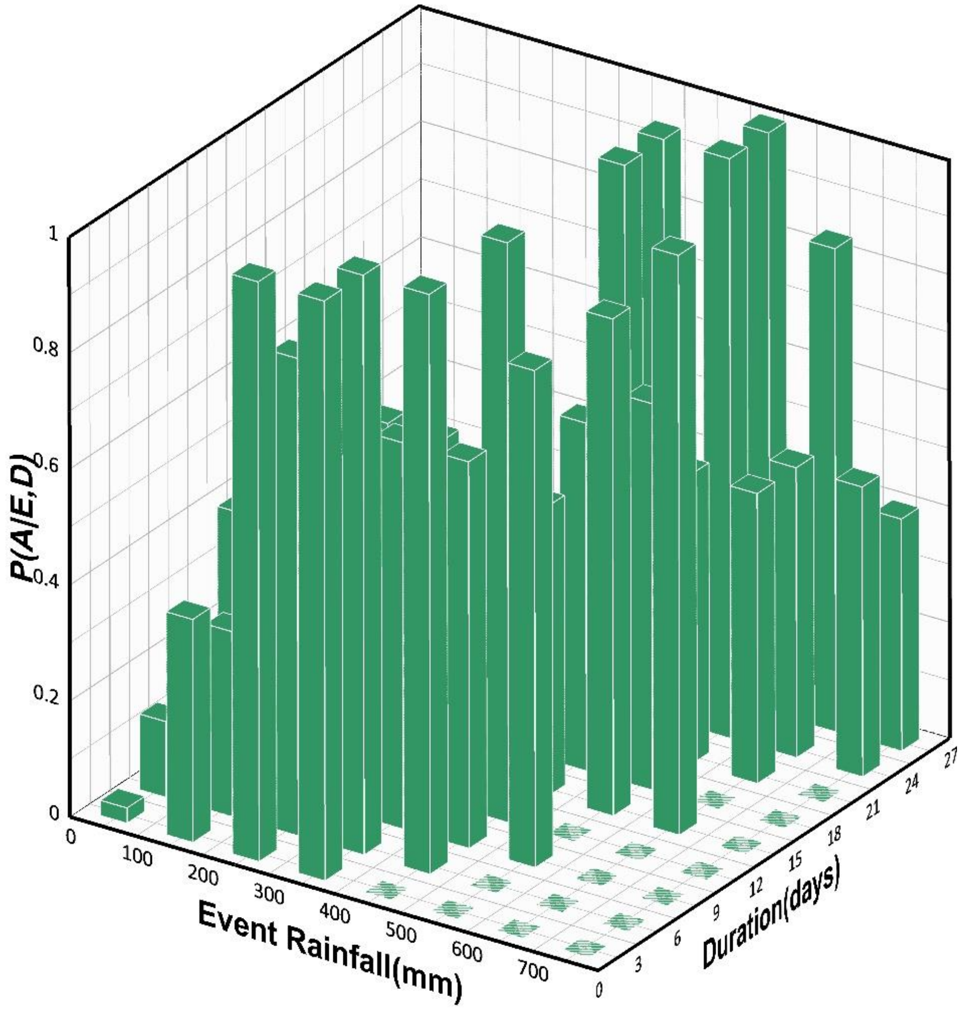


Figure 13. Graph of probability of landslide as a function of rainfall event and rainfall duration.

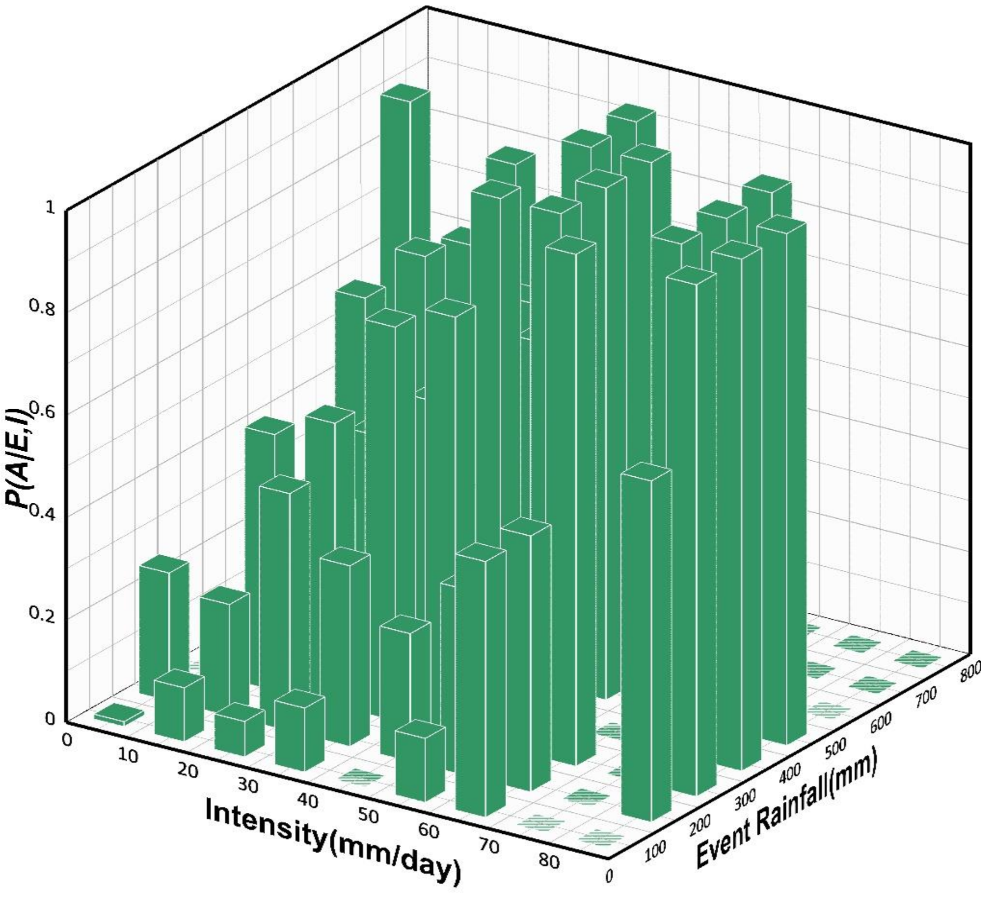


Figure 14 Graph of probability of landslide as a function of rainfall event and rainfall intensity.

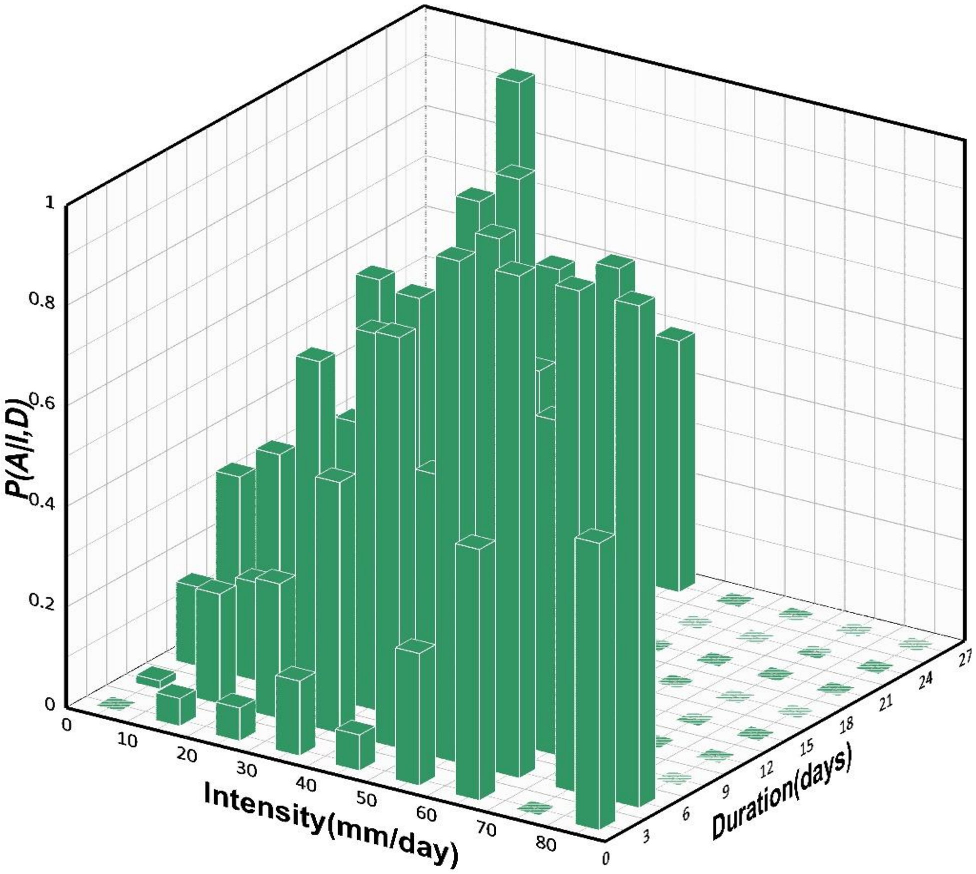


Figure 15 Graph of probability of landslide as a function of rainfall duration and rainfall intensity.

The importance of this type of analysis can be clearly understood from the point that even a very small value of probability cannot be unkempt or neglected for susceptible areas and must be analyzed to find the risk associated for every probability.

5.4 Algorithm-Based Method (CTRL-T)

The precipitation thresholds are rebuilt with the assistance of Calculation of Thresholds for Rainfall-Induced Landslides-Tool (CTRL-T) model which is an algorithm-based model. Extraction of rainfall events using this model are done with help of an algorithm with the accessible everyday precipitation series, then rebuild activating precipitation conditions liable for slides, and figures precipitation thresholds at diverse probabilities of exceedance. The tool requires input constraints such as the dates and location coordinates of incidence of the slides, locations i.e. the rain gauge site coordinates of the rain gauge and periodic precipitation series. The device receipts in to contemplation the delinquent with spatial variability by bearing in mind a circle shaped buffer length with the location coordinate of slide as its midpoint. The authors of earlier works in other places had suggested a buffer circle of 15 km radius, but we can take it as 25km in our study section as a higher search range is compulsory when the grid of rain gauges is scarce i.e. lower rain gauge compactness; furthermore, a less range may upshot to a condition where landslides happen to have no reference rain gauge. The means tracks three stages in its working: (i) The input is accepted as an incessant cable of precipitation episode series and different precipitation episodes or events are rebuilt defining the cumulated event rainfall (E) in mm and event duration (D) in hours. (ii) The choice of rain gauge impacts the rebuilt events in curtailing the effect of spatial inconsistency of spreading of precipitation (this can be fetched by rebuilding numerous or only precipitation situations (MRC) greatest probable to lead to catastrophes and assigning them with a weight; (iii) In the culmination, this tool rebuilds or reconstructs the MRC with the help of selected rainfall event and a weight is assigned to it (w) relative to the cumulated precipitation and the average intensity of an MRC and to the inverse of square of the distance from the rain gauge to the landslide location. For every landslide, the maximum assigned w is considered to find the rain gauge that is representative and in the determination of maximum likelihood rainfall conditions (MPRC). Lastly, using only an MRC having the maximum weight (MPRC) in case of each disaster, the rainfall thresholds at various exceedance probabilities and the respective uncertainties linked with them are computed. These thresholds generally make use of the power law equation, cumulated rainfall Event value (mm) to rainfall duration D (h) and makes use of the frequentist approach proposed in [4], that can be described as:

$$E = (\alpha \pm \Delta\alpha)D^{(\gamma \pm \Delta\gamma)}$$

where α signifies the scaling parameter in turn it describes the intercept and γ is a shape parameter that defines the slope of the power law equation; Δα, Δγ.

These parameters (Δα, Δγ) called delta parameters show the ambiguities connected with both the parameters, which are further defined with the help of a nonparametric bootstrap statistical technique. This tool defines the average values of parameters and the uncertainties associated with them with the use of a bootstrapping method in computing for 5000 synthetic sequence of precipitation circumstances.

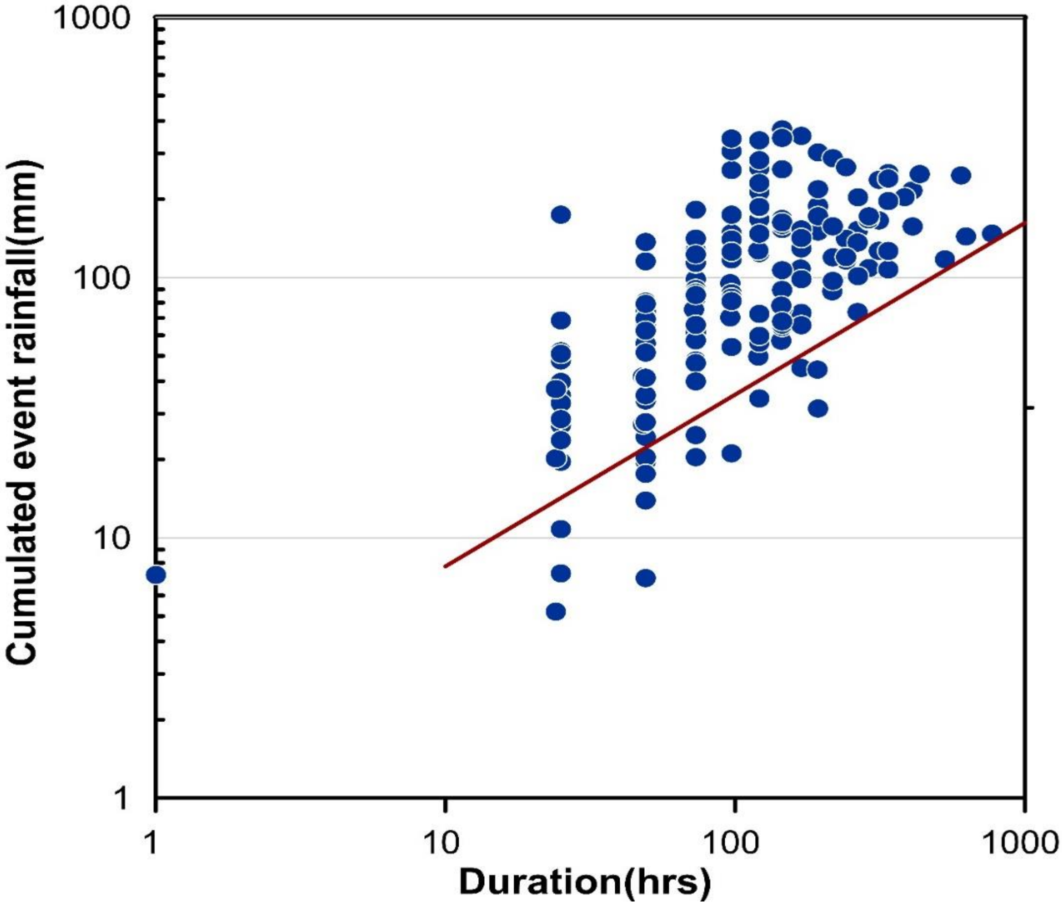


Figure 16 [5% exceedance probability level (T5,B)] Threshold from Cumulated event rainfall-rainfall duration (ED) .

The tool (CTRL-T) was able to reconstruct 714 rainfall events for the given period of stipulated time (2010–2018). It is generally tough to relate a particular landslide incidence with a rainfall episode, because of an anomaly in precipitation quantitation done by gauges measuring rainfall, the larger radius length between rain gauges and landslide location, including the occurrences of numerous landslides at the same place or in nearby region. Taking into account the factors that are mentioned above, 225 landslides were identified as brought by rainfall. The CTRL-T tool gave a result discarding 22 eight landslides, in turn leaving 203 landslides for the further evaluation. The reconstructed precipitation and slide incidence data were used to govern cumulated event rainfall-event duration (ED) thresholds, where

$E = (1.7 \pm 0.4)\, D^{(0.66 \pm 0.01)}$. Figure signifies the thresholds of ED which are plotted on a log curve with the help of 203 precipitation conditions which were the cause for landslides (labelled as points) with a probability exceedance of 5% (line representation) and the area of uncertainty connected with it (i.e. dappled area).

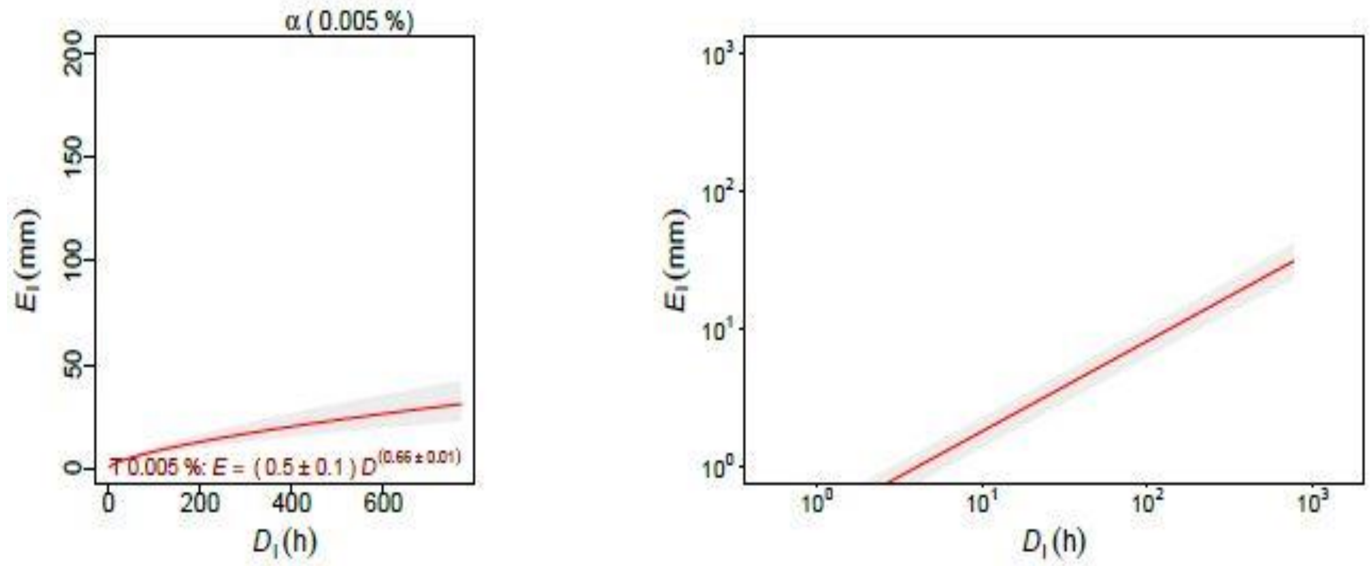


Figure 17 (a) [0.05% exceedance probability level ($T_{0.005,B}$)] Threshold from Cumulated event rainfall-rainfall duration (ED) .

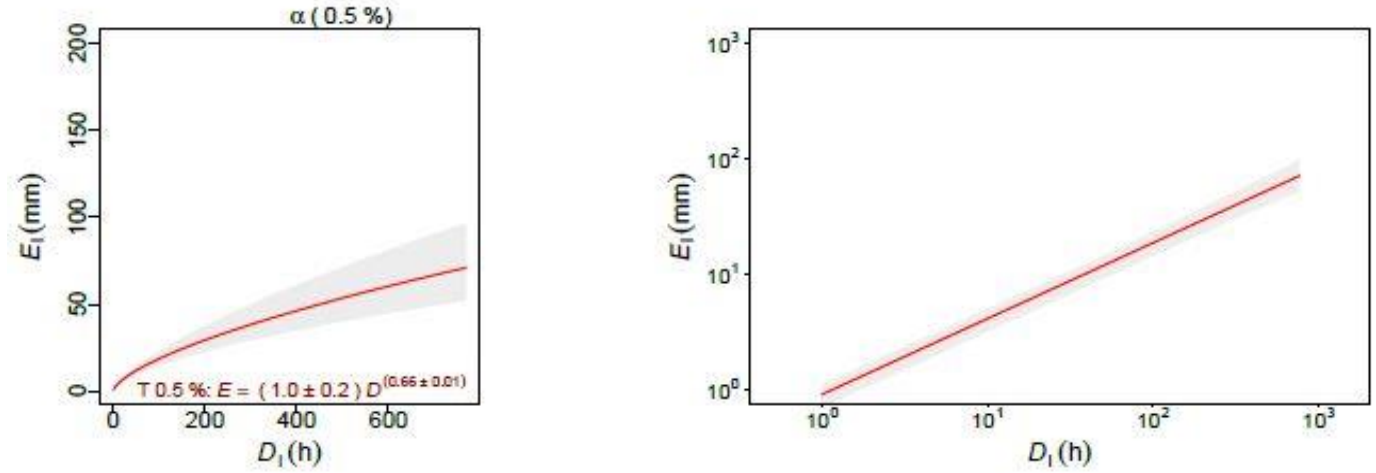


Figure 17(b) [0.5% exceedance probability level ($T_{0.5,B}$)] Threshold from Cumulated event rainfall-rainfall duration (ED) .

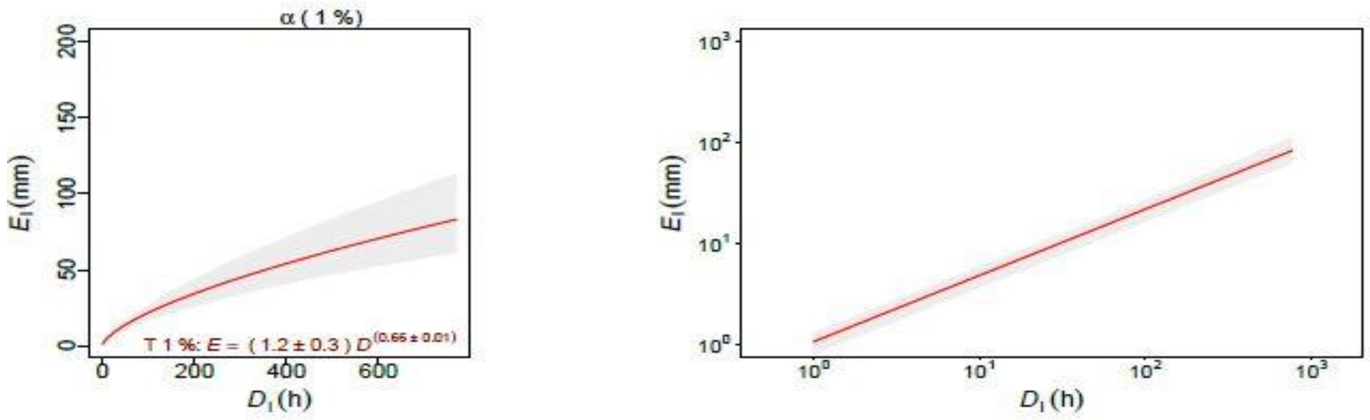


Figure 17(c) [1% exceedance probability level ($T_{01,B}$)] Threshold from Cumulated event rainfall-rainfall duration (ED) .

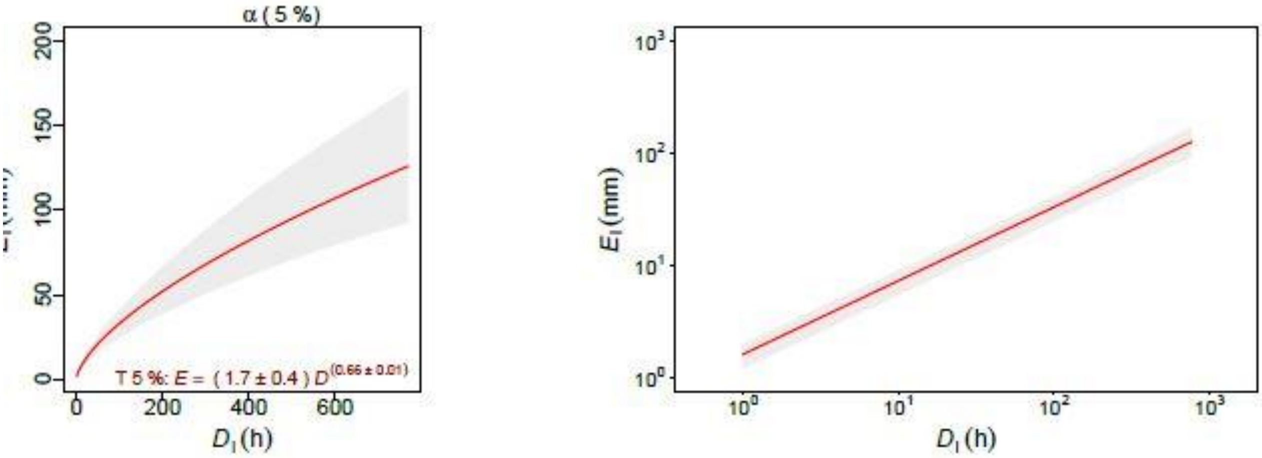


Figure 17(d) [5% exceedance probability level ($T_{5,B}$)] Threshold from Cumulated event rainfall-rainfall duration (ED) .

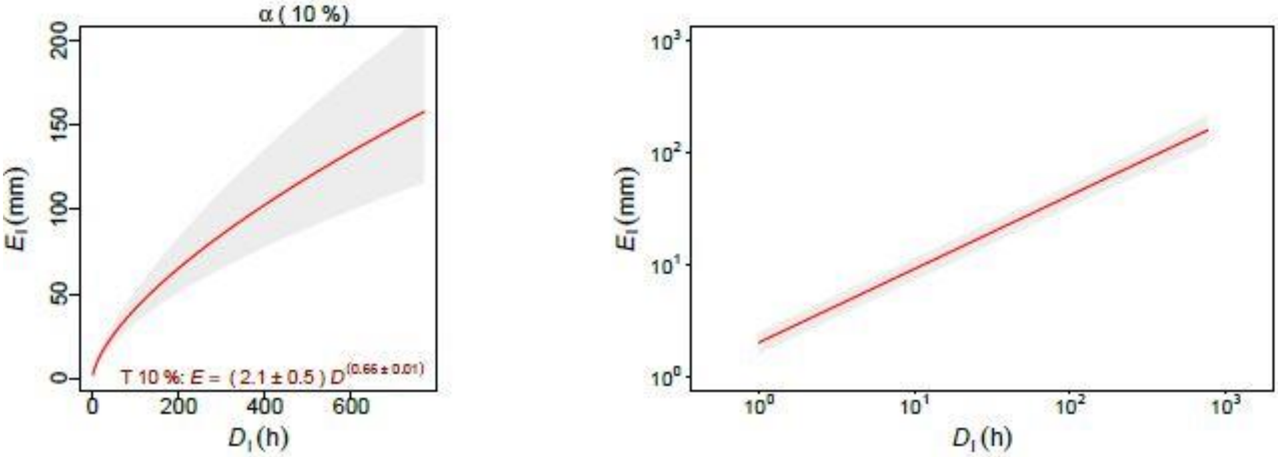


Figure 17(e) [10% exceedance probability level ($T_{10,B}$)] Threshold from Cumulated event rainfall-rainfall duration (ED) .

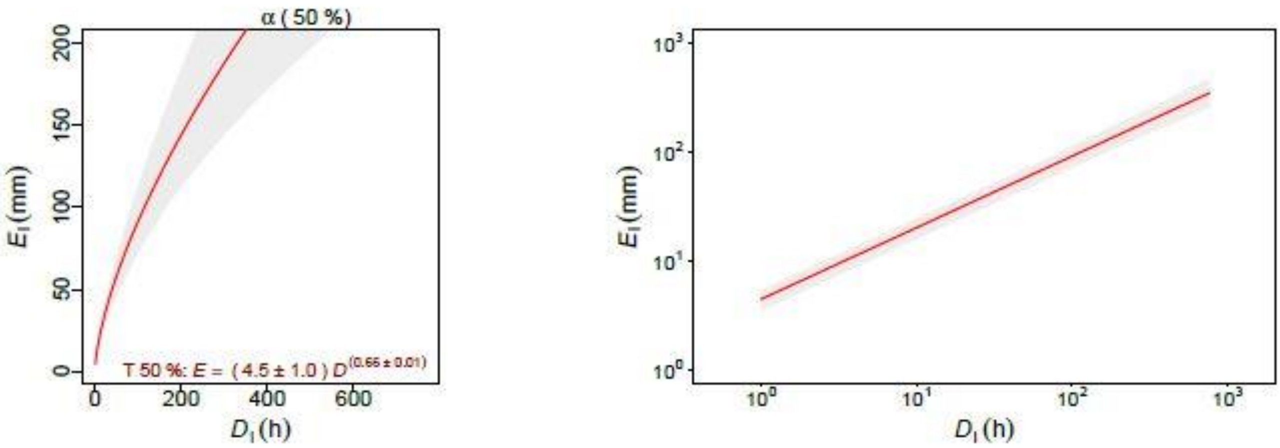


Figure 17(f) [50% exceedance probability level ($T_{50,,B}$)] Threshold from Cumulated event rainfall-rainfall duration (ED) .

Chapter 6

Validation of Thresholds

All the thresholds established using various approaches are validated using the rainfall and landslide data catalogue of the year 2019 from January 1 to Aug 28. The statistics for various models are as follows:

6.1 I-D Thresholds

Statistical Attributes	**ID Threshold**
a = True positives	**23**
b = False positives	**50**
c = False negatives	**03**
d = True negatives	**162**
Efficiency = (a + d) / (a + b + c + d)	**0.78**
Misclassification rate = (b + c) / (a + b + c + d)	**0.22**
Odds ratio = (a + d) / (b + c)	**3.5**
Positive predictive power = a / (a + b)	**0.315**
Negative predictive power = d / (c + d)	**0.98**
Sensitivity = a / (a + c)	**0.89**
Specificity = d / (b + d)	**0.76**
False positive rate = b / (b + d)	**0.24**
False negative rate = c / (a + c)	**0.12**
Likelihood ratio = Sensitivity / (1 – Specificity)	**3.75**

Table 2 Validation statistics of I-D threshold.

6.2 Antecedent Rainfall Thresholds

Statistical Attributes	10 Day Antecedent Rainfall Threshold
a = True positives	25
b = False positives	40
c = False negatives	01
d = True negatives	172
Efficiency = (a + d) / (a + b + c + d)	0.83
Misclassification rate = (b + c) / (a + b + c + d)	0.17
Odds ratio = (a + d) / (b + c)	4.80
Positive predictive power = a / (a + b)	0.38
Negative predictive power = d / (c + d)	0.99
Sensitivity = a / (a + c)	0.96
Specificity = d / (b + d)	0.81
False positive rate = b / (b + d)	0.19
False negative rate = c / (a + c)	0.04
Likelihood ratio = Sensitivity / (1 – Specificity)	5.09

Table 3 Validation statistics of 10 day antecedent rainfall threshold.

Statistical Attributes	20 Day Antecedent Rainfall Threshold
a = True positives	**26**
b = False positives	**44**
c = False negatives	**0**
d = True negatives	**168**
Efficiency = (a + d) / (a + b + c + d)	**0.82**
Misclassification rate = (b + c) / (a + b + c + d)	**0.18**
Odds ratio = (a + d) / (b + c)	**4.41**
Positive predictive power = a / (a + b)	**0.371**
Negative predictive power = d / (c + d)	**1**
Sensitivity = a / (a + c)	**1**
Specificity = d / (b + d)	**0.79**
False positive rate = b / (b + d)	**0.21**
False negative rate = c / (a + c)	**0**
Likelihood ratio = Sensitivity / (1 – Specificity)	**4.82**

Table 4 Validation statistics of 20 day antecedent rainfall threshold.

Statistical Attributes	30 Day Antecedent Rainfall Threshold
a = True positives	26
b = False positives	43
c = False negatives	0
d = True negatives	169
Efficiency = (a + d) / (a + b + c + d)	0.82
Misclassification rate = (b + c) / (a + b + c + d)	0.18
Odds ratio = (a + d) / (b + c)	4.53
Positive predictive power = a / (a + b)	0.38
Negative predictive power = d / (c + d)	1
Sensitivity = a / (a + c)	1
Specificity = d / (b + d)	0.797
False positive rate = b / (b + d)	0.20
False negative rate = c / (a + c)	0
Likelihood ratio = Sensitivity / (1 – Specificity)	4.93

Table 5 Validation statistics of 30 day antecedent rainfall threshold.

Statistical Attributes	**40 Day Antecedent Rainfall Threshold**
a = True positives	**26**
b = False positives	**40**
c = False negatives	**0**
d = True negatives	**172**
Efficiency = (a + d) / (a + b + c + d)	**0.83**
Misclassification rate = (b + c) / (a + b + c + d)	**0.17**
Odds ratio = (a + d) / (b + c)	**4.95**
Positive predictive power = a / (a + b)	**0.39**
Negative predictive power = d / (c + d)	**1**
Sensitivity = a / (a + c)	**1**
Specificity = d / (b + d)	**0.81**
False positive rate = b / (b + d)	**0.188**
False negative rate = c / (a + c)	**0**
Likelihood ratio = Sensitivity / (1 – Specificity)	**5.3**

Table 6 Validation statistics of 40 day antecedent rainfall threshold.

6.3 E-D Threshold (CTRL-T) validation

Statistical Attributes	**ED Threshold (CTRL-T Tool)**
a = True positives	**21**
b = False positives	**80**
c = False negatives	**05**
d = True negatives	**132**
Efficiency = (a + d) / (a + b + c + d)	**0.64**
Misclassification rate = (b + c) / (a + b + c + d)	**0.36**
Odds ratio = (a + d) / (b + c)	**1.8**
Positive predictive power = a / (a + b)	**0.21**
Negative predictive power = d / (c + d)	**0.96**
Sensitivity = a / (a + c)	**0.81**
Specificity = d / (b + d)	**0.62**
False positive rate = b / (b + d)	**0.38**
False negative rate = c / (a + c)	**0.20**
Likelihood ratio = Sensitivity / (1 – Specificity)	**2.14**

Table 7 Validation statistics of E-D threshold obtained from CTRL-T tool.

Chapter 7

Conclusions and Future Scope

7.1 Conclusions

7.1.1 I-D Empirical Approach (I-D Thresholds and Antecedent Rainfall Thresholds)

This study is an attempt to develop the thresholds in the 2-dimensional intensity-duration plane based on the available landslide data catalogue and antecedent rainfall data catalogue for the Idukki region in Kerala State on a regional scale. This effort is the first of its kind in the Idukki region and can be enhanced with the proper availability of short span precipitation data. This analysis was led by means of a data catalogue of 9 years i.e. from 2010 to 2018, which comprised of 225 landslide incidents happening across various parts of the district, and the prime observations can be abridged as:

- For less duration rainfall episodes (24 hours), an incessant precipitation intensity of 0.54 $mmhr^{-1}$ can activate landslides. For the extreme observed time duration of 31 days, landslides can be triggered even for a rainfall intensity as less as $0.3mmhr^{-1}$. These values of thresholds are very low in the perspective of a regional scale threshold, and the reason behind this can be the fact that occurrence of landslides is biased to the antecedent rainfall conditions, excluding the event that immediately precedes.
- After antecedent rainfall conditions were analysed, it was derived that that for the Idukki region, an antecedent precipitation of 70.6 mm during a time span of 10 days and 229.8 mm during a time span of 40 days can activate a landslide event. About 99.56% of the slide events are biased towards the antecedent precipitation conditions when span of 40 days is considered.
- It is clearly evident from the outcomes that the incidence of landslide events is greatly affected by antecedent precipitation conditions than the amount of precipitation that happened on the day of incidence.

7.1.2 Probabilistic Approach

Even though various methodologies have been proposed and worked on, in the works of the present exploration to link landslide incidence with precipitation threshold, this kind of method may not be obliging at all times to comprehend the upshot and to predict and forecast slides as it only takes into account the shower which instigated slides. The central query that ascends in using such methods is the upshot of precipitation which didn't cause slides and its dependency on each other with more than a few precipitation constraints. So as to come over this problem, Bayesian method can be cast-off which takes in to account all the precipitation characteristics and bids more simplicity on slide incidence. The inspection was carried out for a time span of 9 years (2010–2018) with the help of several precipitation parameters counting duration, intensity, and event rainfall. The probabilities for slide incidences were then demarcated using two means (one-dimensional and two-dimensional). The prior technique makes usage of a solo precipitation parameter however the latter one makes usage of a grouping of two precipitation constraints. The deductions from the study are as follows:

- It was recognized that in case of an intensity of 45mm/day the probability of the incidence of a landslide is 0.45 and for an intensity of 30mm/day lasting up to 12 days the probability of the incidence of a landslide is 0.50.
- The usage of a two-dimensional Bayesian technique delivers a healthier understanding of the slide events when related with one dimensional. Even though, it would likewise hinge on the accurateness and lushness of the data catalogue. Samples comprising petite amount of data are usually less informational and in instance of a slight difference in the landslide data it would portray probabilities which can be inconsistent.
- The usage of a probabilistic technique over the deterministic means is unquestionably a healthier substitute to create and set up an early warning system for the zones susceptible to to slide and could be considered as a primary step in interim against landslide threats.

7.1.3 Algorithm-based Approach

To comprehend the connection between rainfall episodes and landslide incidences, several practices were followed and thresholds were generated. The thresholds that were determined generally was short of critical information regarding the choice and selection of rain gauges and in the reconstruction of the rainfall events accountable for landslide events. A lately proposed tool (CTRL-T) which works on reconstruction of rainfall episodes and in the determination of thresholds helps to overcome the drawbacks in the traditional estimation of threshold. This tool was applied to the Idukki Region of the Kerala state using precipitation and landslide information for 2010–2018.

- The thresholds computed represented that a cumulated event rainfall of 25.5 mm for 48 h can be the reason for landslide incidence.
- The critical part in analysis of thresholds is the validation of the established values, which can be attained by means of an independent data catalogue excluding the one that was used for simulation of the threshold.

- Although, to acquire reliable thresholds the accessibility and availability of further activating rainfall situations and slide events including the hourly precipitation data catalogue is essential for the reduction of uncertainties associated with it.

7.2 Limitations

- Lack of widespread and extensive network of rain gauges in the study region to precisely and accurately determine the thresholds.
- Hourly rainfall data is necessary for calculating thresholds which can give more accurate results.

7.3 Suggestions for Future Study

It is expected that this primary effort will drive and encourage more study for the Idukki Region, which is deeply getting affected with the increasing number of landslide incidences among the recent hazards and this will become the initial step in establishing a regional scale warning system for the Idukki region.

Following points can be noted for the future research in the study area:

- Making use of electrical resistivity tomography (ERT) method for the purpose of landslide monitoring.
- Implementation of other methods and finding the best results validating and correlating with field data.

Chapter 8

Related Publications

- M. T. Abraham, **D. Pothuraju**, and N. Satyam, “Rainfall Thresholds for Prediction of Landslides in Idukki, India: An Empirical Approach,” *Water*, vol. 11, no. 10, p. 2113, Oct. 2019.

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