B. TECH. PROJECT REPORT

ON

Applications of Landslide models to improve the efficiency of Early warning system

By:

P SAI KUSHAL

DISCIPLINE OF CIVIL ENGINEERING

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Applications of Landslide models to improve the efficiency of Early warning system

A PROJECT REPORT

Submitted in partial fulfilment of the
requirements for the award of the degree
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in
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Submitted by:
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Declaration of Authorship

We hereby declare that the project entitled **"Applications of Landslide models to improve the efficiency of early warning systems"** submitted in partial fulfilment 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.

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

Signature: ____________________________________

Date: ____________________________________

Certificate

This is to certify that the thesis entitled "**Applications of Landslide models to improve the efficiency of early warning systems**" and submitted by **P Sai Kushal**, Roll No. 160004023, in partial fulfilment 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 students is correct to the best of my knowledge.

Dr. Neelima Satyam
Associate Professor,
Discipline of Civil Engineering,
Indian Institute of Technology Indore.

“Education is the most powerful weapon which you can use to change the world”

- Nelson Mandela

Abstract

Application of Landslide models to improve the efficiency of Early Warning Systems

Landslides are the most common and devastating natural disaster around the world. The damage caused due to landslides is leading to massive loss of life and property including agricultural land. The reduction of the related risk has become paramount for public authorities. The studies on landslides have drawn worldwide attention due to the rapid increase in urbanization in many of these hilly regions and thus its increasing impact on socio-economic aspects. Thus, there is a dire need for understanding landslides, estimating its occurrence potential and formulating strategies to minimize its impact. With 30% of the landslide events around the globe occurring in the Indian Himalayan region, one can say that it has been significantly affected by landslides.

Kalimpong, situated in West Bengal is one of the most affected places in the Darjeeling-Himalayas region. Rainfall is the primary triggering factor for landslides in this region. Shallow landslides are usually triggered by intense rainfall for shorter duration while the deep-seated failures are caused due to comparatively low intensity for longer duration of rainfall. During the study period (2010-2017) most of the landslides were triggered by incessant and high amount of monsoon rainfall. In this study, various relationships concerning rainfall, landslides and some other factors has been attempted.

Firstly, the study deals with assessing landslide hazard using a traditional rainfall threshold model i.e. Antecedent model involving daily and cumulative values of antecedent rainfall for landslide events. A threshold equation was generated using the rainfall and landslide records for 2010-16. Later, SIGMA model has been applied for the region which deals with an algorithm consisting thresholds as multiples of standard deviations. Further, a hydrological model named SHETRAN is applied to get the estimates of soil moisture during the study period and integrated it with ED thresholds using Bayesian approach. Finally, an effort was made to increase the efficiency by adding soil moisture (generated from SHETRAN) to the algorithm and the model was named SIGMA-U. All the above-mentioned models were validated using real time sensor data of 2017. The statistics of validation indicated that SIGMA-U is the most reliable model with an efficiency of 98%, likelihood ratio of 33.33 and can be integrated with real time sensors to form an efficient Landslide Early Warning System (LEWS) for the region.

Keywords: Kalimpong, Landslides, Rainfall, Early warning system.

Acknowledgements

I would like to thank my B. Tech Project supervisor **Dr. Neelima Satyam** for her guidance and constant support in structuring the project and her valuable feedback throughout the course of this project. Her overseeing the project meant there was a lot that we learnt while working on it. We thank her for the time and efforts.

I am grateful to the Institute for the opportunity to be exposed to systemic research, especially, Dr. Neelima Satyam's lab for providing the necessary hardware utilities to complete the project.

Lastly, I offer my sincere thanks to everyone who helped us to complete this project, whose name we might have forgotten to mention.

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List of Abbreviations

I: Intensity
E: Cumulated Rainfall
D: Duration
SD: Standard Deviation
u': Average soil moisture
U: Soil moisture

Dedicated to my beloved parents for being a constant source of inspiration and guidance to me.

– P Sai Kushal

Chapter 1

Introduction

The Indian Himalayan regions have been significantly affected due to the increase in the frequency of landslide occurrence. 30% of the worldwide landslide incidents occur in the Himalayan region with damage amounting to one billion US$ and the loss of 200 people every year. Estimates indicate loss of land due to landslides is up to 120 m/km/yr leading to yearly loss of about 2500 tons/sq.km (NDMA report, 2011). In a global database of landslide disasters given by Froude and Petley (2018), three – quarters of all landslide events between 2004 to 2016 occurred in Asia, with substantial events in the Himalayas. Government records show that landslides in the Himalayan region kill at least one person per 100km and the average losses in this region is up to Rs 100 crore to Rs. 150 crores every year. One of the most affected regions in Darjeeling Himalayas is Kalimpong which is situated in the state of West Bengal.

The primary triggering factor for landslides in the Himalayan sector is rainfall. In a report by Geological Survey of India (GSI, 2016) it identified that 75% of the landslide occurrences in Darjeeling Himalayas during 2006-2013 was triggered by rainfall. Therefore, it is imperative to derive relationships between landslide incidences and rainfall conditions. There are mainly two types of methods to understand this relationship: physical and empirical. Physical process models are based on numerical models which study the relationship between rainfall, pore water pressure, soil type, and volumetric water content that can lead to slope instability. Such a study is usually site specific due to variation in soil properties [24]. It is a challenge to extend this approach to large areas, as the extensive data that is required are usually not available. On the other hand, empirical methods study the landslides that are caused by rainfall events – both the heavy downpour that triggers instantaneous landslides and the low but continuous antecedent rain that destabilizes the slope and triggers the landslide. Though this approach is based on a single parameter, precipitation rates, it is significant to note that rainwater is the cause of many changes in soil properties, pressure variations, etc and hence can be approximated to the changes in rainfall.

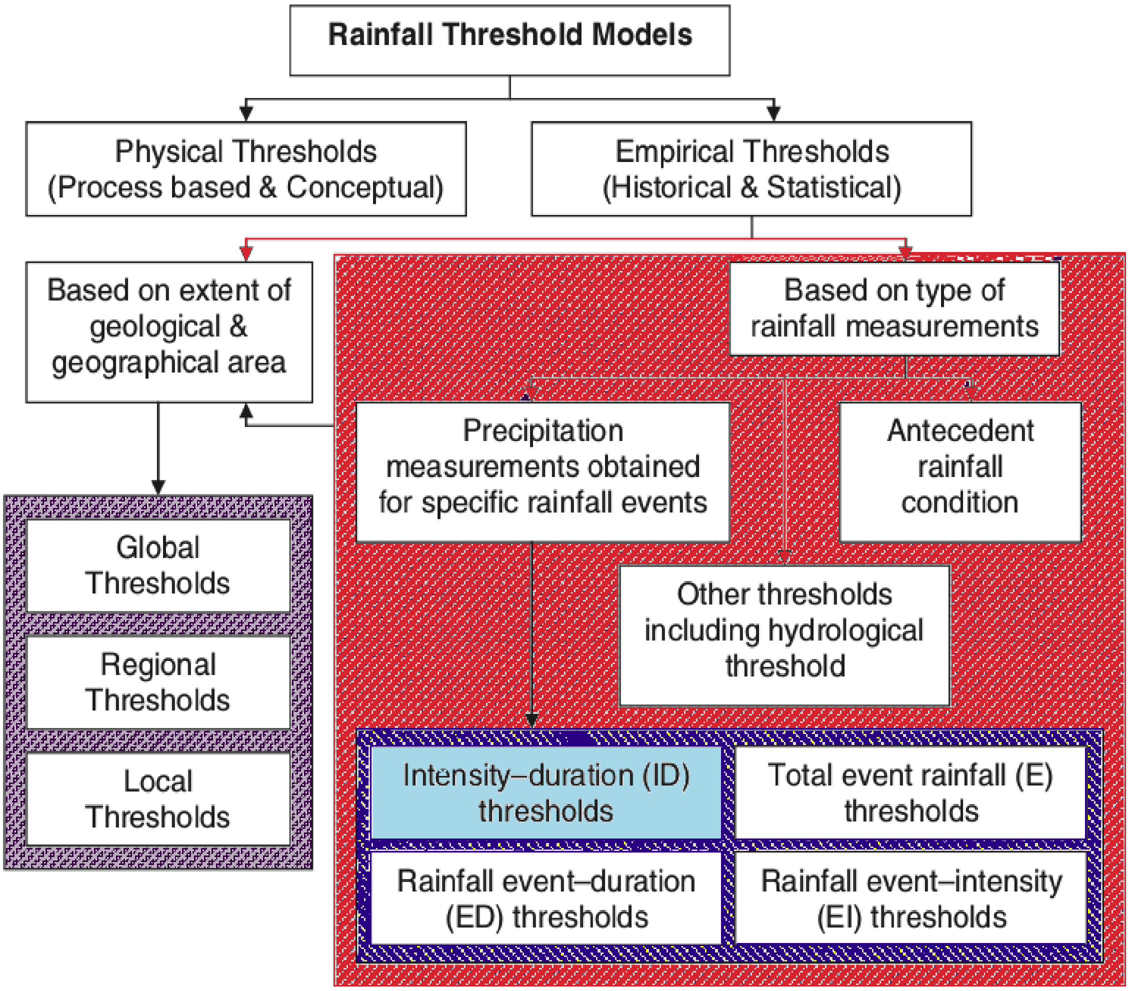


Figure 1 Flow diagram of rainfall threshold models

During the last few decades, many attempts were made across the world to define critical rainfall thresholds based on a number of different rainfall parameter, but the most common are intensity and duration (I-D thresholds) (Caine 1980; Aleotti 2004; Guzzetti et al. 2007; Brunetti et al. 2010; Dikshit and Satyam 2018; Rosi et al. 2016) and total event rainfall and duration (E-D thresholds) (Zhao et al. 2019; Teja et al. 2019; Melillo et al. 2018; Gariano et al. 2018; Peruccacci et al. 2017).However, the studies in this region are minimal. In this study , a total of four models namely **Antecedent** model, **SIGMA** model, **SHETRAN** model, **SIGMA-U** model were implemented. These models were calibrated for 2010-16 and validated using 2017 real time sensor data.The methodology of the models is described in the further chapters of the thesis.

Chapter 2

Study Area

Kalimpong town is a part of the Kalimpong district of West Bengal state, India (Fig. 2). This hilly town belongs to Darjeeling Himalayas, hemmed between rivers Tista in the west and Relli in the east, with an elevation ranging from 355m to 1646m above mean sea level. The slopes in the western face of the town are steep in nature while the eastern slopes are gentle. The moderate temparature variation from 5 ^{O}C to 27 ^{O}C also makes this place attractive for tourists. The havocs associated with landslides are affecting both the agricultural and tourism sectors of the town affecting the economy of the locality. Loss of agricultural land and disruption of transportation facilities makes the monsoon season challenging for people of Kalimpong.

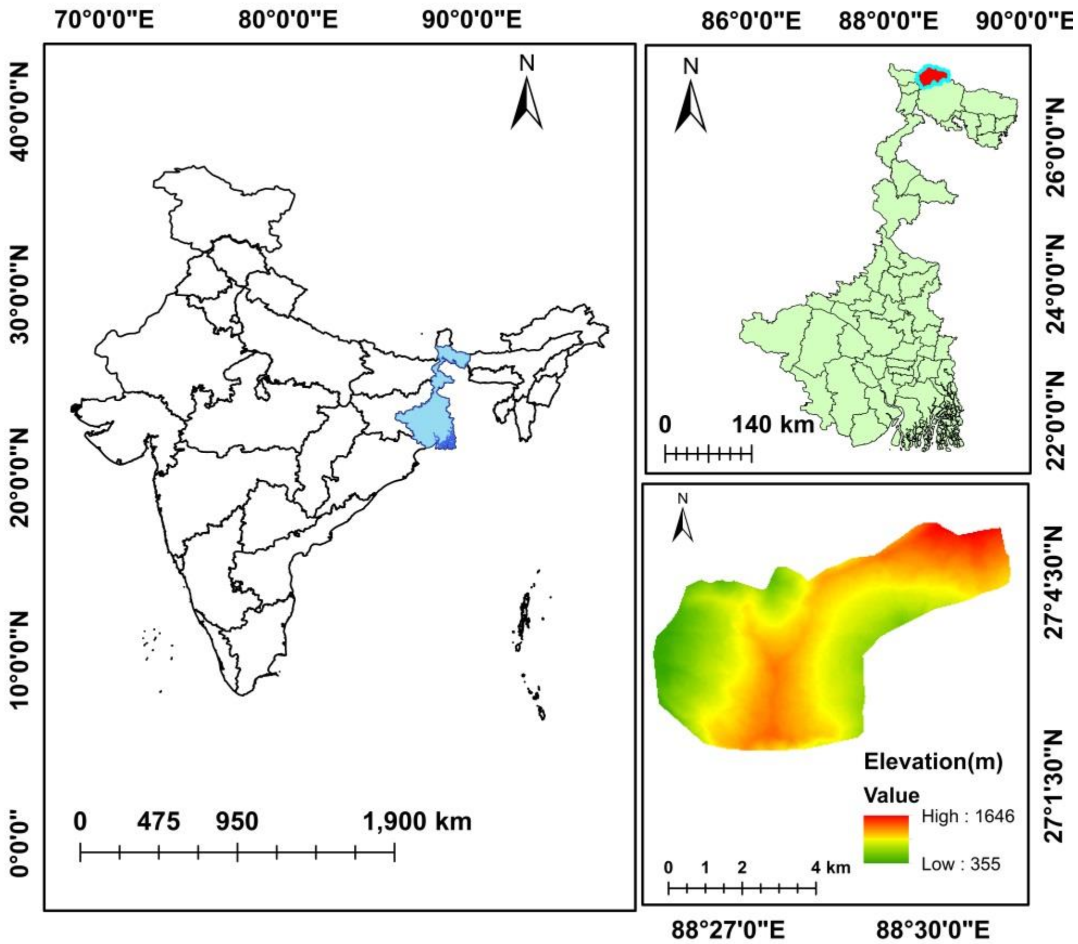


Figure 2 Location details of study area: (a)India (b)West Bengal (c) Digital Elevation Model of Kalimpong [32]

Pre-cambrian high-grade gneiss and quartzite,calc-silicate and quarzite, high–grade schist phyletic etc are the dominant rock types found in the region[58]. Upper sedimentary layers of the young folded mountains gets eroded during heavy rainfalls. The area consists of several joints and cracks that intensifies the probability of decomposing and disintegrating the rock to form unconsolidated matter.The bedrock throughout the study area is composed of Daling series quartz mica shist of golden to silver color[48]. The inclination of bed towards the east and northeast varies from 20^o near river Tista to about 40^o towards town. Morphometrically, the slopes in this region can be classified into escarpment category A (>45^o), steep slope category B (30°-45°) , moderate steep slope category C (20°-30°) and gentle slope category D (10°-20°). Silt to medium grained sand and loam constitutes a major portion of the top soil of the area. According to GSI, more than 60% of the region comprises of colluvium followed by older debris (24%) and young debris (2.5%).

From the historical landslide inventory reports, it was understood that rainfall is the major triggering factor of the landslide hazards in the region. The average annual precipitation in this area was observed to be 1872 mm during the study period and the drainage density of the region is also very high. The area is drained by numerous mountainous natural streams (kholas) and their tributaries (jhoras). The geology of the area allows rainwater to percolate, increasing the pore pressure, therefore the shear strength of the soil decreases. The change in water content due to intense rainfall leads to the saturation of material and a sudden increase in the unit weight. This mechanism reduces the stability and resistance of parent rocks. The precipitation with daily accuracy was collected for this study from the rain gauge maintained in Tirpai, Kalimpong [52]. The months from June to September are considered as monsoon period and the monthly rainfall from 2010-2017 is given in Table 1.

Table 1 The rainfall data (mm) during the monsoon months in Kalimpong town (2010-2017)

Month	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
June	317	337	355	248	396	568	327	154
July	666	678	433	424	371	534	870	812
August	425	526	251	401	572	242	263	432
September	268	384	467	113	265	331	367	288

The catalogue prepared by Dikshit and Satyam (2017) from the reports of Geological Survey of India, newspapers and field surveys is taken for this study. The database contains the spatial and temporal distribution of 61 rainfall induced landslide events during 2010-2016 (Figure 4). The catalogue did not mention the typology of landslides. The major fatal landslides happened in the region were shallow/rapid in nature, but there are some areas which experience continuous sinking because of deep seated movements, especially near major jhoras[52]. During the validation period (year 2017), ground displacements were observed on 7 days at two locations [38]. The annual cumulative rainfall for these years is plotted in Figure 3 and the temporal distribution of landslides along with the average rainfall is shown in Figure 5.

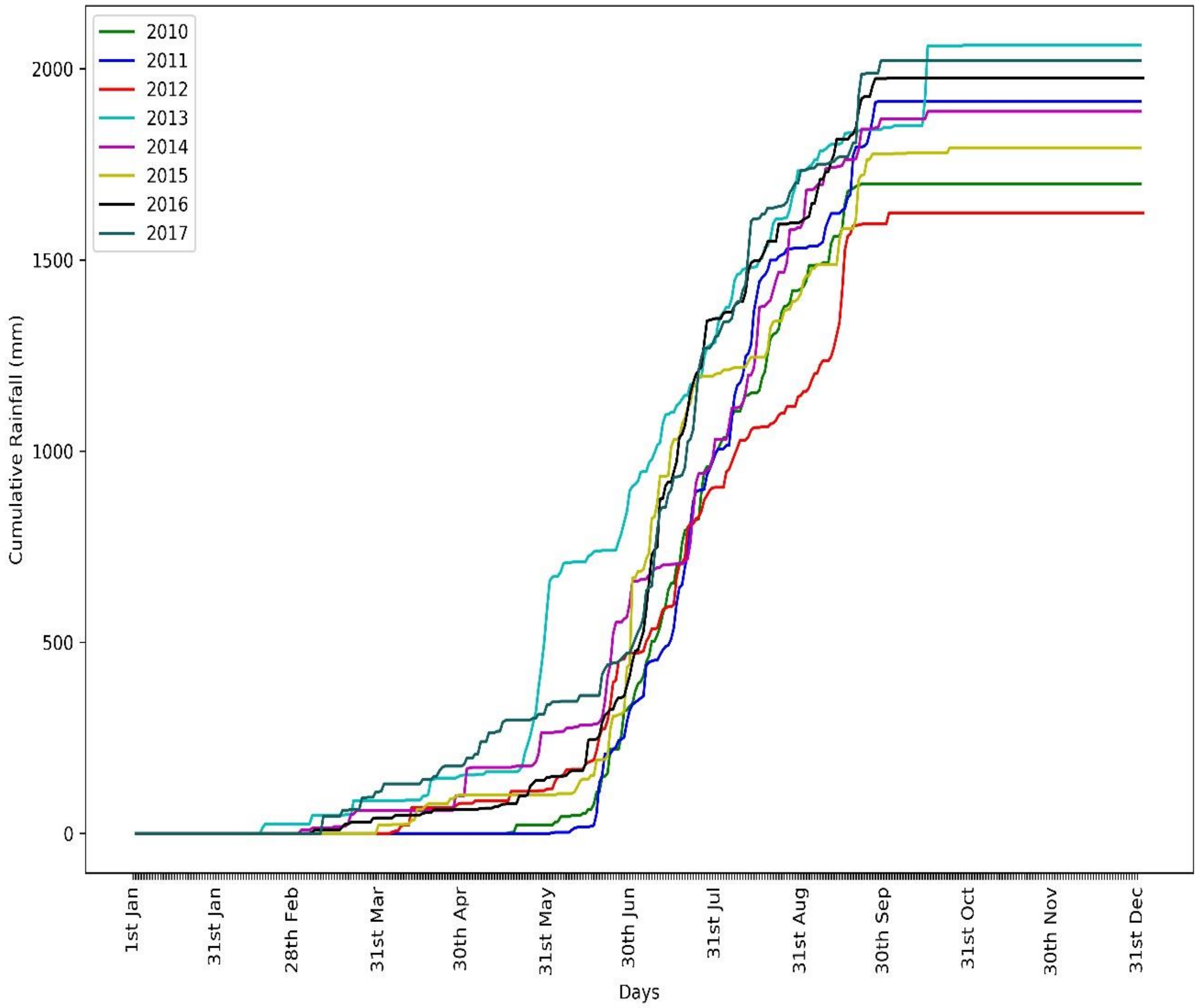


Figure 3 Yearly Cumulative Rainfall

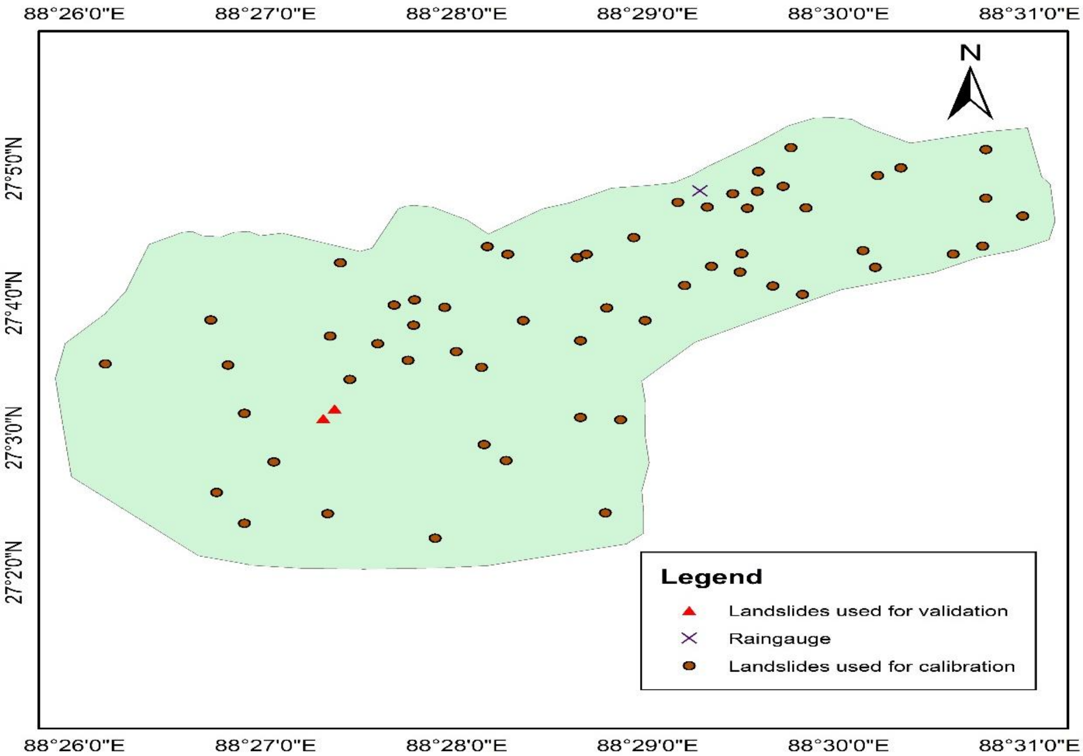


Figure 4 Spatial distribution of rain gauge and landslide events during study period

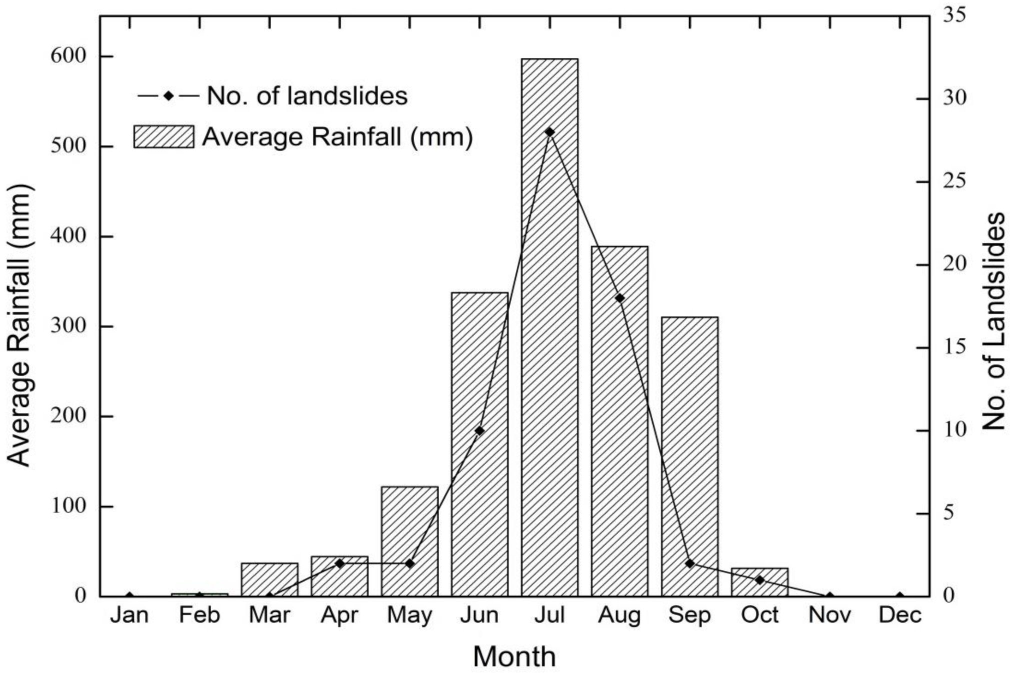


Figure 5 The monthly distribution of landslide occurrence and average rainfall, (2010-2017) in mm

It is observed that the number of landslide events is maximum in the month of July where the rainfall peak is recorded. From Figure 5, it is clear that the number of landslides is directly relalted to the rainfall amount. The temporal distribution of rainfall and landslide occurred in the study area during 2010-2016 has been considered for the detailed analysis and validation has been carried out for subsequent years.

Chapter 3

Literature Survey

The summary of all the literature that I've gone through to decide and implement my objectives is described in this chapter.

3.1 I-D thresholds [35]

In this paper, rainfall thresholds for landslide occurrence have been determined for the Kalimpong region of Darjeeling Himalayas, West Bengal. A threshold for landslide occurrences which describes intensity–duration threshold was estimated using the power law equation.

$$I = \alpha D^{\beta}$$

The relationship obtained for the region is I = 3.52 D−0.41, where I is rainfall intensity (mm/h) and D is duration (h). A rainfall intensity of 0.95 mm/h with a duration of 24 h have a high chance of landslide initiation in this region. According to the results obtained, for 10-day antecedent rainfall an intensity of 88.37 is required for landslide occurrence in this region.

3.2 E-D thresholds [56]

In this paper, the methodology uses an automated tool which determines ED thresholds for various exceedance probabilities. The equation of the ED curve is assumed to be in the form of power law.

$$E = \alpha D^{\beta}$$

The relationship obtained for the region is E = 5.5 D-0.61, where E is the cumulative rainfall (mm) and D is the duration (h).The results show that a cumulated event rainfall of 36.7 mm over a rainfall event of 48 h can trigger a landslide in this region.

3.3 Antecedent thresholds [24]

In this paper, antecedent rainfall is used to determine the threshold equation. The antecedent period is determined by the relation between daily rainfall and antecedent rainfall for landslide occurring events and non-landslide occurring events. Later, a threshold equation is obtained for the region from the graph between daily rainfall and antecedent rainfall. The detailed procedure is explained in the Chapter 5 of the thesis.

3.4 SIGMA model [17]

In this paper, an algorithm is designed to determine the criticality of a particular day. The algorithm uses the cumulative rainfall data ranging from 1-365 days. The thresholds are set as multiples of standard deviations, which are later optimised to remove the false alarms. The detailed procedure of the model is explained in the Chapter 6 of the thesis.

3.5 SHETRAN model [59]

In this paper, a hydrological model is used to simulate the soil moisture for the region which is calibrated by maximising the NSE value. The soil moisture thus obtained is integrated with ED thresholds using a Bayesian approach. The probability for the occurrence of landside for different conditions is obtained. The detailed procedure of the model is explained in the Chapter 7 of the thesis.

3.6 SIGMA-U model [55]

In this paper, the algorithm designed in SIGMA model is modified by adding the soil moisture conditions. This helps in the reduction of false alarms and missed alarms thereby increasing the efficiency of the model. The detailed procedure of the model is explained in Chapter 8 of the thesis.

Chapter 4

Objectives

Rainfall being the most common triggering factor for landslides, early warning systems are usually based on empirical rainfall thresholds that describe the interaction between the primary cause (rainfall) and the final effect (landslide). In a few words, a triggering threshold is represented by a mathematical equation describing the critical rainfall condition above which landslides are triggered. The only input data used for the threshold definition are a dataset of rainfall recordings and a catalogue of landslides for which the time and location of occurrence are known with sufficient approximation. This approach completely bypasses the physical mechanism of triggering, thus simplifying the modelling effort, the computational resources required, and the amount of data needed for the analysis There have been few attempts to define rainfall thresholds for landslides using empirical methods. However, the efficiency of the models is not satisfactory. In this study, an attempt has been made to improve the efficiency of early warning systems.

The objectives of the study are as follows:

- To determine rainfall thresholds using the landslide forecasting models
    - Antecedent model
    - SIGMA model
    - SHETRAN model
    - SIGMA – U model
- To validate the thresholds with real time tilt sensor data
- To propose a Landslide Early Warning System (LEWS) by integrating forecasting models and monitoring data for Kalimpong

Chapter 5

Antecedent model

A threshold can be defined as the minimum level of some quantity for a process to change [20]. For rainfall induced landslides the minimum intensity or duration of rainfall for a landslide to occur is termed as rainfall threshold [25]. Rainfall thresholds have been proposed all over the globe on various scales and its determination can be considered as a preliminary step for landslide hazard assessment. The various threshold types along with their uses and limitations have been described in [10]. The threshold using rainfall intensity duration is the most recognised and well-established method [17]. The determination of rainfall threshold revolves around four variables, i.e., daily rainfall, antecedent rainfall, cumulative rainfall and normalised critical rainfall [24]. The determination of thresholds is dependent on the choice of parameters conditional to the landslide type [24].

Antecedent rainfall influences the soil suction leading to an increase in pore water pressure thereby causing slope instability. Majority of the landslide occurrences in the Himalayan region is due to the effect of antecedent rainfall [8].[35] established that antecedent rainfall is a significant factor for landslide occurrence in Kalimpong.

The challenges in forecasting landslides using antecedent rainfall is to ascertain the number of days to be used [10]. Various authors have used different time periods to determine the correlation between antecedent rainfall and number of days for landslide triggering.[15] examined for 3, 4, 18 and 180 days respectively. [1] used 7, 10 and 15 days whereas [23] assessed 2, 5, 15 and 25 days. In this study, we considered 3, 7, 10, 15, 20 and 30 days and the results have been depicted in Fig. 3.

The thresholds are determined by a scatter plot with daily rainfall data on the ordinate and the antecedent rainfall for various time periods on the abscissa. The red triangle denotes the landslide occurrences whereas the blue triangle shows the maximum annual precipitation in one day without any landslide event.

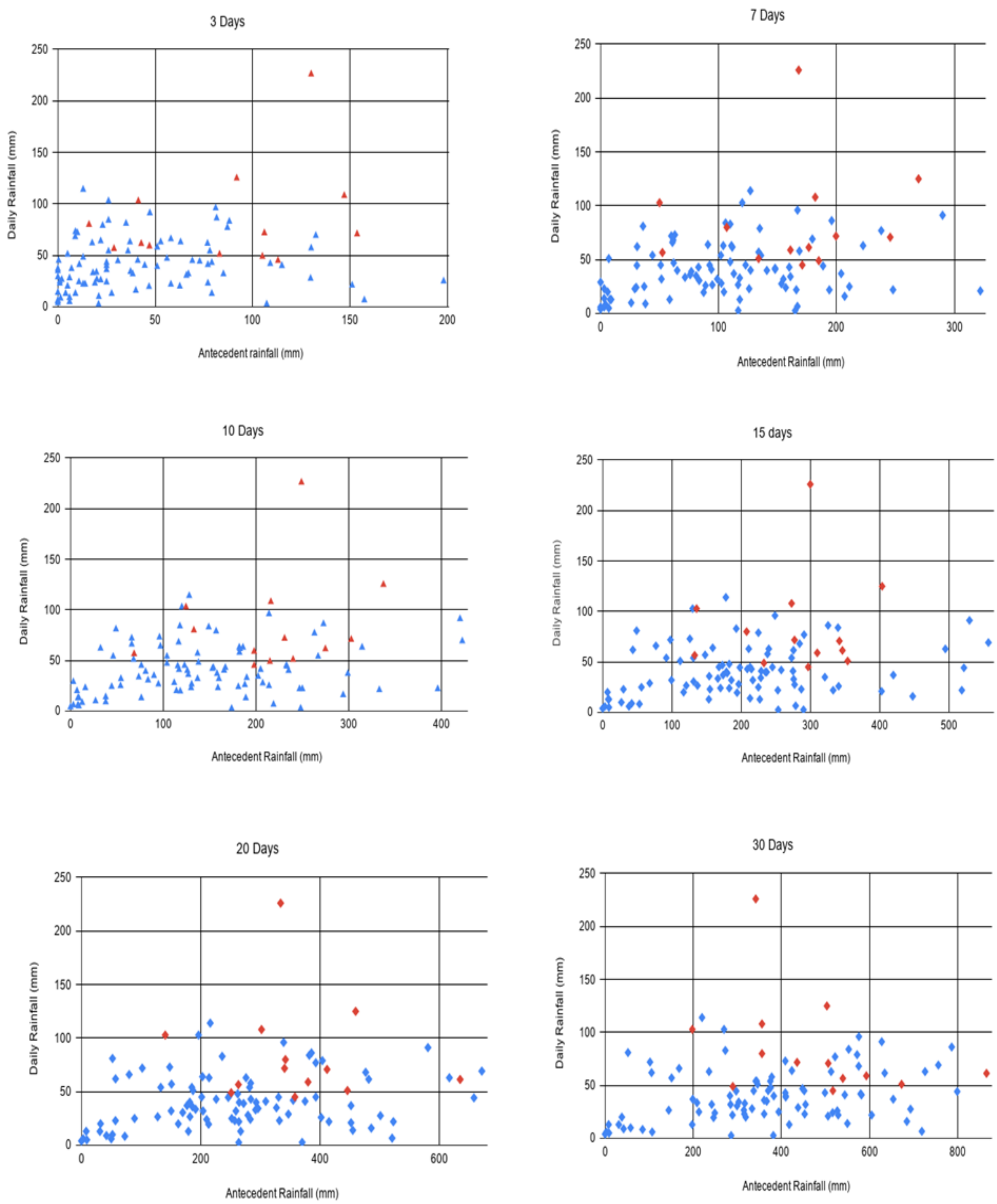


Figure 6 Relationship between daily and antecedent rainfall for 2010-2016

In the relationships shown in the above-mentioned figure, 15-day graph shows the best distinction between landslide occurring events and non-landslide occurring events. Hence, 15-day graph is chosen for threshold determination.

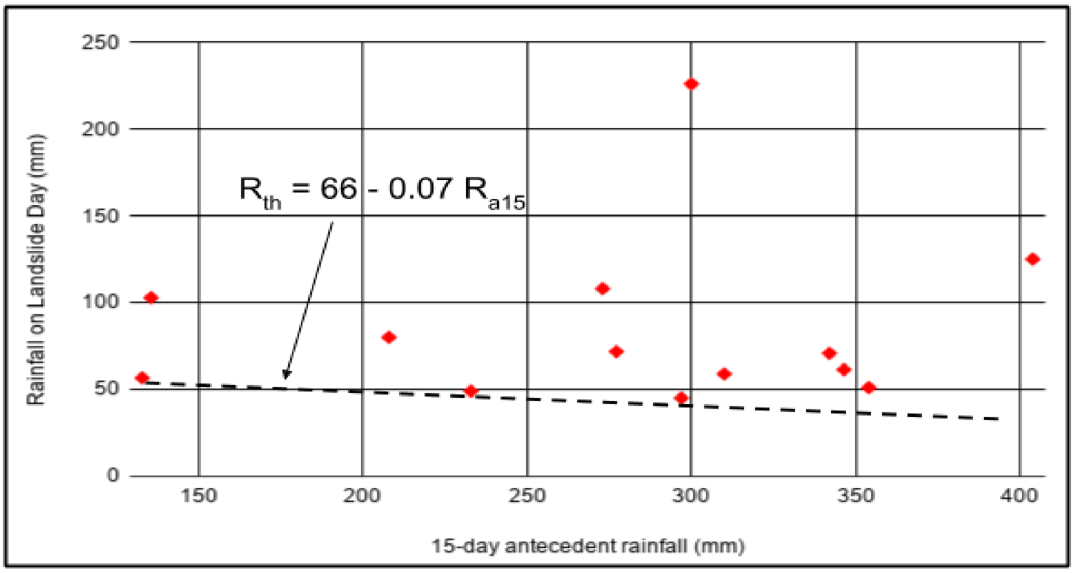


Figure 7 Rainfall Thresholds for Kalimpong region, Rth being the threshold rainfall and Ra15 is the 15- day antecedent rainfall

The equation for the threshold is obtained using the lower end of the plotted points. The distinction between the triggering and non-triggering landslide event for various days corresponds to the determination of the best antecedent rainfall period. The threshold equation from the analysis came out to be $\mathbf{R_{th} = 66 - 0.07\ R_{a15}}$

Chapter 6

SIGMA model

6.1 Methodology

SIGMA model was developed for Emilia Romagna region in Italy [17]. This model uses the standard deviation of a statistical distribution as the key parameter for the analysis and defines thresholds as a function of standard deviation, predicting the potential of rainfall to initiate landslide events in the study area. The daily precipitation data were added at ‘n’ days, with an ‘n’ day wide shifting window which moves at 1-day time steps throughout rainfall data. The values of ‘n’ will vary from 1 to 365. To calculate the cumulative probability distribution for each data set, a standard distribution, which is the target function is chosen as a model [41].This transformation relates the cumulative rainfall(z) with the target distribution (y = aσ) (‘σ’ is the standard deviation of the series and ‘a’ is a multiplication constant). For each ‘n’ day cumulative rainfall series, the values are sorted in ascending order such that

$$z_1 < z_2 < z_3 < \cdots < z_k < \cdots < z_n$$

And a cumulative sample frequency is defined as

$$P_k = \frac{k}{n} - \frac{0.5}{n} = G(y)$$

where $1 \leq k \leq n.$

The transformed value y on the original data z is obtained as :

$$G^{-1}(F(z)) \rightarrow G^{-1}(P_k) = y$$

After applying the transformation function, from a particular value of standard deviation or its multiples, cumulative sample frequency and precipitation can be calculated. The same procedure is repeated for all values of n from 1 to 365 and precipitation curves (σ curves) are plotted. The probability curves derived are used as the input values in the algorithm. A level of warning is predicted for every day based on the rainfall thresholds. Rainfall recordings were cumulated with one day time steps for a particular time interval. These values are compared with the precipitation curves, from shorter to longer time frames [17]. In case of shallow landslides, the analysis should focus on the immediate effect of rainfall: the cumulative rainfall values up to 2 days before the day of analysis is considered. The decisional algorithm used is:

$$C_{1-3} = \left[\sum_{i=1}^{n} P(t+1-i)\right]_{n=1,2,3} \geq [S_n(\Delta)]_{n=1,2,3}$$

where Δ= a.σ, $C_{1\text{-}3}$ is the vector of cumulated rainfall at the time of analysis t and $S_n(\Delta)$ are the thresholds relative to Δ and number of days n [17]. In the case of deep-seated landslides, the algorithm ponders the effect of cumulative rainfall from 4 days up to 63 days [17]. The condition for crossing the threshold is given by:

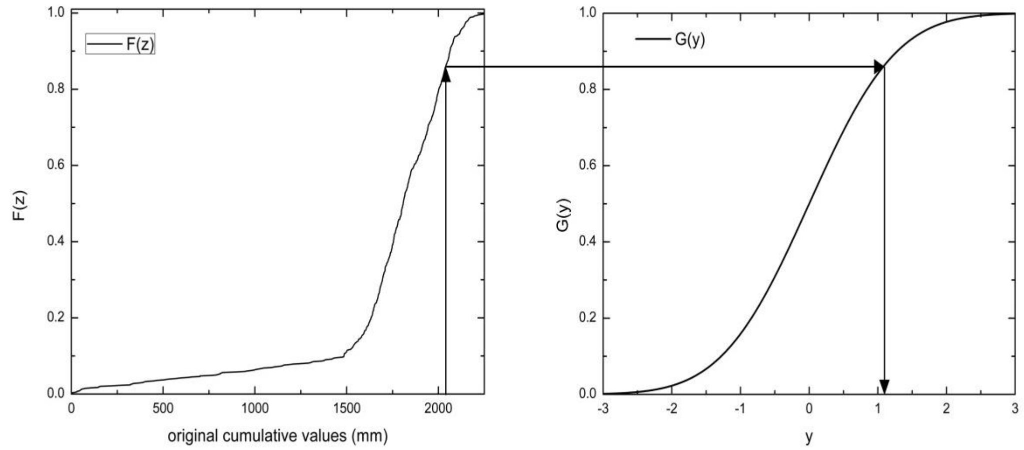
$$C_{4-63} = \left[\sum_{i=1}^{n+3} P(t-2-i)\right]_{n=1,2,\ldots 60} \geq [S_{n+3}(\Delta)]_{n=1,2,\ldots 60}$$

The definitions of vector C are kept the same and have been used in the study for the analysis. The analysis was carried out in the same method proposed by the developers of SIGMA model, to define the thresholds for Kalimpong town.

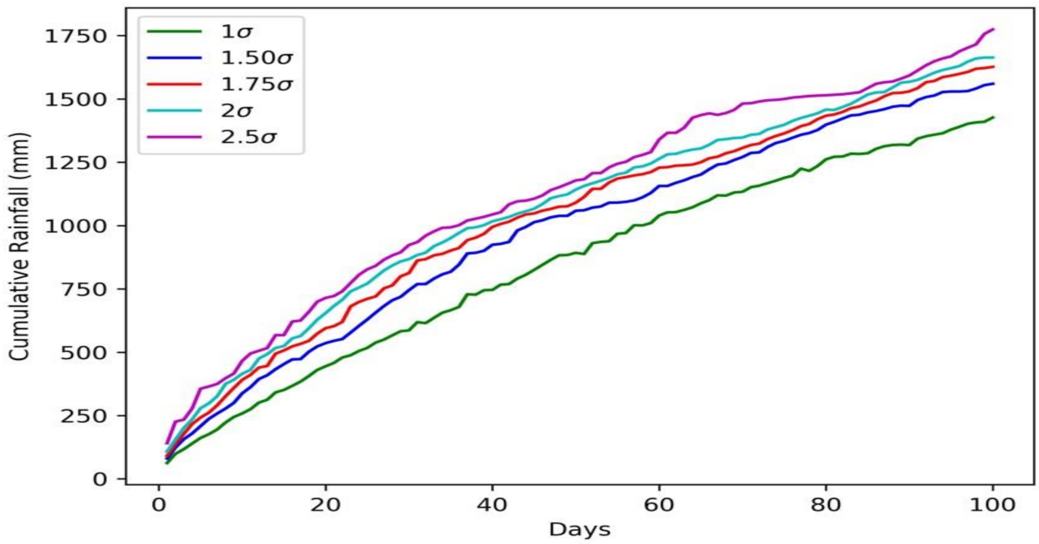
6.2 Analysis

The rainfall and landslide data (2010-2016) for Kalimpong town, has been used for developing rainfall thresholds for the region. For each day, ‘n’-day cumulative rainfall values were calculated with n ranging from 1-365. Cumulative probability distribution curves were plotted after sorting the values in ascending order. For small values of ‘n’, the distributions were found to be closer to log normal and for higher values of ‘n’, the distributions tend towards normal. The asymmetric distribution of data sets has been observed by other researchers as well [17]. Choosing Gaussian distribution as target function, cumulative values corresponding to multiples of sigma were calculated by applying the transformation as shown in Figure 8a.

After applying the transformation, a probability of not overcoming a particular “aσ” value can be calculated using the reverse procedure. For each value of “aσ”, cumulative values for n-days varying from 1-365 were plotted as sigma curves. The values of standard curves were initially taken as 1.5σ, 1.75σ, 2σ and 2.5σ and are plotted in Figure 8b.



(a)



(b)

Figure 8 (a) Transformation of original cumulative distribution in the target distribution for Kalimpong town (b) An example of Sigma curves (σ curves) for cumulative periods up to 100 days (2010-2016)

From the probability distribution plots, sigma curves have been combined using an algorithm, which is the crucial part of SIGMA model. The algorithm defines four different levels of warning such as "High", "Moderate", "Ordinary" and "Absent". These values are used to delineate exceptional rainfall values. The starting algorithm for the proposed model is as shown in Figure 9. It considers the effect of short-term rainfall first and exceedance of threshold will give high criticality alert. If high criticality case does not exist, first moderate criticality and then ordinary criticality conditions were checked. If the result is negative in all cases, absent criticality is defined for a particular time period. The block diagram proposed in Figure 9 has to be considered as a starting point for the work, since it was then calibrated as described in the following paragraphs.

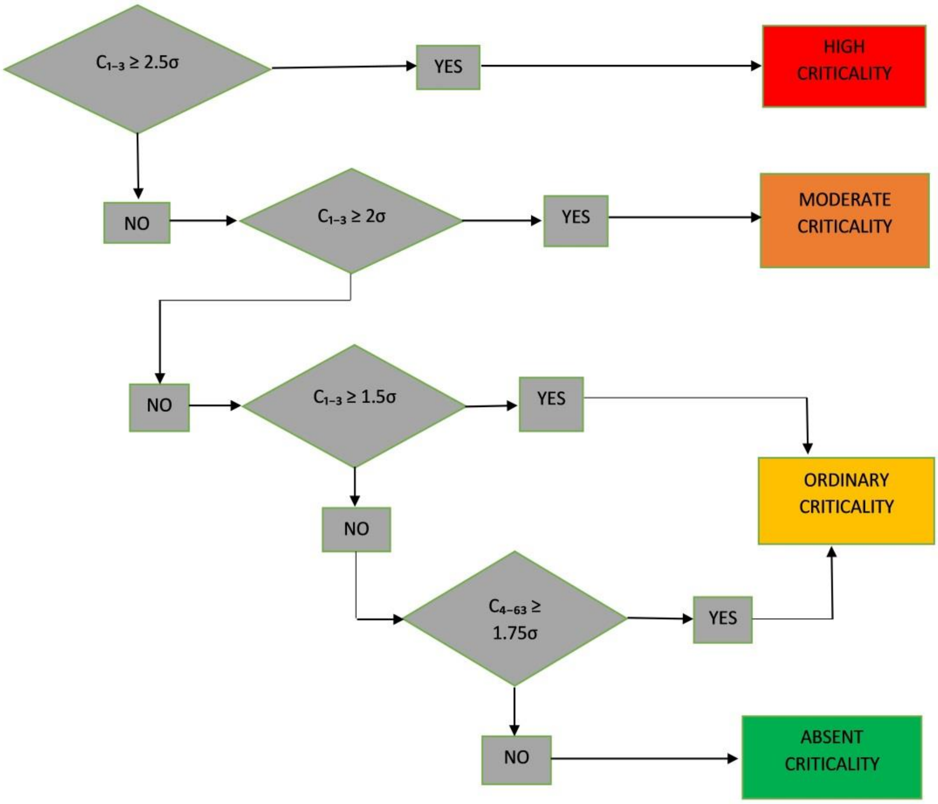


Figure 9 Algorithm used for calibration of the SIGMA model for Kalimpong town.

A threshold is considered to be exceeded if any of the elements in the vector crosses the value. Once a threshold is exceeded, the algorithm defines the level of warning on each day. These outputs were used to calibrate the model (data from 2010-2016). A trial and error procedure has been adopted in the optimization module of the algorithm which relates the daily warning levels with the occurrence of landslides, as in [17]. The value of threshold is progressively raised so that false alarms are avoided. A visualization of the procedure is shown in Figure 10 where standard sigma value of 1.75 was optimized to 1.8. Using the same procedure, other standard values of 1.5, 2 and 2.5 were optimized to 1.6, 2.1 and 2.75 respectively. The thresholds values were increased to minimize false alarms for each event such that no true alarms are missed. The execution of this module terminates once the algorithm catches an event with an observed warning level conforming to the considered threshold. The standard sigma curves remain the same, but the calibration process gives a modified set of sigma curves for the region.

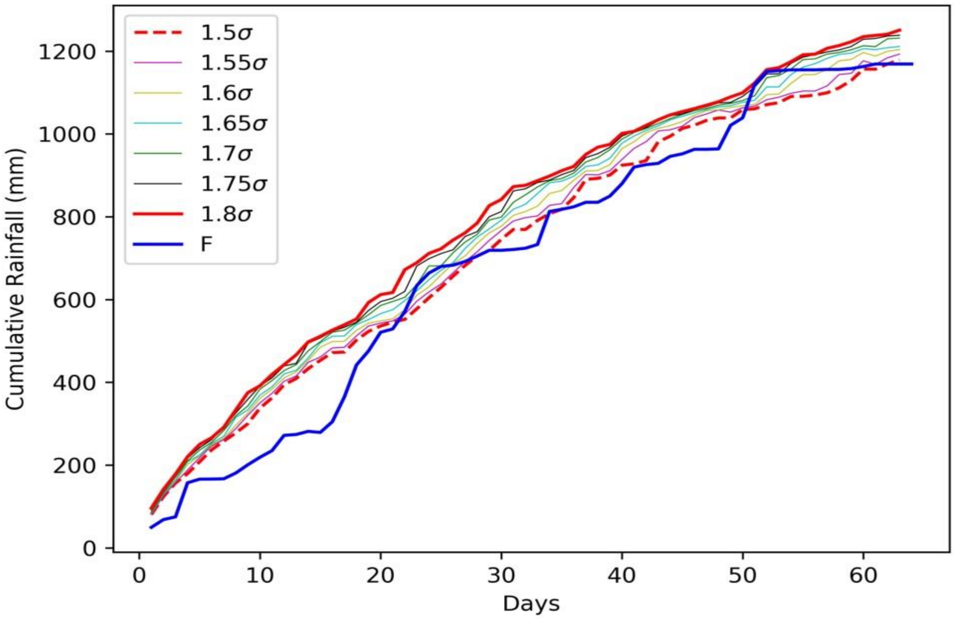


Figure 10 Visualization of calibration algorithm. The threshold value was raised till the cumulative rainfall curve of the event (F) is not crossing the threshold curve. (Standard Threshold of 1.75 is optimized to 1.80)

Table 2 Optimisation results

Former 1.5 $\boldsymbol{\sigma}$	Former 1.75 $\boldsymbol{\sigma}$	Former 2 $\boldsymbol{\sigma}$	Former 2.5 $\boldsymbol{\sigma}$
1.60 $\boldsymbol{\sigma}$	1.80 $\boldsymbol{\sigma}$	2.10 $\boldsymbol{\sigma}$	2.75 $\boldsymbol{\sigma}$

Chapter 7

SHETRAN model

7.1 Methodology

7.1.1 Soil Moisture Simulation using Hydrological model

SHETRAN - Système Hydrologique Européen TRANsport, is a distributed hydrological model. SHETRAN has proved to be a reliable hydrological model and is applied in a wide range of catchments. Water flow, sediment transport and contaminant transport are the three main components of SHETRAN. However, this study only uses the water flow component. Precipitation, potential evapotranspiration, DEM, soil properties and land use are the inputs required. In this study the variation of land cover and soil properties are not taken into consideration. The model is calibrated using soil moisture data downloaded from MERRA-2 dataset. The Nash-Sutcliffe Efficiency (NSE) is maximized by changing the parameters of vegetation and soil properties. The optimal value of NSE is 1.

Table 3 Equations of hydrological processes in SHETRAN

Process	**Equation**
Evaporation	Penman - Monteith
Canopy interception	Rutter
Subsurface flow	Variably saturated flow equation
Overland flow	Saint - Venant
Channel flow	Saint - Venant

7.1.2 Definition of rainfall events and thresholds

Firstly, rainfall events are to be reconstructed. A dry period of 1 day is set for both monsoon and non-monsoon season. After the reconstruction of rainfall events, cumulative rainfall (E) and duration (D) are obtained. Using Frequentist approach, ED rainfall threshold is determined which is assumed to be a power law:

$$E = \alpha D^{\beta}$$

Where α and β are scaling constant and shape parameters respectively.

Thresholds with different exceedance probabilities are evaluated.

7.1.3 Bayes Theorem

Given the joint occurrence of two conditions, two-dimensional Bayesian analysis is used to evaluate the conditional probability of occurrence of a landslide. In this case, antecedent soil moisture conditions and severity of rainfall event are the two factors. The simulated soil moisture is scaled to (0,1). The moisture conditions are then classified into 5 categories. ([0,0.2), [0.2,0.4), [0.4,0.6), [0.6,0.8), [0.8,1]). Based on the severity level, rainfall events are divided into six categories: (T_{min}, T_5, T_{10}, T_{20}, T_{50}). As a result, 30 cell conditions are formed for the analysis.

Two-dimensional Bayesian probability can be defined as:

$$P(A|B, C) = (P(B, C|A)\, P(A))/P(B, C)$$

Where A – event of at least one landslide occurrence.

B, C – antecedent moisture conditions and severity of rainfall

P (B, C| A) – conditional probability of B, C given A.

P(A) – probability of A

P (B, C) – probability of B, C

Consider number of rainfall episodes during period of particular time be N_R; number of incidences of landslides during the same time period be N_A, number of rainfall episodes and soil moisture of magnitude B, C be $N_{B,C}$ and the number of rainfall events causing landslides be $N_{(B, C|A)}$,

$$P(A)=N_A/N_R$$

$$P(B, C) = N_{(B, C)}/N_R$$

$$P_{(B, C|A)} = N_{(B, C|A)}/N_A$$

7.2 Analysis and Results

The model is calibrated for the period 2010 to 2016. The value of NSE turned out to be 0.84 which is optimal. The soil moisture simulated by SHETRAN varied between 0.6064 and 0.9257, which is further scaled down to (0,1). The average soil moisture for the period 2010-16 turned out to be 0.7331. A total of 208 rainfall events were reconstructed and their ED values are obtained, out of which 54 events resulted in landslides and are used for determining the ED threshold.

Table 4 Parameters of ED thresholds

Label	Probabilities	α	β
T_{50}	50	6.03	0.65
T_{20}	20	4.08	0.65
T_{10}	10	3.31	0.65
T_{5}	5	2.38	0.65
T_{min}	0	1.50	0.65

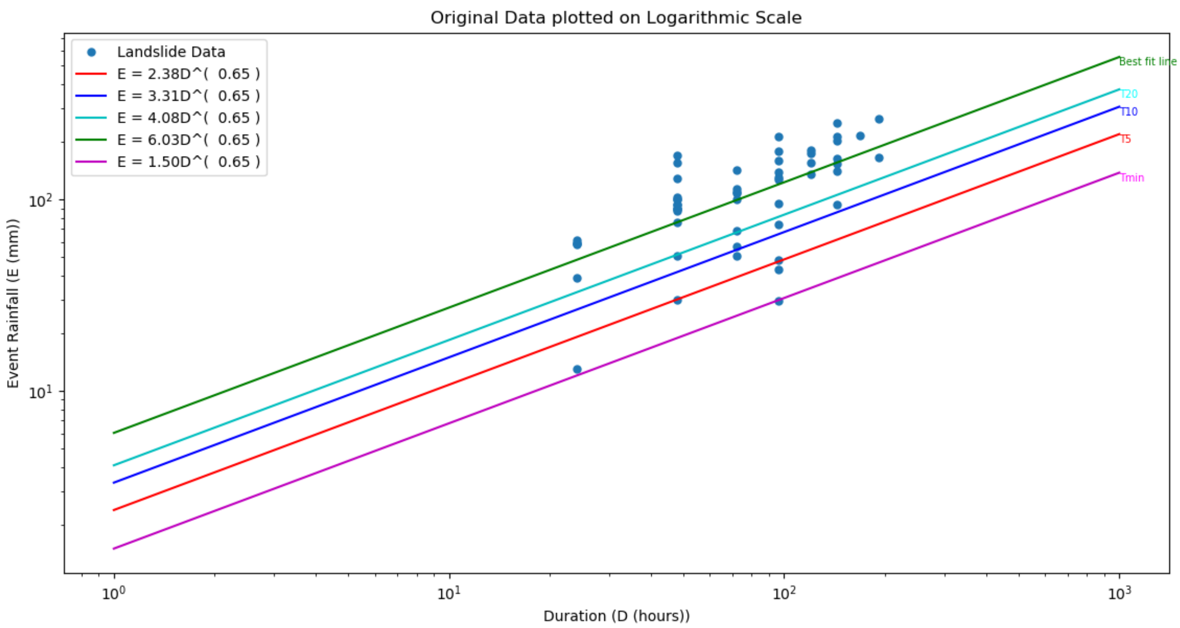


Figure 11 The rainfall thresholds with exceedance probabilities of 5%, 10%, 20% and 50% (T5, T10,T20, T50) and the rainfall threshold without considering the exceedance probability (Tmin)

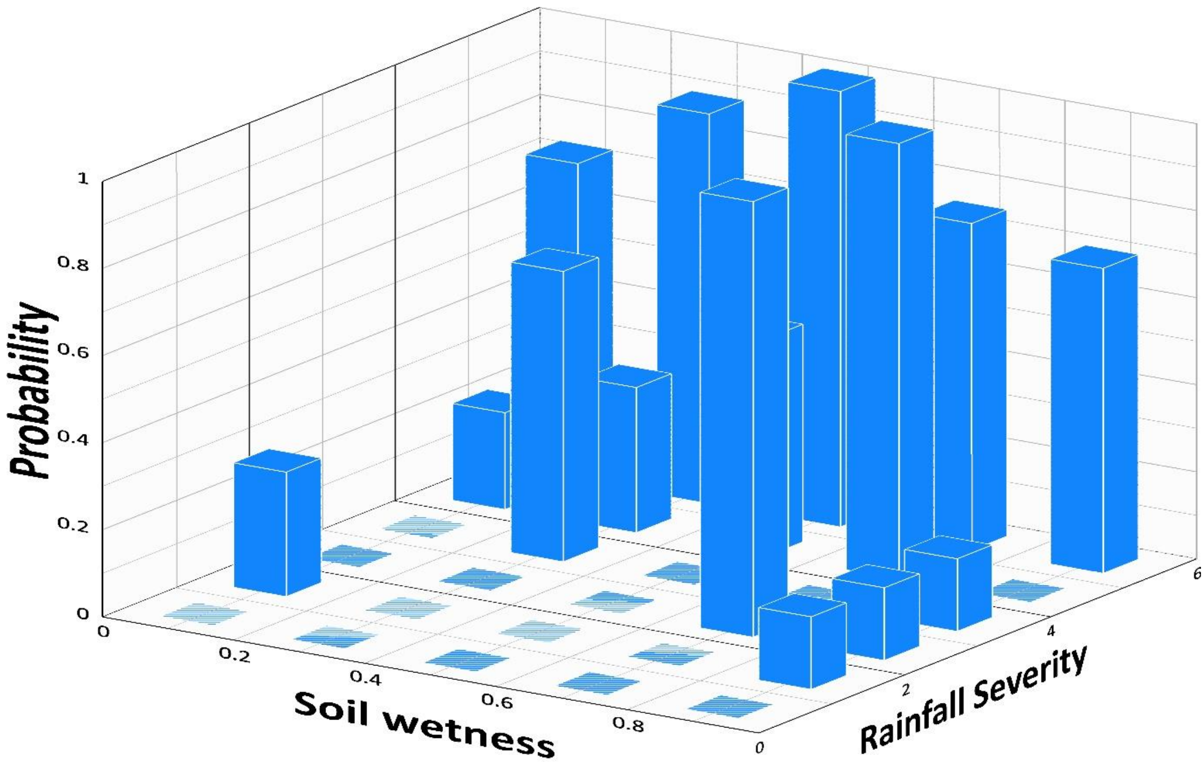


Figure 12 The distribution of landslide occurrence probability based on the two-dimensional Bayesian analysis.

Later ED thresholds and soil moisture conditions are integrated using Bayesian approach which gives the conditional probability of occurrence of a landslide for different cell conditions. These values are plotted in the Figure 12. After analysing the results and the graph a probability of 0.667 is considered critical for the occurrence of landslide.

Chapter 8

SIGMA – U

8.1 Methodology

In this model, an effort has been made to improvise the SIGMA model mentioned in chapter 6. The idea is to integrate the soil moisture simulated from SHETRAN with the SIGMA algorithm. This results in the reduction of false alarms and also, the efficiency increases. Analysis of soil moistures on landslide events from 2010-16 is done and moisture thresholds are determined as a multiple of standard deviations (same as in SIGMA model). Rainfall for longer periods results in the accumulation of moisture in the soil. Therefore, the cumulative rainfall with longer periods in the SIGMA algorithm are replaced by soil moisture thresholds. Also, the soil moisture thresholds are introduced after the cumulative rainfall with periods ranging from 1-3 days, so as to remove the false alarms.

The algorithm is mentioned in Figure 13.

8.2 Results

The algorithm is run for the period 2010-16. The results of back analysis are very encouraging. The statistics of the back analysis are as follows:

Table 5 Back Analysis of SIGMA-U

		SIGMA	**SIGMA-U**	**Variation**	**Variation %**
False Alarms	High criticality	1	0	-1	-100
	Moderate criticality	5	3	-2	- 40
	Ordinary criticality	124	47	-77	- 62.1
Missed Alarms	No of missed landslides	34	32	-2	-6.25
Hits	No of predicted landslides	27	29	2	7.41

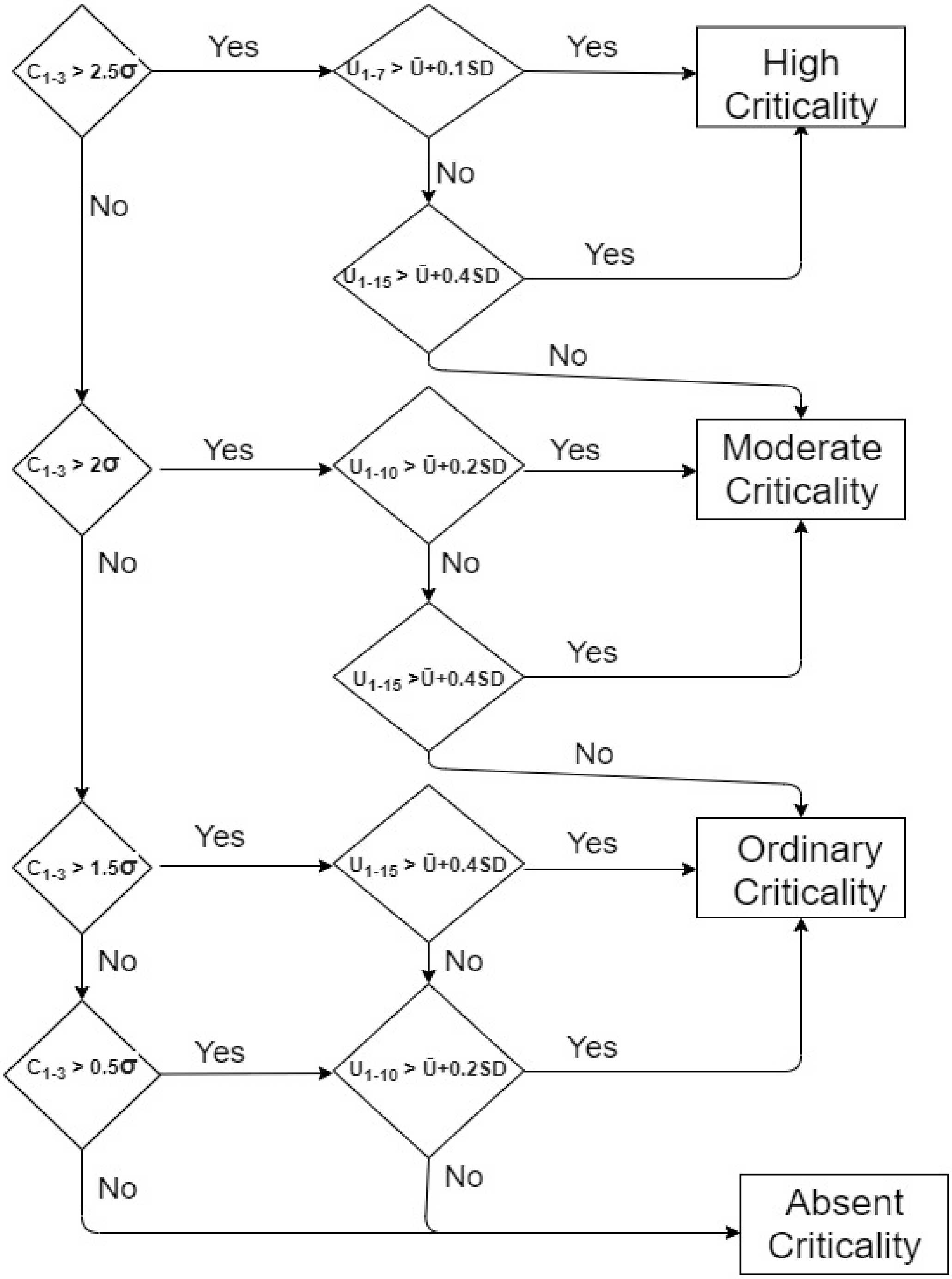


Figure 13 Scheme of the SIGMA-U algorithm. C is cumulative rainfall, U is soil moisture, u' is average soil moisture and SD is standard deviation of soil moisture series.

Chapter 9

Validation with tilt sensors

For the validation of results, rainfall and landslide data of 2017 have been used. The alarms predicted by the landslide forecasting models was compared with the reported landslide events. The Chibo-Pashyor area of Kalimpong, which is called the 'sinking zone' experienced ground displacements during July-August 2017 [37]. These deep-seated movements were triggered by continuous rainfall during the monsoon season. These instances were considered as events of ordinary criticality and used for the validation process. By using a confusion matrix (Figure 14), the alarms and warning levels were verified using the observed data.

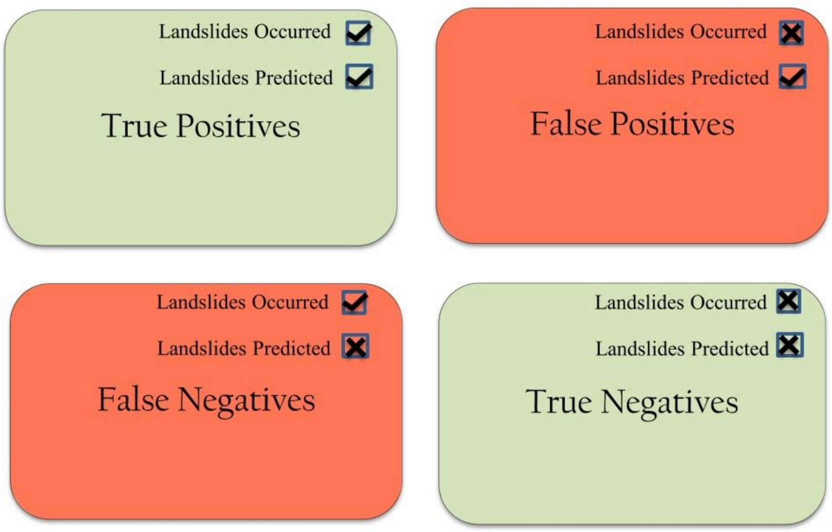


Figure 14 Confusion matrix

Correct predictions can be both true positives and true negatives, defined by the occurrence and non-occurrence of landslide event respectively. Missed alarms are counted as false negatives and false alarms are considered as false positives. Ground displacements were reported by tilt sensors at two locations in Chibo –Pashyor area for seven days: on 28th – 29th July, 2017 and 13th -17th August, 2017.

Table 6 The validation statistics of the forecasting models described in literature review

Statistical Attributes	ID [35]	ED [56]	ED (lower limit) [56]	ED (upper limit) [56]
a = True positives	1	1	1	1
b = False positives	45	41	62	22
c = False negatives	6	6	6	6
d = True negatives	313	317	296	336
Efficiency = (a + d) / (a + b + c + d)	0.86	0.87	0.81	0.92
Misclassification rate = (b + c) / (a + b + c + d)	0.14	0.13	0.19	0.08
Odds ratio = (a + d) / (b + c)	6.16	6.77	4.37	12.04
Positive predictive power = a / (a + b)	0.02	0.02	0.02	0.04
Negative predictive power = d / (c + d)	0.98	0.98	0.98	0.98
Sensitivity = a / (a + c)	0.14	0.14	0.14	0.14
Specificity = d / (b + d)	0.87	0.89	0.83	0.94
False positive rate = b / (b + d)	0.13	0.11	0.17	0.06
False negative rate = c / (a + c)	0.86	0.86	0.86	0.86
Likelihood ratio = Sensitivity / (1 – Specificity)	1.14	1.25	0.82	2.32

Table 7 The validation statistics of the forecasting models described in this study

Statistical Attributes	Antecedent	SHETRAN	SIGMA	SIGMA - U
a = True positives	3	2	7	7
b = False positives	10	20	22	11
c = False negatives	4	5	0	0
d = True negatives	104	338	336	347
Efficiency = (a + d) / (a + b + c + d)	0.885	0.93	0.94	0.97
Misclassification rate = (b + c) / (a + b + c + d)	0.115	0.068	0.06	0.03
Odds ratio = (a + d) / (b + c)	7.64	13.6	15.6	32.18
Positive predictive power = a / (a + b)	0.23	0.091	0.24	0.39
Negative predictive power = d / (c + d)	0.96	0.926	1	1
Sensitivity = a / (a + c)	0.43	0.286	1	1
Specificity = d / (b + d)	0.91	0.944	0.94	0.97
False positive rate = b / (b + d)	0.087	0.056	0.06	0.03
False negative rate = c / (a + c)	0.57	0.714	0	0
Likelihood ratio = Sensitivity / (1 – Specificity)	4.88	5.11	16.27	33.33

Chapter 10

Conclusions and Future scope

10.1 Conclusions

Landslide forecasting has been carried out in the study area using four forecasting models. All the models were calibrated using the rainfall and landslide data from 2010-16 and validation is done using the 2017 tilt sensor data. Improving the efficiency of the Landslide Early warning system has been the driving force of the study. The statistics of the validation are encouraging. As shown in Table 6, the highest efficiency among all the models in the literature review is 0.92 while the likelihood ratios are less than 2.5. The efficiencies of the models implemented in this study varied between 0.89 to 0.97 while the likelihood ratios reached as high as 33.33.

The main conclusions of the study are:

- The efficiencies of the 4 models gradually increased from 0.89 to 0.97.
- The likelihood ratios of antecedent, Shetran, Sigma and Sigma – U are 4.88, 5.11, 16.27, 33.33 respectively.
- SIGMA – U is the best forecasting model that can be integrated with real time tilt sensors to form a reliable and efficient Landslide Early Warning System (LEWS).
    - SIGMA-U model is a simple and efficient tool which can be used for landslide early warning on regional scale. The model predicts warning levels associated with each day, which can be directly linked to the severity of landslide events predicted.
    - The algorithm correctly predicted ordinary criticality levels on all the sliding events reported in 2017. These events were the result of continuous rainfall over a longer time period. It can be concluded that this algorithm- based approach efficiently considers the effect of both long-term and short-term rainfall and even slow movements are predicted correctly, providing a performance better than traditional I-D and E-D thresholds.

10.2 Future Scope

- Electrical Resistivity Tomography (ERT) can be done for landslide monitoring and understanding the geology of landslide prone areas.
- Field Survey can be done to get the soil properties which can used in physical models.
- Landslide Hazard zonation map can be created by setting up a network of tilt sensors.

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