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Rainfall Threshold-Based Landslide Early Warning System for Arunachal Pradesh

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Abstract
Landslides are increasingly recognized as significant natural disasters. Over the years, extensive research has led to the development of predictive models and public awareness strategies aimed at reducing their impact. Landslides typically occur due to slope failure, often exacerbated by heavy rainfall. Efforts to mitigate the damage involve both improving forecasting techniques and enhancing community preparedness. In tropical areas, landslides triggered by rainfall are the most common form of mass movement, primarily due to frequent monsoons. Establishing rainfall thresholds (RT) and conducting a comprehensive examination of patterns of rainfall distribution in spatial and temporal are necessary for predicting these landslides. However, creating a regional rainfall threshold is a complex task. Clustering analysis emerges as a valuable approach to effectively manage and interpret this scattered data. In this study, Rainfall Threshold (RT) equation was developed for northeastern region of Arunachal Pradesh by incorporating daily rainfall data along with 2-day, 3-day and 5-day antecedent rainfall. The study determined that the trend line derived from the 3-day antecedent rainfall and daily rainfall is the most suitable rainfall threshold equation for the area. Consequently, the correlation between rainfall thresholds and landslides emerges as an innovative approach for developing early warning systems in regions prone to landslides.
Keywords: *Cluster analysis, Landslides, Rainfall, threshold analysis and Tropical climate.*

INTRODUCTION

Landslides have a growing influence now a days, particularly as climate change intensifies weather patterns and human activities alter natural landscapes. The increased frequency and severity of heavy rainfall events, coupled with deforestation, unplanned urbanization, and infrastructure development in vulnerable areas, have made landslides more common and destructive. Landslides have become a significant and more frequent natural hazard in India, fuelled by both natural and human-induced factors. Their effects are extensive, impacting human lives, infrastructure and the economy, leading to substantial socio-economic challenges. In mountainous areas, landslides pose a significant natural threat, often causing substantial loss of life and extensive damage to property. Therefore, predicting landslides is crucial to mitigate their devastating impact by offering early warnings to nearby residents about the imminent danger [1].

Various factors like slope, soil, land use, geomorphology, geology, aspect, drainage density causes landslides, but rainfall is a triggering factor for landslides, particularly in areas with steep terrain and unstable soils. Soil saturation due to heavy or continuous rainfall increases its weight and decreases particle cohesion, contributing to these events. This condition combined with gravitational force often leads to slope instability and landslides. During India's monsoon season, the risk of landslides escalates, especially in regions where the land has been deforested or disturbed. Heavy or prolonged rainfall triggers severe landslides in areas with steep slopes, especially where highways and state roads have been constructed.

In regions like the Himalayas, the Western Ghats and the Northeastern states of India, experience considerable infrastructure damage, community displacement and fatalities due to landslides. Additionally, landslides disrupt transportation networks, hinder economic activities and exacerbate environmental degradation, making them a critical issue that requires urgent attention and mitigation efforts.

The Himalayan states, including Uttarakhand, Himachal Pradesh, Jammu & Kashmir, and Northeastern states like Sikkim and Arunachal Pradesh, are particularly susceptible to landslides because of their unstable geological conditions and heavy monsoon rains. Similarly, the Western Ghats in Kerala, Karnataka and Maharashtra face landslides during the monsoon, exacerbated by environmental degradation. North-East India, with its hilly terrain and heavy rainfall, also experiences frequent landslides during the monsoon season. India's Northeast, comprising eight states (Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim and Tripura is eminent for its abundant natural resources, rich biodiversity and vibrant cultural heritage.

In northeastern India, particularly in the mountainous areas of Arunachal Pradesh, this issue is especially critical. Landslides frequently occur along the entire Himalayan Mountain range in northern India. Foothill states such as Himachal Pradesh, Uttarakhand, West Bengal, Sikkim, Meghalaya and Arunachal Pradesh experience severe landslides annually, particularly during monsoon season. The increasing frequency and severity of these landslides negatively impact the region's tourism industry, a crucial economic sector.

According to [2], hills with debris and rainfall from the monsoons frequently cause landslides in tropical climates. Such incidents have a devastating effect on day-to-day living, resulting in large casualties, devastation, property damage and other financial losses. To mitigate these risks, researchers have focused on developing predictability and early warning systems [3,4].

Rainfall-induced landslides are well-known for their extensive spatial and temporal distribution, as well as their high frequency of occurrence [5,6]. Earlier research primarily examined the relationship between landslides and total daily rainfall, often neglecting the importance of antecedent conditions [7].

Monitoring diverse rainfall patterns and creating models are essential for predicting precipitation, which has led to the development of the Rainfall Threshold (RT) concept. RT is a model that identifies a specific threshold value for rainfall, beyond which the likelihood of a landslide increases significantly. It defines critical weather conditions that, when met or surpassed, are likely to trigger landslides [8,9].

Both physical (process-oriented, conceptual) or empirical (historical, analytical) methods can be used to establish RT [5,10]. These approaches correlate the chance of landslides to a number of rainfall characteristics, such as duration, magnitude, cumulative rainfall and antecedent rainfall [2,11].

Antecedent precipitation is crucial in landslides triggered by landslides as it decreases soil suction and raises pore-water pressure within the soil [12]. Recent studies have further investigated the thresholds for rainfall-triggered landslides by analyzing intensity–duration relationships and antecedent precipitation, defined as rainfall accumulated over days preceding the landslide event [12-14].

The research area is situated in a landslide-prone region that yearly landslide impacts, affecting the tourism industry. This study aims to predict the area's future vulnerability to landslides and contribute to strategic management planning for sustainable tourism. This present study aims to develop a Rainfall Threshold (RT) by incorporating daily rainfall data along with 2-day, 3-day and 5-day antecedent rainfall. The study utilized an empirical approach to derive Rainfall Thresholds (RT) through cluster analysis. Previous research by [15], highlighted the efficacy of cluster analysis for determining RT at local scales, although its application at regional scales remains unvalidated. The northeastern state of Arunachal Pradesh was selected for the present study (Fig.1). Five landslide-prone locations were identified for deriving Rainfall Thresholds (RT) (Fig. 1 and Table 1). These locations were chosen based on the availability of rainfall data, along with their distinct geological, geomorphological and geotechnical characteristics, as well as variations in spatial rainfall distribution.

STUDY AREA DESCRIPTION

Arunachal Pradesh, a state in northeastern India known as "The Land of the Rising Sun," is located between 26°28' and 29°30' N latitude and 91°30' and 97°30' E longitude, encompassing 83,743 square kilometres. The region is primarily covered by tropical semi-evergreen forests with limited agriculture, mostly in the form of shifting cultivation. Consequently, the majority of the population resides in valley areas. With forests covering around 80% of the state's area, the Forest Survey of India [16] reports that the state is rich in forest resources. Arunachal Pradesh can be geologically divided into four distinct physiographic regions: the Himalayan range, the Trans-Himalayan range, the Naga-Patkai range and the Brahmaputra plains. The region is characterized by a diverse array of rock types, including shales, sandstones, quartzites, phyllites, schists, gneisses, leucogranites, metavolcanics and carbonates. The major soil types found in the area are medium sand, silty sand, clayey sand, silty clay and low-compressibility clay. The region is divided into various tecnomorphic zones, including the Trans Himalaya, Shiwalik Himalaya, Greater Himalaya and Lesser Himalaya, which significantly increase the region's susceptibility to landslides. The area's physiography is characterized by high elevations, steep inclines, deep ravines, fragmented valleys and mountain-topped ridges. Annual precipitation ranges from 150 to 200 cm, with temperatures varying between 15 and 30 °C. The geography of the state significantly influences its climate due to its location and tectonic activity, it is classified as a Zone V area, indicating very high seismic risk. Five specific landslide locations were selected for this study based on the availability of relevant rainfall data and geographic information. East Siang - Sangam Bridge Collapse Near Pangin, East Siang - Near Sirki Waterfall, East Siang - Rotlung Village Kebang, Papum Pare - Near IG Park and Papum Pare - Leporiang are the locations where these incidents took place in and around Arunachal Pradesh.

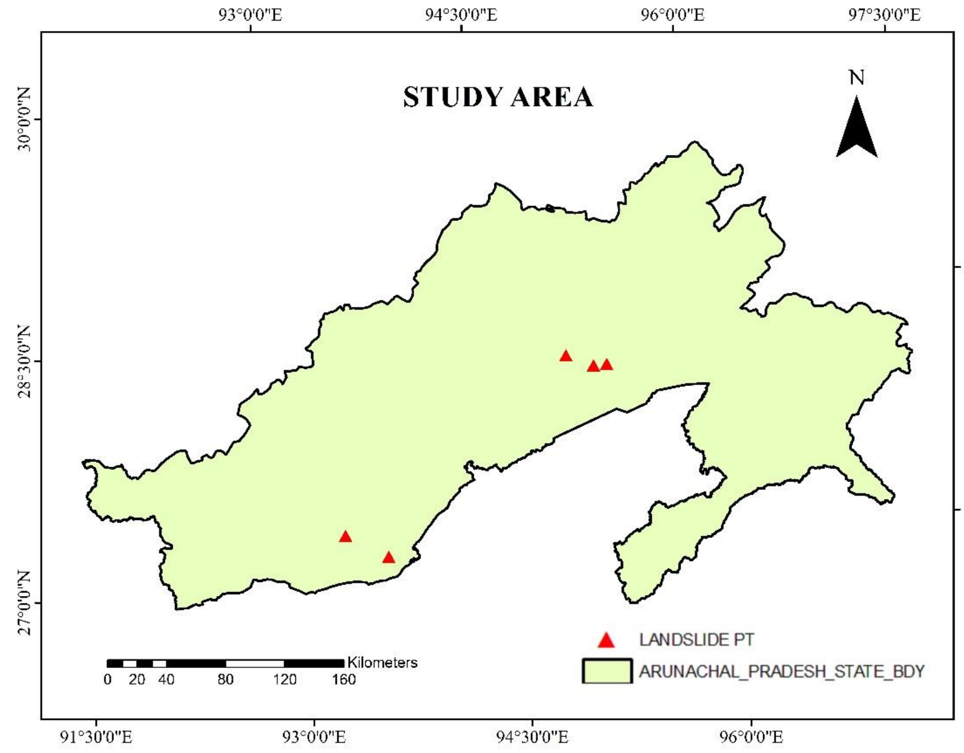

Fig:1 Location map of the study area

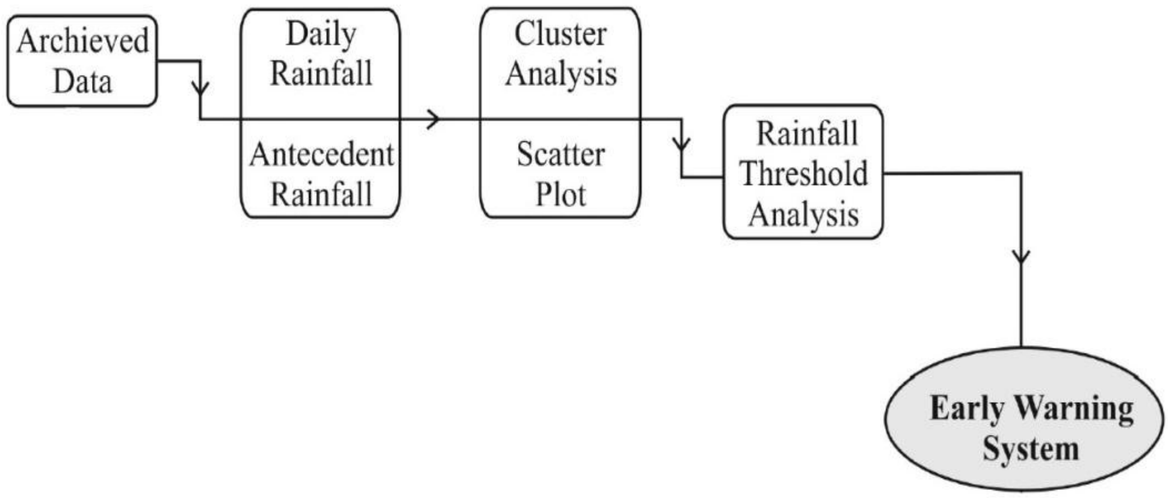

Fig:2 Methodology adopted in present study

METHODS

This study research examines rainfall thresholds in Arunachal Pradesh to explore the potential for implementing an early warning system to mitigate potential landslide impacts. In Previous studies [5,17-20] have demonstrated the effectiveness of rainfall threshold analysis in developing early warning systems. Cluster analysis was performed using the open-source software Waikato Environment for Knowledge Analysis (Weka) to identify the rainfall thresholds. This analytical method groups data based on similar characteristics. Typically, rainfall thresholds are determined using scatter plots comparing variables such as rainfall duration and intensity or a combination of antecedent and daily rainfall, as noted in earlier studies [21-23]. The data was analysed using k-means clustering, a widely recognized and efficient technique. This approach represents clusters with centroids and the squared error function is minimized by optimizing the grouping [24].

A collection of n observations is depicted in our study as rainfall data, is given as (x_1, x_2, ... x_n). Using the K-means clustering algorithm, these "n" observations are divided into K means cluster K (≤ n) sets (S = {S_1, S_2,...S_k}) and their within-cluster variation.

The K-means clustering algorithm is expressed as follows:

$$argmins \sum_{i=1}^{k} \sum_{X \in Si} \|X - \mu i\|^2 = argmins \sum_{i=1}^{k} \left|Si\right| Var\ Si \quad (1)$$

where μi is the mean rainfall of the observations in the cluster Set Si.

This clustering approach is classified as variance-based and employs Euclidean distance to minimize the sum of distances to the nearest point [25]. The Elbow method, a simple technique for determining the ideal number of clusters, is used to identify the optimal K value. Once critical clusters are established, scatter plot analyses are conducted for 2-day, 3-day and 5-day antecedent rainfall versus daily rainfall. This analysis aids in developing rainfall threshold equations for each antecedent rainfall condition, derived from known landslide occurrence data and expressed as linear equations.

$$Y = mx + c \quad (2)$$

In the equation, m and c represent the slope and y-intercept, while y and x denote daily and antecedent rainfall, respectively. A rainfall threshold exceedance curve is then graphically produced using this equation. The graph shows the threshold value exceedance over a given time period for each antecedent rainfall condition. Potential landslide triggering is indicated by positive values on this curve. According to [26], a rainfall threshold exceedance curve that is visually produced might therefore indicate the probability of a landslide based on recorded rainfall data during a specific timeframe.

RESULTS AND DISCUSSION

Rainfall threshold using K-means Clustering

Rainfall threshold analysis was carried out for landslide events at five locations: Sangam Bridge near Pangin, Sirki Waterfall and Rotlung Village Kebang in East Siang; and near IG Park and Leporiang in Papum Pare. The analysis covered 63 days of rainfall data per event -10 days before, the event day and 10 days after (Table 1). Antecedent rainfall for 2, 3 and 5 days was calculated, with a maximum antecedent period of five days, consistent with prior studies by [15, 27-29].

Scatter plots were created to visualize the relationship between daily rainfall and antecedent rainfall over 2, 3 and 5 days. Due to the variability of monsoon patterns, these plots exhibited significant dispersion. To address this, cluster analysis was employed to identify critical landslide-inducing events (Fig.3). The study utilized K-means clustering, with details provided in Table 2. The optimal number of clusters was determined using the elbow method [30]. The cluster most strongly associated with landslide events was isolated and a linear trend line was fitted to the data, as represented by Eq. (2) (Fig. 4).

Table 1: Daily and Antecedent rainfall for five locations in Arunachal Pradesh.

Date	Place	Daily Rainfall (mm)	Antecedent Rainfall:2-day (mm)	Antecedent Rainfall:3-day (mm)	Antecedent Rainfall:5-day (mm)
03.08.2021	East Siang-Sangam Bridge Collapse Near Pangin	1.03	1.9	1.9	1.9
04.08.2021		0.23	1.24	2.93	2.93
05.08.2021		0.82	1.26	1.47	3.16
06.08.2021		1.65	1.05	2.08	3.98
07.08.2021		16.53	2.47	2.7	3.94
08.08.2021		7.19	18.18	19	20.26
09.08.2021		14.73	23.72	25.37	26.42
10.08.2021		12	21.92	38.45	40.92
11.08.2021		20.1	26.73	33.92	52.1
12.08.2021		36.03	32.1	46.83	70.55
13.08.2021		40.56	56.13	68.13	90.05
14.08.2021		24.02	76.59	96.69	123.42
15.08.2021		6.8	64.58	100.61	132.71
16.08.2021		1.17	30.82	71.38	127.51
17.08.2021		20.09	7.97	31.99	108.58
18.08.2021		25.76	21.26	28.06	92.64
19.08.2021		15.77	45.85	47.02	77.84
20.08.2021		17.19	41.53	61.62	69.59
21.08.2021		11.03	32.96	58.72	79.98
22.08.2021		11.87	28.22	43.99	89.84
23.08.2021		5.25	22.9	40.09	81.62
03.08.2021	East Siang-Near Sirki Waterfall	2.74	11.84	11.59	11.59
04.08.2021		0.97	2.99	14.58	14.58
05.08.2021		4.72	3.71	3.96	15.55
06.08.2021		7.46	5.69	8.43	20.27
07.08.2021		33.74	12.18	13.15	16.14
08.08.2021		29.7	41.2	45.92	49.63
09.08.2021		32.55	63.44	70.9	76.59
10.08.2021		28.69	62.25	95.99	108.17
11.08.2021		36.52	61.24	90.94	132.14
12.08.2021		72.04	65.21	97.76	161.2

13.08.2021		54.55	108.56	137.25	199.5
14.08.2021		59.65	126.59	163.11	224.35
15.08.2021		15.69	114.2	186.24	251.45
16.08.2021		4.82	75.34	129.89	238.45
17.08.2021		40.32	20.51	80.16	206.75
18.08.2021		57.66	45.14	60.83	175.03
19.08.2021		54.54	97.98	102.8	178.14
20.08.2021		32.79	112.2	152.52	173.03
21.08.2021		24.1	87.33	144.99	190.13
22.08.2021		35.99	56.89	111.43	209.41
23.08.2021		16.52	60.09	92.88	205.08
17.06.2021	East Siang-Rotlung Village Kebang	6.84	0	0	0
18.06.2021		43.27	6.84	6.84	6.84
19.06.2021		36.67	50.11	6.84	6.84
20.06.2021		32.86	79.94	86.78	86.78
21.06.2021		9.3	69.53	112.8	119.64
22.06.2021		11.57	42.16	78.83	128.94
23.06.2021		23.91	20.87	53.73	133.67
24.06.2021		35.46	35.48	44.78	114.31
25.06.2021		16.8	59.37	70.94	113.1
26.06.2021		28.96	52.26	76.17	97.04
27.06.2021		66.8	45.76	81.22	116.7
28.06.2021		49.83	95.76	112.56	171.93
29.06.2021		24.59	116.63	145.59	197.85
30.6.2021		23.54	74.42	141.22	186.98
1.07.2021		24.95	48.13	97.96	193.72
02.07.2021		18.65	48.49	73.08	189.71
03.07.2021		18.48	43.6	67.14	141.56
04.07.2021		12.52	37.13	62.08	110.21
05.07.2021		7.71	31	49.65	98.14
06.07.2021		14.92	20.23	38.71	82.31
07.07.2021		3.39	22.63	35.15	72.28
21.05.2021	Papum Pare - Near IG park	11.99	0	0	0
22.05.2021		6.06	11.99	11.99	11.99
23.05.2021		0.97	18.05	18.05	18.05
24.05.2021		1.55	7.03	19.02	19.02
25.05.2021		8.47	2.52	8.58	20.57
26.05.2021		3.5	10.02	10.99	29.04
27.05.2021		6.82	11.97	13.52	20.55
28.05.2021		0.38	10.32	18.79	21.31
29.05.2021		2.78	7.2	10.7	20.72
30.05.2021		19.83	3.16	9.98	21.95
31.5.2021		42.2	22.61	22.99	33.31
1.06.2021		16.52	62.03	64.81	72.01
02.06.2021		20.89	58.72	78.55	81.71
03.06.2021		13.07	37.41	79.61	102.22
04.06.2021		17.17	33.96	50.48	112.51

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05.06.2021		24.73	30.24	51.13	109.85
06.06.2021		27.38	41.9	54.97	92.38
07.06.2021		23.78	52.11	69.28	103.24
08.06.2021		34.49	51.16	75.89	106.13
09.06.2021		5.5	58.27	85.65	127.55
10.06.2021		5.27	39.99	63.77	115.88
29.05.2021	Papum Pare - Leoporiang	2.02	0	0	0
30.05.2021		16.56	2.02	2.02	2.02
31.05.2021		24.38	18.58	18.58	18.58
01.06.2021		14.75	40.94	42.96	42.96
02.06.2021		11.13	39.13	55.69	57.71
03.06.2021		10.61	25.88	50.26	68.84
04.06.2021		15.94	21.74	36.49	77.43
05.06.2021		25.48	26.55	37.68	76.81
06.06.2021		35.28	41.42	52.03	77.91
07.06.2021		25.69	60.76	76.7	98.44
08.06.2021		46.18	60.97	86.45	113
09.06.2021		7.28	71.87	107.15	148.57
10.06.2021		4.19	53.46	79.15	139.91
11.06.2021		3.66	11.47	57.65	118.62
12.06.2021		3.43	7.85	15.13	87
13.06.2021		18.1	7.09	11.28	64.74
14.06.2021		20.82	21.53	25.19	36.66
15.06.2021		16.86	38.92	42.35	50.2
16.06.2021		5.5	37.68	55.78	62.87
17.06.2021		13.49	22.36	43.18	64.71
18.06.2021		8.77	18.99	35.85	74.77

Among the three trend lines developed, the one representing the relationship between 3-day antecedent rainfall and daily rainfall was found to be the most appropriate, as all five landslide events positioned above the trend line. Therefore, this trend line is proposed as the rainfall threshold equation for the study area.

$$y = 41.28 - 0.0718x \qquad (3)$$

Notably, the intercept values for all three trend lines (2, 3 and 5-day antecedent rainfall) ranged from 30.33 to 50.6 mm. This suggests that in Arunachal Pradesh, a daily rainfall event of approximately ≥ 30 mm could potentially trigger a landslide, even without antecedent rainfall. The negative coefficient of antecedent rainfall in all equations (Fig.4) indicates an inverse relationship between cumulative antecedent rainfall and the daily rainfall required to trigger a landslide. The study recommends incorporating rainfall intensity in future research to improve the accuracy of the threshold relationship and reduce false positives. Due to the absence of rainfall intensity data for the Arunachal Pradesh, it is essential to adopt a precautionary threshold equation, as presented in Equation (3).

Table 2: Run Characteristics of Cluster Analysis

		2-Day vs Daily Rainfall			3-Day vs Daily Rainfall			5-Day vs Daily Rainfall				
Scheme		K Means Clustering										
Optimization		Elbow Method										
Initial Starting Point		C0	C1	C2	C0	C1	C2	C0	C1	C2	C3	C4
	Antecedent	0.0	1.24	6.84	6.84	0.00	0.0	0.0	0.0	6.84	116.7	173.03
	Daily	11.99	0.23	43.27	36.67	11.99	2.02	11.99	2.02	36.67	66.8	32.79
Final Cluster Centroid	Antecedent	43.6	10.02	97.98	112.56	50.48	11.99	89.84	15.15	77.91	175.03	197.85
	Daily	18.48	3.5	54.54	49.83	17.17	6.06	11.87	4.72	35.28	57.66	24.59
Clustered Instances		67 (64%)	20 (19%)	18 (17%)	37 (35%)	48 (46%)	20 (19%)	43 (41%)	19 (18%)	25 (24%)	7 (7%)	11 (10%)

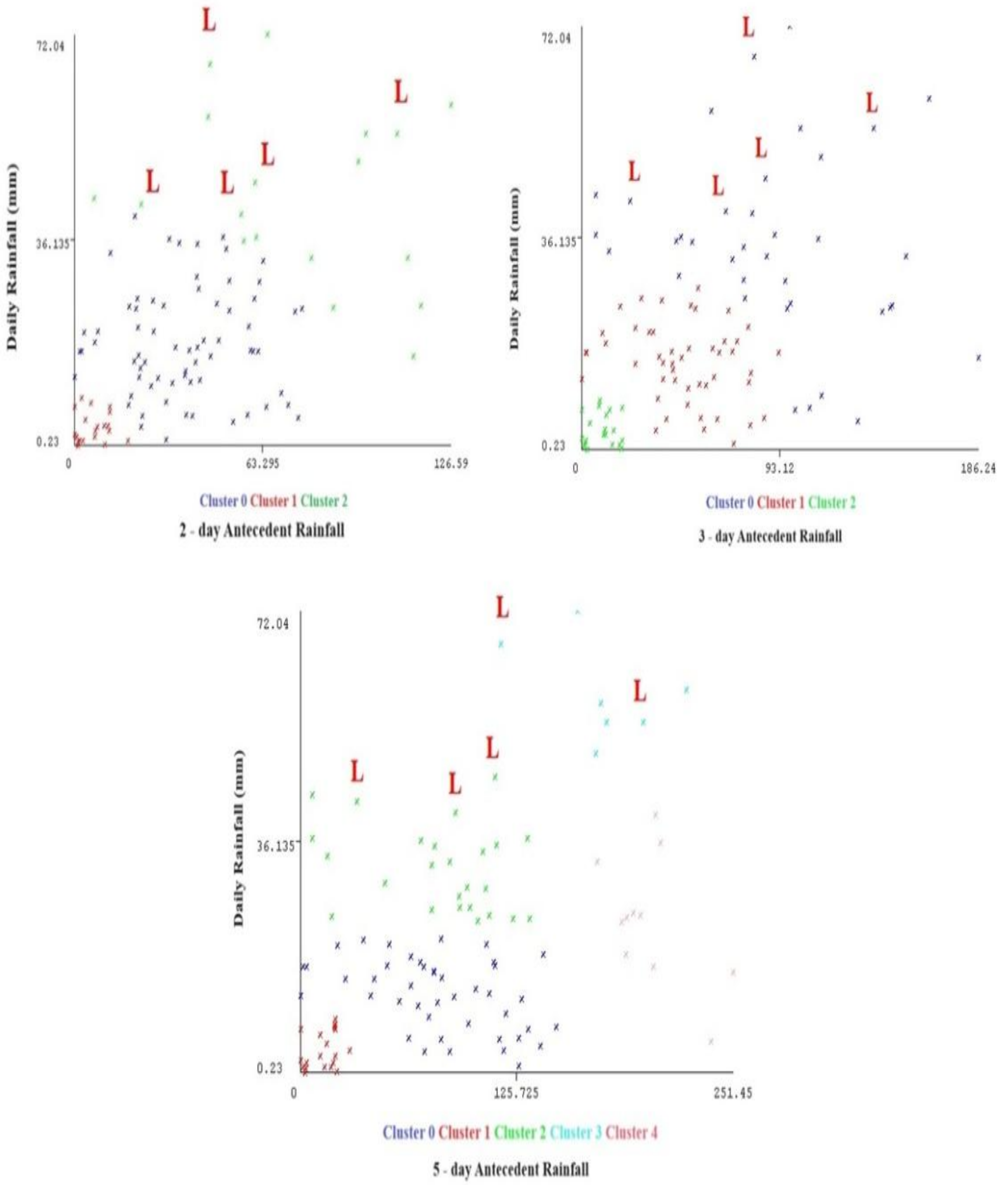
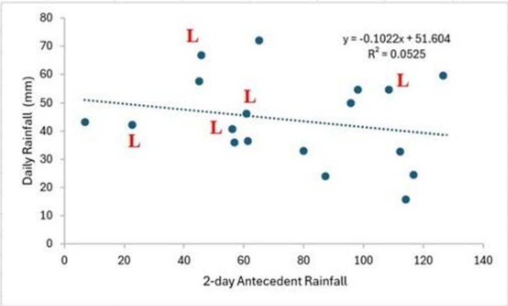
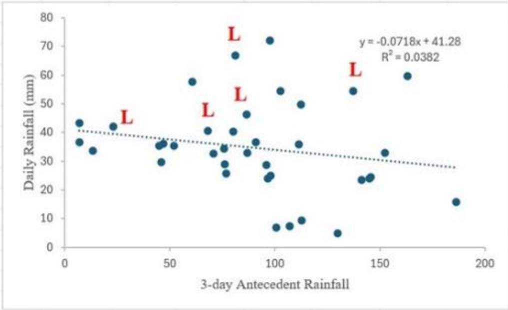


Fig.3 Scatter plot showing the different clusters. Antecedent rainfall vs. daily rainfall 'L' indicates landslide incidence.

Implementation of Early Warning System

The initial step in developing an early warning system for landslides is to assess the area's susceptibility. These systems are particularly effective in regions with steep slopes, where low-cohesion soil overlays crystalline bedrock and is subjected to seasonal monsoon rains. Such conditions increase landslide risk due to the loose soil cover on the crystalline rock, which can lead to the build-up of seepage pressure.





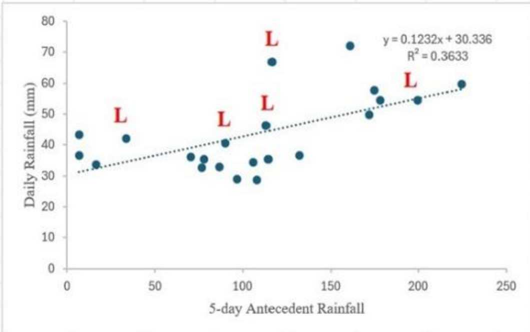


Fig. 4 Linear trend line for isolated cluster favouring landslide.2-day antecedent vs. daily rainfall; 3-day antecedent vs. daily rainfall; 5-day antecedent vs. daily rainfall. 'L' indicates landslide incidence.

Although collecting soil and rock data can be demanding, it is vital for preventing landslide-related casualties and financial damages. By gathering rainfall information for specific areas, such as unstable slopes, antecedent precipitation can be accurately measured. This data can be integrated with daily forecasts to predict when rainfall might surpass critical thresholds.

The proposed approach has the potential to deliver a 24-hour advance warning for unstable areas, significantly reducing casualties and mitigating landslide risks. By analysing and correlating rainfall thresholds, this innovative method offers a novel strategy for landslide early warning systems, particularly in the Eastern Himalayas, where landslides are common. The resulting model is simple, cost-effective and comprehensive, making it adaptable to other regions with similar climate and topography.

CONCLUSION

Landslides are a recurring natural disaster that threatens human lives and the environment globally. This study employs cluster analysis to determine the rainfall thresholds that cause landslides. In Arunachal Pradesh, single-day rainfall is commonly considered the main trigger for landslides, but antecedent rainfall also plays a significant role by increasing soil pore-water pressure. As cumulative antecedent rainfall increases, the amount of daily rainfall required to trigger a landslide decreases. In tropical regions, landslides are therefore influenced by both daily and antecedent rainfall. Crossing the threshold does not guarantee that a landslide will happen each time. Instead, it acts as a signal to trigger an early alert, allowing the community time to take precautions for a possible landslide. The early alert system depends on tracking both daily and antecedent rainfall in landslide-prone regions to evaluate the probability of a landslide using the rainfall threshold equation. Regular tracking of daily rainfall or intensity allows for timely warnings when values approach the threshold. Therefore, regular monitoring of rainfall data is also beneficial for landslide mitigation efforts.

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