Comparative Analysis of Rainfall Thresholds for Landslide Initiation Using Terrestrial Rain Gauges and Satellite Data in Nepal: Challenges and Opportunities

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Abstract: Landslides triggered by intense monsoon rainfall pose a significant hazard in Nepal, leading to substantial loss of life and property. The implementation of Landslide Early Warning Systems (LEWS) based on rainfall thresholds can help mitigate these impacts. These thresholds, which specify the minimum rainfall required to trigger landslides, are essential for effective disaster risk reduction. This study investigates the uncertainties surrounding rainfall threshold definitions for landslide forecasting in Nepal, primarily due to the limited number of Automatic Weather Stations (AWS). It emphasizes the shortcomings of gauge measurements, including their sparse distribution, lack of high temporal resolution, high costs, and delayed reporting. The study also highlights the growing accuracy and potential of satellite rainfall products, which provide higher spatial and temporal resolution, comprehensive coverage, and no missing data. However, it addresses the challenges of developing LEWS using satellite data and recommends enhancing the network of rain gauges and improving landslide documentation systems. Additionally, the comparison of rainfall thresholds indicates that those derived from AWS are slightly higher than those from satellite data, suggesting that terrestrial rain gauges may indicate a greater rainfall requirement for landslide initiation.

Key words: ***Landslides, Landslide early warning system, Rainfall thresholds, Automatic weather station, Satellite rainfall product.***

Introduction

Landslides in Nepal have led to substantial loss of life and property, with 4,125 fatal incidents and 3,837 deaths recorded between 1970 and 2021, averaging 71 deaths annually (Pradhan, 2020). To mitigate these losses, implementing Landslide Early Warning Systems (LEWS) based on rainfall thresholds is crucial. These thresholds indicate the minimum rainfall required to trigger landslides and are essential for effective disaster risk reduction (Reichenbach et al., 1998; Guzzetti et al., 2008; Dahal and Hasegawa, 2008).

However, the reliability of landslide forecasting relies heavily on the quality of rainfall data. Traditional rain gauge measurements present challenges, including high costs, sparse distribution, and insufficient temporal resolution, particularly in developing regions lacking rain gauges. To address these limitations, satellite rainfall data has gained traction due to its global availability, improved spatial and temporal resolution, and enhanced accuracy. Satellite products such as CMORPH, TRMM's TMPA, and GPM's IMERG show promise for enhancing LEWS (Zhao et al., 2022). This study compares thresholds derived from Automatic Rainfall Stations (AWS) and the IMERG dataset using the CTRL-T algorithm (Melillo et al., 2018), highlighting the potential of satellite data for landslide forecasting.

Methodology

The 607 landslide catalogue prepared from the multifaceted approach was used for the analysis. Among them the landslide classified as certain are with the time of the landslide event was used for the analysis. The rainfall data the "IMERG, GPM: Global Precipitation Measurement (GPM) v6" (the spatial resolution of 0.1° ×0.1° and half hour) was used as a satellite rainfall data and the Automatic Weather Station (AWS) operated by Department of Hydrology and Meteorology was used as a terrestrial rainfall product for the determination of rainfall thresholds.

The CTRL-T algorithm was used for the determination of rainfall thresholds. It automates the reconstruction of rainfall events to determine landslide-triggering conditions. It calculates rainfall thresholds at various Non-Exceedance Probabilities (NEPs) using continuous rainfall and landslide data. The algorithm selects representative rain gauges, identifies multiple failure-causing conditions, and assigns probabilities to determine probabilistic thresholds with associated uncertainties. It employs statistical bootstrapping and the frequentist methodology, generating 5000 synthetic series using the power law equation for threshold establishment.

Result

The deployment of the CTRL-T algorithm to determine the most likely rainfall conditions for landslide initiation encountered several limitations. The Automatic Weather Stations (AWS) operated by the Department of Hydrology and Meteorology (DHM) are sparse and have been functioning only since 2019, resulting in a coarse spatial resolution. To improve data representativeness, 22 additional rain gauges were installed in the study area, and a 15 km buffering distance was implemented to fill data gaps. However, due to missing data and interruptions in the dataset, only 31 out of 235 landslide events were included in the analysis. This limited dataset may not adequately represent the conditions necessary for defining accurate rainfall thresholds.

Table1, Comparison between different non-exceedance probabilities (NEP) obtained from IMERG and AWS

NEP	Threshold Equation	
	IMERG (Satellite)	AWS (Rain Gauge)
1%	$T_{1,} E= 2.7 \pm 1.2\ D^{0.46 \pm 0.1}$	$T_{1,} E= 8.0 \pm 6.1\ D^{0.33 \pm 0.1}$
5%	$T_{5,} E= 4.0 \pm 1.6\ D^{0.46 \pm 0.1}$	$T_{5,} E= 11.6 \pm 8.2\ D^{0.33 \pm 0.1}$
10%	$T_{10,} E= 4.8 \pm 1.9\ D^{0.46 \pm 0.1}$	$T_{10,} E= 14.2 \pm 9.6\ D^{0.33 \pm 0.1}$
20%	$T_{20,} E= 6.2 \pm 2.3\ D^{0.46 \pm 0.1}$	$T_{20,} E= 18.2 \pm 11.6\ D^{0.33 \pm 0.1}$
35%	$T_{35,} E= 7.9 \pm 2.9\ D^{0.46 \pm 0.1}$	$T_{35,} E= 23.6 \pm 14.2\ D^{0.33 \pm 0.1}$
50%	$T_{50,} E= 9.8 \pm 3.5\ D^{0.46 \pm 0.1}$	$T_{50,} E= 29.5 \pm 16.9\ D^{0.33 \pm 0.1}$

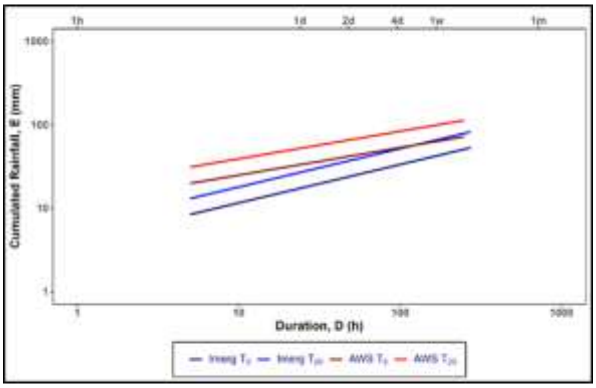

Figure 1, Comparison between different non-exceedance probabilities (NEP) obtained from IMERG and AWS

To facilitate a relative comparison between the thresholds derived from terrestrial rain gauges and the IMERG rainfall dataset (Table 1 and Figure 1), all data from the rain gauges were substituted with the IMERG dataset. This ensured that both datasets had an equal number of missing and available data points, allowing for a consistent evaluation. The analysis of the 31 landslides and their corresponding rainfall durations revealed that the thresholds from terrestrial rain gauges were slightly higher than those obtained from the IMERG dataset. This indicates that a greater amount of rainfall is necessary for landslide initiation when considering terrestrial rain gauges. Conversely, the thresholds derived from IMERG appeared steeper, suggesting that a higher precipitation amount is required over time compared to the terrestrial rain gauge data. Furthermore, the uncertainties associated with the rain gauge data were greater than those of the IMERG data, likely due to the limited number of rainfall events leading to a wider dispersion in the data set.

Discussion and Conclusion

Due to the sparse distribution of terrestrial rain gauges, lack of high temporal resolution, high costs, missing data, and the recent operations of AWS rain gauges, fewer landslides were included in the analysis, resulting in a higher degree of uncertainty. The uncertainties related to the γ parameter at a 5% non-exceedance probability (i.e., Δγ/γ) is 30.3%, and the uncertainties related to the α parameter (i.e., Δα/α) is 70.6%. These high uncertainties are attributed to the very low number of landslides used to define the rainfall thresholds, which can be reduced by increasing the number of landslides. Satellite rainfall data offers significant advantages for determining rainfall thresholds, thanks to its global accessibility, high spatial and temporal resolution, and continuous data availability, which enhances accuracy. By utilizing satellite data, researchers can expand the dataset of rainfall events from 31 to 235, reducing uncertainty associated with thresholds and addressing the limitations of Automatic Weather Station (AWS) rain gauges. This study underscores the benefits of satellite rainfall products in calculating thresholds while also highlighting their limitations. It reveals the high uncertainty in defining rainfall thresholds based on insufficient landslide data, which can hinder effective early warning systems. Although an increase in rain gauges could improve threshold determination, the current thresholds derived from AWS stations in Nepal are not promising. The study emphasizes the need for more AWS installations in Nepal's hilly terrain to enhance monitoring and prediction capabilities and recommends improving both the number and performance of these stations.

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