A Quick Review of Technical Developments in Indonesian Landslides Early Warning Systems

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Abstract. Increasing demand for infrastructure development, driven by population growth and urbanization, has heightened the risk of landslides, especially in regions with limited land resources. Traditional approaches to landslide hazard estimation and site-specific warning systems often rely on conventional slope stability analyses and susceptibility models. However, ensuring public safety necessitates the urgent development of comprehensive early detection and warning systems. While existing literature explores the benefits and functionality of early detection systems, detailed insights into the interplay of various factors governing their development remain underexplored. This review aims to address this gap by identifying and analysing key parameters influencing the development of early warning systems in Indonesia based on historical landslide events. Data on past landslides will be collected, categorized, and evaluated for their suitability as input factors for early detection frameworks. The study further examines existing detection and warning frameworks, offering insights for their enhancement through future research. The findings are expected to provide a comprehensive overview of critical factors influencing the design and implementation of early warning systems, emphasizing their role in mitigating the severe impacts of landslide hazards. Integrating remote sensing data, such as TRMM, GPM, and CMORPH, with advanced hydrological-geotechnical models and community-based strategies emerges as a promising approach. These innovations, coupled with IoT technologies and real-time monitoring, hold potential for developing robust, scalable, and adaptive Landslide Early Warning Systems (LEWS) for global application.

Keywords: *LEWS; Rainfall Threshold; Indonesia; Landslide Triggers*

1 Introduction

Landslides are the common geologic hazards recorded frequently around the mountainous regions throughout the earth, and nearly 600 people annually lost their lives in between 1971-

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1974 [1]. The loses around the planet increases with exponential rise in population and consequent infrastructure setups in hilly regions. Therefore, the occurrence of landslides instills fear in the population while also disrupting the economic growth. The developing nations are fighting this ill-fated phenomenon with limited resources and suffering the most [2]. Several mitigation measures have been suggested by previous researchers, however, only a quick and reliable early estimation of these instabilities may avert the losses to a significant level. Therefore, implementation of landslide early warning system (LEWS) in critical hilly regions are of utmost importance, in addition to heavy mechanical supports. Fathani et al. [3] stressed on socioeconomic-cultural aspects of the region apart from technical-institutional surveys in implementation of LEWS. Present work reviews some of the Landslide Early Warning System in different parts of Indonesia. The research further highlights major triggering factors, geological conditions, and techniques applied in assessing the mass-movements in the region.

Indonesia is the fourth most populous and largest archipelago nation on the planet, consisting of five major and thousands of mini-islands. The tectonic setup of the country led to complex geological conditions owing to numerous old and ongoing volcanic activities. Earthquakes of higher magnitude have frequently shaken the nation & triggered co-seismic landslides. Furthermore, the country witnesses' earthquakes of higher magnitude almost every year, owing to its proximity with the Pacific Ring of Fire. In addition, its geographical location in the tropical climate brings heavy precipitation. Rainfall intensity, duration, and antecedence have a pivotal role in slope instabilities in the country [4-5]. Hadmoko et al. [6] demonstrated that devastation caused by landslides in Indonesia is far more severe than other natural calamities. Between 1990-2005, more than 1112 human lives were lost and 395 were injured owing to a thousand of failures alone in Java Island of Indonesia [6]. In 2007, 65 people became the victims of the Karanganyar Regency landslide [7]. Seismicity in Indonesia has a long history of triggering several landslides and slope failures owing to ongoing tectonic movement [8-10].

Additionally, Indonesia's rapid urbanization, often lacking in comprehensive planning and regulation, has heightened the susceptibility of its cities to natural disasters, notably landslides [35]. A poignant example is the 2005 Leuwigajah landfill disaster near Bandung, where heavy rainfall triggered a massive waste avalanche, resulting in 143 fatalities [36]. Further research in Sukabumi, utilizing GIS-based modeling, revealed that a significant portion of the population resides in areas with medium to high landslide susceptibility, indicating that urban development in these regions may be contributing to increased exposure to landslide hazards [37]. These findings underscore the urgent need to integrate local knowledge and scientific approaches into urban planning to effectively mitigate landslide risks.

Thus, robust comprehension of slope failure mechanisms and interaction of different triggers is of utmost significance for implementation of a sophisticated LEWS [11]. Therefore, practitioners and researchers had scrupulously explored either rain-gauge station or satellite-based rainfall datasets in LEWS development [12-13].

The main aim of this review is to ascertain various factors governing the development of early detection and warning systems based on historical landslide disasters. The study will initially collect and tabulate data on historical landslides categorized against the key factors triggering the landslides depending on the selected location/region of their occurrence. Then, the database will be processed to check their appropriateness as input parameters for the early detection and warning systems. The existing early detection framework will be considered in this review, which can eventually be developed with further research. The review is expected to provide an overview of the factors governing the applicability of early detection and warning systems. Further, the expected knowledge from this overview will comprehend the worker in developing advanced early warning tools for landslide hazards. And, will

significantly reduce the potential risk to public health, occupational health, and safety, thereby saving lives and property. So, the outcomes may promote safe, inclusive and sustainable development of any nation.

2 Early Warning System for Landslides

Landslides are caused by the intricate interaction of a number of elements, the majority of which include geological, topographical, geomorphological, and climatic aspects. As a result, there is a requirement for an early warning system that can diagnose and alert the onset of probable landslides. The severity of the losses that are incurred on annual basis as a result of the sudden and unanticipated occurrence of a landslide is immense. And, it is getting increasingly expensive to find solutions to the accompanying problems, which worsen as a result of the excessive rainfall discharge. There have been periodic implementations of a variety of corrective and preventive measures, but the frequency and scale of landslide occurrences have rendered the regulating measures redundant. It is possible that this is due to a lack of a comprehensive grasp of the unique landslide character, the process of slide onset, as well as in-depth information of the area that is being discussed. Often, precipitation thresholds are used to characterize quantitatively the rainfall conditions that trigger landslides. Diverse approaches were described for selecting rainfall parameters, collecting landslide data, and defining, calibrating, and validating rainfall thresholds [14]. Empirical rainfall thresholds link rainfall circumstances or factors to landslide occurrences.

In recent decades, remote sensing has helped in catastrophe preparedness, response, and mitigation. High-resolution optical satellite pictures have been used to create inventory maps and investigate landslides [15]. Recently, semi-automatic and automated systems to mapping and classifying landslides were established [16]. SAR-based satellite imaging can provide views during cloud cover and emergency scenarios. Earlier SAR-based studies focused on individual landslides for emergency response or updated landslide inventories, notably in sparsely vegetated areas [17-18]. It is true that this kind of natural hazard cannot be stopped completely; however, taking the appropriate preventative measures can lessen the severity of the occurrence of such phenomena.

In order to do this, a robust database and an understanding of the geo-environmental parameters that are related to these hazards are required. Therefore, the time has come to create such a database, along with a complete landslide hazard zonation map and an early warning system, to take the appropriate and required steps for mitigating such a threat. As a result of the fact that landslides have practically reached the level of being a chronic catastrophe in most of the highland regions across the globe, the implementation of landslide early warning systems is becoming increasingly significant on a global scale. An early warning system will assist residents becoming careful, and the authorities will be able to arrange for the timely evacuation in the affected area. In order to produce more accurate slope failure forecasts, a good Landslide Early Warning System (LEWS) requires in-depth hazard and risk assessments, as well as appropriate monitoring techniques. Additionally, this type of system necessitates an in-depth comprehension of the social implications that are associated with these warning systems [19].

The researchers must focus on mass-movements observing systems that look at physical processes holistically. Especially in the developing and under-developed nations, after each unfortunate-events, government resolve to improve risk assessment and management to become complacent in future. An integrated observing system will include a dedicated geosynchronous satellite with multi-wavelengths and cartographic capabilities to trace changes in landforms, soil moisture, lake formation, breach potential, and monitoring of real-time precipitation. AI-based monitoring systems of landslide-prone areas integrated with

scenario-based simulation models of floods in each major catchment [14]. Real-time alerts based on many data kinds require a learning & hierarchical artificial intelligence approach.

Four stages of early warning systems, planning, monitoring, forecasting, and education have been established as described by [20]. Many researchers use the rainfall threshold limit for the initiation of the landslides as an approach for designing early warning systems. These methods have been proved quite useful in the Indonesian conditions, as most of the severe landslides are triggered by rainfall. A Calculation of Thresholds for Rainfall-Induced Landslides-Tool [CTRL-T), was recently developed by Melillo et al. [16], and used by [17] in their study. The software component will automatically extract rainfall events from continuous rainfall data, recreate rainfall circumstances that are responsible for landslide occurrences, and determine rainfall thresholds for a variety of different exceedance probabilities. The following items are required as input for CTRL-T: information on the spatial (geographic coordinates) and temporal (day and time) occurrences of landslides; continuous hourly rainfall data from localized rain gauges; and a few setup options. Several LEWS and their enactments as per different geological, structural, geographical localities have been detailed in table 1. And, table 2 will enunciate various previously designed landslide early warning systems in Indonesia. Authors have further attempted to brief potential techniques for application in future works on the basis of reviewed works.

Table 1. Tools and techniques used for LEWSs in the recent time

S. No.	Author/s	Techniques	Explanation
01	Kong et al. [20]	• Empirical approach (Rainfall threshold). • Physically based approach	• Relationship between rainfall and landslide occurrence. • Back-analyses of historical rainfall data and observed landslides generate empirical relationships. • Important techniques used are radial basis function network; logistic regression method; curved rainfall intensity-duration threshold. • The empirical approach enables landslide predictions, using the local empirical facts. • Physically based approach combines rainfall statistics to infiltration models.
02	Atzeni et al. [19]	• Ground-based interferometric synthetic-aperture radar (GBInSAR)	• By sending and receiving electromagnetic waves, a radar can determine a target's distance and direction. • Backscattered electromagnetic waves are used to measure distance. Real beams or synthetic apertures determine target direction. • SAR's high spatial resolution may boost its ability to detect localized slope movements or extend its working range.
03	Intrieri et al. [22]	• InSAR Technique • Slip Surface Calculation	• Satellite SAR sensors are side-looking radar with tilted LOS. The incidence angle makes the sensor more sensitive to vertical than horizontal deformation. • From superficial displacement vectors, estimate the depth and geometry of a slope failure's sliding surface. The radar targets' vertical and horizontal movement vectors must fall within landslide regions. • Combining ascending and descending information allows one to determine the

			vertical and horizontal (E–W) components of the movement and, therefore, the actual displacement vector.
04	Huang et al. [23]	• WebGIS and Web3D technologies	• On SQL-server, Visual Studio, and Skyline platforms, a multi-structure for application-information and data was developed. • After assembly level integration, the service sector offers simple but realistic operational services, including three-dimensional geographical analysis, real-time monitoring, landslide data consultation and management, early warning analysis, a disaster publication service, and a system management service.
05	Ozturk et al. [24]	• Theory of failure index fragility curve (FIFC)	• Nonlinear dynamic analysis is used to construct analytical fragility curves for typical exposed items. • The FIFC parameters (Fi, Wi) are specified deterministically by an analytical technique. • The software uses shear strength reduction (SSR). It doesn't need artificial settings and considers element deformation. • To depict prospective landslide circumstances, several slope angles and material attributes are matched. FIFC input parameters are limited.
06	Roy et al. [25]	• InSAR and flow model	• The failure slopes were analyzed using Persistent Scatterer Interferometry (PSI) and Small Baseline Subset (SBAS). • The displacement-time series revealed active motions on both landslides' head scarps before failure. • Inverse velocity (INV) and modified inverse velocity (MIV) are used to predict failure window.
07	Hermle et al. [26]	• Multispectral remote sensing	• The method compares two optical remote sensing systems' landslide early warning lead times. • UAS and PlanetScope photos of temporal proximity are used to evaluate the temporal concept because they have the best spatiotemporal resolution.

Table 2. A review of Indonesian lanslide early warning systems

S. No.	**Author/s**	**Brief Findings**	**Scope for identifying technologies for Early detection system**
01	Chikalamo et al. [27]	• A regional scale remote sensing-based rainfall-threshold for successful enactment of LEWS in Bogowonto catchment (Central Java, Indonesia). • Geology, and land-use pattern in the region had been considered in developing an early warning system. • The region witnesses an average annual rainfall ranging from 2500-3000 mm in the catchment.	• Globally available higher resolution spatio-temporal satellite-based rainfall estimates are quite compatible for LEWS development with better accuracy. • Global Precipitation Mission (GPM) is a better satellite for rainfall measurement at a reliable

		• Landslide inventory map was prepared using media reports, field-investigation, past studies, and Indonesian National Agency for Disaster Management (BNPB) database. • Rainfall datasets employed were ascertained from rain-gauges, TRMM, and ERA-Interim forecast. Moreover, the efficiency of satellite precipitation data was statistically analyzed with respect to six available rain-gauges in the region.	spatio-temporal resolution (30 minutes to daily & ~10 km^2). • TRMM is another potential satellite for acquiring higher resolution rainfall-datasets. • Rainfall threshold analysis should consider the land-use and period of occurrence for better LEWS.
02	Fatimah et al. [28]	• An android-application for issuing landslide early warnings was developed for natives. • Antares: an Internet of Things (IoT) based platform for integrating different sensor data pertaining to soil moisture, slope, and ground vibration. • Fuzzy algorithm was introduced to process sensor's data and devise a set of rules for warning signals as per hazard level. • Three levels of alert signals were shown in real-time on the android application as "**safe**", "**be alert**", and "**watch-out**".	• A sensor MPU-6050 records the variation in slope inclination. It consists of a gyroscope and accelerometer. • YL-69 sensor acquires soil moisture database. • Accelerometers comprehends vibration values. • The developed LEWS has a success rate of 90%, and potentially may be implemented at geologically similar terrain.
03	Hidayat et al. [29]	• BLS has developed a LEWS for Indonesia, evolved on the Delft–FEWS platform. • Daily precipitation data, rainfall threshold, TRIGRS were the key resources. • Precipitation data (1-day and 3-day cumulative observed and forecasted precipitation data) were ascertained from the TRMM and the Indonesian Meteorological Climatological and Geophysical Agency (BMKG). • The Pacitan and Brebes regions could be estimated by the developed early warning system in few days advance.	• TRIGRS model may be explored to analyze the factor of safety in the areas prone to instabilities and issue warning signals in case safety factor is less than 1. • The rainfall (antecedent/ daily) datasets could be scientifically structured along with a numerical-physical-empirical slope stability model to devise a robust LEWS. • TRMM facilitate current precipitation information and ERA-Interim forecast datasets available through European Centre for Medium Range Weather Forecast.
04	Karnawati et al. [7]	• A technically equipped and community prepared LEWS was developed for Ledokasari (Indonesia).	• Rainfall dataset using rain-gauge, and crack development using extensometers were

		• Rain-gauge, alarms, extensometers, dry cells, and solar panels were arranged in the early warning system. • Rain-gauges were installed in open to measure precipitation. Extensometers were enacted across the cracks to measure displacement. • Greater than 100 mm rainfall infiltration has been assessed as critical, while, greater than 4 cm movement across cracks was taken to be dangerous.	coupled to generate alert signals. • Community based early warning and response is an ideal approach for any natural hazard combating. • Therefore, community planning and preparedness by providing training to residents will be a key strategy during landslides, floods, or earthquakes.
05	Liao et al. [30]	• LEWS has been generated to estimate rain-induced shallow failures over Java (Indonesia). • The work complies three essential attributes: (a) probability of hazard occurrence areas; (b) satellite-based rainfall data; (c) physical based landslide simulation model (SLIDE program). • Information like "when" & "where" provide impetus in successful enactment of LEWS and predict failures as function of time & location. • LEWS performance has been evaluated using a local landslide inventory, and results show that the system successfully predicted landslides in correspondence to the time of occurrence of the real landslide events. • A modified physical model is used to determine a factor of safety that entertains the impact of rain-water infiltration and soil saturation on shear strength of the geomaterials.	• DEM and soil maps were comprehended through 30-meter ASTER data. • Real-time rainfall dataset can be acquired through TRMM. Also, WRF model's precipitation forecasts information will further aid LEWS. • Integration of spatially distributed remote sensing precipitation products and in-situ datasets in this prototype system enables us to develop a regional, early warning tool in the future for predicting rainfall-induced landslides in the country. • SLIDE software system can be enacted as a reliable slope stability simulator.
06	Apip et al. [31]	• The work encompasses the capability of hydrological-geotechnical modeling using satellite-based precipitation (real-time/nowcast/forecast) for developing shallow LEWS. • A physically-distributed infinite slope stability model has been devised by aligning a grid-based rainfall-runoff system. • The system has the access to precipitation (real-time half-hourly) satellite database named as CMORPH global rainfall product (NOAA-CPC).	• A better comprehension of hydrological response over geotechnical properties of slope-mass in real-time may be enacted in other areas too for designing future LEWS • Satellite-based rainfall monitoring have resolved the challenges of high-resolution temporal and spatial data for better early warning systems.

		• Two model outputs, "time-invariant susceptibility of the area" and "spatio-temporal soil-saturation response of geomaterials" were employed for generating information "where" and "when" shallow landslides may trigger in the catchment. • The hydrological model examines the changing soil saturation germane to rainfall divided in different grid elements. Thereafter, this data aids in investigating critical slope failures based on their safety factor.	• Several hours before, the developed LEWS had predicted two real recent shallow failures and comprehended the impact of rainfall on the spatio-temporal slope stability quite-well. Therefore, the model can be deployed in other areas prone to shallow landslides.

Note: TRMM: Tropical Rainfall Measuring Mission; **BLS**: Balai Litbang Sabo; **FEWS**: Flood Early Warning System; **TRIGRS**: Transient Rainfall Infiltration and Grid-based Regional Slope-stability model; **DEM**: Digital elevation model; **ASTER**: Advanced Spaceborne Thermal Emission and Reflection Radiometer; **WRF**: Weather Research Forecasting.

3 Results and Discussion

Robust LEWS can be a game changer. Hidayat et al. [29] discussed key features of LEWS operations in Indonesia since 2017 and developed by Balai Litbang Sabo (BLS). The structure is hinged on Delft - Flood Early Warning System (FEWS) platform, and issues warning in 4-days advance. The setup considers satellite derived cumulative/ daily observed & forecasted precipitation data, landslide susceptibility map, rainfall threshold, and physico-mechanical attributes of geomaterials. The system examines the probable landslide based on occurred/ forecasted rainfall information, and then for critical regions TRIGRS model runs to simulate the stability factors (FoS). The FoS enumeration requires soil attributes namely cohesion, angle of internal friction, soil weight, saturated hydraulic conductivity, soil depth, initial groundwater table depth, soil diffusivity, volumetric water content, and soil water characteristics curve. Moreover, the warnings are categorized based on the probability of the occurrence of slope failures in different zones. Previously, the system predicted Pacitan and Brebes landslides, 1 to 3 days prior to their initiation. However, the current warning does not entertain seismicity and anthropogenic triggers in its LEWS, therefore more advanced structures are required. Also, high resolution precipitation data along with better forecast satellites will increase the accuracy of the LEWS.

Liao et al. [30] had linked three germane landslide elements to develop a regional early warning system for rainfall-induced shallow-failures in Java (Indonesia). Landslide hotspot identification (susceptibility maps), satellite-based precipitation datasets (forecasted and occurred), assessment of shear-strength variation and factor of safety owing to rainfall infiltration and saturation using a program SLIDE (SLope-Infiltration-Distributed Equilibrium). The model encompasses geotechnical parameters of soils along with geomorphic attributes in the SLIDE [33-34] to enumerate FoS and hence aids in future failure predictions in the region. The developed LEWS had successfully estimated the occurrence of two failure incidents successfully, however, it could be improved by including more instability cases, geological complexities, and various modes of failure.

Apip et al. [31] elaborated the development of LEWS in upper Citarum River catchment (Indonesia) under the aegis of International Consortium on Landslides and the Disaster Prevention Research Institute, Kyoto University (Japan). The system binds the primitive information like "where" and "when" a failure may occur in the basin. The present work amalgamated the techniques of slope stability modeling and hydrological attributes (rainfall

and infiltration) along with failure history during 1985-2008 in the catchment. Satellite (Climate Prediction Center MORPHing techniques) based real-time precipitation data were utilized for comprehending hydrological problems in the slope instability and thereoff proving a reliable flood and shallow slope failure prediction. The susceptibility map owing to the land-use, permanent slope's geotechnical and geometrical attributes were overlain by dynamic soil saturation responses pertaining to rainfall events. Moreover, critical soil saturation data had been estimated to issue shallow slope failure warnings in the area.

Further, Fatimah et al. [28] devised an indigenous LEWS importing three key input parameters namely, slope, soil moisture, and vibration on the Internet of Things (IoT) platform connected to different sensors. The sensor generated datasets are processed using fuzzy intelligent techniques to issue warnings (safe, be alert, and watch-out) over Android smartphones of the natives. The system showed an accuracy of 90% on being examined over 30 datasets.

Karnawati et al. [7] assessed the Karanganyar Regency (Central Java) slope failures and analyzed critical factors responsible for slope failures. Slope geometry, structural features, land use, and lithology were identified for susceptibility maps of the region. Further, the Analytical Hierarchy Approach [32] has been used by integrating precipitation data with susceptibility map to develop hazard map. Moreover, the natives were prepared for hazard management through initiatives like empowerment programs. The field investigation and remote sensing data mapped 60% of the area as susceptible to earth-slides. A set of rain-gauge, extensometers, siren-alarm, and solar battery were arranged scientifically to generate alerts, when rainfall exceeds 100 mm or extensometers detect any displacement of more than 4 cm. Therefore, an ideal community-based LEWS was successfully established in the region. A brief comparison of all these LEWS are presented in table 3.

4 Need for Future Research

To further enhance Landslide Early Warning Systems (LEWS), several areas of future development and research can be considered:

1. **Improved Data Integration:** Incorporating a wider range of global and regional satellite datasets with higher spatial and temporal resolutions can significantly enhance the accuracy of precipitation and soil monitoring for landslide prediction.
2. **Application of AI and Machine Learning:** Leveraging artificial intelligence and machine learning techniques can refine predictive models by analysing complex interactions between geotechnical, hydrological, and meteorological variables.
3. **Strengthened Community Engagement:** Enhancing community-based approaches through training programs, public awareness initiatives, and intuitive interfaces for warning dissemination can boost system effectiveness and public trust.
4. **Advanced IoT and Sensor Networks**: Deploying IoT technologies with sophisticated sensors for real-time monitoring of slope stability, including parameters like soil chemistry, groundwater fluctuations, and seismic activity, can improve early detection accuracy.
5. **Dynamic Risk Modelling:** Developing adaptable risk assessment models that account for changes in land use, urbanization, and climate variability will ensure the systems remain relevant under evolving environmental conditions.
6. **Modular and Scalable Systems:** Creating scalable LEWS frameworks that can be tailored to diverse geological and climatic conditions will enhance their global applicability.
7. **Affordable Solutions for Resource-Limited Regions:** Designing cost-effective, low-maintenance technologies suitable for economically constrained areas will promote widespread adoption in vulnerable communities.

Table 3. A quick comparison and actionable outcomes from the reviewed literature

S. No.	Author/s	Comparison Criteria	Actionable Outcomes
01	Chikalamo et al. [27]	Focus on rainfall thresholds using remote sensing; integration of geology and land-use in LEWS.	• Utilize high-resolution satellite rainfall datasets (e.g., GPM, TRMM) for better accuracy. • Conduct region-specific rainfall threshold analysis while considering land-use dynamics. • Enhance integration of satellite data with ground-based measurements.
02	Fatimah et al. [28]	Development of an IoT-based system with sensors for monitoring soil moisture, slope inclination, and ground vibrations. Mobile application for real-time alerts.	• Deploy IoT sensors (e.g., MPU-6050 for slope, YL-69 for soil moisture) for hazard monitoring. • Create user-friendly mobile applications for disseminating early warnings. • Enhance fuzzy logic algorithms for more accurate alerts. • Conduct trials in diverse terrains.
03	Hidayat et al. [29]	Use of the Delft-FEWS platform for integrating TRMM, TRIGRS, and rainfall data for regional landslide forecasting.	• Implement TRIGRS models to analyze slope stability and safety factors. • Combine numerical and physical slope stability models with rainfall data for robust predictions. • Leverage TRMM precipitation data for high-resolution rainfall monitoring.
04	Karnawati et al. [7]	Community-based LEWS incorporating extensometers, rain-gauges, and alarm systems for alerts.	• Integrate rainfall data and crack displacement measurements for better alerts. • Provide disaster preparedness training to local communities. • Enhance community involvement in data collection and monitoring efforts.
05	Liao et al. [30]	Integration of physical models, hazard maps, and satellite rainfall data for time and location-specific landslide predictions.	• Employ SLIDE software for reliable slope stability analysis. • Use ASTER DEM and soil maps to refine terrain-specific predictions. • Strengthen data integration between remote sensing and in-situ sources for more comprehensive LEWS.
06	Apip et al. [31]	Development of a hydrological-geotechnical modeling system using CMORPH rainfall data for spatio-temporal soil saturation analysis.	• Apply hydrological models to monitor soil saturation and predict landslides. • Utilize CMORPH or similar global satellite products for real-time rainfall monitoring. • Develop grid-based systems to enable accurate, localized predictions of landslides.
07	Chikalamo et al. [27]	Focus on rainfall thresholds using remote sensing; integration of geology and land-use in LEWS.	• Utilize high-resolution satellite rainfall datasets (e.g., GPM, TRMM) for better accuracy. • Conduct region-specific rainfall threshold analysis while considering land-use dynamics.

			• Enhance integration of satellite data with ground-based measurements.

Advancing LEWS along these lines will strengthen their capability to deliver reliable, inclusive, and adaptable solutions for landslide risk mitigation in diverse and changing environments.

5 Conclusion

In conclusion, advancements in Landslide Early Warning Systems (LEWS) highlight the critical role of integrating high-resolution satellite rainfall datasets such as TRMM, GPM, and CMORPH with IoT devices for real-time monitoring of soil moisture, slope stability, and vibrations. Combining remote sensing with ground-based observations, advanced hydrological-geotechnical modeling, and numerical tools like TRIGRS and SLIDE enables precise predictions of \"when\" and \"where\" landslides may occur. Tailoring rainfall thresholds to regional geology and land use further enhances prediction accuracy. Community-driven strategies, including disaster preparedness training and the development of accessible tools like mobile apps and alarms, improve system adaptability and engagement. Testing these systems in diverse terrains and scaling successful models to similar regions ensures robustness and wider applicability. Together, these innovations promise a scalable, accurate, and timely LEWS framework for global disaster mitigation.
Therefore, this review is crucial for economic and community safety, offering precise understanding of landslide forecasts in Indonesia, and further aids global LEWS development.

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