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A REVIEW PAPER ON STUDY OF LANDSLIDE DETECTION, MONITORING, AND EARLY WARNING SYSTEMS

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ABSTRACT

Landslides are serious natural hazards, particularly in hilly and mountainous regions, where heavy rainfall, soil saturation, earthquakes, erosion, unstable geology, deforestation, slope cutting, construction, and inadequate drainage can reduce slope stability. Early signs of instability, such as rising soil moisture, ground displacement, changes in tilt, and increasing rainfall intensity, may precede failure, which makes continuous observation important for timely warning. This paper reviews landslide detection, monitoring, and early-warning approaches, including conventional monitoring, rainfall thresholds, Internet of Things (IoT) sensors, wireless sensor networks, GPS, remote sensing, and geographic information systems (GIS), and cloud-based monitoring. The literature review presents all 25 entries in the supplied literature matrix in descending order of publication year; the summaries follow the information provided in that matrix. The paper also outlines a proposed laboratory scale monitoring approach in which an Arduino Uno microcontroller board acquires data from capacitive soil moisture sensors and an MPU-6050 tilt/accelerometer module installed in a soil-slope model subjected to simulated rainfall. A threshold based decision rule with a persistence condition drives a three-level indicator and buzzer, and readings are shown on the serial monitor and may be logged locally. The thresholds are initial design settings to be calibrated and evaluated, and no experimental results are reported here. The anticipated contribution is an assessment of whether combining environmental and movement measurements can improve monitoring and support timely warnings, together with the limitations that must be addressed before any field use.

Keywords: Landslide Detection, Landslide Monitoring, Early Warning System, Internet of Things, Soil Moisture Sensors, Remote Sensing, Arduino

I. INTRODUCTION

A landslide is the downslope movement of rock, soil, or debris under gravity. Failure occurs when the driving forces acting on a slope exceed the shear resistance available along a potential failure surface. Rainfall can alter this balance by infiltrating the ground, increasing water content and pore-water pressure, and reducing effective stress and shear strength; the timing

and depth of rainfall-induced failure depend on infiltration and hydraulic properties of the soil. Natural predisposing and triggering factors include intense or prolonged rainfall, soil saturation, earthquakes, erosion, and unfavourable geological structure. Human activities such as deforestation, slope cutting, construction, and inadequate drainage can further reduce stability.

Landslides affect human life, roads, bridges, railways, buildings, agricultural land, and the environment. Because movement may be rapid and many susceptible areas are remote, protecting people often depends on detecting precursory conditions and issuing warnings before failure. Landslide early warning systems (EWSs) are recognised as a mitigation measure for reducing risk to life, and they are commonly divided into local systems for individual slopes and territorial systems covering wide areas. Practical guidance on designing slope-scale EWSs stresses that procedures must be adapted to the peculiarities of each site.

Conventional field inspection and manual monitoring have clear limitations. They are intermittent, labour intensive, difficult to maintain during storms, and potentially hazardous to personnel. Sensor-based monitoring addresses some of these limitations by providing continuous, remotely accessible measurements of rainfall, soil moisture, pore pressure, tilt, and displacement. Other technologies operate at larger scales.

Spaceborne, aerial, and ground-based remote sensing allow detection, mapping, and monitoring of hazardous or inaccessible areas while improving operator safety [. Rainfall thresholds, reviewed extensively in the recent literature, remain a central component of regional warning approaches . At the slope scale, low-cost systems that combine tilt and volumetric water-content sensors have been proposed and tested on real slopes . Wireless sensor networks have been deployed in landslide-prone terrain to record correlated rainfall, moisture, pore-pressure, and movement data and to support multi-level warnings. Satellite precipitation estimates and global landslide catalogues provide complementary spatial information . GIS and cloud platforms are further tools for susceptibility assessment and data management, although their value depends on the quality and representativeness of the data supplied to them.

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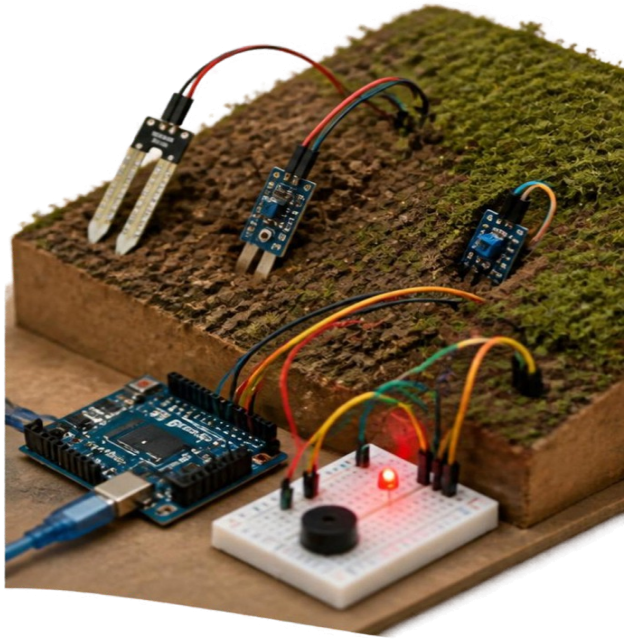


Fig. 1: Laboratory-scale landslide detection and early warning model

II. OBJECTIVES

The objectives of this review and the associated project are:

1. To study the major natural and human-induced causes of landslides.
2. To review existing landslide detection and monitoring techniques, including rainfall gauges, soil moisture sensors, tilt sensors, accelerometers, and other displacement-measurement instruments.
3. To study the applications of IoT and wireless sensor networks in real-time monitoring.
4. To examine the contributions of GPS, remote sensing, and GIS to landslide monitoring and hazard assessment.
5. To review the role of threshold-based and automated early-warning mechanisms.
6. To identify limitations and research gaps in existing systems.
7. To propose a laboratory-scale, multi-sensor monitoring approach and to identify cost-effective improvements for monitoring landslide-prone areas.

III. LITERATURE REVIEW

3.1 Mondal, Liu, and Li (2026): *Development and Deployment of IoT-Based Early Warning System for Rainfall-Induced Landslides Using Surface and Subsurface Sensors and Its Application.* The study develops and deploys an IoT-based early warning system for rainfall-induced landslides in which surface sensors are combined with subsurface sensors on the monitored slope. Tilt, soil-water-content, inclinometer, and rainfall measurements are collected together, so that movement at the surface can be read alongside the changing wetness inside the

slope. These data are used to detect slope changes and to establish warning levels from field monitoring, and the work shows how multi-sensor IoT data can be turned into a practical warning scheme for an actual slope.

3.2 Fitri and Asrizal (2025): *Using Sensors with Internet of Things for Landslide Detection System: A Systematic Literature Review.* This systematic literature review examines how sensors connected through the Internet of Things are used in landslide detection systems. It covers the sensor types most often reported, including soil-moisture sensors, accelerometers, and piezometers, and describes how they supply continuous data for identifying unstable slope conditions. The review also reports the main practical challenges found in the reviewed systems, notably connectivity and cost, which limit wide deployment in remote and landslide-prone areas.

3.3 Singh et al. (2025): *Development of rainfall threshold equation and Bayesian probabilistic analysis for landslide prediction: A case study of Shimla, Northwestern Himalaya, India.* The study develops a rainfall threshold equation for landslide prediction in Shimla, in the Northwestern Himalaya of India, based on rainfall intensity and duration. A Bayesian probabilistic analysis is then applied to assess the likelihood of landslide occurrence under given rainfall conditions. The work therefore moves beyond a single threshold line by attaching probabilities to rainfall conditions for a Himalayan site, which supports regional prediction and warning.

3.4 Badola, Mishra, and Parkash (2025): *Landslide Susceptibility Mapping in Complex Topo-Climatic Himalayan Terrain, India Using Machine Learning Models: A Comparative Study of XGBoost, RF and ANN.* This comparative study maps landslide susceptibility in the topographically and climatically complex terrain of the Indian Himalaya using three machine learning models: XGBoost, Random Forest, and Artificial Neural Network. The models are compared with one another to judge which gives the more reliable classification of landslide-prone terrain. The study contributes a comparison of modern data-driven models for susceptibility mapping in a difficult mountain setting.

3.5 Gonzalez et al. (2024): *A systematic review on rainfall thresholds for landslides occurrence.* This systematic review examines the research published on rainfall thresholds for the occurrence of landslides. It compares how thresholds have been defined and applied and identifies recurring limitations, such as inconsistent rainfall periods, sparse rain gauges, and gaps in regional coverage. The review gives a consolidated view of the state of threshold research and indicates where more consistent data and wider geographical coverage are needed.

3.6 Nocentini et al. (2024): *Optimization of rainfall thresholds for landslide early warning through false alarm reduction and a multi-source validation.* The study investigates how rainfall thresholds used for landslide early warning can be optimized through the reduction of false alarms. The optimized thresholds are validated using multiple sources of information rather than a single dataset, so that their performance is tested more thoroughly. The work

addresses a central difficulty of operational warning systems, which is balancing correct warnings against unnecessary alerts.

3.7 Marin and Marín-Sánchez (2024): *Land Scient_EWS: Real-Time Monitoring of Rainfall Thresholds for Landslide Early Warning – A Case Study in the Colombian Andes.* The study presents Land Scient_EWS, a software-based approach that monitors rainfall thresholds for landslide early warning in real time. It is applied as a case study in the Colombian Andes, where incoming rainfall observations are compared with the thresholds to support an operational warning workflow. The work shows how threshold-based warning can be automated through software so that rainfall conditions are checked continuously.

3.8 Vishnu, Oommen, Chatterjee, and Sajinkumar (2024): *Addressing the Effect of Intra-Seasonal Variations in Developing Rainfall Thresholds for Landslides: An Antecedent Rainfall-Based Approach.* This study examines how intra-seasonal variations in rainfall affect the development of rainfall thresholds for landslides. It adopts an antecedent rainfall-based approach, in which rainfall accumulated before an event is considered in addition to the triggering rainfall. The work shows that seasonal variation and previous wetness influence the reliability of landslide-triggering thresholds, and it supports the inclusion of antecedent conditions when thresholds are derived.

3.9 Satyaningsih et al. (2023): *Dynamic rainfall thresholds for landslide early warning in Progo Catchment, Java, Indonesia.* The study develops dynamic rainfall thresholds for landslide early warning in the Progo Catchment of Java, Indonesia. Ground-based and satellite rainfall estimates are used together with records of landslide occurrences, and the resulting thresholds are evaluated for their ability to identify landslide-triggering rainfall. The work demonstrates how satellite rainfall data can supplement rain gauges for warning in a region where ground observations are limited.

3.10 Maheshwari and Bhowmik (2023): *Detection, Monitoring, and Early Warning of Landslides Using In-Situ Ground-Based Monitoring Techniques: A Review.* This review covers in-situ ground-based techniques for the detection, monitoring, and early warning of landslides. It discusses the monitoring methods and sensor systems installed directly on or within slopes, and the physical and rainfall thresholds that are used to trigger warnings. The review gives a broad account of how on-site instrumentation supports early warning and serves as a useful reference for slope-scale monitoring.

3.11 El Houssaini et al. (2022): *Location-Aware IoT-Enabled Wireless Sensor Networks for Landslide Early Warning.* The study investigates location-aware wireless sensor networks, enabled by the Internet of Things, for landslide early warning. Sensor nodes are deployed on potentially unstable slopes so that the position of each node is known and movement can be tracked continuously. The work focuses on early detection of movement through such networks and shows how knowing the location of the sensing nodes improves the interpretation of slope displacement.

3.12 Chen and Fan (2022): *CNN-LSTM-ATTENTION Deep Learning Model for Mapping Landslide Susceptibility in Kerala, India.* The study proposes a CNN-LSTM-Attention deep learning model for mapping landslide susceptibility in Kerala, India. The model combines convolutional layers, recurrent long short-term memory layers, and an attention mechanism so that spatial patterns and relationships among conditioning factors can be learned together. The work demonstrates the use of a hybrid deep learning architecture for susceptibility mapping in a region frequently affected by landslides.

3.13 Luo, Li et al. (2022): *Evaluation of different machine learning models and novel deep learning-based algorithm for landslide susceptibility mapping.* This study evaluates several machine learning models for landslide susceptibility mapping and introduces a novel deep learning-based algorithm named LSNet. The performance of LSNet is compared with that of conventional machine learning models in assessing susceptibility. The work contributes a new deep learning approach for susceptibility assessment and a comparison that shows how it performs relative to established methods.

3.14 Lee, Park, and Sung (2021): *The optimal rainfall thresholds and probabilistic rainfall conditions for a landslide early warning system for Chuncheon, Republic of Korea.* The study derives optimal rainfall-duration thresholds for a landslide early warning system for Chuncheon, Republic of Korea. Bayesian analysis is then used to estimate the probability of landslide occurrence under particular rainfall conditions. By combining thresholds with probabilistic rainfall conditions, the work supports a warning system for a specific locality that expresses landslide likelihood rather than a simple trigger line.

3.15 Peres and Cancelliere (2021): *Comparing methods for determining landslide early warning thresholds: potential use of non-triggering rainfall for locations with scarce landslide data availability.* This study compares methods for determining landslide early warning thresholds. It examines the potential use of non-triggering rainfall, that is, rainfall events that did not cause landslides, for locations where landslide records are scarce. The work is relevant to regions with limited landslide inventories, since it shows how thresholds can still be defined when few triggering events are documented.

3.16 Azarafza et al. (2021): *Deep learning-based landslide susceptibility mapping.* The study applies a deep neural network to landslide susceptibility mapping and compares its performance with that of established machine-learning classifiers. The comparison is used to judge whether deep learning gives better discrimination between landslide-prone and stable areas. The work adds evidence on the usefulness of deep learning for susceptibility mapping relative to conventional classification methods.

3.17 Abraham, Satyam, Pradhan, and Alamri (2020): *IoT-Based Geotechnical Monitoring of Unstable Slopes for Landslide Early Warning in the Darjeeling Himalayas.* The study presents an IoT-based geotechnical monitoring system for unstable slopes in the Darjeeling Himalayas for landslide early warning. IoT-connected tilt and soil moisture sensors are

installed to monitor slope movement, and the sensor readings are examined in relation to rainfall and antecedent wetness. The work is a close example of low-cost, field-installed tilt and moisture sensing for warning in a landslide-prone Himalayan region.

3.18 Kalantar et al. (2020): *Landslide Susceptibility Mapping: Machine and Ensemble Learning Based on Remote Sensing Big Data.* This study applies machine learning and ensemble learning methods to landslide susceptibility mapping, using remote-sensing big data together with environmental data. The different methods and their ensembles are compared in terms of their mapping performance. The work shows how large remote-sensing datasets can be combined with learning algorithms to produce susceptibility maps over wide areas.

3.19 Pecoraro, Calvello, and Piciullo (2019): *Monitoring strategies for local landslide early warning systems.* This study reviews monitoring strategies for local landslide early warning systems. It describes the instruments and procedures used to observe unstable slopes and explains how monitoring is organised so that it can support warnings at the scale of an individual slope. The work provides guidance on the design of local monitoring and is useful for choosing sensors and procedures for slope-scale systems.

3.20 Xie et al. (2019): *Prediction of slope failure using MEMS tilt sensors under artificial rainfall.* The study investigates the prediction of slope failure using MEMS tilt sensors under artificial rainfall. Tilt and tilt-rate behaviour is measured during rainfall tests to identify slope movement and to support the prediction of failure. The work is a close precedent for laboratory-scale testing because it shows that low-cost tilt sensing in a rainfall-loaded slope can indicate impending failure.

3.21 Segoni, Piciullo, and Gariano (2018): *A review of the recent literature on rainfall thresholds for landslide occurrence.* This study reviews the recent literature on rainfall thresholds for landslide occurrence. It explains how rainfall intensity, duration, and accumulated rainfall are used to identify the conditions linked to landslides and summarises the approaches that have been adopted. The review provides an overview of how thresholds are defined and used, and it serves as a general reference for threshold-based warning.

3.22 Piciullo, Calvello, and Cepeda (2018): *Territorial early warning systems for rainfall-induced landslides.* The study reviews territorial early warning systems for rainfall-induced landslides, that is, systems operating over regional areas. It describes the data and modelling components of these systems and the coordination needed to turn forecasts into public warnings. The work provides an overview of how regional systems are structured and shows that warning depends on organisation and communication as well as on technical models.

3.23 Mirus, Becker, Baum, and Smith (2018): *Integrating real-time subsurface hydrologic monitoring with empirical rainfall thresholds to improve landslide early warning.* This study examines whether real-time subsurface hydrologic monitoring can improve landslide early warning that is based on empirical rainfall thresholds. Real-time measurements of subsurface

wetness are considered alongside rainfall for shallow landslides. The work addresses the limitation that rainfall alone does not describe the actual wetness of the slope and supports combining in-ground measurements with rainfall thresholds.

3.24 Bui et al. (2018): *Design and implementation of site-specific rainfall-induced landslide early warning and monitoring system: a case study at Nam Dan landslide (Vietnam).* The study describes the design and implementation of a site-specific, rainfall-induced landslide early warning and monitoring system, applied as a case study at the Nam Dan landslide in Vietnam. Sensor nodes and rainfall observations are used to monitor soil moisture, pore pressure, and movement at the site. The work illustrates the complete design of a warning system tailored to one slope, from sensing to monitoring and warning.

3.25 Rossi et al. (2017): *Statistical approaches for the definition of landslide rainfall thresholds and their uncertainty using rain gauge and satellite data.* This study examines statistical approaches for defining landslide rainfall thresholds and for quantifying their uncertainty. It uses both rain-gauge data and satellite precipitation data and considers how the choice of dataset affects the resulting thresholds. The work highlights that thresholds carry uncertainty and that this uncertainty should be estimated when thresholds are used for warning.

3.26 Chae, Park, Catani, Simoni, and Bert (2017): *Landslide prediction, monitoring and early warning: a concise review of state-of-the-art.* This paper gives a concise review of the state of the art in landslide prediction, monitoring, and early warning. It provides an overview of prediction approaches, monitoring methods, and warning approaches, and brings them together in one account. The work is a general foundation for the topic and a useful starting point for locating more specialised studies.

3.27 Segoni et al. (2015): *An operational landslide early warning system at regional scale based on spacetime-variable rainfall thresholds.* The study describes an operational landslide early warning system at regional scale based on space-time variable rainfall thresholds. The thresholds change with space and time, and a WebGIS is used to monitor alert levels across different zones. The work demonstrates a working regional system in which threshold-based warnings are issued and displayed through a web-based platform.

3.28 Posner and Georgakakos (2015): *Soil moisture and precipitation thresholds for real-time landslide prediction in El Salvador.* This study examines soil moisture and precipitation thresholds for real-time landslide prediction in El Salvador. It considers how soil-moisture information can be combined with precipitation thresholds to predict landslide conditions in real time. The work is relevant to multi-parameter warning because it shows that soil moisture can complement rainfall in identifying when landslides are likely.

3.29 Segoni, Rossi, and Catani (2014): *Landslides triggered by rainfall: a semiautomated procedure to define consistent intensity-duration thresholds.* The study proposes a semi-automated procedure for defining consistent intensity-duration rainfall thresholds for

landslides triggered by rainfall. The procedure is designed to derive thresholds in a consistent and repeatable manner so that they can be applied in warning systems. The work reduces subjectivity in threshold definition and makes the derivation of thresholds more reproducible.

3.30 Sengupta, Gupta, and Anbarasu (2010): *Rainfall thresholds for the initiation of landslide at Lanta Khola in north Sikkim, India.* The study investigates the rainfall thresholds associated with the initiation of landslides at Lanta Khola in north Sikkim, India. It analyses the rainfall conditions linked to landslide initiation at this site in the Indian Himalayas. The work contributes regional threshold information for a Himalayan location that can support local warning.

IV. CONCLUSION

Landslide detection, monitoring, and early warning are essential for reducing risk in susceptible regions. The reviewed literature shows complementary roles for different approaches. Ground sensors and rainfall data capture local and external conditions; IoT and wireless communication enable continuous remote observation; remote sensing and catalogues provide wide-area context; and GIS supports susceptibility assessment and spatial data management, provided suitable data are available. No single method is sufficient, and each has limitations of scale, data quality, cost, or transferability.

Integrating soil-moisture and tilt measurements in a low-cost laboratory prototype may offer a simple way to explore multi-parameter warning logic, building on the combined moisture–tilt concept reported for real slopes Reliable operational warnings, however, require calibration of the sensors, locally appropriate thresholds, repeatable experiments, field validation, and dependable communication and power. The thresholds proposed here are initial settings only.

Future research should include multi-sensor fusion, better threshold calibration, longer-duration trials, integration with geospatial information, and wireless data transmission for remote deployments.

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