Indonesian Physical Review

Volume 09 Issue 03, September 2026

P-ISSN: 2615-1278, E-ISSN: 2614-7904

Development of a Simple Laboratory-Scale Landslide Simulation System Using a Shaking Table and Artificial Rainfall

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Article Info

Article info:
Received: 18-12-2025
Revised: 10-07-2026
Accepted: 15-07-2026

Keywords:
Landslide Model; Laboratory Scale; Rainfall; Earthquake; Soil Moisture; Accelerometer; Sensor

How To Cite:
E. Yuliza, M. K. Fauzi, R. Ekawati, Refrizon," Development of a Simple Laboratory-Scale Landslide Simulation System Using a Shaking Table and Artificial Rainfall", Indonesian Physical Review, vol. 9, no. 3, p 489-502, 2026

DOI:
https://doi.org/10.29303/ipr.v9i3.636.

Abstract

A landslide mitigation system is essential to reduce the potential risks of disasters. Historical records of both localized and widespread landslide events indicate that the development of sensor-based early warning systems is an effective mitigation approach. The design of such systems requires an understanding of landslide characteristics and sensor responses to physical changes in soil. Therefore, this study developed a simple laboratory-scale landslide simulation system integrating a shaking table, an artificial rainfall, and a sensor system. The novelty of this work lies in integrating two different triggering factors, vibration through a shaking table and rainfall, using artificial rainfall. Two different materials, laterite and soil, were used to obtain ground movement characteristics. The results indicate that each material responded differently to the applied triggering factors. Laterite soil with clayey characteristics became soft and exhibited plasticity behavior under wet conditions and hardened under dry conditions. Consequently, vibration-induced movement in zones with weak soil bonding, while the addition of water primarily caused fluid flow associated with rainfall. In contrast, for sand samples, both vibration and artificial rainfall reduced pore size and enhanced soil bonding. However, an optimal pore size was observed, as excessive saturation led to fractures and collapse. Excess water also promotes fluid flow and liquefaction. Furthermore, the sensor system effectively detected and responded to the observed changes during the experimental procedure.

Introduction

Landslides are natural processes resulting from the loss of slope stability due to geological, hydrological, climatic, catastrophic, and human activity factors [1]–[5]. In Indonesia, landslides are among the four most frequent types of disaster [6], [7]. The high frequency is closely linked to the mountainous region, hilly topography, and relatively high rainfall levels [8], [9]. Increased rainfall affects pore pressure and the stability of land-forming materials, making slopes more susceptible to failure [5], [10]. Additionally, population growth and economic expansion increase landslide risk. These factors are associated with deforestation, land-use changes, poor land management, climate change, and other environmental impacts [5], [7]. However, in many landslide events, increased rainfall is the primary triggering factor[1], [11], [12]. Moreover, Indonesia lies in an active seismic zone, where frequent earthquakes increase the likelihood and severity of landslides. Furthermore, landslides are a secondary effect of earthquakes. One of the significant earthquakes that triggered a devastating landslide was the 2009 West Sumatra earthquake, which measured 7.6 Mw [13].

As a significant natural disaster, landslides caused material damage and loss of life across many regions worldwide[11], [14]–[16]. This disaster could possibly disrupt ecosystems and leave lasting trauma within affected communities. Moreover, the estimated annual economic losses from landslides in the United States and Europe reach $6 billion [17]. On the other hand, landslides cannot be avoided entirely as part of the natural process of reaching their equilibrium state [18]. Effective mitigation strategies are the best approach to minimizing the risks of landslide events [4], [11], [19], [20]. Generally, there are two mitigation strategies: structural and non-structural approaches [9], [21], [22]. Structural mitigation involves physical interventions such as retaining walls, drainage improvements, and reforestation, often requiring significant financial investment. In contrast, non-structural mitigation can be achieved through early warning systems, regional planning, risk management, and other measures. Based on histories of landslide events that occur in limited and widespread areas, developing non-structural mitigation systems is more reliable to implement. Therefore, many researchers have developed landslide mitigation systems, including early warning systems. Various types of landslide early warning systems are being applied to monitor landslide activity.

A landslide early warning system can be developed by utilizing multi-sensor technology to observe and monitor physical slope changes associated with landslides [3], [23]–[26]. Changes in soil moisture and movement are major physical parameters associated with landslide activity. These changes can be detected using soil moisture sensors, accelerometers, inclinometers, and other relevant sensors [3], [7], [11], [27]. In general, before applying sensors for field observations, the response mechanism of each sensor must be examined using a landslide simulator. A laboratory-scale landslide simulator is commonly used to assess sensor responses and analyze landslide characteristics [3], [7], [11], [28]. Furthermore, the development of simulators facilitated the improvement of the understanding of landslide behavior [5]. This simulation system can also be used to obtain threshold values for physical parameters based on sensor responses and event characteristics for warning purposes.

Generally, the development of laboratory-scale landslide simulators facilitates the investigation of landslide mechanisms under controlled environmental conditions. Various studies have developed simulator systems with different configurations and dimensions to represent regional landslide characteristics. Moreover, most studies of laboratory-scale models focus on a single triggering mechanism, typically artificial rainfall or changes in soil moisture. Therefore, the multiple triggering factors remain insufficiently investigated. This limitation reduces the ability of existing laboratory models to represent landslide processes in tectonically active regions, where earthquakes frequently act as triggering factors. Furthermore, a comprehensive understanding of landslide behavior should consider both increased rainfall intensity and seismic activity [8], [9], [15]. This study develops a laboratory-scale landslide simulator by integrating two triggering mechanisms: artificial rainfall to simulate increased groundwater content and controlled vibration to represent earthquake-induced ground motion. The novelty of this model lies in its ability to assess two triggering factors within a single experimental platform while systematically comparing their effects across different soil types.

This study focuses on two representative soil types, namely lateritic and sandy soils, which exhibit contrasting geotechnical properties. Lateritic soil is a residual soil formed in tropical and subtropical regions by intense chemical weathering and is characterized by a high iron oxide content [29]–[31]. Due to its relatively high clay content, lateritic soil exhibits cohesive and plastic behavior [29], [31]. It becomes soft and plastic when wet and hard when dry[31]. Conversely, sandy soil has a loose granular structure, very low cohesion, high porosity, high permeability, and low water retention. While a moderate amount of water can increase apparent cohesion through capillary action, excessive infiltration can reduce soil stability, promote surface runoff, and, under certain conditions, contribute to its liquefaction [32], [33]. By evaluating the responses of these two contrasting soil types to rainfall and vibrations, this preliminary study provides fundamental insights into landslide initiation mechanisms and demonstrates the potential of the proposed simulator as a flexible laboratory platform for studying landslides triggered by multiple factors.

Methodology

This research is a preliminary laboratory-scale study aimed at understanding the mechanisms of landslide initiation by introducing two triggering factors, artificial rainfall and vibration. A small-scale landslide model is equipped with a soil moisture sensor and an accelerometer to measure changes in physical parameters during experiments. Two types of disturbed soils, laterite and sand, were selected because they exhibit contrasting geotechnical characteristics, frequently encountered in tropical regions. Laterite displays relatively high cohesion and plasticity due to its clay content, whereas sand exhibits low cohesion, high permeability, and a loose granular structure. The use of these contrasting materials allows for a comparative evaluation of landslide responses under identical triggering conditions. The research procedure is illustrated in Figure 1.

The first stage involved designing the mechanical and instrumentation system. The mechanical system consisted of a chamber measuring 70 cm (L) × 30 cm (W) × 25 cm (H) equipped with two triggering mechanisms: an artificial rainfall system and a vibration system. An artificial rainfall system was generated using a spray nozzle to increase soil moisture, while vibration was produced by the reciprocating motion of a motorized vibrating table mounted on linear rails beneath the chamber. The instrumentation system was developed using a microcontroller-based data acquisition unit. Two YL-69 soil moisture sensors were buried in the soil, and two MPU-6050 accelerometers were installed on their surface. For each sensor type, one was positioned at the top of the slope (P-1) and the other on its surface (P-2), as illustrated in Figure 2. The sensor data were recorded at a sampling interval of 45 seconds for vibration triggering and 10 minutes for artificial rain.

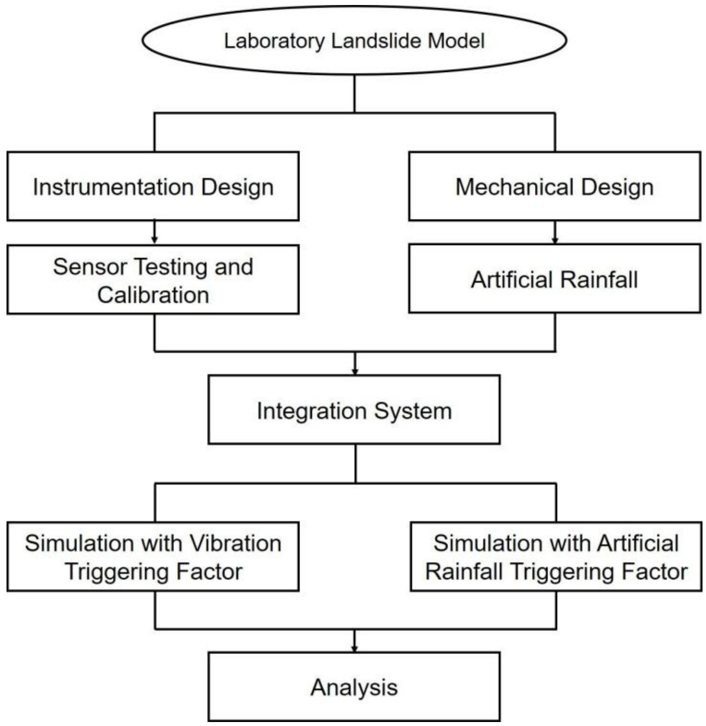

Figure 1. Flowchart for Laboratory Scale of Landslide Model

Figure 2 illustrates the complete laboratory-scale landslide simulation system. Before the experimental investigation, all system components were individually evaluated. The artificial rainfall system was tested to determine the optimal nozzle height, precipitation distribution profile, and rainfall intensity uniformity before its integration into the landslide simulator. The selected rainfall configuration was then used consistently throughout the experiments. The sensor system was also calibrated and evaluated to verify its response to measurable variations in soil moisture and vibration before its installation on the experimental platform. Following these preliminary evaluations, the complete laboratory-scale system was assembled for experimental testing.

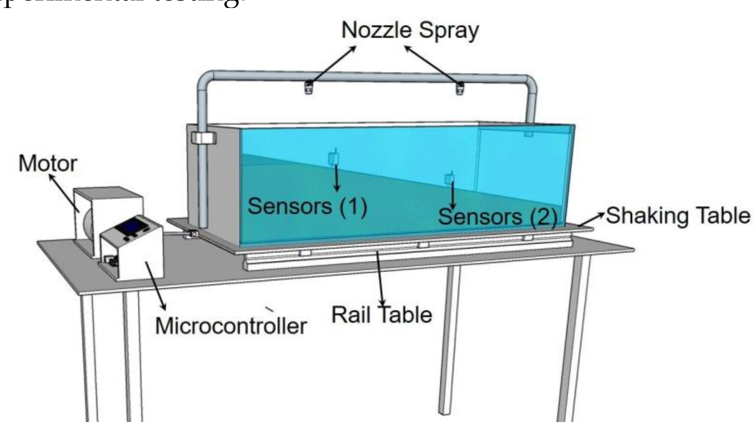

Figure 2. The design of the laboratory-scale landslide model

The experiments were conducted under two independent triggering scenarios: (1) artificial rainfall and (2) vibration-induced ground movements. For each triggering condition, experiments were performed separately on lateritic and sandy soils to compare their responses under identical laboratory conditions. During each experiment, sensor data from both monitoring points were continuously recorded and analyzed to identify changes associated with landslide triggering. Furthermore, this preliminary study aims to improve our understanding of the mechanisms of landslide triggering factors and ground movement. The results obtained provide baseline data for refining the experimental platform and guiding future research.

Results and Discussion

This research was conducted to improve the understanding of landslide characteristics through a laboratory-scale approach. To achieve this objective, a laboratory-scale landslide simulation system was developed, incorporating two triggering factors and environmental monitoring using sensors. According to the methodology section's research outline, a preliminary examination was conducted on the triggering factors and sensor system before their integration into the landslide model. An artificial rainfall system was designed using a spray nozzle to simulate triggering associated with changes in soil water content. The initial laboratory-scale examination of artificial rainfall aimed to determine the optimal nozzle height that produces uniform rainfall distribution for use in the landslide model. These tests assessed the nozzle height, distribution patterns, and rainfall intensity. The performance of the artificial rainfall system was assessed using 35 containers, each with a 4.83 cm diameter, arranged to cover a 37 cm diameter test area, as shown in Figure 3(a).

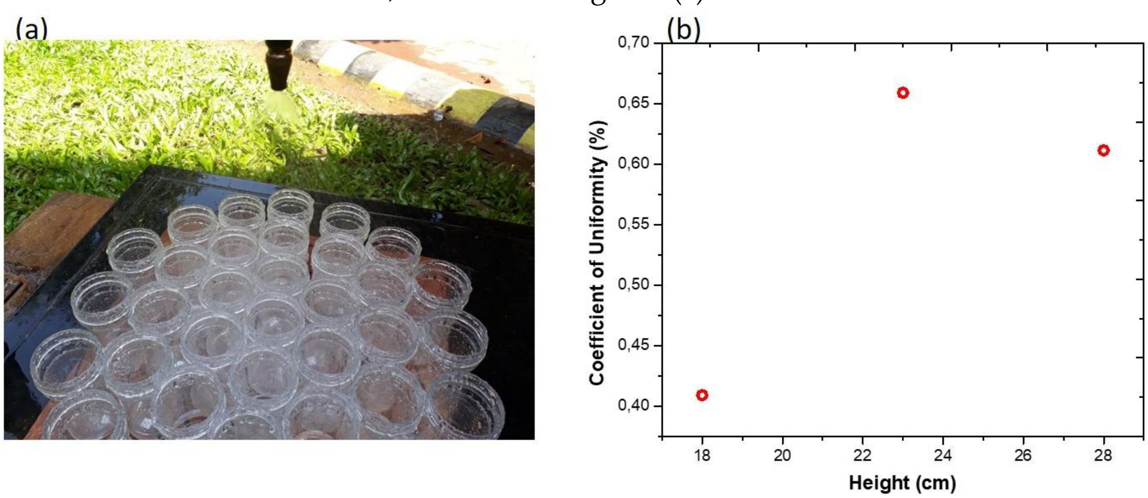

Figure 3 (a) The measurement system of the artificial rainfall model, (b) The uniformity coefficient of the rainfall intensity model

The examination lasted 5 minutes and used three nozzle heights (18 cm, 23 cm, and 28 cm) to determine optimal rainfall parameters, including intensity and distribution patterns. Rainfall intensity at each nozzle height was calculated based on the volume of water collected in the containers. This volume data was further analyzed to determine the coefficient of uniformity (CuC). The CuC value for each variation is shown in Figure 3(b). The results indicate that a nozzle height of 23 cm yields the highest uniformity coefficient (0.659) and an average rainfall intensity of 2.92 mm/min. Generally, the CuC value represents rainfall uniformity, with a value closer to 1 indicating greater uniformity. Based on these findings, a nozzle height of 23 cm is selected for landslide model experiments triggered by rainfall. Furthermore, this experiment focuses on evaluating CuC and does not compare it with natural rainfall intensity thresholds for landslides, because the rainfall intensities that trigger landslides vary widely depending on local conditions.

In the sensor system, a preliminary examination was conducted to evaluate the soil moisture sensor's performance using two types of material samples. Before the examination, the soil samples were dried using the gravimetric method and then placed in prepared containers. Each container was subjected to different volumes of water, and the soil moisture sensor was used to measure the response. The examination results for various water volumes are presented in Figure 4. Based on the data in Figure 4, changes in voltage were observed as the sensor response to variations in soil water content. In general, the sensor demonstrated good sensitivity in effectively indicating changes in material water content. The results also indicated that the sand sample exhibited a more significant response to increasing water volume. This behavior is related to material characteristics, such as grain and pore size, in which larger grains and pores are associated with lower water retention capacity. Furthermore, pore size and water content influence the mechanical strength of each material.

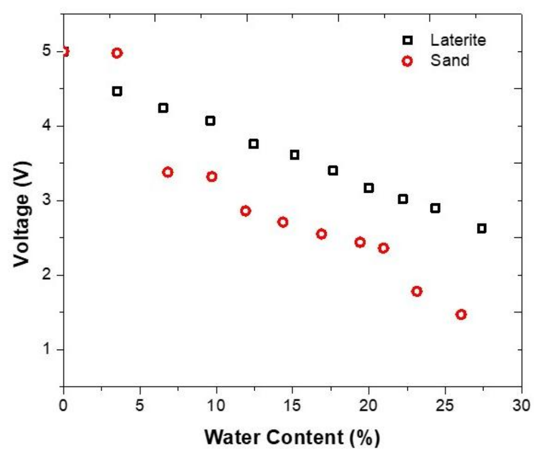

Figure 4. Soil moisture sensor response to the addition of water content

For the MPU-6050 accelerometer, the initial test was performed to obtain its response to changes in tilt angle. This test used a stepper motor that was capable of rotating up to 360°. Calibration was performed using a sensor holder connected to the stepper motor, allowing precise control of the sensor orientation. Generally, the accelerometer measures motion along the X, Y, and Z axes. Therefore, the sensor is tested using the calibrator to obtain the response patterns in each direction by systematically adjusting its orientation within the test system. The accelerometer responses to different angles are shown in Figure 5(a). This initial test also examined using an unloaded landslide model to evaluate the accelerometer's response when the motor-driven vibration trigger system was activated. The results of this test are presented in Figure 5(b), which shows a relatively consistent and stable sensor response.

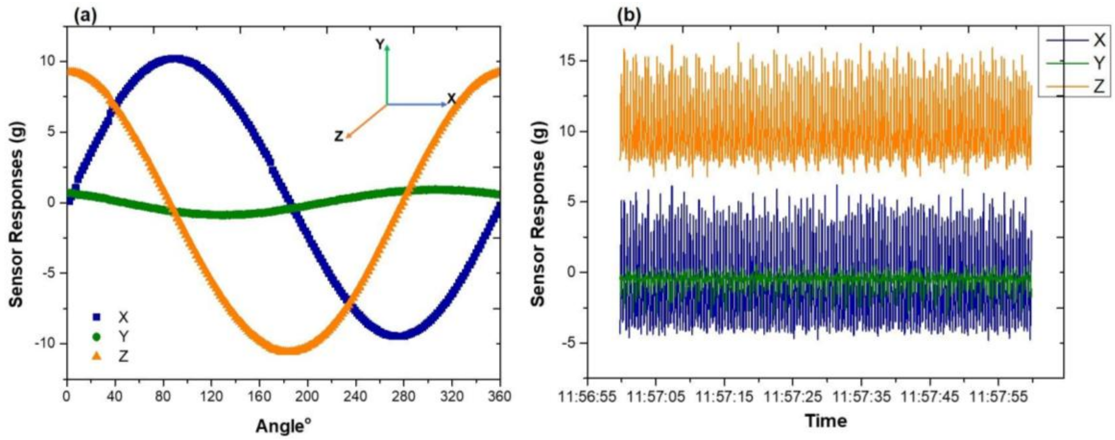

Figure 5 Accelerometer sensor response for different conditions (a) for angle variation up to 360 °, (b) on the unloaded landslide model

Generally, the initial examination of the triggering factors and sensor systems showed satisfactory performance. Therefore, the next step was to integrate all components into a laboratory-scale landslide model. The landslide experiment began with preparing the soil material inside the chamber. Since disturbed soil samples were used, the slope model was formed by shaping and compacting the soil. Compaction was conducted by dropping a load of fixed mass from a constant height onto the soil surface, ensuring uniform compaction across all experiments. The mass of the load, the drop height, and the number of compaction repetitions remain consistent for all treatments. Furthermore, the sample was arranged to form a 45° slope. Thus, although this experiment used disturbed soil samples, an initial treatment was applied to recondition the material by controlled compaction. This first treatment consisted of shaping the soil to the desired slope geometry and compacting it according to a standardized procedure, including a fixed loading mass, drop height, and number of repetitions. This process aims to achieve uniform density and mechanical properties in the soil sample before each test. After the slope model is prepared, the triggering and sensor systems are installed. Finally, laboratory-scale landslide simulation tests are conducted for each soil type under different triggering factors. Furthermore, in each experiment, variation was applied only to the triggering factors used, while material processing and sensor placement remained constant throughout the tests.

The simulation using a triggering factor of vibration

The first experiment used vibration as the triggering factor for ground movement. Since the primary physical change observed was ground movement, an accelerometer was used to measure it. The tests were conducted by applying vibrations for 45 seconds while continuously monitoring and recording the resulting motion using the accelerometer. This experiment was performed for both soil types, with the results for the laterite sample shown in Figure 6 and those for the sand sample shown in Figure 7.

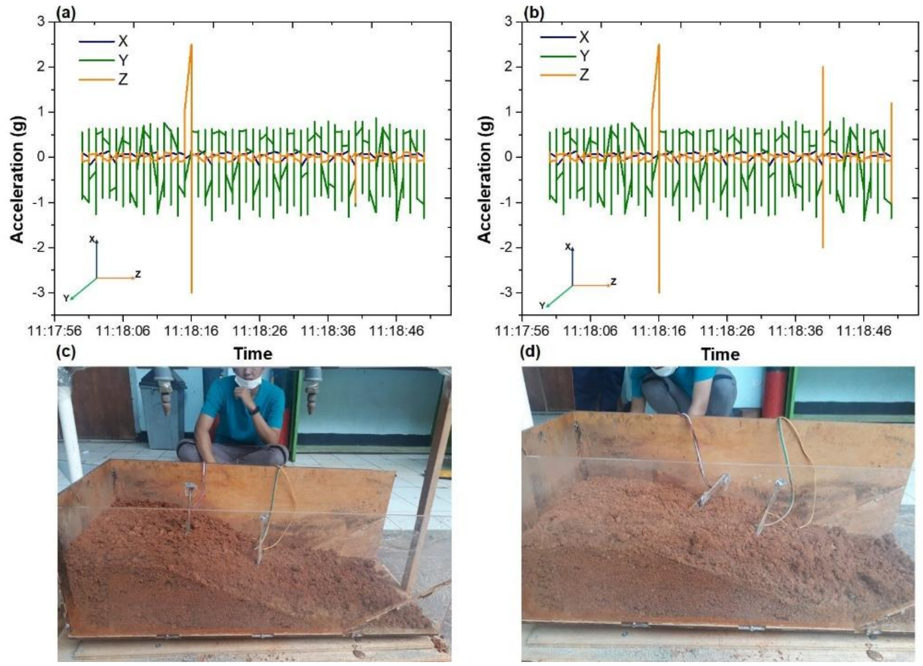

Figure 6. Landslide model experiment using vibration on laterite sample (a) the response of accelerometer sensor at P-1, (b) the response of accelerometer sensor at P-2, (c) Initial condition, (d) final condition after vibration

Figure 6 displays the results of the landslide model test using vibration as the triggering factor for the laterite sample. After 16 seconds of vibration and movement, significant changes were recorded on both sensors, as shown in Figures 6(a) and 6(b). These results also show the slope condition before (Figure 6(c)) and after (Figure 6(d)) vibration treatment, equipped with two sensor locations, sensors (1) and sensors (2).

The simulation using a triggering factor of artificial rainfall

The second experiment investigated a triggering factor in the form of changes in soil water content using an artificial rainfall mechanism. This laboratory-scale experiment was designed as a preliminary study to improve understanding of landslide mechanisms under controlled conditions. The experiment was carried out on two soil types with measurements obtained using soil moisture sensors and an accelerometer. The results are presented in Figure 8 for lateritic soil and Figure 9 for sand soil. For the simulation using an increase in soil water content as a triggering factor, the test on laterite soil samples was conducted for 10 minutes. During this observation period, the laboratory landslide model showed no significant mass movement. However, notable responses were recorded by both accelerometer sensors. The main movement detected involved small soil fragments on the surface that lost their cohesion and gradually shifted downward. Thus, soil moisture levels increased throughout the experiment, as indicated by the soil moisture sensor readings. The limited movement observed can reflect the characteristics of laterite soil, which tends to become soft and plastic as the moisture content increases [31]

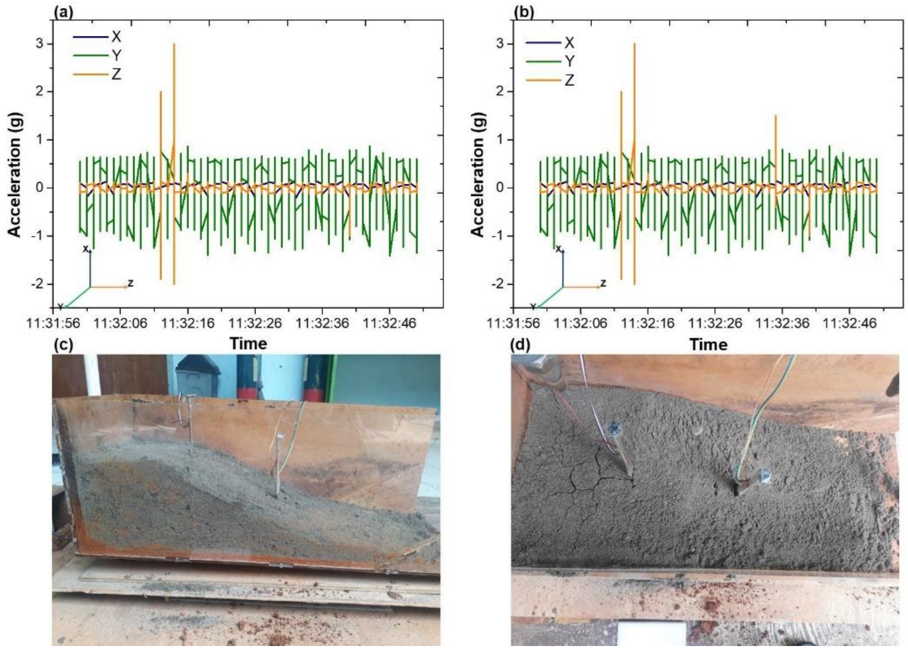

Figure 7. Landslide model experiment using vibration on sand sample (a) the response of accelerometer sensor at P-1, (b) response of accelerometer sensor at P-2, (c) initial condition, (d) final condition after vibration

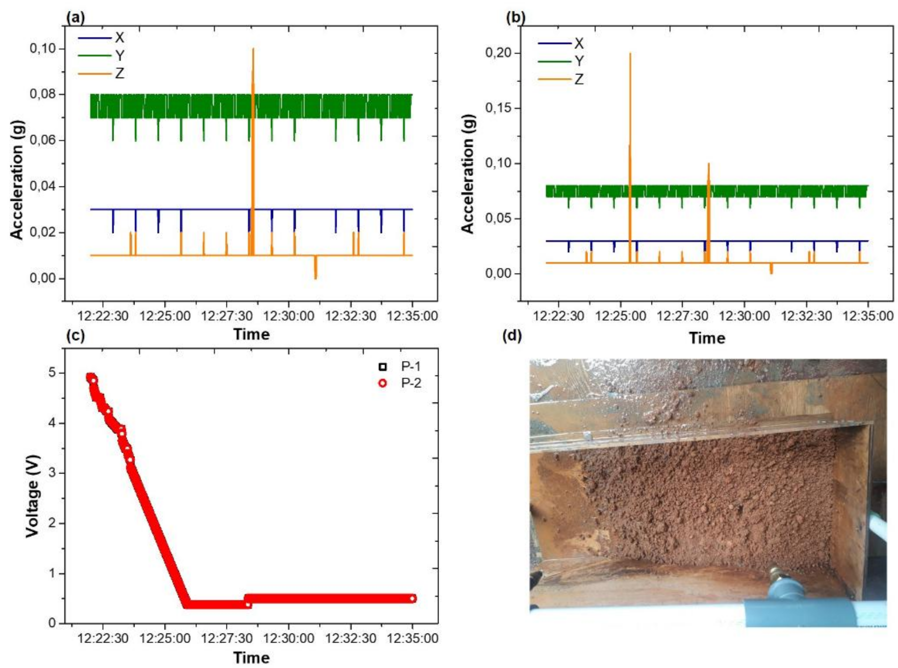

Figure 8. Landslide model experiment using artificial rainfall on laterite sample (a) the response of accelerometer sensor at sensors (1), (b) the response of accelerometer sensors (2), (c) the response of soil moisture sensor, (d) final condition after rainfall

Figure 9 presents the results of laboratory-scale landslide model tests on sand samples, where changes in water content served as the triggering factor. Generally, adding a small amount of water initially increases the apparent bond strength of sand [34]. This occurs because water fills the pores between sand grains and forms bridges, improving cohesion through capillary forces [34], [35]. However, when water content becomes excessive, the bond between particles weakens. As water content continues to rise, the increased pore water reduces effective stress, thereby decreasing bond strength, as illustrated in Figure 9(d). This weakening process is also detected through the accelerometer sensor response. If water continues to accumulate, it may eventually flow along the chamber surface, potentially triggering a fluid-flow mechanism [36]. In this experiment, however, no clear fluidization mechanism was observed, likely due to the limited test duration and the design of the laboratory system. The pore structure of sand allows water to drain efficiently, causing excess water to accumulate at the bottom of the model and then exit the chamber. This process ultimately induces a flow-type movement pattern.

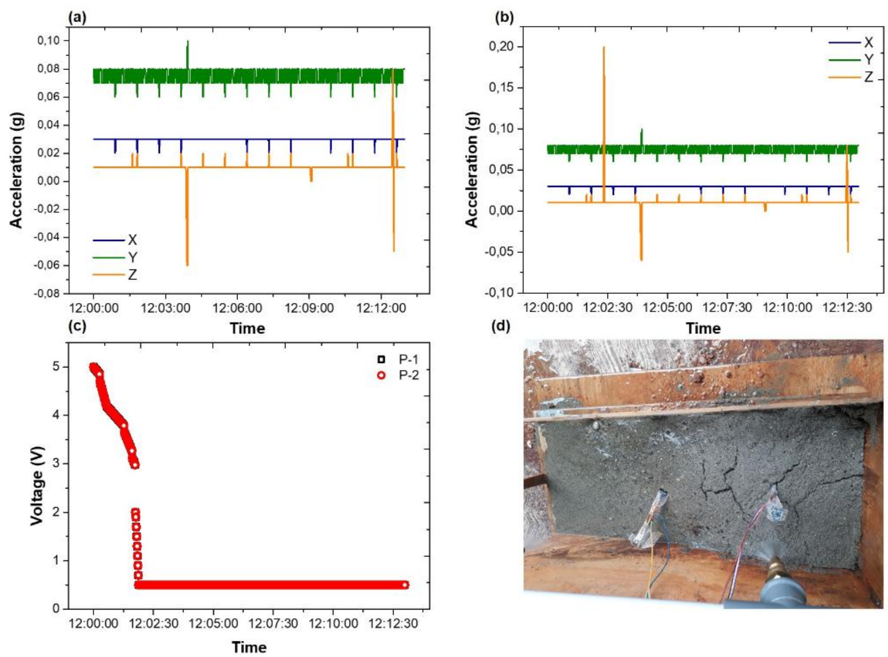

Fig. 9. Landslide model experiment artificial rainfall on sand sample (a) the response of accelerometer sensor at sensors (1), (b) the response of accelerometer sensors (2), (c) the response of soil moisture sensor, (d) final condition after rainfall

The triggering factors and material type strongly influenced the resulting movement patterns. Experiments conducted using two different materials and two different triggering factors produced distinctly different responses. Laterite soil, which is relatively hard when dry but softens and becomes plastic when wet, exhibited contrasting behavior under vibration and rainfall triggers (Figures 6(d) and 8(d)). In this experiment, the laterite soil had a slightly moist texture. During the experiments and observations, vibrations caused weakly bonded particles to detach and move in response to the applied dynamic force. Conversely, when exposed to rainfall, the added water softened the soil and increased its plasticity. Based on observations during the measurements, rainfall primarily affected the surface layer rather than penetrating deeply into the mass soil. Therefore, due to the characteristics of laterite soil, when it becomes extremely dry and hard, it is prone to cracking, and sudden vibrations or heavy rainfall may trigger the formation of large surface cracks. However, these characteristics were not observed in the developed landslide models. This limitation may be related to the model's scale and the vibration mechanism used in the experiments. Furthermore, this preliminary study has shown the performance of the model and sensor system used.

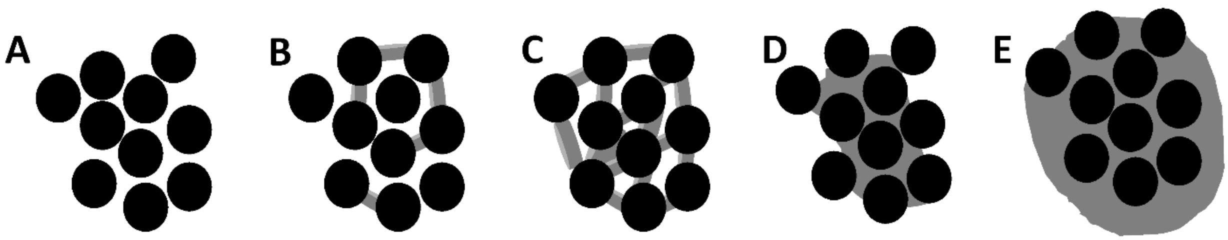

Fig. 10. Added water to the material [34]

In the sandy soil sample, the vibration and artificial rainfall treatments elicited distinct responses. Vibrations produced compaction of the slope within a certain frequency range. Meanwhile, rainfall formed capillary bridges between particles, increasing interparticle bonding strength up to a certain water content. The influence of water content can be further explained by the mechanism illustrated in Figure 10. Figure 10 illustrates the effect of water addition on sand, with condition A representing dry sand and condition E representing fully saturated sand. In general, dry sand lacks interparticle bridges, resulting in very weak interparticle bonding. When a small amount of liquid is introduced, the material enters the pendular stage, in which liquid bridges form at grain contacts and generate cohesive forces. As the liquid content increases, the material progresses to the funicular stage, characterized by the coexistence of liquid bridges and partially fluid-filled pores. Further addition of water leads to the capillary stage, in which most pores are filled with liquid, and capillary suction generated by the liquid menisci produces strong cohesive interactions between particles. Finally, in the slurry stage, the liquid content becomes sufficiently high so that the liquid pressure equals or exceeds the air pressure, causing the cohesive interactions between particles to disappear. Therefore, as water gradually increases, bonding strength increases due to the formation of capillary bridges between the sand grains. However, further water addition reduces stability when all the pores are filled, and saturation occurs [7], [35] . When the material becomes unstable, it tends to seek a new equilibrium through movement and deformation. In fully saturated sand, phenomena such as liquefaction and flow are more likely to occur [36]. According to our laboratory experiment on sand samples, prolonged rainfall can trigger sand movement in the form of sand flows. This type of behavior commonly occurs in natural-slope areas with high rainfall intensity and sandy materials, such as volcanic slopes.

In general, the results of this preliminary study demonstrated that the sensors responded effectively to the defined triggering factors. Observations also revealed distinct response mechanisms for each material used in the experiments. However, due to limitations related to the model scale and triggering mechanisms, the overall characteristics and behavior of the two soil samples could not be fully observed. Furthermore, understanding landslide characteristics requires considering multiple factors, including climate, geological conditions, material properties, and environmental conditions.

Conclusion

This preliminary study presents the development of a laboratory-scale landslide model as an experimental platform for investigating ground movement mechanisms under controlled conditions. This landslide model integrates two triggering factors, vibration and artificial rainfall. Two different materials are used to observe each sensor's movement characteristics and response. Simultaneously, physical changes in the landslide model are monitored using two types of sensors: accelerometers and soil moisture sensors. Generally, before being integrated into the landslide model, each component, including the trigger factors and sensor system, undergoes an initial testing process. The different movement characteristics were obtained by measuring a landslide model with different materials and triggering factors. For laterite samples, vibrations primarily trigger movement in weakly bonded sections, while water addition has minimal impact, primarily causing water runoff rather than material displacement. This behavior is attributed to the clay-rich consensus of laterite soils, which become soft and plastic when wet. In contrast, vibration and water addition initially increase bonding strength for sandy materials by filling existing pores. However, the material undergoes movement beyond a critical threshold, manifesting as cracks, collapse, and fluid flow. Moreover, the sensor system demonstrates good sensitivity to changes. These findings provide a scientific basis for understanding the influence of soil type and triggering factors on landslide initiation and establishing a foundation for future work.

Acknowledgment

The University of Bengkulu financially supported this work through the “Penelitian Fundamental UNIB” program in fiscal year 2021.

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