Experimental Study of Site-Specific Soil Water Content and Rainfall Inducing Shallow Landslides: Case of Gakenke District, Rwanda

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Shallow landslides are among the natural threats causing death and damage. They are mostly triggered by rainfall in mountainous areas where precipitation used to be abundant. The amount of rainfall inducing this natural threat differs from one site to another based on the geographical characteristics of that area. In addition to the rainfall depth, the determination of soil water content in a specific zone has a major contribution to the landslide prediction and early warning systems. Rwanda being a country with hilly terrains, some areas are susceptible to both rainfall and soil water content inducing landslides. But an analytical study of the physical threshold determination of both rainfall and soil water content inducing landslides is lacking. Therefore, this experimental study is conducted to determine the rainfall and soil water content threshold that can be fed in to the landslide early warning system (LEWS) for alert messages using the Internet of Things (IoT) technology. Various experiments have been conducted for the real-time monitoring of slope failure using the toolset composed of a rain gauge, soil moisture sensors, and a rainfall simulating tool. The results obtained show that the threshold for landslide occurrence does not solely correlate with the total rainfall amount (or intensity) or soil moisture, but also influenced by internal (geological, morphological) and environmental factors. Among the sampled sites, the sites covered by forest indicated no sign of slope failure, whereas sites with crops could slip. The experiments revealed that for a specific site, the minimum duration to induce slope failure was 8 hours, 41 minutes with the rainfall intensity of 8 mm/hour, and the soil moisture was above 90% for deeper sensors. These values are used as thresholds for LEWS for that specific site to improve predictions.

1. Introduction

Rainfall-induced shallow landslides are among the most natural disasters that causes deaths and substantial economic losses damaging infrastructure or plants in different mountainous regions around the world [1–3]. In Rwanda, about 1,000 landslide cases have been identified during the past decade [4], affecting a significant number of citizens, agriculture land, livelihoods, and infrastructure that are valued in billions of dollars. For instance, almost 200 people died by landslide incidences during 2016-2018 [5, 6]. The most susceptible areas in Rwanda are the northern and western provinces, which are characterized by mountains and steep slopes [7, 8].

Rainfall-induced landslides are mainly caused by intrinsic factors like geological and geomorphological parameters and extrinsic factors such as hydrological conditions, climatic conditions, earthquakes, and volcanic eruptions [9–11]. Hydrological factors such as rainfall and ground water table location influence the slope stability. The process of
this type of natural disaster is intricate. The water content in the shallow soil is almost absent during the dry season. When it rains, the rainwater starts penetrating into the earth characterized by different permeability properties, and then, the ground becomes moist. It keeps on penetrating until it reaches the layer of low hydraulic conductivity where it accumulates up to the complete saturation level [12] and forces the grains of the soil to separate. The matric suction on the topsoil decreases, and once the ground is fully water-logged, the soil matric suction finally vanishes completely [13], making the ground unstable, and that is a critical condition for landslide risk [14]. Thus, depending on the other geophysical characteristics of the area, a landslide incidence may follow [14]. Chiorean in [15] describes the process of a rainfall-induced landslide as follows: (i) rainfall permeation results in a reduction of the matric suction of the slope soil, (ii) the diminution in soil matric suction decreases the soil shear strength, and (iii) the decrease in soil shear strength afterwards causes the slope to become unbalanced and finally fail. The matric suction \( \psi_m \) plays a crucial role in landslide occurrence and is defined as the difference between pore air pressure \( u_a \) and pore water pressure \( u_w \) [15–18].

\[
\psi_m = u_a - u_w, \tag{1}
\]

\( \psi_m \) is influenced by the movement of water (most of the time rainwater) within soil pores [19]. At the initial state, when the soil is free from water (dry), the soil has the peak value of matric suction, and this attains its lowest value (zero) when the soil is fully saturated [20].

Various mitigation methods have been utilized extensively to reduce the risk of landslide incidence. They include structured measures and nonstructured warning systems. Structural methods require high construction costs and may take many years [21]. Therefore, high precision LEWS is more efficient and should be emphasized.

Numerous studies have been undertaken broadly to reduce the impact of landslides on human lives and economic loss. They include various prediction models, susceptibility models, and landslide early warning systems (LEWS) [3, 10]. Some of the models establish the relationship between landslide occurrence and rainfall intensity through the laboratory field test as well as numerical analysis [22, 23]; others estimated the rainfall intensity and duration that could cause landslide incidences [10, 24–28]. Parameters used in each study are different and depend on the author selection and the availability of data. The most common parameters used in different studies are rainfall (external triggering factor) and internal factors such as slope (inclination, aspect), soil type, lithology, and land cover [29–35].

Past studies have used the laboratory flume test to identify the correlation between soil water content and landslide occurrence where rainfall, soil type (particle size), and slope inclination have been taken into consideration [16, 20, 36–39]. Others used empirical field tests [39, 40] or numerical modelling [3, 41], and various studies conducted on LEWS have generally used historical rainfall data together with landslide occurrence records to determine the rainfall threshold inducing landslides [34, 42–48]. The studies conducted in [22, 49–56] have shown that they have used antecedent rainfall as a key parameter that has a great impact on landslides’ occurrence. In this research paper, the parameters considered are rainfall intensity together with soil moisture content (SMC) that can help to achieve a better landslide prediction modelling tool that might be used for LEWS. Though the preceding studies demonstrated the role that rainfall plays in triggering slope failure and came up with good results, the optimization is needed because of the complexity of conditions causing landslide incidence. Therefore, there is a need to derive the correlation between the present rainfall, antecedent rainfall, and the content of water in the soil at the time of slope failure to determine the site-specific threshold values of these parameters.

In relation to the above, the gaps found in the past studies is the exploration of how rainfall has different effects on slope stability according to the geophysical and environmental characteristics. For example, some experiments used the embankment soil in the slope flume [23, 57, 58] that has no original strength (cohesion) and could not provide a reliable threshold as the one conducted on the terrain. Therefore, the field experiment to determine the SMC and rainfall depth is of great importance for the LEWS. The present study was carried out on site and aimed at (1) analyzing how gradually the rainwater penetrates into the soil during or after rainfall events until the landslide occurrence and (2) identifying the rainfall amount and threshold values for the SMC as a step prior to feed in to the LEWS using IoT technologies. Both quantitative statistical analysis and qualitative techniques were used through environmental covariates, namely, slope, soil type, vegetation (or land coverage), and rainfall intensity as an external parameter. The soil water content inducing landslides will be determined for each selected site. The geographical scope of the study is Gakenke district while the period of study is October 2019–June 2021 (21 months).

2. Materials and Methods

2.1. Study Area. This study was conducted in five sectors (Figure 1(c)) of Gakenke district (Figure 1(b)) located in the northern province of Rwanda (Figure 1(a)). The district shares borders with Rulindo, Burera, Musanze, Nyabihu, Kamonyi, and Muhanga Districts. The district comprises 19 administrative sectors divided into 97 cells, 617 villages. The district has an area of 704.06 km\(^2\) [59]. The population density is 473 residents/km\(^2\). The climate in this district is commonly the type of humid climate with the average annual temperature ranging between 16°C and 29°C. The rainfall is quite plentiful with a scale between 1,100 and 1,500 mm/yr. This district has four main seasons: the small dry season from January to February, a high rain season spans from March to May, marked by plentiful rainfall and landslide incidences, the long dry season extending from June to August, and finally, the short rain season from September to December. The high hills separated by rivers and swamplands characterize this district. The highest altitude
attains 2,647 meters (Mount Kabuye), whereas the lower altitude is 1,362 meters [59].

Due to its climatology and geographical characteristics such as topography and geology, the district is characterized by numerous landslides that cause few to many deaths and property damage in different heavy rainfall events [60–62]. In addition to the frequent and abundant rainfall, high slopes, land cover, and soil texture contribute to the slope failure in this region [63, 64]. The landslides in this region can be classified into two categories: (i) landslides related to natural slopes that initiate from anywhere on a hill slope (Figure 2(a)) and (ii) human-made slopes which are cut slopes related to house plots (Figure 2(b)), roads, or excavation activities.

2.2. Methods. The early warning system is one of the methods that can be used to reduce the risks related to landslides by providing incident information to the citizens prior to the occurrence. Two main methodological approaches can be used for landslide mitigation techniques. The first method uses physically based models considering the infinite soil mechanism; the second counts on experimental studies to determine the rainfall intensity and duration threshold [10, 12]. The challenge associated with the first approach is that the landslide can be detected but not predicted. The second approach can be appropriate, but the threshold for each influencing factor (such as hydrological, land use, lithological, and soil characteristics) should be determined [65]. In the current study, the rainfall intensity inducing shallow landslides is estimated considering the soil-forming factors and environmental covariates. Various experiments and numerical analysis were carried out for estimating the rainfall amount and the soil water content level that may lead to the slope failure.

2.2.1. Daily Rainfall Data. The slope failure in the study area and in the entire country is solely dependent on rainwater. Therefore, the rainfall data were necessary for this study.
Primary and secondary data have been used for both quantitative studies and qualitative assessment. Firstly, historical rainfall and soil moisture data were collected from the Rwanda Meteorology Agency for analysis of their correlation. Data from three rain gauge stations (Figure 3(d)) were used for primary analysis (Figure 4). This analysis was envisaged to identify rainfall amount-induced slope failures and landslide locations in the neighborhood of rain gauge stations.

Secondary, field work was conducted in the surrounding areas that have been characterized by at least two landslide incidences in the past 5 years. In this study, rain gauge and soil moisture sensors were used for real-time data collection.

2.2.2. **Soil Moisture.** In addition to the rainfall data, historical soil water content data were collected from the office in charge of meteorology and were analyzed (Figure 4(d)) on the basis that the SMC has a correlation with precipitation [66–69]. Moreover, studies revealed that the actual soil wetness can be achieved through in situ measurement [9, 70]. The soil moisture sensors were used to collect the soil water content on different sites (Figure 3(d)).

2.2.3. **Slope.** Various studies showed that the slope has a high impact on landslide occurrence. Steep slopes in several regions characterize Gakenke district where the slope angle can be more than 45 degrees. Other studies such as [51, 63] used 5 slope classes, whereas in this study, we grouped the first two classes because landslide cases are very few in areas with slopes less than 15%. According to the data source [71, 72], the slopes are categorized in four classes as indicated by Figure 3(c).

2.2.4. **Soil Types.** Geotechnical properties have an important impact on the slope stability [73]. In each test site, soil samples were collected and taken to the soil mechanics lab at the University of Rwanda to be tested for soil classification and other analysis. The soil classes found on the sampled sites are silty sand, sandy silt, sandy lean clay with gravel, lean clay, and elastic silt.

2.2.5. **Land Cover.** Land use is another factor contributing to the landslide occurrence. There are five different types of land cover in the study area: forest, cropland, grassland, built area, and water, but only the first three could be used in this study.

2.2.6. **Experimenting Tools and Setup.** To identify the rainfall influence on slope instability and its correlation with soil moisture, we used the rainfall simulator (Figure 5) for the direct in situ measurement of the soil humidity in various time durations until the slope starts indicating the sign of sliding such as a horizontal crack on the ground above the slope or sliding of cut slopes. The rainfall amount was recorded along with soil moisture at the interval of 49 seconds. The sensor-based monitoring tool was made of (i) the sensor node comprising three analog capacitive soil moisture sensors manufactured by Paialu, the operating voltage is 3.3~3.5 V to capture soil water content in various ground depths, and Arduino Uno Microcontroller ATmega328P; (ii) weather station consisting the transmitter (MISOL Model: WH40) and the receiver (model: WN5360); the communication between the transmitter and receiver was via wireless with a transmission frequency of 433 mhz and a maximum distance of 100 meters; (iii) a laptop with the Python code data logger to record readings from 3 sensors and convert into CSV file (Figure 6).

Figure 2: Pictures of landslides in the study area during 2016 (a) and 2020 (b) events.
were placed in different ground depths as indicated in Table 1.

2.2.7. Experimental Sites. All field experiments were conducted in the surrounding zones that have the historical background of landslides (Figure 3(d)). Different representative sites were chosen according to the geotopographical and environmental features including slope, soil types, and land use as indicated in Table 2.

At least two experimental tests were done at each site plot to test the reoccurrence of the slope failure. After the first two tests, one more test was conducted for that indicated at least one landslide to prove the reliability of the results.

3. Results and Discussion

3.1. Soil Classification Test Results. Five main sites were chosen as sample sites (SA, SB, SC, SD, and SE). Samples of soil were taken for the laboratory test of soil particle size distribution analysis because this plays an important role on different hydrologic features such as water retention characteristics and slope failure as well. The table below (Table 3) summarizes the relative composition of the soil in the sampled sites.

As shown in Table 2, from each site, two or three plots were sampled (except site SB) to identify the soil-related effects on the infiltration process. Some of the plot samples were found to have different soil textures. For
instance, the soil types on site SA were silty sand and sandy silt for SA1 and SA2, respectively. Likewise, site SE plots had elastic silt and lean clay for SE1 and SE2, respectively.

3.2. Simulation Results. The rainfall simulation was applied to the selected sites while recording the rainfall amount and soil moisture content (using a wireless rain gauge and three sensors, respectively) until the slope sliding (or crack) is observed or not. The activity took different durations depending on the site. The limit of rainfall simulation and duration was based on the rainfall events that induced landslides recently (Figure 4) or in the past [51]. Out of twenty-nine (29) experimental tests carried out on 11 plots, sixteen of them (55.5%) resulted in slope failure (or crack) as shown in Table 4.

As shown in Table 2, most sites are characterized by steep and very steep slopes, while the laboratory results indicate that lean clay and elastic silt are the most dominant soil classes in the sampled sites. The results in Table 4 show that landslides are possible in all categories of soil except in sandy lean clay with gravel, which is less represented among the

![Figure 4: Past daily rainfall in the district of Gakenke from three rain gauge stations and one soil moisture station: (a) Janja, (b) Minazi, (c) Nemba, and (d) Rushashi soil moisture station.](image)

![Figure 5: Rainfall simulator.](image)
Figure 6: The block diagram and tool set of monitoring equipment: (a) block diagram, (b) sensor node box, (c) inside box, and (d) rain gauge with a digital display.

Table 1: In-ground depth placement of sensors.

| Sensor | SA1 | SA2 | SB | SC1 | SC2 | SC3 | SD1 | SD2 | SD3 | SE1 | SE2 |
|--------|-----|-----|----|-----|-----|-----|-----|-----|-----|-----|-----|
| Sensor1| 0.2 | 0.2 | 0.2| 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 |
| Sensor2| 0.6 | 0.6 | 0.5| 0.6 | 0.7 | 0.6 | 0.6 | 0.6 | 0.6 | 0.5 | 0.6 |
| Sensor3| 1.2 | 1.1 | 0.9| 1.2 | 1.3 | 1.2 | 1.1 | 1.2 | 1.2 | 1.2 | 1.2 |

Table 2: Geotopographical characteristics of representative sites in the study area.

| #  | Site | Location (sector, cell, village) | Plot | Slope (°) | Land cover | Number of experiments |
|----|------|----------------------------------|------|-----------|------------|----------------------|
| 1  | SA   | Minazi, Raba, Ndegamire          | SA1  | 26.4      | Crops      | 3                    |
| 2  | SA   |                                   | SA2  | 35.3      | Grass      | 2                    |
| 3  | SB   | Mataba, Buyange, Gabiro          | SB   | 41.8      | Forest     | 2                    |
| 4  | SC   |                                   | SC1  | 47.2      | Crops      | 3                    |
| 5  | SC   | Rushashi, Mbogo, Gisanze         | SC2  | 28.9      | Crops      | 3                    |
| 6  | SC   |                                   | SC3  | 39.7      | Grass      | 3                    |
| 7  | SD   | Gekenke, Rusagara, Museke        | SD1  | 49.5      | Forest     | 3                    |
| 8  | SD   |                                   | SD2  | 31.3      | Crops      | 3                    |
| 9  | SD   |                                   | SD3  | 29.8      | Grass      | 3                    |
| 10 | SE   | Nemba, Gisozi, Karukara          | SE1  | 28.6      | Forest     | 2                    |
| 11 | SE   |                                   | SE2  | 24.4      | Crops      | 3                    |
selected sites because the sampled sites are those that had landslides in the past.

3.3. Correlation between Rainfall and Soil Moisture Content.

The shortest time used to simulate rainfall and provoke slope failure was 8 h41 at a rainfall rate (intensity) of 8 mm/h. This occurred on site SD2 where the land is covered by crops at the slope of 31.3°. The soil moisture at the point of failure was 82%, 92%, and 95% Figure 7(a). In addition to other factors, the short duration to simulate slope failure is linked to the antecedent rainfall indicated by high initial soil moisture.

The nearby site SD3 was selected with a different land cover (grass) and the slope inclination of 29.8°. The slope failure was observed for all three tests on this site after 9 h36, 11 h58, and 9 h37 with the rainfall intensity of 7.2 mm/h. This took different duration of rainfall simulation to induce landslide, but the soil moisture content recorded by the three sensors was above 80% for the top sensor, while the deeper sensors recorded more than 90% as shown in Figures 8(a)–8(c). Furthermore, three tests conducted on site SC3 resulted in slope failure. This site has a slope inclination of 28.9° and the land used for agriculture (covered by crops). The maximum soil moisture content attained by the three sensors was 98%, while the least value was 86% recorded by the top sensor (sensor1) during the first test (Figure 8). As shown in Table 4, the duration for each test was different due to factors like the initial soil moisture content (prior to the experiment) or other internal geological factors.

It was also observed that the two sites were characterized by lean clay. It indicates that this soil type is more susceptible to landslides because even on sites SC1 and SC3, two tests out of three resulted in slope failure. On site SC1, the rainfall simulation of 10 h59 and intensity of 9.4 mm/h did not result in slope failure, while the last two tests at the intensity of 7.8 mm/h resulted in slope failure after 10 h27 and 10 h23, respectively. On the other hand, the first two tests on site SC3 resulted in slope failure; however, the last did not even show up any sign of sliding. Figure 9 shows the correlation between rainfall and soil moisture content for the two sites.

The land covered by Eragrostis spectabilis type of grass has shown to be resistive to rainwater infiltration in the soil. This is the only one site among the grass-covered plots (Figures 10(a) and 10(b)) that did not show up any sign of slope failure for the first two tests. However, out of the three tests carried out on site SA1, only one slope failure was observed as shown in Table 4. Generally, the simulation took a long duration on sites that did not show up any sign of failure compared to those manifested landslides. The reason was to test the effect of daily total cumulative rainfall and duration on landslide occurrence. Figures 10(a)–10(f) show that the simulated cumulative rainfall was about 100 mm while the duration was more than 11 hours (Table 4).

The common feature for the sites that did not show up any sign of slope failure is the land cover, as they are covered by forest (Figures 10(c)–10(f)), whereas the other one is covered by grass (Figures 10(a) and 10(b)). Figures 10(a)–10(f) also indicate that, even though it required a long duration of

| Sample | Gravel (%) | Sand (%) | Fines (%) | LL (%) | PL (%) | PI (%) | Group symbol | Group name                |
|--------|------------|----------|-----------|--------|--------|--------|---------------|---------------------------|
| SA     | 1          | 52       | 48        | 37     | 25     | 12     | SM            | Silty sand and sandy silt |
| SB     | 24         | 24       | 53        | 41     | 23     | 18     | CL            | Sandy lean clay with silt |
| SC     | 0          | 10       | 90        | 42     | 25     | 17     | CL            | Lean clay                 |
| SD     | 0          | 3        | 97        | 66     | 37     | 29     | MH            | Elastic silt              |
| SE     | 0          | 10       | 90        | 42     | 23     | 16     | CL            | Elastic silt and lean clay|

Table 3: Soil particle size and classification.
simulation and the high amount of total rainfall, in some cases, the saturation level was less than 90% for the three sensors (Figures 10(a) and 10(c)–10(f)). This means that it requires a long time to make the soil fully saturated with the slopes covered by forest or protected by *Eragrostis spectabilis*.

From the figures above, the linear regression of both rainfall and soil moisture (Figure 11) is observed due to the continuous simulation of rainfall. In practice, this is not the case because rainfall is characterized by discontinuous events (with interevent periods) of different durations. Even though one-day rainfall can reach the values simulated in this study, the duration expands to many hours or else can be related to the previous rainfall events (antecedents). Hence, the use of soil moisture sensors for LEWS has a crucial importance because their data are informative to the antecedent rainfall.

The first two figures (Figures 11(a) and 11(b)) compare cropland and forestland, respectively. As shown by the slope lines of the best fit, the slope of 0.4 indicates that the infiltration rate was faster for crop land than that of forest land and got saturated before forest land (slope = 0.2). Likewise, in Figures 11(c) and 11(d), slope = 0.7 for cropland and 0.4 for forestland.

3.4. Slope Failure, Total Rainfall, and Intensity. The numerical analysis of rainfall intensity and duration (Table 4) shows that each site required different duration and rainfall intensity to initiate the slope failure. This shows that the thresholds for the two parameters are not identical and in case to be identical, all other factors should be identical which is almost impossible for different sites. As shown in Figure 12, there are many landslide cases that occurred when the rainfall intensity was lower than that of the highest intensity.

3.5. Slope Failure and Geoenvironmental Factors. It is not forthright to explain the correlation between hydrological and mechanical processes occurred before and during the slope failure. Although the triggering factors may be clearly known, the process itself is complex. Rainfall has been
Figure 8: Variation of soil moisture content versus rainfall for three tests on site SC2 (a–c) and site SD3 (d–f).
Figure 9: Variation of soil moisture content versus rainfall for three tests on site SC1 (a–c) and site SC3 (d–f).
Figure 10: Variation of soil moisture content versus rainfall for sites SA2 (a, b), SB (c, d), and SE1 (e, f).
Figure 11: Rainfall vs. soil moisture: (a) SD2, (b) SD1, (c) SE2, and (d) SE1.

Figure 12: Slope failure vs. total rainfall and intensity.
discussed in the literature as external landslides’ causing factor, but cannot be considered alone without the physical characteristic changes of the soil at the near stage of sliding. The rainfall intensity and duration that are the basis of the hazard prediction cannot be determined because their values cannot be the same in all susceptible areas characterized by different environment factors. Therefore, the field experimental analysis was crucial in this study to identify the threshold of both rainfall and soil water content leading to water-induced shallow landslides in different susceptible locations.

3.5.1. Landslides, Slope, and Land Cover. Although steep slopes are associated with landslide occurrence, in this study, it has been realized that very steep slopes (45° and higher) are not more prone to soil failure compared to the slopes < 45° and >25° (Figure 13). Two reasons that may justify this statement are as follows: (i) the most very steep slopes are characterized by sturdy rocks that make the slopes to be more stable; (ii) due to the high inclination, much rainfall water runs off instead of seeping into the soil compared to the moderate slopes. Apart from the slope inclination, the rainwater runoff also depends on the land cover and soil texture.

There was no landslide indication observed on all sites covered by forest, although long duration has been used for simulating rainfall (more than 11 hours). This is an indication of the role of forest cover to slope stability. In the study area, most of the forest areas are at the same time covered by Eragrostis spectabilis, which is a natural grass type found in the high mountains in the study area. Site SA2 was covered by this type of grass and did not show up any sign of slope failure.

3.5.2. Landslides, Slope, and Soil Types. Table 4 shows that the soil types in most of the sampled sites are lean clay and elastic silt. The results do not really indicate which soil type is more susceptible to landslides. But the sites were selected based on the historical background of landslide events, and the laboratory tests reveal the two types of soil that are most dominant among the sampled sites. It was noted that the sites (lean clay or elastic silt) that did not indicate any sign of slope failure are those that were protected by forest or have the high slope angle. Therefore, lean clay and elastic silt are the most affected by landslides compared to the other types of soil in the sampled sites (Figure 14).

3.6. Rainfall and Soil Moisture Thresholds. The maximum records of rainfall and soil moisture content from the experiments conducted in this study help us establish thresholds for both parameters in the specific sites (area of study). As stated earlier, three sensors were placed in various depths underground for knowing which one can better predict landslide incidence. Red dots in Figure 15 are more clustered in the right lower corner of the figures, indicating that the slope failure was observed when sensor 1 recorded greater than 80% and 90% for sensors placed deeper (sensor 2 and sensor 3). The minimum rainfall inducing slope failure as indicated by the same figure is around 70 mm. Therefore, we can conclude that these values can be used for local LEWS. On the other hand, rainfall can be used for regional LEWS as it is not possible identifying the soil moisture content at each and every site. Even though a rainfall of more than 100 mm did not cause slope failure according to this study, such daily rainfall depth is also dangerous as the increased rainwater runoff may cause floods, which can also depend on different factors (which is out of the scope of this study). It was also noted that the sites that did not experience any slope failure are those lands covered by forest or types of grass that reinforce the shear strength of the topsoil. But under normal circumstances, a one-day rainfall of more than 70 mm should be taken into consideration for early warning systems by considering the antecedent rainfall and other geofactors.
As mentioned before, most of the nonlandslide cases in this study are related to the forestland cover that persists to rainwater penetration and requires more rainfall duration. This explains the reason of having less incidences with high total rainfall as shown in Figure 15. It was also explained that rainwater runoff was much more in very steep slopes than steep or medium slopes. Hence, the probability of slope failure increases with soil permeability which is dependent on the soil texture, rainfall intensity, and duration.

4. Conclusions

In this study, field experiments were conducted at various sites selected surrounding the areas that had landslide events in the past. The study consisted of the measurement of rainfall and soil water content using a rain gauge and soil moisture sensors. The site sample profile considered different parameters such as slopes, angles, soil texture, soil depths, and land coverage.

The experimental results show that rainfall triggers slope failure, and the total rainfall amount inducing this hazard depends on various other parameters. Rainfall alone cannot be considered as a parameter to predict slope failure, and it has an implication on the hydrological properties of the soil. In addition, the level of soil water content at the near stage of slope failure differs from one site to another depending on the internal and external features. In general, steep slopes are more susceptible to shallow landslide incidence compared to the very steep slopes. Furthermore, we noticed that land coverage plays an important role in the slope stability due to more time required for saturation of land covered by natural grass or forest than that covered by plants. This is because the vegetation adjusts the hydrological equilibrium of the involved location through the evapotranspiration process, whereas roots add some reinforcement by increasing soil shear strength [81–82] and the degree of slope stabilization varies according to the vegetation [83–86].

According to the experimental results in this study, the following major insights are taken: (i) a common threshold for rainfall intensity or soil water content could not be derived for LEWS. Instead, location-specific thresholds have to be determined using empirical models. Then, the identified threshold can specifically be used to predict the slope failure in areas with identical (or almost) geomorphological features. (ii) The daily rainfall of more than 70 mm and soil water content of more than 90% may lead to the landslide hazard depending on other geofactors in specific sites. (iii) The thresholds found in this study can be used in designing local LEWS for areas having almost similar environmental covariates or soil forming factors, especially for cut slopes (manmade slopes) such as in-house plots or roads. (iv) This study proposes similar experiments to be conducted at various sites to derive site-specific thresholds to feed into local IoT-based LEWS as the parameters differ from one zone to another.

4.1. Future Work. In the next stage of our research, we expect to perform the environmental and soil analysis during the development of the prototype for LEWS.

Data Availability

All data used to achieve the objectives of this study are available online (ACEIoT portal at University of Rwanda). The uniform resource locator (URL) is found under reference [74].

Conflicts of Interest

The authors declare no conflict of interest.

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