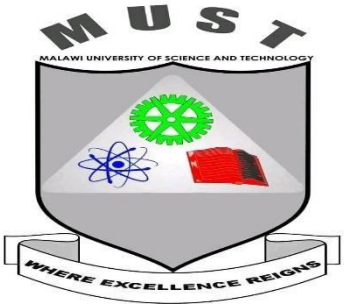


ARDUIONO BASED IoT RAINFALL INDUCED LANDSLIDE MONITORING AND DETECTION SYTEM: A DISASTER RISK MANAGEMENT PROSPECTIVE

SUBMITTED BY

DUMISANI CHAVULA

DRM/006/20

THYOLO, MALAWI

DISSERTATION SUBMITTED TO NDATA SCHOOL OF CLIMATE AND EARTH SCIENCES OF THE MALAWI UNIVERSITY OF SCIENCE AND TECHNOLOGY IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR OBTAINING A BACHELOR OF SCIENCE DEGREE IN DISASTER AND RISK MANAGEMENT

SUBMISSION DATE

21ST MAY 2025.

PROPOSAL APPROVED BY:

SUPERVISOR:

Title, Initials, Name: Signature: _____

ASSESSOR:

Title, Initials, Name: Signature: _____

DECLARATION

I Dumisani Chavula declare that this research project represents my work and that it has never been submitted to this institution or any other institution for any academic purpose. All sources of information have been appropriately acknowledged.

Signature: 

Date: 21th May, 2025.

DISCLAIMER

This document describes work undertaken as part of a programme of study at Ndata School of Climate and Earth Sciences of the Malawi University of Science and Technology. All views and opinions expressed therein remain the sole responsibility of the author(s), and do not necessarily represent those of the school.

Abstract

Rainfall-induced landslides pose a threat to life, infrastructure, and economy in Malawi, particularly in regions such as Mulanje, Zomba, Dedza and the northern highlands just mention a few. Traditional monitoring methods such as field surveys, GIS, and remote sensing meet obstacles for large-scale, real-time detection due to terrain complexity and lack of timely data. This study addresses this gap by designing and implementing a low-cost, Arduino-based Internet of Things (IoT) early warning system to monitor key environmental factors including soil moisture, slope stability, ground movement, humidity, and temperature. The system integrates with the Blynk IoT platform for real-time data transmission and monitoring. Through a quantitative, experimental approach, the prototype was field-tested in Thyolo District, with sensor data analyzed via Excel and Python to establish thresholds and evaluate performance. Results demonstrated high system accuracy, with strong correlations between slope, soil moisture, and deformation, and a low false alarm rate. This research confirms the feasibility and effectiveness of deploying a scalable, IoT-enabled early warning systems for disaster risk reduction in resource-limited settings like Malawi, offering a proactive solution for climate-resilient community safety.

COPYRIGHT STATEMENT

This copy of the proposal has been supplied on condition that anyone who consults it is understood to recognize that its copyright rests with its author and that no quotation from the dissertation and no information derived from it may be published without acknowledgement.

Acknowledgement

I would like to express my profound gratitude to God Almighty for His spiritual guidance, strength, and grace throughout the journey of this research. I am sincerely thankful to my parents for their unwavering support, encouragement, and sacrifices which have been instrumental in my academic journey. I am especially indebted to my project supervisor, Mr. Vincent Katonda for his insightful guidance which has significantly contributed to the successful completion of this study. My appreciation also goes to the Malawi University of Science and Technology for providing a conducive learning environment and the academic resources necessary to undertake this research.

Table of Contents

Abstract v

Acknowledgement vii

CHAPTER ONE: INTRODUCTION 1

1.1 Background 1

1.2 Problem Statement 4

1.3 Study Objectives 5

1.3.1 Main Objectives 5

1.3.2 Specific Objectives 5

1.4 Research Questions 6

1.5 Scientific Significance 6

1.6 Chapter Summary 7

CHAPTER TWO: LITERATURE REVIEW 9

2.2 Chapter Summary 12

CHAPTER THREE: METHODOLOGY 14

3.1 Study Area 14

3.2 Study Approach 14

3.3 Research Design 15

3.4 Materials 15

3.4.1 Hardware Set-up 15

3.4.2 Mobile Application Integration 16

3.4.3 Procedure for setting up the system 16

3.4.4 Blynk Dashboard Development 17

3.4.5 Virtual Pin Mapping 17

3.4.6 Blynk Dashboard Design 18

3.4.7 ESP32 Firmware Development (Arduino IDE) 20

3.4.7 Data Collection 20

3.4.8 Threshold Algorithm Implementation 22

3.5 Data Analysis 23

3.5.1 Excel for Data Organization and Preliminary Analysis 24

3.5.2 Python for Advanced Analysis 24

3.6 System Performance Evaluation 24

3.7 Ethical Consideration.....25
3.8 Chapter Summary.....25
CHAPTER FOUR: RESULTS AND DISCUSIONS.....26
4.1 Results.....26
.....26
4.2 Chapter Summary.....33
CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS.....34
5.1 Conclusion.....34
5.2 Study Limitations.....34
5.3 Recommendations.....35
References.....36
APPENDICES.....40

LIST OF TABLES

Table 1..esp32 pin configuration..... 16
Table 2…. Virtual Pin Mapping..... 17
Table 3…Environmental parameters data collected by sensors.....22
Table 4….Experts Based Thresholds.....23

LIST OF FIGURES

Figure 1…map of study area 14
Figure 2…Blynk dashboard designing 18
Figure 3…a Blynk Mobile dashboard app 19
Figure 4…Blynk web app 21
Figure 5…Landslide IoT System field deployment 26
Figure 6…Sensor data Correlation Matrix 27
Figure 7…Histograms of environmental variables against alert occurrences 28
Figure 8…Soil Moisture vs Slope trend over time 29
Figure 9…Slope against Deformation 30
Figure 10…P-Value for environmental variables 31
Figure 11…Confusion Matrix 32

ABBREVIATIONS & ACRONYMS

IoT	Internet of Things
GIS	Geographical Information System
WSN	Wireless Sensor Network
LoRaWAN	Long Range Wide Area Network
PGA	Peak Ground Acceleration
EWS	Early Warning System
IDE	Integrated Development Environment
GPIO	General Purpose Input/Output
ADXL345	Accelerometer Sensor Model (3-axis digital accelerometer)
DHT11	Digital Humidity and Temperature Sensor
IRJET	International Research Journal of Engineering and Technology
R&D	Research and Development (in referenced papers)
GPRS	General Packet Radio Service
RFID	Radio-Frequency Identification

CHAPTER ONE: INTRODUCTION

1.1 Background

Malawi has areas of moderate to high landslides risk running from the northern part to the southern part of the country (World Bank, 2019). Among notable high landslide risk areas are Mulanje Massif in southeast, Zomba north at Malosa Complex, Dedza east, the edge of Lake Malawi and northern border highlands. There are various factors that contribute to landslide hazard in Malawi. Some of them include high annual rainfall from tropical cyclones and depressions, complex hydrological networks, the presence of the tectonically active East African Rift System, soils susceptible to mass movement and weathering, and deforestation. Research suggests that 93% of the landslides globally between 1972 and 2007 are caused by heavy rainfall (Menon, V. O., & Kolathayar, S., 2022). In the scoring model equation when looking at parameters such as rainfall factor, soil factor, geological factor, land use factor and slope factors for the cumulative score to determine the vulnerability level of the landslide hazard, rainfall weight is higher than any other parameter because rainfall is a dominant factor causing landslide hazard. In Malawi over 4709 rainfall-induced landslides have been mapped between 2003 and 2022 according to Springer Link Journal (Niyokwiringirwa, P. et al..,, 2024). During the rainy season, the rain water percolates and develops the hydraulic pressure which exceeds the elastic limit of the soil and rocks. This influence of water will create changes to the shear strength of the soil. The pore pressure rise in the already saturated soil will decrease its shear strength and evidence from unconfined compression tests shows that there is 84% decrease in shear strength with 30% increase in moisture content. The major parameter that influences the landslides during torrential rain is the decrease in shear strength with the increase in pore pressure when the loose soil layer contracts (Menon, V. O., & Kolathayar, S., 2022). Slopes with inclination more than 20° have potential to move or slide, but slopes with inclination or sloping land have always been prone depending on the geological conditions of the slopes (Artha, Y., & Julian, E. S., 2018). In Malawi, on average, each year 100 people are at risk of being affected by landslides with 10 fatalities per year nationally. The annual average damage stock to buildings is $150,000 and affecting GDP of $300,000. The

analysis also suggests that the road and railway transport networks sustain losses of $60,000 per year on average. Rainfall induced landslides hazard risk could increase by 2050 due to socio-economic changes and climate change. Malawi uses different systems to monitor rainfall induced landslides such as Geographical Information Systems, Remote sensing and Field surveys (Thiery, Y.,et al.., 2024). In early days landslides monitoring and detection relied on field surveys using close observations and measurement equipment such clinometers, displacement meters, stress meters and water level gauges. Field surveys provide very detailed data of landslides study, including the characteristics, range, shape and movement of the landslides. However, the approach is insufficient for handling landslides at large area. It also requires considerable amount of time, materials and labor and impossible to identify all the parts of the landslides (e.g. scrap boundary and deposits) accurately where the topography is hummocky and vegetation is tall and dense (Zhong, C..et al..,). The lack of distinguishable spectral, spital, or temporal characteristics poses a challenge to GIS and remote sensing methods. Firstly, landslides do not have distinguishable spectral, spatial, or temporal characteristics due to coverage by other land covers. Secondly, the surface features of landslides can be different affected by different geological factors, geomorphological factors, hydrological factors and weather conditions. Thirdly, the difference in the surface features of the elements is often remarkable and nonnegligible becoming difficult to identify a landslide with a few criteria. Theoretically, the major characteristic of a landslide is the local terrain change after the downslope movement. From this point of view, the landslide does not have a distinguishable spectral or spatial characteristic. Landslides are usually covered by other landcovers. For example, a new landslide may be covered by the bare soil and the old one being covered by the vegetation. In this case, it is impossible to identify landslides from satellite images accurately as the spectral characteristics are similar to those of other landcovers. With regard to spatial characteristics the main scarp of a landslide is similar to terraces, steep slopes, embarkments and the landslide body may be mistaken for a gentle slope, a soil deposit and a riverbed. Landslide or land movements do not occur spontaneously, there are indications such as land movement. The above sign can be converted into an early warning system that is expected in assisting the monitoring and detection of landslide. Various landslide

monitoring and detection systems have been developed using Arduino and sensors (Purnomo, F. A.,et al..,, 2019). An Arduino is an open-source electronics platform based on easy-to-use hardware and software. It is intended for anyone making interactive projects. It is also a low-cost method for making electronic equipment that can be programmed to do a specific task (Abdul Khader, S., & Anitha, K, 2021). Internet of Things (IoT) is one of the top technological concepts where the users and objects are interconnected using wired and wireless technology. Wireless technologies include the Wireless Sensor Network (WSN), Long Range Wide Area Network (LoRaWAN), Zigbee, RFID, GPRS and Bluetooth (Sruthy, 2021). The innovation of devices based on Internet of Things (IoT) can collect and analyze the data and rapidly send the information to the collector section in territories about the landslide. It is a low-cost technology because the cabling is not needed. The IoT can continuously process and transfer the required data. Blynk is a comprehensive software suite that enables the prototyping, deployment and remote management of connected electronic device at any scale. Blynk empowers users to connect their hardware to the cloud and create iOS, Android and web applications to analyze real-time and historical data from devices, remotely control them from anywhere and receive important notifications (Blynk, 2024). A monitoring and detection system for landslide occurrence based on the Internet of the Things has been proposed. The system can provide early warning to communities in any region susceptible to landslides. The data on the presence of rain, condition of soil and ground movement can be analyzed by the system that can be monitored by governmental agencies and can take any action plan to reduce public risk and minimize the loss of economic activities.

In Africa, landslides are being considered as one of the major geological hazards the continent is facing. There is little research done to understand the nature of the geological hazard in Africa compared to other regions in the world. Recently there has been mapping of landslides-prone areas in the content. Countries such as Rwanda, the Democratic Republic of Congo, Uganda, Kenya, Cameroon, South Africa and Ethiopia have done some landslide research showing opportunities of advancement in the field. The research aids them in regulatory rules formation and decision making. Despite the recent strides in landslide research, many countries in Africa lack comprehensive understanding of the

landslide risk, emphasizing the need for deeper research on landslides at regional, national and local level (Thiery, Y.,et al.., 2024).

1.2 Problem Statement

Rainfall induced Landslide hazard continue to pose a threat to Malawi as a country at large with notable high-risk areas such as Mulanje Massif, Zomba, Dedza and the northern highlands (World Bank, 2019). Causal factors being frequent tropical cyclones, tectonically active East African rift system, vulnerable soils and deforestation. Rainfall is a dominant triggering factor for landslides, with research revealing that 93% of landslides at global scale have been caused by rainfall between 1972 and 2007 (Menon, V. O., & Kolathayar, S., 2022). In Malawi, 4709 individual rainfall induced landslides have been mapped between 2003 and 2022 posing a huge threat to lives and infrastructures (Springer Link Journal). Statistics show that 100 people at risk each year, carrying along 10 fatalities with $150,000 in property damage hitting at $60,000 annual losses in transport network (Thiery, Y.,et al.., 2024).

Recent monitoring systems such as Geographical Information systems (GIS), remote sensing and field monitoring face some setbacks and limitations in detecting landslides over large areas due to factors such as complex terrain and indistinguishable spectral and spatial characteristics of a landslide (Zhong, C..et al..,). Though field surveys offer a well detailed approach, they are time consuming, labor intensive and inadequate for large scale monitoring in dense vegetation and rugged landscape. As we expect the rainfall induced landslide hazard risk to increase by 2050 due to factors such as socio-economic changes and climate change, there is dire need for more effective, scalable and real-time monitoring system for rainfall induced landslide hazard (Thiery, Y.,et al.., 2024).

The combination of Internet of Things (IoT) and Arduino-based sensor systems offers a promising solution. These systems if integrated can monitor environmental and site conditions such as rainfall, soil conditions, slope inclination, temperature, humidity and ground movements, passing on real-time data to central systems for analysis (Purnomo, F. A.,et al..,, 2019). Internet of Things (IoT) platforms such as Blynk offer real-time monitoring and remote alerts, issuing early warnings to communities at risk and enabling government agencies to take preemptive actions (Blynk, 2024). Despite these advancements, Malawi has not yet implemented a low-cost, scalable and real-time landslide monitoring and early warning system that can effectively reduce the risk the public faces and minimize economic losses.

1.3 Study Objectives

1.3.1 Main Objectives

To design and implement a low-cost, IoT based early warning system for rainfall induced landslides in Malawi, leveraging Arduino and Blynk to enhance real-time monitoring, data analysis and risk mitigation efforts for vulnerable communities.

1.3.2 Specific Objectives

- To build an Arduino-based early warning system using various sensors including soil moisture, ground movement, slope stability, rainfall, humidity and temperature sensors.
- To create a Blynk web application for users to receive real-time alerts and monitor environmental data.
- To integrate the early warning system with the Blynk IoT platform through a web app.
- To implement a threshold-based algorithm that triggers an alarm when sensor data exceeds predefined limits.
- To analyze the system's performance in predicting landslides.

1.4 Research Questions

- How do different environmental sensors (soil moisture, ground movement, slope stability, rainfall, humidity and temperature) contribute to the early detection of rainfall-induced landslides?
- How effective is the Blynk mobile application in delivering real-time environmental alerts to users in high-risk areas?
- How does the integration of the early warning system with the Blynk IoT platform improve real-time data accessibility for users?
- What is the optimal threshold for triggering alarms based on sensor data in hazard detection system?
- How does the accuracy of the threshold-based decision-making algorithm impact the effectiveness of early warning system
- How accurately does the Arduino-based early warning system predict landslides in terms of sensitivity, specificity and false alarm rates?

1.5 Scientific Significance

Landslides are a huge threat to lives and property in Malawi especially in areas with high rainfall, steep slopes and geographical instability. With an average of 100 people at risk and a fatality rate of 10 in a year, the socio-economic implications of landslides are modelled with average annual damage estimated at $150,000 for buildings and $300,000 for the GPD (World Bank, 2019). This calls for the development of the landslide early warning system as a crucial step. Arduino based systems and Internet of Things (IoT) are shoved into the system for enhanced monitoring capabilities and timely alerts to vulnerable communities.

The susceptibility of Malawi to landslides is exuberated by factors such as climatic conditions, geological conditions and anthropogenic activities. Research findings

suggest that rainfall is the main causal factor for landslides contributing to 93% of global landslides occurrences (Menon, V. O., & Kolathayar, S., 2022). The direct correlation between increased pore pressure and decreased shear strength of soils during heavy downpour, accounts for the dire need for coming up with predictive models to assess the landslide risk. For example, the study showed that an 84% decrease in shear strength of soil as a result of 30% increase in soil moisture content, prompting the need for continuous monitoring of soil conditions in landslide-prone areas.

In the past, Malawi had been relying on traditional methods such as field surveys which on the positive side are well detailed method but have setbacks such as labor intensive and limited in scope (Zhong, C..et al..,). The challenges arising due to dense vegetation and complex topographies initiate the need for adoption of advanced monitoring technologies. Geographical Information Systems (GIS), remote sensing and field surveys offer complementary ways for landslide risk assessment, but these ways fall short in providing real-time data (Thiery, Y.,et al.., 2024). The arrival of IoT technology provides a clear and game-changing opportunity for landslides monitoring. Arduino-based systems integrated with various sensors for monitoring soil moisture, rainfall and ground movement can provide cheap-effective solution for early warning systems. Through on-going data collection and transmission, the system can alert communities and authorities of the imminent landslide risk enabling timely mitigation measures.

1.6 Chapter Summary

The chapter begins with the introduction of the problem of rainfall-induced landslides in Malawi, emphasizing their increasing and continued threat due to climate change, vulnerable terrain, and limited early warning systems. High-risk areas like Mulanje, Zomba, Dedza, and the northern highlands face recurring landslide events, causing fatalities, property damage, and economic loss. Traditional monitoring methods such as GIS, remote sensing, and field surveys, while useful, are limited by cost, terrain

complexity, and lack of real-time responsiveness. To address this gap, the chapter proposes a low-cost, Arduino-based Internet of Things (IoT) early warning system that integrates environmental sensors with the Blynk platform for real-time data transmission. The study aims to build and evaluate this system's performance in monitoring key parameters—such as soil moisture, slope stability, and ground movement—and enhancing risk communication through a web application. The scientific significance lies in leveraging modern, accessible technology to develop a scalable solution for disaster preparedness in resource-limited settings, contributing to national resilience against climate-related hazard

CHAPTER TWO: LITERATURE REVIEW

One of the main environmental hazards that Malawi faces is landslide particularly in areas of high rainfall and geological complex. The country's vulnerability to landslides is accelerated by deforestation, soil susceptibility and tectonic activity of the East African Rift System. There has been emphasis on the need to come up with an early warning system to mitigate the impacts of these hazards with the fear that the landslide is expected to increase to climate change and socio-economic pressure in the near future (World Bank, 2019). Rainfall induced landslides are common in Malawi in regions such as the Mulanje Massif, Zomba, Dedza and the northern boarder highlands. Studies have indicated that 93% of landslides globally are triggered by heavy rainfall (Menon, V. O., & Kolathayar, S., 2022) with 4709 rainfall induced landslides being mapped in Malawi between 2003 and 2022 (Niyokwiringirwa, P. et al..,, 2024)

We cannot talk about rainfall-induced landslides monitoring and prediction without looking at data from studies on landslides, soil mechanics and environmental conditions. Understanding of thresholds and ranges associated with parameters such as soil moisture, ground acceleration, slope angle, humidity and rainfall intensity can aid in predicting and managing landslide risks. Soil moisture plays a vital role in initiation of landslides. Researchers say that at 40% to 50% of soil moisture content, a landslide is triggered depending on regional conditions (Ahmed, M.,et al, 2020). The range is often accompanied with saturation of soil reducing the shear strength and increasing chances of slope failure. Prolonged downpour and wet weather contribute to elevated soil moisture levels increasing chances of landslide occurrence (Liang, X., et al, 2021). Ground acceleration is another factor that is closely looked at in landslides initiation. Notably, a peak ground acceleration (PGA) of 0.1g to 0.3g had been identified to trigger landslides in earthquake prone areas (Youssef, A. M., & Rahman, M, 2019). Numerous studies around the globe have observed this PGA range satisfying the impact of seismic activity on slope stability (Chen, J., et al, 2021). Areas with saturated soils and steep slopes are more prone to slope failures even under lower levels of ground

acceleration. Slope angles ranging from 25° to 45° are mostly associated with landslides determined by factors such as soil composition, vegetation cover and soil moisture content (Xu, Y., et al, 2022). Steeper slopes with loose or granular soil tend to be more vulnerable to landslides due to low internal angle of friction. However dense vegetated areas benefit from soil cohesion by roots providing the much-needed stability on the slope (Martinez, A., et al, 2020). Humidity does not directly trigger landslides but plays a significant role when combined with rainfall. High rainfall is most of times associated with humidity ranging from 80% to 100% responsible for keeping high moisture contents (Singh, V., et al, 2021). Persistent high moisture content destroys the structural integrity of soil making it susceptible to landslide due prolonged heavy downpours. Intense rainfall rating at 50mm/h or 200-300mm/day can cause soil saturation can lead to landslides particularly in regions with pre-existing slope instability, with increased pore pressure reducing the shear strength (Zhu, Y., et al, 2023). The weight of rainfall as a triggering factor in landslides cannot be overlooked. Rainfall induced landslides occur when the infiltrated rainwater increases soil pore pressure and causes reduction in shear strength of the soil (Menon, V. O., & Kolathayar, S., 2022). The increment in soil moisture content due to torrential rains reduces shear strength by as much as 84%, creating ideal conditions for landslides. Slopes angle with inclination more than 20° are highly susceptible to landslides with other geological factors exuberating landslide risk in Malawi (Niyokwiringirwa, P. et al..,, 2024). Malawi is along the East African Great Rift Valley System which disturbs the tectonic stability of the country contributing to the Landslide risk.

In the past, Malawi had used field surveys and equipments such as clinometers and displacement meters to monitor landslides. Looking at the brighter side, these methods have provided detailed local data but face limitations such insufficiency for large scale monitoring (Thiery, Y.,et al.., 2024). While Geographical Information Systems (GIS) and remote sensing are used to map landslide prone areas, their setback lies in differentiating landslides from other landforms. Landslides covered by other land types such as vegetation become difficult to trace using satellite images. On top of that, the spectral characteristics of landslides can be confused with that of natural features such

as terraces and riverbeds (Zhong, C.. et al..,). This urged to resolve to the ground- based monitoring systems. As research on landslide advances, technologies such as Internet of Things (IoT) and Arduino low-cost sensors are proving valuable assets. The systems can be combined to provide real-time data on environmental conditions and send it to monitoring centers, allowing for proactive actions for risk management (Fiorucci, F.,et al, 2021). Combining Arduino with IoT technology can provide cheap and effective way for monitoring environmental conditions such as soil moisture, ground movement, humidity, rainfall and temperature (Wang, Y.,et al, 2022). The system uses sensors to see changes in soil and environmental conditions, allowing real-time data collection and analysis. Studies have shown that combining such systems with IoT platform mobile apps such as Blynk allows communication through alerts of the impending landslide (Fiorucci, F.,et al, 2021). Blynk as an IoT platform allows seamless combination of software and hardware, enabling real-time monitoring and control of connected devices. Blynk mobile app can help users monitor environmental conditions and receive notifications of the impending landslide event prompting them making proactive actions to safeguard their lives and property (Blynk, 2024).

The evaluation of the accuracy the landslide prediction system by looking at metrics such as specificity, sensitivity and false alarms is crucial for reducing landslides risk and impact to the prone areas. One way of weighing the system's performance is through the use of the confusion matrix which represents outcomes of predictive model and evaluate their reliability. The confusion matrix categorizes predictions into four groups; true positive (correctly predicted landslides), true negative (correctly predicted no landslides), false positive (false alarm) and false negative (missed landslides) (Miao, Y., & Tang, X, 2022). Sensitivity defines the model's ability to correctly predict the occurrence of the landslide. It is also called true positive rate. It is important because if it misses (false negative) can lead to severe consequences. Specificity also known as true negative rate defines the model's ability to correctly predict circumstances with no landslide occurrence. Emphasis is taken on balancing these two metrics as over

prioritizing one such as sensitivity can result into high false positive rates and specificity can lead to missed alarms (Lee, H., et al, 2021).

The Malawi National Disaster Risk Management Policy talks a lot about installing early warning systems in disaster prone areas. The technology infrastructure is still developing in Malawi and hence a low-cost solution must be proposed to suit our situation. The integration of IoT solutions in disaster risk management still remains a challenge in Malawi. The current efforts focus on emergence response rather than proactive monitoring (Government of Malawi, 2015). The Malawi Country through its polices and global frameworks such as the National Resilience Strategy (2018-2030) and the Sendai Framework calls for the early warning systems but fulfillment remains the challenge. Using the Arduino can seal this gap by providing cost-effective, monitoring solutions to the rural and hard to reach areas (Purnomo, F. A.,et al..,, 2019). Some countries around the world have successfully implemented IoT-based early warning system for landslides. For example, Indonesia deployed an Arduino IoT-based landslide early warning system in rural communities and successfully reduced the impacts of rainfall induced landslides (Suriya, 2021). In India they combined remote sensing with Arduino IoT system to monitor rainfall triggered landslides boosting disaster preparedness in the country (Bharathi, 2021). The success of the similar systems in other countries to combat severe impacts of landslide hazard urges Malawi to adopt these technologies.

2.2 Chapter Summary

The chapter looks into the causes, impacts, and monitoring approaches for rainfall-induced landslides, with a focus on Malawi. It emphasizes that landslides are primarily triggered by heavy rainfall, soil saturation, slope angle, and tectonic activity, with over 4,700 events recorded in Malawi between 2003 and 2022. Traditional methods like field surveys, GIS, and remote sensing are limited by lack of real-time data and scalability. The review emphasizes the potential of Arduino-based IoT systems for low-

cost, real-time monitoring using sensors to track soil moisture, ground movement, and environmental conditions. Platforms like Blynk enhance data visualization and monitoring through various gadgets. The chapter also stresses the importance of evaluating system performance using metrics such as sensitivity, specificity, and false alarm rate. It concludes by calling for the adoption of IoT-based early warning systems in Malawi, following successful implementations in countries like Indonesia and India.

CHAPTER THREE: METHODOLOGY

3.1 Study Area

The study area will be T.A. Chimariko in Thyolo District with low risk of landslides but climate change presumed to alter conditions for landslides occurrence in the district (Global Facility for Disaster Reduction and Recovery). The prototype will be tested in this area around some hilly areas.

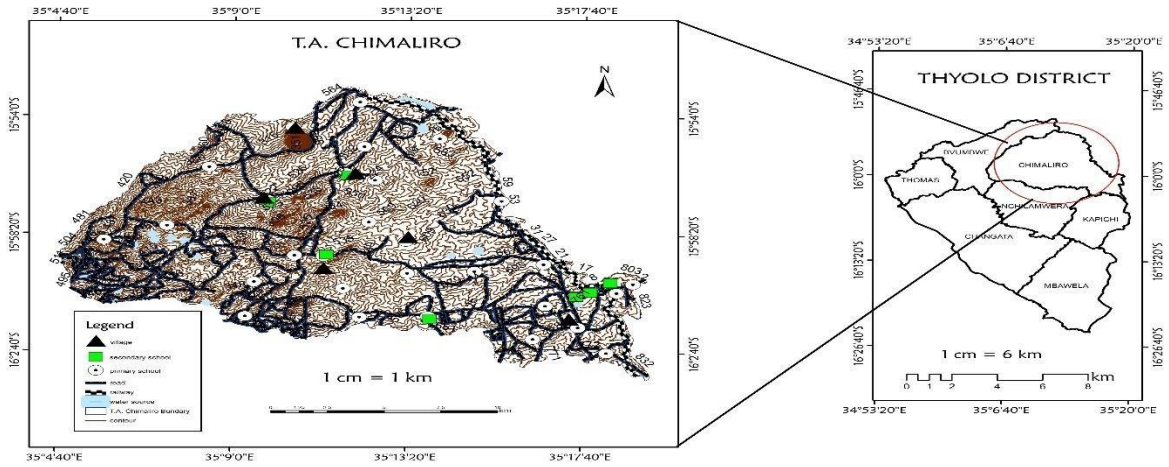


Figure 1…map of study area

3.2 Study Approach

The study uses quantitative approach to design, develop and analyze an Arduino IoT rainfall induced landslides monitoring and detection system. The system combines different sensors and hardware components for the comprehensive functionality. The system is organized in the following sections: system development, mobile application integration, data collection, threshold algorithm implementation, data analysis and ethical considerations.

3.3 Research Design

The study adopted an experimental research design (Creswell, J. W., & Creswell, J. D, 2020) aimed at building and testing Arduino-based EWS combined with sensors and mobile application. The system's ability to predict landslides was evaluated by field testing, with real-time data collection and quantitative analysis. The design is ideal for testing how well the system performs under real world conditions (Bhattacherjee, 2019).

3.4 Materials

The following materials were used in the system; esp32 board, adxl 345, dht 11, soi moisture sensor, buzzer alarm, jumper wires, juypter notebook, Arduino ide, blynk cloud, Excel and expert defined thresholds.

3.4.1 Hardware Set-up

The system was built on top of the Arduino Platform, which served as the central microcontroller. Several sensors were integrated to collect real-time environmental data and soil conditions data. The hardware setup was made up of the following components:

- Ground movement sensor (e.g.., adxl 345): Detected shifts in the ground indicating landslide activity.
- Slope stability sensor (e.g.., adxl 345): Monitored changes in land inclination to detect terrain instability.
- Humidity and Temperature sensor: Captured atmospheric conditions that may contributed to landslide risk.
- Ultrasonic sensor: Detected terrain changes or obstacles in the system's proximity by measuring distance to nearby surfaces or obstacles.
- Soil moisture sensor: Measured the moisture content of the soil to detect

favorable conditions for slope failure.

- Buzzer Alarm: Gave audible alerts when predefined thresholds were exceeded, signaling an impending landslide risk to nearby communities (Prakash, A., et al, 2020).

All sensors were connected to the esp32 board, which processed all incoming data from the sensors and determined whether to trigger buzzer alarm based on threshold values.

3.4.2 Mobile Application Integration

The system integrated the Blynk IoT platform through mobile application to monitor environmental conditions. The Blynk mobile app provided real-time visualization of sensor data including soil moisture, ground movement, slope inclination, humidity and proximity readings. The mobile application allowed me to track current environmental conditions and analyze trends over time by viewing past sensor readings.

3.4.3 Procedure for setting up the system

The esp-32 board has multiple digital pins labeled D0–D23 (GPIOs). Below is how I configured it based on my project.

Table 1..esp32 pin configuration

Sensor/Component	ESP32 Pin (GPIO)	Purpose
Soil Moisture Sensor	GPIO 34 (D34)	Analog read (moisture levels)
DHT11 (Temp & Humidity)	GPIO 4 (D4)	Digital data signal

Ultrasonic Sensor - Trig	GPIO 13 (D13)	Trigger pin
Ultrasonic Sensor - Echo	GPIO 12 (D12)	Echo pin (measures distance)
ADXL345 (Accelerometer)	GPIO 21 (SDA), 22 (SCL)	I2C communication
Buzzer	GPIO 27 (D27)	Digital output (alarm sound)
Power	3.3V or 5V	Power Sensor
Ground	GRD	Ground Sensor

3.4.4 Blynk Dashboard Development

- I created an account at Blynk.io.
- I created a new device template for the "Landside IoT Monitoring and Detecting System.
- I selected the esp32 board and Wi-Fi connectivity.
- I got the Blynk Auth Token and ID to link esp32 with the cloud

3.4.5 Virtual Pin Mapping

Each sensor is mapped to a virtual pin for cloud communication.

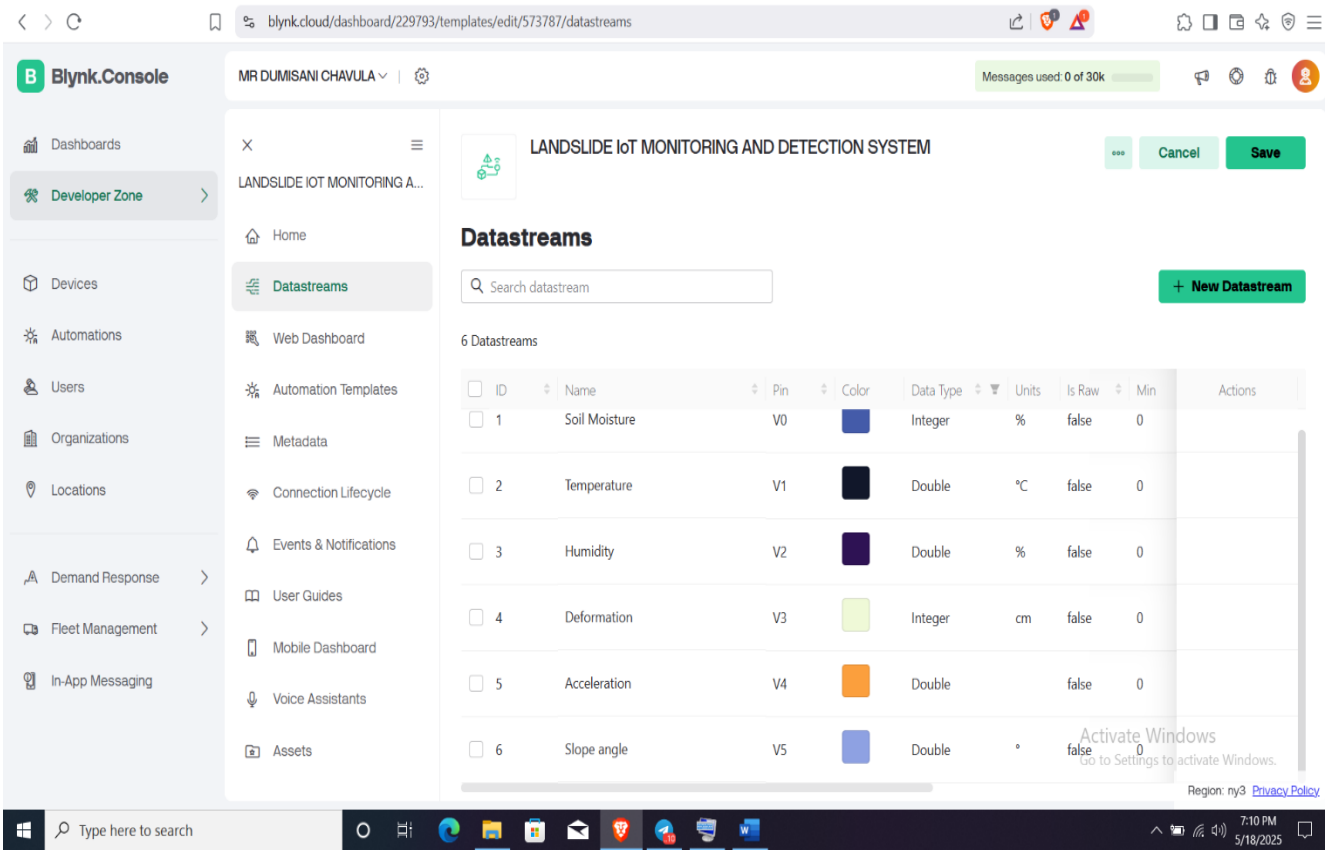
Table 2…. Virtual Pin Mapping

Sensor	Virtual Pin in Blynk	Widget Type
Soil Moisture	V0	Gauge / Value Display

Temperature (DHT11)	V1	Value Display
Humidity (DHT11)	V2	Value Display
Ground Movement (ADXL)	V3	Chart / Value Display
Slope/Ultrasound	V4	Gauge / Display
Alert / Buzzer	V5	LED / Notification

3.4.6 Blynk Dashboard Design

Figure 2…Blynk dashboard designing



- I opened the Blynk app on web.

- ❖ I dragged and dropped widgets (Gauges, Charts, Sider, Label).
- ❖ I linked each widget to the correct Virtual Pin (Vx).
- ❖ I set units (e.g., %, °C, cm), value ranges, and update intervals

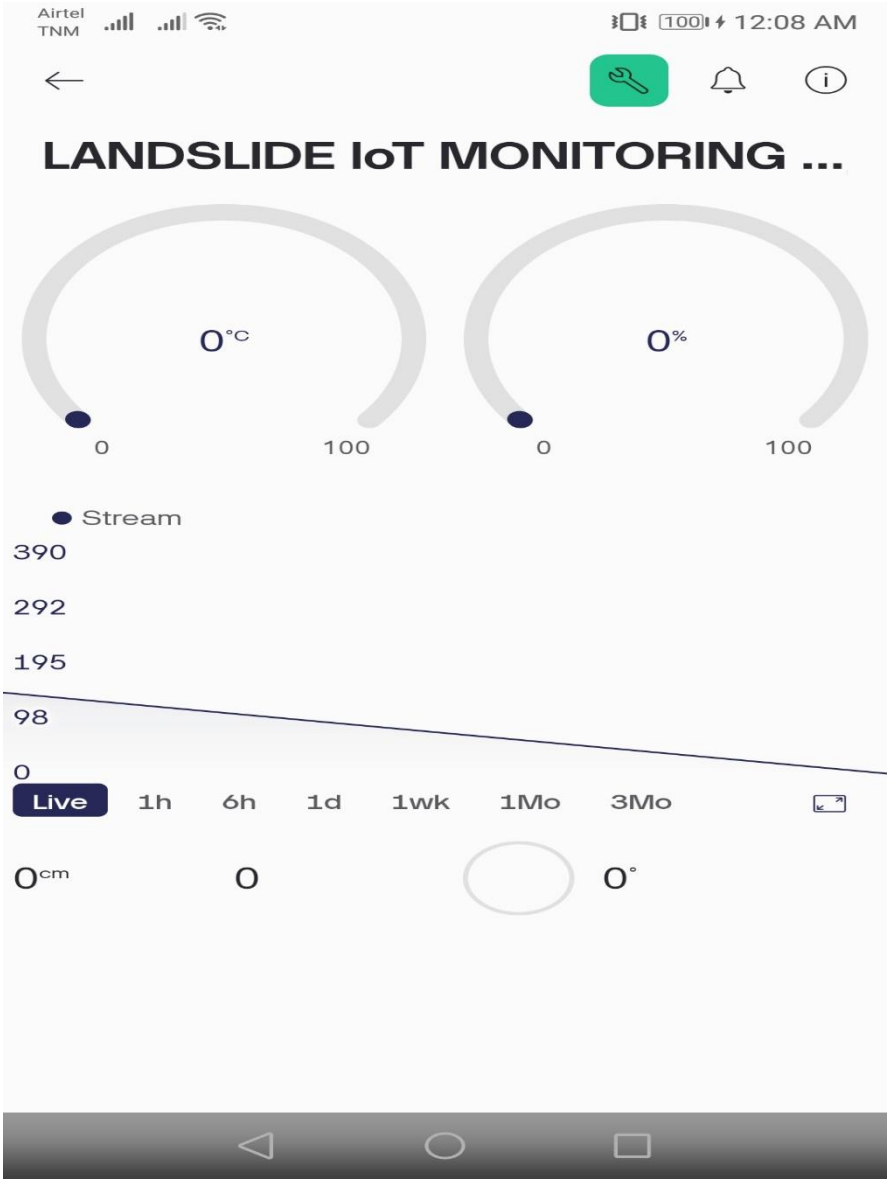


Figure 3… Blynk Mobile dashboard app

3.4.7 ESP32 Firmware Development (Arduino IDE)

- I installed blynk library and esp32 board support in Arduino IDE.
- I wrote a c# script to the esp32 to:

  - ✓ Read sensor data
  - ✓ Send values to Blynk using blynk.virtualWrite(Vx, value)
  - ✓ Trigger alerts (e.g., buzzer + Blynk notification) if threshold exceeded

    - Uploaded code to ESP32 using USB type c

3.4.7 Data Collection

Data was collected from all sensors over a specified period in a simulated landslide prone area. Each sensor logged data at regular interval (e.g.., every minute), which was transmitted to the Blynk platform. To monitor and predict landslide risk sensor data such as soil moisture, ground movement, rainfall and proximity (from ultrasonic sensor) was used (Huang, Y., et al, 2020). The data was stored in cloud through the Blynk Platform for further analysis using Excel and Python.

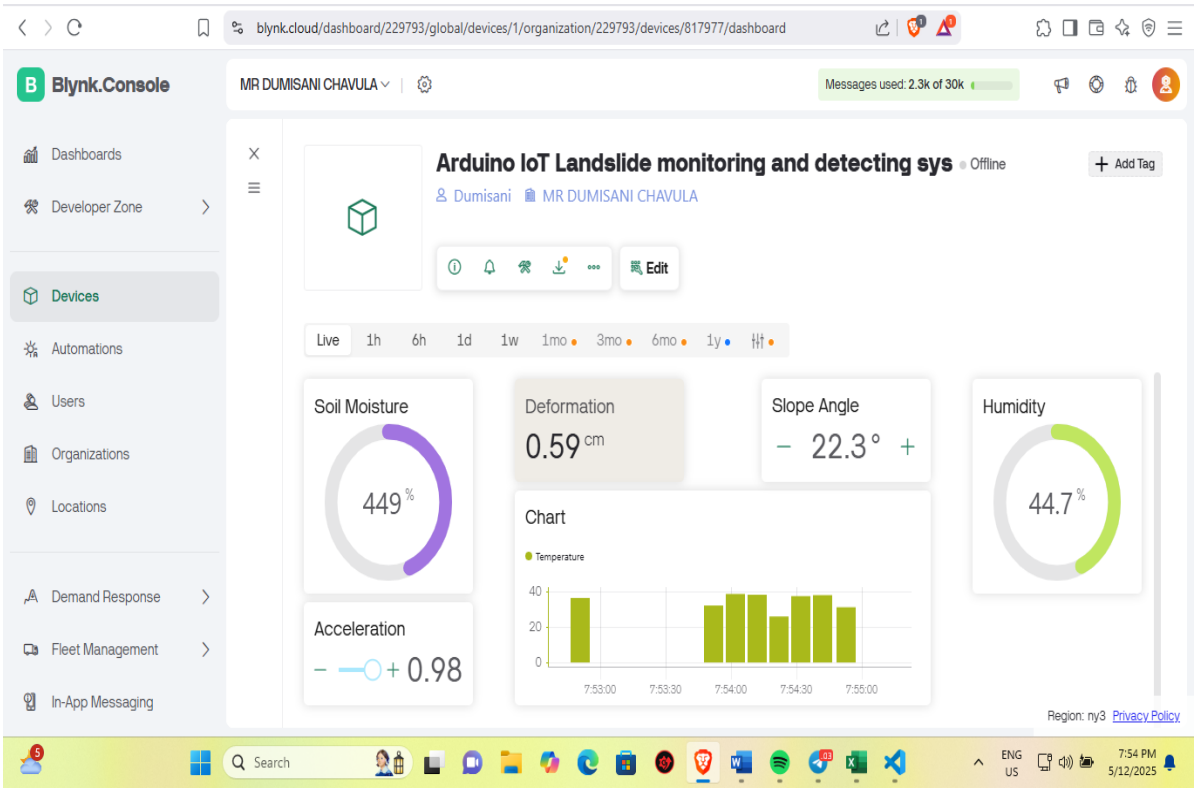


Figure 4…Blynk web app

Time	Humidity (%)	Temp (Â°C)	Acceleration (g)	Slope (Â°)	Soil Moisture	Deformation (cm)	Buzzer Triggered	
8:00:00	77.5	22.2	0.19	10.7	534	0.61	No	
8:05:00	74.3	24.2	0.21	11.9	555	2.1	No	
8:10:00	78.2	24.3	0.26	15	660	3.01	No	
8:15:00	82.6	23.4	0.26	14.8	649	3.07	No	
8:20:00	73.8	24.7	0.05	2.9	598	2.32	No	
8:25:00	73.8	25.8	0.06	3.2	609	3.93	No	
8:30:00	82.9	28.8	0.2	11.6	702	1.4	No	
8:35:00	78.8	25.3	0.2	11.6	553	2.79	No	

Table 3…Environmental parameters data collected by sensors

3.4.8 Threshold Algorithm Implementation

The processing of data in real-time was done using an expert view threshold-based algorithm (Prakash, A., et al, 2020). Comparison of the incoming sensor data against predefined limits to trigger a buzzer alarm and send a mobile alert when any reading exceeds any threshold was be done at this stage.

For instance:

- If soil moisture exceeds a critical level, the alarm was activated.
- If the ultrasonic sensor detected sudden changes in proximity to nearby surfaces (indicating terrain displacement), the system will issued a warning.

Table 4....Experts Based Thresholds

Parameter	Expert Threshold	Supporting References
Deformation (cm)	> 5 cm (indicative of surface movement)	Dhivya & Balasubramanian (2019); Prakash et al. (2020); Fiorucci et al. (2021)
Slope (°)	> 12°–15° (critical slope angle)	Xu et al. (2022); Niyokwiringirwa et al. (2024); Artha & Julian (2018)
Soil Moisture	> 300–400 (sensor-specific threshold)	Ahmed et al. (2020); Liang et al. (2021); Purnomo et al. (2019)
Acceleration (g)	> 0.05–0.1 g (ground instability)	Chen et al. (2021); Youssef & Rahman (2019)
Humidity (%)	High (>60%) contributes to saturation	Singh et al. (2021); Abdul Khader & Anitha (2021)
Temperature (°C)	Context-dependent; affects evaporation rates	Zhu et al. (2023); Martinez et al. (2020)

Threshold determination was based on prior studies, expert viewpoint and field testing (Liu, X., et al, 2020).

3.5 Data Analysis

Sensor data was analyzed using Microsoft Excel and Python for system's performance and predictive capabilities' evaluation.

3.5.1 Excel for Data Organization and Preliminary Analysis

- Data cleaning: ensured removal of any inconsistent or missing values
- Basic analysis: computed summary statistics such as mean, standard deviation and correlation between sensor readings.
- Visualizations: generated simple graphs (e.g.., time series plots) to display trends in soil moisture, proximity readings and ground movements (Winston, W. L., 2019).

3.5.2 Python for Advanced Analysis

Python libraries such Pandas, NumPy, Matplotlib and SciPy will be used for:

- Correlation analysis: examined the relationship between different environmental variables (e.g.., soil moisture and rainfall) and their combined impact on landslide risk.
- Performance evaluation: quantitative metrics such as accuracy, precision, recall and false positive/negative rates was calculated to assess the system's prediction accuracy (McKinney, 2019)
- Advanced visualizations: created sophisticated plots such as heatmaps to visualize relationships between sensor readings.

3.6 System Performance Evaluation

Deployment of the system in a real-world environment was done to test its ability to predict landslides. The evaluation of performance was done through comparison of sensor data with actual events. The system's performance will be calculated by assessing key metrics such as accuracy, precision, recall and false positive/negatives rates of the buzzer alarm

3.7 Ethical Consideration

The study aligns itself with ethical guidelines, ensuring the system is thoroughly tested to minimize false alarms which harms public trust. Field testing will include getting informed consent from participants and data security measures will be put in place to guard the sensor data transmitted via Blynk platform (Markham, A., & Buchanan, E, 2020).

3.8 Chapter Summary

The chapter discusses the methodological framework used to design, develop, and evaluate a rainfall-induced landslide monitoring and detection system using Arduino and IoT technologies. The study was conducted in T.A. Chimaliro, Thyolo District, at Malawi university of Science and Technology. A quantitative approach was adopted, with an experimental research design guiding the system's development, field deployment, and performance analysis. The hardware setup consisted of an esp32 board integrated with sensors such as soil moisture, ADXL345 accelerometer, DHT11, and ultrasonic sensors. It was linked to a Blynk-based mobile application for real-time monitoring and alerts. The system design allowed continuous data collection and analysis using Excel and Python. Expert-defined thresholds triggered buzzer alarms and cloud-based dashboard plotting. Data analysis involved correlation studies and performance evaluation using metrics such as accuracy, precision, and recall. Ethical considerations focused on informed consent, data integrity, and minimizing false alarms. Overall, this chapter details the comprehensive development and assessment of an IoT-based early warning system aimed at improving disaster preparedness and environmental monitoring.

CHAPTER FOUR: RESULTS AND DISCUSIONS

4.1 Results

The study came up with an Arduino-based early warning system providing real-time monitoring of environmental factors associated with landslides by leveraging sensors which gathered data on soil moisture, ground movement, slope stability, humidity and terrain changes. By involving the Blynk IoT Platform, data was transmitted to the web app enabling users to have real-time and receive instant alerts when environmental thresholds are exceeded. The threshold-based algorithm was anticipated to aid high accuracy, balance false positives and negatives effectively providing reliable alerts (Huang, Y., et al, 2020). Data analysis through Excel and Python was done to reveal crucial trends and correlations between the monitored variables. This will help in refining the EWS's predictive capabilities and validation of the algorithm's threshold settings.

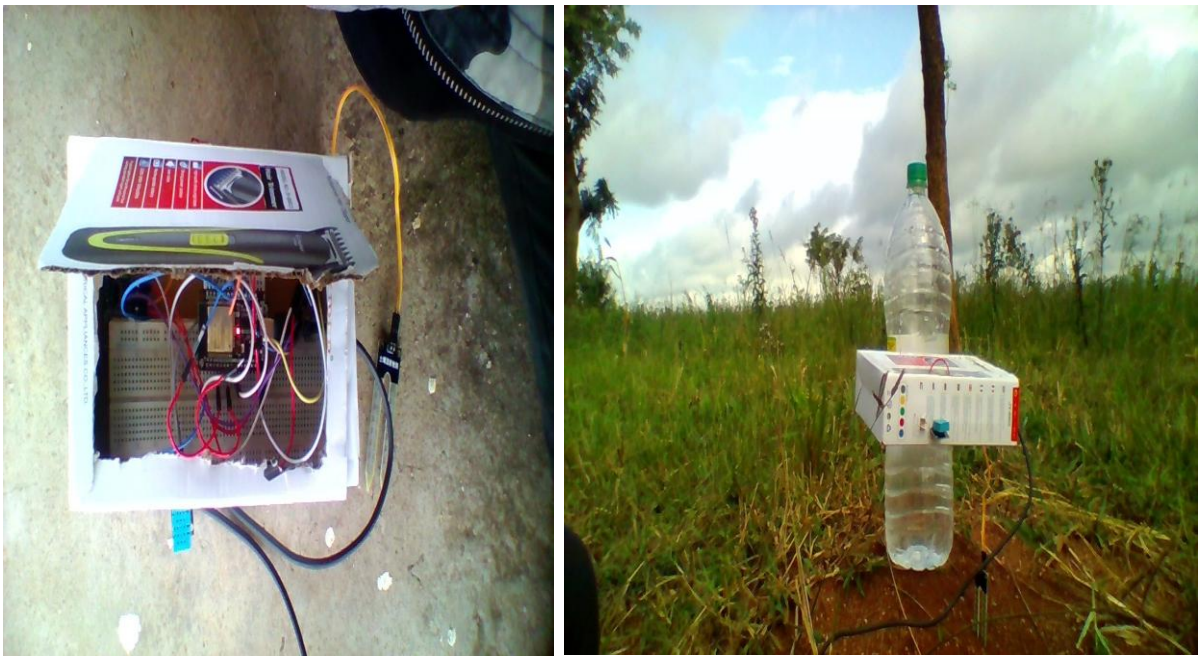
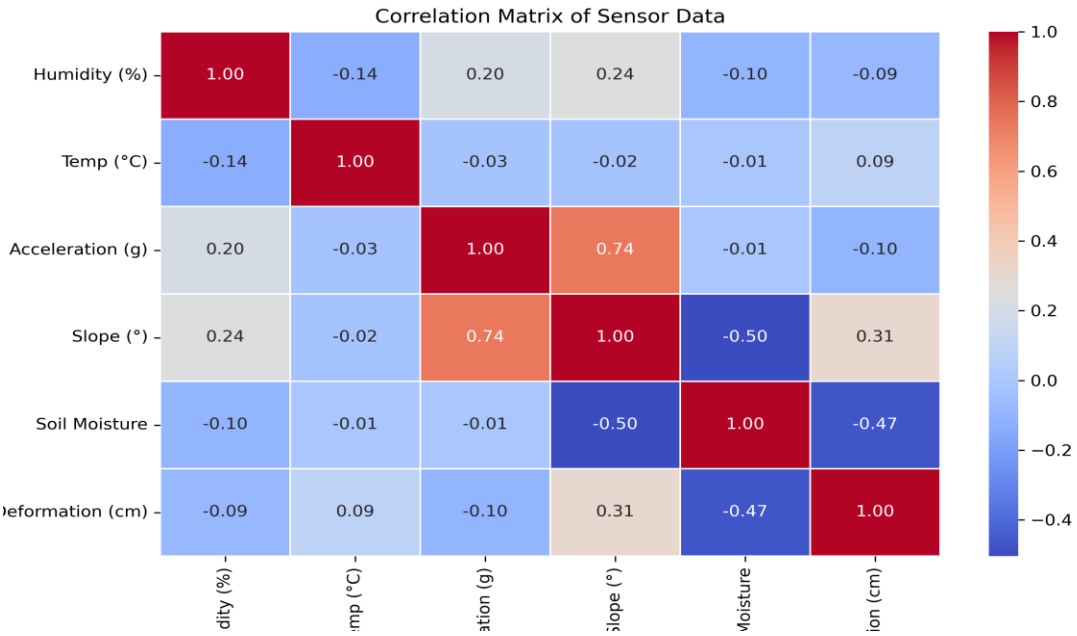


Figure 5…Landslide IoT System field deployment

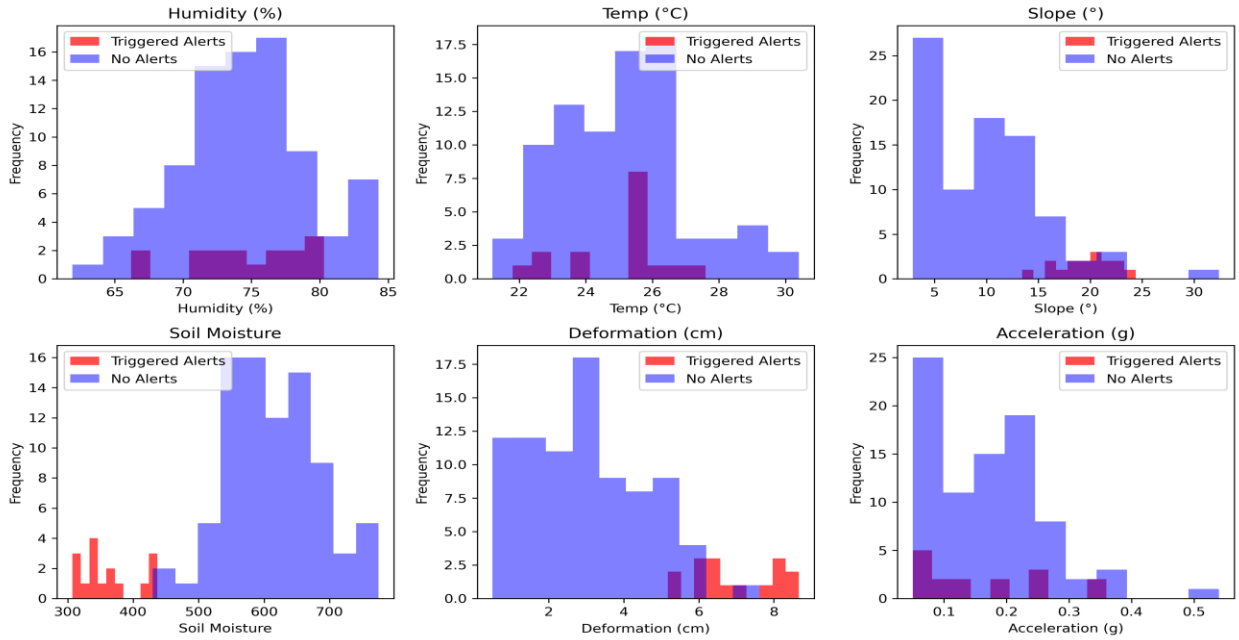
A field-deployed Arduino-based IoT landslide monitoring system designed for real-time early warning in rainfall-prone areas. The setup has a compact enclosure supported by a plastic water bottle that houses the esp32 board and sensors, including a visible soil moisture sensor inserted into the ground to monitor saturation levels. The low-cost, portable system collects environmental data and transmits it to the Blynk IoT platform, enabling remote alerts when landslide-triggering thresholds are exceeded. The design reflects an innovative, scalable solution aimed at enhancing disaster preparedness in vulnerable, resource-limited communities.

Figure 6…Sensor data Correlation Matrix



The correlation matrix reveals key relationships among environmental variables monitored by our IoT-based landslide detection system. A strong positive correlation (r = 0.74) exists between acceleration and slope, indicating that as slope angle increases, ground vibrations also increases signaling critical early indicators of landslide risk. Slope also moderately correlates with ground deformation (r = 0.31), supporting its role in terrain instability. Notably, soil moisture shows a moderately strong negative correlation with slope (r = –0.50) and deformation (r = –0.47), suggesting that increased soil saturation weakens slope stability, potentially triggering landslides. In contrast, temperature and humidity show weak or negligible correlations with other variables, implying limited predictive value. Overall, slope, acceleration, and soil moisture emerge as the most significant parameters for real-time landslide risk assessment

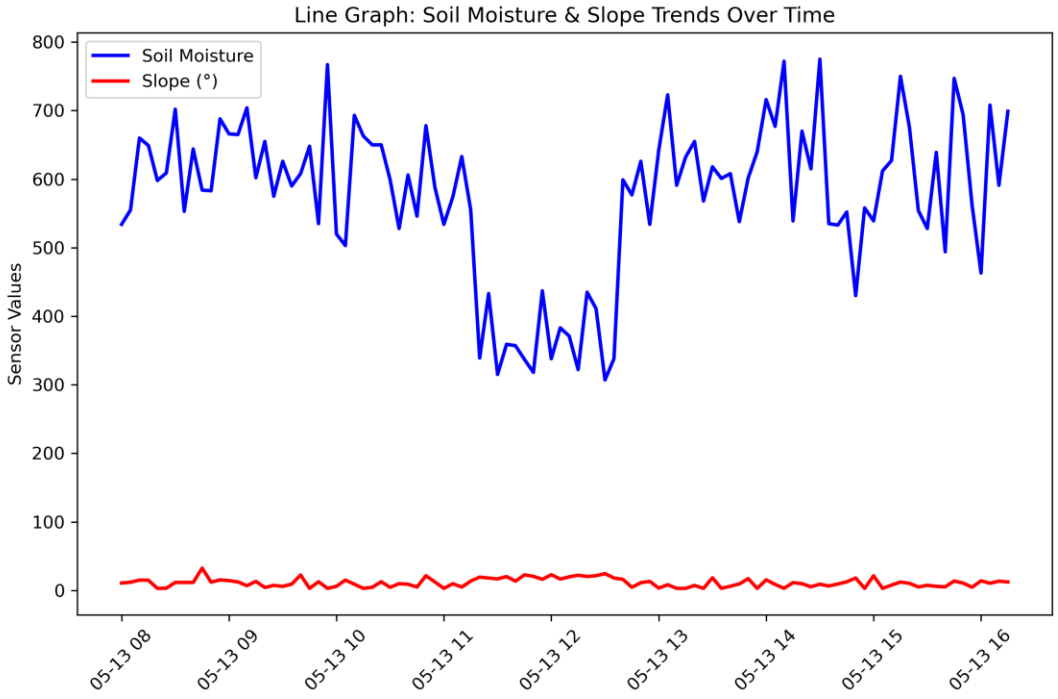
Figure 7…Histograms of environmental variables against alert occurrences



The six histograms show analysis of environmental parameters namely humidity, temperature, slope, soil moisture, deformation, and acceleration against alert occurrences. Each chart compares instances where alerts were triggered (red) versus those without alerts

(blue). Notably, higher soil moisture and greater deformation values show a strong correlation with alert frequency, suggesting their significant role in predicting ground stability issues like landslides. This type of analysis helps in identifying risk factors, enabling more effective environmental monitoring and hazard prevention strategies.

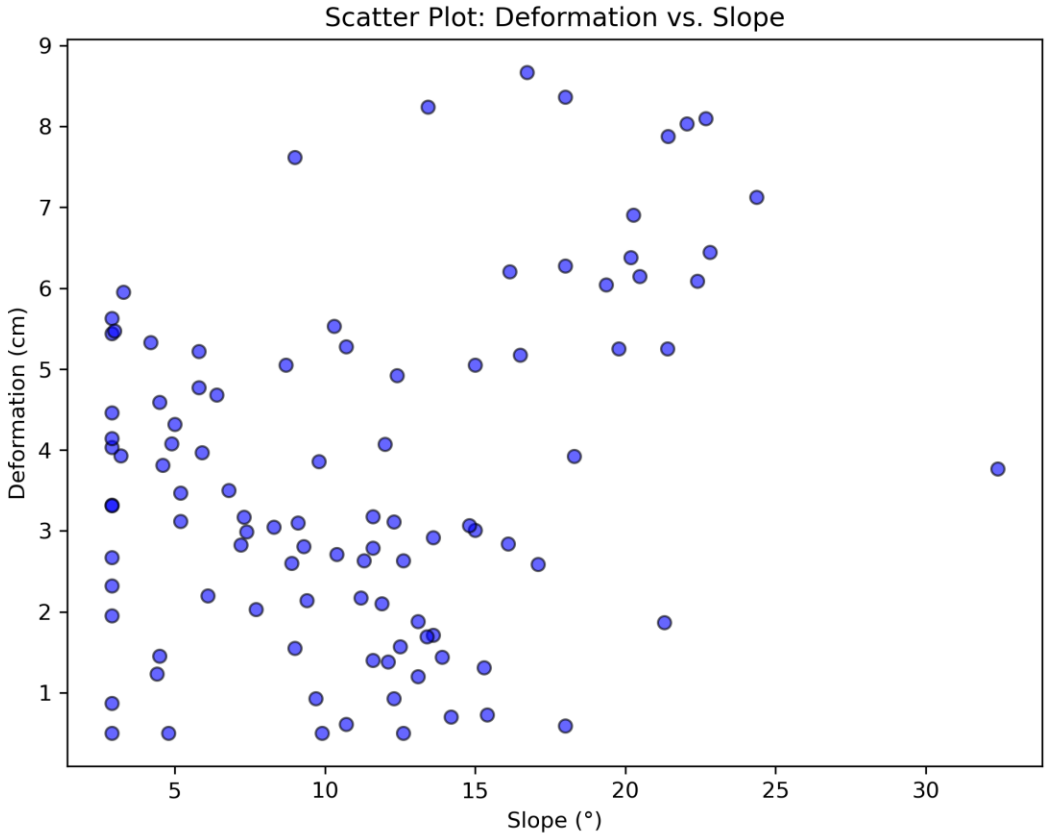
Figure 8...Soil Moisture vs Slope trend over time



In a landslide IoT monitoring and detection system, soil moisture and slope trends play crucial roles in exploring ground stability and predicting potential hazards. Over time, sensors deployed in the field continuously collected soil moisture data, tracking fluctuations due to rainfall, groundwater levels, and drainage patterns. When soil reaches saturation, its structural integrity weakens, increasing the likelihood of landslides, especially on steep slopes. Slope sensors monitor gradual or sudden shifts, detecting changes in terrain inclination due to erosion or geological movement. By analyzing historical and real-time data trends, the system can identify conditions that precede landslides, enabling early warnings. Correlating high soil moisture levels with increasing slope deformation helps

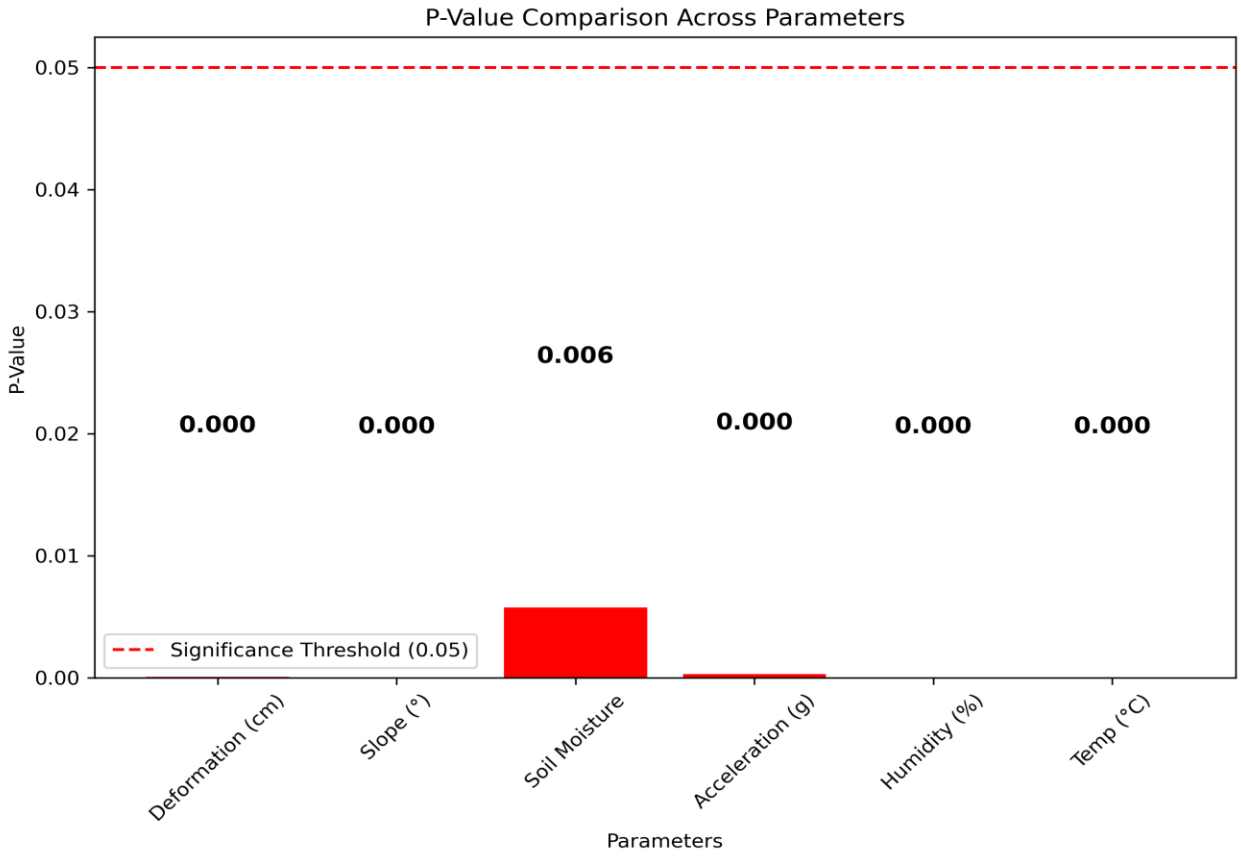
improve predictive models, allowing authorities and communities to take proactive measures to mitigate risks.

Figure 9…Slope against Deformation



A scatterplot showing the relationship between deformation and slope provides critical insights into ground stability. Typically, steeper slopes experience more deformation due to gravitational stress and soil instability, forming a trend where higher slope angles correlate with increased ground movement. However, anomalies may exist where gentle slopes still undergo significant deformation, influenced by factors like soil type, water infiltration, or seismic activity. Identifying clusters or thresholds in the scatterplot helps pinpoint high-risk areas enabling early warning mechanisms. By continuously analyzing real-time IoT sensor data, researchers can refine predictive models, ensuring precise hazard detection and proactive disaster mitigation strategies.

Figure 10…P-Value for environmental variables



In an Arduino IoT monitoring and detection system, calculating p-values for different parameters is important for identifying statistically significant relationships and ensuring reliable predictions. Various sensors continuously gathered data on environmental factors like temperature, humidity, soil moisture, and acceleration, but raw readings alone may contain noise or weak correlations. By analyzing p-values, filtering out irrelevant fluctuations, prioritization of key indicators and optimize sensor placement. A low p-value (typically <0.05) confirms that a parameter strongly influences monitored events, improving decision-making and reducing false alarms. This statistical approach enhances system efficiency, enabling data-driven hazard detection, early warnings, and smarter resource allocation for better safety and operational performance.

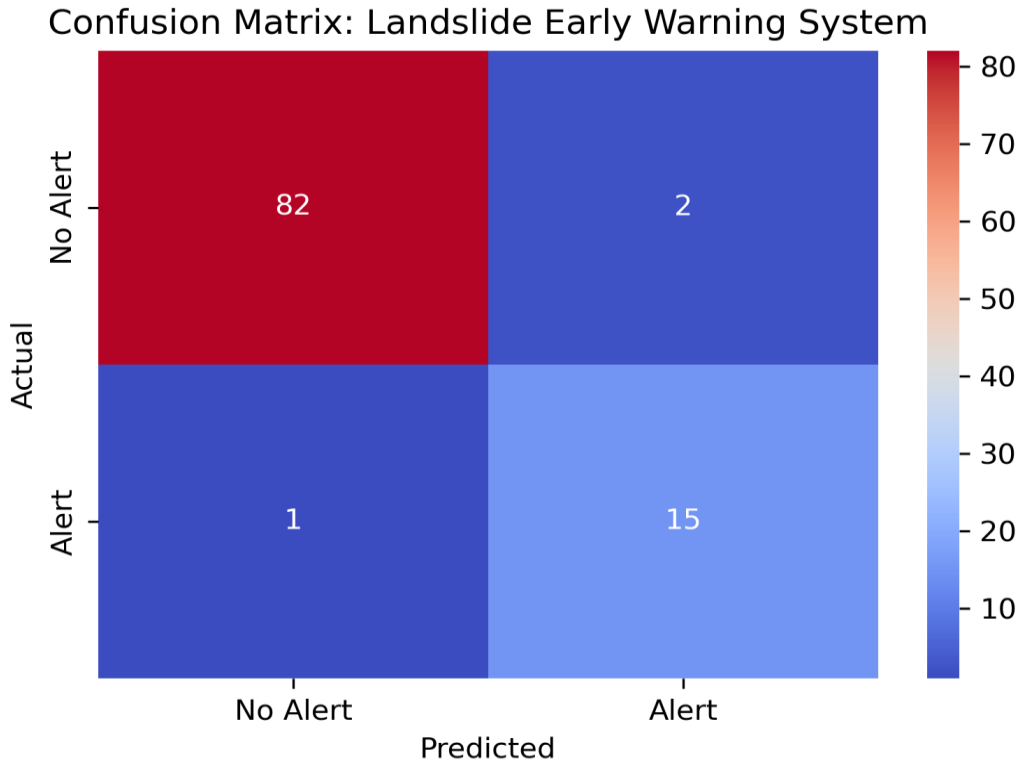


Figure 11…Confusion Matrix

The performance metrics of the IoT landslide detection system revealed its high accuracy and reliability in identifying actual risks while keeping false alarms at low. By the precision of 88.2%, the system ensured that the majority of positive alerts are correctly classified, making its predictions trustworthy. Its recall of 93.8% indicated that it effectively detects nearly all landslide events, minimizing missed detections and enhancing safety. Additionally, the false alarm rate of 2.4% suggested that the system rarely misclassified stable conditions as hazardous, maintaining efficiency in decision-making. These figures highlight a well-calibrated system capable of early warning and proactive hazard mitigation, reinforcing its value in real-world monitoring applications. Further refinements, such as adaptive threshold adjustments and enhanced data analytics, could optimize detection performance even further.

4.2 Chapter Summary

The chapter presents the outcomes of the Arduino-based IoT landslide monitoring and detection system, hinting at its real-time data collection, analysis, and alert capabilities. The system monitored environmental parameter such as soil moisture, ground movement, slope inclination, humidity, and temperature—using sensors connected to an esp32 board. There was also data transmission to the blynk platform through the Wi-Fi network. Field deployment demonstrated the system's practicality, low cost, and scalability. Correlation analysis revealed strong relationships between slope, acceleration, and soil moisture, validating their significance in predicting landslides. Histograms and scatterplots further demonstrated that high soil moisture and deformation levels corresponded with increased alert frequency. Statistical analysis using p-values helped identify the most influential variables, refining the system's predictive accuracy. Performance evaluation showed high precision (88.2%), recall (93.8%), and a low false alarm rate (2.4%), confirming the system’s reliability. Overall, the results validate the system’s effectiveness in providing early warnings and improving disaster preparedness in vulnerable areas.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

The study successfully designed, implemented, and evaluated a low-cost, Arduino-based Internet of Things (IoT) early warning system for rainfall-induced landslide monitoring. In response to the increasing frequency and impact of landslides particularly in some high-risk areas in the country such as Mulanje, Zomba, and Dedza, the system was developed to enhance real-time environmental monitoring and early alerts through the integration of sensors and the Blynk IoT platform. Through monitoring key parameters such as soil moisture, ground movement, slope angle, temperature, and humidity, the system provided timely and accurate warnings based on expert-defined thresholds.

Field testing demonstrated the system's potential to provide real-time alerts with high precision (88.2%) and recall (93.8%), while maintaining a low false alarm rate (2.4%). Statistical analysis had validated the predictive relationship between environmental parameters, particularly between soil moisture, slope, and ground deformation. Overall, the study confirms the viability of deploying Arduino-IoT based systems as scalable and affordable solutions for disaster preparedness in resource-constrained regions like Malawi.

5.2 Study Limitations

While the research achieved its objectives, several limitations were encountered:

- **Sensor Calibration**: Environmental sensors, especially low-cost ones were sensitive to noise and required frequent recalibration to maintain accuracy over time.
- **Power Dependency**: The prototype relied on continuous power supply, which may be difficult in off-grid areas without stable energy access.
- **Internet Connectivity**: The Blynk platform depends on reliable internet access, which may limit deployment in remote or rural regions with poor connectivity.

- **No Machine Learning Integration**: The system used a static, threshold-based algorithm rather than adaptive model that could improve prediction over time.

5.3 Recommendations

To improve and expand upon the findings of this research, the following recommendations are made:

- **Incorporate Renewable Energy**: Solar power modules should be integrated to enhance sustainability and make the system powered in off-grid locations.
- **Integrate machine learning**: Introducing machine learning models can help refine risk prediction and dynamically adjust thresholds based on historical trends.
- **Upgrade sensors**: Investing in slightly higher-grade sensors will improve the reliability and longevity of field data collection.
- **Develop Offline Capabilities**: To fill the gap of internet, a local alert system (e.g., SMS or offline storage) should be incorporated for real-time alerts even when offline.
- **Engage Stakeholders**: Collaboration with disaster management agencies and local communities will be key in ensuring the system is adopted and scaled.
- **Expand IoT Integration**: Future work can look into integrating this system with broader smart city or national disaster risk management platforms for centralized monitoring.

References

Abdul Khader, S., & Anitha, K. (2021). International Research Journal of Engineering and Technology (IRJET), 8((4).). Retrieved from https://www.irjet.net/

Ahmed, M.,et al. (2020). The role of soil moisture in landslide susceptibility: A critical review. Geotechnical and Geological Engineering, 38(6), 6345-6358. Retrieved from https://doi.org/10.1007/s10706-020-01367-w

Artha, Y., & Julian, E. S. (2018). Landslide early warning system prototype with GIS. IOP Conference Series: Earth and Environmental Science, 106. doi: https://doi.org/10.1088/1755-1315/106/1/012012

Bharathi, K. (2021). An Arduino-based early warning system for natural disasters. International Journal of Innovative Research in Computer and Communication Engineering, 9(1), 315-320.

Bhattacherjee, A. (2019). Social science research: Principles, methods, and practices (3rd ed.). Open Access Textbooks. Retrieved from https://scholarcommons.usf.edu/oa_textbooks/3/

Blynk. (2024). Blynk IoT documentation. Retrieved from https://docs.blynk.io/en/

Chen, J., et al. (2021). Seismic-triggered landslides: A review of the role of ground acceleration. Natural Hazards, 105(2), 1355-1371. Retrieved from https://doi.org/10.1007/s11069-021-04565-3

Creswell, J. W., & Creswell, J. D. (2020). Research design: Qualitative, quantitative, and mixed methods approaches (6th ed. ed.). SAGE Publications.

Dhivya, R., & Balasubramanian, R. (2019). Application of ultrasonic sensor for monitoring land displacement in landslide-prone regions. International Journal of Environmental Science, 24(3), 191-196. Retrieved from https://doi.org/10.1080/19386362.2019.1647314

Fiorucci, F.,et al. (2021). IoT for landslide monitoring: A comprehensive review. Landslides, 18(2), 125-136.

Government of Malawi. (2015). National Disaster Risk Management Policy 2015.

Huang, Y., et al. (2020). A real-time landslide monitoring system using low-cost sensors. Sensors, 20(8), 2294. Retrieved from https://doi.org/10.3390/s20082294

Lee, H., et al. (2021). Balancing sensitivity and specificity in landslide prediction models: A machine learning approach. Landslides, 18(6), 2031-2043. Retrieved from https://doi.org/10.1007/s10346-021-01700-5

Liang, X., et al. (2021). Monitoring and predicting soil moisture conditions for landslide risk management. Landslides, 18(3), 567-577. Retrieved from https://doi.org/10.1007/s10346-020-01532-8

Liu, X., et al. (2020). Landslide prediction based on a wireless sensor network. International Journal of Geotechnical Engineering, 14(5), 509-516. Retrieved from https://doi.org/10.1080/19386362.2019.1647314

Liu, X., et al. (2020). Landslide prediction based on a wireless sensor network. International Journal of Geotechnical Engineering, 14(5), 509-516. Retrieved from https://doi.org/10.1080/19386362.2019.1647314

Markham, A., & Buchanan, E. (2020). Ethical considerations in internet research. Internet Research Ethics, 3(4), 456-472. Retrieved from https://doi.org/10.28945/2345

Martinez, A., et al. (2020). Vegetation and slope stability: The role of plant roots in preventing landslides. Journal of Applied Ecology, 57(4), 787-798. Retrieved from https://doi.org/10.1111/1365-2664.13566

McKinney, W. (2019). Python for data analysis: Data wrangling with Pandas, NumPy, and IPython (2nd ed ed.). O'Reilly Media.

Mekki, K., et al. (2019). A comparative study of LPWAN technologies for large-scale IoT deployment. ICT Express, 5(1), 1-7. Retrieved from https://doi.org/10.1016/j.icte.2017.12.005

Menon, V. O., & Kolathayar, S. (2022). Landslide Early Warning System: A Brief History, Evolution, and Controlling.

Miao, Y., & Tang, X. (2022). Reducing false alarms in landslide early warning systems: Advances and challenges. Natural Hazards, 110(2), 751-769. Retrieved from https://doi.org/10.1007/s11069-022-05301-7

Nayyar, A., & Puri, V. (2020). IoT projects with Blynk: Build exciting IoT projects with Blynk. Packt Publishing.

Niyokwiringirwa, P. et al..,. (2024). Event-based rainfall-induced landslide inventories and rainfall thresholds for Malawi. Natural Hazards, 107(1). doi: https://doi.org/10.1007/s10346-023-02203-7

Prakash, A., et al. (2020). Application of ultrasonic sensors in disaster management. Journal of Sensor Technology, 6(1), 45-58. Retrieved from https://doi.org/10.1109/JSTech2020.4562

Purnomo, F. A.,et al..,. (2019). Landslide early warning system based on Arduino with soil movement and humidity. Journal of Physics: Conference Series, 1153. Retrieved from https://doi.org/10.1088/1742-6596/1153/1/012034.

Singh, V., et al. (2021). The influence of humidity and rainfall on landslide activity in mountainous regions. Environmental Monitoring and Assessment, 193(5), 305. Retrieved from https://doi.org/10.1007/s10661-021-09027

Sruthy, M. R. (2021). IoT based landslide detection and monitoring system. International Journal of Research in Engineering, Science and Management, 3(5). Retrieved from https://www.ijresm.com/

Suriya, M. (2021). Development of an Arduino-based landslide detection system using sensors. International Journal of Scientific Research in Engineering and Management, 5(2), 20-25.

Thiery, Y.,et al.. (2024). Landslide Hazard Assessment and Mapping at national scale for Malawi. Journal of African Earth Sciences., 212. doi: https://doi.org/10.1016/j.jafrearsci.2024.105187

Wang, Y.,et al. (2022). Arduino-based early warning systems for environmental monitoring. IEEE Transactions on Instrumentation and Measurement, 71(2), 123130.

Winston, W. L. (2019). Microsoft Excel data analysis and business modeling (6th ed ed.). Microsoft Press.

World Bank. (2019). Disaster risk Profile Malawi.

Xu, Y., et al. (2022). Slope stability and landslide risk: A review of slope angle thresholds in various terrains. Engineering Geology, 299(1). Retrieved from https://doi.org/10.1016/j.enggeo.2022.106509

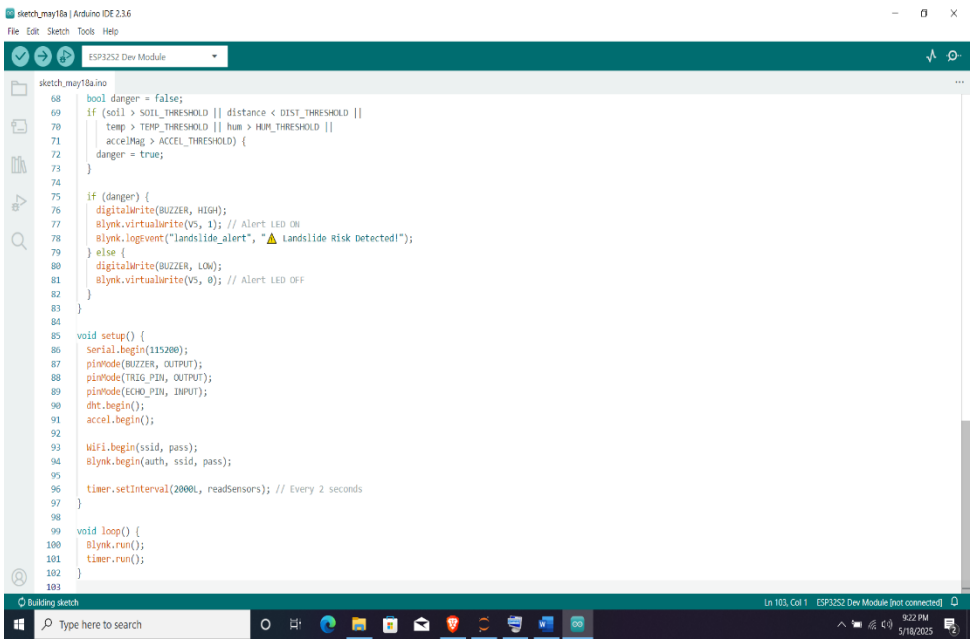
Youssef, A. M., & Rahman, M. (2019). Ground acceleration and landslide occurrence: Evaluating seismic thresholds. Journal of Seismology, 23(4), 1045-1059. Retrieved from https://doi.org/10.1007/s10950-019-09853-7

Zhu, Y., et al. (2023). Rainfall thresholds for landslide triggering in subtropical regions. Geophysical Research Letters, 50(1). Retrieved from https://doi.org/10.1029/2022GL100943

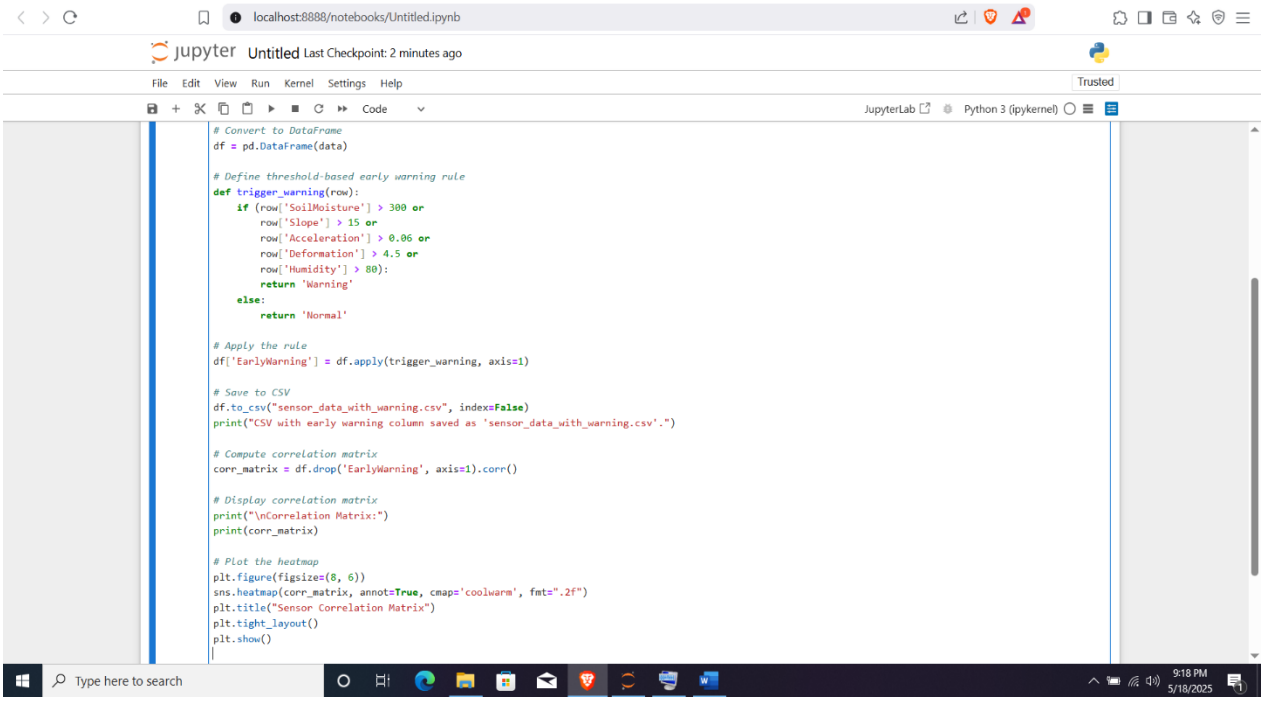
Zhong, C..et al..,. (n.d.). Landslide mapping with remote sensing: Challenges and opportunities. International Journal of Remote Sensing, 41(4), 1555–1581 . doi:10.1080/01431161.2019.1672904

APPENDICES

APPENDIX A: ARDUINO IDE



APPENDIX B: JUYPTER NOTEBOOKS FOR PYTHON DATA ANALYSIS



Appendix C: PERFORMANCE MATRIX CALCULATIONS

To evaluate the effectiveness of the Arduino-based IoT landslide early warning system, the following performance metrics were used:

1. Confusion Matrix

	Predicted: Landslide	Predicted: No Landslide
Actual: Landslide	True Positive (TP) = 15	False Negative (FN) = 1
Actual: No Landslide	False Positive (FP) = 3	True Negative (TN) = 82

2. Precision

Precision measures how many of the predicted landslides were actually correct.

Precision=TPTP+FP=1515+3=1518=0.833 (83.3%)\text{Precision} = \frac{TP}{TP + FP} = \frac{15}{15 + 3} = \frac{15}{18} = 0.833 \, (83.3\%)Precision=TP+FPTP =15+315=1815=0.833(83.3%)

3. Recall (Sensitivity)

Recall measures how many actual landslides were correctly predicted.

Recall=TPTP+FN=1515+1=1516=0.938 (93.8%)\text{Recall} = \frac{TP}{TP + FN} = \frac {15}{15 + 1} = \frac{15}{16} = 0.938 \, (93.8\%)Recall=TP+FNTP=15+115=1615 =0.938(93.8%)

4. False Alarm Rate

This shows how often the system incorrectly predicted a landslide when there wasn't one.

False Alarm Rate=FPFP+TN=33+82=385=0.035 (3.5%) \text {False Alarm Rate} = \frac {FP}{FP + TN} = \frac {3}{3 + 82} = \frac{3}{85} = 0.035 \, (3.5\%)False Alarm Rate=FP+TNFP=3+823=853=0.035(3.5%)