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Final Report for ALDOT Project 931-054

MONITORING AND ASSESSMENT OF LANDSLIDES ALONG ALABAMA HIGHWAYS

Submitted to

The Alabama Department of Transportation

Prepared by

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16. **Abstract**

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ABSTRACT

Rainfall-induced landslides are a common occurrence along Alabama highways leading to significant damage to infrastructure and disruption to traffic. There are no current approaches in use to predict when these slides are likely to occur, which limits the ability of ALDOT personnel to respond or intervene. This study developed a monitoring and assessment program for landslides along Alabama highways with the goal of increasing the usability of current monitoring data and to provide approaches to predict when slopes are likely to move. This study explored different monitoring options and deployed automated monitoring tools at two high priority landslide sites in Alabama. In addition to monitoring at these sites, different options for monitoring deformations were tested during a large-scale experiment at the Advanced Structural Engineering Laboratory. A database of landslide events in Alabama was developed using historical inclinometer data provided by ALDOT. This database was compared with precipitation and soil moisture data to understand both patterns of landslide triggering and to develop a geotechnical health monitoring plan that can provide warnings when movements are likely to occur at unstable sites. The findings from this work highlight the importance of monitoring data to understand landslide movements and have identified thresholds that can be used to both assess areas where landslides are likely to have occurred following large storm events and to provide warnings of potential movements at landslide sites using forecast data. This report documents available options for landslide monitoring, findings from monitoring of two landslide sites, a comparison of the processed inclinometer database with previously published thresholds for landslide triggering, and development of a geotechnical health monitoring plan that can provide warnings when unstable movements are likely to occur. Recommendations for implementing this research into ALDOT practice are discussed, along with areas for future research.

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1 Introduction

1.1 Background

Rainfall-induced landslides are a common occurrence in many parts of Alabama (Montgomery et al. 2019). When landslides occur along highways they can lead to significant damage to infrastructure and disruption to traffic. Designing effective repairs for a landslide requires an understanding of the failure mechanisms and soil properties (Duncan, Wright, and Brandon 2014). While in-situ and laboratory testing can be used to assess soil strengths, monitoring is often used to understand the failure mechanism that is leading to movements at unstable sites. This typically includes placing inclinometers, to measure lateral deformation, and piezometers, to measure groundwater levels, at key locations around the site. Readings are then taken at regular intervals to identify patterns of movement and fluctuations in the water table. This process can be very labor intensive, especially if readings need to be taken on a daily or weekly basis.

Automated landslide monitoring and alert systems have been developed for many areas across the world. These systems rely on both local instrument-based monitoring and remote sensing-based measurements. Common types of local monitoring include inclinometers, shape arrays, pore pressure transducers, soil moisture sensors, tilt sensors, surveys, and rain gauges. These measurements provide important data on the response of the landslide over time to different types of loading. Remote sensing tools are also used to assess landslide risk at a larger scale and include tools such as rainfall monitoring, soil moisture estimates, and aerial surveys (e.g., uncrewed aerial vehicles or UAVs, LiDAR). The measurements collected from both local monitoring and remote sensing data are then often integrated to identify thresholds that may indicate a landslide is likely to occur. This can be done for individual sites, large regions, or even globally (e.g, D. Kirschbaum and T. Stanley 2018). These thresholds are then used to issue warnings to stakeholders.

Monitoring precipitation at landslide sites is critical to be able to identify when movements are likely to occur. Installing and maintaining rain gauges at each monitoring site may not be feasible, but free, publicly available gridded precipitation data may be adequate for monitoring. High resolution (0.25°x0.25°) data are available in real time that are based on remote sensing, interpolation of data from rain gauges, and reanalysis of multiple data sources (e.g., National Center for Environmental Prediction Reanalysis). One disadvantage of these regional datasets is they may not accurately capture intense, localized precipitation events. However, a prior analysis of previous precipitation-induced landslides in Alabama indicates that most are caused by tropical depressions or other large storm systems (Montgomery et al. 2019), which last for several days and produce rainfall over a large area.

The objective of this study was to develop a monitoring and assessment program for landslides along Alabama highways. The goal of this work was to increase the usability of monitoring data collected by ALDOT and to allow for continuous monitoring of high-priority landslides to quickly identify problems and prioritize interventions or repairs. This study explored different montioring options and deployed automated monitoring tools at two high priority landslide sites. In addition to monitoring at the these sites, different options for monitoring deformations were tested during a large-scale experiment at the Advanced Structural Engineering Laboratory. A database of landslide events in Alabama was developed using historical inclinometer data provided by ALDOT. This database was compared with precipitation and soil moisture data to understand both patterns of landslide triggering and to develop a geotechnical health monitoring plan that can provide warnings when movements are likely to occur at unstable sites.

The findings from this work highlight the importance of monitoring data to understand landslide movements and have identified thresholds that can be used to both assess areas where landslides are likely to have occurred and to provide warnings of potential movements at landslide sites. This report documents available options for landslide monitoring, findings from instrumentation installation and monitoring of two landslide sites, a comparison of the processed inclinometer database with previously published thresholds for landslide triggering, and development of a geotechnical health monitoring plan that can provide warnings when unstable movements are likely to occur. Recommendations for implementing this research into current ALDOT practice are discussed. Topics related to this study that could benefit from future research are also discussed.

1.2 Project Objectives

The overall purpose of this research was to develop a geotechnical health monitoring program that can be implemented at landslide sites along Alabama highways. This was accomplished by identifying instrumentation options that can be used to monitor landslide sites, creating tools to store and analyze monitoring data, and creating a system to identify regions where slopes are likely to become unstable in order to prioritize interventions. Specific objectives for this project include:

1. Collect detailed information on landslide monitoring technologies.
2. Evaluate benefits and drawbacks of selected monitoring technologies and deploy instrumentation at two landslide sites.
3. Develop tools to collect and display monitoring data from current and future landslide sites.
4. Evaluate relationships between precipitation and landslide movements using previously collected landslide databases and remote sensing data.
5. Develop guidance for ALDOT on implementation of geotechnical health monitoring and assessment for unstable slopes.

1.3 Scope of Work

The following tasks were performed to accomplish the research objectives of this project:

- Task 1: Complete a detailed review of landslide monitoring technologies with a focus on low cost and low maintenance options
- Task 2: Develop a web-based data portal to collect and display monitoring data from current and future landslide sites

- Task 3: Evaluate selected instrumentation through experiments and trial deployments in the field
- Task 4: Implement the monitoring program at two high-priority landslide sites
- Task 5: Create a condition assessment approach for landslide sites and warning thresholds to alert for potential movements

2 Review of Landslide Monitoring Options

2.1 Introduction

Monitoring of slopes along highways can involve a wide range of objectives such as: (1) monitoring changes in behavior and assessing performance, (2) acquiring parameters for design purposes, (3) implementing early warning systems, (4) risk management, (5) understanding failure mechanisms and triggering factors, and (6) evaluating new instrumentation options (Smethurst et al. 2017). Once unstable slopes have been identified, monitoring is critical for identifying where movements are occurring and assessing changes that may signal an imminent larger failure. Current monitoring approaches often rely on manual measurements of displacement, groundwater elevation, and climate variables, such as precipitation. Periodic readings of inclinometers and observation wells are common landslide monitoring strategies (Smethurst et al. 2017) and are used extensively by ALDOT. However, this process is labor intensive and may not provide data frequently enough to clearly recognize changes in behavior. An alternative approach is to employ infrastructure health monitoring, which leverages data collected from multiple sensors to assess the condition of critical infrastructure in near real time. This is a new approach for geotechnical monitoring. More work is needed to identify which data are most critical to catching failures before they occur and develop techniques to present and utilize large amounts of data in a way that is meaningful and useful for decision makers (Uhlemann et al. 2016). Auflič et al. 2023 categorized some of the landslide monitoring techniques from studying 75 recorded landslides between 2005 and 2021 from Euro- GeoSurveys as shown in Figure 1. It is worth noting that a comprehensive approach to landslide monitoring includes both movement and environmental factors in order to relate movement events to their triggering mechanisms such as rainfall, temperature, and soil moisture content (Uhlemann et al. 2016). In selecting the options for implementing a monitoring plan, it is ideal to have high resolution, low cost, ease of data processing, and high durability (Smethurst et al. 2017), but it is rare to be able to meet all of these objectives. Some of the main monitoring techniques used for landslides are discussed in this chapter.

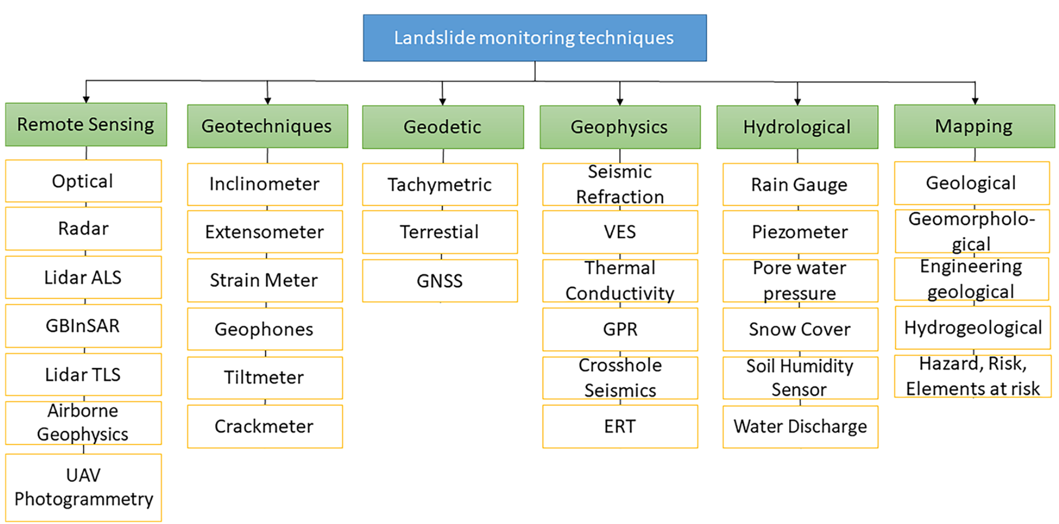

Figure 1: Landslide monitoring options (Auflič et al. 2023).

2.2 Monitoring Options for Landslide Sites

Landslide monitoring is essential for understanding and mitigating potential hazards. Geotechnical methods are the primary and most common techniques used for landslide detection, with sensors installed on the surface or in subsurface boreholes, providing data either periodically or continuously. Geodetic methods monitor the movement of specific points, with techniques like terrestrial laser scanning (TLS) and photogrammetry being widely used for landslide detection. Hydrological parameters, such as precipitation, groundwater levels, and pore water pressure, are key to predicting landslides and defining thresholds. These measurements can be taken periodically or continuously, contributing to more accurate forecasting. Choosing the appropriate landslide monitoring approach depends on the landslide's characteristics, site-specific conditions, and the acceptable level of risk or damage.

2.2.1 Inclinometers

Inclinometers are extensively utilized for subsurface movement monitoring, particularly in landslide-prone areas. They are primarily employed to quantify the magnitude and rate of displacement and to identify the depth of the movement zone (Dunnicliff J. 1982). The standard inclinometer setup typically comprises a measuring probe, a cable, a guide tube, and a readout device. The probe is equipped with two wheels at each end, facilitating smooth movement along two sets of tracking grooves in the casing (Sombathy, Mendes, and Q. Huang 2021). The groove maintains the orientation of the probe along the casing and the casings are often oriented so that the A direction of the casing aligns with the maximum movement, while the B direction is orthogonal. The probe carries a gravity-sensing transducer. As shown in figure 2 the probe measures the inclination angle. The absolute inclination of the casing can be calculated by multiplying each part length of L by the sine of the inclination angle as shown in the following equation, n is the number of parts along the casing (Stark and Choi 2008):

$$\text{Total deflection} = \sum_{i=1}^{n} \sin(\theta_i)(L_i)$$

Over time, inclinometer technology has advanced considerably. Recent innovations in Micro-Electro-Mechanical Systems (MEMS) have resulted in cost-effective, highly precise alternatives to traditional, expensive commercial systems. Additionally, there are fixed in-place inclinometers, which, although less commonly used due to their higher cost, offer continuous and high-temporal resolution data. Inclinometers are the first instrumentation option in unstable slopes as the movement type, direction, and magnitude can be observed even before the movements reach the ground surface. However, their performance depends on proper casing installation, careful data collection, and accurate data processing. For example, it is crucial to fix the bottom of the inclinometer below the slide plane to obtain reliable data. Two common approaches for calculating horizontal movement are differential movement, which is the difference between two consecutive readings, and accumulative movement, which is the difference of each reading with respect to the bottom of the inclinometer.

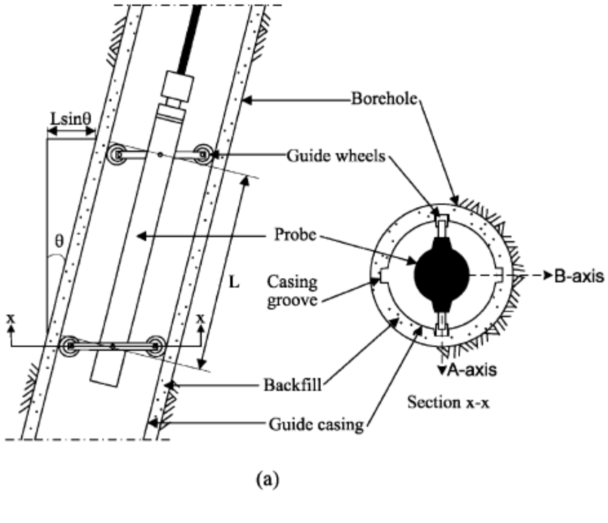

Figure 2: Schematic diagram of (a) Inclinometer equipment (b)Principle of inclinometer operation (Stark and Choi 2008).

2.2.2 Tilt Sensors

Tilt sensors provide the same type of data as inclinometers but can have significantly greater precision depending on the model. Unlike inclinometers, tilt sensors provide the changes in inclination at a single point either on the ground surface or within a borehole (García, Hördt, and Fabian 2010). However, real-time monitoring and high temporal resolution can be achieved with these low-cost and easy to install sensors. High-resolution data from tilt meters has been shown to be effective at detecting rainfall-triggered landslides in previous studies (e.g., Uhlemann et al. 2016 and Qiao et al. 2020). However, tilt sensors are more effective in detecting rotational movements than translational movements (Auflič et al. 2023) and can be affected by environmental noise, such as vibrations from traffic or machinery and changes in temperature. Very high resolution tilt sensors commonly employ an electrolytic sensor which produces an output voltage proportional to the sensor's tilt angle relative to gravity. As shown in Figure 3, when the sensor is inclined, the conductivity between electrodes a and c will be greater than between electrodes c and b (J. H. Lee and S. S. Lee 2011).

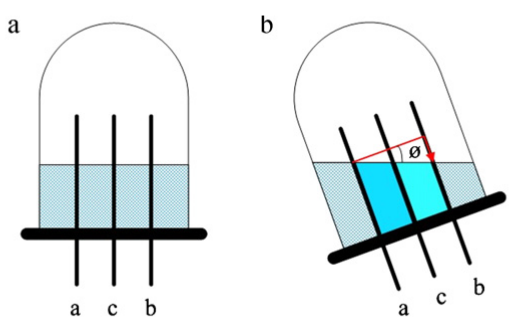

Figure 3: Electrolytic tilt sensor mechanism: (a) Before tilt and (b) In the state of tilt (J. H. Lee and S. S. Lee 2011).

With the development of MEMS technology, accelerometer-based tilt sensors have become more common. These sensors can be manufactured in smaller and lighter models (Wang et al. 2022) than traditional tilt sensors and are commonly available at a significantly lower cost. These sensors work by measuring changes in the orientation of the gravity vector over time and are therefore effective at detecting large changes in tilt, but can be affected by other sources of acceleration, such as vibration.

2.2.3 Extensiometer

Extensiometers are low-cost tools that can measure relative displacements of two points. The base point should be located in a stable area to measure the displacement of unstable regions. Extensoimeters can be installed either in boreholes or on the ground surface (Auflič et al. 2023). Figure 4 shows a chain of extensiometers connected by extension rods and equipped with displacement transducers. Extensiometers are less commonly used for landslide monitoring than inclinometers.

Figure 4: Slope Extensiometers used to measure strains in a large area (https://sisgeo.com/).

2.2.4 Vibration Monitoring

Recent studies have indicated that landslide monitoring can be performed by deploying acoustic emission (AE) monitoring systems with waveguides. An active waveguide consists of a steel tube installed within a pre-drilled borehole, with the annular space between the tube and the borehole wall backfilled with granular materials, such as gravel or sand. When slope movement occurs, high-energy AE signals are generated from the interaction of the tube and the granular backfill and are transmitted through the steel tube to the ground surface (Figure 5). The key advantage of this system is its ability to provide near real-time alarms of landslide movement with high sensitivity at a low cost. However, the waveguide must be deeper than the potential shear zone and the movements must be significant enough to generate AE that can be detected over the ambient noise in the area (Dixon et al. 2018; Smethurst et al. 2017; Uhlemann et al. 2016). Alarms from these systems can be in the form of SMS messages, emails, or website updates. This technique is likely to be effective for monitoring shallow landslides in quiet areas, but unlikely to work along highways where slide planes can be several meters deep and ambient vibrations are significant.

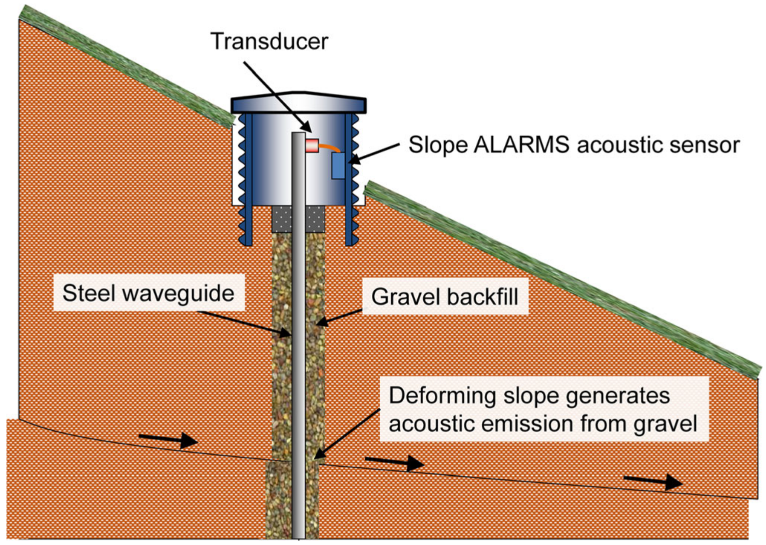

Figure 5: AE monitoring system using an active waveguide (Dixon et al. 2018).

2.2.5 Fiber optics

Fiber optic sensing using Distributed Acoustic Sensing (DAS) is a recent advancement in vibration-based landslide monitoring. DAS measures vibrations by analyzing changes in the properties of light traveling through a fiber optic cable. Unlike AE technology, DAS does not face limitations related to high-frequency elastic waves, making it a valuable tool for monitoring landslides (Longoni et al. 2022). Fiber optic cables can also be used as strain or displacement sensors (e.g.,Iten, Puzrin, and Schmid 2008, Zheng et al. 2018) to determine landslide movements. These can provide very high resolution data, but the equipment required to carry out the measurements is still prohibitively expensive for routine landslide monitoring.

2.2.6 Water Level Sensors

A rising water table generates positive pore water pressure, which can trigger shallow landslides. The simplest and most common method for monitoring water levels involves automatic or manual measurement of groundwater using a water level logger, piezometer, or measuring tape in observation wells and boreholes (Dunnicliff J. 1982). Several relatively low cost options are available for continuously recording water levels, including devices from Onset and Van Essen instruments that were used in this study (described in Chapter 3). Integrating water level sensors with other monitoring devices and communication technologies can provide good data to assist with landslide predictions and early warnings, but the data must be collected often enough to understand fluctuations over time.

2.2.7 Pore Pressure Transducers

Pore water pressure is most likely the first indicator of failure in many slopes. Instability is often triggered by changes in effective stress, which are caused by increases in pore water pressure (Duncan, Wright, and Brandon 2014). Therefore, monitoring pore water pressures using various types of piezometers or buried pore pressure transducers is common practice in landslide monitoring (Smethurst et al. 2017). Depending on the application, various types of sensors are used, ranging from those operating with hydraulic and pneumatic pressure to those utilizing vibrating wire technology. Field monitoring should be automated and include a sufficient number of measurement points to accurately capture the transient pore-water pressure profiles resulting from heavy rainfall (A. B. Huang et al. 2012). Multi-point vibrating wire piezometers measure pore water pressure in multiple borehole points with a single cable.

2.2.8 Water Content Sensors

Soil water content data can improve the predictability of landslides. Dielectric measurements, resistivity measurements, and neutron scattering techniques are commonly used in water content sensors. These sensors can provide near real-time and continuous measurements of soil moisture. Certain sensors determine dielectric permittivity of the soil, which changes with its water content, by measuring the travel time of electromagnetic waves propagating through the soil. (Bittelli 2011). Resistivity-based sensors measure the electrical conductivity of the soil, which is directly related to the moisture content if the ion content in the soil is constant. Figure 6 illustrates some of the commercial sensors for measuring the water content of soil by measuring dielectric permittivity. Sensors 1 to 4 are Frequency Domain Reflectometry (FDR). Sensors 5 to 7 are Transmission Line Oscillation (TLO), consisting of two parallel rods that shape a transmission line. Sensors 8 to 11 are Time Domain Reflectometry (TDR), and sensor 12 is Time Domain Transmissometry (TDT) which is a technique analogous to TDR (Ferrarezi, Nogueira, and Zepeda 2020).

Figure 6: Different types of commercial soil moisture sensors(Ferrarezi, Nogueira, and Zepeda 2020).

2.2.9 Suction Sensors

All water movement in unsaturated soils is directly dependent on soil water tension, as water in both soils and on surfaces naturally moves from areas of higher potential to areas of lower potential. The majority of soil water flows occur at low water tensions, and only tensiometers allow for the direct and precise measurement of these small tensions in water. These sensors work by allowing the water in the soil to make contact with the water in a tensiometer through a porous ceramic material, which is permeable to water. This wetted porous ceramic creates an optimal pore/water interface, allowing the soil water tension to be directly transmitted to a pressure transducer, which provides a continuous signal (https://www.metergroup.com/). As soil becomes saturated due to heavy rainfall, the water tension measured by the tensiometer decreases indicating high water content. A rapid decrease in tension may indicate the loss of strength of soil (Godt, Baum, and Lu 2009). These sensors can provide direct measurements of soil suction, but often have a slow response time and are very prone to desaturation of the porous ceramic. While very useful for lab testing and carefully controlled field monitoring, they are not as useful for the sites in this study.

2.2.10 Shape Array

The ShapeArray is a type of in-place inclinometer that consists of rigid stainless steel segments connected by flexible joints that allow movement. Each rigid segment is equipped with three MEMS accelerometers capable of measuring along three axes. Similar to inclinometers, the tilt of each segment, when multiplied by its length, provides the displacement. The resolution of a ShapeArray can be changed by adding or removing segments and when equipped with automated data collection, these devices can provide continuous measurements of deformations. ShapeArrays should be installed in vertical boreholes for landslide monitoring. Their high accuracy (0.02 mm/day) and high temporal resolution make them an excellent choice for monitoring landslides (Yan et al. 2021), but the high cost and data processing requirements limit their applicability to high priority sites.

Fig 7 shows a diagram of a deployed shape array and tilt angle relative to gravity in a triaxial accelerometer.

2.3 Remote Sensing Data for Landslide Monitoring

Assessing the risk of landslides over a large region using manual and in-situ measurements is both costly and time-consuming. Satellite-based data and other sources of gridded data products are now commonly available and can provide both high temporal and spatial resolution compared to ground-based measurements for landslide monitoring. Remote sensing technologies can provide critical data for tracking surface deformations, changes in land cover, and hydrological parameters, such as soil moisture and precipitation, which are essential for evaluating landslide prediction. While this is an area of active research, some of the key accomplishments in this area are reviewed here.

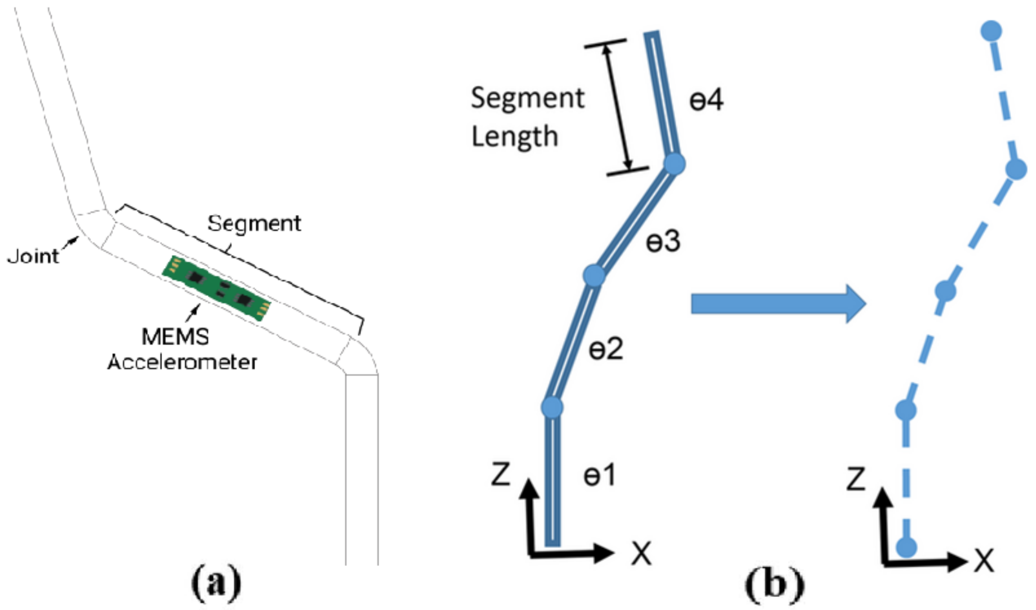

Figure 7: (a) A schematic illustration of a sensorized segments and joints. (b) Tilt angles and positions for a multi-segment shape array (https://www.measurand.com/).

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2.3.1 Satellite-based Displacement Monitoring

Creating landslide inventories through land surveying is often time-consuming, costly, and challenging. In recent decades, advanced remote sensing methods have been developed to assess land conditions and monitor landslides more efficiently. Techniques such as Light Detection and Ranging (LiDAR), Interferometric Synthetic Aperture Radar (InSAR), and Differential SAR Interferometry (DInSAR) have been employed to monitor displacements over large areas, providing valuable data for landslide assessment and early warning systems (Ray, Jacobs, and Cosh 2010).

2.3.2 Precipitation

Traditional rainfall gauges are limited to point measurements and may not cover large or remote areas. Using high-resolution satellite data and data products that assimilated satellite data with ground-based measurements provide continuous rainfall data sources over wide regions, improving the ability to predict landslide risks in areas lacking ground-based data. When selecting an appropriate precipitation product, several factors must be considered, including the available period of data, temporal resolution, spatial resolution, and the agreement between ground-based measurements and the satellite product. As example, the tropical Rainfall Measuring Mission (TRMM) satellite, a joint mission between NASA and the Japanese Aerospace Exploration Agency (JAXA), provides rainfall measurements from November 1997 to March 2015 at varying temporal and spatial scales. After TRMM, the Global Precipitation Mission (GPM), also developed by NASA and JAXA, began in 2015, offering more detailed rainfall estimates with higher spatial resolution (10 km^2) and a temporal resolution ranging from half-hourly to monthly (Chikalamo et al. 2020).

2.3.3 Soil Moisture

In the last decade, advancements in remote sensing for soil moisture retrieval have been significant (Brocca et al. 2012; Skulovich and Gentine 2023; T. A. Stanley et al. 2021). The Soil Moisture and Ocean Salinity (SMOS) mission by the European Space Agency (ESA) use a microwave sensor and the Soil Moisture Active and Passive (SMAP) mission by NASA combines radar and radiometer sensors to to provide direct measurements of soil moisture content in the top five cm of soil. These near-surface measurements are used within a land surface model to provide an estimate of soil moisture at greater depths. Other microwave sensors have also provided accurate soil moisture data, including the Advanced Scatterometer (ASCAT) on MetOp-A and MetOp-B satellites, and the Advanced Microwave Scanning Radiometer (AMSR-E) and AMSR2 aboard Aqua and GCOM-W1 satellites (Brocca et al. 2012).

2.4 Landslide Warning Approaches

Landslide Early Warning Systems (LEWS) are gaining increasing attention due to their cost-effectiveness in protecting lives and property from landslide hazards. The primary aim of these systems is to alert responsible individuals and organizations so that preventive measures can be taken promptly, reducing the risk of severe damage. One of the key components of LEWS is the use of precipitation thresholds, which serve as indicators for potential landslide events based on rainfall intensity and duration. These thresholds are widely utilized in both regional and global landslide monitoring systems. (Fang et al. 2023; Guzzetti, Gariano, et al. 2020; Pecoraro, Calvello, and Piciullo 2019). An efficient Landslide Early Warning System (LEWS) must accurately identify triggering and non-triggering factors of landslides and integrate the key parameters that influence these events. Hydrological factors, such as rainfall, soil moisture, groundwater levels, and pore water pressure, are often dominant triggers. It is essential to gather data for these parameters from the best available datasets, such as high-resolution satellite measurements and ground-based sensors, to improve the precision and reliability of the system. For issuing alert levels in a LEWS, it is critical to evaluate multiple parameters that contribute to slope instability. Among these, displacement is a key indicator of ongoing ground movement, while weather parameters like precipitation and antecedent rainfall are essential in assessing climate-triggered landslides. The integration of these factors enhances the reliability of warnings. Another important aspect of a LEWS is the lead time, which is the interval between when a warning is issued and the expected time of the forecasted landslide event. This interval is crucial, as it determines how much time responsible organizations, authorities, and affected individuals have to act in order to mitigate or reduce the potential damages (Pecoraro, Calvello, and Piciullo 2019).

2.4.1 Precipitation Threshold-based Warning Approaches

LEWS commonly depend on establishing thresholds differentiating landslide events from non-landslide events (Conrad et al. 2021). Detailed information including topography, geology, and soil characteristics is often difficult to obtain for regions susceptible to landslides and it can vary significantly within a single study area. Consequently, predicting the likelihood of landslide occurrence has typically relied on analyzing past rainfall events that have led to landslides using factors like the mean rainfall intensity (I), rainfall duration (D), and/or cumulative rainfall (E) from a storm event (e.g, Guzzetti, Peruccacci, et al. 2008).

2.4.2 Global Landslide Warning Approaches

One of the initial attempts to develop a global landslide threshold was done by Guzzetti, Peruccacci, et al. 2008. They listed internationally developed thresholds prior to 2008 and suggested a new global landslide threshold. D. B. Kirschbaum et al. 2010 developed the Global Landslide Catalog (GLC), an online database that tracks rainfall-triggered landslides from 2007 to the present by conducting a systematic inventory of landslides. By integrating satellite-based precipitation estimates from the Global Precipitation Measurement (GPM) mission with a landslide susceptibility map, they have provided a near-global, satellite-based platform that delivers a near real-time warning system for landslides across the globe. The advantage of the global landslide warning is the ability to forecast landslides in areas that lack sufficient information on landslide inventories and regional studies.

2.4.3 Instrument-based Warning Approaches

Instrument-based warning systems for landslides are designed to monitor and assess the stability of slopes through a network of various ground sensors. These sensors gather crucial data to detect potential landslide events and issue timely warnings. The network typically includes a combination of geotechnical, meteorological, and geodetic measurements (Pecoraro, Calvello, and Piciullo 2019). Traditional field observations, while valuable, are limited in their ability to detect real-time changes in landslide activity. Such readings are often taken periodically, which means they may miss critical shifts when they occur. Moreover, active landslides can pose significant safety risks to personnel, especially during storms or heavy rainfall, when movement is more likely, and visibility is reduced. Data gathering could not be done under these circumstances which are crucial for landslide predictions. This reflects the importance of a near real-time monitoring approach in instrument-based warning systems. Ground-based remote monitoring systems include more than just field sensors. They typically consist of data acquisition units to record sensor measurements. The system relies on remote telemetry (such as radio, satellite, or cell phone links) for transmitting data. While there may be a slight delay in updating the data—typically from minutes to hours—the term "near-real-time monitoring" is used to describe this system, which still reflects field conditions accurately enough to support decision-making in almost real-time (Reid et al. 2012).

3 Instrumentation Testing and Deployment

3.1 Introduction

One of the objectives of this research project was to evaluate different types of instruments available for slope monitoring and to compare results between instruments and with remote sensing data, such as those reviewed in Chapter 2. To accomplish this objective, instruments were deployed at two sites with a history of slope movements and in different tests conducted at Auburn University. This chapter describes the selected locations for the testing and presents comparisons between the instruments.

3.2 Selected Sites

The two sites selected for detailed monitoring are located on SR-219 near Centreville and SR-35 near Section and are shown in Figure 8. The location of the Laceys Spring landslide on US-231 is also shown for reference. The two sites were selected in consultation with ALDOT personnel in order to find locations where additional instrumentation was likely to be valuable for future slope stability studies and where there was historical data for comparisons. Each of the sites is described below followed by a discussion of the results of the monitoring completed so far. Monitoring of these sites will continue beyond this project.

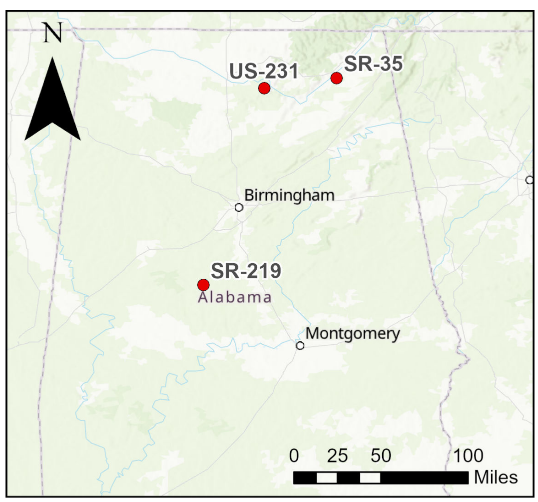


Figure 8: Locations of the two sites (SR-219 and SR-35) selected for monitoring in this study and the location of the US-231 landslide.

3.2.1 SR-35 near Section, AL

The first site selected for monitoring in this study is a an area of continuing instability on SR-35 in Jackson County (Figure 9). Movements at this location have occurred on a regular basis for many years and are impacting lanes in both directions

Figure 9: Location of monitored site on SR-35 in Jackson County, north of Section, AL.

(a)

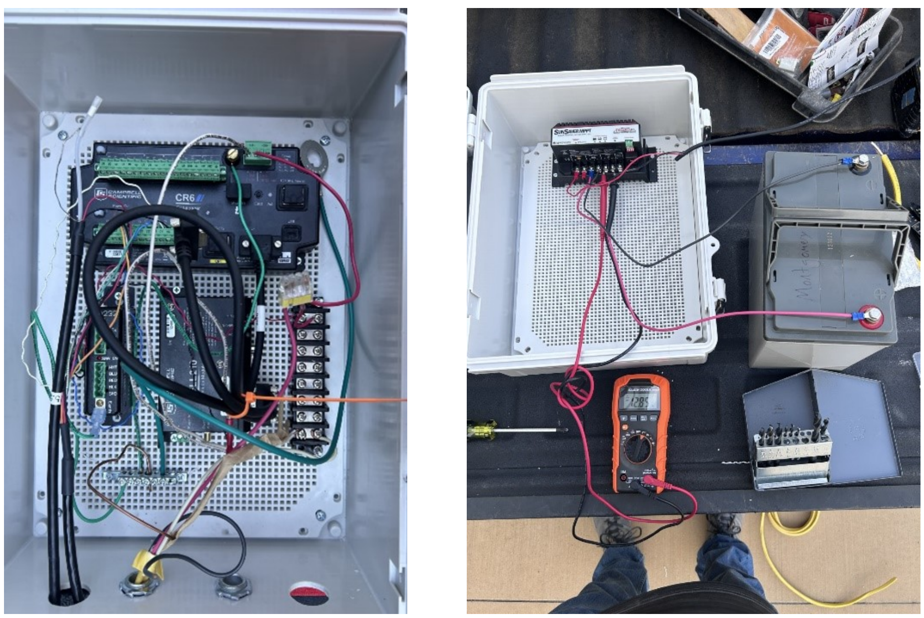
(b)

Figure 10: Photos from the monitored site on SR-35 in Jackson County, north of Section, AL. Figure a (facing northeast) shows a vertical offset in the roadway, where the scarp of the slide likely crosses the highway, and the drainage ditch on the south side of the road. Figure b shows the location of original instrumentation along the southbound guardrail.

(Figure 10a). Prior to this study, the site was monitored with inclinometers and monitoring wells (Figure 10b), but they were read by hand, which limits the amount of data collected and requires lane closures to collect data.

The monitored site on SR-35 is located near the contact between the Pottsville and Pennington formations (Szabo et al. 1988), which is the same as the large landslide that occurred on US-231 near Lacey Springs in 2020 (Xuan et al. 2023). This geologic environment consists of shale, limestone, sandstone, and mudstone and slope stability problems in the Pottsville formation are common (Montgomery et al. 2019).

The research team evaluated the site and decided to install a rain gauge (Campbell TE525) to capture precipitation, a water level sensor to monitor one of the observation wells, a soil moisture sensor (Campbell CS655) to compare with the remote sensing based measurements of soil moisture, and a ShapeArray (Measurand) to monitor one of the inclinometer casings. Given the difficulty with manual readings in this location, a data logger (Campbell CR6) with a cellular modem (CELL210) was selected to record and transmit the data at the site. The required power for the sensors and data logger is provided by a 55 amp-hour AGM battery coupled with a 30 watt solar panel (SolarTech). A SunSaver solar controller (SS-MPPT-15L) was used to manage charging of the battery. Both the data logger and battery were placed in plastic cases (Figure 11) mounted to a wood post, while the rain gauge and cellular antenna were mounted to a metal pole adjacent to the wood post. The final configuration of the monitoring system is shown in Figure 12 and photos from installation are shown in Figure 13.



(a) (b)

Figure 11: Photos of the wiring and configuration of the (a) data logger and cellular modem and (b) the battery and solar controller used at SR-35.

3.2.2 SR-219 near Centreville, AL

The second site selected for monitoring is along SR-219 in Bibb County near Centreville, Alabama. Figure 14 shows a map of the site with the locations of geophysical surveys that were conducted by Auburn University 2019 and boreholes that had been previously drilled by ALDOT. Locations B1 - B4 have inclinometers and wells, while B5 has a well and no inclinometer. A slow moving landslide was reported on the west side of the road in 2010 and has continued moving since that time. Cracking in the road suggests that the scarp of the landslide intercepts line R1 at the ground surface at

Figure 12: Photo of the finished monitoring station at SR-35 near Section, AL. The rain gauge and cellular antenna are shown on the left, while the datalogger housing and solar panel are shown on the right with the graduate students from Auburn.

(a) (b)

Figure 13: Photos of the instrument installation process at SR-35, including (a) Stephanie Abbett (ALDOT) assisting with wiring of the water level sensor and (b) installation of the ShapeArray.

approximately X=43 feet and continues past B4.

The landslide site lies within the mapped portion of the Gordo formation of the Tuscaloosa group (Szabo et al. 1988), although it is close to the boundary of the Gordo and Coker formation, which typically underlies the Gordo formation. The Gordo formation consists of massive beds of cross-bedded sand, gravelly sand, and lenticular beds of locally carbonaceous partly mottled moderate-red and pale-red-purple clay. The lower part of the Gordo formation is predominantly a gravelly sand consisting chiefly of chert and quartz pebbles The Coker formation consists of micaceous sand and clay with a few thin gravel beds containing quartz and chert pebbles (Szabo et al. 1988).

The research team evaluated the site and decided to install a rain gauge (Onset RG3) to capture precipitation and multiple water level sensors in the existing wells (TD Diver). Cellular reception at this location is limited, so a manual data collection strategy was used with each instrument having a built-in datalogger. The manually read data loggers are less expensive than cellular-connected loggers and can be effective at sites that are regularly visited and have easy access. One of the challenges with deploying water level loggers was the use of 1" monitoring wells at both sites, while most of the standard water level loggers are meant for wells with inside diameters of 1.5" or 2". Using larger diameter wells would reduce the cost and increase the number of options available for water level loggers. Photos from installation are shown in Figure 15.

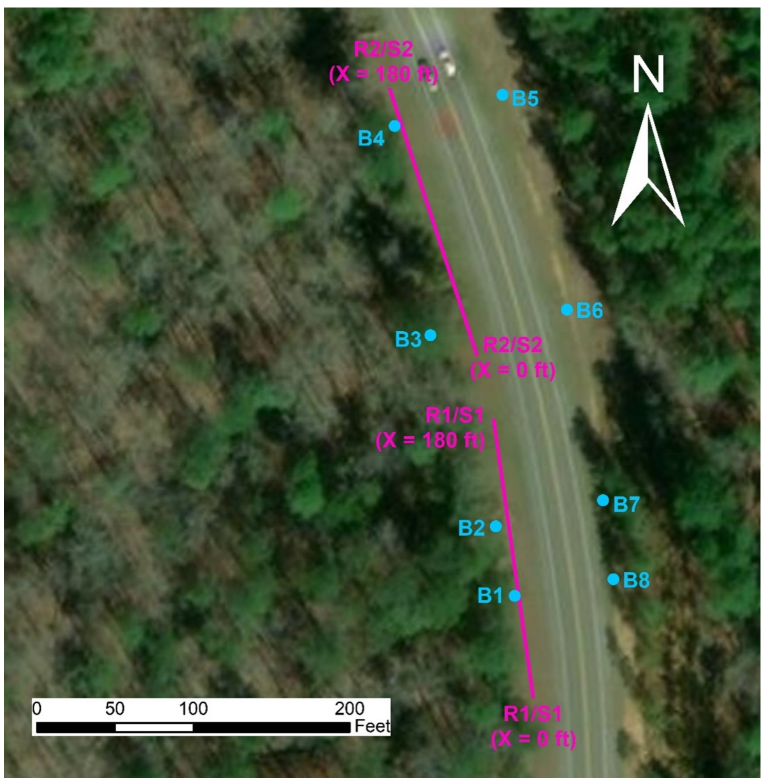


Figure 14: Location of monitored site on SR-219 in Bibb County, south of Centreville, AL.

3.3 Monitoring Data from SR-35

Monitoring of SR-35 began in October 2023. The recorded data from SR-35 is shown in Figure 16. The water level logger at the site has not shown any water in the well and so data from that sensor is not included. The Shape Array has shown

(a) (b)

Figure 15: Photos from SR-219 in Bibb County, south of Centreville, AL showing (a) installation of the rain gauge and (b) installation of one of the water level sensors in an existing observation well.

no significant movement at the site with the largest change in displacement occurring in March 2024 following a relatively large one day storm. The movements are still very small (smaller than would be detected with a traditional inclinometer) and the storm fell below the warning thresholds being developed for this study (discussed in Chapter 4). The soil moisture sensor showed significant variations in soil moisture with storm events, but unfortunately stopped working in February 2024. The fluctuations were consistent with remote sensing-based measurements and so the team decided that replacing the sensor was not required.

The monitoring data up to this point has not shown any significant movement or high groundwater, so it is difficult to draw conclusions regarding the reliability or effectiveness of the instrumentation from this data alone. It is clear that the ShapeArray is able to detect much smaller movements than would be possible with traditional inclinometers, which gives hope that it will be able to provide advance warning of any potential slide. The reasons for not observing any water in the well are unclear at this time, but previous well readings at this site also showed dry conditions most of the time. It is recommended that monitoring of this instrumentation continue to compare with other observations at the site.

3.4 Monitoring Data from SR-219

Monitoring of SR-219 began in March 2023. Figure 17 shows the results from the water level loggers installed at SR-219 compared with rainfall at the site. The water level loggers have shown a very rapid response to rainfall along with a seasonal pattern of lowering water levels that begins in the spring and continues through the summer. This is consistent with expected patterns for Alabama. The rain gauge data has largely been consistent with the remote sensing-based observations in pattern, but having the site-specific data provides much more detailed measurements.

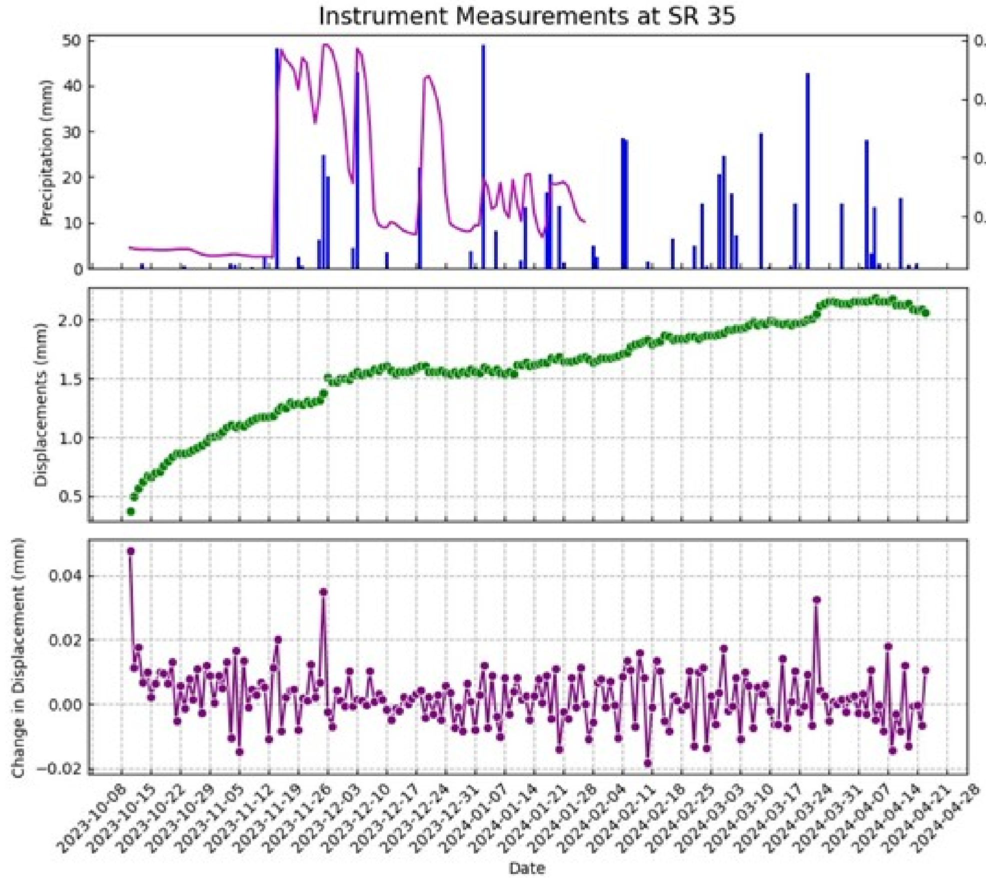


Figure 16: Data recorded at SR-35 during 2023 and 2024 from the rain gauge, soil moisture sensor, and Shape Array. The water level logger has not shown any water in the monitored well.

No significant movements have occurred at SR-219 during the monitoring period, so conclusions cannot be drawn relating the water level observations with the patterns of movement. One key observation from this site is that the rapid rise and fall in water levels in response to rainfall cannot be observed with quarterly readings of wells. Deploying sensors like the TD Diver is relatively easy and inexpensive and can provide much more detailed information on water level fluctuations at site. The TD Diver has a built-in data logger, so although data can be recorded multiple times per day, it can be downloaded quarterly or even on longer intervals. This allows for flexibility in data collection, while still obtaining good resolution with time.

3.5 Additional Instrumentation Testing at Auburn University

The instruments deployed at the two sites have provided good data on current conditions, but without a significant landslide event it is difficult to draw conclusions about the ability of these devices to monitor instability. To supplement the field deployments, several tests were conducted at Auburn University to evaluate the ability of different sensors to detect movements. This testing include shake table tests to evaluate accelerometers, standpipe tests to evaluate water level log-

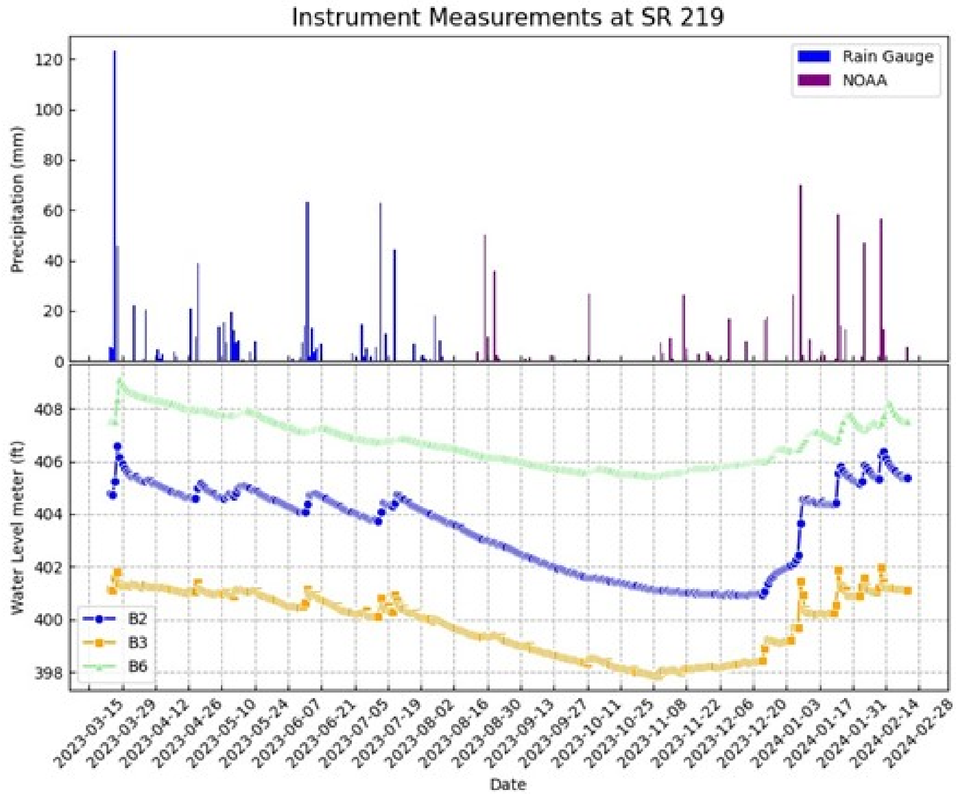


Figure 17: Data recorded at SR-219 during 2023 and 2024 from the rain gauge and water level loggers.

gers, slope tests to evaluate soil moisture sensors and tilt sensors, and monitoring of internal deformations in a full-scale mechanically stabilized earth (MSE) wall (Okafor 2024). Many of the tests were used to select instruments for deployment and to refine designs of data collection and processing approaches and did not include quantitative comparisons of performance. An exception to this is the MSE wall test, which was used to compare displacment measurements from a shape array with traditional inclinometer readings and automated tilt measurements. The results from the instrumented MSE wall are described below.

3.5.1 Instrumented MSE Wall

A full-scale MSE wall was constructed and tested (Figure 18) for a separate ALDOT project at the Advanced Structural Engineering Laboratory (ASEL) at Auburn University in May 2023 and is described by Okafor 2024. As part of this test, one of the ShapeArrays purchased for this project and three tilt sensors were installed on the MSE wall (Figure 19). The casings for the ShapeArray and inclinomenter were installed next to each other with about 150 mm spacing in between. Both casings were positioned at 0.6 m from the back of the facing panels into the reinforced mass (Figure 20). One of the tilt sensors was buried in the backfill in front of the inclinometer casings (Figure 19). The other two tilt sensors were placed near the face of the wall with one on the facing panel (exposed to the air) and one buried in the backfill right beyond the panel. The testing process involved deflating bags in the foundation to simulate settlement and then surcharging the wall with sand bags and then large concrete beams. After the end of the test, the wall was disassembled in stages.

Figure 18: Photo showing the MSE wall at the end of load testing with all imposed surcharge loads (Okafor 2024).

(a) (b)

Figure 19: Photos from the MSE wall testing in the geotechnical chamber at ASEL showing (a) completed installation of a ShapeArray next to a traditional inclinometer casing and (b) the tilt sensor placed adjacent to the two inclinometer casings before being buried.

Figure 21 compares the ShapeArray results and the traditional inclinometer readings. Two ShapeArray lines are shown to demonstrate the effect of including a correction for settlement of the array in the casing. The corrected data (solid line in Figure 21) is in better agreement with the inclinometer readings and shows the importance of including this correction, especially for small displacements. The magnitudes of displacement were very small with the maximum value of about 1 mm. This is far smaller than can be reliably detected with a traditional inclinometer in the field, but it gives additional confidence in the reliability of the very small displacements being measured at SR-35 (Figure 16).

Figure 22 shows the results from two of the tilt sensors during the testing phase. Both of these sensors were buried,

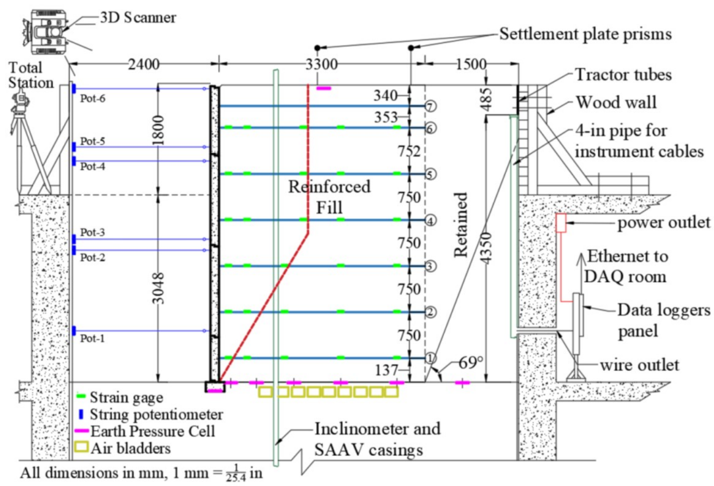


Figure 20: Cross-section showing instrument locations within the test MSE wall (Okafor 2024).

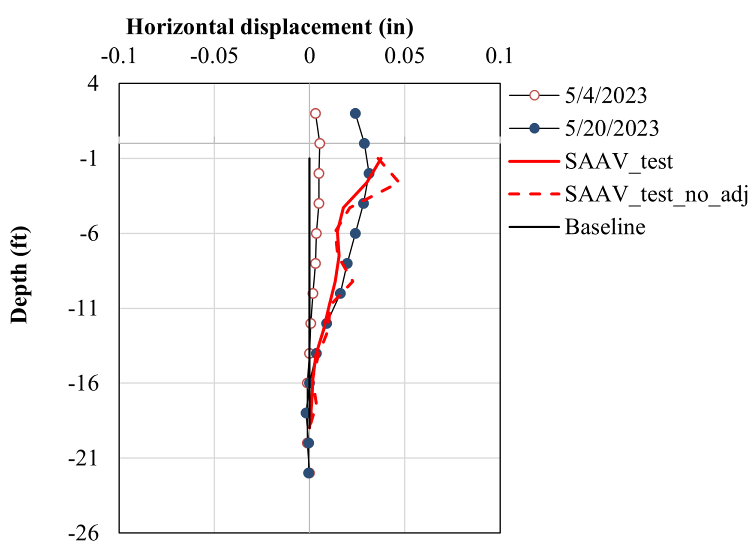


Figure 21: Change in displacement of the inclinometer casings as measured using traditional inclinometers (dots) before and after the testing of the MSE wall compared with the ShapeArray with and without corrections for settlement of the array in the casing.

but at different locations in the backfill. Sensor 12156 was buried right in front of the inclinometer casing, while 0E90D was buried right behind one of the MSE panels. A third sensor was placed on one of the wall panels, but the data from this sensor was too noisy to see any clear trends. Several lines are shown in Figure 22 to demonstrate milestones in the testing.

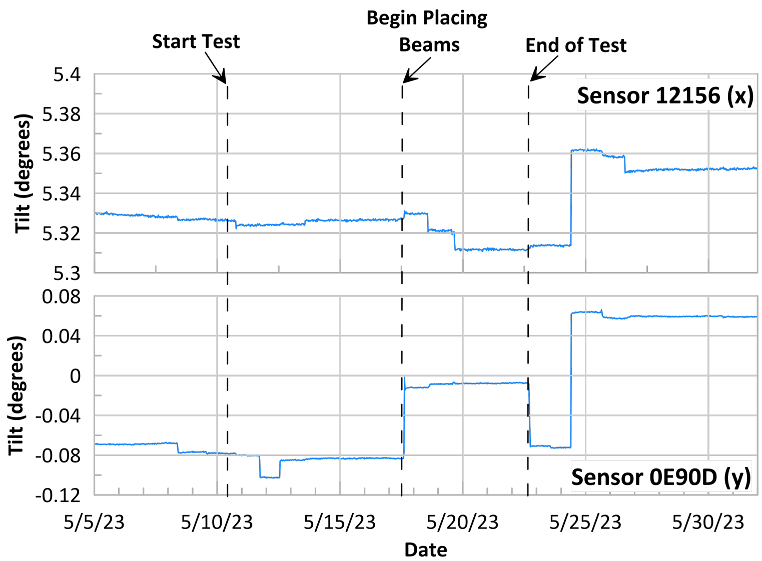


Figure 22: Comparison of tilt sensor measurements for two of the buried sensors with significant milestones in the MSE wall testing program. Details of the testing program are provided by Okafor 2024.

The tilt sensors showed very small changes in tilt during the testing phase (0.02 degrees for 12156 and 0.07 degrees for 0E90D). This small change means that even low levels of noise (people walking near the sensor or temperature fluctuations) can make the data difficult to interpret. The buried sensors were less susceptible to these influences and so burying the sensors in the field is highly recommended. Sensor 12156 was directly in front of the inclinometer casing and so the tilt results can be compared with the inclinometers. Taking the 0.02 degrees of tilt and assuming using the height of the moving mass is approximately 14 feet (Figure 20), gives 0.059 inches of displacement, which is very consistent with the final inclinometer readings. Sensor 0E90D indicates larger displacements, but was located closer to the wall. Okafor 2024 found that facing displacements were less than 1 mm (0.04 inches), so the tilt sensor may be overestimating the movement of the wall or the simple conversion of tilt to displacement is not accurate for this case.

Overall, the testing results demonstrate that both the tilt sensors and the ShapeArray are performing very well under controlled conditions. The results from the sensors are comparable with those from traditional inclinometers, assuming proper corrections are made. The testing did show that the tilt sensors should be buried to reduce noise and do not give direct measurements of displacements. It is important to note that the MSE wall remained stable during the testing, so these comparisons are only for very small displacements.

3.6 Summary

Different options for instrumenting unstable slopes were examined and applied to two high priority landslide sites located on SR-35 near Section, AL and SR-219 near Centreville, AL. In addition, testing was performed at Auburn University to evaluate and calibrate each of the selected instruments and to compare results using a ShapeArray, traditional inclinometer, and tilt sensor in a test on a near full-scale MSE wall. The experimental results demonstrated that all of the sensors can perform well in a laboratory setting, but the tilt sensors were very sensitive to noise levels and were not used in a field deployment.

At SR-35, an automated data collection strategy was employed to monitor precipitation, groundwater level, and slope movement through a ShapeArray. The equipment was installed on the shoulder of the road and has not shown any significant movement or groundwater within the monitored observation well. Data collection will continue in order to assess the ability of the instruments to detect movements at this site.

At SR-219, a rain gauge and three water level loggers were deployed to record continuous measurements, but a manual data collection strategy was employed due to the limited cell service in this location. No significant movements have occurred at SR-219 during the monitoring period, so conclusions cannot be drawn relating the water level observations with the patterns of movement. One key observation from this site is that the rapid rise and fall in water levels in response to rainfall cannot be observed with quarterly readings of wells. It is antinicpated that this higher resolution data will allow for correlations to be drawn between observed movements and groundwater levels.

4 Triggering Thresholds for Landslide Sites using Precipitation and Soil Moisture

4.1 Introduction

Chapters 2 and 3 has highlighted some approaches that can be used for site-level monitoring, but fully instrumenting each potentially unstable slope is cost prohibitive. In addition, collecting readings from these instruments may require significant effort if sites are in remote areas without reliable cellular connections. This chapter explores whether remote sensing data, such as precipitation and soil moisture can be used to predict when landslides are likely to occur by focusing on triggering thresholds. These thresholds define a limit at which further precipitation is likely to lead to a landslide. Previous analyses of landslide triggering thresholds have primarily focused on large regional databases of landslides (e.g., D. B. Kirschbaum et al. 2010), but this study seeks to explore the use of ALDOT's inclinometer database to evaluate these thresholds specifically for use on Alabama highways.

4.2 Background

Precipitation intensity-duration (ID) thresholds are among the most common types used for landslide predictions, but multiple studies have highlighted limitations in the use of these thresholds, including many false positives. Bogaard and Greco 2018 and Segoni et al. 2018 described the absence of thorough hydro-meteorological analysis in empirically-based rainfall intensity-duration thresholds for landslide initiation. They discussed the theory that rainfall serves as the final "push" for initiating landslides, while other factors such as soil moisture, infiltration, storage, and drainage capacity play vital roles. Mirus et al. 2018 concluded that utilizing subsurface moisture conditions provides a more robust index for enhancing the precision of rainfall thresholds compared to cumulative antecedent rainfall. Several studies have considered proxies for the subsurface moisture and matric suction conditions in different forms to improve the typically empirical thresholds (Wicki et al. 2020) and reduce the number of false positive and true false negative points (Marino et al. 2019).

4.3 Landslide Database

Accurate and detailed landslide inventories are crucial for effective hazard assessment and mitigation strategies. However, compiling such inventories with precise temporal and spatial information poses significant challenges (D. B. Kirschbaum et al. 2010). In this study, the database was developed using inclinometer data provided by ALDOT. The ALDOT database consists of inclinometer readings obtained from areas that were previously identified as unstable and had inclinometers installed to determine the magnitude and depth of sliding. Quarterly or more frequent readings were conducted using digital inclinometer probes, resulting in a dataset comprised of 151 inclinometers from 33 sites.

Several sites were removed from the full database due to a lack of precise coordinates or inclinometers that were used to monitor something other than a landslide like a rockfall in Jackson County and a retaining wall in Franklin County. This reduced the database to 118 inclinometers located at 24 sites. In addition to inclinometer data, we utilized Detailed Damage Inspection Reports (DDIRs) submitted for emergency assistance from the Federal Highway Administration (FHWA) in this study to enhance the landslide inventory in Alabama (Knights, Montgomery, and Carcamo 2020). Figure 23 shows the spatial distribution of landslide site from two different databases in the study region. The red points indicate data collected from the inclinometer database, and the blue points indicate the landslide points from the emergency relief reports.

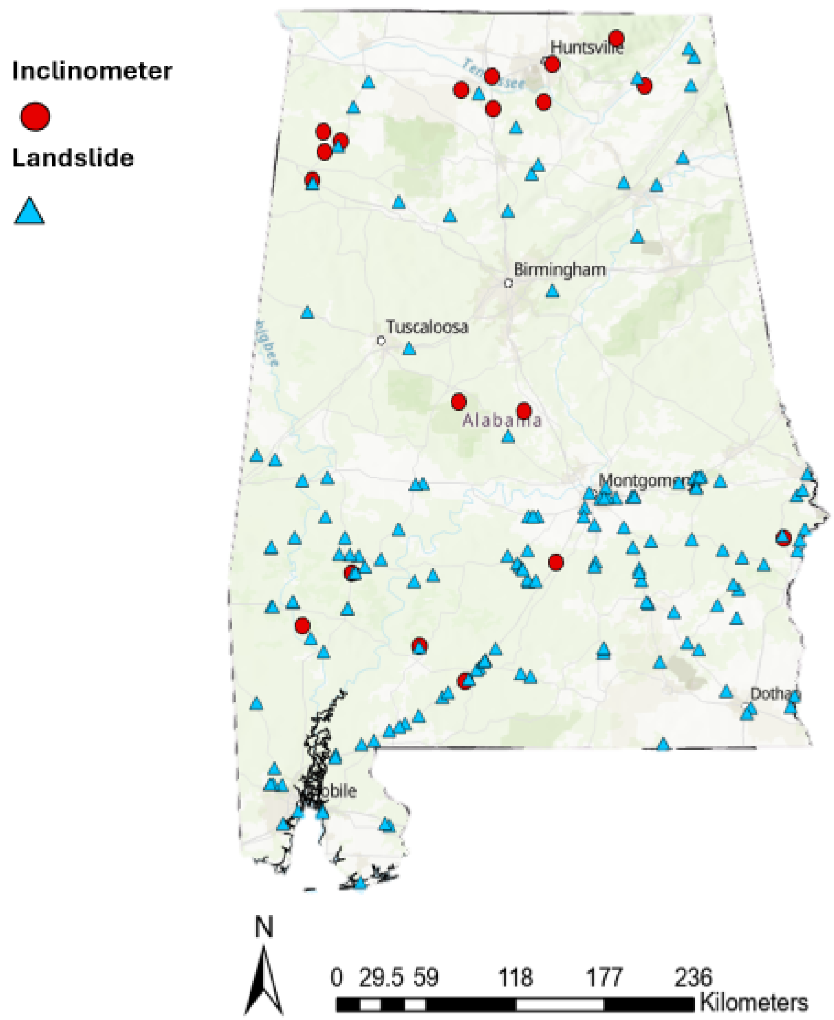


Figure 23: Spatial distribution of landslide sites from the processed inclinometer and emergency relief reports database.

4.3.1 Data Processing

An inclinometer monitors deformation perpendicular to the axis of the casing, offering a profile of subsurface horizontal deformation. The depth at which shear movement is detected by a slope inclinometer indicates the location of the failure surface. This is a critical measurement for understanding slope instability, as it helps to pinpoint the exact layer or zone where the ground is moving (Stark and Choi 2008). ALDOT utilized biaxial inclinometers at the sites considered in this study, which provide measurements in both the A- and B-directions every 2 ft (.61 m) for each reading date. Typically, the A-direction aligns with the direction of the maximum displacement. We extracted displacements along the inclinometer from DigiPro2 software (Durham Geo Slope Indicator) and created CSV files for processing.

Inclinometer readings are subject to various sources of errors, such as rotation errors of the sensor axis, errors in base readings, and variability in casing measurements near the ground surface. Mikkelsen 2003 reviewed the types of errors in inclinometer measurements and empirically estimated that the random error in inclinometer readings is approximately ±0.16 mm (±0.006 in) for an individual reading. This random error accumulates at a constant rate over the entire length of the casing. Therefore, the accumulated random error for a 30-meter (100 ft) casing with readings taken every 0.5 meters would be approximately +1.24 mm (0.049 in) at the top of the casing. Random errors cannot be detected and resolved. In contrast, systematic errors accumulate arithmetically along the casing. For the same example of the 30-meter (100 ft) casing with readings taken every 0.5 meters (1.64 ft), the systematic error, with an increment of 0.11 mm (0.036 in) for each individual reading, would be approximately 6.60 mm (0.26 in) at the top of the casing. Unlike random errors, systematic errors can be resolved if the source of the error is identified. One source of random error in the ALDOT inclinometer database was the erroneous readings at the base of the casing. We filtered erroneous readings by removing readings with significant changes in displacement (>2.5 mm) (>0.1 in) at the bottom of the casing. Furthermore, readings with spikes in displacement at a single depth without movement at other depths were assumed to be erronous and removed. Quantifying other sources of error can be more challenging.

The most common analysis for inclinometer data involves plotting the relative shape of the casing compared to its initial condition. These cumulative lateral deformation versus depth plots are used to identify potential slide planes (Machan and Bennett 2008). We generated cumulative lateral deformation versus depth plots for all dates in a single profile for each A-direction and B-direction using Python 3.10 libraries: pandas, NumPy, os, and matplotlib. These profiles were reviewed carefully to detect potential slide planes. Subsequently, we narrowed down the database to 60 inclinometers with identifiable slide planes to proceed with our analysis of 20 sites. The slide planes were categorized as either single planes at a specific depth or as multiple planes at various depths. Single planes were assumed to be no shallower than 10 ft (approximately 3 meters). Inclinometers that displayed irregularities suggesting errors with unknown sources were excluded from further analysis.

After filtering out potentially erroneous readings, casing displacements were extracted from the top of the slide plane. Instead of surface displacements, the displacements at the slide plane were utilized because they showed less variability throughout the readings. For defining the thresholds based on inclinometer movements, we plotted the cumulative distribution of the change in displacement at the top of the slide plane (Rahimikhameneh et al. 2024). Around half of the readings showed a change in displacement of less than 1mm (0.04 in), which likely falls within the instrument's measurement uncertainty. Conversely, 13% of readings exhibited displacements exceeding 5 mm (0.2 in). These thresholds are applied to differentiate between landslide events (change in displacement larger than 5 mm or 0.2 inches between two readings) and periods of no minimal movement (change in displacment smaller than 1 mm or 0.04 in between two readings). However, events with displacements between 1 and 5 mm (0.04 in and 0.2 in) pose a challenge: they could indicate small landslide events or be attributed to measurement errors. As no clear method exists to distinguish between these possibilities, such readings were excluded from this analysis.

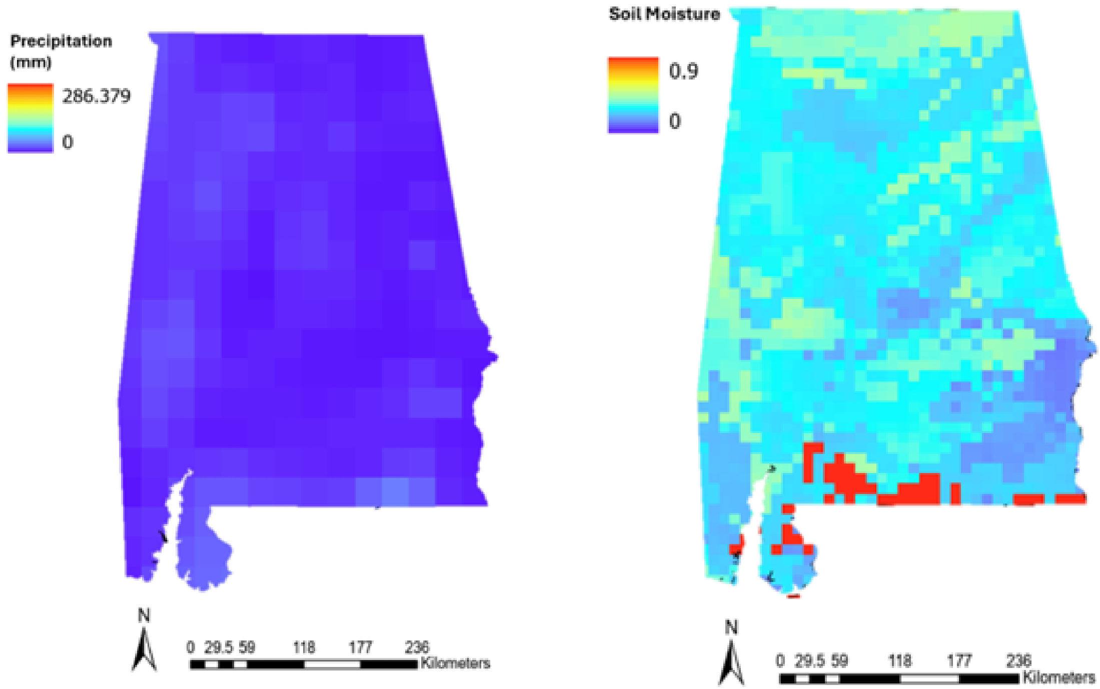
4.4 Methodology

The precipitation dataset used in this project is the CPC Unified Gauge-Based Analysis of Daily Precipitation over CONUS data provided by the NOAA PSL, Boulder, Colorado (https://psl.noaa.gov). The product has a coverage cell range of 28 km by 28 km. Daily precipitation from CPC NOAA was grouped into discrete storm events by using a rainy-day threshold of 1 mm (0.04 in), as is commonly used for ID threshold development (e.g., Leonarduzzi, Molnar, and McArdell 2017). In the process of creating the intensity-duration thresholds, following a common approach, the cumulative rainfall for each storm event was calculated and then divided by the number of days the storm persisted.

Soil moisture data from NASA Soil Moisture Active Passive (SMAP) (https://appeears.earthdatacloud.nasa.gov) were used for this project. The Level 4 product was used (Reichle et al. 2022), which has a 9-km by 9-km resolution. Specifically, this study used the root zone moisture, which represents a vertical average of soil moisture between 0 to 100 cm, as this was found to be the most applicable to shallow landslides by Marino et al. 2019. Note that this depth is far shallower than the range of slide planes at the sites in the database and the scale of the measurement (9-km by 9-km) means that it is more of a regional measurement of average wetness instead of a site-specific measure of volumetric water content. NASA SMAP data is available after March 31st, 2015. As an example, we extracted and presented CPS NOAA Precipitation and SMAP Soil Moisture data from January 3, 2020, in Figure 24 (a) and (b).

We used Python (v3.11) and ArcGIS Pro (v3.0, ESRI) for data processing. The lack of information on landslide initiation instances introduces uncertainty in distinguishing between triggering and non-triggering storm events. In our study, when a landslide event is detected between two inclinometer readings, we assumed the event with the largest cumulative precipitation triggered the landslide. The same assumptions were applied to the landslide database derived from emergency relief reports. In the latter database, the largest cumulative precipitation within a month before the occurrence of the landslide was considered as a landslide-triggering storm event. The intensity was calculated by dividing the cumulative precipitation by the duration of the storm. We did not normalize the rainfall intensity by mean annual precipitation, as annual precipitation remains relatively consistent across Alabama, ranging from 127 to 152 cm (50 to 60 inches) per year. The exception is the Mobile area, where precipitation levels differ; however, none of the studied sites are located in this region.

As previously mentioned, many sites had multiple installed inclinometers. Rather than analyzing each inclinometer independently, inclinometers at the same site were grouped to define a failure status for the entire site. Reading intervals where none of the inclinometers at a site recorded movements meeting the criteria for a landslide (change in displacement > 5 mm or 0.2 in.) were categorized as stable and each inclinometer was analyzed separately as a non-landslide point. When a landslide was detected in at least one inclinometer at each monitoring site, the entire site was categorized as landslide for that reading interval. An example of the classification of inclinometer readings into landslide and non-landslide intervals is shown in Figure 25 for landslide sites on SR-69 and SR-5. The inclinometer readings are also compared with precipitation



(a) (b)

Figure 24: Example of extracted data from January 3, 2020 showing (a) CPS NOAA Precipitation (mm in one day) and (b) SMAP Soil Moisture (volumetric moisture content). The Alabama boundary file was obtained from USGS (2023).

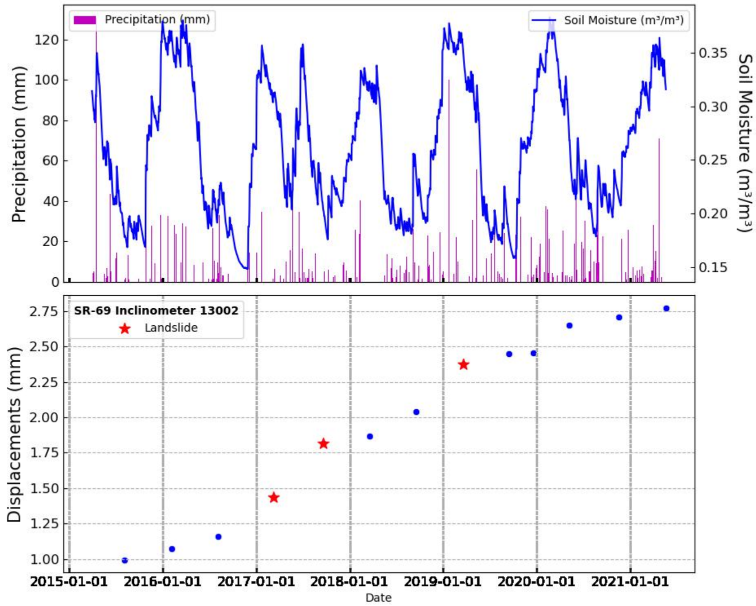
and soil moisture measurements at those locations.

We used the soil moisture measured by SMAP at each site at on the first day of the storm and divided it by the average soil moisture of that point between 2015 to 2021. This is referred to as the normalized soil moisture and represents an index of the moisture conditions in the vicinity of the slide area relative to the average conditions at that same location. A normalized soil moisture of 1.0 represents an average condition for that location, while a value less than 1.0 is drier than average and greater than 1.0 is wetter than average. This normalization was performed in order to compare soil moisture conditions across the state without having to deal with uncertainty related to the actual moisture values.

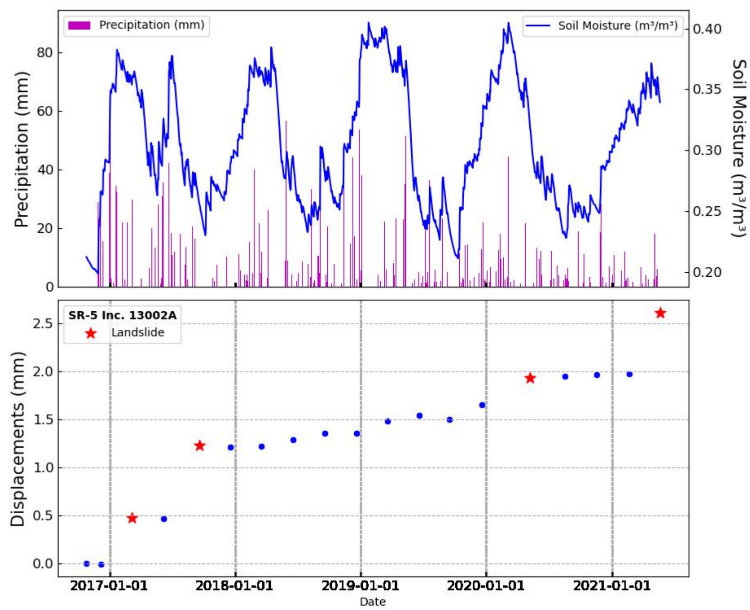
4.5 Results

The relationship between maximum accumulated rainfall, observed movements, and normalized soil moisture is shown in Figure 26 for landslide and non-landslide reading intervals. The landslide points are situated within the red box, characterized by changes in movements larger than 5mm or 0.2 in, while non-landslide points are found within the blue box, where changes in movements are less than 1mm or 0.04 in. Values falling between these two thresholds were excluded, as they were previously labeled as unknown events.

The data in Figure 26 shows significant scatter, but some approximate trends of both precipitation and soil moisture



(a)



(b)

Figure 25: Time series of inclinometer displacement (red star indicates landslide), daily rainfall (purple bars), and soil moisture (SMAP L4, blue line) for (a) SR-69 Inclinometer 13002 and (b) SR-5 Inclinometer 13002A.

and large movements can be observed.The average normalized moisture content for events with displacements greater than 5 mm (0.2 in) is 1.05, while the average value for events with displacements less than 1 mm (0.04 in) is 0.91. For movements greater than 20 mm (0.78 in), all but one point had above-average moisture contents (normalized value greater than 1.05). This is in line with the results presented by Bogaard and Greco 2018 and demonstrates the importance of soil moisture conditions in landslide triggering.

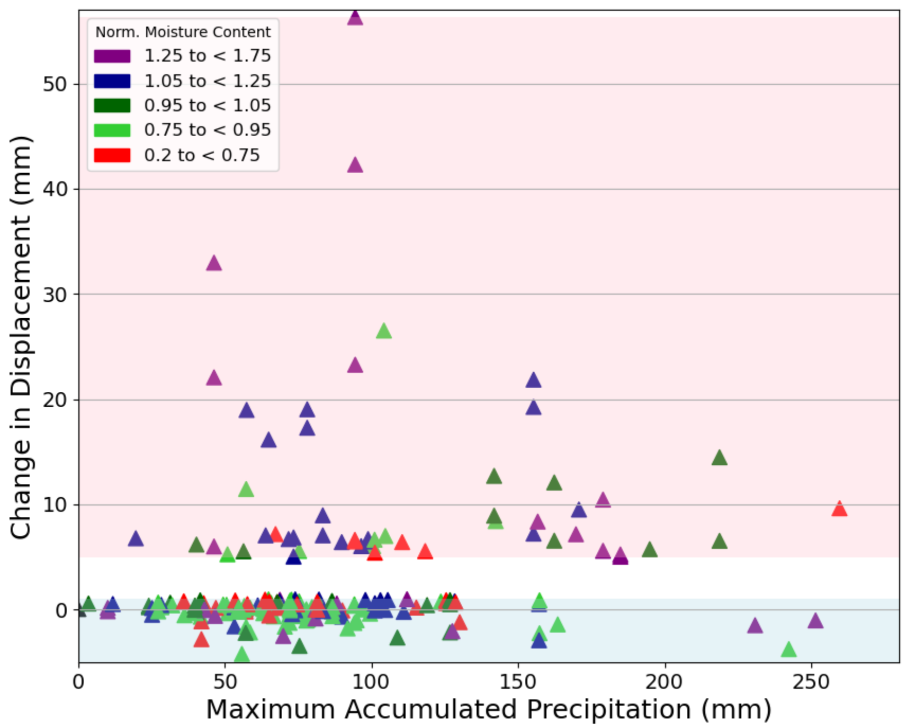


Figure 26: The relation between the maximum accumulated precipitation in a single storm and the change in displacement in the inclinometer over that reading interval is shown by the points. The color of the points represents the normalized soil moisture content at the start of the storm.

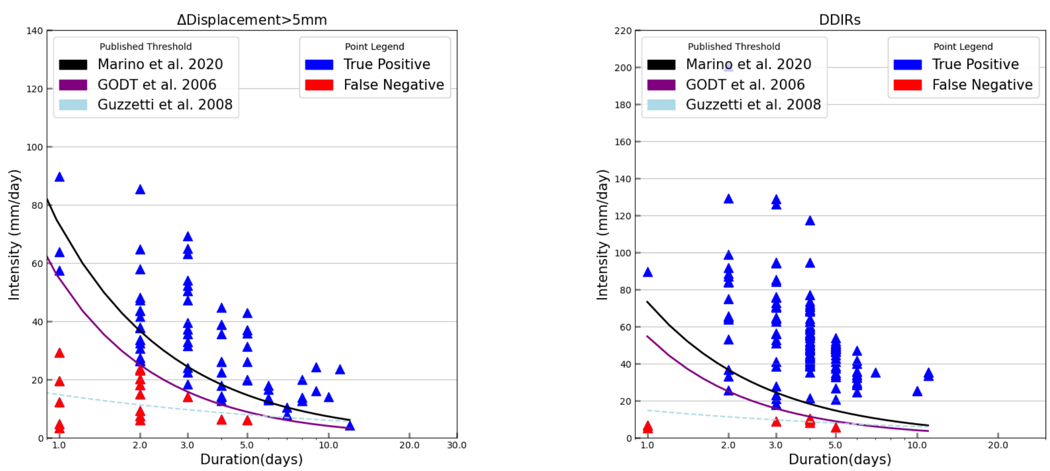
4.6 Comparison with Existing Triggering Thresholds

We conducted a comparison of storms that triggered landslides, utilizing data from the processed inclinometer database and emergency relief reports, against previously established thresholds by Godt, Baum, and Chleborad 2006;Guzzetti, Peruccacci, et al. 2008; Marino et al. 2019 to assess their accuracy for application across the state of Alabama. Figure 27(a) illustrates that the Godt, Baum, and Chleborad 2006 curve provides a good fit for predicting the majority of landslide points from the inclinometer data. Out of 84 points, 68 landslide points (blue color) were correctly predicted by the Godt, Baum, and Chleborad 2006 threshold, while 16 points (red color) fell below the curve indicating a false negative point. It is important to note that the role of normalized soil moisture in improving the prediction was not taken into account in this step, as the points belong to the entire database spanning from 2001 to 2021 and SMAP has data only after 2015.

Figure 27(b) illustrates the database of emergency relief reports compared with the previously established thresholds. The total number of landslide points derived from this database is 164. Of these, 132 landslide points were correctly predicted by the Godt, Baum, and Chleborad 2006 curve (blue points) while only 8 points were false negatives (red points). These points often have very low rainfall Intensity. Approximately 80% of the landslide events in both databases were correctly predicted by the Godt, Baum, and Chleborad 2006 threshold.

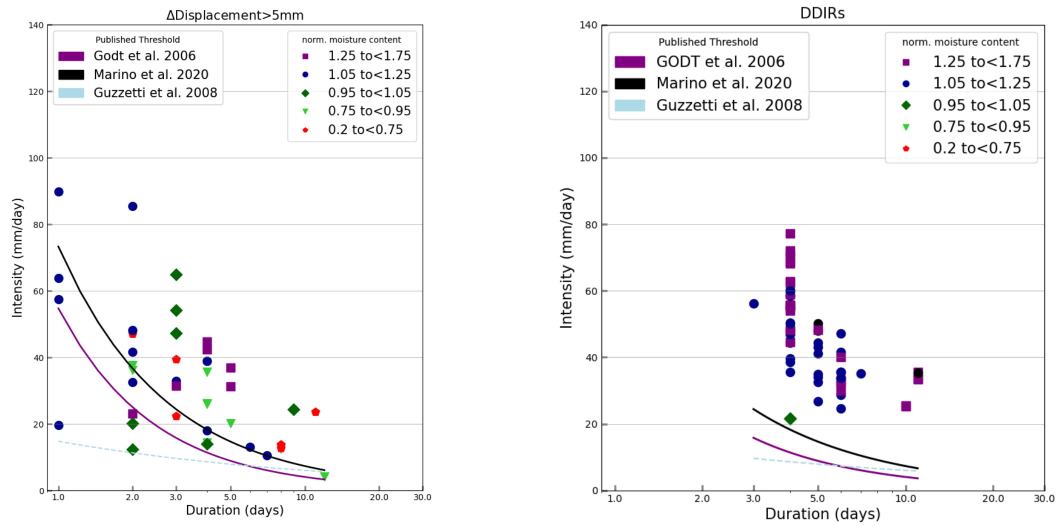
4.6.1 Landslide points Considering Soil Moisture

We integrated the soil moisture and precipitation data to evaluate the effectiveness of using soil moisture measurements to understand triggering patterns. The soil moisture value at the start of each storm was determined, normalized, and then assigned to both landslide-triggering and non-landslide-triggering events. To evaluate the significance of normalized soil moisture, we defined five categories of normalized soil moisture values ranging from 0.2 to 1.75. Values between 0.2 and 0.95 indicate drier-than-average moisture conditions, while values from 1.05 to 1.75 suggest wetter-than-average conditions. Values between 0.95 and 1.05 were considered to be approximately average. Figure 28 shows the results for the landslide events with the symbol for each point representing the normalized moisture content measured on the first day of the storm. Figure 28(a) shows that three points from the inclinometer database fall below the threshold established by Godt et al. They have average and above-average moisture content. Figure 28(b) shows that there are no points under the curve for the emergency relief reports database and all points have a normalized soil moisture condition above 1. It is worth noting that the number of points has been reduced compared to Figure 27, as soil moisture measurements are only available after March 31, 2015.



(a) (b)

Figure 27: Comparison of the landslide points with previously developed triggering thresholds for the (a) inclinometer database from this study and the (b) emergency relief (DDIR) database from Montgomery et al. 2019.



(a) (b)

Figure 28: Comparison of the landslide points grouped by normalized soil moisture with previously developed triggering thresholds for the (a) inclinometer database from this study and the (b) emergency relief (DDIR) database from Montgomery et al. 2019.

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4.6.2 Non-Landslide Points

Figure 29 presents data for non-slide events (less than 1 mm or 0.04 in displacement), alongside three ID thresholds developed previously by Godt, Baum, and Chleborad 2006, Guzzetti, Peruccacci, et al. 2008, and Marino et al. 2019. There are a relatively large number of false positive points (non-landslide points falling above the triggering threshold) in the inclinometer database, which is consistent with previous studies. Figure 29 shows that the Godt, Baum, and Chleborad 2006 threshold would give 107 false positive (false alarm) points out of 825 non-landslide points in the inclinometer database (false positive rate of 13%). Examining the soil moisture conditions of the false positive points offers a potential path towards reducing the number of false alarms that would be triggered with these thresholds. Approximately 68% of false positive points have moisture content drier than average (less than 1), while Figure 28 showed that the false negative points all had at or above average moisture conditions.

To further examine the relationship between normalized soil moisture and landslide triggering, we plotted histograms of normalized soil moisture for false and true positive events (Figure 30). Figure 30a shows the distribution of false positives is centered at a normalized soil moisture of 0.8 - 0.9, while the true positives (Figure 30b) tend to have higher (>1.0) normalized soil moisture conditions. Notably, there are no true positive events with normalized soil moisture values below 0.65 and few false positive events with normalized moisture contents greater than 1.2. Taken together, these figures suggest that threshold curves that incorporate moisture conditions may offer improved capability to determine if a storm will trigger

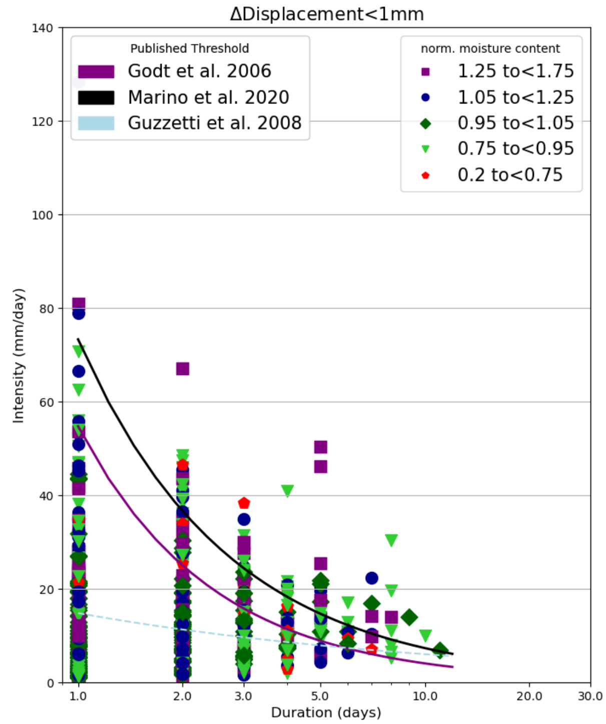
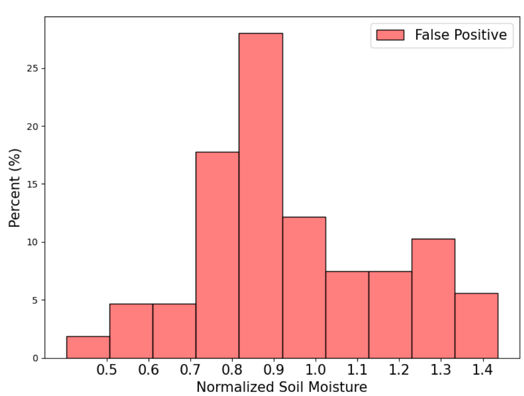
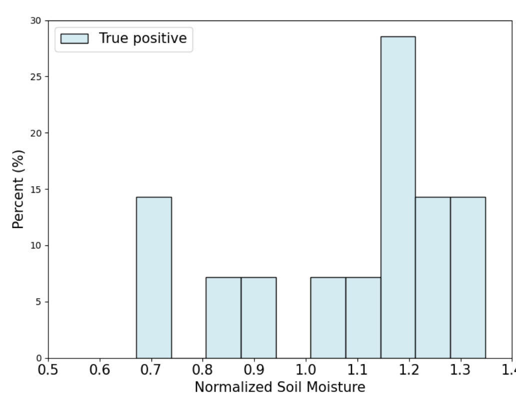


Figure 29: Non-landslide events (displacements less than 1mm or 0.04 in) alongside three previously developed thresholds by Godt, Baum, and Chleborad 2006, Guzzetti, Peruccacci, et al. 2008, and Marino et al. 2019.

a landslide. Future studies could consider directly incorporating an index like normalized soil moisture into the triggering thresholds to reduce the rate of false positives.



(a)



(b)

Figure 30: Histogram of normalized soil moisture values for (a) false positives and (b) true positive points from the triggering threshold by Godt, Baum, and Chleborad 2006.

4.7 Summary

This chapter described the creation of a new database of landslide and non-landslide events based on inclinometer readings collected at sites with unstable slopes around Alabama. Extensive processing was done on the inclinometer data to eliminate erronous or unreliable readings and to extract the changes in displacment at the slide plane. After processing, landslide events were defined by a change in displacement exceeding 5 mm (0.2 in) between two inclinometer readings, while non-landslide events were identified by changes in displacement less than 1 mm (0.04 in). Readings falling between these two limits were not considered in the analysis as they could not be definitively categorized as either landslide or non-landslide with the available information.

The inclinometer database was compared with measured precipitation data from NOAA and normalized soil moisture from NASA's SMAP Level 4 dataset. The normalized soil moisture served as an index of the average moisture conditions in the vicinity of the landslide site. The landslide database from emergency relief slides described by Montgomery et al. 2019 was also included in the analysis.

The two databases were compared with different triggering thresholds and the threshold proposed by Godt, Baum, and Chleborad 2006 was found to accurately predict approximately 80% of the landslide points across the two databases. Similar to previous studies, all of the examined thresholds had a large number of false positive points when examining the non-landslide data (i.e., non-landslide points falling above the threshold). These are a problem as they would represent false alarms that might erode confidence in the use of the thresholds.

The normalized soil moisture data appears to be effective at distinguishing between storms that are likely to produce a landslide or not. Specifically, 70% of the inclinometer dataset and all points within the DDIR database exhibited normalized soil moisture values above 1 indicating that they occured during wetter than average conditions. Similarly, 68% of the points identified as false positives (i.e., predicted landslides that did not occur) had normalized soil moisture values below 1. This pattern underscores the potential correlation between higher soil moisture levels and the likelihood of landslide occurrence and should be explored during the development of future triggering thresholds.

This chapter has focused on using recorded precipitation to understand landslide triggering, which is very useful for analyzing observations, but has limited value for forward predictions as the true rainfall is not known ahead of time. It would be more useful to base predictions on forecast data, which would be available before a landslide occurs in order to provide warning to potential stakeholders. The lessons learned from this study will be applied to the development of warning thresholds using forecast data in the next chapter.

5 Developing a Warning System for Unstable Slopes

5.1 Introduction

The previous sections have highlighted some of the options for monitoring unstable slopes and demonstrated how precipitation and soil moisture measurements can be combined to identify storms that are likely to cause previously unstable slopes to move. This chapter will focus on presenting the development of a warning system for potential movements at unstable locations and provide recommendations for monitoring future landslide sites. The warning system, along with tools to view data from monitored sites, have been implemented into a web-based portal using ArcGIS to allow for sharing the relevant data with stakeholders. The research team will work with ALDOT to implement these tools into future landslide assessments.

5.2 Methodology for a Slope Warning System using Forecast Data

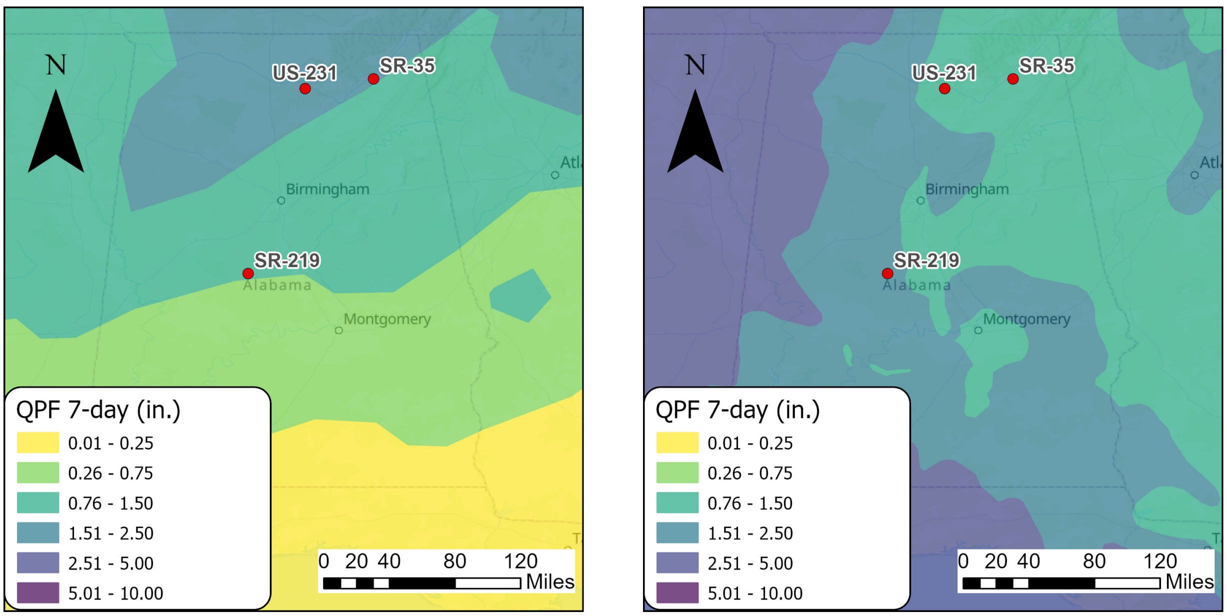
Traditionally, precipitation-based thresholds for landslide triggering have used observed precipitation recorded during either experiments or estimated at sites with observed landslides. This process was used in Chapter 4 to examine how well existing thresholds predict observations in the ALDOT landslide database. This approach was shown to be very effective for past observations, but its usefulness is limited for providing warnings for future movements as these thresholds rely on knowing how much precipitation occurred leading up to the landslide.

To overcome these limitations, this chapter develops a second set of thresholds using a combination of observed precipitation, precipitation forecasts, and normalized soil moisture data. This allows for predictions of slope movements to be made on a daily basis using forecast data. Other studies have used forecast data to issue landslide warnings (e.g., Khan et al. 2022) but have focused on large-scale regions and are not as useful for understanding potential movements at individual sites. This chapter is focused on developing a warning system that is specific to unstable slopes along Alabama highways and, therefore, considers only data from these sites. Applicability to other locations and other types of slopes will be explored in future studies.

Several data sources were identified for use in the warning system. These include both forecast and recorded precipitation from NOAA and the normalized soil moisture data described in Chapter 4. A brief description of each data source and the processing steps taken are described below followed by a discussion of the analysis and recommendations for the warning system.

5.2.1 Forecast Data

Forecast precipitation information from the NOAA Weather Prediction Center was selected for use in the warning system as these forecasts are produced daily and have been extensively validated (e.g., https://www.wpc.ncep.noaa.gov/html/hpcverif.shtml). The specific product used was the WPC Quantitative Precipitation Forecasts (QPFs) for 7-day precipitation. Historical forecasts were available for a period from 2017 to 2021, which allowed for comparisons with the landslide data. An example of the output from the WPC QPF is shown in Figure 31 for December 25, 2019 and September 11, 2024. The forecast for December 2019 corresponds to the approximate date when movements at the Lacey's Spring landslide on US-231 likely began. This date falls between two inclinometer readings, but does correspond to the first warning that would have been issued using the approach outlined in this chapter. Both forecasts in Figure 31 show areas of significant precipitation (notably around the area of US-231 and SR-35 in the December 2019 forecast), but neither shows any areas with predictions exceeding 5 inches (127 mm) of predicted precipitation. It is important to remember that this is a cumulative forecast over a seven day period and not a daily intensity as was described in the previous chapter. Therefore, the thresholds from chapter 4 cannot be directly applied to these data.



(a) (b)

Figure 31: Map of Alabama showing the NOAA WPC Quantitative Precipitation Forecast (QPF) in inches. Figure (a) is for a forecast period covering December 25 - 31, 2019, while Figure (b) is for a forecast period covering September 11 - 17, 2024.

To process the data for the warning framework, daily forecast products were downloaded in a shapefile format as precipitation in inches. The Python package geopandas was used to extract data for each inclinometer location from the shapefiles. This process is repeated for each day in the monitoring period to produce a table with seven-day precipitation forecasts for each site on each day. As previously discussed, the seven-day cumulative forecast was used for this study. Other forecast products were available, but this was the only forecast product where a complete set of historical forecasts was available to compare with the database developed in Chapter 4. Future work could consider other forecast products or even attempt to use multiple forecasts (i.e., 24, 48, and 96 hour forecasts), but other data sources would need to be identified to develop warning thresholds.

5.2.2 Recorded Precipitation

Precipitation datasets were retrieved from the NOAA Climate Prediction Center (CPC). Specifically, the CPC Unified Gauge-Based Analysis of Daily Precipitation was selected for this study, which is the same dataset that was used in Chapter 4. This product provides monthly and daily gridded surface precipitation data with a spatial resolution of 0.25 degrees latitude by 0.25 degrees longitude over the continental United States. An example of the output from the CPC daily precipitation data for December 24, 2019 and September 10, 2024 is shown in Figure 32. These dates correspond to the day before the forecast periods for Figure 31. The data from December 24, 2019 shows several areas of significant rainfall with US-231 recording 2 inches (50 mm) of rain in a single day, while the recorded rainfall from September 10 shows little to no rain was recorded in Alabama.

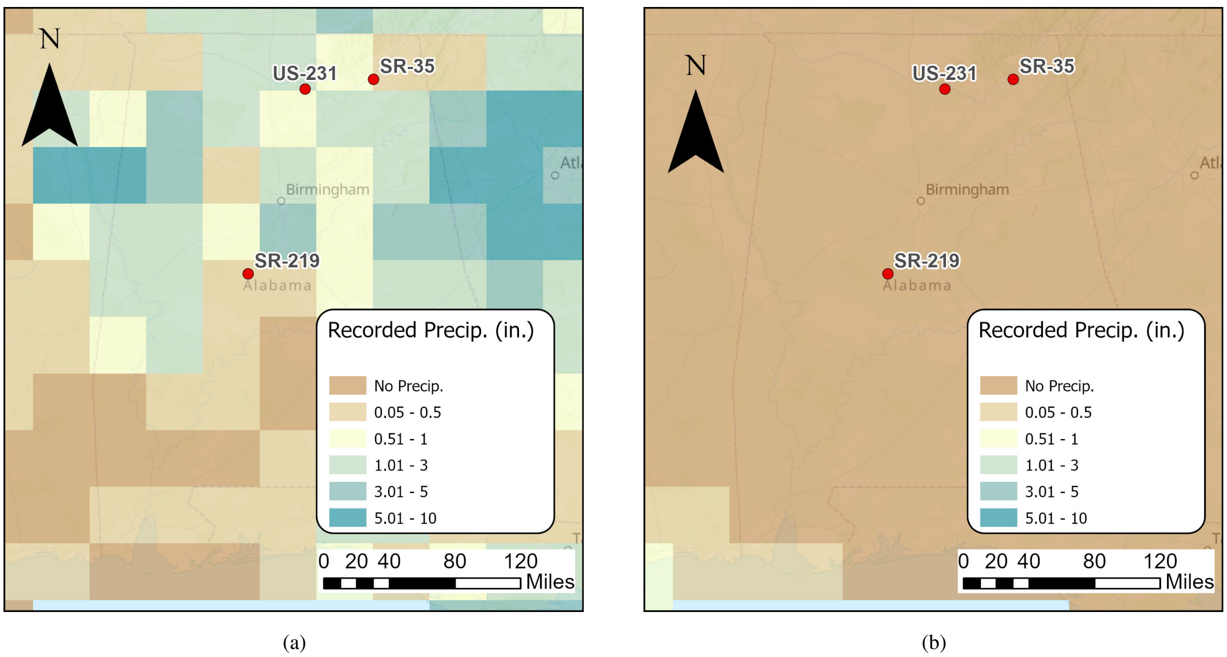
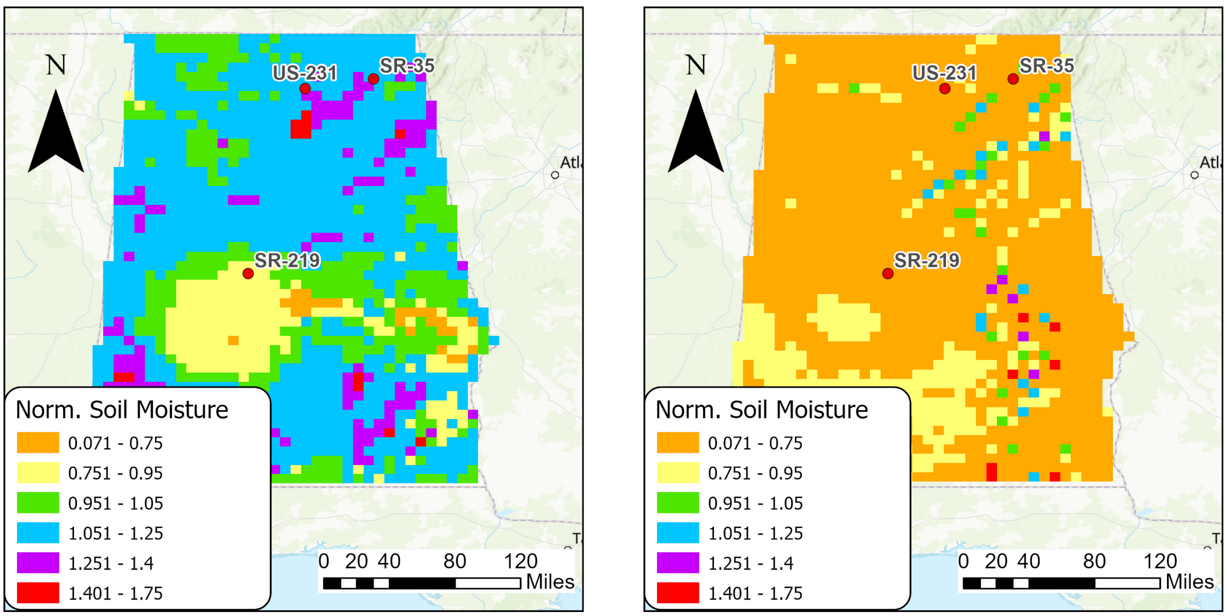


Figure 32: Map of Alabama showing the recorded rainfall in inches on (a) December 24, 2019 and (b) September 10, 2024.

The data files for the recorded precipitation were downloaded from the NOAA CPC as NetCDF files which were opened and processed in ArcGIS Pro Software. First, the NetCDF files were converted to rasters, from which values were extracted for each of the site locations. This process was repeated for each day in the monitoring period and accumulated precipitation values were totaled for the past seven days. The output from this processing was a table with accumulated precipitation values for the past seven days for each site.

5.2.3 Normalized Soil Moisture

As discussed in Chapter 4, the soil moisture measurements from NASA's SMAP instrument are useful for monitoring the average moisture conditions in different regions. The specific soil moisture values may not be accurate, but they can be converted to an index by normalizing them by the average soil moisture from SMAP for that location. This was done in Chapter 4 and was shown to help reduce false positives when using existing thresholds. For the warning system, daily values of root zone soil moisture were downloaded from the Level 4 SMAP data using appEEARS (https://appeears.earthdatacloud.nasa.gov). This allows for direct extraction at specific points (i.e., landslide locations), but the same data are also available in raster format for studying regional patterns. An example of the normalized soil moisture conditions in Alabama on December 24, 2019 and September 9, 2024 are shown in Figure 33. This shows the significant contrast in normalized moisture conditions in the winter versus the late summer in Alabama. It is also interesting to note that the area near both the US-231 slide and the SR-35 slide were experiencing significantly wetter than average conditions (normalized values near 1.4) on December 24, 2019.



(a) (b)

Figure 33: Map of Alabama showing the normalized soil moisture conditions on (a) December 24, 2019 and (b) September 9, 2024.

5.2.4 Developing Warning Thresholds

The data from the sources described above were integrated and compared with observations of slope instability from the inclinometer database described in Chapter 4. Fifteen sites from Chapter 4 had inclinometer readings that fell within the period of available forecast data (2017-2021). For each forecast day (e.g., December 8) at each site, the precipitation over the previous seven days (December 1-7 for this example) was summed to get the accumulated precipitation prior to the forecast day. This accumulated value was added to the forecast value to get the total precipitation for comparison with the thresholds. The normalized soil moisture from the day before the forecast (December 7 for this example) was also recorded.

The goal of the warning thresholds was not to predict which specific storm would lead to a failure, but rather to provide some advance warning of when a failure was likely to occur at a site. To meet this goal, the research team selected a window of 90 days prior to a failure to attempt to issue a warning. This window was selected based on the common ALDOT reading intervals of the inclinometers at active landslide sites (every 3 months). All forecast days were divided into one of three categories. The first category was for forecast days where no movement larger than 1 mm (0.04 in) was observed in the next 90 days in any of the inclinometers at the site. This was the "no failure" category and used the same criteria as Chapter 4. The second category was for forecast days within 90 days of an inclinometer reading interval with movements larger than 5 mm (0.2 in) at the site. This was the "failure category" and used the same criteria as Chapter 4. The third category included days where inclinometer readings at the site fell between these two limits and it was not possible to determine if a failure had occurred or not. These data were excluded from the analysis.

Figure 34 shows the total precipitation (sum of accumulated over the previous seven days and forecast for the next seven days) and normalized soil moisture (1.0 indicating average conditions for that site) for forecast days in the landslide database. The warning was issued when either or both of the following criteria were met: the combined 7-day antecedent rainfall and 7-day forecast exceeded 160 mm, or the normalized soil moisture on the current day was greater than 1.5. Figure 34a shows the non-failure category (meaning that no failure was observed in the 90 days following this day), while Figure 34b shows the days that fall within 90 days of a failure. This figure shows there is a large amount of overlap between the two categories (failure and non-failure) as was observed in Chapter 4. One difference is there are no non-failure points at normalized soil moisture values greater than 1.5 and there are very few non-failure points with a total precipitation greater than 9 inches (230 mm).

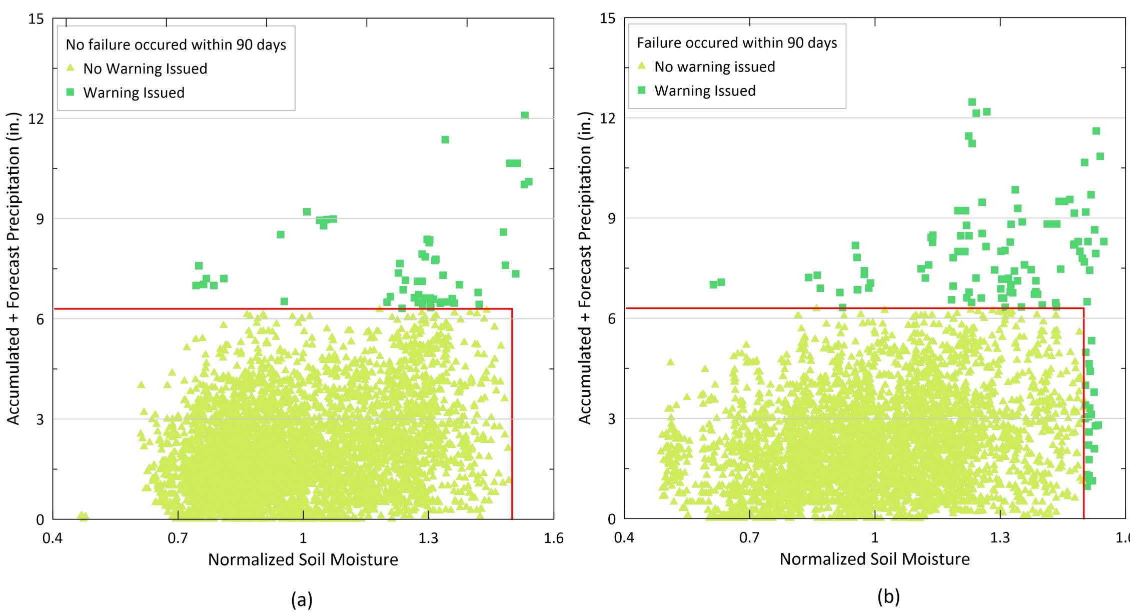


Figure 34: Comparison of the proposed warning thresholds for total (accumulated and forecast) precipitation and normalized soil moisture for (a) forecast days without a failure within 90 days and (b) forecast days with a failure occurring within 90 days. The squares indicate forecast days when a warning would have been issued.

Figure 34 also shows the proposed warning thresholds developed for this study. These thresholds were determined by attempting to minimize false positive warnings, while maximizing the number of failures where some warning would have been provided. The proposed total precipitation threshold is 6.3 inches (160 mm) and the proposed normalized soil moisture threshold is 1.5. The symbols in Figure 34 indicate the points where a warning would have been issued if these thresholds had been in place at the time.

5.2.5 Comparison of Proposed Warning Thresholds with Database

There are more than 5,500 forecast days in the database where no failure was observed within the next 90 days (Figure 34a) and a warning would have been issued on only 62 (1.1%) of those days representing a low false positive rate. Future work could examine whether site-specific adjustments to these thresholds could further lower this false positive rate, but this was not considered necessary at this stage.

Figure 34b shows the 211 warnings that would have been issued on days where a failure was observed within 90 days of the warning. This means that a total of 273 warnings would have been issued during the four year study period across the 15 sites. Approximately 77% of the warnings had a failure occur within 90 days of the when the warning would have been issued.

There are a lot of forecast days in Figure 34b where no warning would have been issued, but these do not necessarily represent missed warnings as a warning does not need to be issued on every day leading up to a failure. Rather, it is important to understand how many of the observed failures in the database would have had no warning issued. Of the 250 individual inclinometer readings in the database, 36 had a change in displacement larger than 5 mm (0.2 inches) as shown in Figure 35. A warning would have been issued within 90 days of the reading interval for 25 of these failures (70%). Of the 11 failures where no warning would have been issued, only 4 had a change in displacement larger than 0.3 inches, which indicates that many of the missed warnings would have been unlikely to cause significant damage.

Overall, the proposed thresholds have a low false positive rate for non-failure cases (approximately 1%) and were able to provide a warning prior to 70% of the observed failures. This indicates that the proposed thresholds are doing a very good job of distinguishing between conditions (combination of precipitation and soil moisture) that are likely to lead to significant movement of unstable slopes along Alabama highways. There are a large number of cases in the database where the inclinometers provided displacements that could not be categorized as a failure or a non-failure (approximately 40% of the readings) and so these readings are not included in this comparison.

5.3 Recommendations for Implementing Warning Thresholds

The warning thresholds described above have been implemented in an automated ArcGIS program, which obtains the forecast data, recorded precipitation, and soil moisture directly from NASA and NOAA and performs the necessary calculations to determine which areas of the state pass the warning thresholds for either total precipitation or normalized soil moisture. These data can be updated daily in order to monitor changes in conditions over time and provide guidance to maintenance personnel that a visit to a site may be needed to clear drainage features, seal cracks, and perform other pre-

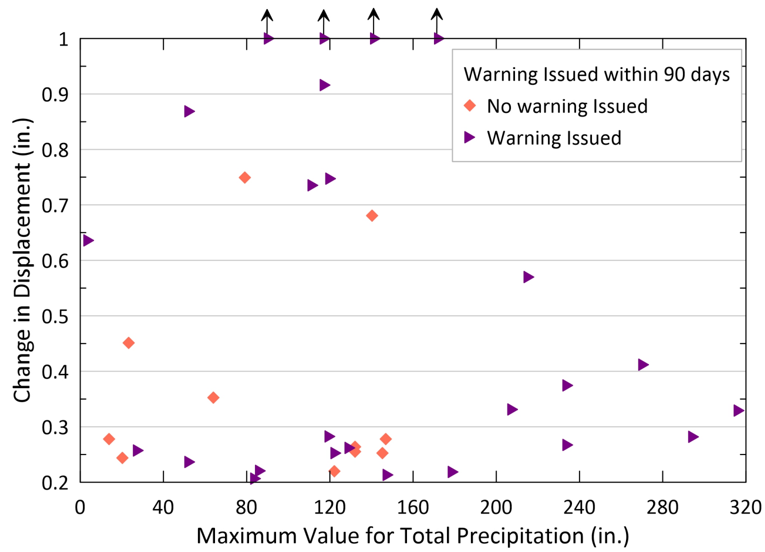


Figure 35: A comparison of the change in displacement from inclinometer readings from failure locations with maximum total precipitation (sum of 7-day accumulated and forecast) during the reading period. Different symbols are used to indicate whether a warning would have been issued within 90 days of the reading interval or not.

ventative maintenance that may reduce the likelihood of slope movement. Combining these warning thresholds with the landslide triggering thresholds from Chapter 4 would allow for identification of locations where movements are likely to have occurred and where damage inspections may need to be performed.

An example of applying the warning thresholds to the Lacey's Spring landslide on US-231 is shown in Figure 36. Cracking in the southbound lanes was reported in February 2019, which lead to the installation of the inclinometer shown in the figure. The major landslide occurred following heavy rain in February 2020. The inclinometer readings are compared with the relevant data for the warning thresholds in the figure. Precipitation data was only collected for the period with inclinometer readings, so it could not be used to assess if a warning would have been issued prior to February 2019, but the normalized soil moisture was available and was above the threshold of 1.5 in January 2019. This would have led to the first warning being issued before the site moved enough for cracks to form in February 2019. A series of warnings would have also been issued in February 2019 based on the high soil moisture conditions and again in December 2019 before the inclinometer readings that indicated movement patterns had changed. A series of warnings would have been issued between December 2019 and February 2020 in the lead up to the observed failure.

This example has the benefit of hindsight in knowing when the large failure occurred, but the comparison of the thresholds across the database (Figure 35) show similarly good results in providing warning before large movements occur. The only way to know if these thresholds can perform as well in the future is to begin testing them at sites with a history of slope movements to see if they can provide useful warnings of future movements. Auburn researchers will work with ALDOT to begin this implementation and future studies can assess the data collected during this implementation phase to determine if updates are needed.

5.4 Summary

This chapter reanalyzed the landslide database developed in Chapter 4 using both accumulated antecedent precipitation and forecast precipitation, along with normalized soil moisture. This approach is able to provide predictions of future landslide events based on current forescasts rather than evaluating triggering based on past events as was done in Chapter 4. The objective of the warning thresholds would be to allow time for ALDOT personnel to visit a site and collect measurements, inspect for damage, and potentially perform preventative maintenance, such as cleaning drainage features or sealing cracks.

To develop the warning thresholds, an automated data retrieval and processing tool was developed in ArcGIS to obtain recorded precipitation during the previous seven days, forecasted precipitation for the next seven days, and the current normalized soil moisture conditions. The recorded precipitation and normalized soil moisture were taken from the same sources as Chapter 4, while the forecast data was obtained from NOAA's Weather Prediction Center. These data were obtained for each site and each day in the inclinometer database for a period between 2017 and 2021. This included 250 individual inclinometer readings with 36 landslide events. Each day was treated as an independent opportunity to provide

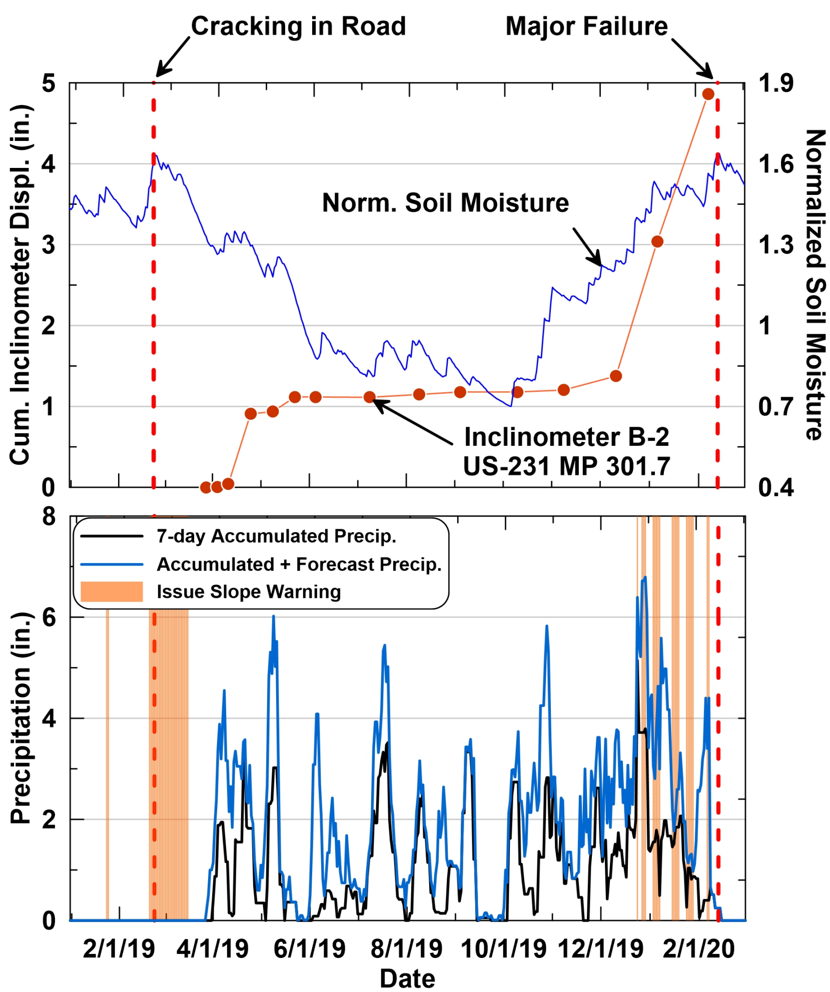


Figure 36: Example of applying the proposed warning thresholds to the Lacey's Springs landslide on US-231.

a warning of a potential slope failure and various thresholds for both total precipitation (summation of the accumulated precipitation during the previous seven days and forecast precipitation for the next seven days) and normalized soil moisture were evaluated. The analysis showed that using a total precipitation threshold of 6.3 in (160 mm) and a normalized soil moisture threshold of 1.5 for issuing a warning gave a low rate of false positives (1%), while providing a warning prior to 70% of the observed failures.

The use of these thresholds was demonstrated with an analysis of the data from the US-231 Lacey's Spring landslide. The proposed thresholds would have led to warnings first being issued in January 2019 before cracking was observed in the roadway and again in February 2019 and December 2019 as the rate of movement was increasing. The performance of the thresholds for future events can only be evaluated through the implementation of these warnings as part of a geotechnical health monitoring plan. Recommendations for this implementation are provided in Chapter 6.

6 Conclusions and Recommendations

6.1 Summary

This study focused on providing data and recommendations to improve the monitoring and assessment of landslides along Alabama highways. Many options are available for monitoring landslides including visual observations, automated or manually read instruments, and remote sensing data. An ideal monitoring approach will have high spatial and temporal resolution, low cost, simple data processing, and high durability (Smethurst et al. 2017), but it is rare to be able to meet all of these objective. Chapter 2 reviewed available monitoring options and provided a discussion of some of the advantages and disadvantages of each. Current landslide monitoring used by ALDOT relies primarily on manually read inclinometers and observation wells, which provides direct measurements of landslide behavior, but has low temporal resolution (commonly readings are taken quarterly) and observations that are limited to locations with a borehole. This study explored the use of other monitoring tools through both literature review and testing at Auburn University, including ShapeArrays and tilt sensors for monitoring movement and water level loggers for continuously recording groundwater levels. In addition, different sources of remote sensing data were explored to expand the spatial resolution beyond instrumented locations.

This study deployed instruments at two high priority landslide sites located on SR-35 near Section, AL and SR-219 near Centreville, AL as described in Chapter 3. At SR-35, an automated data collection strategy was employed to monitor precipitation, groundwater level, and slope movement through a ShapeArray. The equipment was installed on the shoulder of the road and has not shown any significant movement or groundwater within the monitored observation well. Data collection will continue in order to assess the ability of the instruments to detect movements at this site.

At SR-219, a rain gauge and three water level loggers were deployed to record continuous measurements, but a manual data collection strategy was employed due to the limited cell service in this location. No significant movements have occurred at SR-219 during the monitoring period, so conclusions cannot be drawn relating the water level observations with the patterns of movement. One key observation from this site is that the rapid rise and fall in water levels in response to rainfall cannot be observed with quarterly readings of wells. It is anticipated that this higher resolution data will allow for correlations to be drawn between observed movements and groundwater levels.

Chapter 4 described the creation of a new database of both landslide and non-landslide points based on inclinometer readings collected at sites with unstable slopes around Alabama. Extensive processing was done on the inclinometer data to eliminate erroneous or unreliable readings and to extract the changes in displacement at the slide plane. After processing, landslide events were defined by a change in displacement exceeding 5 mm (0.2 in) between two inclinometer readings, while non-landslide events were identified by changes in displacement less than 1 mm (0.04 in). Readings falling between these two limits were not considered in the analysis as they could not be definitively categorized as either landslide or non-landslide with the available information. The inclinometer database was compared with measured precipitation data from NOAA and normalized soil moisture from NASA's SMAP Level 4 dataset. The normalized soil moisture served as an index of the average moisture conditions in the vicinity of the landslide site. The landslide database from emergency relief slides described by Montgomery et al. 2019 was also included in evaluations.

Chapter 5 reanalyzed the landslide database developed in Chapter 4 using both accumulated antecedent precipitation and forecast precipitation, along with normalized soil moisture in an attempt to develop warning thresholds. This approach is able to provide predictions of future landslide events based on current forecasts rather than evaluating triggering based on past events as was done in Chapter 4. The objective of the warning thresholds would be to allow time for ALDOT personnel to visit a site and collect measurements, inspect for damage, and potentially perform preventative maintenance, such as cleaning drainage features or sealing cracks. To develop the warning thresholds, an automated data retrieval and processing tool was developed in ArcGIS to obtain recorded precipitation during the previous seven days, forecasted precipitation for the next seven days, and the current normalized soil moisture conditions. The recorded precipitation and normalized soil moisture were taken from the same sources as Chapter 4, while the forecast data was obtained from NOAA's Weather Prediction Center. These data were obtained for each site and each day in the inclinometer database for a period between 2017 and 2021. This included 250 individual inclinometer readings with 36 landslide events. Each day was treated as an independent opportunity to provide a warning of a potential slope failure and various thresholds for both total precipitation (summation of the accumulated precipitation during the previous seven days and forecast precipitation for the next seven days) and normalized soil moisture were evaluated.

6.2 Conclusions

The goal of this work was to increase the usability of monitoring data collected by ALDOT and to allow for continuous monitoring of high-priority landslides to quickly identify problems and prioritize interventions or repairs. The deployment of instrumentation at SR-35 and SR-219 demonstrated that continuous monitoring could be added to instruments installed at existing sites without making significant modifications to current ALDOT monitoring practices and can provide higher resolution data.

Testing was performed at Auburn University to evaluate and calibrate each of the selected instruments and to compare results using a ShapeArray, traditional inclinometer, and tilt sensor in a test on a near full-scale MSE wall. The experimental results demonstrated that all of the sensors can perform well in a laboratory setting, but the tilt sensors were very sensitive to noise levels and were not used in field deployment. Similarly, water content sensors and soil suction sensors (tensiometers) were found to work well for laboratory conditions, but required additional maintenance and troubleshooting compared with the other types of sensors. These devices are only recommended for use when the data they provide are critical to a project.

The two landslide databases evaluated in Chapter 4 were well fit using the triggering threshold proposed by Godt, Baum, and Chleborad 2006, which accurately predicted approximately 80% of the landslide points across the two databases. This triggering threshold is recommended for use in Alabama, but does produce a large number of false positive points (i.e., non-landslide points falling above the threshold). Normalized soil moisture data appears to be effective at distinguishing between storms that are likely to produce a landslide or not. Specifically, 70% of the inclinometer dataset and all points within the DDIR database exhibited normalized soil moisture values above 1 indicating they occurred during wetter than average conditions. Similarly, 68% of the points identified as false positives (i.e., predicted landslides that did not occur) had normalized soil moisture values below 1. This pattern underscores the potential correlation between higher soil moisture levels and the likelihood of landslide occurrence and should be explored during the development of future triggering thresholds.

Rather than develop new triggering thresholds based on recorded data, this study developed a new set of warning thresholds that can be used as part of a geotechnical health monitoring plan to provide advance warning of potential slope movements. The analysis in Chapter 5 showed that using a total precipitation (accumulated plus forecast) threshold of 6.3 in (160 mm) and a normalized soil moisture threshold of 1.5 for issuing a warning gave a low rate of false positives (1%) while providing a warning prior to 70% of the observed failures. The use of these thresholds was demonstrated with an analysis of the data from the US-231 Lacey's Spring landslide. The proposed thresholds would have led to warnings first being issued in January 2019 before cracking was observed in the roadway and again in February 2019 and December 2019 as the rate of movement was increasing. The performance of the thresholds for future events will need to be evaluated.

6.3 Recommendations for Implementation

This study evaluated multiple sensors and data collection strategies that could be used as part of a geotechnical health monitoring plan for landslides in Alabama. Some of the recommendations for this are detailed below:

- Automated data collection should be considered for at least one monitoring well at each monitored site (preferably the well that is considered most critical to evaluating stability). Data from SR-219 has shown that the well response to rainfall can occur very quickly following rain and quarterly readings will only capture general trends and may miss these fluctuations. The cost to instrument a single well is less than $500 and data collection can occur at the same time other readings are being collected. For critical sites, automated data collection through a cellular connection is a good option.
- One of the challenges with deploying water level loggers was the use of 1" ID monitoring wells at the two sites in this study. Many of the standard water level loggers are meant for wells with inside diameters of 1.5" or 2" and devices that can fit in 1" ID wells are often marketed as "micro" or "minature" with a higher cost. Using a smaller diameter well will provide a faster response time to changes in groundwater conditions and may be especially important in low-permeability materials. For automated monitoring in coarser soils, using a larger diameter wells (e.g., 1.5" ID) would reduce the cost and increase the number of options available for water level loggers.
- Tilt sensors offer a relatively low-cost way to add shallow sensors, but the MSE wall test at ASEL found that these sensors are very sensitive to noise and it can be difficult to distinguish between tilt fluctuations due to noise and those due to small movements. Many of the successful case studies using tilt sensors have focused on quiet environments (away from sources of noise) and on detecting large movements. These devices may be more useful for instrumenting rock slopes or other locations where drilling is difficult, but are not likely to be useful for routine monitoring of landslides along highways unless the sensors can be buried to avoid influences of noise.
- ShapeArrays have provided continuous and reliable measurements of deformation in both the laboratory and the

field. These devices are expensive and require a dedicated data logger. So, they should be considered for critical sites where having daily or weekly warnings of movements will be useful.

In addition to the instrumentation recommendations provided above, a second aspect of a geotechnical health monitoring plan is the ability to visualize and analyze the collected data. One of the major challenges in the current study was the level of noise and uncertainty within the inclinometer readings. Several approaches were devised to process and filter the data and these have been coded into a program that can be used by ALDOT in the future. Even with this processing, a significant amount of data could not be used due to either erroneous readings or uncertainty in the noise level. The reasons for the noise in the collected data were not clear, but an evaluation of the approaches used to collect inclinometer data should be conducted to minimize sources of error and preliminary processing should be performed either in the field or soon after collection to determine if errors have affected a reading. This will help build additional confidence in the reliability of the measurements that show small displacements, whereas currently, it is not clear if these readings are due to actual movements or noise.

This study has developed a GIS database of monitored sites, which can be added to and updated in the future as new sites are added and new readings are collected. All data collection and processing for the study was done within the ArcGIS framework to allow for easy publishing to online maps. Auburn researchers will work with ALDOT to transition these systems into their processes and hopefully implement them in their routine monitoring of unstable slopes.

The warning thresholds developed in Chapter 5 are ready for implementation into ALDOT's monitoring practice. An automated code has been developed to download and process the necessary inputs and identify areas that should receive a warning of potential slope movements. These can be published as a raster file and displayed using ArcGIS on a desktop or online. While the thresholds have been very effective at predicting landslides in the current database, it is unknown how they will perform in a forward analysis. Auburn researchers will work with ALDOT to implement these warnings and collect feedback on the effectiveness. These can then be updated in future studies as needed.

6.4 Recommendations for Future Research

Several areas were identified during this study that could benefit from future research. The tilt sensors showed promising results but are very sensitive to noise. Burying these sensors may be effective for reducing this noise, but attempts to do this with the devices obtained for this project were not successful. An alternative approach may be to use the tilt sensors as in-place inclinometers by placing them in an inclinometer casing. If they were removable, they could serve as a way to understand the timing of movements, while traditional inclinometer measurements collected by hand could provide the depth and magnitude of the movement. A prototype device was created during this study, but has not yet been tested. This is an area where additional work is needed.

The examination of landslide triggering thresholds showed that soil moisture seems to play a role in the likelihood of a large storm either triggering a landslide (true positive) or not triggering a landslide (potential false positive). Additional work is needed to see if including the soil moisture (potentially through a normalized value like in this study) in these threshold equations could improve the predictions and reduce the number of false positives. Reducing the number of false positives is key to improving the adoption of these thresholds in practice as false positives can reduce confidence in the predictions.

This study has presented a new set of warning thresholds for predicting when landslide movements are likely to occur, but more data are needed to evaluate the accuracy of these thresholds for forward predictions. It is hoped that using these warnings to perform preventative maintenance will be a potential way to reduce the impacts of landslides on Alabama highways, but the effectiveness of this approach will need to be evaluated in future studies.

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