Integrating precipitation and soil moisture measurements to understand landslide movements along Alabama highways

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ABSTRACT

Landslides along Alabama highways are a relatively common occurrence in many regions of the state. These landslides can lead to damage to transportation infrastructure and significant traffic disruptions. The current practice identifies landslide locations primarily through maintenance personnel reports or motorist complaints. Once an unstable region is identified, the suspected slide area is commonly instrumented with inclinometers, which are then read at regular intervals to understand the slide plane location and identify changes in behavior. This inclinometer data has been collected at unstable sites across the state for many years and provides a unique dataset to understand how precipitation events influence landslide behavior along highways. Previously developed precipitation thresholds considering storm magnitude and duration were consistent with landslide events observed around the state, but there are many non-triggering events that fall above the thresholds (false positives). Approximately 70% of false positive storm events occurred during drier than average periods based on normalized soil moisture data from NASA's SMAP instrument, while large movements occurred primarily during periods of average or above average soil moisture. This suggests that adding soil moisture data to landslide threshold predictions may help to reduce false positive events and to assess the likelihood of large movements occurring. These findings are now being used to develop improved warning thresholds that can highlight when landslides are likely to occur, allowing inspections and preventative maintenance to be prioritized.

INTRODUCTION

Landslides are a common geohazard across the world and can have major economic impacts on transportation infrastructure (Klose 2015). The likelihood of a landslide occurring in a given location depends on many factors, including the topography, geology, and climatic conditions in the region. The likelihood of rainfall-induced landslides is commonly assessed using statistically-based thresholds based on factors like the mean rainfall intensity (I), rainfall duration (D), and/or cumulative rainfall (E) from a storm event (e.g., Rossi et al. 2017). These threshold relationships can be developed using local, regional, or global databases of landslide events. Ground-based observations are frequently combined with remote sensing and statistical analysis to provide precipitation datasets (Guzetti 2016, Xie et al. 2017, Kirschbaum et al. 2020). 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 (e.g., Bogaard and Greco 2018, Segoni et al. 2018). Including antecedent rainfall (rainfall occurring prior to a landslide) can improve predictions in some cases, but antecedent rainfall is a proxy for the subsurface moisture and matric suction conditions, which are the more critical factors in predicting landslide occurrence (Mirus et al. 2018).

Previous studies have shown that including soil moisture data can improve predictions of rainfall-induced landslides compared with precipitation-only thresholds (Ray and Jacobs 2007, Mirus et al. 2018, Yang et al. 2019, Marino et al. 2020, Stanley et al. 2021). Soil moisture can be estimated using site-specific instrumentation data (Mirus et al. 2018, Babaeian et al. 2019), but this can be expensive if a large number of sites need to be monitored. Recently, remote sensing-based soil moisture datasets have become more common (Ray and Jacobs 2007, Rodriguez-Fernández et al. 2017, Reichle et al. 2018, Wang et al. 2022, Skulovich and Pierre 2023) and have been used to improve landslide predictions at regional and global scales (Marino et al. 2020, Stanley et al. 2021). These remote sensing-based products tend to measure shallow soil moisture (depths of ~1 m).

Landslides are a common phenomenon in most regions of Alabama (Montgomery et al. 2019, Knights et al. 2020) and landslides along highways can lead to damage to roadways and disruption to traffic (Figure 1a). Many of these landslides have occurred during periods of heavy precipitation, but no previous study has examined the predictability of these landslides using ID thresholds or examined soil moisture conditions at the time of these failures. For this study, inclinometer data were collected from unstable sites across Alabama and processed to identify periods where movement was occurring (landslide events) and without observable movement (non-landslide events). Precipitation data for these monitoring periods were obtained from NOAA and soil moisture measurements were obtained from NASA SMAP L4 (Richle et al. 2018). The precipitation data were separated into individual storms and used to compare with existing ID thresholds. The comparisons show that the ID thresholds do a good job of predicting the landslide events, but there are a large number of non-landslide events that fall above the thresholds (false positives). The normalized SMAP data show that approximately 70% of these false positive events occurred during drier than average periods, while 72% of the landslide events occurred during wetter than average periods. The combination of rainfall data and soil moisture information is now being used to develop warning thresholds for highways in Alabama.

(a) (b)

Figure 1. Photos from a landslide on AL-35 in Jackson County, north of Section, AL showing (a) settlement in the road and (b) an inclinometer casing along a highway.

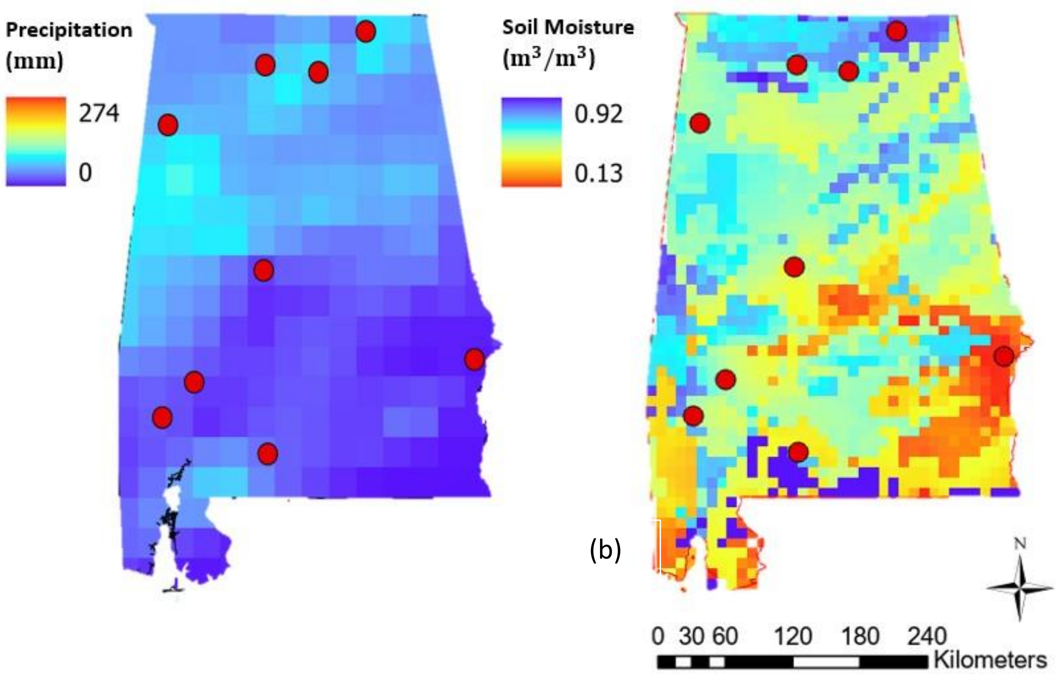
METHODOLOGY

This study used three main sources of data: (1) a database of inclinometer readings provided by the Alabama Department of Transportation (ALDOT); (2) Precipitation data for the state of Alabama; and (3) satellite-based soil moisture measurements. Each of these data sources along with the necessary processing are discussed in the following sections. All processing was done using ArcGIS Pro (v3.0, ESRI) and Python (v3.10).

Inclinometer Data. ALDOT commonly uses inclinometers (Figure 1b) to monitor potentially unstable sites. Multiple inclinometer casings are normally installed within the suspected slide area and are read quarterly or more frequently using a digital inclinometer probe. The full database contains readings from 157 inclinometers installed at 54 sites across the state. For this study, inclinometers were selected that have at least one year of readings after March 2015 (the start date for the soil moisture data) and that show a single well-defined slide plane (as opposed to multiple slide planes or no clear slide plane). Future studies will consider cases with multiple slide planes. This reduces the available data to 20 inclinometers from nine sites (Figure 2).

The inclinometers for the nine sites considered in this study are all embankment sections, but the slide planes are located in the native material under the roadway fill. The nine sites split evenly into three geologic settings with three of the sites having failure planes in interbedded sand and clay deposits, three with failure planes in Prairie Clays (Montgomery et al. 2023), and three with failure planes in weathered shale layers. Landslides can be categorized into three general groups: slides occurring within weathered shale layers, slides occurring within interbedded sands and clays, and slides within high-plasticity clays. The average slope at the site ranges from 15 – 30% and the slide planes are located at depths of 2.4 to 11.5 meters below the ground surface with an average depth of 5.2 meters.

The inclinometer data provided by ALDOT provides profiles of casing displacement in both the A- and B- directions for each reading date. Inclinometer readings have multiple sources of noise, including variability in casing measurements near the ground surface, measurement errors, and possible issues with initial readings of the displacement profiles. This study filtered erroneous readings by removing readings with significant changes in displacement (>2.5 mm) at the bottom of the casing and readings with spikes in displacement at a single depth without movement at other depths. Other sources of error can be more difficult to quantify. Mikkelsen (2003) provided a review of sources of error in inclinometer measurements and estimates that the random error in inclinometer readings is $\pm$ 0.16 mm for an individual reading, but these errors accumulate over the entire length of the casing. For a 30-meter casing with readings every 0.5 meters, Mikkelsen (2003) estimates that the accumulated random error at the top of the casing would be $\pm$ 1.24 mm with the total error (random and systemic sources) being as high as $\pm$ 7.8 mm. These numbers offer some insight into how much movement is needed to distinguish sliding from measurement uncertainty.



(a) **(b)**

Figure 2. Example of extracted data from January 3, 2020 for (a) CPS NOAA Precipitation and (b) SMAP Soil Moisture. Landside locations are shown as red points and the Alabama boundary file from USGS (2023).

After removing potentially erroneous readings, the depth of the slide plane was manually identified for each inclinometer and casing displacements were extracted from the top of the slide plane. The displacements at the slide plane were used instead of surface displacements as they were less variable throughout the year. The cumulative distribution of the change in displacement at the top of the slide plane for all readings is shown in Figure 3a. Approximately 50% of the readings showed changes in displacements at the slide plane less than 1 mm (likely within the measurement uncertainty of the instrument), while 13% have displacements greater than 5 mm. These two thresholds will be used to distinguish between landslide events (>= 5 mm of movement between two readings) and periods of little to no movement (< 1 mm of movement between two readings). Events with displacements between 1 and 5 mm could be due to small landslide events or could be measurements with larger errors. There was not a clear way to separate these two possibilities and so these readings were not included in this comparison.

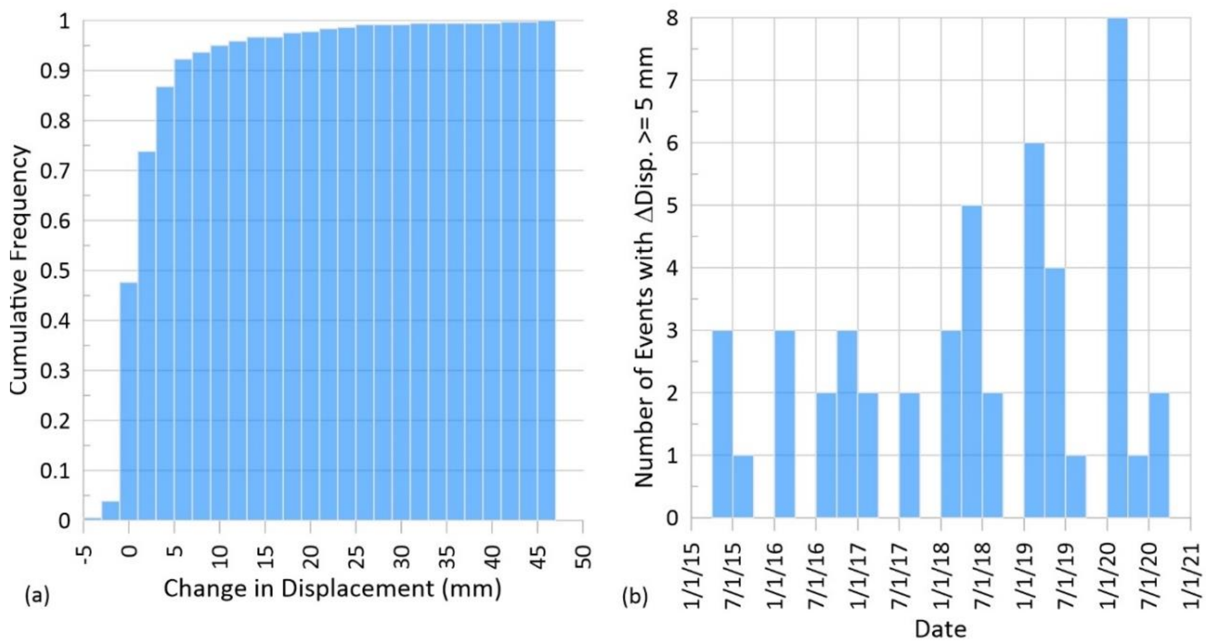


Figure 3. Histograms of the inclinometer data collected from this study showing (a) the cumulative frequency of changes in displacement between two subsequent readings and (b) the distribution during the monitoring period of slide events with greater than 5 mm of displacement.

Precipitation Data. 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 (Figure 2). Daily precipitation from CPC NOAA was grouped into discrete storm events by using a rainy-day threshold of 1 mm, as is commonly used for ID threshold development (e.g., Leonarduzzi et al. 2017). Consecutive days with rainfall were classified as the same storm event and the cumulative rainfall and the number of days of each storm were calculated. The data was not normalized by mean annual precipitation as the annual precipitation is relatively constant across Alabama (127 – 152 cm or 50 – 60 inches per year) with the exception of the Mobile area, but none of the sites are located in this region.

Soil Moisture Data. 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 (Richle et al. 2018), which has a 9-km by 9-km resolution. The root zone moisture with the vertical average of soil moisture between 0 to 100cm, was used as this was found to be the most applicable to shallow landslides by Marino et al. (2020). 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 matric suction. Figure 2 shows an example of the soil moisture data for a single day in Alabama.

RESULTS

The comparison between precipitation, soil moisture, and inclinometer displacement for a landslide site on State Route AL-219 south of Centreville, AL is shown in Figure 4a. Both the precipitation and soil moisture data show wetter periods in the late winter and early spring and drier periods occurring in the fall as expected for this region. The periods of significant movement qualitatively agree with this pattern with larger movements occurring in the early part of the year. The seasonal change in shallower soil moisture is consistent with observations from other remote sensing studies and with shallow in-situ measurements at nearby sites within International Soil Moisture Network (ISMN) (Dorigo et al. 2011). The magnitude of fluctuation in soil moisture is higher than would likely be observed at larger depths (closer to the slide plane) and so is considered to be more of an index for the wetness of the region rather than a quantitative measurement of the effective stress conditions within the landslide. Similar patterns can be seen for AL-69 (Figure 4b), although the movements are smaller, and the moisture contents are generally lower. Figure 3b shows a histogram of landslide events with more than 5 mm of displacement for all of the inclinometers in the database and confirms the pattern shown for these two sites of more landslide events occurring in the late winter and early spring.

Figure 4 highlights one of the challenges with using soil moisture data across multiple sites as the two sites have both different average values and magnitudes of fluctuation. In order to develop a consistent index, the soil moisture values at each site were normalized by the mean moisture content from the entire monitoring period. A normalized moisture content less than 1.0 indicates drier than average conditions, while a moisture content greater than 1.0 indicates wetter than average conditions. As previously discussed, drier than average conditions are common in late summer and fall in Alabama with wetter conditions in the late winter and early spring.

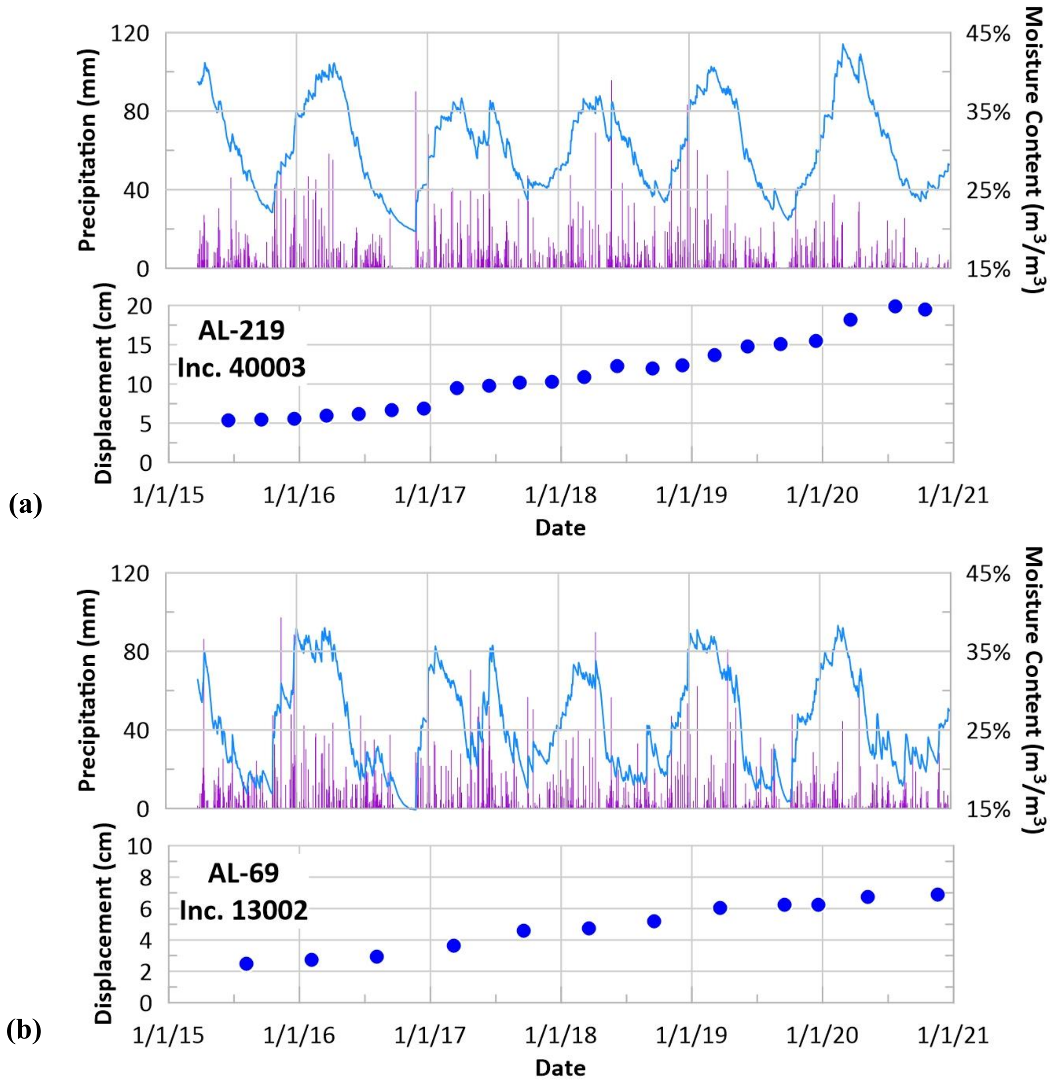


Figure 4. Time series of inclinometer displacement, daily rainfall (purple bars), and soil moisture (SMAP L4, blue line) for (a) AL219 Inclinometer 40003 and (b) AL 69 Inclinometer 13002.

Figure 5 shows the relationship between accumulated precipitation, observed movements, and normalized moisture content. The points in this figure are shown for the storm with the largest accumulated precipitation during the reading interval. The color and shape of the symbol indicates the normalized moisture content. The average normalized moisture content for events with displacements greater than 5 mm is 1.12, while the average for events with displacements less than 1 mm is 0.97. For movements greater than 20 mm, all but two of the points had above average moisture contents (normalized value greater than 1.05). This indicates that there is likely some association between larger movements and higher moisture content.

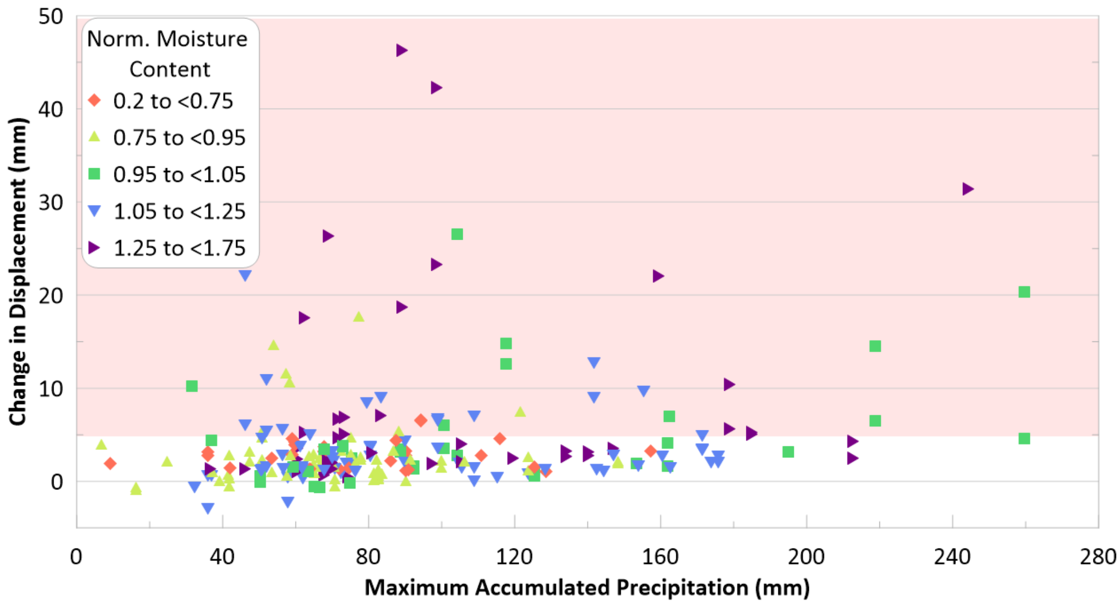
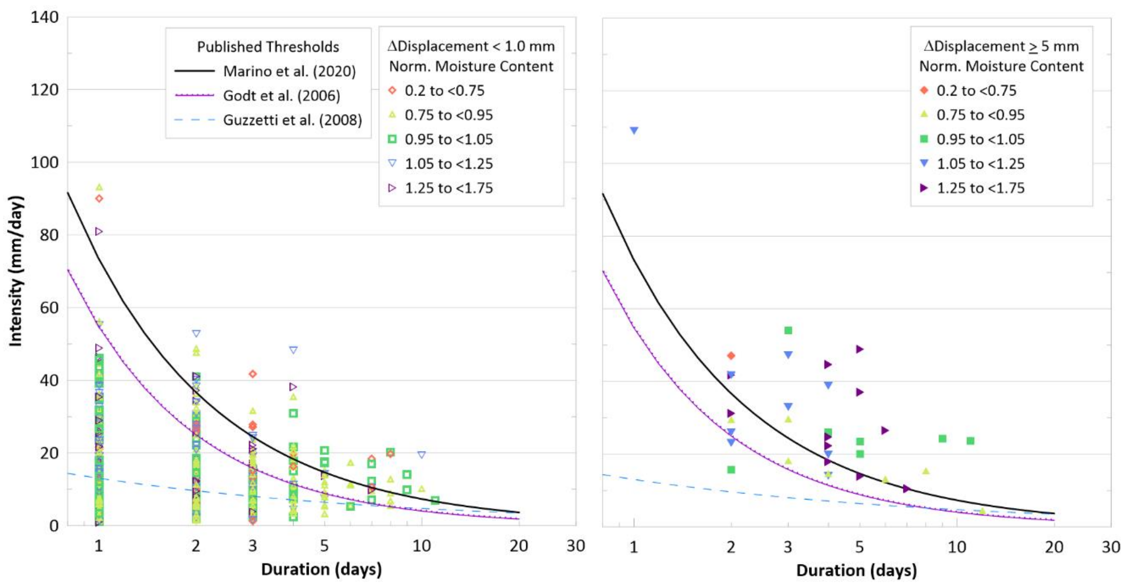


Figure 5. The relation between the maximum accumulated precipitation in a single storm and the change in displacement in inclinometer over that reading interval is shown by the points. The color of the points represents the normalized soil moisture content at the start of the storm.

Figure 6 compares the inclinometer database processed in this study with three previously developed ID thresholds (Guzzetti et al. 2008, Godt et al. 2006, Marino et al. 2020). These thresholds are commonly used to assess which storms are likely to trigger landslides. Figure 6a shows data for non-slide events (less than 1 mm in displacement), while Figure 6b shows the data for the slide events ($\geq$ 5 mm in displacement). The symbol for each point represents the normalized moisture content measured on the first day of the storm, with hollow symbols used for non-landslides and filled symbols for landslides.

The landslide events are remarkably well fit by the relationship developed by Godt et al. (2006) for the Seattle region. As Figure 6b shows, the two points that fall below the Godt et al. threshold have average and above average moisture contents, respectively, which likely made movements more likely even with a less intense storm. On the other hand, there are many non-landslide points that fall above the thresholds, which would indicate false positives. For both the Godt et al. (2006) and the Marino et al. (2020) relationships, approximately 70% of the false positive points had moisture contents that were drier than average (less than 1.0). Taken together these figures suggest that threshold curves that can account for moisture conditions may be better able to differentiate between storms that are more or less likely to cause landslides. This conclusion is similar to that reached by Stanley et al. (2021) for their global landslide prediction model. Future work will focus on developing region-specific thresholds for Alabama that can directly incorporate the effects of soil moisture.



(a) **(b)**

Figure 6. Intensity and duration data from the current database are shown along with three ID threshold curves for (a) non-landslide events (displacements less than 1 mm) and (b) landslide events (displacements greater than 5 mm).

CONCLUSION

Inclinometer data collected from nine sites along Alabama highways were analyzed to determine how well previously developed intensity-duration (ID) thresholds fit the observations and what role soil moisture may have played in the observed movements. Displacements at the depth of the slide plane were extracted from the inclinometer data and two thresholds were established to define non-landslide events (changes in displacement of less than 1 mm) and landslide events (changes in displacement greater than 5 mm). Movements between these thresholds were small enough to be within the uncertainty range in the data and were not considered in the database. The processed displacement data were correlated with precipitation data from NOAA and soil moisture data from NASA's SMAP instrument. The ID threshold curve proposed by Godt et al. (2006) provides a very good fit for the landslide data. The two false negative points had higher than average soil moisture values, while approximately 70% of the false positive points had drier than average soil moisture. This indicates that including soil moisture may improve predictions of rainfall events that are likely to cause movements at potential landslide sites. More work is needed to develop and test new thresholds.

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