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Journal

GEOTECHNICAL FRONTIERS 2025: SOIL CHARACTERIZATION AND IMPROVEMENT, 368(GSP 368)

ISSN

0895-0563

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Publication Date

2025-02-27

DOI

10.1061/9780784486016.002

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Soil Moisture Estimates from Remote Sensing, In-Situ Testing, and Laboratory Testing at an Active Landslide

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ABSTRACT

Soil moisture is a critical parameter that affects processes such as erosion, groundwater recharge, flood/drought prediction, ground construction, and slope stability. Point measurements of moisture are often conducted using time-intensive techniques, such as the nuclear density gauge or sampling followed by laboratory testing. Advances in geophysical and remote sensing techniques may be able to derive geospatial estimates of moisture efficiently over large areas. However, a scalable approach for estimating the temporal and spatial variations of soil moisture has yet to be widely adopted in geotechnical engineering practice. This study compares site-specific thermal imagery, time domain reflectometry measurements, laboratory gravimetric moisture measurements, and electromagnetic induction measurements at the Oak Ridge earthflow in Northern California with a vision towards deriving spatially continuous maps of near-surface moisture. Scalable techniques such as UAV-enabled thermal imagery and electromagnetic induction show promise in providing estimates of near-surface soil moisture, which benefits applications in construction, agriculture, and geotechnical hazard management.

INTRODUCTION

Soil moisture strongly influences the stability of natural and engineered slopes, and affects the geomechanical properties of rock and soil (Zhou et al. 2016, Wong et al. 2016). Seepage through the rock or soil mass softens the material and results in increased pore pressures, while water flow near the surface may result in piping or erosion. For compacted soils, moisture content (MC) has an impact on the compaction characteristics and soil material behavior, especially for clayey soils. Water occurrence and flow play a controlling factor in slope stability (Talebi et al. 2007), especially during intense and prolonged rainfall (Cai and Ugai 2004, Bordoni et al. 2015). As a result, reliable estimates of in-situ soil moisture are crucial for mitigating hydrology-dependent geohazards that are expected to become more prevalent due to climate change. Measuring both the spatial and temporal variation of moisture can provide valuable insights into the hydrogeologic regime of a slope and potentially contribute to explaining the mechanism of instability of a natural or engineered slope.

Common techniques for measuring or estimating soil moisture include the gravimetric method, neutron probes, the nuclear density gauge, and time domain reflectometry (TDR). While these techniques have yielded reliable results in fields ranging from agriculture (Kashyap et al.

2021) to geotechnical engineering (Kodikara et al. 2014, Curioni et al. 2014), they can be time-consuming to derive for larger sites as they provide point measurements, and thus are not scalable.

The advent of geophysical and remote-sensing technologies makes it increasingly feasible to derive estimates of moisture at larger scales. For example, Mira et al. (2010) sought to understand the effect of soil moisture on its thermal emissivity in laboratory conditions, and Hain et al. (2011) was able to apply the findings using satellite-based thermal sensors on a large scale. Zekkos et al. (2022) derived geospatial estimates of moisture content using infrared imagery collected by an Unmanned Aerial Vehicle (UAV), during a reconnaissance study of the Edenville dam failure. Gomberg et al. (2024) showed the application of multispectral imagery for moisture content assessment. Zwissler et al. (2017) derived infrared-based geospatial estimates of moisture content at a mine tailings facility. Shanahan et al. (2015) and Huth and Poulton (2007) deployed electromagnetic induction (EM) surveys to monitor the spatial and temporal variation of soil conductivity, and then related conductivity to soil moisture in agriculture and agroforestry, respectively. Martini et al. (2017) utilized repeated electromagnetic induction surveys and a wireless soil moisture monitoring system to validate soil moisture mapping on a hillslope over field scale. While remote sensing-derived moisture estimates and applications are becoming more accessible, continued work is needed to validate and determine the utility of these methods.

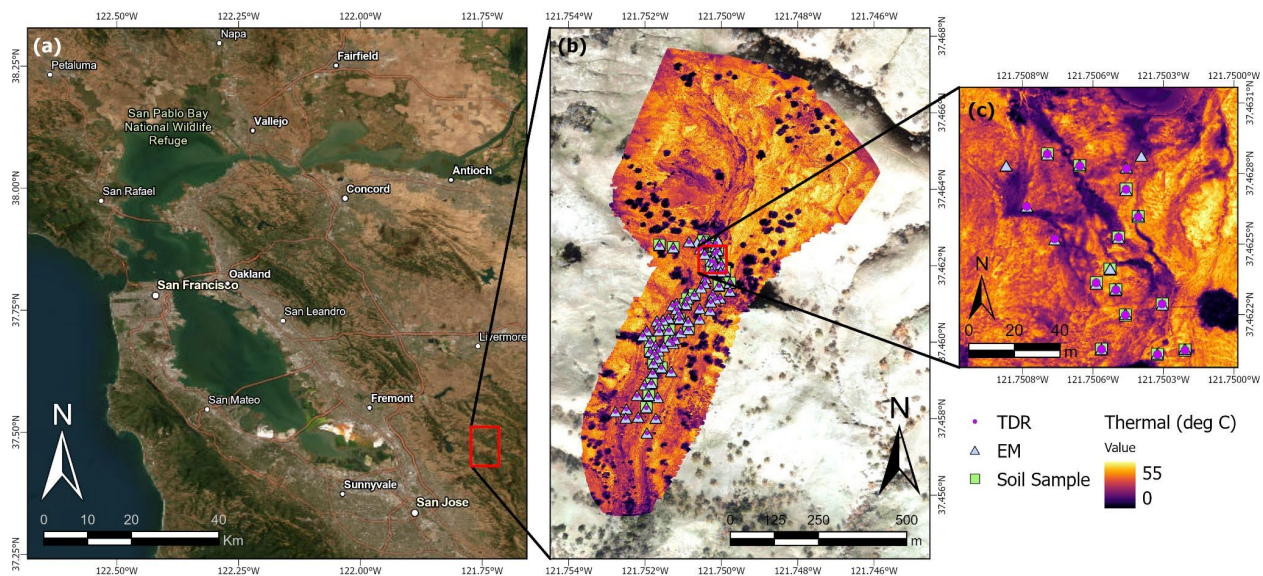


Figure 1. (a) The location of the Oak Ridge earthflow is shown in the red highlighted area within the wider San Francisco Bay Area. (b) TDR, soil sampling, EM surveys, and thermal data locations within the limits of the study area; the full earth flow continues farther downslope (south). (c) A zoomed inset illustrating example locations where point measurements were taken in a region with varying thermal data.

This study advances non-conventional moisture measurement methods by evaluating UAV-enabled thermal imagery, TDR, laboratory gravimetric, and EM techniques. These four methods are compared at a portion of the Oak Ridge earthflow in Northern California's Diablo Range approximately 20 km northeast of San Jose (Figure 1a). Nereson and Finnegan (2019) describe the climate of the site as alternating between dry summers and wet winters. The geology consists of detrital sandstone and argillaceous *mélange* from the Franciscan Assemblage, with surface conditions varying from intact rock to colluvium. For this study, the loamy soils in and

around the active earthflow zone were targeted. Data collection occurred on May 25 to 26, 2023 with sunny conditions and air temperatures ranging from 60-80° Fahrenheit.

METHODS USED IN THIS STUDY

Soil sampling and gravimetric moisture measurements are described in ASTM D2216 and require oven-drying a sample at $110 \pm 5^{\circ}\text{C}$ until it reaches a constant mass. The soil's moisture content is then calculated by comparing its original and dry weights. This method provides a direct measurement of moisture content, is often used to calibrate other techniques, and is useful as a benchmark when comparing different methods against each other.

Soil sampling was conducted at the same locations as TDR measurements. Two Emlid RS2+ multi-band GPS receivers were deployed in Real-Time Kinematic (RTK) mode to achieve precise (2-5 cm location accuracy) GPS positioning for data acquisition. During sampling, surficial debris was removed and then a sample weighing from 0.5 to 1.5 kg was taken from approximately the upper 12 cm of soil using a spade shovel. Samples were placed in sealable plastic bags and then taken to the lab for testing.

Time Domain Reflectometry (TDR) is a widely used non-destructive method that takes advantage of the change in a soil's refractivity due to moisture. TDR sensors function by sending high-frequency electromagnetic pulses through metal rods (or other waveguides) and measuring the time it takes for this pulse to return (Whalley 1993, ASTM D6780). In-situ soil moisture measurements were performed using a Hydrosense 2 TDR sensor with two 12 cm long probes spaced 5 cm apart and a reported accuracy of $\pm 3\%$ volumetric water content. Variations in return times are associated with changes in the dielectric permittivity of the surrounding media. To obtain in-situ moisture measurements via the TDR sensor, the probe was inserted perpendicular to the surface. The moisture measurement from this sensor reflects the average of the moisture of the upper 12 cm of soil at the measurement location. TDR measurements are affected by the presence of voids or poor contact with the soil, which can be especially prevalent in drier and stiffer soils.

Thermal infrared remote sensing (TIR) provides a geospatial assessment of ground surface temperature. Ground temperature can be used as a proxy for moisture content since wetter soils have overall lower temperatures than drier soils. The measured temperature is a function of a soil-liquid's thermal inertia, which is dependent on its thermal conductivity and its heat capacity. Due to having a higher heat capacity, wetter soil will have lower temperatures in the infrared band compared to dry soil or vegetation.

Thermal and optical remote sensing data were collected via an XT2 dual optical and thermal sensor on board a DJI Matrice 300 RTK. The XT2 collects radiometric thermal data at a resolution of 640 pixels by 512 pixels. Flights conducted for this campaign had a thermal ground sampling distance (GSD) of approximately 17 cm and an optical GSD of approximately 3 cm, and were conducted between 2 and 3 pm. Because of the lower resolution of the infrared cameras relative to RGB cameras, thermal flights were completed at 80% front and side overlap for orthomosaic generation. The XT2 thermal sensor uses an uncooled microbolometer, which is highly sensitive to slight changes in electrical resistance that are amplified to visually represent changes in temperature. A source of uncertainty in thermal imaging is the emissivity of the measured surface. Given the relatively high emissivity of all natural materials on the site, emissivity-based corrections were not performed in this study. The data from the flight was processed using Pix4Dmapper software, and the output was stitched using ArcGIS Pro to develop

an orthomosaic thermal map in °C. The location of TDR measurements and gravimetric soil samples were overlain on the thermal map, as shown in Figures 1b and 1c, so that the temperatures from each of those point locations could be extracted.

Electromagnetic Induction (EM) is a rapid, non-contact, non-invasive, geophysical method that uses an induced electromagnetic field to detect spatial differences in the subsurface (Doolittle and Brevik 2014). An electrical current passed through a transmission coil creates a primary magnetic field that induces eddy currents in conductive materials within the subsurface. These currents generate a secondary magnetic field measured by a receiving coil. The relative impedance change between the two coils is unitless and is measured in parts per million (PPM). The received signal is decomposed into orthogonal components known as the in-phase and quadrature components.

EM data was collected using a GEM2 frequency domain electromagnetic device (FDEM) produced by Geophex Ltd., which utilizes continuous energy transmission of multiple frequencies simultaneously (Won et al. 1996). The device has a fixed transmitter-receiver spacing of 1.66 m and was operated at a height of 0 m by placing the sensor on the ground and allowing it to collect data for 10 seconds. The sampling size of this device is the average over the length of the device, thus providing a spatial average of 1.66 m centered on the TDR/gravimetric point measurements. The depth of investigation varies based on the frequency of operation and the electrical resistivity of the subsurface. The effects of orientation were not considered, although the device was positioned to maximize homogeneity over the sampling area. The GEM2 sampling rate was set to 10 Hz and was operated in horizontal coplanar mode for all surveys. Frequencies of 18330 Hz, 38310 Hz, 60330 Hz, 80010 Hz, and 90000 Hz were used simultaneously. Frequency is inversely related to the depth of investigation (DOI) such that higher frequencies return shallower DOIs. Since this study focuses on methods applied to the shallow subsurface, only the results from the 90,000 Hz frequency survey were used, as this represents the shallowest DOI (approximately 0.5 to 1.5 m depending on subsurface physical properties). The raw PPM signal for each frequency was converted to apparent resistivity using Won et al.'s (1996) correlations. The apparent resistivity is significantly affected by factors like variations in moisture content, grain size, and mineralogy, thus making it a potential non-contact method for mapping moisture content (Allred et al. 2008, Doolittle and Brevik 2014).

RESULTS AND DISCUSSION

Of the 76 TDR and EM measurements obtained, 32 were co-located with gravimetric moisture content measurements of soil samples. The 76 locations are shown in Figure 1b to illustrate the geospatial distribution of measurements using the different methods.

TDR and Gravimetric Moisture Content Results. Figure 2 shows the volumetric moisture content from TDR measurements plotted against co-located gravimetric moisture contents. These two parameters are related through Equation 1. However, the dry density of the samples was not measured, and so this conversion was not applied. Instead, the line in Figure 2 shows a linear regression of gravimetric moistures against volumetric measurements with an R^2 of 0.84. This is consistent with previous work by Olszewska and Nowicka (2015). Badewa (2018) also showed a positive linear relationship with an R^2 of 0.89 to 0.90 for soils measured up to 30 cm in depth.

$$w_{c,vol} = w_{c,grav} \cdot \rho_{dry} \quad (\text{Eq. 1})$$

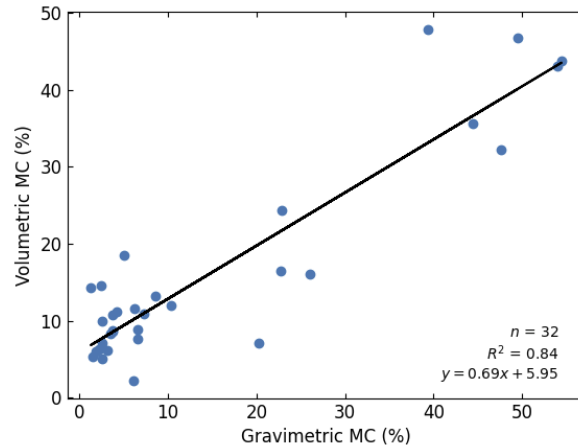


Figure 2. TDR volumetric MC plotted against lab gravimetric MC with a linear regression trend line.

Thermal and EM Results. Temperature values were extracted from the thermal orthomosaic at the point measurement locations. To evaluate how the size of the area used to extract thermal values affects specific points, the averaging area was systematically adjusted to observe its influence on the extracted values. The mean temperatures were calculated within radial buffers ranging from 0 to 200 cm. Figure 3 illustrates the differences in interpreted temperatures resulting from varying the radial buffer sizes. Figure 3a specifically shows that as the radial buffer size increases, the change in temperature also increases up to an average of 9% for a radius equal to 200 cm, although values at individual points may be significantly larger.

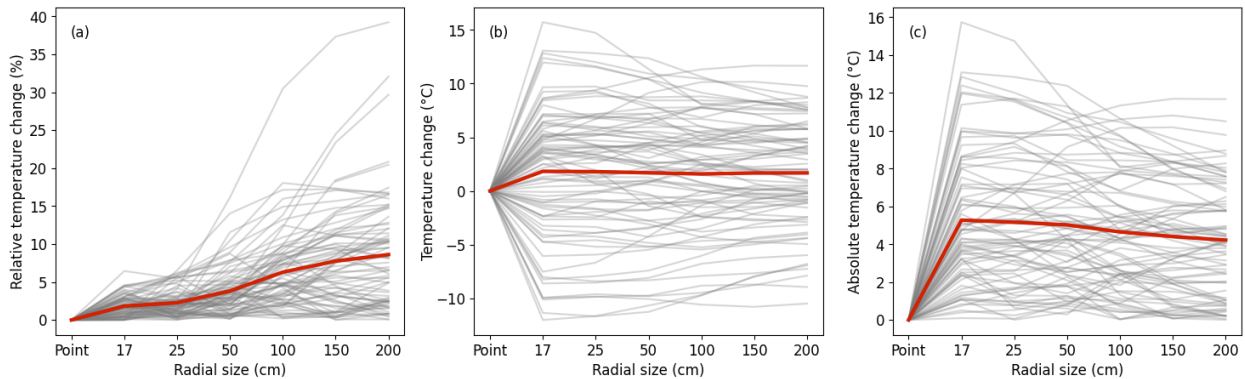


Figure 3. Effect of measuring thermal values by discrete points versus by increasing radial buffers; the red lines indicate the average for each measurement across all locations. (a) Normalized temperature change as a percentage across varying radial distances from the point of measurement. (b) Temperature change (ΔT) in $^{\circ}\text{C}$ across radial distances. (c) Magnitude of temperature change in absolute values.

The smallest radial size used was 17 cm, to match the smallest resolvable radius based on the thermal ground sampling distance (GSD) of 17 cm from the aerial survey. Any smaller radial size would coincide with the point measurement itself (resulting in a zero radius). This explains the sharp change in the trend between the point measurement and the first measurement with a buffer in Figures 3b and 3c. However, at greater radial buffer sizes, there is no notable increase in

temperature change compared to the values with a 17 cm radius, as indicated by the relatively constant red lines representing the average across all locations. As a result, to avoid averaging effects that could blur thermal values at high buffer radii, this study focuses on measurements using the 17 cm radial buffer. This size of radial buffer captures more accurate thermal values that reflect the influence of neighboring points without sacrificing spatial resolution.

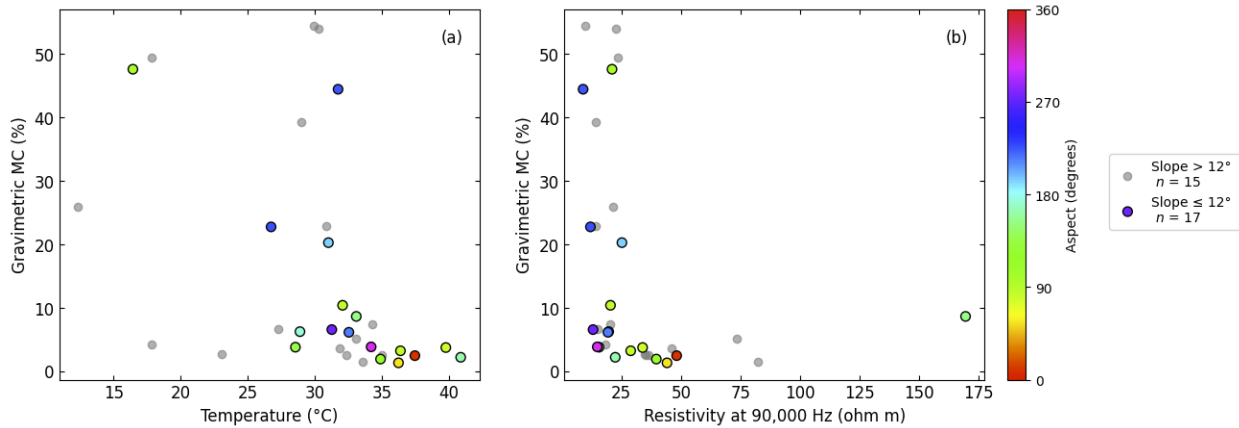


Figure 4. (a) Thermal measurements versus moisture content and (b) EM apparent resistivity versus moisture content. In both plots, data points with a slope greater than 12° are shown in gray color while points equal to or less than 12° are colored by aspect.

Figure 4a shows the temperature measurements extracted from the thermal map plotted against the gravimetric moisture content point measurements. A reduction in moisture content is observed with increasing temperature, but the data show scatter for reasons discussed subsequently. The results from this study are consistent with other studies that suggest that the relationship between temperature and soil moisture content is non-linear (Zhang et al. 2020, Daanen et al. 2007, Gullidge and Schimel 1998). Figure 4b shows the co-located EM apparent resistivity for the highest frequency of 90,000 Hz plotted against the gravimetric moisture content. Similar to TIR, scatter is present in the data but an inverse trend is observed where increasing resistivity corresponds to lower moisture contents.

Discussion of Results. Table 1 provides a comparison of the data collected from the various methods. The table lists the number of valid data points from each method and a summary of the relative effort expended to collect and process the data, as well as other aspects including areal coverage.

The gravimetric measurement is a direct measure of moisture content and for that reason it is used as a baseline reference. The TDR measurement is an indirect measurement of moisture content and is limited by the depth and spacing of the probes (12 cm and 5 cm for this study, respectively). The data scatter in Figure 2 that compares gravimetric lab measurements with field TDR measurements can be attributed to a variety of factors. Although the samples taken for gravimetric testing were meant to match the TDR volume of investigation, the gravimetric samples may involve a slightly smaller or larger volume. More importantly, TDR testing is affected by external factors such as soil heterogeneity, poor sensor contact, temperature effects, and organic content. Temperature variations can affect the dielectric properties of the soil, which was not analyzed in this study. Sensor contact and organic content were not noted during field measurements, although small variations in sensor contact or organic material can have a

significant effect on moisture measurements. These factors likely contributed to the variation from a 1:1 relationship between the TDR and gravimetric measurements.

There is also significant material variation across the site given its geomorphologic history (as discussed in the introduction), which affects the measurements across all the methods investigated. Soil/subsurface heterogeneity was not considered in this study, but it is likely a significant source of variability in the results for all methods. For TDR measurements, differences in soil composition such as grain size distribution and organic content will affect thermal variability and contact quality. The accuracy of moisture content readings from TDR suffers when the soils are drier as well as with larger grain size, since the increase in air voids interferes with the soil's measured refractivity. Thus, TDR estimates of moisture content may vary for different soil characteristics (e.g., proportion of sand or clay content), even if the soils show the same moisture content when tested gravimetrically in the laboratory.

The TIR and EM methods both exhibit greater scatter at higher moisture contents and lower resistivity/temperatures. Similar to TDR, this is likely affected by soil variability and the volume of investigation. Additionally for TIR, non-soil entities such as shadows or boulders may impact thermal readings. Variations in soil composition (e.g., clay-rich versus sand-rich) have different dielectric properties which affects both the thermal and EM measurements. TIR and EM also have significantly different volumes of investigation compared to gravimetric and TDR measurements. For example, TIR will only penetrate the top ~5 cm of soil, and the results are subject to the sensor resolution. EM will penetrate significantly deeper (0.5 to 1.5 m depending on soil electrical resistivity), and it is averaging over the 1.66 m length of the sensor. In steep environments, EM can also be influenced by the material around the sensor rather than the material only directly below it. Given that TIR has a shallower depth of investigation, and because moisture content typically increases with depth, the higher scatter in Figure 4a is expected. Figure 4b shows the opposite: high moisture contents at the surface have almost no difference in apparent resistivity because EM is sampling a significantly deeper and larger area where moisture contents/electrical resistivity are likely more consistent.

In addition to the considerations of soil variability and the volume of investigation, TIR is subject to additional environmental factors. For example, TIR's accuracy can be impacted by vegetation, cloud cover, atmospheric conditions, slope aspect, slope inclination, and relative topographic position (e.g., channel versus hillslope). Figure 4a demonstrates that when the slope is controlled by selecting relatively flat areas (slopes less than 12°), the relationship between temperature and moisture content becomes stronger and with less scatter. These points were also colored by aspect since it is well documented that incident thermal energy varies significantly with aspect (Gomberg et al. 2024). While no clear trend with aspect is observed, it is postulated that if sufficient points were measured, there would be a trend between temperature/moisture content and aspect. This is because south-facing slopes are more likely to have lower moisture content due to being exposed to higher solar radiation. While further work is needed to verify and quantify these effects, this study underscores the necessity of ensuring that any generated thermal map needs to be calibrated with ground references, preferably at locations with different soil types. The measurements would also benefit from being normalized to a baseline such as night-time measurements, which would capture diurnal thermal variations rather than relying on a single measurement taken at a specific time of day. Diurnal temperature measurements will help isolate atmospheric and environmental variability from the thermal data, making the results more repeatable.

Table 1. Summary of data collected, and relative effort between methods for obtaining usable data.

	Gravimetric Lab Testing	TDR	EM Surveys	Thermal Flight Extent
Quantity of Collected Data	32 samples	76 points	76 surveys	~0.5 km ²
Data Type	Point	Point	Line/Continuous Points	Area
Depth of Investigation	12 cm	12 cm	Frequency and resistivity dependent, 50 to 150 cm	0 to 5 cm
Data Collection Time	Slow	Fast	Moderate	Moderate
Processing Time	Slow	Fast	Moderate	Moderate
Processing Effort	Low	Low	Moderate	High

All the moisture measurement methods in this study were affected by a dataset that was skewed towards lower moisture contents. More samples with higher moisture contents may reduce the scatter of the results, as well as potentially strengthen the relationships observed.

CONCLUSION

Each moisture measurement technique offers unique advantages and limitations, primarily in terms of depth of investigation, speed, and scalability. Gravimetric methods provide reliable “ground truth” data, but are labor-intensive to collect and limited in scale and depth of investigation. TDR offers a similar depth of investigation with much faster data collection but is vulnerable to methodological errors. TIR is efficient for surface temperature measurements over large areas, but it requires further calibration to establish strong correlations with moisture content due to the very shallow depth of investigation and its susceptibility to variables like topography and the thermal properties of the subsurface. EM, on the other hand, can probe greater depths (up to an order of magnitude, as shown in Table 1) and provides scalable measurements, though it similarly necessitates the interpretation of subsurface structures and calibrating the relationship between EM-derived apparent resistivity and moisture content. This work demonstrates that the scalability of indirect methods such as TIR and EM is particularly valuable for applications where large-scale moisture mapping is critical, such as geohazard monitoring or construction. Further research that takes into account in-situ samples from a wider range of moisture contents and from more complex terrain is needed to refine their accuracy. Ultimately, the choice of technique depends on the specific application, balancing the need for depth, speed, and spatial coverage with the inherent limitations of each method.

ACKNOWLEDGMENTS

The authors would like to thank Prof. Noah Finnegan of the University of California, Santa Cruz, for providing access and insights related to the Oak Ridge earthflow.

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