Field Validation of a Low-Cost IoT-Based System for Real-Time Monitoring of Hydrologic and Physical Behavior of Slope

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***Abstract*—Slope failures are frequently governed by coupled hydro-mechanical interactions that evolve under natural climatic variability. However, real-time slope monitoring remains technically challenging, resource-intensive, and often dependent on specialized instrumentation. This paper introduces a field-deployed, low-cost Internet-of-Things (IoT) system designed to capture both hydrologic response and slope deformation within a full-scale embankment constructed at a $1\text{H:}1\text{V}$ inclination (depth $\approx 1.22\text{m}$; plan area $1.83\text{m} \times 1.07\text{m}$) composed of high-plasticity clay. The proposed distributed architecture integrates tilt sensors with volumetric moisture and matric potential sensors, all logged at 15-minute intervals via a cloud-based platform. Complementary meteorological data–including precipitation, temperature, and humidity–were concurrently collected from an on-site weather station to provide co-registered boundary conditions. Following manufacturer calibrations, sensors were installed, and the distributed system was continuously operated under natural environmental exposure. Over the initial four months of monitoring, pitch and roll variations remained within $\pm 1.5^{\circ}$, with a resolution of 0.02°, effectively capturing subtle rotational responses associated with shrinkage during drying periods. Near-surface volumetric water content stabilized between 0.135 and $0.150\ \text{m}^3/\text{m}^3$, while deeper layers exhibited higher values (~ 0.19–$0.26\ \text{m}^3/\text{m}^3$), accompanied by elevated matric suction indicative of downward moisture gradients and seasonal desaturation. This study demonstrates: (i) a scalable three-tier IoT architecture encompassing edge sensing, cloud-based processing, and web-based data visualization; (ii) robust, cost-efficient monitoring of millimetric-scale deformation under real climatic forcing; and (iii) continuous, integrative data streams suitable for early-warning analytics and performance-based infrastructure design. This field validation bridges the gap between controlled laboratory testing and in-situ decision support for slope stability management.**

***Index Terms*—IoT; Communication; Distributed System; Remote Monitoring; Slope Movement, Soil moisture.**

I. Introduction

Highway embankment slope failures pose significant economic and safety risks, with landslides causing over $2 billion in annual losses in the United States alone [1]. Traditional monitoring approaches that rely on periodic expert inspections, topographic surveys, and sophisticated equipment such as terrestrial laser scanners, extensometers, and inclinometers are labor-intensive, time-consuming, require specialized expertise, and impose substantial operating costs, thereby limiting accessibility and scalability [2], [3].

Recent advances in Internet of Things (IoT) technologies [4] have enabled the development of cost-effective, remote monitoring systems for slope stability assessment [5]. These IoT-based systems utilize low-cost sensors such as tilt sensors, moisture sensors, and tensiometers to detect early slope movements and monitor soil hydrological parameters [1]. Research demonstrates that these systems can detect subtle movements, with capabilities of identifying displacements as small as $1mm$ and rotations of 0.02^o in a laboratory environment [2]. These wireless networks overcome limitations of wired systems by providing cost-effective, low-maintenance monitoring with flexible communication [3].

Advanced AI-powered approaches to enhance monitoring capabilities by integrating real-time data with Machine Learning (ML) models [6] to predict subsurface conditions and calculate safety factors. In contrast, incorporating real-time monitoring with inverse displacement analysis enables early warning systems to estimate slope failure timing, thereby supporting timely evacuation and infrastructure protection [7]. Laboratory-based slope monitoring systems are developed to detect movement and analyze slope stability over time. However, there are limited studies on the IoT-integrated coupled hydrological-mechanical behavior under field conditions.

This paper presents a cost-effective IoT-based system for real-time monitoring of slope movements and hydrologic responses under extreme climatic conditions in the field. We developed a distributed system, arranged with components executing on IoT devices at the sensing slope and centralized servers on the cloud side. We constructed a slope model using highly plastic clay (CH) to simulate slope movement and deformation under environmental conditions outside the laboratory. IoT-based hydrologic and positional sensors, including an MPU-6050 tilt sensor, TEROS 11 soil moisture sensors, and TEROS 21 water potential sensors (tensiometers), were installed. To capture environmental parameters, we deployed an ATMOS 41 weather station. An Arduino board was used to collect and transmit aggregated tilt sensor data to a cloud-based platform for real-time detection of potential slope movements. Data from the TEROS 11, TEROS 21, and ATMOS 41 sensors were collected and stored on the Zentra cloud platform for continuous monitoring of weather and soil conditions.

II. Related Work

Recent work increasingly employs IoT technologies for remote landslide and slope stability monitoring [8], [9], [10], [11], [12]. However, long-term, field-scale validation, particularly in the United States, remains limited. Only a few studies integrate IoT platforms with hydrologic sensing to capture in situ responses to natural weather variability, and most deployments are short-term or conducted in a laboratory setting. Extended field monitoring has been documented chiefly by Guo et al. (2024) in China [13] and Butler et al. (2019) in the United Kingdom [9]. This section reviews existing IoT monitoring approaches, focusing on sensor configurations, communication protocols, and analytical methods, and delineates the novelty of the present study.

Paswan et al. [11] assessed a tilt-based IoT monitoring system for rainfall-induced landslides using a laboratory slope subjected to controlled precipitation. Although effective for validating sensor behavior under idealized conditions, the experiment did not capture the hydro-mechanical complexity associated with natural climatic variability, including fluctuating temperature, humidity, and irregular rainfall. This study advances that work by deploying and validating the system under direct environmental exposure, enabling observation of coupled hydrologic and mechanical slope responses to real-world weather dynamics.

Butler et al. [9] demonstrated a field-scale IoT monitoring system in Bournemouth, UK, using dielectric moisture sensors and tilt meters with SigFox communication. Similarly, Marciano et al. [14] deployed a deep-seated landslide monitoring system in the Philippines, incorporating tri-axial accelerometers and capacitive moisture sensors installed to depths of 40 m, which transmitted data via GSM networks. While these efforts mark essential progress in real-world implementation, the present study differs in that it leverages a flexible, cloud-based architecture and explicitly examines hydro-mechanical slope responses under extreme climatic variability. These conditions more closely represent weather-driven instability.

Several studies have highlighted the role of predictive modeling in landslide monitoring. For example, [8] combined conventional sensors with ML models to generate early warnings from historical trends. Karunarathne et al. [10] introduced a three-tier IoT architecture, which comprises data acquisition, curation, and presentation, and is supported by big data and ML analytics. Sreevidya et al. [15] developed an ML-enabled early warning system that utilized IoT sensors to track geotechnical variables, including soil moisture and shear strength, achieving 98% accuracy with no false negatives. Firoozi et al. [16] further underscored the combined potential of IoT and AI for real-time monitoring, predictive maintenance, and enhanced infrastructure resilience.

Compared with prior work, our system incorporates matric suction sensing while maintaining a low-cost hardware suite (MPU-6050, TEROS 11/21, ATMOS 41). The MPU-6050 provides 0.02^o tilt sensitivity, and the TEROS 21 yields 10% + 2 kPa accuracy, enabling dependable surface-tilt and hydrologic measurements during the four-month deployment. Although conventional borehole inclinometers offer sub-millimeter deformation resolution ($\approx$ 0.1–0.3 in per 100 ft) at substantially higher installation costs, our configuration provides a practical and economical alternative for jointly capturing deformation and hydrologic responses in natural slopes. In contrast to these ML-driven approaches, our study prioritizes direct, real-time measurement of the soil's physical and hydrologic responses to immediate climatic stimuli. This enables an actionable assessment of slope conditions without requiring extensive historical data, which is often unavailable for site-specific contexts such as highway embankments.

Much of the landslide-monitoring literature either relies on conventional sensing [17], targets narrow hazard scenarios [18], or is validated only in controlled laboratory settings [11]. Even successful field-validated IoT systems remain limited in scope: Oguz et al. [19] capture hydrologically driven failures, while Indukala et al. [20] focus on rapid, seismically triggered events. The Norwegian system provides detailed technical integration but lacks deformation sensing; the Indian system offers staged validation but omits coupled hydro-mechanical measurements. Neither achieves millimetric deformation detection with concurrent soil-moisture and suction data at sub-hourly resolution. Our system directly addresses these gaps by providing high-precision, in situ detection of subtle slope movements paired with hydrologic measurements in a low-cost, field-ready IoT platform. Accuracy is validated against standard instruments and benchmarked against recent systems (Table I). Deployment on a U.S. highway embankment demonstrates the system's ability to deliver 1 mm of site-specific, operationally relevant data under real climatic forcing.

A. System Architecture

The proposed system employs a three-layer architecture designed for scalability and modularity, shown in Figure 1. The first layer, the remote monitoring layer, consists of field-deployed sensors and hardware that continuously measure key slope parameters related to soil hydrology and physical behavior. Data are recorded via a microcontroller and data logger and transmitted through an IoT gateway to the cloud. The second layer, the cloud layer, is the primary processing and storage component. Collected data are stored on platforms such as ThingSpeak and ZENTRA Cloud, where they are analyzed to identify trends, anomalies, and potential triggers of slope failure. The third layer, the user interface, provides engineers and maintenance personnel with an intuitive, web- and mobile-based dashboard. This interface visualizes both real-time and historical data, enabling timely interventions and data-driven decision-making to enhance slope monitoring and risk mitigation.

B. Sensor Calibration

Time-series accelerometer readings from the MPU-6050 tilt sensor show tilt variations along the x, y, and z axes. Initially, these raw digital values are converted into gravitational units (g), where 1g is equivalent to 9.8 m/s². We then convert

TABLE I
A COMPARISON OF RECENT IOT-BASED LANDSLIDE MONITORING SYSTEMS.

Study	Key Hardware	Cost	Duration	Performance / Innovation
Pol et al. (2024) [8]	Geophones, Inclinometers, Rain Gauge, VWC, and Vibration sensors, Arduino, ESP8266.	Low-Cost	Real-time	ML prediction from multi-sensor inputs.
Butler et al. (2019) [9]	Tilt, VMC, and Temperature sensors, BlueFox, SigFox.	Not Stated	6 months	Successful field deployment; no suction sensor.
Karunaratne et al. (2020) [10]	3-axis Tilt, VMC and Temperature sensors, SigFox, LoRa.	Low Maintenance	6+ months	Scalable framework; real-time; lacks suction.
Paswan et al. (2023) [11]	MEMS Tilt and VMC sensors, Rainfall Gauge.	Low-Cost	Lab-scale	$0.01°$ resolution; lab-only limitation.
Guo et al. (2024) [13]	Beidou, Deep Deformation and Surface Displacement sensors, Rain Gauge, LoRa.	High Cost	2 yrs	$> 90\%$ warning accuracy; high-end system.
Marciano et al. (2014) [14]	Tri-axial Tilt, VMC (6 m) sensor, CAN, GSM.	Cost-Efficient	Not Stated	Deep-borehole IoT; lacks suction.
Sreevidya et al. (2021) [15]	Geophysical (VMC, Strength, Rain, Slope), IoT.	Not Stated	Not Stated	98% prediction accuracy.
Firoozi et al. (2024) [16]	Tilt Sensor, Piezometers (theoretical).	High-Cost	N/A	Conceptual only.
Huang et al. (2012) [17]	FBG Piezometers (60m).	High-Cost	2008–2010	High-precision; not IoT.
Abraham et al. (2020) [18]	MEMS Tilt, VMC sensor, IoT network.	Low-Cost	2 yrs	10-min interval; no suction.
Oguz et al. (2022) [19]	VMC and Suction Sensors, Piezometers, 4G.	Not Stated	Not Stated	Detailed hydrological IoT; lacks tilt.
Indukala et al. (2024) [20]	Geophones, IoT, LoRaWAN.	Not Stated	Not Stated	Detects seismic triggers; no hydro-mech sensors.

these acceleration values into angular measurements using trigonometric functions. In particular, we determine the pitch and roll angles by using the atan2 function, which robustly computes the arctangent from the two-argument accelerometer readings, while considering the correct quadrant of the angle.

$$\text{pitch} = \arctan\left(\frac{a_x}{\sqrt{a_y^2 + a_z^2}}\right) \times \frac{180.0}{\pi} \tag{1}$$

$$\text{roll} = \arctan\left(\frac{a_y}{\sqrt{a_x^2 + a_z^2}}\right) \times \frac{180.0}{\pi} \tag{2}$$

where a_x, a_y, and a_z are the acceleration values in the x, y, and z dimensions measured in gravitational units, respectively.

The TEROS 11 sensor uses the dielectric permittivity and collects the raw sensor output (ρ) from soil to measure the volumetric moisture content (VMC). The factory-calibrated formula is used to convert the raw value to VMC (θ):

$$\theta(\mathrm{m}^3/\mathrm{m}^3) = 3.879 \times 10^{-4} \times \rho - 0.6956 \tag{3}$$

The TEROS 11 sensor uses a high measurement frequency, which makes it less sensitive to soil texture and EC. Therefore, the TEROS 11 sensor generic calibration provides good accuracy ($\pm 0.03\,\mathrm{m}^3/\mathrm{m}^3$) for most mineral soils up to $8\,\mathrm{dS/m}$ saturation. For the calibration, a linear equation works well within typical mineral soil ranges, with a maximum at approximately $0.70\,\mathrm{m}^3/\mathrm{m}^3$ in pure water.

Similarly, TEROS 21 also measures soil water potential using the dielectric permittivity of porous ceramic discs. Total water potential is expressed as:

$$\Psi_t = \Psi_p + \Psi_g + \Psi_o + \Psi_m \tag{4}$$

where Ψ_p is pressure potential, Ψ_g is gravitational potential, Ψ_o is osmotic potential, and Ψ_m is matric potential. The sensor mainly measures matric potential (Ψ_m), the dominant factor in most soils.

In measuring matric potential, pressure and gravitational contributions are generally negligible, whereas osmotic potential becomes significant only under conditions of restricted ionic movement. Sensor calibration is mainly independent of soil type, as the device measures the water potential of

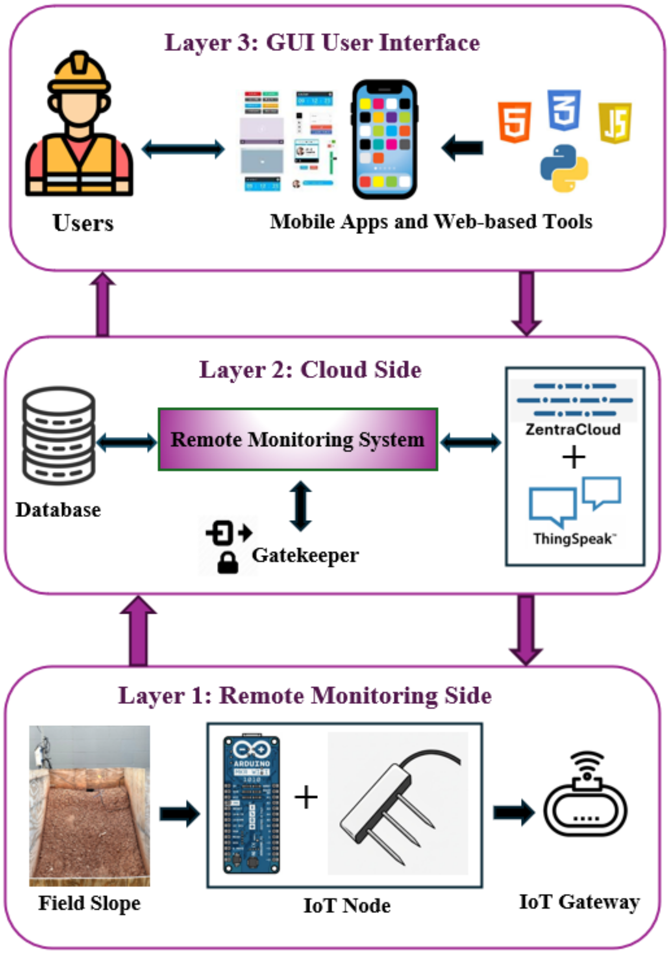

Fig. 1. System Architecture.

the ceramic discs once equilibrium with the surrounding soil is achieved. The sensor functions effectively across all soil types, provided that adequate hydraulic contact is maintained to ensure proper equilibration.

III. Implementation

A. Physical Implementation

The laboratory work was conducted at the Engineering Classroom and Research Building (ENCARB). The constructed slope was transferred to an outdoor setting beside the ENCARB at Prairie View A&M University in Waller County, Texas, U.S. The compacted slope was constructed with a dimension of 1.83m × 1.07m and 1.22m deep. Construction activities are presented in Figure 2. The soil was collected from the Sprint Sand & Clay site (Figure 2a), located near Katy, TX 77493, U.S. One wooden test box was constructed in the laboratory (Figure 2b). The wooden box was filled with high plastic clayey soil and maintained a steep slope with a 1H:1V geometry. Appropriate structural support was ensured during the construction of the wooden box, taking into account various stress levels caused by environmental factors such as heavy rainfall and storms that might occur throughout the research project. Multiple sensors were installed during the slope construction to assess the climatic variation, including moisture, temperature, and tensiometers.

Fig. 2. Physical Slope Model. (**a**) Soil collection from site; (**b**) Preparation of wooden box; (**c**) Soil backfilling, controlled compaction for stability; (**d**) Installed moisture, temperature, tensiometers sensors at various depths with data logger connected to the sensors for continuous monitoring; (**e**) Exposed to natural environmental conditions with a weather station installed outside the test section.

After placing the first layer of fine-grained soil in the test box, the subgrade bottom was compacted at the proper moisture content (Figure 2c). Subsequent layers were compacted depth by depth according to the design specifications (Figure 2c). Each layer was compacted to 95% of the optimum moisture content. After backfilling each layer, holes were drilled (Figure 2d) to install moisture and temperature sensors, as well as tensiometers (Figure 2d), at corresponding depths to closely monitor volumetric soil moisture, temperature, and soil suction (matric potential). In this study, soil moisture observations at four different depths are presented.

Figure 3 illustrates how far apart the moisture sensors, tensiometers, and tilt sensors were implemented. A tilt sensor was implemented on the top surface of the slope to detect even small amounts of movement. Also, the first layer of moisture and temperature sensors with a tensiometer was positioned 155 mm below the top surface. The second and third depth moisture sensors and the tensiometer were spaced 304.8 mm apart. The bottom sensors and tensiometer were situated 76.4 mm above the base of the slope. All the sensors were connected to automated data loggers, which continuously monitored and recorded all measurements every 15 minutes. A weather station equipped with rain gauges recorded precipitation, wind speed, air temperature, and humidity near the slopes. The constructed slope was exposed outside the laboratory to the natural environmental conditions (Figure 2e).

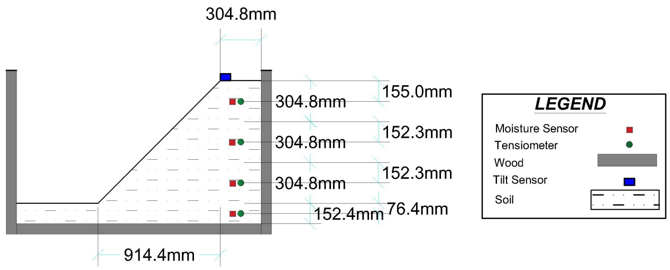

Fig. 3. Schematic of the instrumented slope, constituted of high-PI clayey soil, within the wooden box. The layout shows the placement of the tilt sensor near the crest and paired moisture and tensiometer sensors embedded vertically into the slope at 304.8 mm intervals.

This data is essential for analyzing field moisture migration at different soil depths in response to climatic variations.

The sensors used in this study are TEROS 21 soil water potential sensors and TEROS 11 moisture and temperature sensors. The sensors were calibrated following the user's manual before field installation. All the sensors and weather station data are connected to an automatic ZL6 data logger, which transmits the collected sensory data to ZENTRA Cloud for storage and visualization. As shown in Figure 3, tilt sensors have been implemented at the top edge of each soil slope model to monitor the slope's rotational movement. It was aligned with the slope's x-axis and y-axis to measure pitch and roll, respectively. After placing the sensors in the slope model, the tilt sensor was connected to an Arduino MKR WiFi 1010, which provided wireless connectivity via a WiFi network. The Arduino board transmitted real-time data from the tilt sensor to ThingSpeak, a cloud-based platform, to be meticulously analyzed to discern patterns and anomalies indicating impending slope movement.

Traditional optical inclinometers cost $5,000$–$15,000$ with $\pm 0.01^o$ precision but require manual readings, while standard tensiometers cost $800-2{,}500$ and offer ± 0.15kPa accuracy over a limited range. In contrast, our IoT system operates at roughly one-sixth the total cost, provides continuous monitoring, and delivers comparable practical accuracy, approximately $\pm 0.03°$ for tilt and ± 3kPa for suction, making it a significantly more cost-effective alternative for field deployments.

Measured input-to-visualization latency for tilt sensor cycles (i.e., Arduino $\rightarrow$ ThingSpeak $\rightarrow$ cloud $\rightarrow$ GUI) averaged approximately 148 ms on-device with additional cloud-processing and GUI refresh overhead, yielding an end-to-end latency commonly in the order of 10-30s. Error sources were mitigated using an IP67 enclosure, temperature-compensation routines, and shielded cabling to reduce environmental and electrical interference. Data security was ensured through HTTPS encryption, API key authentication, and a lightweight approach. 50 KB/day data footprint.

B. GUI User Interface

Figure 4 shows the dashboard of the developed GUI, which visualizes time-series data from multiple IoT and hydrological sensors, enabling comprehensive monitoring of environmental and soil conditions. To quantify soil moisture variation, the TEROS 11 sensors measure the volumetric water content (m^3/m^3). In contrast, the TEROS 21 sensors record the matric potential (kPa), reflecting the energy state of water within the soil matrix. These measurements provide valuable insight into soil hydrologic behavior, as displayed on the dashboard. Figure 5 illustrates the pitch and roll graphs, which represent tilt sensor outputs in degrees and are used to monitor the physical stability and orientation of the system continuously. Plotting these variables against time enables detailed soil response and environmental trends analysis across different sensor nodes, each identified by a unique port number.

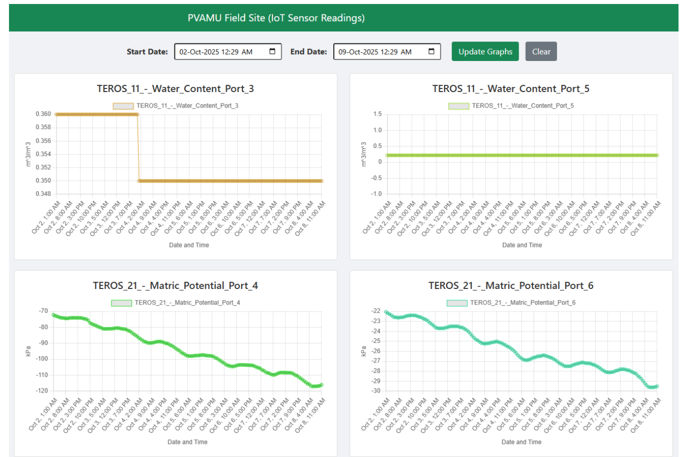

Fig. 4. GUI: Volumetric Water Content and Soil Matric Potential Data.

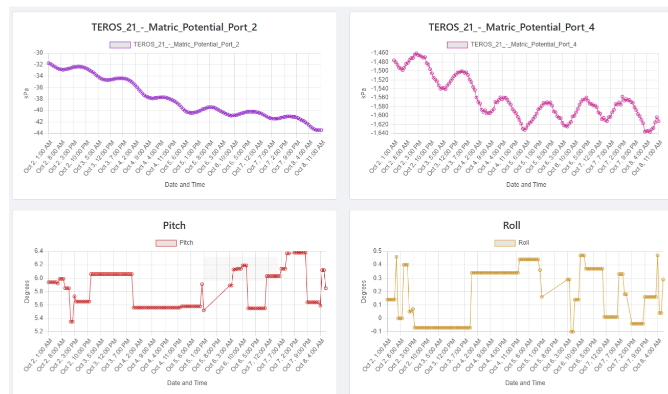

Fig. 5. GUI: Geotechnical and Hydrological Sensor Data.

As illustrated in Figure 6, the TEROS 11 sensor at Port 5 recorded a gradual decline in volumetric water content from approximately 0.370 to 0.360 m^3/m^3 over two weeks, indicating a distinct drying event around September 24 that established a new, lower moisture baseline. This trend aligns with data from the TEROS 21 sensors, which exhibited increasing matric potential values, signifying intensified soil water tension during desaturation. Short hourly fluctuations–daily cycles characteristic of natural evapotranspiration processes-are superimposed on this drying phase particularly evident in

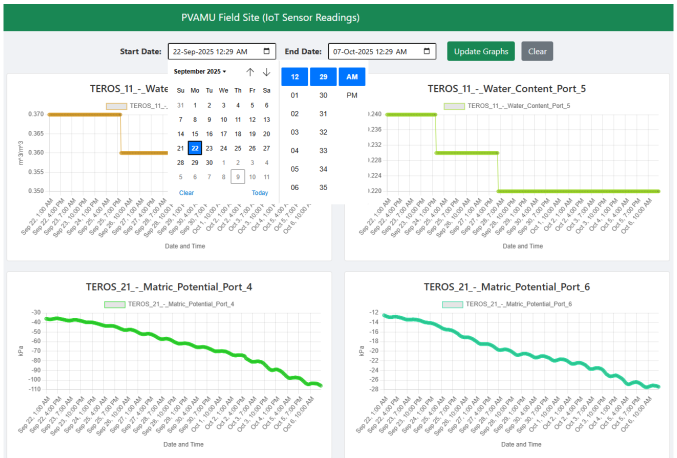

Fig. 6. GUI: Time-Series Data of Soil Water Content and Matric Potential.

the matric potential records. Complementary tilt sensor data further confirm system stability and soil response, with the pitch showing irregular step-like shifts and the roll displaying more frequent, variable oscillations. It captures the coupled hydrologic and physical dynamics of the monitored slope.

IV. Experimental Results

Data collection commenced on April 22, 2024, and the present analysis focuses on the initial four months of monitoring. The recorded pitch and roll angles reflected slope stability during this period, predominantly within the range of -1.5^o to +1.5^o. The system could detect rotations as small as 0.02^o, highlighting its high sensitivity. Observed minute angular variations under drying conditions indicate the onset of shrinkage-induced cracking within the clay model. Hydrologic measurements indicate that the near-surface volumetric moisture content (VMC) remained relatively low, ranging from 0.135 to 0.15 m^3/m^3, whereas deeper layers exhibited VMC values between 0.26 and 0.19 m^3/m^3. Elevated matric suction during this initial monitoring period confirms the soil's drying state and the absence of significant external hydrologic inputs.

A. System Performance and Cost Analysis

A quantitative evaluation of the IoT system's performance was conducted to validate its robustness. We measured input-to-visualization latency for tilt sensor cycles, which was approximately 10-30 seconds, confirming the system's near real-time monitoring capability. To provide a quantitative analysis of the hydro-mechanical coupling, a machine learning analysis was conducted. A Random Forest (RF) model was trained using only the hydrological sensor data (soil moisture, matric suction) to classify the slope's stability state.

A feature importance analysis was performed 7 to identify the most dominant predictors. The results provide a direct quantitative link between deep soil hydrology and slope instability, confirming that subsurface conditions are the most influential factors in this relationship. Soil moisture at 6 inches was identified as the most critical predictive feature (0.638 importance), followed by water potential at 6 inches (0.318 importance).

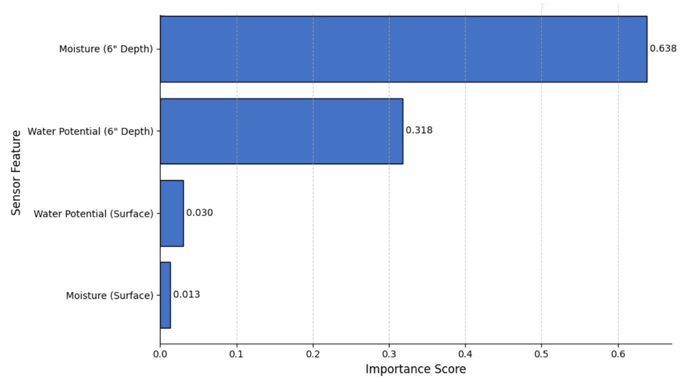

Fig. 7. Feature Importance for the ML model, proving the dominance of subsurface hydrological data as slope failure predictors.

In contrast to traditional optical inclinometers ($5,000–$15,000), our entire IoT system operates at roughly one-sixth the cost while providing comparable practical accuracy (approximately $\pm 0.03^o$ for tilt). Error sources were mitigated using an IP67 enclosure and shielded cabling. Data security was ensured through HTTPS encryption and API-key authentication.

V. Conclusions

This paper proposed a field-scale, IoT-based monitoring system on a slope constructed from highly plastic clay to capture coupled hydrologic and mechanical responses under natural climatic conditions. Preliminary results indicate that the distributed system, which integrates tilt sensors with hydrologic instrumentation, operated reliably during continuous field deployment, transmitting synchronized data to the cloud in real time. The slope exhibited stability, with pitch and roll variations generally confined within $\pm 1.5^o$, demonstrating the system's high sensitivity (0.02^o) in detecting micro-movements associated with clay shrinkage and volumetric changes during drying cycles. The three-layer architecture, comprising edge sensing, cloud-based data processing, and a GUI, demonstrated both scalability and robustness, enabling continuous real-time monitoring of slope responses and associated environmental variables. The system's reliability and cost-effectiveness highlight its potential for integration into transportation infrastructure management, particularly for early-warning applications and performance-based slope design. Future work will focus on multi-seasonal and multi-site validation to quantify long-term hydro-mechanical coupling under varying boundary conditions. Also, incorporating ML analytics with the IoT data stream could enhance predictive capabilities, supporting automated alerts, failure probability forecasting, and adaptive maintenance strategies.

Acknowledgments

This work is funded by the National Center for Infrastructure Transformation (NCIT), contract no. #69A3552344813.

REFERENCES

[1] M. J. B. Alam, L. S. Manzano, R. Debnath, and A. A. Ahmed, "Monitoring slope movement and soil hydrologic behavior using iot and ai technologies: A systematic review," *Hydrology*, vol. 11, no. 8, 2024.

[2] R. Debnath, A. A. Ahmed, and M. J. B. Alam, "On developing smart iot-based distributed system for remote detection of slope movements," in *ICNC*. IEEE, 2025, pp. 356–361.

[3] G. Q. Anh, T. B. Duong, V. K. Solanki, and D.-T. Tran, "Landslide monitoring system using an iot wireless sensor network," in *Modern Approaches in IoT and Machine Learning for Cyber Security: Latest Trends in AI*. Springer, 2023, pp. 219–235.

[4] A. A. Ahmed, "An actor-based formal model and runtime environment for resource-bounded iot services," *Algorithms*, vol. 15, no. 11, 2022. [Online]. Available: https://www.mdpi.com/1999-4893/15/11/390

[5] D. K. Yadav, S. Jayanthu, S. K. Das, S. Chinara, and P. Mishra, "Critical review on slope monitoring systems with a vision of unifying wsn and iot," *IET Wireless Sensor Systems*, vol. 9, no. 4, pp. 167–180, 2019.

[6] A. A. Ahmed and V. Bhadani, "Wanderwatch: Lorawan-based monitoring system for wandering risk patients," in *2025 International Conference on Computing, Networking and Communications (ICNC)*, 2025, pp. 468–472.

[7] J. Xu and Y. Zhang, "Ai-powered digital twin technology for highway system slope stability risk monitoring," *Geotechnics*, vol. 5, 2025.

[8] R. Pol, V. Manoj, M. Bhalerao, O. Altaf, and A. Mulani, "A real time iot based system prediction and monitoring of landslides," *International Journal of Food and Nutritional Sciences*, vol. 11, 07 2024.

[9] M. Butler, M. Angelopoulos, and D. Mahy, "Efficient iot-enabled landslide monitoring," in *2019 IEEE 5th World Forum on Internet of Things (WF-IoT)*, 2019, pp. 171–176.

[10] S. M. Karunarathne, M. Dray, L. Popov, M. Butler, C. Pennington, and C. M. Angelopoulos, "A technological framework for data-driven iot systems: Application on landslide monitoring," *Computer Communications*, vol. 154, pp. 298–312, 2020.

[11] A. P. Paswan and A. K. Shrivastava, "Evaluation of a tilt-based monitoring system for rainfall-induced landslides: Development and physical modelling," *Water*, vol. 15, no. 10, 2023.

[12] S. T. Ahmed, A. A. Ahmed, A. Annamalai, and M. F. Chouikha, "A scalable and energy-efficient lorawan-based geofencing system for remote monitoring of vulnerable communities," *IEEE Access*, vol. 12, pp. 48 540–48 554, 2024.

[13] J. Guo, F. Meng, and J. Guo, "Gradual failure of a rainfall-induced creep-type landslide and an application of improved integrated monitoring system: A case study," *Sensors*, vol. 24, no. 22, p. 7409, 2024.

[14] J. S. Marciano, C. G. Hilario, M. A. B. Zabanal, E. V. Mendoza, B. L. Gumiran, B. F. Flores, M. O. Peña, and K. H. Razon, "Monitoring system for deep-seated landslides using locally-developed tilt and moisture sensors: System improvements and experiences from real world deployment," in *GHTC*. IEEE, 2014, pp. 263–270.

[15] P. Sreevidya, C. Abhilash, J. Paul, and G. Rejithkumar, "A machine learning-based early landslide warning system using iot," in *ICNTE*. IEEE, 2021, pp. 1–6.

[16] A. A. Firoozi and A. A. Firoozi, "Smart geotechnics: enhancing infrastructure resilience with iot and ai," *JCEU*, vol. 14, pp. 89–101, 2024.

[17] A.-B. Huang, J.-T. Lee, Y.-T. Ho, Y.-F. Chiu, and S.-Y. Cheng, "Stability monitoring of rainfall-induced deep landslides through pore pressure profile measurements," *Soils and Foundations*, vol. 52, 2012.

[18] M. T. Abraham, N. Satyam, B. Pradhan, and A. M. Alamri, "Iot-based geotechnical monitoring of unstable slopes for landslide early warning in the darjeeling himalayas," *Sensors*, vol. 20, no. 9, 2020.

[19] E. A. Oguz, I. Depina, B. Myhre, G. Devoli, H. Rustad, and V. Thakur, "Iot-based hydrological monitoring of water-induced landslides: a case study in central norway," *Bulletin of Engineering Geology and the Environment*, vol. 81, no. 5, p. 217, 2022.

[20] P. Indukala, U. Gosh, and M. V. Ramesh, "Iot-driven microseismic sensing system and monitoring platform for landslide detection," *IEEE Access*, 2024.