

DRILL: Deployment & Reading of In-ground Low-cost Soil Moisture Logging Sensors Using an Autonomous Ground Robot

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Abstract—Accurate soil moisture data is crucial to precise irrigation and manual deployment of existing sensors is labor-intensive and expensive, especially in cornfield environments. We present DRILL, an unmanned ground vehicle (UGV) for autonomously deploying and reading low-cost biodegradable soil moisture sensors. The platform consists of a mechanical drilling head (linear actuator, auger drill, 16-slot encoded sensor dispenser, and a chute for guiding) and a reading head with a vector network analyzer (VNA), combined with a vision-guided navigation system for logging soil moisture data without human intervention. The robot platform has been experimentally validated in real-world farm environments over an extensive period and achieved a success rate of 93.75% for the deployment cycle and 100% for the reading cycle, with a mean cycle time of under a minute per sensor. Out of 330 sensor readings with the VNA, overall 73.3% produced valid peaks in 100-160 MHz range indicating a valid soil moisture reading and over 95.3% during the first half of the study, suggesting sensor aging. With a mean in-ground plane alignment error of 1.3 cm in X and 0.6 cm in Y , well within the 4 cm tolerance in each axis, DRILL demonstrates a scalable platform for autonomous soil monitoring and timely data collection in precision agriculture.

I. INTRODUCTION

The rise of precision agriculture has been crucial to promising a future where food production is keeping up with the growing population rates [1], [2]. Increasing the efficiency of agricultural practices allows for enhancing the production output of farmlands, reducing waste, and increasing profits. The rise of robotics and Internet of Things (IoT) use in agriculture has empowered farmers to make informed decisions about crop management at a high spatial and temporal resolution and played a major role in increasing yield [3], [4], [5]. The use of robotics has facilitated but is not limited to detecting diseases or nutrient deficiencies at an early stage, automating harvesting and physical leaf sample

*This material is based upon work supported by the IoT4Ag Engineering Research Center funded by the U.S. National Science Foundation (NSF) under the NSF Cooperative Agreement Number EEC-1941529.

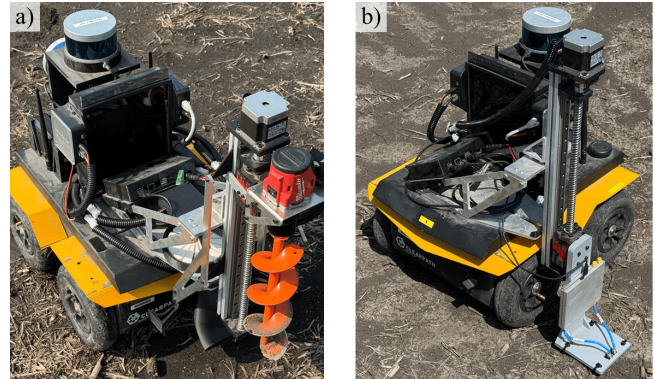
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This paper has a supplementary material available at <https://youtu.be/bvfgjFKx720>, provided by the authors.



(a) Robot in drilling configuration (b) Robot in reading configuration

Fig. 1: Proposed autonomous ground robot platform DRILL: Deployment & Reading of In-ground Low-cost soil moisture Logging sensors.

collection processes, and improving food security [6], [7], [8], [9].

Agriculture consumes over 70% of the global freshwater reserve [10]. Therefore, the use of robotics and IoT also enables the accurate and systematic measurement of another extremely important metric, which is soil moisture. Real-time monitoring of soil moisture eliminates traditional labor-intensive practices that rely on manual estimation and guessing. Accurate information on the moisture content of the soil reduces water resource waste and prevents damage to crops due to over-irrigation. This can also prevent nutrients leaching into the soil and preserve soil quality. Some crops have varying water requirements at different growth stages. Thus, precise soil moisture logging helps optimize the irrigation process throughout the growing season [11], [12]. IoT-enabled soil moisture sensors provide farmers data-driven control over irrigation, increase productivity, and lower costs while saving water resources.

Soil moisture sensors come in a wide range depending on the application. The low-cost resistive sensors are largely inaccurate, while the capacitive sensors are accurate but costly [13], [14]. Some recent works have developed low-cost and biodegradable inductor-capacitor (LC) sensors for passive monitoring of soil moisture wirelessly, which have shown promising results [15], [16], [17].

Recent work in remote sensing demonstrates platforms which integrate hyperspectral sensors mounted on Unmanned Aerial Vehicles (UAVs) for soil moisture estimation [18], [19]. To obtain soil moisture data beyond the surface level, a limitation of the UAVs, Unmanned Ground Vehicles (UGVs)

are also being deployed for contact-based soil moisture measurement using time-domain reflectometry (TDR) probing [20], [21]. Robotic core sampling is also being used for a more accurate gravimetric soil moisture measurement [22]. However, despite the clear advantages of an automated soil moisture monitoring platform, its large-scale adoption remains limited and passive biodegradable sensors have not been fully integrated into a robotic platform yet [23], [24]. The technical challenges consist of the accuracy of sensor placement, reliable data logging, and robust autonomous navigation in outdoor farm environments [25], [26], [27].

In this work, we present DRILL, a UGV designed for autonomously deploying in-ground low-cost biodegradable soil moisture logging sensors in complex, real-world agricultural environments. Our contributions are:

- **Modular hardware design:** Drilling and sensing heads actuated by a lead-screw, an automatic sensor dispensing carousel with 16 slots, a guide chute for precise deployment after drilling, and an integrated inductive loop antenna with vector network analyzer (VNA) for sensor reading.
- **Electronics and embedded control:** ROS for vision guidance and robot control, intel-based mini PC for data logging, Arduino microcontroller for low-level control, all housed in weatherproof enclosures and connected by serial communication.
- **Vision-guided navigation:** ArUco marker-based visual servoing for autonomous robot navigation, precise antenna-to-sensor alignment and sensor reading.
- **Field testing and validation:** Bi-weekly operation and data collection with the robot for over 6 weeks, quantified cycle times, success rates, soil-moisture correlation graphs, and sensor quality measurements.

II. SYSTEM DESIGN

The system consists of two novel modular configurations: One for drilling and sensor dispensing (Fig. 1a) and the other for sensor reading and data logging (Fig. 1b). The drilling configuration is designed with reliability in focus. In this configuration, the robot uses a robust mechanical system to drill 5 cm deep into the soil and a rotating carousel to automatically dispense the biodegradable sensors. After completion of the sensor deployment, the robot is switched to the reading configuration which is designed with a precision focus. In this configuration, the robot uses an RGB camera to autonomously navigate the field with an ArUco marker-based vision-guided navigation algorithm to align itself with the sensors. Additionally, soil moisture sensor logging is done in this configuration by the VNA.

A. Hardware Overview

The robotic platform is based on a ClearPath Jackal UGV, a compact mobile robot known for its durability in all-terrain conditions, making it a good fit for our agricultural use case. The UGV is fitted with two LiDAR sensors (Velodyne VLP-16) for localization and mapping [28]. Powering the platform is an on-board computer with Intel Core i5-4570T CPU.

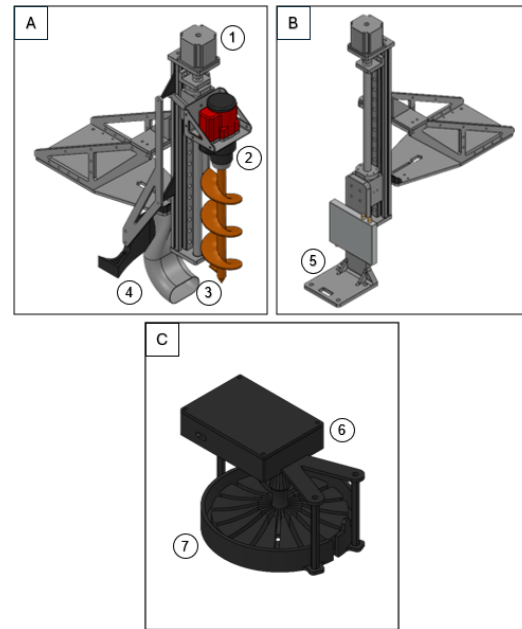


Fig. 2: (A) Sensor deployment configuration: 1) stepper motor, 2) drill and auger, 3) sensor chute, 4) soil plow. (B) Sensor reading configuration: 5) vector network analyzer (VNA). (C) Sensor dispenser: 6) rotary encoder, 7) sensor carousel.

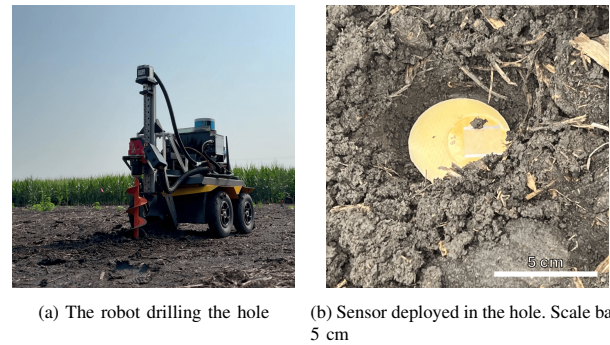


Fig. 3: Overview of the sensor deployment procedure: Digging a 5 cm deep hole with the auger drill, dropping a sensor by rotating the carousel, and driving forward to fill the hole back with dirt using the plow.

This computer is used for visual servoing and autonomous navigation. The additional electronics for the drilling and reading configurations are housed in a separate electronics box.

A component-level overview for the two configurations is shown in the form of Computer Aided Design (CAD) in Fig. 2. In the drilling configuration, a Milwaukee impact driver drill paired with an auger bit is used to drill holes in the soil (Fig. 2A). A mechanical binary absolute rotary encoder, that has 128 pulses per revolution, within the sensor dispenser system tracks the position of up to 16 biodegradable soil moisture sensors [15] housed on a rotating carousel (Fig. 2C). Upon arriving at the desired sensor location, the drill, controlled by a custom PCB, starts spinning the auger. The lead screw is then lowered, drilling a hole approximately 5 cm deep into the soil as shown in Fig. 3a. Next, the auger is lifted up and the robot drives forward, positioning the sensor chute above the hole. Once a hole is completed, an Adafruit FS90R servo rotates the sensor dispenser by 22.5° and a

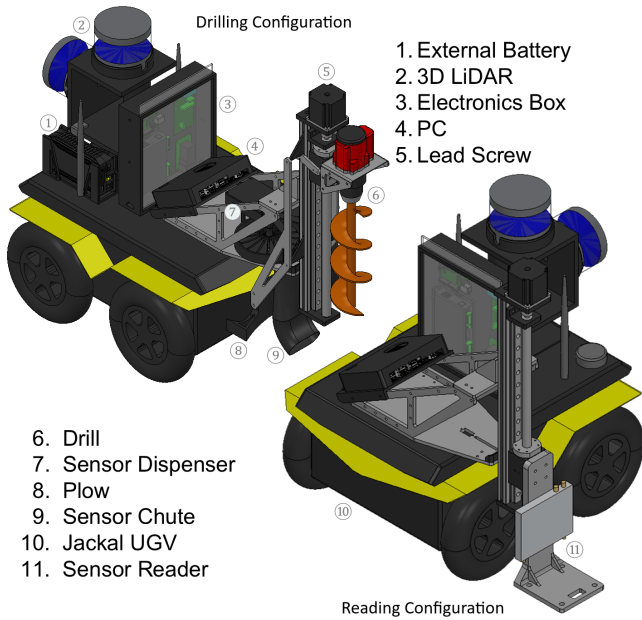


Fig. 4: Computer Aided Design (CAD) models of the proposed platform showcasing the individual components of each configuration.

sensor falls out of the dispenser into the sensor chute. The sensor chute guides the soil moisture sensor, aligning the sensor parallel to the ground before it drops into the hole as shown in Fig. 3b. It is important for the soil moisture sensor to be deployed horizontally when touching the ground to be read by the VNA. The plow is then fully lowered, and the robot drives forward, filling the hole and covering up the sensor back with dirt. This cycle is repeated until all sensors are deployed in the field.

Following deployment, the system can be easily reconfigured to the sensor reading configuration. After thumb screws removal, the drill head is replaced with a reading head which consists of a VNA and a sensor reading inductive loop antenna. The sensor arm assembly is rotated 90° , allowing the robot to drive alongside fiducial markers placed adjacent to each sensor during the deployment phase. During each sensing cycle, the robot navigates toward a marker, lowers the reading head to the ground to establish contact with the sensor, logs the data, and then retracts the reading head back. The sensor data logged are stored locally on the LattePanda Mu mini-PC for later retrieval and analysis.

B. Electronics Overview

The brain of the robot electronics is an Arduino Uno microcontroller and a LattePanda Mu PC, housed in a custom electronics box, shown in Fig. 4. All of the electrical wiring is routed within the sealed electronics enclosure or hidden beneath the robot’s carriage for protection and accessibility. The LattePanda Mu has an Intel Core i3-N305 CPU and is used to interface with a LibreVNA Vector Network Analyzer (VNA) [29] that performs the sensor readings. The LattePanda is powered by the internal battery of the robot, which is connected to the serial port of the Arduino for

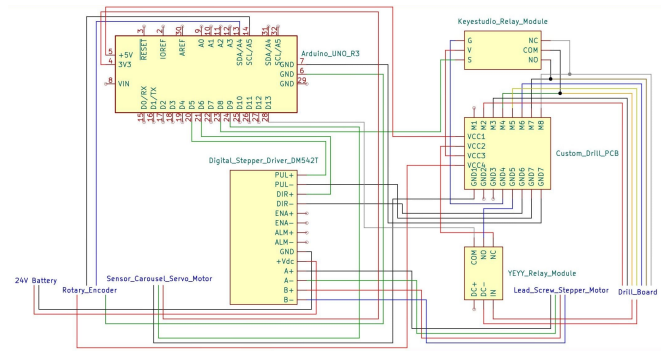


Fig. 5: Electrical schematic of robot showing the integration between Arduino UNO, stepper motor driver, relay modules, and a custom PCB for the drill.

5V power and communication. Two additional batteries are required to power the lead screw and the drill motor, which use a TalentCell PB240A1 and a Milwaukee drill battery, respectively. All systems operate on 24 VDC. The electrical schematic of the system is shown in Fig. 5. These electronics come together to power and control this modular system of drilling, deploying, and reading in-ground soil moisture sensors.

C. Software Overview

The proposed robotic system employs a distributed computing framework, utilizing multiple CPUs of different architectures to handle specific tasks. The drivetrain of the ClearPath Jackal UGV is managed using the Robot Operating System (ROS), which handles motor velocity control and visual servoing-based navigation. An Arduino UNO microcontroller located inside the electronics enclosure (Fig. 4) works simultaneously with the LattePanda Mu single-board computer to manage key functionalities such as drilling, sensor deployment, and sensor reading.

A Python script was utilized to automate running the LibreVNA GUI and scan the sensor when the robot is in the desired position. The script finds the phase in degrees of Z_{11} , Z_{21} , and S_{21} from a range of 10–200 MHz. Z_{11} and Z_{21} are the impedance parameters measured using the VNA; specifically, Z_{11} represents the input impedance at Port 1 of the VNA and Z_{21} represents the transfer impedance from Port 1 to Port 2 of the VNA. S_{21} is the scattering parameter that represents the forward transmission from Port 1 to Port 2. Additionally, a MATLAB script was used to post-process the sensor data.

D. Vision-guided navigation

Accurate soil moisture readings require the robot to precisely navigate and position itself relative to the location of the deployed sensors. However, traditional GPS-based navigation systems are unreliable in agricultural environments with dense canopy coverage, such as cornfields, due to signal interference. To overcome this challenge, we propose a ArUco marker-based visual servoing method for autonomous navigation, where the markers serve as fiducial references in the field. During deployment, an ArUco marker is placed adjacent to each sensor with a fixed known offset. In the

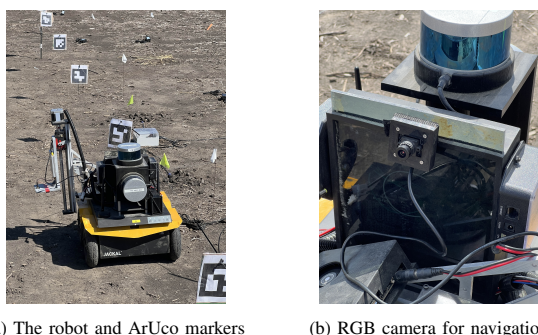


Fig. 6: Robot settings for vision-guided navigation using an RGB camera. Each soil moisture sensor is paired with a distinct ArUco marker.

reading mode, the robot uses image processing to detect these markers and localize itself relative to each one. An overview of the robot and marker configurations for visual servoing-based navigation is illustrated in Fig. 6a.

ArUco pose estimation is a computer vision technique used to determine the 3D pose of a marker relative to a camera. Each ArUco marker has a unique binary ID and defined physical dimensions, enabling consistent identification and localization. Before pose estimation can be performed accurately, the onboard RGB camera, as shown in Fig. 6b, is calibrated to correct for lens distortion and intrinsic optical characteristics. Camera calibration was performed using 30 checkerboard images achieving a re-projection error of 6%, yielding intrinsic parameters such as focal length, optical center, and distortion coefficients.

Using intrinsic parameters obtained by calibration, the pose estimation pipeline starts by detecting the ArUco markers from the RGB camera feed, extracting the position of each corner, and mapping the 2D image points to known 3D coordinates. An OpenCV algorithm computes the marker's rotation and translation vectors, calculating the robot's pose relative to the marker and the associated sensor. The pose information is used by the robot's on-board CPU to calculate the velocity commands and move the robot using ROS messages to the desired position for sensor reading.

Once the robot successfully reaches a target soil moisture sensor by navigating to a corresponding marker, communication is established between the on-board PC and the LattePanda using UDP sockets over a shared WiFi network, where the robot transmits a message in the form of a 'REACHED' flag to the LattePanda computer. The flag is picked up by a helper python script running on the computer which passes on the commands to the Arduino microcontroller for initiating the sensor reading and data logging sequence. The communication pipeline is illustrated in Fig. 7.

III. EXPERIMENTAL RESULTS

A series of sensor deployment and reading experiments were conducted outdoors using the robot to evaluate its performance under realistic outdoor field conditions. The trials were carried out on a bare soil plot within a cornfield testbed. An untilled bare plot was chosen instead of a planted

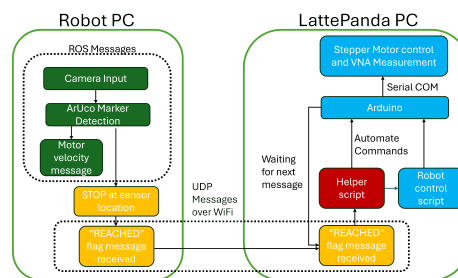


Fig. 7: Chart showing the communication systems of the robot for the sensor reading configuration. Robot PC is used for autonomous navigation. The LattePanda PC is used to control components of the sensor deployment and sensor reading modules.

plot to accurately capture the moisture content of the soil, undisturbed by plant uptake. At the beginning of the growing season, prototype biodegradable soil moisture sensors were deployed using the robot in its drilling configuration. A total of 30 sensors were deployed in the test bed, divided into 3 rows with 10 sensors evenly spaced per row and marked with white flags. Following the deployment, sensor readings were collected twice a week for a 6 week period to assess the reliability of the reading system, the sensors, and the accuracy of detection.

Two types of experiments were conducted to validate the system performance. The first assessed the efficiency of the sensor deployment and reading cycles, while the second evaluated the accuracy of the VNA-based sensor readings.

A sensor drilling cycle is defined as the full sequence of operations required to deploy one sensor: activating the drill, lowering it into position, boring a 5 cm hole, retracting the drill, releasing the sensor via the dispenser, and passing the plow over the hole to cover it. A sensor reading cycle refers to the time it takes for the system to lower the reading head with the VNA, acquire sensor data, and retract the reading head to its original position.

For the analysis of drilling and reading efficiency as shown in Table I, the time required to complete a single cycle was recorded. The success rate of each cycle and the total number of trials conducted were also documented to evaluate the reliability and speed of the system. This experimental methodology showcases the ability of the robot to successfully deploy and collect soil moisture sensor data over an extended period of field operation.

For sensor reading tests as shown in Table II, data from the 30 deployed sensors was collected twice a week for 6 weeks. Each reading was analyzed to determine whether the VNA detected a peak response within the 100-160 MHz frequency range. The presence of a peak indicated that moisture content was detected. Thus, the successful detection of a peak within this range was used as the criterion for the success of data collection. The decrease in sensor readings between weeks 4-6 is due to the degradation of sensor performance over time.

A. Deployment and Reading Results

The success rate of both the drilling and sensing mechanism along with the average duration of each type of cycle is

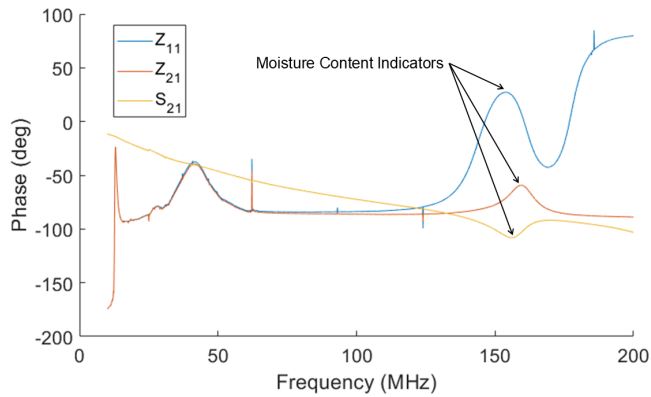


Fig. 8: Soil sensor data from a sample sensor showing the detected peaks within the 100-160 MHz frequency range indicating a valid reading and detection of soil moisture content.

TABLE I: System performance

Configuration	Mechanism Results		
	Trials (#)	Success Rate (%)	Average Time ^a
Drilling	16	93.75%	1 min 13 s
Sensing	16	100%	44 s
Total	32	96.88%	58.5 s

^aPer Cycle

shown in Table I. To correspond with the sensor dispenser's storage capacity, 16 drilling cycles and 16 sensing cycles were performed, resulting in 32 total trials. Of these trials, 93.75% of drilling cycles and 100% of sensing cycles were successful. The reduction in the success rate of the drilling cycle can be attributed to the failure of the plow system during the final trial. This can be remedied by redesigning the plow system to be more robust. However, the combined success rate of 96.88% for both the drilling and sensing cycles demonstrates robust sensor deployment and reading. Furthermore, the average duration of the drilling cycle was 1 min 13 s and the average duration of the sensing cycle was 44 s. Combining the average time of both cycles, the cycle duration was 58.5 s.

Once the data retrieved by the robot has been collected, a MATLAB script analyzes the data by finding the peaks of the phase of Z11, Z21, and S21 between 100–160 MHz. The intensity of these peaks, shown in Fig. 8, will be used as part of a future work to correlate with soil moisture levels. In Table II, the success rate of the VNA sensor is provided. 330 trials were conducted over 6 weeks. Of these trials, the MATLAB analysis detected at least one distinguishable peak in 242 of the 330 trials. This is a success rate of 73.33%. Although some of the missed peaks are due to misalignment and inaccuracies with the VNA system, the trend of decreasing success rate over time indicates that these prototype biodegradable sensors become less reliable over time. However, the observed increase in success rate from week 5 to week 6 occurred due to heavy rainfall during week 6, which elevated the soil moisture levels to higher than average and increased the likelihood of degrading sensors responding to moisture content by producing peaks. Since the VNA sensor had a success rate above 90% for the

TABLE II: Sensor reading accuracy

Week #	VNA Reading Accuracy	
	Trials	Success Rate (%)
1	30	100%
2	60	100%
3	60	88.33%
4	60	78.33%
5	60	33.33%
6	60	53.33%
Total	330	73.33%

TABLE III: Sensor reading alignment error

Mean Error		Max Error		Allowable Tolerance	
X (cm)	Y (cm)	X (cm)	Y (cm)	X (cm)	Y (cm)
1.3	0.6	3	2	4	4

first 3 weeks at 95.33% before decreasing substantially, we can conclude that the VNA sensing configuration coupled with the soil moisture sensors is reliable enough for real-world applications in the short term, but will require the deployment of more robust sensors and/or multiple sensors for redundancy during longer periods of operation.

B. Vision-guided Navigation Results

An outdoor field test was performed to test the performance of the vision-guided navigation system. The robot was commanded to autonomously navigate in a straight line along one row to 10 of the deployed sensors by detecting the ArUco markers placed adjacent to them. After successfully reaching a sensor, the reading head of the robot along with the VNA was lowered to take a sensor reading and then retracted. This sequence was automated and repeated for all of the ten sensors.

During the experiment, the in-plane alignment errors in X and Y between the sensor reader and the ground-truth location of the buried sensor were recorded and reported in Table III. The X axis is parallel to the driving direction of the robot and the Y axis is perpendicular to the driving direction. In some cases, sensor reading alignment errors are caused due to reflective artifacts on the ArUco marker, which leads to an unreliable detection. The inductive loop of the sensor reader has a fixed radius of 4 cm. Therefore, the maximum tolerable error in either direction is approximately 4 cm. An error larger than this threshold will result in the reader missing the sensor and an unreliable reading. The maximum alignment error for all of the conducted trials was below this threshold. It demonstrates that the robot is capable of navigating autonomously by accurately detecting the ArUco markers and taking reliable sensor readings without any human intervention.

IV. CONCLUSION

This paper presents DRILL, a robotic platform for autonomously drilling and reading in-ground low-cost biodegradable soil moisture logging sensors. The robot addresses the need for more data-driven practices in the agricultural field by offering a method to deploy low-cost biodegradable soil moisture sensors without human intervention. By combining novel mechatronic systems for

drilling and sensing with an integrated RGB camera for perception, the robot demonstrates reliable deployment and sensor reading capabilities. Additionally, a visual-based navigation approach was proposed using ArUco markers as fiducials. The robot platform was experimentally validated in a real-world farm environment. The testing reported that the drilling mechanism had a 93.75% success rate and the sensing mechanism had a 100% success rate. The sensor reading tests with the VNA also had a 73.33% success rate in detecting soil moisture content over a period of 6 weeks. The operational efficiency of the robot was also evaluated, and the average sensor deployment cycle time was found to be under a minute per sensor. This rapid cycle enables frequent and scalable soil moisture monitoring across agricultural fields, addressing the need for timely data acquisition in precision agriculture. These results validate the robot's functionality and reliability, laying the groundwork for scalable, autonomous soil monitoring.

To further enhance the operational efficiency and robustness of the robotic platform, future work will include developing a deep learning-based buried sensor location detection pipeline eliminating the need for ArUco markers. Additionally, manufacturing of the plow system of the robot will be explored with tougher materials for it to better withstand the forces exerted due to pushing the heavy dirt. The reading configuration of the robot will also be modified to take more than one sensor reading with the VNA per cycle for reducing the chances of unreliable data due to misalignment errors. Further research will also investigate the use of multi-robot swarms to reduce deployment times and increase coverage.

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