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Towards Automation in Agriculture: Use of LiDAR for Moisture Remote Sensing in Soilless Media

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***Abstract*—Accurate monitoring of substrate moisture is essential for closed-loop irrigation control in controlled-environment agriculture. Rockwool, a widely used soilless growth medium, requires precise water management to maintain optimal air-water balance and ensure crop performance. Existing measurement approaches are predominantly contact-based, relying on embedded dielectric or solution-equilibration sensors that may suffer from placement sensitivity, local heterogeneity, and long-term drift. This study investigates a non-contact alternative based on active LiDAR sensing for moisture estimation in rockwool cubes. An Intel RealSense L515 solid-state LiDAR camera was used to acquire depth and infrared (IR) return data under controlled experimental conditions. Water content, ambient illumination (0-341.9 lux), and sensor-to-target distance (0.5-0.7 m) were systematically varied to evaluate robustness against key environmental and geometric confounders. For each trial, approximately 120 frames were captured and reduced to summary statistics of depth, IR intensity, confidence, match quality, and region-of-interest (ROI) characteristics. A regression-based framework employing median imputation, standard scaling, and Ridge regression was implemented to predict gravimetric mass, which was subsequently mapped to a normalized wetness score ranging from 0 to 100. On a held-out test set, the proposed model achieved a Mean Absolute Error of 5.755 wetness score points and an R^2 value of 0.959, indicating strong agreement with measured mass across dry, medium, and wet conditions. Results demonstrate that LiDAR-derived geometric and radiometric features encode sufficient information to infer rockwool moisture under moderate variations in lighting and distance. The findings support the feasibility of compact LiDAR sensors as practical, non-invasive moisture monitoring tools for automated irrigation systems in vertical farming and greenhouse environments.

***Keywords-component*—Automation in Agriculture; Moisture Detection; Remote-sensing; LiDAR; Rockwool Substrate**

I. Introduction

Rockwool (stone wool) is widely used as a soilless growth substrate in controlled-environment agriculture due to its favorable air–water characteristics and compatibility with precise fertigation strategies. Maintaining the substrate water content within an appropriate range is critical, since rockwool water content strategies can influence crop performance and productivity [1]. Accurate and timely measurement of moisture in rockwool is therefore a key enabling capability for closed-loop irrigation control.

Existing rockwool monitoring approaches are often based on contact or embedded sensors. For instance, dielectric (capacitance-based) methods have been proposed to estimate water content and electrical conductivity (EC) in rockwool substrates [2]. Other automated approaches measure water status and nutrient concentration in rockwool slabs using sensor elements that equilibrate with the slab solution [3]. While these techniques can be effective for point measurement and process control, they require physical insertion or integration with the substrate and may be sensitive to sensor placement, local heterogeneity, and operational drift over long deployments.

Non-contact optical sensing provides an alternative avenue for moisture estimation. In near-infrared (NIR) spectroscopy and reflectance-based approaches, moisture alters absorption and scattering properties, enabling moisture prediction using multivariate models [4]. However, passive reflectance measurements can be sensitive to ambient illumination and view geometry, and they typically do not provide geometric context (e.g., surface shape, distance) that is useful for robust deployment in greenhouse environments.

Handheld near-infrared (NIR) spectroscopy [5] and thermal imaging cameras [6] have been used for moisture or water-stress estimation; however, they can be impractical for robotic automation due to cost, integration complexity, and power consumption. In contrast, active depth sensing via time-of-flight (ToF) and LiDAR cameras offers the ability to acquire dense 3D geometry while also providing a returned-signal strength (intensity/amplitude) channel that can correlate with material reflectance. The Intel RealSense LiDAR Camera L515

Figure. 1. Intel RealSense L515 LiDAR camera used for non-contact moisture sensing experiments.

is a compact solid-state LiDAR (indirect ToF) sensor designed for indoor use and capable of high-rate depth capture [7]. Intel documentation notes that L515 operation depends on returned-signal quality and can be affected by ambient light (notably sunlight and some artificial lighting), surface reflectivity, and sensor configuration [8]. Independent experimental evaluation has also shown that L515 (and similar RGB-D sensors) can exhibit degraded depth estimation in challenging scenes such as transparent and translucent materials, underscoring the importance of careful characterization when deploying ToF/LiDAR sensing in real applications [9].

Motivated by the need for practical, non-contact moisture monitoring for soilless cultivation, and inspired by the results of our previous research on rockwool cubes using UV-Vis-NIR spectroscopy (illustrated in Fig. 2), this work investigates the feasibility of detecting moisture levels in rockwool cubes using an Intel RealSense L515 LiDAR camera (shown in Fig.1). We conduct controlled experiments that vary (i) water content, (ii) environmental lighting, and (iii) camera-to-target distance, to quantify the sensitivity of LiDAR-derived observables to moisture while explicitly probing key confounding factors that impact signal quality and repeatability.

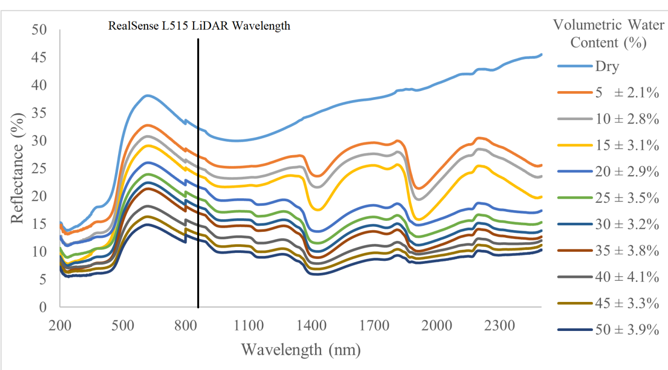

Figure. 2. Spectral signature of rockwool across different volumetric water content levels obtained from UV-Vis-NIR spectroscopy.

II. Materials and Methods

A. Experimental Setup

Moisture measurements were acquired using an Intel RealSense L515 LiDAR depth camera. The L515 is a solid-state time-of-flight LiDAR sensor capable of providing synchronized depth, infrared (IR) intensity, and per-pixel confidence and match-quality outputs. The sensor was rigidly mounted to ensure fixed orientation relative to the target during each trial.

Horticultural rockwool cubes (illustrated in Fig.3) were used as the test substrate due to their widespread application in controlled-environment agriculture and vertical farming systems. The cubes were positioned directly beneath the sensor optical axis. All measurements were conducted indoors to minimize uncontrolled environmental variability.

Three sensor-to-target distances were investigated to evaluate geometric sensitivity. In addition, ambient illumination was varied and recorded in lux. The evaluated distances and illumination range are summarized in Table I.

Figure. 3. A dry rockwool sample used for data collection.

TABLE. I
Sensor-to-target distances and illumination range.

Parameter	Value
Distance levels (m)	0.5, 0.6, 0.7
Illumination range (lux)	0.0 – 341.9

B. Moisture Ground Truth Definition

Moisture content was defined gravimetrically. Each rockwool condition was weighed using a calibrated digital scale (Uline H-9884), and three baseline states were established: dry, medium, and wet. The corresponding masses are shown in Table II.

TABLE. II
Baseline gravimetric measurements for moisture conditions.

Condition	Mass (g)
Dry	5.55
Medium	23.75
Wet	47.16

A total of 101 experimental trials were collected across all environmental conditions. The distribution of samples per moisture level is provided in Table III.

C. Data Acquisition and Feature Extraction

Each experimental trial consisted of approximately 120 consecutive frames captured by the L515 sensor. Automatic

TABLE. III
NUMBER OF TRIALS COLLECTED PER MOISTURE CONDITION.

Condition	Number of Trials
Dry	41
Medium	30
Wet	30

region-of-interest (Auto ROI) mode was enabled during acquisition. For each frame, depth, IR intensity, confidence, and match-quality data were extracted within the selected ROI.

Trial-level summary statistics were computed by aggregating pixel-wise values across frames. Both mean and standard deviation metrics were calculated for each signal channel. The merged modeling dataset consisted of trial-level summary features and the associated ground-truth mass values.

Seventeen features were used as model inputs. These included geometric descriptors (distance and illumination), depth statistics, infrared statistics, confidence and match statistics, and ROI radius summaries.

D. Wetness Score Formulation

Rather than performing categorical classification, moisture was modeled as a continuous variable. The regression target was the measured mass $m(g)$.

For interpretability, predicted mass values were linearly mapped to a normalized wetness score $S \in [0, 100]$ according to Eq.1 and mass values from II.

$$S = 100 \cdot \frac{m - m_{\text{dry}}}{m_{\text{wet}} - m_{\text{dry}}} \tag{1}$$

E. Regression Modelling

A regression-based framework was implemented to estimate rockwool mass from LiDAR-derived features. The modeling pipeline was constructed using scikit-learn. Missing values were handled via median imputation, followed by standardization to zero mean and unit variance. Ridge regression with L2 regularization was employed to mitigate multicollinearity and reduce overfitting.

The dataset was randomly partitioned into training and testing subsets using a 75:25 split. Model performance was evaluated on the held-out test set using Mean Absolute Error (MAE) and the coefficient of determination R^2.

III. RESULTS AND DISCUSSION

A. Regression Performance

The Ridge regression model demonstrated strong predictive performance on the held-out test set, as provided in Table IV. Results indicate that approximately 95.9% of the variance in gravimetric moisture content was explained by the selected feature set and the model had a mean wetness score error of 5.76 points. Considering that only three discrete ground-truth baselines were available (dry, medium, wet), this level of agreement suggests that the regression framework successfully interpolated between discrete mass levels.

TABLE. IV
REGRESSION PERFORMANCE ON HELD-OUT TEST SET.

Metric	Value
MAE	5.755
R^2	0.959

B. Prediction Behavior Across Moisture Levels

Qualitative inspection of representative predictions revealed that dry and wet samples were generally estimated near their respective extremes (0 and 100). Medium-moisture samples exhibited a slight systematic underprediction, with predicted scores often falling below the nominal midpoint of 50.

This behavior is consistent with regression toward the mean, particularly when training data consist of discrete clusters rather than a continuous distribution. Since the model was trained on three gravimetically defined baselines, intermediate values were learned through interpolation rather than direct supervision. Consequently, medium samples may have been influenced by feature overlap with lower-moisture conditions.

Despite this effect, prediction errors remained bounded, and no systematic collapse toward either extreme was observed. The relatively low MAE confirms that deviations were limited in magnitude.

C. Effect of Distance and Illumination Variation

The experimental design intentionally incorporated variations in sensor-to-target distance and ambient illumination. The strong predictive performance across all collected trials indicates that the selected feature set successfully compensated for moderate geometric and lighting variability.

Depth-based features were expected to exhibit distance sensitivity. However, normalization through standard scaling and the inclusion of explicit distance and illumination inputs enabled the regression model to account for these variations. The high R^2 value suggests that moisture-dependent signal changes dominated over distance-induced variability within the tested range of 0.5-0.7 m.

Similarly, illumination varied from 0.0 to 341.9 lux. Although the L515 is an active LiDAR sensor and less sensitive to ambient light than passive optical systems, infrared intensity and match-quality metrics may still be influenced by environmental lighting conditions. The results indicate that such effects did not degrade predictive stability within the tested illumination range.

D. Physical Interpretation of LiDAR-Derived Features

Moisture content in rockwool modifies both its optical and structural properties. Increased water content alters surface reflectance characteristics, affects infrared scattering, and may modify depth return stability due to changes in absorption and surface microstructure.

The inclusion of IR intensity statistics, depth variance metrics, and confidence/match measures allowed the regression model to capture these multi-modal effects. The strong predictive accuracy suggests that LiDAR-derived signals encode sufficient information to infer substrate wetness without direct contact measurement.

Unlike purely intensity-based imaging approaches, the L515 provides both geometric and radiometric descriptors. The combination of depth stability metrics and IR reflectance statistics likely contributed to robustness against environmental variability.

IV. Conclusion

A non-contact methodology for estimating rockwool moisture content using an Intel RealSense L515 LiDAR camera was presented. Trial-level summary statistics of depth, infrared intensity, confidence, and match-quality signals were extracted under varying sensor-to-target distances and illumination conditions. A regression-based framework was implemented to predict gravimetric mass, which was subsequently mapped to a normalized wetness score ranging from 0 to 100.

The proposed approach achieved strong predictive performance, with a Mean Absolute Error of 5.755 wetness score points and an R^2 value of 0.959 on a held-out test set. These results demonstrate that LiDAR-derived geometric and radiometric features contain sufficient information to infer substrate moisture content under controlled indoor conditions. Robust performance across distances of 0.5-0.7 m and illumination levels up to 341.9 lux indicates that the method is resilient to moderate environmental variability.

The study confirms the feasibility of using compact LiDAR sensors for substrate moisture monitoring in controlled-environment agriculture. Compared to contact-based sensing methods, the proposed technique offers the advantages of non-invasive measurement, reduced wiring complexity, and potential scalability to multi-cube monitoring systems.

Future work should incorporate additional intermediate moisture levels to strengthen regression calibration, evaluate angular variability, and expand testing to broader illumination and greenhouse operating conditions. Integration with automated irrigation control systems represents a promising direction for real-time decision support in vertical farming applications.

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