Pertanika J. Sci. & Technol. 34 (1): 263 - 282 (2026)

SCIENCE & TECHNOLOGY

Journal homepage: http://www.pertanika.upm.edu.my/

A Practical Calibration Approach for Low-cost Soil Moisture Sensor in the Tropical Agricultural Area

Sigit Kurniawan[1]*, Mohd Nadzri Mohd Reba[2], Mahmud Idris[1], Mazwan[3], Tanto[4], and Yulia Efronia[5]

[1]*Electronic Engineering Study Programme, Politeknik Jambi, 36125 Kota Jambi, Jambi, Indonesia*
[2]*Geoscience and Digital Earth Centre (INSTeG), Research Institute for Sustainable Environment (RISE), Universiti Teknologi Malaysia (UTM), 81310 UTM Johor Bahru, Johor, Malaysia*
[3]*Mechanical Engineering Study Programme, Politeknik Jambi, 36125 Kota Jambi, Jambi, Indonesia*
[3]*Software Engineering Study Programme, Politeknik Jambi, 36125 Kota Jambi, Jambi, Indonesia*
[4]*Electrical Engineering Study Programme, Politeknik Jambi, 36125 Kota Jambi, Jambi, Indonesia*

ABSTRACT

Utilisation of low-cost sensor (LCS) for soil moisture measurement is increasing along with the advancement of integrated agricultural technology and environmental data collection. One such low-cost sensor, SKU:SEN0193, demonstrates that its measurement accuracy heavily depends on the calibration model. Unlike the commercial sensor, the LCS has less document related to the operation, especially the conversion equation to precisely estimate the soil moisture from the voltage records. Attaining LCS consistency is no straightforward task when many LCS had less been tested on the field at longer period to determine the durability attribute. The main challenge in applying the SKU:SEN0193 for soil moisture measurement is to determine the accuracy, reliability and suitability of records in long-term measurement routine. The present study focussses on developing a calibration model using field gravimetric measurement for accuracy assessment and to evaluate sensor reliability and durability through long-term calibration exercises. Results showed that calibration model produces promising relation to the gravimetric soil moisture with R^2=0.81 and RMSE=1.02 %. Though, the SKU:SEN0193 encountered an average output difference of about 7% variation between measurement records that manifested in kurtosis peaks and significant changes in skewness distribution patterns. This study found that SKU:SEN0193 exhibits good durability through the consistent negative skewness distribution patterns and

ARTICLE INFO

Article history:
Received: 16 December 2024
Accepted: 19 November 2025
Published: 06 February 2026

DOI: https://doi.org/10.47836/pjst.34.1.12

E-mail addresses:
sigit@politeknikjambi.ac.id (Sigit Kurniawan)
nadzri@utm,my.id (Mohd Nadzri Mohd Reba)
mahmud@politeknikjambi.ac.id (Mahmud Idris)
mazwan@politeknikjambi.ac.id (Mazwan)
tanto@politeknikjambi.ac.id (Tanto)
yulia@politeknikjambi.ac.id (Yulia Efronia)
* Corresponding author

e-ISSN: 2231-8526

negligible differences in kurtosis peaks of when the sensor did not experience malfunction or significant deviation during the several tests.

Keywords: Calibration, low cost sensor, SKU:SEN0193, soil moisture

INTRODUCTION

Low-Cost Sensors (LCS) generally have limitations, including a higher degree of inaccuracy compared to expensive sensors. Small disturbances in LCS can cause significant differences in output trends. Such limitation may due to sensor manufacturers typically focuss only on specific parameters being measured, while other parameters are often overlooked to reduce production costs (Kim et al., 2023). The LCS typically exhibits low bias and precision during measurements (Mathieu-Campbell et al., 2024) so that model calibration is necessary to realign the output record with actual measurement on the field (Pereira et al., 2022) as well as improving consistency across sensors or within a single sensor (Kureshi et al., 2022), and maintaining the performance against drift for long-term use (Narayana et al., 2022). Using LCS without calibration can lead to inaccurate readings and low reliable data (Nagahage et al., 2019), improper sensor selection and inaccurate prediction models, especially when machine learning (ML) is involved (Kureshi et al., 2022). Nevertheless, the LCS has great potential for use in non-commercial monitoring systems or integration with IoT networks.

Soil moisture is a critical component in agriculture and soil science, influencing water availability for plants and overall crop productivity (Pereira et al., 2022). The utilisation of Low-Cost Sensors (LCS) for soil moisture measurement is increasing in line with the advancement of integrated agricultural technology and environmental data collection especially in the tropical region. Low-cost sensor, like the SEN0193, which employs capacitive sensing methods, can offer accessible and practical solutions for monitoring the soil moisture (Kulmány et al., 2022). However, the accuracy is often compromised by environmental and soil-specific factors, necessitating in calibration modeling. Systematically calibrating the SEN0193 could improve the accuracy, reliability, and durability, and thus ensuring data consistency and reliability across diverse conditions (Rasheed et al., 2022).

Several common calibration methods used on the field soil moisture measurements including thermogravimetric, frequency domain and time domain reflectometry, neutron scattering (Placidi et al., 2020; Rasheed et al., 2022) and calibration using standard sensors refers to a sensor used in the industry such as ThetaProbe (Adla et al., 2020). The thermogravimetric method is highly reliable for determining soil moisture within a range of 0–100%. This method completely depends on soil structure (Nagahage et al., 2019) and the data is only valid for single time measurement (Rasheed et al., 2022). FDR and TDR measure soil moisture based on dielectric permittivity by transmitting electromagnetic waves and analysing the time or frequency changes after the waves pass through the medium. The measurement provides reliable data only for the soil with moisture content below 50% or in dry condition. Neutron scattering is the best soil moisture measurement over large area and at specific soil depth, but the data is questionable for shallow soil layers at depths less than 0.3 m (Nagahage et al., 2019). Occasionally, the LCS calibration can also be performed by comparing sensor readings with reference sensors (Adla et al., 2020).

The thermogravimetric method is commonly used for calibrating the capacitive soil moisture sensors, like SKU:SEN0193. Basically, the accuracy is defined by sampling techniques and handling (Placidi et al., 2020), mineral or salt content in the sample, electrical conductivity (Al-Rawi, 2024; Kanso et al., 2020; Nagahage et al., 2019), the accuracy of the weighing instrument and drying time (Gianessi et al., 2024) and water reabsorption by the sample (Adla et al., 2024). The present study defined the advantages of thermogravimetric variant by which improvision of accuracy for capacitive sensor to measure soil moisture can be possible. Comparison between water and soil mass in thermogravimetric method allows all types of sensors to be used without considering other soil properties and thus make this method more straightforward. This variant also has a low degree of drift because the capacitive sensor reading depends entirely on the data acquisition speed. Sample collected in containers, in the form of aluminum cups or polycarbonate containers, can reduce the water evapouration provided that it was stored at room temperature during the calibration process (Hidayat et al., 2024; Nagahage et al., 2019). Even though the accuracy of weighing scale has been occasionally mentioned, the impact was minimum. Only the drying time is crucial and longer drying time is always recommended Aringo et al. (2022), e.g., 24 hours and 48 hours respectively by Markovic et al. (2024) and Lopez et al. (2022). As of the time of this paper, there has been no comparative study discussing drying time selection systematically, although the volume and type of soil being dried clearly affect the required drying time.

The accuracy of LCS is significantly dependent on the calibration model in which specific convention expression is applied with the voltage output as the functional input. For SKU:SEN0193, information or operational document related to the conversion model is not available and this issue has already been highlighted in some LCS studies (Majumder et al., 2023; Pereira et al., 2022). The calibration model should give soil moisture estimates which is close to the actual ground soil moisture and this could be possible if the quality of the developed calibration model is assessed (Adla et al., 2020). Some studies also approved that sensor errors and drifts can be minimised by calibration model to increase sensitivity towards real changes in the physical object being measured (Yang et al., 2024). Besides, other utilisation of calibration model is to reduce the measurement biases or extreme data outliers that always hampered in sensor reading and ultimately reducing the precision level of LCS (Mathieu-Campbell et al., 2024, Nieto et al., 2021).

The present paper highlights the potential of SKU:SEN0193 in soil moisture measurement in terms of its accuracy, reliability and durability at the tropical agricultural area and the developed calibration model which is a novel of its kind. Therefore, this study focussses on the selected objectives as follows; (1) performing the calibration directly at the field to establish higher collocation and correlation between the sensor output and field soil moisture measurement. (2) comparing two SKU:SEN0193 sensors in order to asses the consistency and applying the calibration model to both sensors for reliability check; and (3) applying the durability test on both sensors at designated time period by ensuring the potential error remains minimum. The accuracy, reliability and suitability tests conducted in this study provides insights about the limitation and advantage of the SKU:SEN0193 for precision agriculture efforts where the soil moisture becomes one of the crucial parameters required.

DATA AND METHODOLOGY

The Low Cost Sensor SKU:SEN1903 (DFROBOT, Shanghai, China) is a capacitive soil moisture sensor manufactured by Long Whale Fashion UK LTD, China by DFRobot.com. It operates at a voltage of 3.3 ~ 5.5 VDC, has dimensions of 3.86 × 0.905 inches (L × W), and produces an output voltage of 0 ~ 3.0 VDC. Using the capacitive measurement method, this sensor detects soil moisture changes based on variations in capacitance caused by contact with surrounding materials. Made of fibreglass with copper electrodes coated in an anti-corrosion material, this sensor is more durable. Compared to resistive soil moisture sensors, which are prone to oxidation, this capacitive sensor offers better stability and more reliable performance for long-term use.

The performance of LCS SKU:SEN0193 is evaluated using two methods: (1) field testing and (2) laboratory testing (Kanso et al, 2020). Field testing is conducted to obtain calibration data directly in the field according to the proposed method. Additionally, field testing is used to evaluate the durability of the LCS by placing the sensor in the field and observing the stability of sensor readings over time. Meanwhile, laboratory testing aims to evaluate the repeatability and variability of the sensor, with the expectation that measurement consistency can be achieved under controlled conditions. The soil samples are kept stable and unaffected by external factors. In the sensor-to-sensor variability test, two sensors are installed on the same soil sample in a closed container, and soil moisture readings from both sensors are taken simultaneously to compare their outputs.

Laboratory Sensor Testing

The laboratory test aims to evaluate the repeatability of the sensor and sensor-to-sensor variability in the LCS. The approach is based on simulating real environmental conditions in the laboratory with specific procedures as follows. Soil samples were taken from the same location as the field-testing site to maintain consistency in environmental parameters. The sample depth was 5 cm, and the samples were collected in plastic tubes with plastic seals to prevent evapouration during storage. The sample volume taken was 750 cm^3 to ensure sufficient representation of the soil under laboratory testing conditions. The soil samples were placed in an isolated chamber with controlled temperature to prevent evapouration. Two units of the LCS sensor were installed in the sample tubes with a distance of 10 cm between them. This distance was designed to minimise the influence of interference between the sensors. The sensors were connected to a datalogger to record measurement data in every minute. Data collection was conducted continuously for 8 hours. The data obtained from both sensors was then analysed to evaluate sensor repeatability and sensor-to-sensor variability using statistical analysis.

Field Sensor Testing

Field testing was conducted twice. The first test aimed to measure soil moisture and collect samples for thermogravimetric calibration, while the second one is to evaluate the sensor's durability. Both exercises took place in Muaro Jambi, Jambi, Indonesia, at coordinates -1.624, 103.69 (Figure 1a). The testing location is situated in a pineapple plantation (Figure 1b), with peat soil type and a peat layer depth reaching up to 3 metres.

(a) (b)

Figure 1. Field sensor testing: (a) Map of location of field testing, (b) topography of the location

In the first test, measurements were conducted at 24 points, with each point spaced 10 meters apart to capture soil moisture variations (Figure 1a). Each point was measured over a 5-minute period, resulting in a total measurement time of 120 minutes for all 24 points. Before collecting soil samples, soil moisture was measured using a datalogger connected to the LCS. The sensor output, in the form of voltage values representing soil moisture, was then converted into digital data using a 10-bit ADC on an Arduino Uno board (Hidayat et al., 2024). The datalogger was used to display the soil moisture readings at the designated points as sensor voltage (Figure 2).

Figure 2. Sensor installation at the location

Measurements were taken by inserting the sensor probe at a depth of 10 cm from the soil surface. This depth was chosen as it represents the soil layer that plays a significant role in plant growth, aligning with the relevance of the sensor application in agriculture. Additionally, soil moisture at this depth is highly sensitive to changes in environmental conditions. Later, the soil from the 10 cm depth was collected and placed into a 50 cm diametre aluminum cup. Each cup was sealed to minimise any water loss.

The collected samples were then weighed using a digital scale with an accuracy of 0.01 grams to record the wet mass. Next, the samples were dried in an oven at 104°C for 48 hours to ensure maximum evapouration. After the drying process was completed, the samples were weighed again to record their dry mass. The purpose of this process is to measure the water content in the soil sample by calculating the difference between the wet and dry masses. The soil moisture value was calculated using equations 1 and 2 (Aringo et al., 2022).

$$\theta_g = \frac{M_w - M_d}{M_d} \quad [1]$$

$$\theta_v = \theta_g \, \rho \quad [2]$$

where θ_g is the gravimetric water content (g/g), M_w is the soil sample before oven drying (g), M_d is the soil sample after oven drying (g), ρ is the soil bulk density (g/mL). The volumetric water content (mL/mL), θ_v, is determined based on the multiplication of bulk density and gravimetric water content of the soil sample and it also can be converted to percentage units to simplify data analysis (Toková et al., 2019). The soil moisture estimate for each sample was recorded according to the sample code, which indicates the sampling location, and this value was then compared with the LCS reading at each point to obtain the calibration model.

The second test was conducted at the same location by placing the datalogger with the LCS at a single measurement point. The test lasted for 5 days, from July 27 to August

1, 2024. This test aimed to identify anomalies in the LCS SKU:SEN0193 over a short period, considering the battery power supply and extreme environmental changes during data collection. Stability testing becomes unfeasible if the data variation is too large, as this can shift the distribution peak, making the data difficult to analyse. The test was conducted during the dry season, with an average daytime temperature of 33°C, a nighttime temperature of 24°C, and an average air humidity of 74%. The sensor was placed at the same depth as in the previous test (5 cm), and the datalogger was powered by a 6V 4.5Ah battery. Data collection occurred every 15 minutes, assuming that soil moisture changes take place approximately once per hour (Nagahage et al., 2019). The collected data, including the date and time (datetime) and sensor voltage, were then stored on an SD card attached to the datalogger. This data was later processed with statistical analysis.

Data Analysis

The field test analysis is divided into two parts. The first part is regression analysis to develop an accurate calibration model, while the second part is distribution statistical analysis to evaluate the durability of the sensor based on field measurements. All sensor measurement data is stored in CSV format and processed using Jupyter Notebook software with Python programming. The calibration model is constructed using the Least Squares (LS) method, with the soil moisture from the gravimetric test (Y, %) as the dependent variable and the sensor voltage readings (X, Volt) as the independent variable. The LS method was chosen due to its simplicity in the relationship between the two variables and the relatively small dataset size ($n < 32$). The dataset is split into two parts: training data to build the calibration model and testing data to evaluate the model's performance. Several calibration models are tested, including linear regression, polynomial regression, and exponential regression. The best calibration model is selected based on the highest coefficient of determination (R^2). For model validation, the root mean square error (RMSE) method is used to calculate the difference between the predicted data and the testing data. This approach follows the methodology used by Ferrarezi et al. and Chandel et al. (Ferrarezi et al., 2020; Chandel et al., 2024). The R^2 and RMSE values are defined as shown in Equations 3 and 4 (Chandel et al., 2024).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Yi - \bar{Y}i)^2}{\sum_{i=1}^{n}(Yi - \bar{Y})^2} \qquad [3]$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Yi - \bar{Y}i)^2} \qquad [4]$$

where n is the number of data points used to build the model, Yi is the actual value of the sensor output, Yl is the predicted value of the sensor output, and Y is the average of the actual sensor output values.

The durability analysis focussses on detecting bias and drift from the sensor. To assess potential bias and drift in the sensor's measurement data, skewness and kurtosis tests are conducted daily. The calculations for skewness and kurtosis are as shown in Equations 5 and 6 (Bono et al., 2020).

$$G = \frac{n\sum_{i=1}^{n}(x_i - \bar{x})^2}{(n-1)(n-2)s^2} \qquad [5]$$

$$K = \frac{1}{n}\frac{n\sum_{i=1}^{n}(x_i - \bar{x})^2}{s^2} \qquad [6]$$

where n is the number of values in the sensor data, X_1 is the i-th value of the data, $\bar{X}$ is the average output of the sensor, and s is the sta ndard deviation (SD) of the data. Equation (5) yields a negative, zero, or positive value. If G=0, the distribution is normal; if G is negative, the data set tends to have values above the mean, and conversely, if G is positive. Furthermore, equation (6) can be zero, less than zero, or greater than zero. If K<0, it indicates a sharp distribution with a peak, while K>0 suggests a distribution that spreads sideways, and K=0 indicates that the sensor data has a normal distribution (Ozansoy & Fahrioglu, 2020).

The laboratory testing analysis to determine the consistency of LCS SKU:SEN0193 output uses the calculation methods of mean value, standard deviation (SD), and coefficient of variation (CV) (Ferrarezi et al., 2020). The mean value is used to indicate the general trend of the sensor output, while the relationship between the mean value and the maximum-minimum values shows the level of data dispersion. A small standard deviation (SD) indicates that the sensor's outliers are stable and do not have significant outliers (Hidayat et al., 2024). The coefficient of variation (CV) is used to measure the consistency of sensor readings, with a small CV indicating the precision of the sensor. The evaluation is performed for both individual sensors and sensor-to-sensor comparisons, as explained in the methodology by Kanso et al. (2020) and Ferrarezi et al. (2020). The formulas for calculating the mean value, SD, and CV are given in Equations 7, 8, and 9.

$$\bar{X} = \frac{\sum_{i=1}^{n} Xi}{n} \qquad [7]$$

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(Xi - \bar{X})^2}{n}} \quad [8]$$

$$CV(\%) = \frac{\sigma}{\bar{X}}100 \quad [9]$$

where n is the number of values in the sensor data, X_1 is the i-th value of the data, $\bar{X}$ is the average output of the sensor, σ is the standard deviation (SD), and CV is coefisien corellation. The consistency of the output from both sensors is also tested using the skewness and kurtosis parameters as shown in Equations 5 and 6. The skewness parameter is used to evaluate whether the distribution patterns of both sensors differ, indicating the presence of bias, while the kurtosis parameter is used to show the level of fluctuation occurring in each sensor, which causes peak changes and indicates drift (Ozansoy & Fahrioglu, 2020).

RESULTS AND DISCUSSION

Based on the objectives described above, each issue to be addressed is explained in each section related to the testing results. First, how to obtain a calibration model from LCS SKU:SEN0193 measurements through direct field measurements with the sensor and sample testing using thermogravimetric methods. Second, how to assess the reliability of LCS based on repeatability analysis, both for a single sensor and across sensors, based on laboratory testing with the same sample. Third, how to evaluate the sensor's durability based on LCS field testing over 5 days, which is analysed using skewness and kurtosis tests to detect the presence of bias and drift in the sensor.

Sensor Accuracy

Based on the measurements from 24 sensor sampling points, as shown in Figure 3, it was observed that some data exhibited a high level of outliers, rendering them unsuitable for calibration model development. To construct the calibration model, 17 data points, approximately 70% of the total samples, were selected for model construction, while the remaining 7 data points, representing 30% of the samples, were used for model testing. The selection of measurement data for model development was guided by the trend patterns of sensor data relative to gravimetric values.

The sensor calibration graph, which utilises the gravimetric method as depicted in Figure 4, demonstrates the relationship between the sensor output voltage and soil moisture conditions. This indicates a correlation between the sensor output and soil moisture, with a correlation index R of -0.76. The negative value indicates that the sensor output is inversely related to soil moisture level.

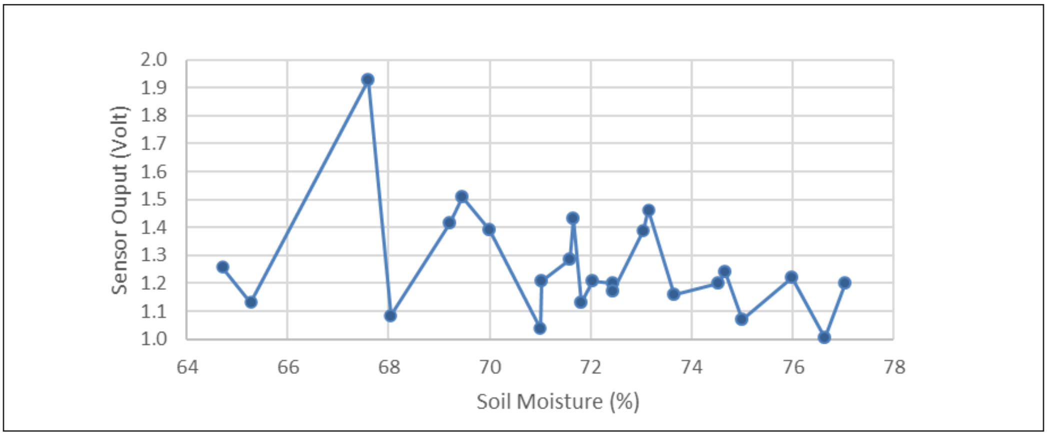

Figure 3. Data points collected from 24 sampling locations

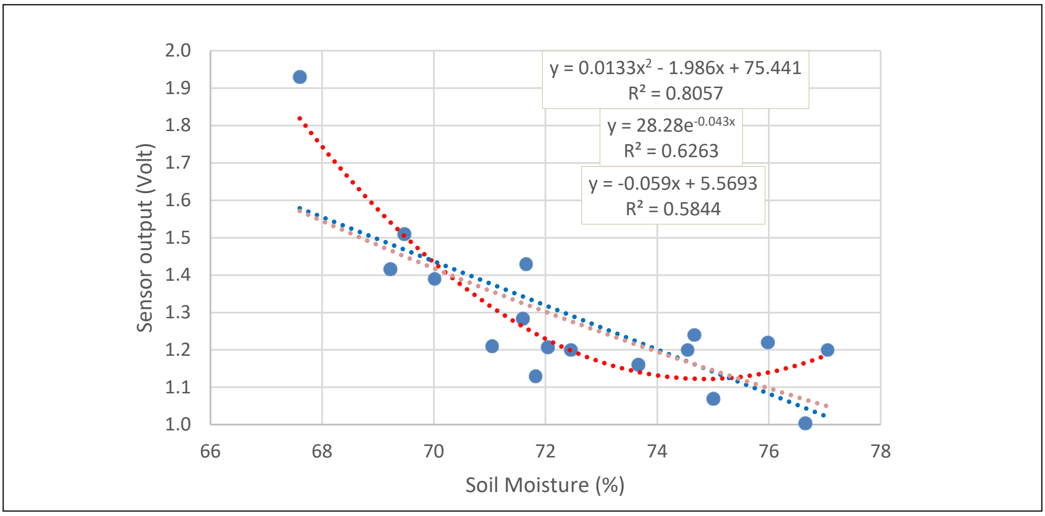

Figure 4. Calibration curve of LCS SKU:SEN0193 using thermogravimetric method

Table 1
The fitting matrix of each regression

Fitting Model	R	R^2	RMSE	MAE
Polynomial Regression	-0.76	0.81	1.02	1.39
Exponential Regression	-0.76	0.63	0.24	0.58
Linier Regression	-0.76	0.58	0.25	1.87

Note. R is used to determine the positive or negative correlation between sensor output and soil moisture

The fitting values for each regression are shown in Table 1. The calibration curve has a correlation coefficient of R^2=0.81, RMSE=1.02, and MAE=1.39 for polynomial fitting. In contrast, exponential fitting has R^2=0.63, RMSE=0.24, and MAE =0.58. While linear fitting shows R^2=0.58, RMSE=0.25, and MAE=1.87. The second-order polynomial model has the highest R^2 compared to other models, indicating that this model has better correlation. These results are consistent with the calibration model reported by Placidi et al. (2020) for different soil types.

These findings indicate that the relationship between soil moisture content and the output of LCS sensor is quadratic, despite variations in soil types and moisture measurement ranges (66–78%). The RMSE for the second-order polynomial model is 1.02%, which is higher than that of other models. The polynomial model's sensitivity to outliers is the main factor contributing to this high value. Nevertheless, an RMSE of 1.02% is still acceptable for a soil moisture measurement range of 1–100%, depending on the accuracy requirements of the measurement device.

Other researchers (Peirera et all, 2022; Nagahage et all, 2019; Kulmany et all, 2022) have reported lower RMSE values due to testing conducted in laboratory conditions with limited sample sizes, unlike field testing, which involves a more varied sample distribution. The MAE for the second-order polynomial model is also higher than that of the exponential model. This is attributed to the greater accumulation of errors (RMSE) in the polynomial model. Conversely, the exponential model tends to have lower RMSE and MAE values because its calibration is less affected by outliers. However, the proportion of outliers in these measurement results is relatively small (<30% of the total data). Thus, the second-order polynomial calibration model is still considered acceptable.

Based on the fitting results of the three models, Polynomial order 2 model is the preferred choice. This selection is based on its relatively high R^2 value compared to the other models. In addition, the RMSE and MAE values of this model are still within the acceptable tolerance for determining soil moisture. The transfer function for LCS SKU:SEN0193 is based on Polynomial fit, as shown in equation 10.

$$V = -0.0133\theta^2 - 1.986\theta + 75.441 \qquad [10]$$

where V is the sensor output voltage (V), θ is the gravimetric soil moisture (%), *75.44* is the offset value. From equation (10), the sensitivity of LCS SKU:SEN0193 can be determined based on the derivative of equation (10) to be $-0.026\theta - 1.98$ V/%, indicating that the sensor's sensitivity is influenced by the soil moisture value, as also stated by Cheruiyot et al. (2024). This means that the higher the soil moisture content, the more sensitive LCS SKU:SEN0193 becomes due to its capacitive nature, which is highly responsive to the presence of water. Conversely, this capacitive property does not respond similarly to air. As stated by Chandel et al., capacitive-based soil moisture sensors exhibit a flat output in certain regions, while in others, the output has a specific slope (Chandel et al., 2024). The results of this study show that LCS SKU:SEN0193 can be calibrated directly in the field using the thermogravimetric method. Although the calibration model of this sensor varies depending on the type of soil being measured, most calibration results for LCS SKU:SEN0193 follow a high-order polynomial model. This model has several limitations, including sensitivity to outlier data and a limited measurement range, which depends on the range of available data. Therefore, a larger dataset covering a broader soil moisture range is needed to minimise the impact of outliers on the calibration process.

This calibration model is specifically suitable for peat soil conditions at the measurement location with a moisture range between 68% and 78%. However, this model is less accurate if the soil moisture at the location is below 65%, as the calibration equation (10) shows a high offset value. This situation reflects typical peat soil conditions during normal seasons with slow evapouration rates. During extreme dry seasons, soil moisture can drop below 15%, while in the rainy season, soil moisture can exceed 350% (Ahmad Ryan Nur Rahman, 2021)

For sandy soils, a more appropriate calibration model is the exponential model. Meanwhile, for organic-rich soils such as peat, the more suitable calibration model is a third-order polynomial model (Pereira et al., 2022). The mineral content of the soil, such as salts, is also an important factor in determining soil moisture capacitively, as these mineral elements interact with water. The process of water release from minerals affects the capacitive sensor readings, especially when temperature increases (Adla et al., 2020).

LCS SKU:SEN0193 operates at a frequency of 1.5 MHz, where the imaginary part (ε'') of the relative permittivity ($\varepsilon r*$) plays a crucial role. This part is influenced by three main factors: (i) frequency, (ii) moisture, and (iii) soil salinity and ion content. Therefore, a specific calibration model is needed for each soil type, as the loss factor (ε'') significantly affects the accuracy of the sensor at this frequency (Placidi et al., 2020). A quadratic model can generally represent the calibration data of LCS SKU:SEN0193 sensor. However, the coefficients of the equations in this model are highly dependent on the material properties and geometric structure of the soil (Bobrov et al., 2019).

Based on the analysis above, the calibration of LCS SKU:SEN0193 sensor can be performed directly in the field. Although the accuracy of the model produced is not as high as that of the laboratory calibration model, this method minimises measurement bias more effectively. This is because the development of LCS SKU:SEN0193 calibration model is highly dependent on the type of soil being measured. The soil type affects the calibration results because the material properties of the soil, whether mineral or organic, can interact with water. This interaction, especially under conditions of increased soil temperature, can cause shifts in the sensor readings. The calibration model obtained is generally a second-order polynomial, which is very sensitive to outlier data and has a limited range according to the soil moisture values measured gravimetrically. To improve accuracy, this sensor requires an additional feature to measure Soil Electrical Conductivity (SEC) as compensation for soil moisture values. The addition of this feature will help reduce sensor inaccuracies when used on soils with high salinity.

Sensor Reliability

The results of the repeatability and variability tests for LCS SKU:SEN0193 are presented in Table 2. This test was conducted to evaluate the consistency of sensor readings, using soil samples from the site placed in an isolation room to prevent water evapouration. Data was collected every minute for 8 hours, resulting in 500 measurement data points. Table 2 shows the comparison of the mean, standard deviation (SD), and coefficient of variation (CV) values for two LCS SKU:SEN0193 placed side by side on the same soil sample. The measurement results show that each sensor has a different average value, where Sensor S1 has an average of 71.52%, while Sensor S2 has an average of 78.06%. These two sensors produce a 7% difference in output, which is quite significant. The standard deviation for Sensor S1 is 0.36%, while for Sensor S2 it is 0.83%, indicating that Sensor S2 has a larger data bias compared to Sensor S1. CV analysis shows that the data variation from Sensor S2 is higher than from Sensor S1, with values of 0.5 and 1.07, respectively. This comparison shows that the output from Sensor S1 is more consistent than Sensor S2. The difference in mean values and SD indicates that the calibration model for LCS SKU:SEN0193 cannot be universally applied to all sensors, due to its low precision as a product. Furthermore, the readings from LCS SKU:SEN0193 can also vary depending on sample uniformity (Duarte & Nuñez, 2024) and sensor installation in the soil.

Table 2
Statistics of repeatability and variability of LCS SKU:SEN0193 in controlled soil

N=500 Sampling Data					
No. Sensor	**Min-Max**	**Average**	**Median**	**SD**	**CV (%)**
S1	70.00-71.80	71.52	71.55	0.36	0.5
S2	75.49-79.71	78.06	78.12	0.83	1.07

Note. (SD) is used to evaluate sensor repeatability based on repeated measurements under identical conditions

Sensor S1 and Sensor S2 show different distribution patterns, as shown in Figure 4. The distribution of Sensor S1 is skewed to the left (negative skew) with a sharp peak, indicating that many values are concentrated around the average value. In contrast, Sensor S2 has a distribution pattern similar to Sensor S1 but with a flatter peak, indicating that the data from Sensor S2 is more spread out and not tightly concentrated around the average value.

These results align with the findings presented by Pereira et al. (2022), who stated that the calibration model of LCS SKU:SEN0193 has varying coefficients, influenced not only by soil type related to soil granulometry but also by the use of reference voltage in the ADC conversion of the sensor's output to a digital value, which uses a reference voltage of 3.3V, not 5V. However, this statement requires further verification, as an increase in the reference voltage of the ADC may actually reduce the sensor's sensitivity.

In this case, the authors argue that the difference in readings is more likely caused by the placement of the sensor on the soil sample. If the sensor element in LCS SKU:SEN0193 is not fully covered by the soil, it may create gaps that cause differences in readings (Kanso et al., 2020). Therefore, the soil granulometry factor plays a significant role and is one of the limitations of LCS SKU:SEN0193. This sensor uses a probe-mount configuration with two elements, rather than a rod model with two separate probes. This means that the distribution of the soil sample on the sensor's surface can affect the dielectric material structure measured by the sensor, which in turn causes differences in readings.

If this condition occurs, the differences in readings should only cause a data bias between Sensor 1 and Sensor 2, while the kurtosis peak should not change significantly. In other words, only a shift in the distribution peak should occur, without significant changes in the peak height. However, in reality, the resulting patterns are different, suggesting the presence of other factors besides sensor placement.

Another factor contributing to the variability between sensors in LCS SKU:SEN0193 is manufacturing defects. These defects can cause errors in sensor readings, which in turn generate error data and outliers that may affect the distribution characteristics of the output. These errors often cause the data distribution to skew towards a normal distribution, although it does not fully reflect the reality of the actual measurements (Nieto et al., 2021). For example, in the data distribution of Sensor S2, it is observed that its distribution is closer to a normal distribution compared to a skewed distribution, indicating an adjustment or a decrease in sensor sensitivity. Based on these results, it can be concluded that Sensor S2 is likely malfunctioning or has poor manufacturing quality, which impacts the performance and accuracy of the sensor's measurements.

In its application, to reduce sensor-to-sensor variability when using SKU:SEN0193 sensor in a larger area with multiple installed sensors, one sensor can be designated as a reference (calibrated sensor), while the other sensors (uncalibrated sensors) can be used as soil moisture measurement tools by applying a machine learning-based data processing approach, as demonstrated by Adla et al (Adla et al., 2020).

LCS SKU:SEN0193 exhibits very high variability between sensors, even though it demonstrates high repeatability, as evidenced by the low coefficient of variation (CV) value, which is ≤ 1%. This high variability is caused by several factors, such as improper sensor placement in the soil, variations in supply voltage (3.3 V or 5 V), and sensor bias and malfunction due to inconsistencies in the manufacturing process. Based on testing and statistical distribution analysis, the dominant factor affecting this is sensor malfunction.

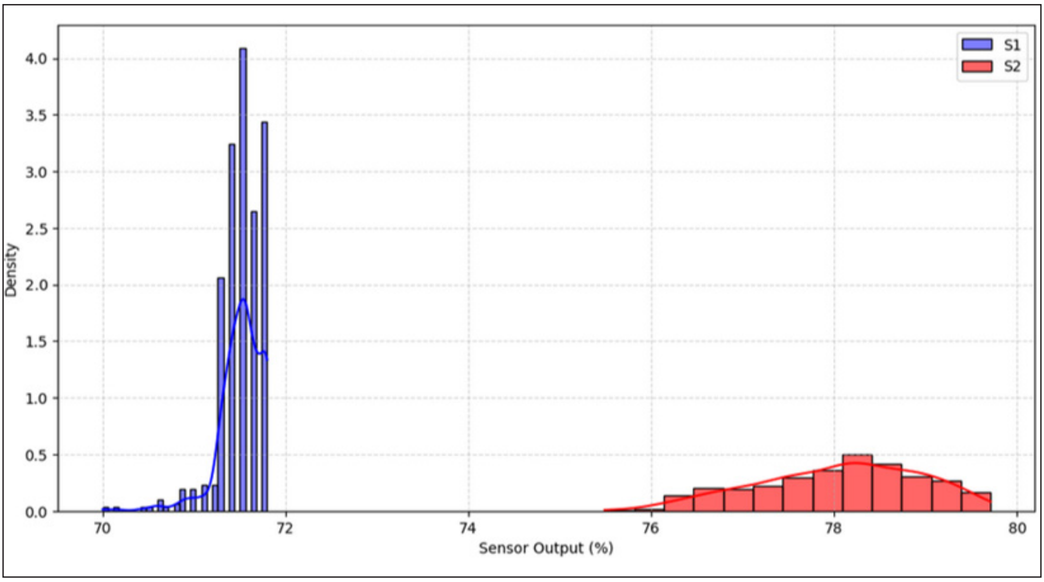

Figure 4. Histogram and density plot of two sensors of SKU:SEN1903

This is evident from the large difference in kurtosis peaks and the change in skewness distribution patterns approaching normal distribution due to the high fluctuations and outliers in Sensor S1. With these results, it can be concluded that the reliability of LCS SKU:SEN0193 is low, as there is a high degree of variability between sensors of the same type. In its application, careful selection of this sensor is necessary before using it as a calibration tool to minimise errors in the calibration model.

Sensor Durability

The sensor durability test was conducted by placing the sensor in the field for 5 days, with results shown in Figure 5. The results indicate that the sensor's output remained stable during the testing period, with increases and decreases in humidity readings caused by variations in soil moisture at the location and the evapouration process. Generally, soil moisture levels rose and fell in accordance with changes in temperature and environmental humidity, particularly in the morning during sunrise and at night (Fan et al., 2022). Additionally, the sensor's output increase remained within the bounds of the calibration model and the soil moisture levels at the field location, ranging from 73% to 75%.

Figure 6 shows the distribution plot of sensor data over the 5-day measurement period. From the figure, it can be seen that there are no significant differences in the mean, variance, standard deviation, or distribution patterns. The daily average soil moisture measurements fall within a narrow range of 73.58% to 73.75%, indicating that LCS SKU:SEN0193 readings are consistent from day to day without any significant fluctuations. This is in line with the stable measurement conditions, as there were no significant weather changes. The low variance and standard deviation, ranging from 0.19 to 0.24 and 0.43 to 0.49 respectively, show that the data dispersion around the mean is not significant, and there are no extreme outliers. On the third day, there was a slight increase in variance and standard deviation. This increase was due to the transition in soil moisture levels between the second and third days, which caused the data variation and standard deviation calculations to be higher than on the other days, as seen in Figure 6.

Figure 7 shows the distribution plot of sensor data over the 5-day measurement period. From the figure, it can be seen that there are no significant differences in the mean, variance, standard deviation, or distribution patterns. The daily average soil moisture measurements are within a narrow range of 73.58% to 73.75%, indicating that LCS SKU:SEN0193 readings are consistent from day to day without significant fluctuations. This is consistent with the measurement conditions, which did not experience any significant weather changes. The low variance and standard deviation, ranging from 0.19 to 0.24 and 0.43 to 0.49 respectively, show that the data dispersion around the mean is not significant and there are no extreme outliers. On the third day, there was a slight increase in variance and standard deviation. This increase was caused by the transition in soil moisture between the second and third days, which led to larger data variation and standard deviation calculations compared to the other days, as seen in Figure 5.

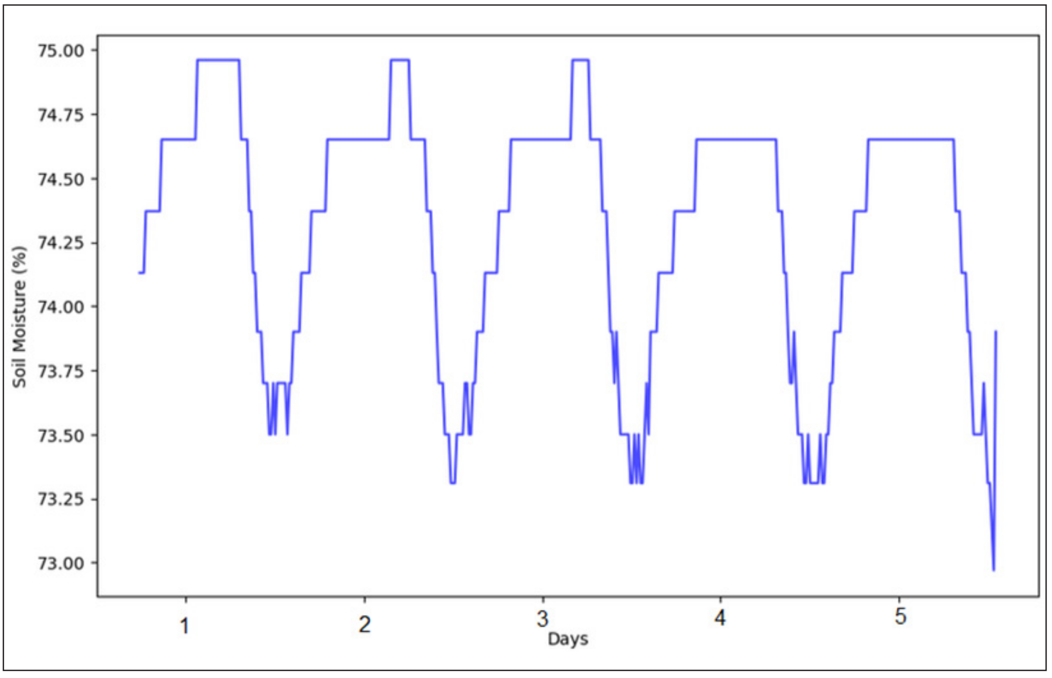

Figure 6. Daily measurement in site of LCS SKU:SEN0193

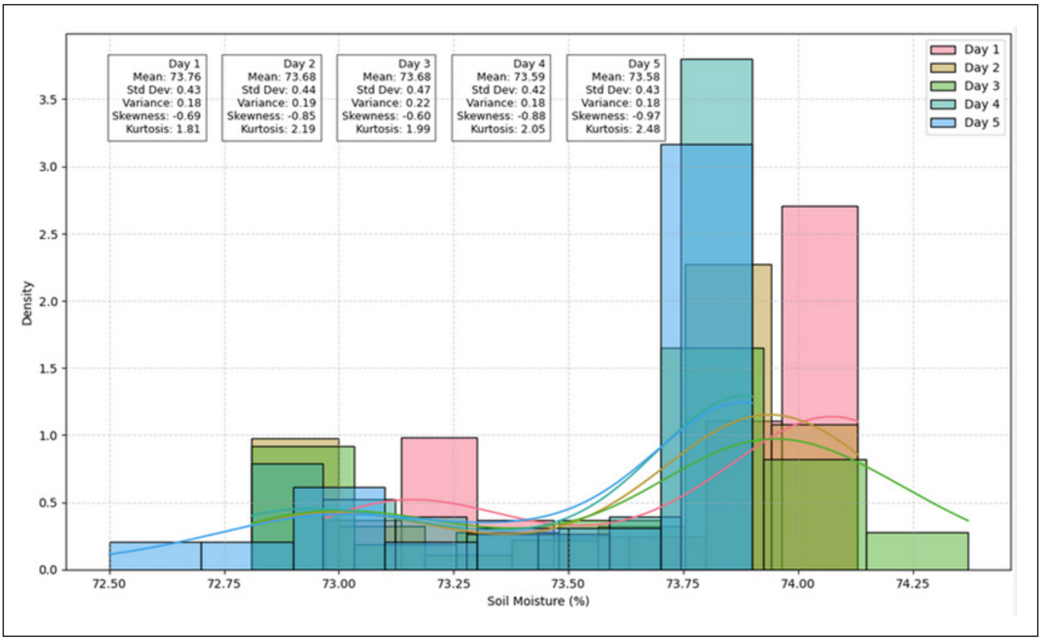

Figure 7. Statistical distribution for 5 days measurement of LCS SKU:SEN0193

The distribution plot over the 5 days shows that the data reading distribution pattern of LCS SKU:SEN0193 is mostly above its average value or tends to shift towards higher values (negative skewness). This aligns with the statement by Nieto et al. (2021) that soil moisture sensors tend to follow a skewed distribution rather than a normal distribution. The consistent skewness pattern across all days, with values ranging from -0.69 to -0.97, indicates that there was no significant bias throughout the 5-day use of the sensor for soil moisture measurement in the field. The kurtosis peak of LCS SKU:SEN0193 also showed no significant difference, with kurtosis values ranging from 1.81 to 2.48 (or <3). This indicates that the sensor data distribution is relatively even, with few extreme outliers. The consistency of these kurtosis values further confirms that during the sensor testing, no drift or malfunction occurred that would cause extreme fluctuations in sensor readings.

CONCLUSION

Based on the research results, the direct calibration of LCS SKU:SEN0193 in the field is effective for creating a calibration model, although its accuracy is lower compared to laboratory calibration. This calibration model is highly dependent on the type of soil being measured and is sensitive to outlier data. LCS SKU:SEN0193 shows high variability between sensors but has good repeatability with a low coefficient of variation (≤ 1%). The sensor's measurement durability is also good, with consistent mean values, standard deviation, and stable data distribution.

The main contribution of this study is the development of a direct field calibration method using gravimetric comparison. The study also emphasises the importance of distribution analysis to understand sensor characteristics and detect calibration errors. Further development challenges include increasing sample size in gravimetric calibration and detecting outlier data. This research is beneficial for the application of LCS SKU:SEN0193 sensor in precision agriculture and soil analysis, where many sensors are needed to reduce costs and ensure measurement accuracy.

ACKNOWLEDGEMENT

The authors acknowledge the financial support from the Ministry of Higher Education Indonesia via the Research Grant Scheme (265/PKS/D.D4/PPK.01.APTV/VII/2024), Politeknik Jambi and INSTeG UTM via In Cash and In-kind Funding.

REFERENCES

Adla, S., Bruckmaier, F., Arias-Rodriguez, L. F., Tripathi, S., Pande, S., & Disse, M. (2024). Impact of calibrating a low-cost capacitance-based soil moisture sensor on AquaCrop model performance. *Journal of Environmental Management*, *353*, Article 120248. https://doi.org/10.1016/j.jenvman.2024.120248

Adla, S., Rai, N. K., Karumanchi, S. H., Tripathi, S., Disse, M., & Pande, S. (2020). Laboratory calibration and performance evaluation of low-cost capacitive and very low-cost resistive soil moisture sensors. *Sensors*, *20*(2), Article 363.https://doi.org/10.3390/s20020363

Ahmad Ryan Nur Rahman. (2021). *Otomatisasi pintu air irigasi lahan gambut dengan metode fuzzy inference system Takagi-Sugeno*. In *Laporan Penelitian Research Fellowship Pantau Gambut*. https://pantaugambut.id/storage/widget_multiple/ahmad-ryan-nur-rahman-5i93E.pdf

Al-Rawi, M. A. M. (2024). Low-cost soil moisture sensors' assessment for their accuracy after calibration through the gravimetric method. *Sabrao Journal of Breeding and Genetics*, *56*(1), 353-369.https://doi.org/10.54910/sabrao2024.56.1.32

Aringo, M. Q., Martinez, C. G., Martinez, O. G., & Ella, V. B. (2022). Development of low-cost soil moisture monitoring system for efficient irrigation water management of upland crops. *IOP Conference Series: Earth and Environmental Science*, *1038*(1). https://doi.org/10.1088/1755-1315/1038/1/012029

Bobrov, P. P., Belyaeva, T. A., Kroshka, E. S., & Rodionova, O. V. (2019). Soil moisture measurement by the dielectric method. *Eurasian Soil Science*, *52*(7), 822-833. https://doi.org/10.1134/S106422931905003X

Bono, R., Arnau, J., Alarcón, R., & Blanca, M. J. (2020). Bias, precision, and accuracy of skewness and kurtosis estimators for frequently used continuous distributions. *Symmetry*, *12*(1), Article 19. https://doi.org/10.3390/sym12010019

Chandel, A., Swami, D., & Joshi, N. (2024). Calibration complexities: Full-scale error impact and simultaneous variation of salinity, temperature, and moisture content on sensor performance in soil. *Environment, Development and Sustainability*. https://doi.org/10.1007/s10668-024-04812-1

Cheruiyot, E., Mito, C., & Menenti, M. (2024). An improved method of soil moisture metre calibration for satellite data validation at watershed scale. *Earth Science Informatics*, *17*(1), 117-129. https://doi.org/10.1007/s12145-023-01170-w

Duarte, J. R., & Nuñez, D. N. C. (2024). Low-cost soil moisture sensor calibration. *Brazilian Journal of Science*, *3*(2), 132-142.https://doi.org/10.14295/bjs.v3i2.517

Fan, X., Lu, Y., Liu, Y., Li, T., Xun, S., & Zhao, X. (2022). Validation of multiple soil moisture products over an intensive agricultural region: Overall accuracy and diverse responses to precipitation and irrigation events. *Remote Sensing*, *14*(14), Article 3339.https://doi.org/10.3390/rs14143339

Ferrarezi, R. S., Nogueira, T. A. R., & Zepeda, S. G. C. (2020). Performance of soil moisture sensors in Florida sandy soils. *Water*, *12*(2), Article 358.https://doi.org/10.3390/w12020358

Gianessi, S., Polo, M., Stevanato, L., Lunardon, M., Francke, T., Oswald, S. E., Said Ahmed, H., Toloza, A., Weltin, G., Dercon, G., Fulajtar, E., Heng, L., & Baroni, G. (2024). Testing a novel sensor design to jointly measure cosmic-ray neutrons, muons and gamma rays for non-invasive soil moisture estimation. *Geoscientific Instrumentation, Methods, and Data Systems*, *13*(1), 9-25.https://doi.org/10.5194/gi-13-9-2024

Hidayat, M., Hazarika, H., & Kanaya, H. (2024). Calibration and performance evaluation of cost-effective capacitive moisture sensor in slope model experiments. *Preprints*. https://doi.org/10.20944/preprints202410.2280.v1

Kanso, T., Gromaire, M.-C., Ramier, D., Dubois, P., & Chebbo, G. (2020). An investigation of the accuracy of EC-5 and 5TE capacitance sensors for soil moisture monitoring in urban soils: Laboratory and field calibration. *Sensors*, *20*(22), Article 6510.https://doi.org/10.3390/s20226510

Kim, D., Shin, D., & Hwang, J. (2023). Calibration of low-cost sensors for measurement of indoor particulate matter concentrations via laboratory and field evaluation. *Aerosol and Air Quality Research*, *23*(8), Article 230097.https://doi.org/10.4209/aaqr.230097

Kulmány, I. M., Bede-Fazekas, Á., Beslin, A., Giczi, Z., Milics, G., Kovács, B., Kovács, M., Ambrus, B., Bede, L., & Vona, V. (2022). Calibration of an Arduino-based low-cost capacitive soil moisture sensor for smart agriculture. *Journal of Hydrology and Hydromechanics*, *70*(3), 330-340.https://doi.org/10.2478/johh-2022-0014

Kureshi, R. R., Mishra, B. K., Thakker, D., John, R., Walker, A., Simpson, S., Thakkar, N., & Wante, A. K. (2022). Data-driven techniques for low-cost sensor selection and calibration for the use case of air quality monitoring. *Sensors*, *22*(3), Article 1093.https://doi.org/10.3390/s22031093

López, E., Vionnet, C., Ferrer-Cid, P., Barceló-Ordinas, J. M., Garcia-Vidal, J., Contini, G., Prodolliet, J., & Maiztegui, J. (2022). A low-power IoT device for measuring water table levels and soil moisture to ease increased crop yields. *Sensors*, *22*(18), Article 6840.https://doi.org/10.3390/s22186840

Majumder, S., Kasirao, G., Himavarsha, P., Himanshi, Chaudhary, S., Sekopo, K. P., Tanwar, T., & Verma, J. (2023). Assessing low-cost capacitive soil moisture sensors: Accurate, affordable, and IoT-ready solutions for soil moisture monitoring. *International Journal of Environment and Climate Change*, *13*(11), 2233-2242.https://doi.org/10.9734/ijecc/2023/v13i113386

Marković, M., Matoša Kočar, M., Barač, Ž., Turalija, A., Atılgan, A., Jug, D., & Ravlić, M. (2024). Field performance evaluation of low-cost soil moisture sensors in irrigated orchards. *Agriculture*, *14*(8), Article 1239. https://doi.org/10.3390/agriculture14081239

Mathieu-Campbell, M. E., Guo, C., Grieshop, A. P., & Richmond-Bryant**, J. (2024).** Calibration of low-cost particulate matter sensors (PurpleAir): Model development for air quality under high relative humidity conditions. *EGUsphere*, 2024, 6735-6749.https://doi.org/10.5194/amt-17-6735-2024

Nagahage, E. A. A. D., Nagahage, I. S. P., & Fujino, T. **(2019).** Calibration and validation of a low-cost capacitive moisture sensor to integrate the automated soil moisture monitoring system. *Agriculture*, 9(7), Article 141.https://doi.org/10.3390/agriculture9070141

Narayana, M. V., Jalihal, D., & Shiva Nagendra, S. M. (2022). Establishing a sustainable low-cost air quality monitoring setup: A survey of the state-of-the-art. *Sensors*, *22*(1), Article 394.https://doi.org/10.3390/s22010394

Nieto, F. J., Aguilera, U., & López-De-Ipiña, D. (2021). Analysing particularities of sensor datasets for supporting data understanding and preparation. *Sensors*, *21*(18), Article 6063.https://doi.org/10.3390/s21186063

Ozansoy, R., & Fahrioglu, C. (2020). Skewness and kurtosis analysis of high impedance fault currents. *Proceedings of the Australasian Universities Power Engineering Conference (AUPEC)*, 1-6.

Pereira, R. M., Sandri, D., & Silva Júnior, J. J. da. (2022). Evaluation of low-cost capacitive moisture sensors in three types of soils in the Cerrado, Brazil. *Revista Engenharia na Agricultura (REVENG)*, *30*, 262-272. https://doi.org/10.13083/reveng.v30i1.14017

Placidi, P., Gasperini, L., Grassi, A., Cecconi, M., & Scorzoni, A. (2020). Characterisation of low-cost capacitive soil moisture sensors for IoT networks. *Sensors*, *20*(12), Article 3585.https://doi.org/10.3390/s20123585

Rasheed, M. W., Tang, J., Sarwar, A., Shah, S., Saddique, N., Khan, M. U., Khan, M. I., Nawaz, S., Shamshiri, R. R., Aziz, M., & Sultan, M. (2022). Soil moisture measuring techniques and factors affecting the moisture dynamics: A comprehensive review. *Sustainability*, *14*(18), Article 11538.https://doi.org/10.3390/su141811538

Toková, L., Igaz, D., & Aydin, E. (2019). Measurement of volumetric water content by gravimetric and time domain reflectometry methods at field experiment with biochar and N fertiliser. *Acta Horticulturae et Regiotecturae*, *22*(2), 61-64.https://doi.org/10.2478/ahr-2019-0011

Yang, Y., Chen, T., Lin, W., Jing, M., & Xu, W. (2024). Research progress on calibration of bridge structural health monitoring sensing system. *Advances in Bridge Engineering*, *5*, Article 32.https://doi.org/10.1186/s43251-024-00143-3