# VALIDATION REPORT

## SOILSENSE - UCO

**Entity:** AgrifoodTEF – Universidad de Córdoba

**Company:** SoilSense

**Date:** 10/03/2026

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# 1. Customer information

## 1.1. Contact

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## 1.2.Description

SoilSense is a Danish company founded in 2017, with the purpose of addressing global water scarcity by making it easier to optimize the use of water resources. We are working with farmers, municipalities, agricultural organizations, universities, funds, and corporate partners that are interested in saving water and optimizing the food-chain by addressing irrigation inefficiencies.

## 2. Requested services

### 2.1. Physical testing and data collection of agricultural sensors. Laboratory conditions. (ID: S00383)

*The agricultural sensor data collection service focuses on obtaining precise information from various agricultural sensors to support validation or testing purposes. This service ensures reliable and accurate data capture. The data collected can subsequently be used for testing agricultural models, technologies, or equipment, facilitating detailed analyses to evaluate their operational performance and identify potential improvements.*

### 2.2. Physical testing and data collection of agricultural sensors. Real conditions. (ID: S00383)

*The agricultural sensor data collection service focuses on obtaining precise information from various agricultural sensors to support validation or testing purposes. This service ensures reliable and accurate data capture. The data collected can subsequently be used for testing agricultural models, technologies, or equipment, facilitating detailed analyses to evaluate their operational performance and identify potential improvements.*

### 2.3. Testing and Validation of Soil Sensors. (ID: S00383)

*The validation service would evaluate SoilSense sensor precision by comparing real-time sensor moisture readings with soil moisture levels from lab-analysed samples collected nearby. Soil samples would be taken under various conditions to ensure a robust comparison, enabling a clear assessment of the sensors' accuracy across different environments.*

## 3. Materials and Methodology

### 3.1.Location of soil samples

Soil samples were collected from two distinct locations within the Rabanales Experimental Farm (Rabanales University Campus, University of Córdoba), selected to represent contrasting soil conditions within the same agroclimatic environment. The sampling sites were chosen based on their differing soil classifications and textural characteristics, ensuring variability in physical properties relevant to sensor performance evaluation.

**Figure 1.** Location of the sampling zones. Rabanales Experimental Farm.

Two sampling zones were identified within the study area. Zone 1 (0 - 35 cm) consisted of an olive-brown clayey horizon (66% clay; 18% sand) with a strongly developed medium granular structure, few gravel-sized coarse fragments, carbonate presence, and occasional slickensides. In contrast, Zone 2 (0 - 23 cm) showed a sandy (24% clay; 66% sand) horizon with a moderately developed fine granular structure and a higher abundance of coarse fragments ranging from gravel to stone size. Both zones exhibited abundant fine roots and abrupt lower boundaries.

### 3.2.Characterization of soil samples

Two contrasting soil samples were selected for the study to represent different soil structural and textural conditions. One of the samples was a Calcic Vertisol (FAO), characterized by a high clay content (66% clay; 18% sand) and pronounced shrink-swell behaviour, while the second sample corresponded to a Stagnic Luvisol (FAO), characterized by a comparatively sandier surface texture (24% clay; 66% sand). Soil samples for both soil types were collected from the upper soil layer up to a depth of approximately 20-30 cm (arable layer). The selection of these soils was intended to capture variability in physical properties relevant to the experimental objectives and to provide a comparative framework for subsequent analyses.

Before the experimental setup, and due to the large volume of soil, the soil samples were placed under laboratory conditions to be air-dried. To ensure a continuous and homogeneous drying process, the samples were periodically turned using shovels for approximately two weeks. Once the soil was air-dried, it was homogenised and then transferred subsequently into the experimental pots where the sensors were later installed (Figure 2). Thereafter, each pot was brought to saturation with water to generate calibration curves for the sensors during the progressive evaporation of retained water.

**Figure 2.** Set up and sensor distribution.

One sensor was installed in each pot at the same depth (12 cm), allowing all sensors to operate under comparable soil conditions. This experimental setup was designed to assess both the variability among pots and the measurement precision of each sensor, while minimizing the influence of external factors on sensor performance.

**Table 1.** Characterization of soil samples.

| Pot ID | Soil type | Substrate weight (kg) | Standard Sensor ID | New Sensor ID | Datalogger ID |
|---|---|---|---|---|---|
| **P1** | Vertisol | 37.98 | Top | 1 Verle | Verle-9158 |
| **P2** | Vertisol | 38.14 | Bottom | 2 Verle | |
| **P3** | Vertisol | 37.62 | Top | 1 Jasmin | Jasmin-9165 |
| **P4** | Vertisol | 37.97 | Bottom | 2 Jasmin | |
| **P5** | Luvisol | 24.28 | Top | 1 Verle | Verle-9158 |
| **P6** | Luvisol | 24.38 | Bottom | 2 Verle | |
| **P7** | Luvisol | 24.14 | Top | 1 Jasmin | Jasmin-9165 |
| **P8** | Luvisol | 24.76 | Bottom | 2 Jasmin | |

## 3.3.Statistical analysis

The statistical procedures were defined and applied using a structured and reproducible approach for the subsequent services. The analysis focused on soil preparation, the detection of anomalous results, and the definition of metrics to assess measurement precision.

### *3.3.1. Volumetric moisture measurement*

Sensor measurements were collected over a wide range of volumetric moisture conditions during the evaporation process using the sensors installed in the experimental pots. The data recorded by the sensors were automatically transmitted to the company’s cloud-based platform, where measurements were stored and managed. For validation purposes, the corresponding datasets were subsequently downloaded from this platform and were later validated against volumetric moisture values obtained from soil samples collected concurrently with each sensor measurement.

To monitor the evolution of moisture content in the pots, soil water content was determined gravimetrically and later converted to volumetric moisture content using bulk density as follows:

$$water\ content\ (kg) = W_{p,0} - W_{p,i}$$

where:

$W_{p,0}$: initial pot weight (kg).

$W_{p,i}$: pot weight at time *i* (kg).

$$\theta_g = \frac{M_w}{M_s}$$

where:

$\theta_g$: gravimetric moisture content.

$M_w$: water mass (kg).

$M_s$: soil mass (kg).

$$\theta_v = \theta_g \cdot \left(\frac{\rho_a}{\rho_w}\right)$$

where:

$\theta_v$: volumetric moisture content.

$\theta_g$: gravimetric moisture content.

$\rho_w$: water density (g/cm$^3$).

$\rho_a$: bulk density (g/cm$^3$).

### *3.3.2. Outlier detection methodology*

Outlier detection was conducted using a robust statistical approach specifically designed for small datasets and focused on the analysis of sensor measurement errors. In this context, residuals were defined as the differences in volumetric water content between the reference measurements and the corresponding sensor readings.

Residuals were calculated for each observation as:

$$r_i = \theta_{\text{ref},i} - \theta_{\text{sens},i}$$

where $r_i$ is the residual associated with observation $i$, $\theta_{\text{ref},i}$ is the volumetric water content obtained from the reference method, and $\theta_{\text{sens},i}$ is the volumetric water content measured by the sensor.

The median of the residuals was computed as a robust estimator of central tendency:

$$\tilde{r} = \text{median}(r_1, r_2, \dots, r_n)$$

where $\tilde{r}$ denotes the median residual and $n$ is the total number of observations. The median was used instead of the mean due to its robustness against extreme values, which is particularly relevant for small sample sizes where distributional assumptions are difficult to verify.

The dispersion of the residuals was quantified using the Median Absolute Deviation (MAD), defined as:

$$\mathrm{MAD} = \mathrm{median}(\mid r_i - \tilde{r} \mid)$$

where $\mid r_i - \tilde{r} \mid$ represents the absolute deviation of each residual from the median. MAD provides a robust measure of variability that is minimally influenced by outliers.

To compute robust standardized residuals for anomaly detection, the MAD was scaled using a normalization constant:

$$\sigma_{\mathrm{rob}} = 1.4826 \cdot \mathrm{MAD}$$

where $\sigma_{\mathrm{rob}}$ represents the robust dispersion estimator derived from the residuals. This scaled value was used to normalize individual residuals as follows:

$$z_i = \frac{r_i - \tilde{r}}{\sigma_{\mathrm{rob}}}$$

where $z_i$ denotes the dimensionless robust standardized residual associated with observation $i$, $r_i$ is the residual for observation $i$, and $\tilde{r}$ is the median of the residuals defined previously.

An observation was classified as anomalous when the absolute value of the standardized residual exceeded a predefined threshold:

$$\mid z_i \mid > 2.5$$

This threshold was selected as a commonly accepted criterion for robust outlier detection in small datasets, providing a balance between sensitivity to atypical measurements and protection against the influence of extreme values.

### *3.3.3. Model precision validation metrics*

Model precision was evaluated using a two-level statistical approach. First, independent linear regressions were performed for each sensor to assess device-specific precision based on the residuals between reference and sensor volumetric water content measurements. This allowed the identification of sensor-dependent variability and systematic deviations under controlled conditions. Second, a complementary global regression was conducted by aggregating all observations to estimate the average performance of the sensing system. This unified analysis was interpreted as a system-level precision indicator rather than as validation of individual sensors.

The Mean Absolute Error (MAE) was calculated as an indicator of sensor accuracy and to facilitate comparison with the manufacturer's nominal error specification. MAE was computed as:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} \mid \theta_{\mathrm{ref},i} - \theta_{\mathrm{sens},i} \mid$$

where $\theta_{\mathrm{ref},i}$ represents the reference volumetric water content, $\theta_{\mathrm{sens},i}$ corresponds to the sensor-estimated value, and $n$ is the number of observations.

Model precision was also quantified using the Root Mean Square Error (RMSE), which was calculated as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (\,\theta_{\mathrm{ref},i} - \theta_{\mathrm{sens},i})^2}$$

where $\theta_{\mathrm{ref},i}$ and $\theta_{\mathrm{sens},i}$ are the reference and sensor-based volumetric water content values, respectively, and $n$ is the number of observations. RMSE expresses prediction error in the same units as the measured variable and was used as a complementary and stricter metric than MAE, as squaring residuals amplifies large deviations and provides a conservative estimate of precision.

RMSE values were also compared with the manufacturer's nominal accuracy (±3%). Although the underlying statistical definition of this specification is not provided, RMSE offers a practical approximation of overall system error under experimental conditions. Owing to its sensitivity to large errors, RMSE was interpreted alongside robust residual-based metrics described previously, enabling differentiation between systematic model instability and random measurement variability, particularly in small datasets.

## 4. Results and discussion

Sensor performance was evaluated through independent sensor analyses and a complementary global model to characterize both individual sensor behaviour and the average performance of the sensing system. The results presented below correspond to the Vertisol soil and Luvisol soil.

### 4.1. Independent sensor validation

Residual statistics and robust dispersion metrics for each sensor are summarized in Table 2. Standard deviation values reflected differences in measurement consistency. Given the limited number of observations per sensor, the median was adopted as a more robust estimator of central tendency than the mean.

The Median Absolute Deviation (MAD) values were consistently low, indicating limited dispersion of residuals around the central value and suggesting stable intra-sensor behaviour. The use of MAD was particularly appropriate due to the small sample size and its robustness to extreme values.

**Table 2.** Residual statistics for independent sensor validation.

| **Statistic** | **Vertisol Soil** | | | | **Luvisol Soil** | | | |
|---|---|---|---|---|---|---|---|---|
| | 1Verle | 2Verle | 1Jasmin | 2Jasmin | 1Verle | 2Verle | 1Jasmin | 2Jasmin |
| **Std. deviation (%)** | 2.58 | 1.86 | 3.64 | 1.19 | 3.96 | 2.77 | 3.07 | 1.94 |
| **Median (%)** | 3.82 | 2.43 | 5.25 | 1.64 | 5.28 | 3.38 | 4.41 | 2.93 |
| **MAD (%)** | 0.25 | 0.71 | 0.79 | 0.17 | 0.61 | 0.35 | 0.42 | 0.21 |

Robust standardized residuals were calculated to identify anomalous observations. Although some values (*n* = 4) exceeded the adopted threshold, no outliers were removed from the independent sensor analyses. This decision was taken due to the very limited number of observations per sensor, as removing data points could compromise the statistical representativeness of the individual regressions.

Mean Absolute Error (MAE) indicated moderate systematic deviations that varied between sensors. Sensor specific RMSE values (Table 3) revealed substantial variability in precision among the evaluated sensors. RMSE values close to or below the manufacturer’s stated accuracy of ±3% indicated good agreement with volumetric reference measurements and performance consistent with nominal specifications. In contrast, sensors exhibiting RMSE values clearly exceeding this threshold showed reduced precision, which was consistent with the presence of systematic bias rather than random measurement noise.

**Table 3.** Precision values for independent sensor validation.

| | **Vertisol Soil** | | **Luvisol Soil** | |
|---|---|---|---|---|
| **Sensor** | **MAE (%)** | **RMSE (%)** | **MAE (%)** | **RMSE (%)** |
| **1Verle** | 3.64 | 3.72 | 5.61 | 5.72 |
| **2Verle** | 2.64 | 2.88 | 3.91 | 4.06 |
| **1Jasmin** | 5.15 | 5.46 | 4.33 | 4.40 |
| **2Jasmin** | 1.69 | 1.70 | 2.75 | 2.78 |

The graphical representation of individual regressions highlights these differences in sensor behaviour:

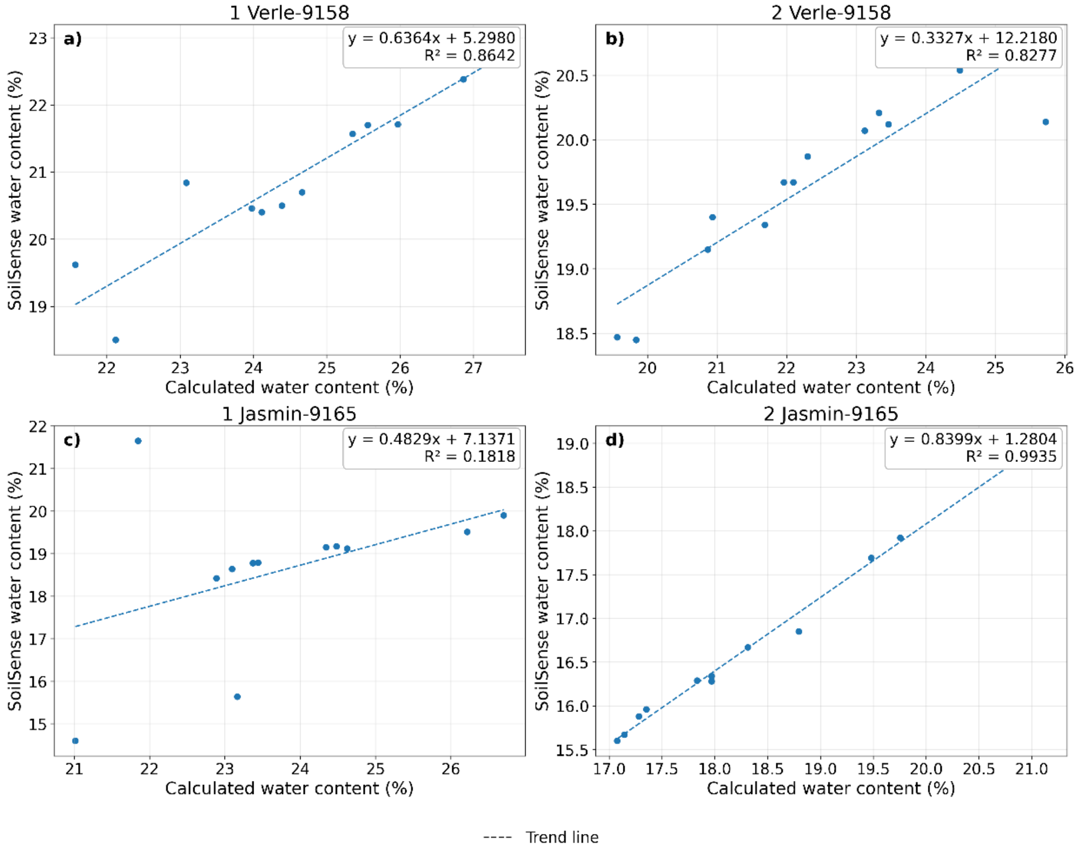

**Figure 3.** Regression models - Vertisol: 1 Verle (a), 2 Verle (b), 1 Jasmin (c), 2 Jasmin (d).

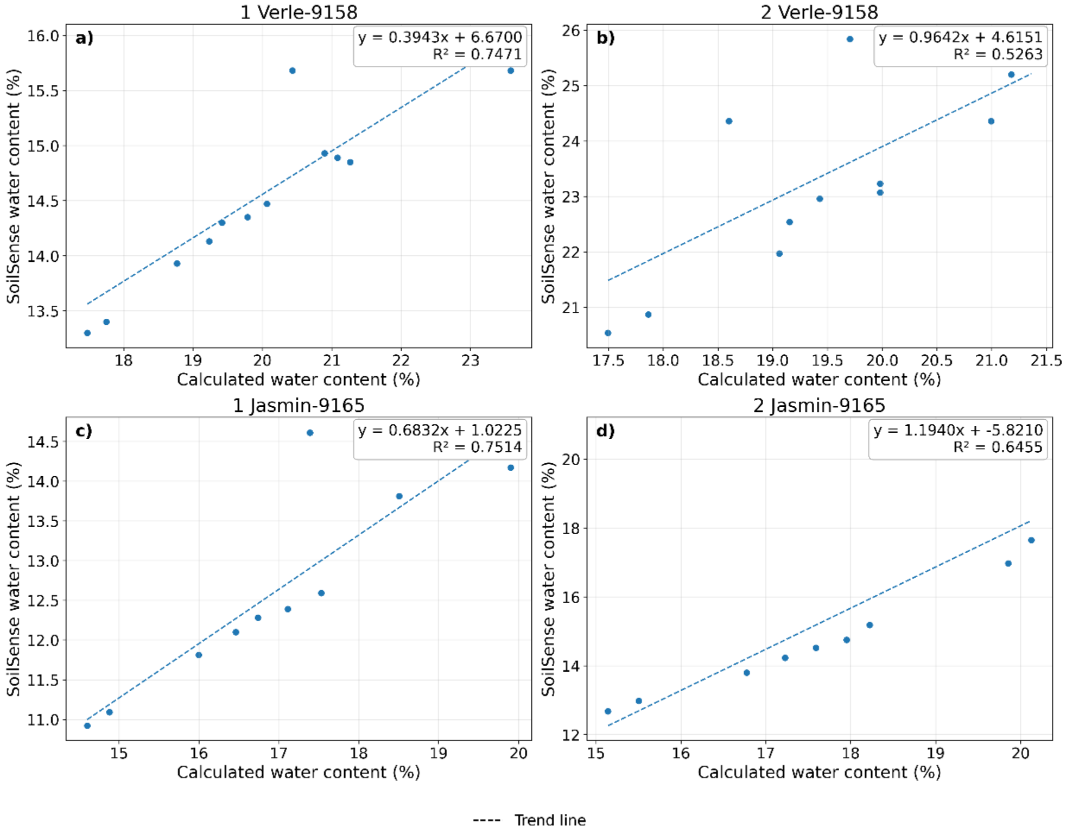

**Figure 4.** Regression models - Luvisol: 1 Verle (a), 2 Verle (b), 1 Jasmin (c), 2 Jasmin (d).

Regression statistics (Table 4) confirmed that sensors with higher intercept values tended to exhibit inflated RMSEs, indicating dominant additive bias, whereas sensors with lower intercepts showed better overall performance.

**Table 4.** Regression statistics for independent sensor validation.

| Statistic | Vertisol Soil | | | | Luvisol Soil | | | |
|---|---|---|---|---|---|---|---|---|
| | 1Verle | 2Verle | 1Jasmin | 2Jasmin | 1Verle | 2Verle | 1Jasmin | 2Jasmin |
| **R²** | 0.86 | 0.83 | 0.18 | 0.99 | 0.75 | 0.53 | 0.75 | 0.65 |
| **Slope** | 0.63 | 0.33 | 0.48 | 0.84 | 0.39 | 0.96 | 0.68 | 1.19 |
| **Intercept** | 5.30 | 12.22 | 7.14 | 1.28 | 6.67 | 4.61 | 1.02 | -5.82 |

## 4.2.Global model validation

A global analysis was performed by aggregating all sensor measurements to estimate the average performance of the sensing system. Residual statistics for the global model are presented in Table 5. Compared to individual analyses, increased dispersion was observed, reflecting the combined effects of sensor-specific errors and micro-environmental variability.

**Table 5.** Residual statistics for the global model.

| Statistic | Global model – Vertisol | Global model – Luvisol |
|---|---|---|
| **Std. deviation (%)** | 2.29 | 3.01 |
| **Median (%)** | 3.09 | 4.17 |
| **MAD (%)** | 1.37 | 1.09 |

Outlier detection was applied to the global dataset, and anomalous observations were removed due to the larger sample size and their influence on error metrics. This approach was not applied to individual sensors, as noted previously. In this case, nine values were removed.

Following outlier removal, the global model errors decreased markedly (Table 6), particularly in Vertisol soil, where RMSE was reduced from 3.65% to 2.77%, reaching values within the manufacturer's stated accuracy of ±3%. This improvement indicates enhanced measurement consistency and a reduced influence of extreme observations under clay-rich conditions characterized by pronounced shrink-swell behaviour. In contrast, for Luvisol soil, which presents a sandier surface texture, RMSE decreased from 4.46% to 3.95% after outlier removal, yet remained above the nominal ±3% specification. This suggests that, under coarser-textured conditions, sensor performance exhibited greater residual variability. Overall, the comparison between MAE and RMSE confirms that error reduction was more pronounced in the clay-dominated soil, whereas the sandier soil maintained higher dispersion even after excluding anomalous measurements.

**Table 6.** Precision values for the global model before and after outlier removal.

| | Vertisol Soil | | Luvisol Soil | |
|---|---|---|---|---|
| **Model** | **MAE (%)** | **RMSE (%)** | **MAE (%)** | **RMSE (%)** |
| **Global** | 3.24 | 3.65 | 4.25 | 4.46 |
| **Global (without outliers)** | — | 2.77 | — | 3.95 |

The effect of outlier removal is illustrated in the following figures:

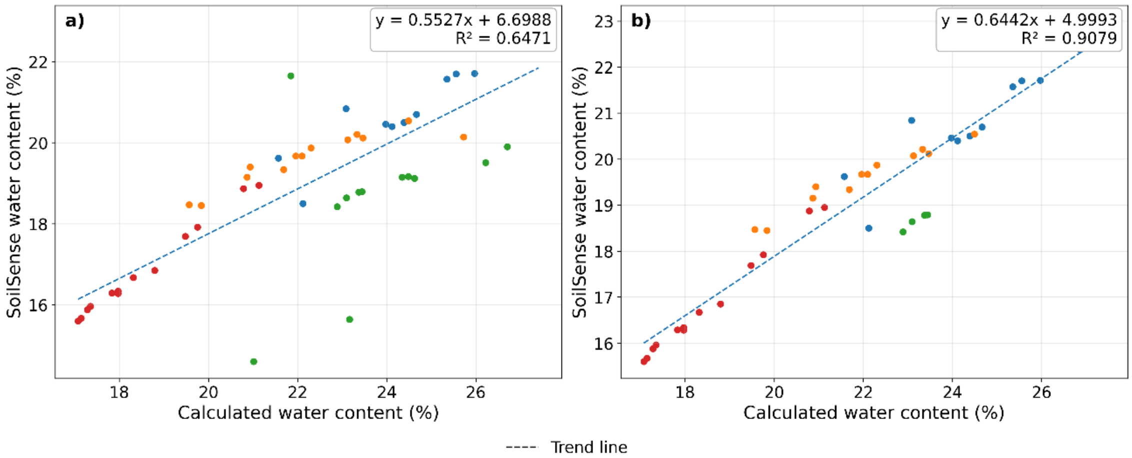

**Figure 5.** Regression model - Vertisol: Global model (a), Global model without outliers (b).

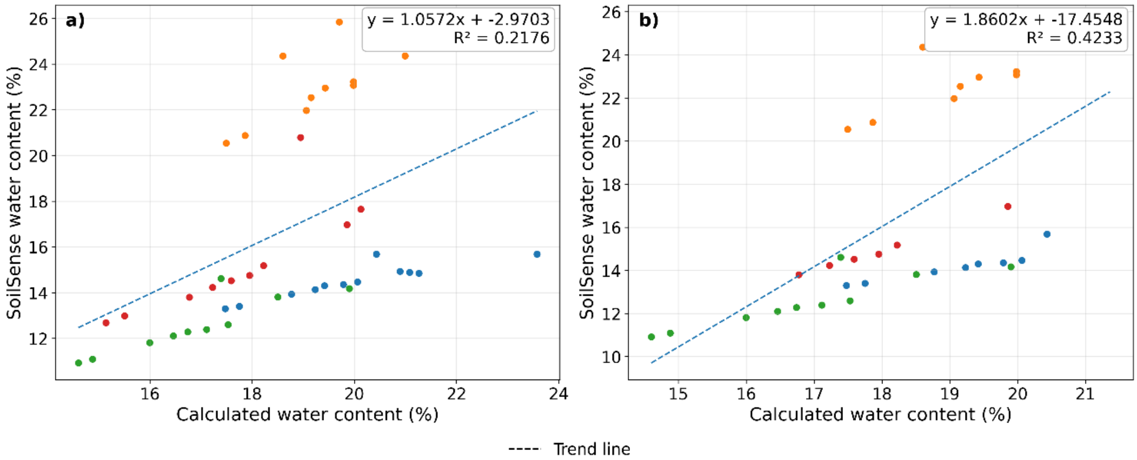

**Figure 6.** Regression model - Luvisol: Global model (a), Global model without outliers (b).

Regression statistics for the global model (Table 7) further confirmed the improvement after outlier removal, with increased R² values and reduced intercepts, indicating a decrease in systematic bias.

**Table 7.** Regression statistics for the global model.

| **Statistic** | **Vertisol Soil** | | **Luvisol Soil** | |
|---|---|---|---|---|
| | Global model | Global model (without outliers) | Global model | Global model (without outliers) |
| **R²** | 0.65 | 0.91 | 0.22 | 0.42 |
| **Slope** | 0.55 | 0.64 | 1.05 | 1.86 |
| **Intercept** | 6.69 | 4.99 | -2.97 | -17.45 |

Overall, these results demonstrate that independent sensor validation is essential to identify sensor-specific biases and precision differences, while the global analysis provides a complementary estimate of the average performance that can be expected when deploying this sensor type under comparable conditions.

## 5. Conclusions

The validation confirmed that sensor precision is both device-dependent and soil-dependent. Mean Absolute Error (MAE) values provided a direct estimate of the typical magnitude of measurement deviation, while the Root Mean Square Error (RMSE), being more restrictive due to the squaring of residuals, was used to assess the influence and severity of extreme errors. Together, these metrics offered a comprehensive evaluation of sensor performance.

At the global level, prior to outlier removal, MAE values were 3.24% in the Vertisol and 4.25% in the Luvisol. The value obtained in the Vertisol can be considered close to the manufacturer's nominal accuracy (±3%), whereas the Luvisol clearly exceeded this specification. Corresponding RMSE values (3.65% and 4.46%, respectively) were higher, reflecting the greater penalization of extreme deviations. After removing anomalous observations, error levels decreased substantially in the clay-rich Calcic Vertisol (RMSE = 2.77%), reaching consistency with the nominal specification. In contrast, although error metrics were reduced in the sandier Stagnic Luvisol (RMSE = 3.95%), they remained above ±3%, indicating persistent variability under coarser-textured conditions.

Overall, MAE indicated that average performance in the Vertisol was close to nominal expectations, whereas RMSE revealed the impact of occasional large deviations. These results highlight the importance of considering both typical error magnitude and the contribution of extreme values when evaluating soil moisture sensor accuracy across contrasting soil environments.