



EVALUATION OF LOW-COST CAPACITIVE MOISTURE SENSORS IN THREE TYPES OF SOILS IN THE CERRADO, BRAZIL

Rodrigo Moura Pereira^{1*} , Delvio Sandri¹  & João José da Silva Júnior¹ 

1 - University of Brasilia, Brasília, Distrito Federal, Brazil

Keywords:

Soil water content
Electronic prototyping
Capacitance probe

ABSTRACT

Soil moisture sensors enabled new automation and computerization solutions in agriculture. However, its use still requires prior calibrations to attest its accuracy to estimate soil moisture. Thus, in this study a prototype for soil moisture monitoring was developed using the capacitive sensor SKU:SEN0193 integrated with the Arduino microcontroller. The prototype was calibrated based on the relationship between volumetric moisture and sensor output voltage in deformed samples of Red-yellow Latosol (RYL), Regolitic Neosol (RN), and Red Latosol (RL) of the Cerrado region, Federal District, Brazil. The calibration of sensors resulted in a second-degree polynomial model with R^2 between 0.93 and 0.96 for RYL, 0.89 and 0.92 for RN, and 0.86 and 0.88 for RL. Root mean square errors (RMSE) of volumetric moisture were 0.08, 0.12, and 0.15 $\text{cm}^3 \cdot \text{cm}^{-3}$ for RYL, RN, and RL, respectively. Sensors at operating voltage of 5.00 V showed less variability of readings, with coefficient of variation (CV) between 0.21 and 1.54%, while sensors at 3.30 V showed CVs between 3.27 and 17.84%. It is recommended to calibrate the SKU:SEN0193 for each soil type in order to obtain reliable estimates of water content for RYL, RN, and RL.

Palavras-chave:

Conteúdo de água no solo
Prototipagem eletrônica
Sonda de capacitância

AVALIAÇÃO DE SENSOR CAPACITIVO DE BAIXO CUSTO PARA MEDIDA DA UMIDADE EM TRÊS TIPOS DE SOLO DO CERRADO

RESUMO

Sensores de umidade do solo tem possibilitado novas soluções de automação e informatização na agricultura. Entretanto, sua utilização ainda necessita de calibrações para atestar sua acurácia na estimativa da umidade do solo. Assim, objetivou-se avaliar o sensor capacitivo SKU:SEN193 integrado ao microcontrolador Arduino. A calibração foi realizada a partir da relação entre a umidade volumétrica e a tensão de saída dos sensores em amostras deformadas de Latossolo Vermelho Amarelo (LVa), Neossolo Regolítico (NR) e Latossolo Vermelho (LV) da região do Cerrado, Distrito Federal, Brasil. A calibração dos sensores resultou em modelos polinomiais de segundo grau com R^2 entre 0,93 e 0,96 para LVa, 0,89 e 0,92 para NR e 0,86 e 0,88 para LV. O erro quadrático médio (RMSE) foi de 0,08, 0,12 e 0,15 $\text{cm}^3 \cdot \text{cm}^{-3}$ para o LVa, NR e LV, respectivamente. Sensores atuando na tensão de operação de 5,00 V apresentam menor variabilidade de leituras com coeficiente de variação (CV) entre 0,21 e 1,54%, enquanto que sensores de 3,30 V apresentam CV's entre 3,27 e 17,84%. Recomenda-se a calibração individual do sensor SKU:SEN193 para cada tipo de solo para obtenção de estimativas confiáveis do conteúdo de água em LVa, NR e LV.

INTRODUCTION

Soil moisture is an important parameter in the growth and development of agricultural crops and depends mainly on soil physical properties and weather conditions. The gravimetric method is the most accurate to measure soil water content, although being destructive, laborious, and not providing real-time soil moisture data (ADLA *et al.*, 2020).

In indirect methods, measurements are performed by associating measurable variables that vary according to soil moisture, such as the neutron probe, time and frequency-domain reflectometry (TDR and FDR), tensiometry, capacitance, gamma-ray attenuation, porous capsule, and ground penetrating radar (GPR) methods, among others (LEKSHMI *et al.*, 2014). Each indirect method for soil moisture estimation has different characteristics regarding cost, accuracy, resolution, response time, and measurement parameters associated with soil water content (DOBRIYAL *et al.*, 2012), besides the need for calibration of these methods, which usually require technical knowledge.

The capacitance probe method is a non-destructive technique in which soil water content is estimated by measuring the capacitance between electrodes inserted in the soil. In the capacitance method the soil acts as a dielectric storing energy with the application of an external electric field (PLACIDI *et al.*, 2020). The capacitance probe provides the absolute value of moisture at any depth and in real time (DUKES *et al.*, 2010). Coelho *et al.* (2006), highlighted that model calibration varies according to the soil type and which polynomial models can be fit with considerable accuracy.

Components from the low-cost electronics market generally lack technical information in detail and must be used with prior evaluations to attest their functionality and technical specifications (CHAN *et al.*, 2020). Placidi *et al.* (2020), observed that the SKU:SEN0193 sensor, when used in soils with no bulk density variation, showed reliable relationship between output signal and gravimetric water content in a sandy soil in a region of Italy. Nagahaje *et al.* (2019), evaluated the same sensor and observed mean square error of $0.09 \text{ cm}^3 \cdot \text{cm}^{-3}$ in

an organic soil in a region of Japan. However, there are still no studies evaluating this sensor regarding its ability to estimate water content in soils in the region of the Brazilian Cerrado.

Therefore, this study aimed to evaluate the SKU:SEN0193 sensor for estimation of water content in deformed samples of Red-yellow Latosol, Regolitic Neosol, and Red Latosol in the Cerrado region, Federal District, Brazil. For this, calibration models that related sensor output signal with variation of volumetric moisture were developed and tested for each soil evaluated.

MATERIALS AND METHODS

Capacitive sensor and Arduino platform

The study was conducted in the Soil Physics and Water Analysis laboratories of the Faculty of Agronomy and Veterinary Medicine, University of Brasília, Campus Darcy Ribeiro, in the period between October and November 2020. The SKU:SEN0193 sensor (DFROBOT, Shanghai, China), is a low-cost capacitive soil moisture sensor easily acquired on the market that operates in the range between 3.0 and 5.5 V. The sensor can be easily integrated with open-source microcontrollers such as Arduino, ESP32, and others. In comparison to capacitive sensors available in the Brazilian market, the SKU:SEN0193 sensor its purchased at a cost that vary between R\$ 4.00 and R\$ 30.00 per unit, while other commercial sensors cannot be purchased for less than R\$ 250.00 per unit.

Nine capacitive soil moisture sensors, model SKU:SEN0193, with dimensions of 9.8 x 2.3 cm, integrated with the Arduino microcontroller were evaluated. The manufacturer's datasheet informs that the sensor operates in the voltage range between 3.3 and 5.0 V, with output voltage between 0.0 and 3.0 V, operating current of 5 mA, and weight of 15 g (Figure 1). Placidi *et al.* (2020), performed electrical characterization of the SKU:SEN0193 sensor and observed that the capacitance of the sensor in the air was in the order of 6.5 pF. Radi *et al.* (2018) found that the frequency of the sensor ranged from 260 Hz in a wet soil up to 520 Hz in a soil with low moisture.

The controller board used was the Arduino Mega 2560, which has the ATMEGA2560

microcontroller, 54 digital input/output pins, 16 analog ports with 10-bit resolution, 16 MHz oscillator, USB connection, and power jack pin (Figure 1).

Sensor operating voltage was verified before installation in soil samples through air and water readings. This procedure was performed to check the functioning of sensors before their installation on the soil. The electrical signal of the sensor output (V_{out}) was visualized on the serial monitor of Arduino IDE through conversion of analog values into voltage. For this, a float-type variable that stores the conversion obtained by Equation 1 was applied.

$$\text{float } V_{out} = \text{sensorValue} * \left(\frac{V_{in}}{1,023}\right) \quad (1)$$

where,

V_{out} = sensor output voltage; sensorValue = analog signal of the sensor; V_{in} = sensor input voltage, 1,023 = analog-to-digital conversion factor.

After verifying the functioning of sensors, it was found that six sensors showed V_{out} values only when operated on the V_{in} voltage of 3.30 V and another three functioned only when connected to the V_{in} of 5.00 V. Thus, three sensors were defined for evaluation of Red-yellow Latosol and three for

Regolitic Neosol, both operating at V_{in} of 3.30 V, and the other three were defined for Red Latosol, operating at V_{in} of 5.00 V.

Soil samples

Deformed samples of Red-yellow Latosol (RYL) collected in a maize growing area (15° 56' 56.32" S; 47° 55' 46.16" W) and Red Latosol (RL) (15° 57' 30.0" S; 47° 55' 08.6" W) and Regolitic Neosol (NR) (15° 58' 48.27" S; 47° 56' 57.54" W) collected in natural areas of Cerrado, both at depths of 0 to 0.2 m, sieved in a #2.0 mm mesh sieve, and air-dried were used.

The soil samples used for sensor calibration consisted of nine PVC tubes, three for each soil type, with internal diameter of 6.97 cm and height of 9.86 cm. Soil samples were filled and placed for capillary saturation for 24 hours. Subsequently, the sensors were inserted in the central part of each soil sample and maintained at room temperature to dry the soil and obtain calibration data.

During the drying cycle, the V_{out} data of sensors, concomitantly with the weight of the set of soil sample + sensor was obtained (Figure 2). Afterwards, the weight of the set was corrected to obtain the weight of the wet soil in the soil sample, which was adopted as reference to obtain volumetric moisture.

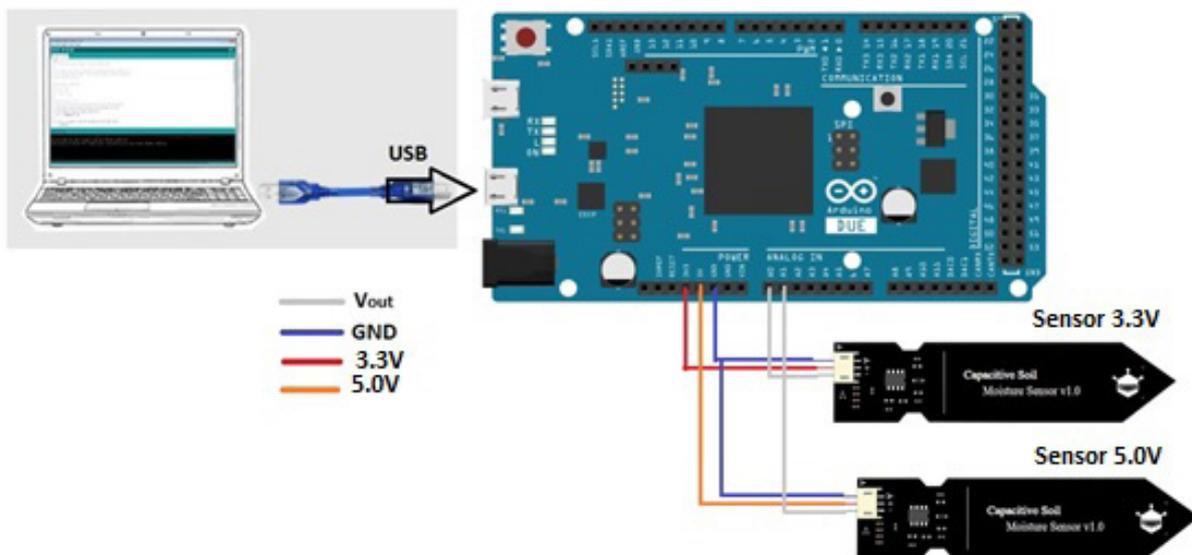


Figure 1. Connection between capacitive sensors SKU: SEN0193 of 3.3 and 5.0 V with the Arduino MEGA 2560 microcontroller board

After obtaining calibration data, the soil samples were again saturated and maintained in a new drying cycle in which data of V_{out} and weight of the set were obtained. Data from the second drying cycle were later used to evaluate calibration generated from the data obtained in the first drying cycle.

After the second drying cycle, sensors were removed from soil samples and the soil was placed in an oven at 105 °C for 72 hours. After soil drying, data of mass of dry soil were used to obtain the bulk density and variation of volumetric moisture during the two drying cycles.

Soil density was estimated by Equation 2 and total porosity by Equation 3.

$$Ds = \frac{Ms}{Vt} \quad (2)$$

$$Pt = 1 - \frac{Ds}{Dp} \quad (3)$$

where,

Ds = soil bulk density ($g.cm^{-3}$); Ms = mass of dry soil (g); Vt = total volume of the soil sample (cm^3) and Dp = particle density ($2.65 g.cm^{-3}$), according to Table 1.

Analysis of variability between sensors

Variability of V_{out} between sensors was obtained in two stages. In the first stage, V_{out} values in air at room temperature (26 °C) and in distilled water (24 °C) were compared. For this, 20 readings of each sensor were analyzed through analysis of variance (ANOVA). Measurement noise was estimated from the coefficient of variation of the V_{out} values of each sensor (Table 2).

The second stage occurred during collection of volumetric moisture data (Θ [$cm^3.cm^{-3}$]) in RYL, RN, and RL, in which methodology by Adla *et al.* (2020) was applied using the Spearman's correlation coefficient between values of V_{out} and Θ



Figure 2. SKU:SEN0193 sensors installed in the soil samples filled with Regolitic Neosol (A), Red Latosol (B), and Red-yellow Latosol (C)

Table 1. Physical and granulometric properties of Red-yellow Latosol (RYL), Regolitic Neosol (RN), and Red Latosol (RL)

Soil type	Clay	Silt	Sand	Texture	Ds^*	Pt^*
	%			$g.cm^{-3}$	$cm^3.cm^3$	
RYL	59.2	36.7	4.1	clayey	1.00	0.619
RN	14.3	8.6	77.2	sandy loam	1.28	0.514
RL	72.7	25.1	2.2	very clayey	0.94	0.643

(Table 2). Spearman’s correlation was used for being a non-parametric test that measures the strength of the monotonic relationship between paired data without any presupposition regarding data distribution and nature of the physical relationship between them (HAUKE & KOSSOWSKI, 2011).

Calibration of capacitive sensors

Calibration of moisture sensors consists of establishing the relationship between sensor response and a reference value. Once the relationship is established, the model is calibrated reversely, i.e., predicting the reference value through sensor response (BURKE, 2020). Calibration accuracy is the measurement of how similar sensor estimates are to the real value, also being defined as the maximum difference between a measured value and a real value determined from a standard procedure (CARR & BROWN, 2001).

Volumetric soil moisture (Equation 4) obtained by gravimetry was adopted as reference value, while the output voltage (V_{out}) of capacitive sensors was adopted as the sensor response value for

prediction of soil moisture variation.

$$\theta_v = \left(\frac{M_1 - M_2}{M_2} \right) * D_s \tag{4}$$

where,

θ_v = volumetric soil moisture ($cm^3.cm^{-3}$); M_1 = mass of wet soil in each measurement (g); M_2 = mass of dry soil, obtained at the end of measurements after soil drying in an oven at 105 °C (g), and D_s = soil bulk density in each soil sample ($g.cm^{-3}$).

Evaluation of calibration of capacitive sensors

Moisture data obtained by gravimetry were compared to the V_{out} data of sensors, generating second-degree polynomial models of calibration analyzed from the fitted coefficient of determination (R^2_{aj}) and the significance test of coefficients.

In order to evaluate sensor accuracy, simple linear regression models were adopted, in which volumetric moisture obtained by gravimetry was compared with volumetric moisture estimated by the sensor. Statistical indices used to quantify accuracy are shown in Table 3.

Table 2. Equations used to obtain the coefficient of variation (CV) and Spearman’s correlation coefficient to analyze variability between SKU:SEN0193 capacitive sensors in air, distilled water, and soil samples of RYL, RN, and RL

Statistical index	Equation
Coefficient of variation (CV [%])	$CV = \frac{s}{\bar{V}} * 100$
Spearman’s Correlation coefficient (r_s)	$r_s = \frac{\frac{1}{n} \sum_{i=1}^n (R(V_i) - R(\bar{V}_1))(R(\theta_i) - R(\bar{\theta}_1))}{\sqrt{\left(\frac{1}{n} \sum_{i=1}^n (R(V_i) - R(\bar{V}_1))^2\right) \left(\frac{1}{n} \sum_{i=1}^n (R(\theta_i) - R(\bar{\theta}_1))^2\right)}}$

s = standard deviation of V_{out} values; \bar{V}_1 , $\bar{\theta}_1$ = mean value of V_{out} ; $V_i = V_{out}$ value; θ_i = volumetric moisture value observed; $R(x)$ = ranking of x and n is the number of data points used to calculate r_s .

Table 3. Statistical indices to evaluate the accuracy of calibration models

Statistical index	Equation	Range (ideal value)
Coefficient of determination (R^2)	$R^2 = \frac{[\sum_{i=1}^n (P_i - \bar{P})(O_i - \bar{O})]^2}{\sum_{i=1}^n (P_i - \bar{P})^2 \sum_{i=1}^n (O_i - \bar{O})^2}$	0 to 1 (1)
Mean absolute error (MAE)	$MAE = \left(\sum_{i=1}^n O_i - P_i \right) / n$	0 to ∞ (0)
Root-mean square error (RMSE)	$RMSE = \sqrt{\left(\sum_{i=1}^n (O_i - P_i)^2 \right) / n}$	0 to ∞ (0)

O_i = volumetric moisture value observed; \bar{O} = mean value of volumetric moisture; P_i = volumetric moisture value estimated by the sensor after fit by calibration model; n = number of observations

RESULTS AND DISCUSSION

Variability between sensors

Mean V_{out} values in air and water of the six sensors operating at V_{in} of 3.30 V were 2.92 V and 1.67 V, respectively, and of the three sensors operating at V_{in} of 5.00 V were 3.78 V and 2.34 V, respectively. Results of F test demonstrated occurrence of significant variations of V_{out} among all sensors (Table 4). However, when values of the coefficient of variation (CV) were analyzed, it was observed that sensors operating at 3.30 V showed values of 3.27% in air and 17.84% in contact with distilled water. Despite significant variability, the results obtained by sensors operating at 5.00 V showed significantly lower CV's than those observed at 3.30 V, both in air and water, indicating increased stability and reproducibility. Nagahaje *et al.* (2019), evaluated variability between SKU:SEN0193 sensors in soils with high organic

matter content and observed significant variability and coefficients of variation of 0.05 and 0.10% for soil samples with 80% moisture.

For all relations between Θ and V_{out} , the Spearman's correlation coefficient (r_s) was negative and significant at 5% probability level (Table 5). Sensors showed mean r_s of -0.81, -0.84, and -0.97 for RYL, RN, and RL, respectively. The greatest differences of r_s between V_{out} and Θ were observed in sensors for RYL and RN, both operated at 3.30 V, while sensors in RL, operated at 5.00 V, showed correlations above -0.90 and minimal differences between r_s values. Adla *et al.* (2020), evaluated correlation between volumetric moisture and estimations by commercial capacitive sensors, models SMEC300 and SM100 (Spectrum Technologies, Inc., Plainfield, IL, USA), in soils with sandy and silt loam texture, obtaining mean r_s values of 0.92 and 0.94, respectively.

Table 4. ANOVA and coefficient of variation (CV) of V_{out} of SKU:SEN0193 sensors operating at 3.30 V_{in} and 5.00 V_{in} obtained in air at 26 °C and in distilled water at 24 °C

Sensor with V_{in} of 3.3 V					
Condition	Source of variation	DF*	Sum of squares (V_{out})	Mean square (V_{out})	F
Air	V_{out}	5	1.0644	0.21288	858***
	Residue	114	0.0283	0.00000	
	CV (%)	3.27			
Water	V_{out}	5	10.5880	2.11800	158302***
	Residue	114	0.0020	0.00000	
	CV (%)	17.84			
Sensor with V_{in} of 5.0 V					
Air	V_{out}	2	0.00331	0.00165	159.9***
	Residue	57	0.00059	0.00000	
	CV (%)	0.21			
Water	V_{out}	2	0.08275	0.04138	6289***
	Residue	57	0.00037	0.00000	
	CV (%)	1.54			

*Degree of freedom; ***Significant at $p < 0.001$

Table 5. Spearman's correlation coefficient (r_s) between sensor output voltage (V_{out}) and variation of volumetric moisture (Θ) in soil samples of RYL, RN, and RL

Soil Type	Sample of sensors (replicates)			
	S1	S2	S3	Mean
RYL _{3.3V}	-0.78	-0.98	-0.68	-0.81
RN _{3.3V}	-0.72	-0.97	-0.84	-0.84
RL _{5.0V}	-0.98	-0.98	-0.97	-0.97

Calibration of capacitive sensors

Models fitted for RYL and RN, both using sensors at 3.30 V, showed curve fits with different variations for the same soil moisture range. Despite differences between models (Figure 3), equations in RYL and RN showed coefficients significant at 1% probability level. Models fitted in RL with sensor at 5.00 V showed the smallest differences between curves and values of coefficients. However, it was observed that coefficients of models in RL showed significance between 1.00 and 5.00%, indicating the need for individual calibration of sensors in both soils evaluated. Use of moisture sensors without prior calibration can result in erroneous estimates of soil water content, which can have negative impacts in studies on drainage, irrigation management, and soil water dynamics (LIMA *et al.*, 2018).

Quadratic models were adequate to adjust calibration data, although not being the usual behavior of this sensor, as other studies presented calibration models different from the one presented in this study. Radi *et al.* (2018), evaluated the SKU:SEN0193 sensor in a sandy loam soil and observed exponential calibration models. The authors also observed that variation of room temperature between 26 and 40 °C, although not significantly altering the fit model, can slightly change coefficients of calibration equations. In organic matter-rich soil, Nagahaje *et al.* (2019), under laboratory conditions, fitted a third-degree polynomial model for calibration of the SKU:SEN0193 sensor.

For RYL (Figure 3A), soil moisture variation between 0.20 and 0.50 cm³.cm⁻³ was observed with different V_{out} values between the three sensors (replicates). This behavior is generally reported as a result of the influence of two factors, granulometry and soil bulk density (LIMA *et al.*, 2018). As the soil of RYL samples has the same granulometric distribution, differences in density may have influenced sensor responses.

Soil bulk densities in the soil samples for sensors S1 and S2 in RYL were 1.02 and 1.03 g.cm⁻³, respectively, while sensor S3 in RYL in the sample with density of 0.95 g.cm⁻³ showed V_{out} values always above those observed in samples S1 and S2, which had similar densities and showed more

similar responses when compared to S3. Results in RN also showed distinct V_{out} values between sensors for the moisture range between 0.10 and 0.40 cm³.cm⁻³, although with less discrepancy when compared to the sensors in RYL. Soil bulk density of samples in RN was 1.29, 1.28, and 1.28 g.cm⁻³ for soil samples of sensors S1, S2, and S3, respectively.

Decreased difference between densities in RN may have reduced the effect of variation of V_{out} values. However, difference between responses may be associated with intrinsic variability, as observed in the study of variability between sensors used in RN (Table 6), in which r_s values ranged between -0.72 and -0.97. Otherwise, sensors at 5.00 V in RL showed V_{out} values closer to humidity variation, between approximately 0.20 and 0.60 cm³.cm⁻³, and bulk densities for sensors S1, S2, and S3 in RL were 0.94, 0.95 and 0.94 g.cm⁻³, respectively.

The R²_{aj.} values of models fitted in RYL were 0.96, 0.93, and 0.96 for sensors S1, S2, and S3, respectively (Figure 3A). For RN, R²_{aj.} values were also above 0.9 in all fitted models (Figure 3B). For RL, R²_{aj.} values were below 0.90 in all fitted models (Figure 3C), although there was greater similarity between the fit curves. Lima *et al.* (2018), evaluated capacitive soil moisture sensors, model CS616 (Campbell Scientific Inc., Utah, USA-CSI), in deformed and undeformed samples of Yellow Argisol and Haplic Cambisol in the region of Cruz das Almas, Bahia State, Brazil, using calibration equations obtained by gravimetry in deformed samples and observed R² values of 0.67 for exponential model, 0.83 for linear model, and 0.93 for quadratic model.

According to the results, calibration of the SKU:SEN0193 sensor must consider variability between sensors installed in the same soil type, as responses may be related not only to bulk density, but also to the characteristics of construction of sensors that result in variability of V_{out} values for the same soil moisture range. Another factor that apparently improves the performance of the SKU:SEN0193 sensor integrated with the Arduino microcontroller is its operation at V_{in} of 5.0 V, as shown in the study of variability between sensors and behavior of calibration curves (Tables 4 and 5 and Figure 3).

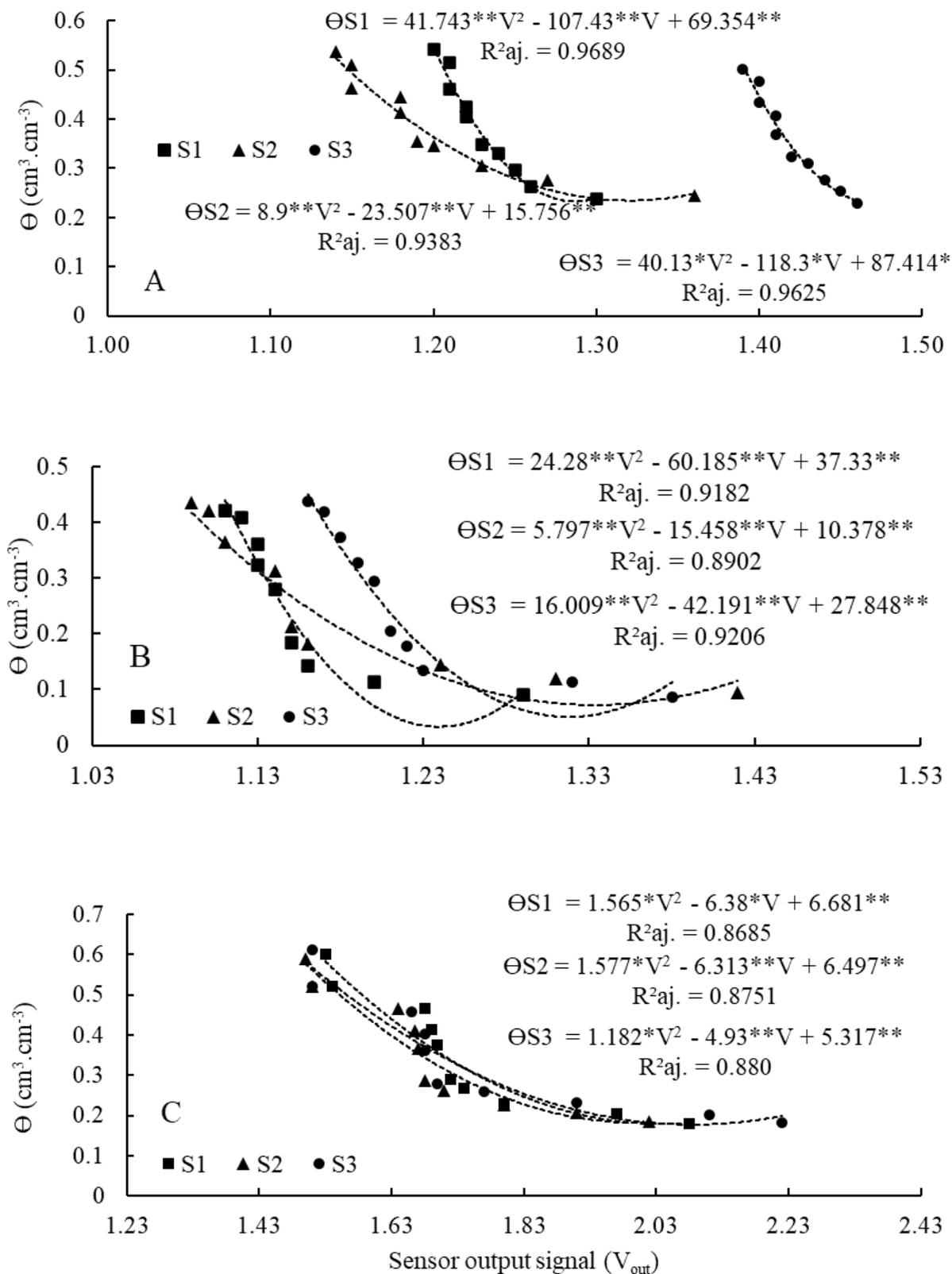


Figure 3. Individual calibration equations for capacitive sensors in RYL at 3.3 V (A), RN at 3.3 V (B), and RL at 5.0 V (C). S1: Sensor 1; S2: Sensor 2; S3: Sensor 3. General equations for RYL, RN and RL with all sensors for each soil type (D) **Significant at $p < 0.01$; * significant at $p < 0.05$

Evaluation of calibration

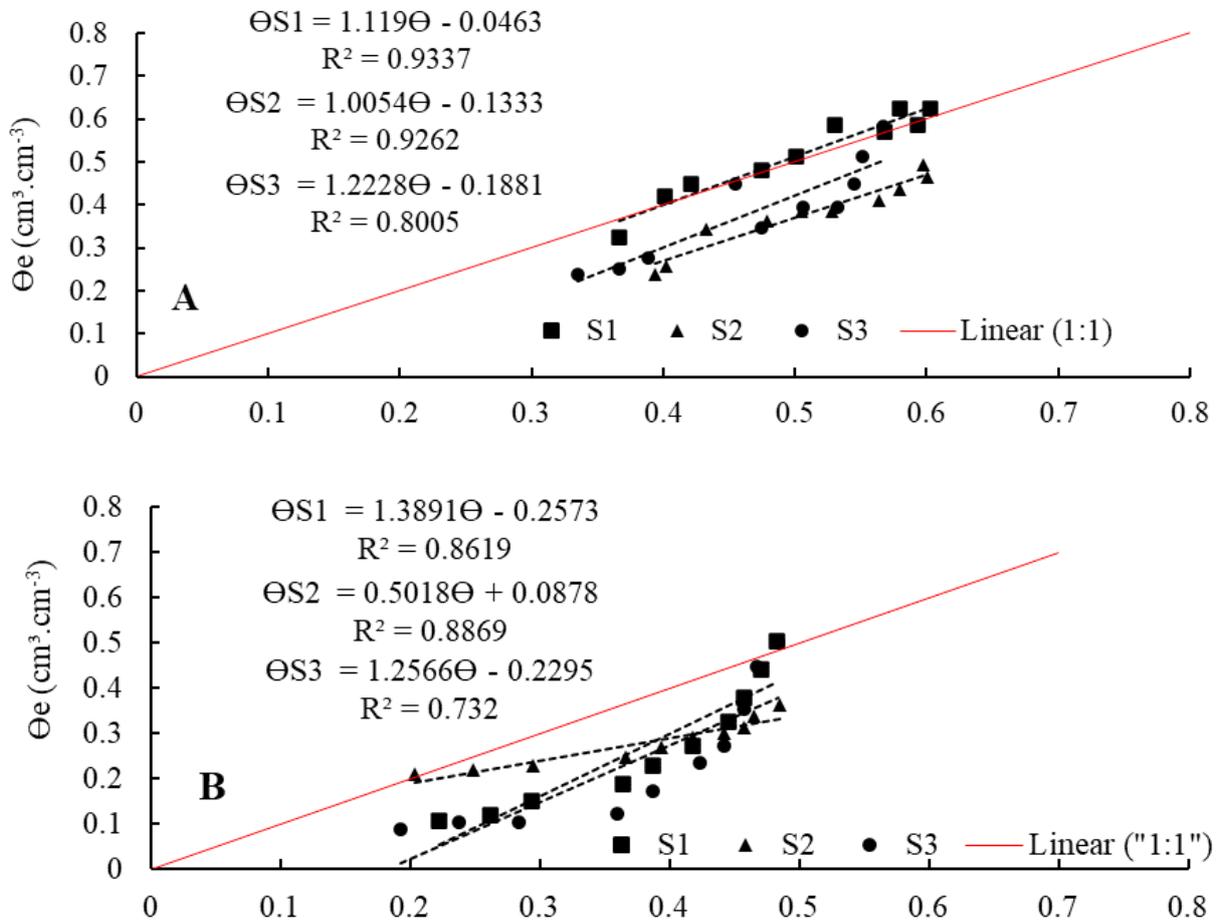
In the comparative analysis between R² values and the 1:1 line between data measured and estimated by sensors (Figure 4), the best fits were observed for sensors in RYL, with R² values between 0.92 and 0.93 for sensors S1 and S2, respectively (Figure 4A), and sensor S1 showing the smallest deviations from the 1:1 line. Otherwise, sensor S3 showed inferior performance in relation to the other sensors in RYL with R² of 0.80. Evaluation of sensors in RN (Figure 4B) showed inferior performance compared to calibration models, with R² values of 0.73, 0.86, and 0.88 for sensors S3, S1, and S2, respectively. The three sensors in RN showed systematic deviations with underestimation of values of volumetric moisture.

Sensors in RL showed similar behavior, with R² of 0.81, 0.85, and 0.83 for sensors S1, S2, and S3, respectively (Figure 4C). Underestimation of values, was similar between sensors evaluated in RL. Nagahaje *et al.* (2019), observed

underestimations of volumetric moisture by the SKU:SEN0193 sensor in an organic soil at readings between 0.20 and 0.60 cm³.cm⁻³. This behavior was observed in comparison to the volumetric moisture obtained by gravimetry and to the SM-200 sensor (Delta-T Devices Ltd, Cambridge, UK).

Root mean square error (RMSE) values in both soil types showed different responses between sensors (Table 6). The lowest RMSE values, 0.02 and 0.08 cm³.cm⁻³, were observed in sensors S1 and S3 in RYL, respectively. The other sensors in the three soil types showed similar RMSE values, with variation between 0.11 and 0.15 cm³.cm⁻³ in the three soil types. The three sensors evaluated in RL showed similar RMSE values, although different in relation to RYL and RN, suggesting the need for specific calibration for each soil type.

Adla *et al.* (2020), evaluated low-cost capacitive sensors, models SMEC300 and SM100 (Spectrum Technologies Inc.), and obtained RMSE values for sandy texture soils between 0.11 and 0.08 cm³.cm⁻³



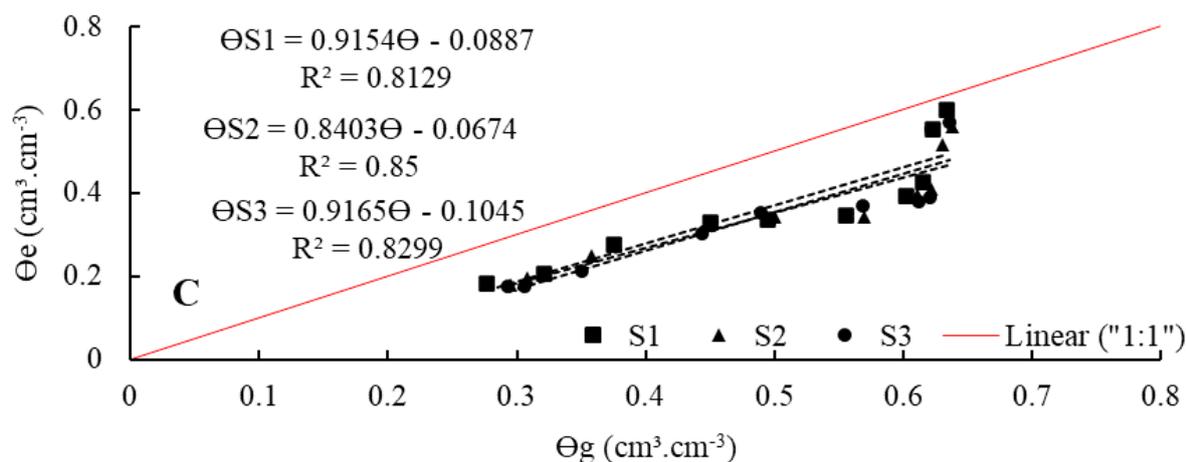


Figure 4. Evaluation of calibration applied to sensors installed in deformed samples of Red-yellow Latosol (a), Regolitic Neosol (c), and Red Latosol (c)

Table 6. Indicators of statistical accuracy for sensors evaluated in deformed samples of RYL, RN, and RL. Coefficient of determination (R^2), mean absolute error, MAE ($\text{cm}^3.\text{cm}^{-3}$) and root mean square error, RMSE ($\text{cm}^3.\text{cm}^{-3}$)

Sensor	RYL			RN			RL		
	R^2	MAE	RMSE	R^2	MAE	RMSE	R^2	MAE	RMSE
S1	0.93	0.02	0.02	0.86	0.11	0.12	0.81	0.13	0.14
S2	0.92	0.13	0.13	0.88	0.10	0.11	0.85	0.14	0.15
S3	0.80	0.08	0.09	0.73	0.13	0.15	0.82	0.14	0.15

for the SMEC300 sensor and between 0.10 and 0.08 $\text{cm}^3.\text{cm}^{-3}$ for the SM100 sensor. Nagahaje *et al.* (2019), observed that the SKU: SEN0193 sensor in a soil with high organic matter content showed RMSE values of 0.09 and 0.07 $\text{cm}^3.\text{cm}^{-3}$ for dry and saturated soil samples, respectively. The authors also recommended specific calibration for each soil type as accuracy depended on the constituent material of the soil. Considering an order of sensor performance between soil types, mean absolute error (MAE) values of 0.07, 0.11 and 0.13 $\text{cm}^3.\text{cm}^{-3}$ were obtained for sensors evaluated in RYL, RN, and RL, respectively.

CONCLUSIONS

- Integration between capacitive sensors and the Arduino board enabled to obtain the variation of volumetric soil moisture in real time. Volumetric moisture was correlated with sensor output voltage, with effective

correlation between sensor readings and soil water content.

- Variability between sensors must be considered in the calibration procedure, as readings may show different responses for the same moisture condition. Thus, it is recommended to operate sensors at the voltage of 5.00 V with individual calibration. This procedure is able to reduce reading variability between sensors.
- Calibration of the SKU:SEN0193 sensor proved to be specific for each soil type and bulk density. In general, the sensor showed systematic underestimations of volumetric moisture, regardless of soil type and bulk density.

AUTHORSHIP CONTRIBUTION STATEMENT

PEREIRA, R.M.: Conceptualization, Data curation, Formal Analysis, Investigation, Writing – original draft; **SANDRI, D.:** Conceptualization,

Project administration, Supervision, Validation, Writing – review & editing; **SILVA JÚNIOR, J.J.:** Conceptualization, Investigation, Supervision, Validation, Writing – review & editing.

DECLARATION OF INTERESTS

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

- ADLA, S.; RAI, N. K.; KARUMANCHI, S. H.; TRIPATHI, S.; DISSE, M.; PANDE, S. Laboratory calibration and performance evaluation of low-cost capacitive and very low-cost resistive soil moisture sensors. **Sensors**, v. 20, n. 263, p. 1-27, 2020.
- BURKE, S. Regression and Calibration. **LCGC Europe Online Supplement**, 2020. Available in: <https://www.webdepot.umontreal.ca/Usagers/sauves/MonDepotPublic/CHM%203103/LCGC%20Eur%20Burke%202001%20-%202%20de%204.pdf>. Access in: Dec. 14, 2020.
- CHAN, K.; SCHILLEREFF, D. N.; BAAS, A. C. W.; CHADWICK, M. A.; MAIN, B.; MULLIGAN, M. Low-cost electronic sensors for environmental research: pitfalls and opportunities. **Progress in Physical Geography**, v. 25, p. 1-34, 2020.
- CARR, J. J.; BROWN, J. M. **Basic Theories of Measurement. In Introduction to Biomedical Equipment Technology**. 4^a ed. Londres: Pearson, 2001.
- COELHO, E.F.; VELLAME, L.M.; COELHO FILHO, M.A.; LEDO, C.A.S. Desempenho de modelos de calibração de guias de onda acopladas a TDR e a multiplexadores em três tipos de solos. **Revista Brasileira de Ciência do Solo**, v. 30, p. 23-30, 2006.
- DOBRIYAL, P.; QURESHI, A.; BADOLA, R.; HUSSAIN, S. A. A review of the methods available for estimating soil moisture and its implications for water resource management. **Journal of Hidrology**, v. 458, p. 110-117, 2012.
- DUKES, M. D.; ZOTARELLI, L.; MORGAN, K.T. Use of irrigation Technologies for vegetable crops in Florida. **Horttechnology**, v. 20, n. 1, p. 133-142, 2010.
- HAUKE, J.; KOSSOWSKI, T. Comparison of values of Pearson's and Spearman's correlation coefficients on the same sets of data. **Questiones Geographicae**, v. 30, n. 2, 2011.
- LEKSHMI, S.; SINGH, D. N.; BAGHINI, M. S. A critical review of soil moisture measurement. **Measurement**, v. 54, p. 92-105, 2014.
- LIMA, J. G. A.; OLIVEIRA, A. S.; SOUZA, L. S.; SILVA, N. D.; VIANA, P. C. Calibration of soil a soil moisture sensor with disturbed and undisturbed soil samples from Bahia. **Revista Brasileira de Engenharia Agrícola e Ambiental**, v. 22, n. 10, p. 696-701, 2018.
- NAGAHAJE, E. A. A. D.; NAGAHAJE, I. S. P.; FUJINO, T. Calibration and validation of a low-cost capacitive moisture sensor to integrate the automated soil moisture monitoring system. **Agriculture**, v. 9, n. 141, p. 1-10, 2019.
- PLACIDI, P.; GASPERINI, L.; GRASSI, A.; CECCONI, M.; SCORZONI, A. Characterization of low-cost capacitive soil moisture sensors for IoT networks. **Sensors**, v. 20, n. 3585, p. 1-14, 2020.
- RADI, M.; NGADISIH, M. F. S.; NUHA, M. S.; RIZQI, F. A. Calibration of capacitive soil moisture sensor (SKU:SEN0193). *In: INTERNATIONAL CONFERENCE ON SCIENCE AND TECHNOLOGY (ICST)*, 4., 2018, Yogyakarta. **Proceedins[...]**. Yogyakarta: ICST, 2018.