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SOIL WATER CONTENT ESTIMATED BY RESISTIVE SENSORS

SENSORES RESISTIVOS NA ESTIMATIVA DO CONTEÚDO DE ÁGUA NO SOLO

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ABSTRACT: Agricultural automation is an alternative for more precise and sustainable agriculture. Sensors are used to collect information and contribute to monitoring and decision-making in production environments, mainly in irrigated agriculture. In this context, the objective of this study was to compare different models of soil moisture sensors under the same reading conditions. Two sensor models were evaluated: FC-28 (Sensor A) and HL-69 (Sensor B). The Student's t-test was applied at 5% significance level to compare the means of the readings between the sensor models (A and B). A study comparing sensors of the same model was conducted in a split-plot experimental design, in a 4×9 factorial arrangement (four sensors × nine readings) in sampling units (stainless-steel rings) with different soil water contents, with 95 replications. Linear response models with a plateau were used when the sensors showed reading variations as a function of the increase in soil water content. The data obtained were analyzed in the software R. The results showed that both sensors require independent, and a mathematical model should be developed for each sensor. The divergent results between the evaluated sensors denote low rigor in device standardization during manufacturing.

Keywords: *sensor calibration, precision irrigation, soil moisture.*

RESUMO: A automação dos sistemas agrícolas é uma alternativa para uma agricultura mais precisa e sustentável. Sensores são utilizados no levantamento de informações, contribuindo para o monitoramento e tomada de decisão no ambiente de produção, especialmente na agricultura irrigada. Neste contexto, objetiva-se comparar diferentes modelos de sensores de umidade do solo para verificar a semelhança em suas respostas quando submetidos às mesmas condições de leitura. Foram avaliados dois modelos de sensores FC-28 (Sensor A) e HL-69 (Sensor B). Para comparação da média das leituras realizada entre os modelos de sensores (A e B), foi aplicado o teste t de Student, a 5% de probabilidade. Para o estudo comparativo de representantes de mesmo modelo foi estabelecido um delineamento experimental com parcela subdividida no esquema fatorial 4x9, com quatro sensores, nove leituras em diferentes conteúdos de água nas amostras de solo em anel de inox e 95 repetições por tratamento. Quando os sensores apresentaram patamar de variação de leitura em função do aumento no conteúdo de água no solo foram utilizados modelos lineares de resposta com platô. Os dados obtidos foram analisados pelo software R. Os resultados demonstram que todos os sensores estudados apresentam calibração independente, sendo necessário a construção de um modelo matemático para cada sensor. A divergência entre resultados dos sensores avaliados demonstra baixo rigor em sua confecção.

Palavras-chave: *calibração de sensor, irrigação de precisão, umidade do solo.*

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INTRODUCTION

Agriculture is one of the largest water-consuming sectors in the world. Therefore, the conscientious use of water is essential for the sustainability and quality of production (SILVA et al., 2022; HARA; GONÇALVES, 2018). According to García et al. (2020), the use of irrigation in agriculture is significantly important in this context, as it should be managed with the appropriate timing and quantity of water, according to the needs of the crop and its phenological stages.

Therefore, improving techniques that enhance water use efficiency can contribute to the preservation of water resources (HARA; GONÇALVES, 2018). Thus, monitoring soil moisture variation by quantifying soil water content is essential, as it enables the correct management of irrigation systems (KAMIENSKI et al., 2019).

Continuous determination of soil moisture is important for precise and immediate control of water availability, ensuring accuracy and speed in decision-making (RIBEIRO et al., 2018; NAGAHAGE et al., 2019).

There are direct and indirect methods to determine soil water content. The most used direct method is gravimetry, which requires the sample to remain in an oven for several hours before evaluation (REICHERT et al., 2020; SERRANO et al., 2020). According to Silva et al., (2020), indirect methods can also express soil water content with accuracy. The use of moisture sensors enables more precise control and monitoring of variations (OLIVEIRA et al., 2018; SERRANO et al., 2020). FC-28 and HL-69 sensors are commonly used because they provide real-time information about soil electrical resistance, which is directly connected to soil moisture (BATISTA et al., 2016). However, indirect sensors require calibration, as the result can be affected by differences in soil physical, chemical, and biological characteristics (JIMÉNEZ et al., 2020; REICHERT et al., 2020). Resistive sensors have two rods with electrodes, through which electric currents pass, thus showing the soil electrical resistance between the rods. The resistance values are inversely proportional to the water content (PIZETTA et al., 2017).

Soil moisture sensors can monitor variations in soil electrical resistance, but the results are dependent on soil texture and soluble salt concentration. The higher the water concentration, the lower the soil resistance to electric current, as they are inversely proportional (OLIVEIRA et al., 2018; CUNHA; ROCHA, 2015).

According to Oliveira et al. (2018), resistive soil moisture sensors offer advantages due to their low acquisition cost, simple operation, and easy availability on the market. Soil moisture sensors are alternatives for quick and safe readings of soil water content, when calibrated according to the conditions of use (GOMES et al., 2017). These sensors present an excellent cost-benefit ratio for soil moisture monitoring and have been a viable and affordable alternative for water management in precision irrigated agriculture (GONZÁLEZ-TERUEL et al., 2019).

In this context, the objective of this study was to compare different models of resistive soil moisture sensors, and sensors of the same model, through the development of calibration curves, as well as to assess the similarity between their results under the same reading conditions.

MATERIAL AND METHODS

This study was carried out at the State University of Goiás, Southwest campus, Santa Helena de Goiás University Unit, in the Agricultural Engineering Laboratory. The soil used in the sampling unit was classified as a Typic Hapludox (Latossolo Vermelho Distrófico; SANTOS et al., 2018), which was collected at a depth of 0.80 m in an agricultural area. The collected soil was crushed, air-dried, homogenized, and sieved (2 mm). This soil was used in all sampling units; this procedure was carried out to prevent differences in the soil physical and chemical properties among the sampling units.

The soil was subjected to physical and chemical analysis, using the methodology described in the Soil Analysis Methods Manual of the Brazilian Agricultural Research Corporation - EMBRAPA (TEIXEIRA et al., 2017). The density of the soil used in the sampling units was 1.05 g cm-3. The sampling unit consisted of a stainless-steel ring with a diameter of 0.05 m and a height of 0.05 m containing moistened soil arranged in three layers. Each layer of soil added—corresponding to one-third of the final weight—was compressed and scarified before the addition of the next layer.

The soil used in the sampling units was homogenized to minimize variations in soil characteristics. The soil density was standardized to create a similar environment for sensor readings, thus, variations in readings were connected to sensor characteristics.

A high ion content in the soil solution alters the reading without necessarily changing the soil water content. Soil density also contributes to decreases in the soil electrical resistivity. The results of the physical and chemical analysis of the soil used in the sampling units are shown in Table 1.

Table 1. Physical and chemical analysis of the soil (Typic Hapludox) used in the sampling units

Granulometry			Ca	Mg	Al	H+Al	K	Density	pH
$g\ Kg^{-1}$				------------------cmolc dm^{-3}----------				$g\ cm^{-3}$	
Clay	Silt	Sand							
590.0	120.0	290.0	2.1	1.3	0.0	3.1	0.12	2.95	5.0

The soil in the sampling units were subjected to a saturation procedure (EMBRAPA, 2011); the moisture sensors were then installed and remained in the samples until the end of the experiment (Figure 1). The sensors were kept in the sampling units to avoid disturbances and maintain contact with the soil.

(A) (B)

Figure 1. Sampling units with soil under saturation process (A) and saturated soil with a sensor for determining soil water content (B).

The models of the resistive sensors used were FC-28 (Sensor A) and HL-69 (Sensor B). They were connected to microcontroller (Arduino UNO) programmed to take readings every three seconds and store the results on an SD card. The readings were taken after the soil had dried naturally in an open container at room temperature for 48 hours; the samples were then placed in an airtight container and kept for 24 hours. This procedure was carried out to avoid potential moisture gradients in the sampling units during the readings.

The sampling units were weighed before the sensor readings to calculate the gravimetric soil water content (EMBRAPA, 2011). The sensor readings were taken for five minutes. The sensors were removed from the soil at the end of the natural soil drying process, and the sampling units were placed in an oven to determine their dry weights. The gravimetric soil water content in the sampling units was calculated by the standard method (EMBRAPA, 2011).

The sensor models (sensors A and B) were compared in a completely randomized experimental design with forty replications. The comparison of data from sensors A and B showed a significant difference between them by the Student's t-test, at 5% significance level. A Boxplot was developed for each model (sensors A and B) for a graphical analysis of the data.

Sensors of the same model were compared using a split-plot experimental design, in a 4×9 factorial arrangement consisting of four sensors of the same model and nine readings of different soil water contents, totaling 36 treatments, with 95 replications.

In this second experiment, the data for sensors A and B were evaluated separately. The data were subjected to descriptive statistical analysis, considering the coefficient of variation (CV, %) as low (CV < 12%), intermediate (12% < CV < 24%), or high (CV > 24%) (WARRICK; NIELSEN, 1980).

The data were also subjected to the procedure described by Snedecor and Cochran (1989), which tests the homogeneity of the data from two linear models (F); the evaluated parameters include the angular coefficient (a) and the intercept (b). When no significant difference was found between the parameters, the data indicate a cluster; when the parameters present variation, the data should be analyzed separately.

Each dataset formed in this analysis was fitted to linear regression models. When the data presented a plateau, they were explained using the modified maximum curvature method (MEIER; LESSMAN, 1971) of the linear model with plateau (PARANAÍBA et al., 2009), which defines the sensor's sensitivity range. All statistical data analyses were performed using the R software (The R Foundation for Statistical Computing).

RESULTS AND DISCUSSION

The comparison of data from sensors A and B showed a significant difference between them by the Student's t-test (Table 2). The sensor models showed different results; thus, they were evaluated individually. Figure 2 shows that the reading range of sensor A did not overlap with the reading range of sensor B, as confirmed by the significant difference between the readings of the sensors (Table 2).

Table 2. Comparison of sensor readings (sensors A and B; in analog units) by the Student's t-test, expressed as mean ± standard deviation.

Sensor	Mean ± Standard deviation	*p*-value
A	73.624 ± 30.539	0.000**
B	576.797 ± 245.262	

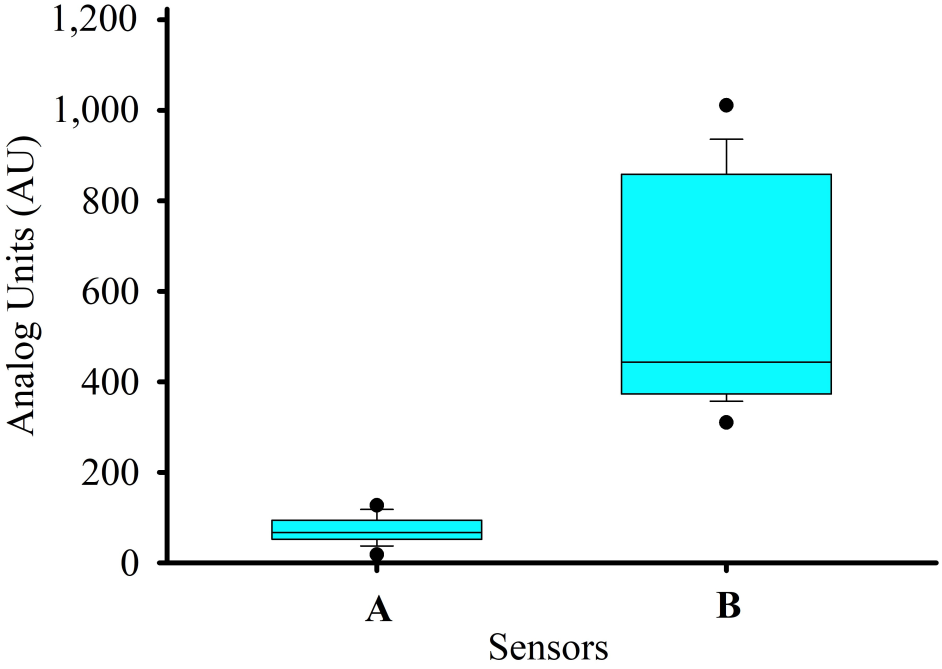

Figure 2. Boxplot of sensor readings (in analog units – AU) to estimate soil water content (sensor A: FC-28 model; and sensor B: HL-69 model) in a percentage range of gravimetric soil water content from 12% to 55%.

The sensors have a reading scale in analog units (AU) that ranges from 0 to 1023 AU (low to high electrical resistance, respectively), according the manufacturer's description. However, the sensors do not utilize the entire reading range, but rather are restricted to a specific range depending on the model. Sensor A had a reading range of 5 to 137 AU, whereas sensor B had a range of 276 to 1023 AU for the same soil water contents (Figure 2). Sensors' sensitivity can be affected by soil characteristics (REICHERT et al., 2020), as shown by the sensors evaluated in the present study, which yielded divergent results under the same reading conditions. According to Silva et al. (2020), sensors used for indirect determination of soil water content require calibration before use. The sampling units showed gravimetric soil water content percentages from 55% (when saturated) and 12% (near wilting point), with this gradient achieved through natural soil drying. Considering the difference in readings between the sensors A and B, the following analyses were conducted based on two different datasets. The ability of sensors to measure gravimetric soil water content was evaluated by the coefficient of variation (CV), which showed low values (CV < 12%) (Table 4), except for the first reading of sensors A1 and A3, which showed intermediate CV (12% < CV < 24%) (WARRICK and NIELSEN, 1980), denoting a high capacity to measure soil water content.

Table 4. Descriptive analysis of soil resistivity by amplitude (analog units) and coefficient of variation (CV; %) of 95 readings of each sensor at different soil moistures. A and B refer to the sensor models and the numbers refer to four replications.

Readings		A1	A2	A3	A4	B1	B2	B3	B4
1	Amplitude	0.044	0.103	0.029	0.063	0.029	0.039	0.024	0.049
	CV	19.38%	5.94%	18.74%	11.15%	0.35%	0.51%	0.29%	0.55%
2	Amplitude	0.005	0.010	0.029	0.015	0.186	0.049	0.044	0.020
	CV	0.80%	0.91%	4.68%	2.87%	2.79%	0.73%	0.61%	0.27%
3	Amplitude	0.015	0.015	0.024	0.015	0.195	0.054	0.054	0.034
	CV	1.31%	0.93%	5.43%	1.86%	2.95%	0.76%	0.80%	0.46%
4	Amplitude	0.010	0.005	0.010	0.024	0.029	0.049	0.059	0.020
	CV	0.87%	0.55%	1.45%	2.53%	0.46%	0.69%	0.99%	0.26%
5	Amplitude	0.005	0.010	0.015	0.010	0.127	0.107	0.146	0.132
	CV	0.32%	0.70%	1.75%	0.72%	2.63%	1.85%	3.10%	3.46%
6	Amplitude	0.010	0.034	0.015	0.020	0.151	0.063	0.088	0.049
	CV	0.44%	3.73%	1.38%	1.49%	2.58%	1.00%	1.31%	0.71%
7	Amplitude	0.010	0.005	0.024	0.010	0.020	0.034	0.029	0.137
	CV	0.52%	0.43%	0.86%	0.55%	0.18%	0.27%	0.26%	1.32%
8	Amplitude	0.015	0.015	0.024	0.020	0.112	0.068	0.161	0.200
	CV	0.79%	0.75%	1.11%	0.85%	0.68%	0.42%	1.06%	1.45%
9	Amplitude	0.005	0.010	0.010	0.010	0.063	0.215	0.078	0.181
	CV	0.52%	0.53%	0.39%	0.59%	0.44%	1.22%	0.56%	1.30%
10	Amplitude	0.015	0.068	0.015	0.015	0.063	0.073	0.039	0.132
	CV	0.42%	1.49%	0.53%	0.72%	0.30%	0.41%	0.24%	0.81%

The study for assessing the possibility of mathematically modelling the data of sensors of a same model (Table 5 and 6) showed absence of significance concomitantly for the observations: homogeneity in the data; and differentiation of angular and linear coefficients. This result denotes that the data of each sensor representing model A or B should be modeled independently, as they cannot be grouped. Despite sensors of the same model, the mathematical regression that correlates gravimetric soil water content with the sensor reading is independent for each sensor model representative.

Table 5. Comparison of readings (analog output of the Arduino microcontroller) from resistive soil moisture sensors of the same model (A1, A2, A3, and A4), according to Snedecor & Cochran (1989), for estimating values that can be grouped to form a mathematical model that estimates the digital reading of each soil moisture level.

Methods	F	Angular coefficient	Linear coefficient	Result
A1 × A2	**	**	**	Not grouped
A1 × A3	ns	**	**	Not grouped
A1 × A4	**	**	**	Not grouped
A2 × A3	ns	**	**	Not grouped
A2 × A4	**	**	**	Not grouped
A3 × A4	**	**	**	Not grouped

** = significant at 1%; ns = not significant.

Table 6. Comparison of readings (analog output of the Arduino microcontroller) from resistive soil moisture sensors of the same model (B1, B2, B3, and B4), according to Snedecor & Cochran (1989), for estimating values that can be grouped to form a mathematical model that estimates the digital reading of each soil moisture level.

Methods	F	Angular coefficient	Linear coefficient	Result
B1 × B2	**	**	**	Not grouped
B1 × B3	ns	**	ns	Not grouped
B1 × B4	ns	**	*	Not grouped
B2 × B3	ns	**	*	Not grouped
B2 × B4	ns	**	ns	Not grouped
B3 × B4	ns	**	**	Not grouped

** = significant at 1%; ns = not significant.

Sensor B showed greater homogeneity; the amplitudes indicated that the results found were similar. However, the slope of the models differed, and the interception point on the axes contributed to the divergence. Sena et al. (2020) evaluated a capacitive sensor (model ECH2O EC-5) with linear model fit to correlate tension with soil moisture in different soil textures. Although the reading pattern of the sensor used in the present study was the same as that used by Sena et al. (2020), the difference in the sensor model may have affected the data fit to the model. The data from some sensors of model A satisfactory fitted to a linear model, considering the coefficient of determination of the equations (Figure 3). Diniz et al. (2019) evaluated a resistive sensor (model FC-28) in an irrigation system and found a coefficient of determination of 0.985. Alda et al. (2020) evaluated the calibration of two commercial models of resistive sensors in four different soil types and found a model fit with an R^2 of 0.87. Additionally, Almeida et al. (2018) evaluated the calibration of a capacitance sensor and found a R^2 of 0.98 for a Spodosol of sandy texture.

Pizetta et al. (2017) evaluated the calibration of a low-cost sensor (Eletrodex) using the standard oven method in different soil classes; the sensor results fitted linear equations with low coefficients of determination: 0.699 for a Typic Hapludult, 0.725 for a Typic Hapludox, and 0.48 for a Typic Hapludoll.

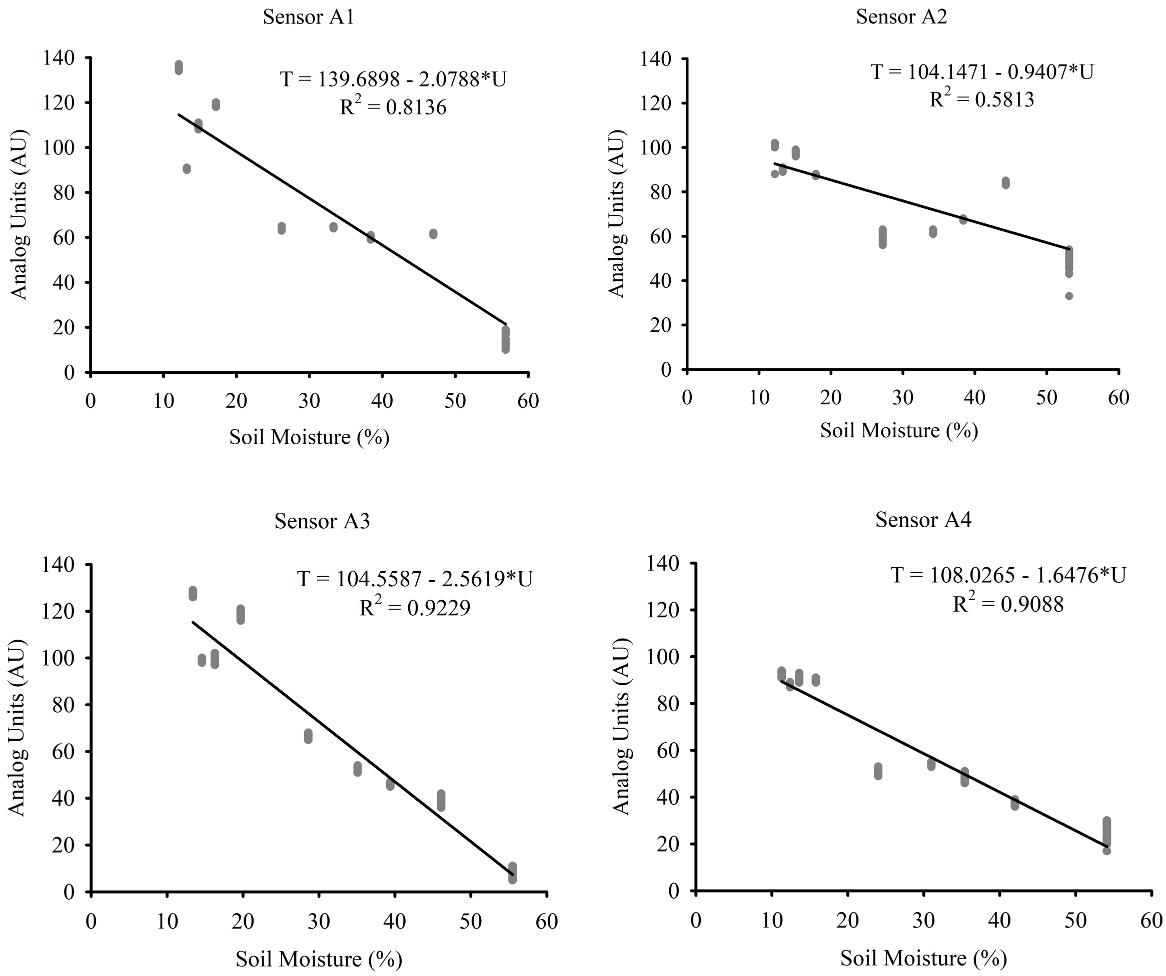

Figure 3. Graphs of correlation between soil moisture (%) and soil moisture readings (in analog units – AU) by the sensor model A.

This result reinforces the need of tests to verify the operation and calibration, as well as the validation of the regression model for each sensor. The use of sensors that result in low coefficients of determination is not recommended, as their readings may not accurately represent the actual soil conditions, making it difficult to control the soil water content. According to Degenhardt et al. (2002), R^2 represents the certainty of predicting a real value; the higher the value, the better the data fit.

All tested model B sensors performed soil water content readings restricted to a certain range. This result denotes the existence of a reading limit, beyond which the soil water content measured by the sensor does not present significant variation, limiting its usefulness (Figure 4).

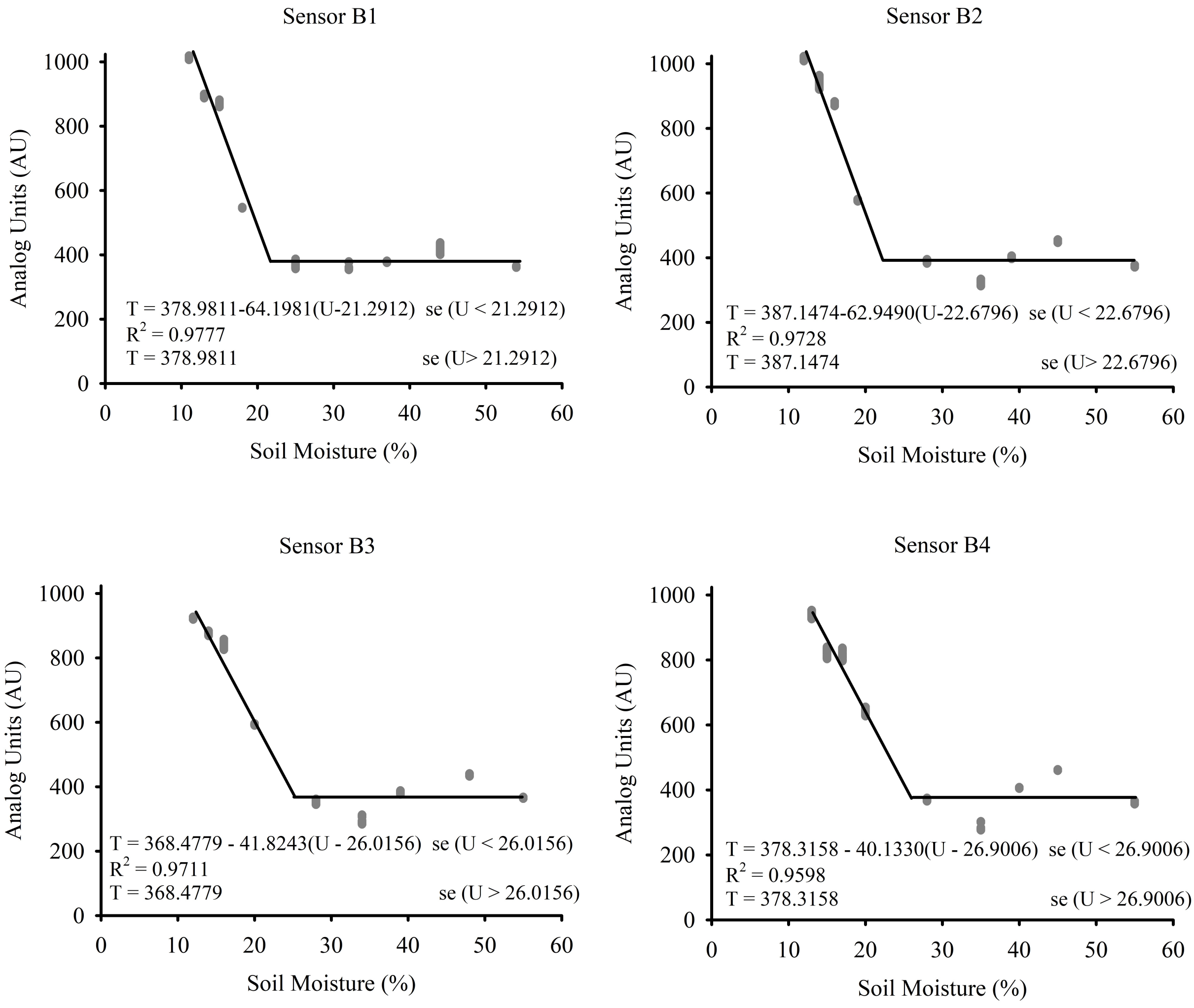

Figure 4. Graphs of correlation between soil moisture (%) and soil moisture readings in analog units – AU) by the sensor model B.

Sensors B1, B2, B3, and B4 showed stabilization of sensor values (plateau) at percentages of 21.29%, 22.68%, 26.025%, and 26.90% of the gravimetric soil water content, respectively (Figure 4). Within the sensor sensitivity range, the data fitted a linear model with a coefficient of determination higher than 0.96.

CONCLUSIONS

Calibration modeling is necessary for each sensor for accurate determination of soil water content.

The evaluated sensors can estimate soil moisture with satisfactory precision.

The divergence of results between the sensors denotes low rigor in device standardization during manufacturing.

Sensors B showed soil water content readings restricted to a specific range.

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