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MODELAGEM MATEMÁTICA E ANÁLISE DE DESEMPENHO DE UM SENSOR RESISTIVO DE BAIXO CUSTO PARA ESTIMATIVA DO CONTEÚDO VOLUMÉTRICO DE ÁGUA EM SUBSTRATO

MATHEMATICAL MODELING AND PERFORMANCE ANALYSIS OF A LOW-COST RESISTIVE SENSOR FOR VOLUMETRIC WATER CONTENT ESTIMATION IN SUBSTRATE

MODELADO MATEMÁTICO Y ANÁLISIS DE RENDIMIENTO DE UN SENSOR RESISTIVO DE BAJO COSTO PARA LA ESTIMACIÓN DEL CONTENIDO VOLUMÉTRICO DE AGUA EN SUSTRATO

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Resumo

O uso de sensores de baixo custo representa uma alternativa promissora para expandir o acesso ao monitoramento hídrico em substratos. Este estudo avaliou o desempenho de uma sonda resistiva integrada a um sistema baseado em Arduino para estimar o conteúdo volumétrico de água, a partir das relações entre o tempo de secagem e o sinal de saída do sensor. O experimento foi conduzido utilizando um substrato comercial submetido à secagem controlada, com determinação simultânea do conteúdo volumétrico de água pelo método gravimétrico e aquisição da saída do sensor (bits). Modelos lineares, logarítmicos, exponenciais e polinomiais (de segunda e terceira ordem) foram ajustados e avaliados por meio do coeficiente de determinação (R^2), da raiz do erro quadrático médio (RMSE) e dos critérios de informação (AIC e BIC). Adicionalmente, aplicou-se a regressão linear segmentada para representar as variações na resposta do sensor ao longo de toda a faixa de umidade, sendo calculados indicadores de desempenho que incluíram sensibilidade, coeficiente de variação e erro absoluto em unidades físicas. Os modelos polinomiais apresentaram o melhor desempenho global, com o modelo de terceira ordem exibindo a maior precisão (R^2 = 0,9777; RMSE = 0,0285, enquanto os modelos logarítmico e exponencial exibiram desempenho inferior (R^2 < 0,90$). A análise segmentada revelou regimes de resposta distintos, com alta sensibilidade sob condições de baixa umidade, uma transição abrupta na faixa intermediária e previsibilidade reduzida sob condições de maior saturação. O erro absoluto ao longo dos segmentos variou de 0,0024 0,0145 $cm^3\ cm^{-3}$, indicando boa exatidão do sistema. Esses resultados são consistentes com os valores reportados na literatura internacional para sensores de baixo custo. O sistema demonstrou desempenho satisfatório aliado ao baixo custo de implementação (R$ 88,46 ≈ US$ 15,80), comprovando sua viabilidade técnica e aplicabilidade prática para o monitoramento da umidade em substratos.

Palavras-chave: Agricultura de precisão; Sensores de baixo custo; Modelagem matemática; Regressão segmentada; Manejo da irrigação.

Abstract

The use of low-cost sensors represents a promising alternative to expand access to water monitoring in substrates. This study evaluated the performance of a resistive probe integrated with an Arduino-based system to estimate volumetric water content based on drying time and sensor output signal relationships. The experiment was conducted using a commercial substrate subjected to controlled drying, with simultaneous determination of volumetric water content by the gravimetric method and acquisition of sensor output (bits). Linear, logarithmic, exponential, and polynomial models (second- and third-order) were fitted and evaluated using the coefficient of determination (R^2), root mean square error (RMSE), and information criteria (AIC and BIC). Additionally, segmented linear regression was applied to represent variations in sensor response across the moisture range, and performance indicators including sensitivity, coefficient of variation, and absolute error in physical

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Pages: 1-24

units were calculated. Polynomial models showed the best overall performance, with the third-order model presenting the highest accuracy (R^2 = 0.9777; RMSE = 0.0285), whereas the logarithmic and exponential models exhibited inferior performance (R^2 < 0.90). The segmented analysis revealed distinct response regimes, with high sensitivity under low moisture conditions, a sharp transition in the intermediate range, and reduced predictability under wetter conditions. Absolute error across the segments ranged from 0.0024 to 0.0145 $cm^3\ cm^{-3}$, indicating good accuracy of the system. These results are consistent with values reported in the international literature for low-cost sensors. The system demonstrated satisfactory performance combined with low implementation cost (R$ 88.46 ≈ US$ 15.80), demonstrating its technical feasibility and practical applicability for substrate moisture monitoring.

Keywords: Precision agriculture; Low-cost sensors; Mathematical modeling; Segmented regression; Irrigation management.

Resumen

El uso de sensores de bajo costo representa una alternativa prometedora para expandir el acceso al monitoreo hídrico en sustratos. Este estudio evaluó el rendimiento de una sonda resistiva integrada a un sistema basado en Arduino para estimar el contenido volumétrico de agua a partir de las relaciones entre el tiempo de secado y la señal de salida del sensor. El experimento se llevó a cabo utilizando un sustrato comercial sometido a un secado controlado, con la determinación simultánea del contenido volumétrico de agua mediante el método gravimétrico y la adquisición de la salida del sensor (bits). Se ajustaron y evaluaron modelos lineales, logarítmicos, exponenciales y polinomiales (de segundo y tercer orden) utilizando el coeficiente de determinación (R^2), la raíz del error cuadrático medio (RMSE) y los criterios de información (AIC y BIC). Adicionalmente, se aplicó una regresión lineal segmentada para representar las variaciones en la respuesta del sensor a lo largo del rango de humedad, y se calcularon indicadores de rendimiento que incluyeron la sensibilidad, el coeficiente de variación y el error absoluto en unidades físicas. Los modelos polinomiales mostraron el mejor rendimiento global, presentando el modelo de tercer orden la mayor precisión (R^2 = 0,9777; RMSE = 0,0285), mientras que los modelos logarítmico y exponencial exhibieron un rendimiento inferior (R^2 < 0,90). El análisis segmentado reveló distintos regímenes de respuesta, con una alta sensibilidad en condiciones de baja humedad, una transición abrupta en el rango intermedio y una predictibilidad reducida en condiciones de mayor humedad. El error absoluto a través de los segmentos osciló entre 0,0024 y 0,0145 $cm^3\ cm^{-3}$, lo que indica una buena exactitud del sistema. Estos resultados son consistentes con los valores reportados en la literatura internacional para sensores de bajo costo. El sistema demostró un rendimiento satisfactorio combinado con un bajo costo de implementación (R$ 88,46 ≈ US$ 15,80), demostrando su viabilidad técnica y aplicabilidad práctica para el monitoreo de la humedad en sustratos.

Palabras clave: Agricultura de precisión; Sensores de bajo costo; Modelado matemático; Regresión

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segmentada; Gestión del riego.

1. Introduction

Water availability in the cultivation medium is one of the primary factors conditioning initial plant growth, directly influencing physiological processes such as nutrient uptake, cell expansion, and photosynthesis. In seedling production systems, particularly for forest species, proper substrate moisture management is decisive for obtaining vigorous seedlings suitable for transplanting. In these systems, the substrate replaces the soil as a growth medium, presenting distinct physical and hydraulic characteristics, which demands tighter control of the available water content (BUENO et al., 2020).

The use of commercial substrates has intensified due to their uniformity and high porosity, favoring root development. However, these characteristics also make the system more sensitive to variations in water content, which can quickly result in water deficit or excess. Thus, moisture monitoring becomes essential to maintain adequate conditions for seedling development (NEMALI et al., 2007; MONTESANO et al., 2018).

In this context, moisture sensors have been widely used as decision-support tools for irrigation management, allowing indirect estimations of water content and enabling greater water-use efficiency (MARKOVIĆ et al., 2024).4 In soilless systems, continuous substrate moisture monitoring has proven particularly efficient for real-time irrigation control (MONTESANO et al., 2018).

Despite these advantages, the adoption of commercial sensors is still limited by high costs, especially in small and medium-sized nurseries. As an alternative, low-cost sensors associated with open-source microcontrollers, such as Arduino, have been proposed as affordable solutions for water monitoring. Systems based on this approach have demonstrated potential for irrigation automation with lower investment and greater operational flexibility (FERRAREZI et al., 2015; GONZÁLEZ-TERUEL et al., 2019).

However, the application of these sensors requires specific calibration, since

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Pages: 1-24

their response is influenced by the medium's properties. In commercial substrates, this variability is even more significant, making generalized equations inadequate. Studies indicate that low-cost sensors can exhibit good performance when properly calibrated, although their accuracy depends on usage conditions (ADLA et al., 2020).

Furthermore, the choice of the mathematical model used in calibration directly influences the quality of the estimates. Different models may show distinct performances, requiring evaluation through statistical criteria for selecting the most appropriate equation (MANE et al., 2024). Defining these relationships also allows for the establishment of operational limits for irrigation management, contributing to maintaining the ideal water status during seedling production (BAÑÓN et al., 2022).

The economic feasibility of systems based on open-source hardware, such as Arduino, acts as a catalyst for the democratization of precision agriculture. However, the low cost of these devices imposes technical challenges, such as the need for robust mathematical models to compensate for the physical limitations of resistive sensors in porous and heterogeneous media.

In this context, the present study aimed to evaluate the performance and mathematical modeling of a low-cost moisture monitoring system based on an Arduino microcontroller and a resistive probe, defining operational criteria and predictive models for estimating volumetric water content in commercial substrate.

2. Material and methods

2.1 Nature and data source

This study presents an advanced analytical approach based on the reanalysis of experimental data obtained by Mendes et al. (2021). The relevance of this approach lies in the transition from a preliminary characterization to a fine-tuning of estimation models. While the preceding investigation validated the technical feasibility of the sensor (FC-28), the present work proposes a scientific revisit focused on the rigorous comparison of different equation architectures. The

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distinctive feature of this analysis is the reduction of residual errors and the optimization of global water content prediction, converting laboratory data into robust tools for the management and control of precision irrigation systems.

2.2 Data acquisition system and hardware

The data acquisition system consisted of a contact electrical impedance sensor (resistive type), model FC-28, operating between 3.3 and 5.0 V. This was coupled to an electronic module based on the LM393 comparator, integrated with an Arduino Pro Mini microcontroller (ATmega328P, 5 V, 16 MHz) and a CH340G USB-TTL converter for serial communication. The interface between the probe and the electronic module utilized a two-way shielded cable (0.5 m). The system, powered via USB connection, operated within the Arduino IDE environment, allowing real-time signal reading through the serial monitor. Structurally, the workflow followed the sequence: sensor–module–microcontroller–converter–computer, resulting in the continuous acquisition of data in digital units (bits) (Figure 1).

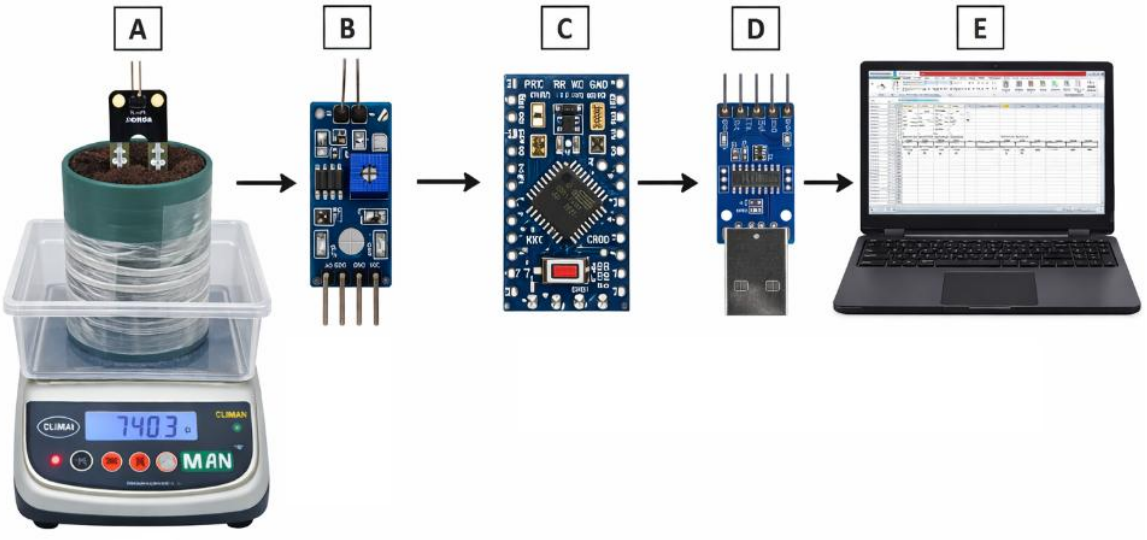


Figure 1: Experimental system composed of the FC-28 resistive probe coupled to the LM393 module (A and B), Arduino Pro Mini microcontroller (C), CH340G USB–TTL converter (D), and data acquisition via computer (E).

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Electrical connections were performed to ensure signal acquisition stability and measurement integrity. The resistive probe was connected to the LM393 module using shielded cable with soldered connections, aiming to improve signal stability and reduce electrical contact variations. The module was powered at 5V and operated in analog mode, with the A0 output connected to the A0 input of the microcontroller, while the VCC and GND terminals were connected to their respective power supply lines. Signal reading was performed by the microcontroller's internal analog-to-digital converter, with 10-bit resolution, adopting the supply voltage as reference (Vref = 5V). Communication with the USB-TTL converter was established through soldered connections between the VCC, GND, and serial communication pins (TX and RX), with a cross-connection between TX and RX. The system was powered directly via the USB interface, eliminating the need for an external power source.

2.3 Substrate characterization and experimental drying protocol

The substrate used was a commercial type (Bioplant®), composed of a mixture of Sphagnum peat, coconut fiber, rice husk, pine bark, vermiculite, and mineral additives (MENDES et al., 2021). The material was previously dried in a forced-air oven at 105 °C and placed in PVC containers (75 mm in diameter and 15 cm in height), resulting in an average volume of 662.68 cm^3. The filling of the containers was standardized to replicate the nominal density provided by the manufacturer (0.15 g cm^{-3}), obtaining an experimental average bulk density of 0.155 g cm^{-3} (± 0.006), which is in compliance with standards for high-aeration organic substrates.

The experiment was conducted with five replicates (independent samples). Strict density control during assembly aimed to ensure structural homogeneity among replicates, minimizing porosity variations that could interfere with the continuity of the liquid phase and the electrical response of the sensors. After assembly, the samples were saturated with distilled water for 24 hours and subjected to drainage until moisture stabilization. Subsequently, they were weighed

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on a precision scale (0.001 g) and placed in an oven at 65 °C for gradual drying.

During the drying process, which lasted a total of 105 hours and 15 minutes, successive readings of the probe signal and sample weighings were performed, initially at hourly intervals and subsequently at longer intervals until complete dryness. In each reading, time (h), mass (g), and the output signal (bits) were recorded. For the output signal acquisition, a single resistive sensor was used, carefully selected from a batch of ten units after prior stability tests. The choice of a single device aimed to reduce systematic uncertainty and mitigate inter-device variability, ensuring that the observed variations were strictly due to the water dynamics of the medium.

2.4 Data processing and mathematical modeling

To fit the mathematical models and construct the calibration curves, the arithmetic mean of the five replicates was used, consolidating a database with 26 average observations. Physically inconsistent values, such as negative residual volumetric water content, were truncated to zero.

Gravimetric water content was determined by the ratio between the mass of water and the mass of dry substrate, according to Equation (1):

$$U = \frac{m_{water}}{m_{dry_substrate}} \quad (1)$$

Where: U is the gravimetric water content (g g^{-1}), m_{water} is the mass of water in the sample (g) and $m_{dry_substrate}$ is the mass of the dry substrate (g).

Volumetric water content was obtained from the gravimetric water content and the substrate bulk density, according to Equation (2):

$$\theta = U\rho_b \quad (2)$$

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Where: θ is the volumetric water content ($cm^3\ cm^{-3}$) and ρ_b is the substrate bulk density ($g\ cm^{-3}$).

For mathematical modeling, different models were fitted to describe: i) the probe output signal as a function of volumetric water content; and ii) the volumetric water content as a function of drying time. The tested functions were: linear model, represented by $y = a + bx$; logarithmic model, $y = a + bln(x)$; exponential model, $y = ae^{bx}$; second-order polynomial model, $y = a + bx + cx^2$; and third-order polynomial model, $y = a + bx + cx^2 + dx^3$, where y represents the dependent variable, x the independent variable, and a, b, c, and d are the estimated coefficients.

Adjustments were performed by regression using the complete experimental data. For the logarithmic model applied to the time variable, only positive values of the independent variable were considered, while for the exponential model, only positive values of the dependent variable were used. The quality of the fits was evaluated using the coefficient of determination (R^2), the root mean square error (RMSE), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC), calculated by Equations 3, 4, 5, and 6, respectively:

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2} \quad (3)$$

$$RSME = \sqrt{\frac{1}{n}\sum(y_i - \hat{y}_i)^2} \quad (4)$$

$$AIC = nLn\left(\frac{RSS}{n}\right) + 2k \quad (5)$$

$$BIC = nLn\left(\frac{RSS}{n}\right) + kLn(n) \quad (6)$$

Where: y_i are the observed values, $\hat{y}_i$ are the estimated values, $\bar{y}$ the mean of the observed values, RSS the residual sum of squares, n the number of observations, and k the number of model parameters.

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The selection of the calibration equation was based on the joint analysis of these indicators, prioritizing models with higher coefficients of determination and lower RMSE, AIC, and BIC values. Additionally, the analysis considered the non-linear behavior of the sensor across the moisture range, allowing for the evaluation of global model suitability and the potential need for a segmented interpretation of the sensor response.

To represent possible variations in sensor sensitivity across the volumetric water content range, a complementary analysis was performed using segmented linear regression. This approach consisted of dividing the database into distinct moisture intervals, defined by the distribution of experimental points, and fitting independent linear models to each segment. The fits were evaluated using the coefficient of determination (R^2), allowing for the verification of local model suitability compared to the global fit.

Furthermore, to evaluate sensor performance in different volumetric water content ranges, complementary indicators were calculated from the segmented linear regression models. Sensor sensitivity was determined by the slope of the fitted line in each segment, representing the rate of signal change as a function of volumetric water content, according to Equation (7):

$$S_{ens} = \frac{dS}{d\theta} \tag{7}$$

Where: S_{ens} is the sensor sensitivity (bits per unit of volumetric water content), S is the probe output signal (bits), and θ is the volumetric water content ($cm^3\ cm^{-3}$).

The coefficient of variation (CV) was used to evaluate the relative dispersion of data in each segment, calculated according to Equation (8):

$$CV = \frac{\sigma}{\bar{S}} \tag{8}$$

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Where: σ is the signal standard deviation (bits) and $\bar{S}$ is the mean of the output signal (bits).

The mean percentage error was estimated using the Mean Absolute Percentage Error (MAPE), according to Equation (9):

$$MAPE = \frac{1}{n}\sum \left|\frac{S_i - \hat{S}_i}{S_i}\right| 100 \quad (9)$$

Where: S_i represents the observed signal values, $\hat{S}_i$ the values estimated by the model, and n the number of observations.

The mean absolute error in physical units of volumetric water content was also calculated, obtained from the relationship between the signal error and sensor sensitivity, according to Equation (10):

$$MAE_\theta = \frac{1}{n}\sum \left|\frac{S_i - \hat{S}_i}{\frac{dS}{d\theta}}\right| \quad (10)$$

Where: MAE_θ represents the mean absolute error expressed in volumetric water content ($cm^3\ cm^{-3}$), allowing for a direct interpretation of error magnitude in physical terms; S_i represents the observed signal values, $\hat{S}_i$ the values estimated by the model, n the number of observations, S is the probe output signal (bits), and θ is the volumetric water content ($cm^3\ cm^{-3}$).

These indicators were calculated for each regression segment, allowing for the evaluation of variations in sensitivity, precision, and sensor stability across the analyzed moisture range.

Statistical analyses and mathematical model fittings were performed in the

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Pages: 1-24

Python programming environment (version 3.14.3). Data manipulation and structuring were conducted using the *pandas* library, while numerical operations and regression fittings were carried out with the *NumPy* library. Statistical indicators, including the coefficient of determination (R^2), root mean square error (RMSE), information criteria (AIC and BIC), mean absolute percentage error (MAPE), and coefficient of variation (CV), were implemented through computational routines developed using these libraries. Results were visualized using the matplotlib library. The adoption of this computational environment ensured the reproducibility of the analyses and provided greater control over the fitting and model evaluation procedures.

Aiming at the practical applicability of the system, a survey of component costs was conducted. Values were converted from Brazilian Real (BRL) to US Dollars (USD) based on the exchange rate of April 2026 ($1.00 = R$ 5.60).

3. Results and discussion

The variation in volumetric water content over time evidenced a non-linear behavior, characterized by a progressive reduction of the substrate water content at distinct rates throughout the drying process. To describe the relationship between the sensor response (bits) and the actual volumetric water content, different mathematical models were fitted, as presented in Table 1 and Figure 2.

The third-order polynomial model stood out as the most appropriate, presenting the highest coefficient of determination ($R^2 = 0.9777$) and the lowest AIC (-169.89) and BIC (-165.01) values. These information criteria penalize unnecessary increases in model complexity; therefore, the results indicate that the cubic model provided the best balance between flexibility and predictive capacity. The second-order polynomial model also showed satisfactory performance ($R^2 = 0.9695$), whereas the logarithmic and exponential models were less suitable for describing the drying process.

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Table 1: Parameters and statistical indicators of the models fitted for volumetric water content as a function of drying time.

Model	Fitted equation	R^2	RMSE	AIC	BIC
Linear	$\theta = 0.6137 - 0.0063t$	0.9533	0.0412	-155.45	-153.02
Logarithmic	$\theta = 0.6611 - 0.0918 \ln(t)$	0.6012	0.1165	-99.20	-96.84
Exponential	$\theta = 0.7648\, e^{-0.0266t}$	0.8448	0.0751	-125.44	-123.00
2nd-order Polynomial	$\theta = 0.6451 - 0.0091t + 0.000029t^2$	0.9695	0.0333	-164.13	-160.47
3rd-order Polynomial	$\theta = 0.6286 - 0.0060t - 0.000064t^2 + 0.00000066t^3$	0.9777	0.0285	-169.89	-165.01

Note: θ = volumetric water content ($cm^3\ cm^{-3}$); t = drying time (h). R^2 = coefficient of determination; RMSE = root mean square error; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. Source: Authors (2026)

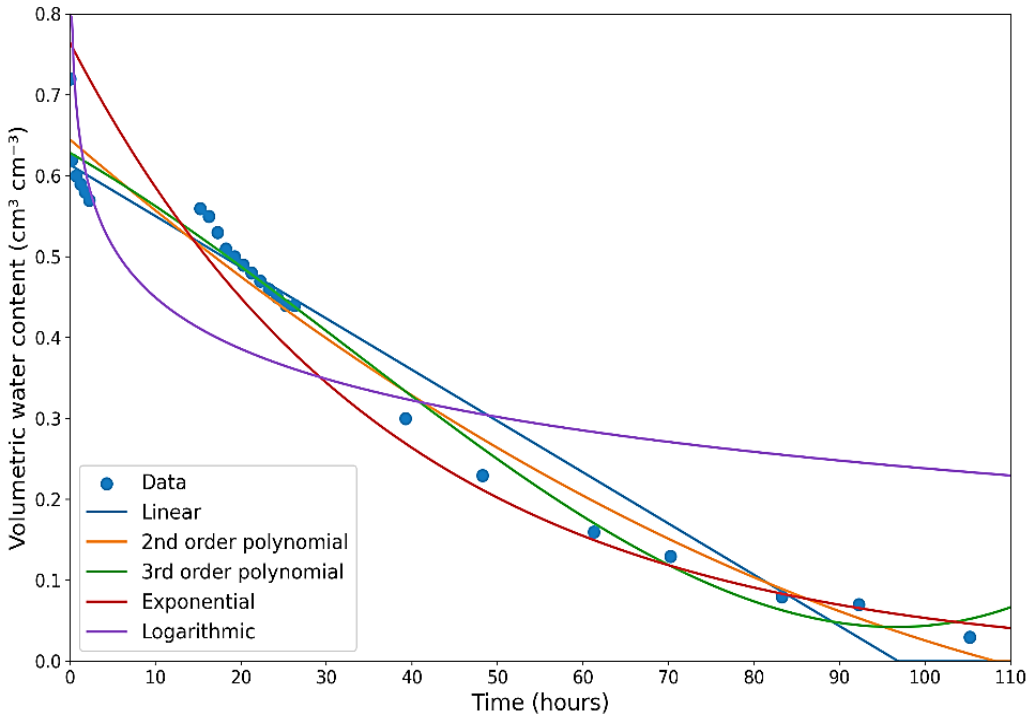


Figure 2: Fitted curves for volumetric water content as a function of drying time. Source: Authors (2026)

This behavior stems from the physical mechanisms intrinsic to the drying process, in which water removal occurs intensely in the initial stage, followed by a gradual reduction in the loss rate associated with the lower availability of free water in the porous medium. In commercial substrates, this dynamic is accentuated by high macroporosity and structural heterogeneity, factors that hinder representation

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by linear models. Recent studies corroborate that modeling drying in agricultural porous media demands non-linear approaches for a faithful representation of water transport processes (NAGAHAGE et al., 2019; DUARTE et al., 2024).

Regarding the relationship between the probe output signal and volumetric water content, the third-order polynomial model again presented the best overall statistical performance (Table 2; Figure 3), with R^2 = 0.9545, RMSE = 62.33, and the lowest AIC (173.30) and BIC (177.28). The second-order polynomial model also showed satisfactory performance (R^2 = 0.9402), whereas the logarithmic and exponential models produced lower goodness-of-fit. These results indicate that the probe response is markedly non-linear and cannot be adequately represented by simplified global functions across the entire moisture range.

Specifically, a reduction in sensor sensitivity was observed in intermediate moisture intervals, where variations in moisture resulted in minor fluctuations in the recorded signal. This performance oscillation suggests that, despite the statistical robustness of the cubic fit, the physical interpretation of the sensor requires a detailed analysis of the different response zones of the device.

Table 2: Parameters and statistical indicators of the models fitted for the output signal as a function of volumetric water content.

Model	Fitted equation	R^2	RMSE	AIC	BIC
Linear	$S = 1020.46 - 1476.25\theta$	0.9318	76.34	177.41	179.40
Logarithmic	$S = 109.35 - 300.84 \ln(\theta)$	0.8219	116.79	184.89	186.78
Exponential	$S = 1216.66\, e^{-3.0712\theta}$	0.8485	113.78	193.37	195.36
2nd-order Polynomial	$S = 968.10 - 775.53\theta - 1218.33\theta^2$	0.9402	71.47	176.77	179.76
3rd-order Polynomial	$S = 1036.18 - 2521.47\theta + 6633.09\theta^2 - 9199.79\theta^3$	0.9545	62.33	173.30	177.28

Note: S = probe output signal (bits); θ = volumetric water content ($cm^3\ cm^{-3}$). R^2 = coefficient of determination; RMSE = root mean square error; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion. Source: Authors (2026)

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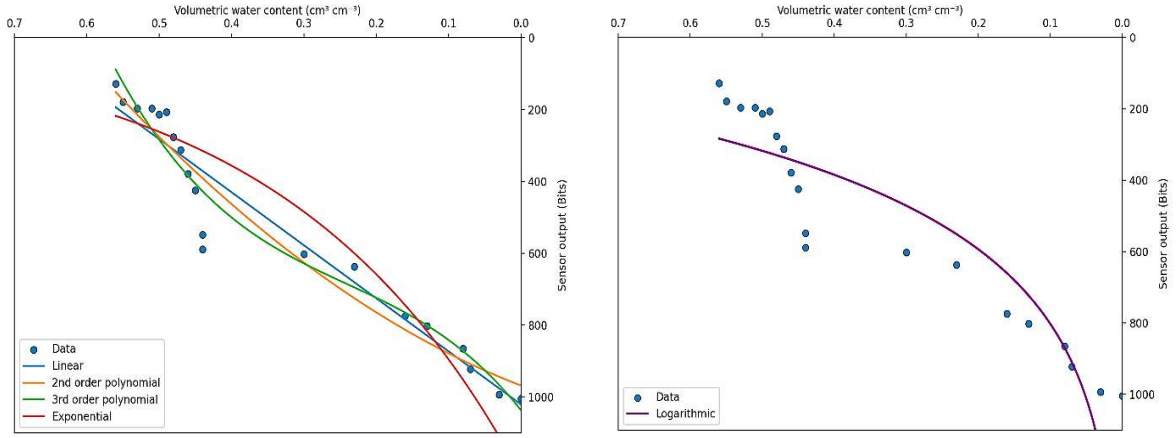


Figure 3: Fitted curves for the probe output signal as a function of substrate volumetric water content. Source: Authors (2026)

The non-linear response observed in the experimental data can be attributed to the complex physical properties of the Bioplant® substrate, especially its high macroporosity and structural heterogeneity. In substrates with these characteristics, water is not uniformly distributed; macropore filling occurs initially, followed by retention in micropores with higher matric energy. This dynamic behavior directly influences the electrical conductivity of the medium, since the formation of effective conductive paths depends on the continuity of the liquid phase between the sensor probes. Additionally, hysteresis effects in water retention and particle reorganization during the drying process may contribute to variations in the signal response, reinforcing the complexity of the biophysical relationship between volumetric water content and electrical output (ADLA et al., 2020; NAGAHAGE et al., 2019; OKASHA et al., 2021).

A detailed analysis of the calibration curves reveals that the resistive sensor exhibits higher sensitivity at the extremes of the evaluated range, notably in conditions near saturation and during the final stage of drying. In contrast, a trend toward signal stabilization is observed in intermediate moisture ranges. This pattern is intrinsic to low-cost sensors, whose response depends on water connectivity within the pores; thus, at intermediate levels, water distribution may not guarantee a conductivity variation proportional to the altered water volume, resulting in regions of low analog sensitivity. Recent studies corroborate this behavior, highlighting that

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Vol: 13.12
DOI: 10.66104/rntaae04
Pages: 1-24

the dielectric and electrical properties of the porous medium are decisive for the accuracy of microcontroller-based devices (ADLA et al., 2024; NAGAHAGE et al., 2019; OKASHA et al., 2021). Additionally, resistive sensors are inherently influenced by the electrical conductivity of the medium, including ionic concentration and salinity, which may limit their applicability under field conditions when compared to capacitive sensors.

Regarding mathematical modeling, the comparison between fits indicates that, although the third-order polynomial model presented the best overall statistical performance, the use of a single equation for the entire moisture range may still be physically limited. The presence of distinct response regimes suggests that segmented calibration is a more robust approach, allowing the use of specific equations for different moisture intervals. This strategy captures local sensitivity variations with greater fidelity and is widely recommended to improve the operational precision of affordable monitoring systems (GONZÁLEZ-TERUEL et al., 2019; OKASHA et al., 2021). Given this evidence, the global fit was complemented by the application of segmented linear regression, aiming to separately describe the response intervals and consolidate a reliable basis for irrigation management (Figure 4).

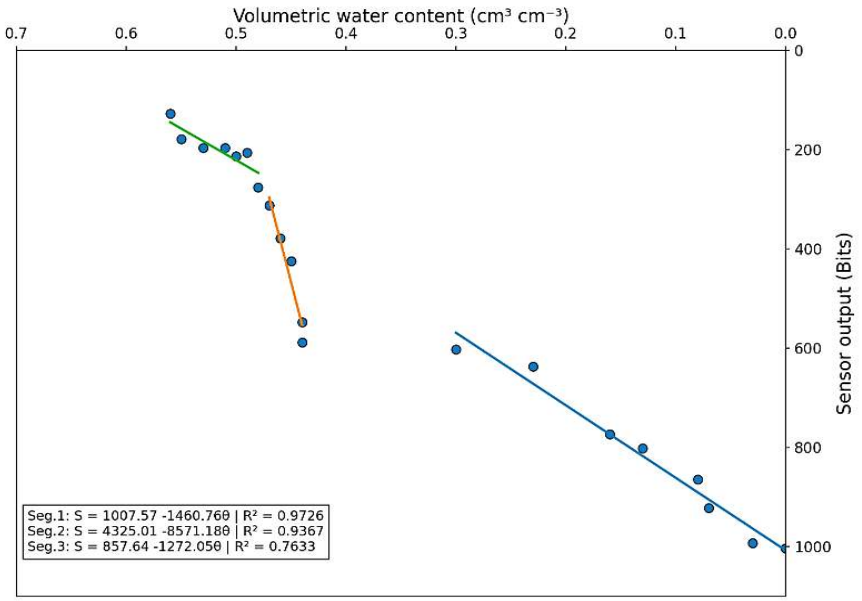


Figure 4: Segmented linear regression of the probe output signal as a function of volumetric water content, indicating the fitted equations for each segment. Source: Authors (2026)

REMUNOM
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Vol: 13.12
DOI: 10.66104/rntaae04
Pages: 1-24

In the lower volumetric water content interval (0.0000 to 0.3000 $cm^3\ cm^{-3}$), a strong linear relationship was observed (R^2 = 0.9726), indicating high sensor sensitivity to changes in water content. In the intermediate range (0.4400 to 0.4700 $cm^3\ cm^{-3}$), the model also showed a high fit (R^2 = 0.9367), but with a markedly steeper slope, characterizing an abrupt transition region in the device response.

In the higher moisture range (0.4800 to 0.5600 $cm^3\ cm^{-3}$), the linear fit presented lower performance (R^2 = 0.7633), indicating reduced predictability of the resistive sensor under wetter conditions. In this range, the progressive increase in water continuity between the probe rods tends to stabilize the electrical resistance of the medium, decreasing the proportionality between additional moisture increments and the output signal.

These results confirm that the response of the resistive probe is not uniform across the evaluated range and is strongly influenced by water distribution within the pore system and by liquid-phase connectivity, which control the electrical conductivity of the substrate. Thus, while global models are suitable for general representation and statistical comparison, segmented regression provides a more realistic description of local sensor behavior.

To quantify this behavior, additional sensor performance indicators were determined for each moisture segment, including sensitivity (dS/dθ), the coefficient of variation (CV), the mean percentage error, and the absolute error expressed in physical units of volumetric water content, as presented in Table 3.

Table 3: Performance indicators of the segmented models for the probe output signal as a function of volumetric water content.

Moisture range ($cm^3\ cm^{-3}$)	Sensitivity (dS/dθ)	Coefficient of variation (%)	Error (%)	Error ($cm^3\ cm^{-3}$)
0.00–0.30	-1460.76	18.28	2.63	0.0136
0.44–0.47	-8571.18	25.61	4.63	0.0024
0.48–0.56	-1272.05	22.15	9.44	0.0145

Note: dS/dθ = sensor sensitivity; CV = coefficient of variation; Error (%) = Mean Absolute Percentage Error (MAPE); Error ($cm^3\ cm^{-3}$) = mean absolute error converted to volumetric water content. Source: Authors (2026)

The results in Table 3 corroborate the previously discussed physical interpretation, showing substantial variation in sensor sensitivity and precision

REMUNOM
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Received: 27/04/2026 - **Accepted:** 13/06/2026
Vol: 13.12
DOI: 10.66104/rntaae04
Pages: 1-24

across the moisture range. In the lower moisture segment, the high sensitivity ($dS/d\theta$ = -1460.76) and low absolute error (0.0136 $cm^3\ cm^{-3}$) indicate good capacity to detect water-content variations, which is associated with lower liquid-phase connectivity and greater influence of water depletion on electrical resistance.

In the intermediate range, the sensor showed the highest nominal sensitivity ($dS/d\theta$ = -8571.18), accompanied by the lowest absolute error (0.0024 $cm^3\ cm^{-3}$), indicating that small changes in volumetric water content produced pronounced signal variations in this transition zone.

In the higher moisture segment, sensitivity decreased markedly ($dS/d\theta$ = -1272.05), while the percentage error increased to 9.44%, indicating greater instability of the fit under wetter conditions. This behavior is consistent with the tendency toward electrical stabilization of the medium as water continuity increases, reducing the sensor's ability to respond proportionally to additional moisture increments.

The magnitude of the observed errors falls within the range reported in international literature for low-cost devices. Resistive and capacitive sensors typically exhibit errors between 0.02 and 0.05 $cm^3\ cm^{-3}$, depending on the properties of the medium and the analyzed moisture range (NAGAHAGE et al., 2019; OKASHA et al., 2021; SCHWAMBACK et al., 2023). Percentage errors between 4.76% and 7.36% have also been recently described, reinforcing the inherent trade-off between cost and precision in these devices (AL-RAWI, 2024).

Table 4 presents a comparison between the errors observed in the present study and those reported in international literature, demonstrating the consistency of the results obtained.

The errors obtained in this study (0.0024 to 0.0145 $cm^3\ cm^{-3}$ across the segmented ranges) are within or below the range commonly reported in the literature and, in some cases, are lower than those observed in mineral soils. This result reinforces that the performance of the evaluated resistive sensor is compatible with the state-of-the-art for low-cost devices. These substrates, predominant in seedling production, have high macroporosity and lower bulk

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Vol: 13.12
DOI: 10.66104/rntaae04
Pages: 1-24

density, characteristics that alter water distribution and the electrical conductivity of the medium (NEMALI et al., 2007; FRAGKOS et al., 2025).

Table 4: Comparison between the errors observed in the present study and those reported in the literature for low-cost moisture sensors.

Study	Evaluated medium	Sensor type	Metric	Error
Present study	Commercial substrate	Resistive (FC-28 Arduino)	Absolute error	0.0024 – 0.0145 ($cm^3\ cm^{-3}$)
Nagahage et al. (2019)	Soil	Low-cost capacitive	RMSE	0.05 – 0.09 ($cm^3\ cm^{-3}$)
Okasha et al. (2021)	Soil	Low-cost capacitive	RMSE	0.014 ($cm^3\ cm^{-3}$)
Schwamback et al. (2023)	Soil	Low-cost sensors	RMSE	0.054 – 0.078 ($cm^3\ cm^{-3}$)
Al-Rawi (2024)	Soil	Resistive / capacitive	Error (%)	4.76 – 7.36%
Fragkos et al. (2025)	Substrate	Commercial sensor	RMSE	0.022 – 0.043 ($cm^3\ cm^{-3}$)

Note: RMSE = root mean square error. The values presented refer to different experimental conditions and should be interpreted as typical performance ranges for low-cost moisture sensors. Source: Authors (2026)

Although the physical heterogeneity of the substrate prevents the direct extrapolation of models developed for soils, the similarity in the order of magnitude of the errors indicates that the system's performance remains consistent across both media. This technical stability, combined with the cost estimate presented in Table 5, solidifies the economic feasibility of the proposed solution. The use of affordable components enables monitoring with higher spatial density in nurseries, making the developed system a technically robust and economically attractive alternative compared to high-cost commercial sensors.

The feasibility of low-cost sensors in agronomic applications has been consistently demonstrated, especially regarding their capacity to provide reliable measurements when subjected to rigorous evaluation protocols. Recent studies indicate that devices built with affordable components can present performance compatible with commercial instruments, consolidating their application in environmental monitoring and water management systems (SÁNCHEZ-BENÍTEZ et al., 2022).

REMUNOM
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Vol: 13.12
DOI: 10.66104/rntaae04
Pages: 1-24

Table 5: Components used in the system and estimated acquisition cost in Brazilian Reais (R$) and US Dollars (US$). Source: Authors (2026)

Component	Specification	Quantity	Unit Cost (R$)	Total Cost (R$)/(US$)
Moisture sensor + converter module	FC-28 + LM393	1	26.26	26.26/2.09
Microcontroller	Arduino Pro Mini (ATmega328P)	1	30.00	30.00/3.39
USB–TTL Converter	CH340G	1	19.00	19.00/4.69
Cable	2-way shielded cable	0.5	23.40	11.70/5.36
Connections	Jumpers	6	-	1.50/0.27
Total				88.46/15.80

The results of the present study reinforce this perspective, showing that the evaluated resistive system provides adequate accuracy for estimating volumetric water content with a significantly reduced implementation cost (R$ 88.46). Beyond financial savings, the definition of precise mathematical models and the identification of sensitivity ranges allow for the establishment of rigorous operational limits, favoring the maintenance of the ideal water status during seedling production in substrates.

In summary, careful calibration transforms low-cost sensors into robust tools for efficient irrigation management. Integration with microcontrollers not only enhances technical feasibility but also allows for greater spatial monitoring density, a fundamental aspect for the democratization of precision agriculture in smaller-scale production systems.

Despite the promising results, some limitations should be acknowledged. The analysis was conducted using a single sensor unit, which does not account for potential variability among devices of the same model. In addition, the calibration was performed for a specific commercial substrate, and its direct application to other substrates or mineral soils should be carried out with caution, requiring prior validation.

4. Conclusions

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Vol: 13.12
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Pages: 1-24

Polynomial models presented the best overall performance in estimating volumetric water content, particularly the third-order model (R^2 = 0.9777; RMSE = 0.0285), demonstrating a superior ability to represent the non-linear behavior of the drying process. For the relationship between the signal and moisture, polynomial fits were also superior (R^2 > 0.95), while the logarithmic model showed inferior performance.

Segmented regression revealed different sensor response regimes across the moisture range, with high sensitivity at low moisture levels (R^2 = 0.9726), a sharp transition in the intermediate range (R^2 = 0.9367), and lower fit under wetter conditions (R^2 = 0.7633), associated with increasing continuity of the liquid phase in the substrate.

Performance indicators confirmed this trend, with absolute errors of 0.0136, 0.0024, and 0.0145 $cm^3\ cm^{-3}$ for the lower, intermediate, and wetter segments, respectively. These values remain consistent with those reported in the international literature for low-cost moisture sensors, reinforcing the reliability of the obtained results.

The system demonstrated satisfactory performance combined with a low implementation cost (R$ 88.46 ≈ US$ 15.80), proving its technical feasibility for moisture monitoring in substrates. The combination of global and segmented models proved to be the most appropriate approach to represent sensor behavior and increase the reliability of the estimates.

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