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Development and Automation of a Photovoltaic-Powered Soil Moisture Sensor for Water Management

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Abstract: The objective of this study was to develop and calibrate a photovoltaic-powered soil moisture sensor (SMS) for irrigation management. Soil moisture readings obtained from the sensor were compared with gravimetric measurements. An automated SMS was used in two trials: (i) okra crop (*Abelmoschus esculentus*) and (ii) chili pepper (*Capsicum frutescens*). All sensors were calibrated and automated using an Arduino Mega board with C++. The soil moisture data were subjected to descriptive statistical analysis. The data recorded by the equipment was correlated with the gravimetric method. The determination coefficient (R^2), Pearson correlation (r), and root mean square error (RMSE) were adopted as criteria for equipment validation. The results show that our SMS achieved an R^2 value of 0.70 and an r value of 0.84. Notably, there was a striking similarity observed between SMS and gravimetric data, with RMSE values of 3.95 and 4.01, respectively. The global model developed exhibited highly efficient outcomes with R^2 (0.98) and r (0.99) values. The applicability of the developed SMS facilitates irrigation management with accuracy and real-time monitoring using digital data. The automation of the SMS emerges as a real-time and precise alternative for performing irrigation at the right moment and in the correct amount, thus avoiding water losses.

Keywords: tensiometer; soil moisture; solar energy; automation

1. Introduction

Water resource management and increasing freshwater productivity are among the most effective options for conserving water resources, especially in irrigated agriculture [1–5]. In terms of water use, irrigated agriculture is the largest consumer of freshwater [6,7]. Given these aspects and issues, improving water use efficiency and irrigation water savings will enhance the effects and factors related to irrigation management. Technologies in the research field are essential in contributing to water management and soil conservation [8,9].

The expansion and diffusion of new technologies, along with the growth of the technology market, have led to dependence on and increased demand for technologies in the agricultural sector. They are essential in managing inputs used in the agricultural and livestock markets, such as controlling the amount and timing of water to be applied to the soil [10–12]. The increasing demand for water use in irrigated crops over the last three decades has constantly raised awareness about the rational use of water resources [13–16].

Therefore, effective irrigation management is crucial and aims to apply the exact amount of water that the plant needs at the right time [17,18]. However, it is important to know and monitor variables such as soil moisture. The methods used to determine soil moisture can be classified as direct and indirect [19–23]. Direct methods are those that quantify soil moisture by weighing (e.g., gravimetric), and indirect methods, through reflectance, neutron moderation, and soil stress (e.g., frequency domain reflectometry—FDR, time domain reflectometry—TDR, and tensiometers) [24,25]. Furthermore, methods that measure the tension generated by water retained in soil particles have evolved and adapted to technological advancements [26–29].

Among the methods that offer ease of application and indirect measurement, the tensiometric method stands out [30–32]. In irrigation management, a moisture sensor can be used, which is designated as the primary device for measuring the matric potential of water in the soil, which can be converted into current soil water content [33–35].

The development of tensiometers has emerged, intending to expand their operating range and, most importantly, meet the technological advancements in irrigation management [31,36,37]. The creation of digital reading systems that allow precise, effective, and rapid measurement of the matric potential of water in the soil has become essential [28,31]. Currently, developed sensors are installed directly in the soil and, with the aid of reading equipment, enable the collection of soil moisture data, analyzing the interrelationships between soil and water, thus allowing greater control, precision, and savings during cultivation.

With the advancement of digital agriculture 4.0, there has also been a greater diffusion of automation, especially in irrigated systems, due to the search for technological alternatives that help achieve greater control and productivity, generate higher profitability and sustainability, and reduce labor costs [38,39]. The integration of embedded sensors for data collection automation has become an accessible and viable alternative for advancing agriculture, which, along with other technologies, assists in real-time data collection, processing, analysis, and transfer of crop status, resulting in quick and cautious decision-making [10,40,41]. In addition, the use of the Internet of Things (IoT), data analytics, sensor nodes, and solar energy contribute to technological development and are growing in the rural environment. These elements lead to savings and income, reduce energy consumption from conventional sources, and significantly contribute to the sustainability of productive rural activities.

Considering the above, the applicability of digital agriculture 4.0 in crop management further contributes to meeting the water needs of crops, optimizing water use, and advancing technological advancements in irrigated systems, assisting in quick and precise irrigation management decision-making.

Therefore, the objective was to develop a soil water tension sensor for moisture determination, powered by solar energy, with automation using Arduino programming techniques calibrated by determining soil moisture through the oven drying method for different crops.

2. Materials and Methods

2.1. Study Dynamics and Characterization

An automated soil water tension sensor (using a pressure sensor) was developed to estimate soil moisture. Temperature and air humidity sensors were also integrated into the system, which was powered by a photovoltaic module. The negative pressure is related to the operating principle of the pressure sensor. The sensor assumes that the soil has a pressure of −100 kPa, and when the sensor is inserted into the soil, it calculates the pressure differential, allowing for the collection of data on water retention in the soil, like the operating principle of manual tensiometers. The design of the moisture sensor was like the one developed by Livingston [42], with precision technologies [43,44].

The soil moisture readings estimated by the sensor were compared with measurements obtained through the gravimetric method [45]. For calibration purposes, the sensor was used in two experiments in a protected environment. The first experiment involved okra [*Abelmoschus esculentus* (L.) Moench] subjected to 5 irrigation levels (50%, 75%, 100%, 125%, and 150%) determined based on crop evapotranspiration (ET_c), with a surface drip irrigation system employed. The second experiment involved chili pepper [*Capsicum frutescens* (L.)] subjected to 4 irrigation levels: 50%, 75%, 100%, and 125% of ET_c, with two drip irrigation systems: surface and subsurface. Both experiments were conducted in 15-L pots filled with clayey Red Latosol soil, which was sieved and homogenized. A localized drip irrigation system with 90% water application efficiency and a pressure of 8 m water column with a flow rate of 1.40 L h^{-1} was used for irrigation. It is worth mentioning that the moisture and temperature sensors were calibrated using meteorological data obtained from the thermohygrometer in the greenhouse of the State University of Goiás—UEG, Santa Helena University Unit.

2.2. Assembly of the Automated Moisture Sensor

The moisture sensor has a structure similar to a conventional tensiometer [42]. It consists of a polyvinyl chloride (PVC) pipe with dimensions of 60 cm × 5 cm, as shown in Figure 1. The components include:

- A set of photovoltaic modules (12 V each);
- A temperature and humidity sensor (DHT11);
- A pressure sensor (BMP280);
- A LCD display with 16 × 2 blue backlight (2-lines × 16-characters);
- An Arduino Mega board;
- Rechargeable battery with a voltage of 9 V and 250 mAh.

A set of 12 V (3 Watts) solar panels was necessary to power all the components and charge the battery in the system. All the data generated by the sensors were displayed on the LCD screen (Figure 1), located on the surface of the moisture sensor and directly connected to a breadboard. The LCD has 16 columns by 2 rows, a blue backlight, and white writing.

The temperature sensor element is an NTC transmitter, and the humidity sensor is of the DHT11 type. The internal circuit reads the sensors and communicates with an 8-bit microcontroller through a one-way serial signal, both connected to a controller. The protocol used to transfer data between the microcontroller and DHT11 involves a single-wire bus (ELETROGATE, 201-A). The ambient temperature and humidity sensor (Figure 1) was positioned near the LCD screen, requiring direct contact with the environment, and should not be enclosed.

According to Table 1, the equipment used for assembling and programming the moisture sensor, the number of necessary units, the unit price, and the total price to produce the equipment are presented.

The connections with the Arduino board were made through the Serial Data Line and SCL (Serial Clock Line) pins, allowing various ports on the Arduino board to easily connect to the other sensors used (Figure 2). The connection was made using the I2C module, linking the I2C screen to the Arduino Mega board.

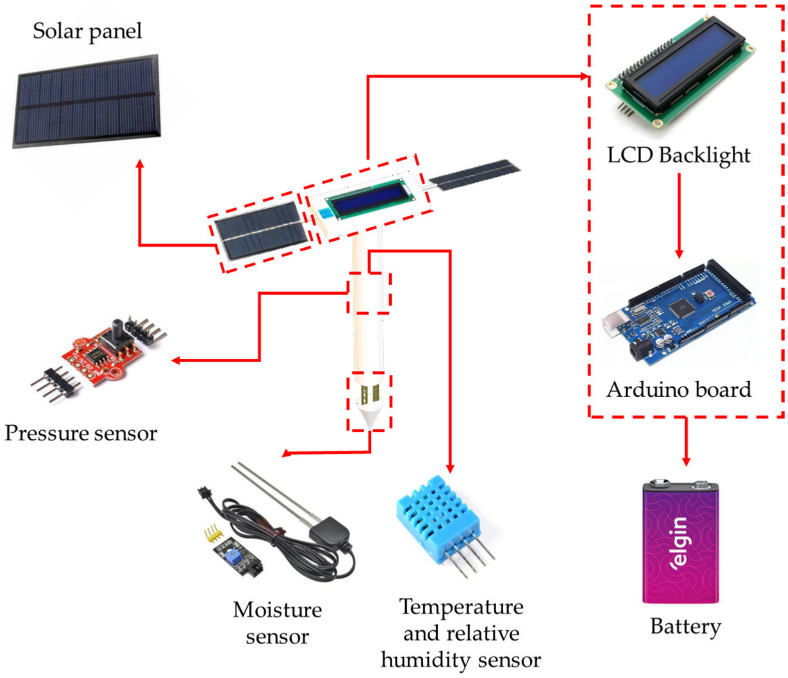

Figure 1. A graphical representation of the solar-powered soil moisture sensor and its main components.

Table 1. Parts used to assemble the humidity sensor, followed by price and technical specifications.

Quantity	Description	Unit Amount (USD)	Total Amount (USD)	Specifications
1	Arduino maker kit	70.64	70.64	Includes 136 pieces.
1	Pressure and Temperature Sensor (BMP280)	3.10	3.10	Operating voltage: 3 V; Current consumption: 2.7 µA; Interfaces: I2C and SPI; Pressure measurement range: 300–1100 hPa (equivalent +9000 to −500 m above/below sea level); Accuracy: ±0.12 hPa (±1 m equivalent); Temperature range: −40 to 85 °C; Temperature accuracy: ±1.0 °C.
1	Corrosion Resistant Soil Moisture Sensor, Arduino, Model S12	9.35	9.35	Operating voltage: 3.3 to 12 V DC input; Current: less than 20 mA; less than 30 mA (output); Output: Digital and analogue; Probe dimensions: 60 × 19 × 9 mm; Module dimensions: 36 × 15 × 7 mm; Probe cable length: 1 m.
1	Room temperature and humidity sensor (DHT11)	2.68	2.68	Power 3.0 to 5.0 VDC (5.5 VDC maximum); Humidity measurement range: 20 to 95% RH; Temperature measurement range: 0° to 50 °C; Humidity measurement accuracy: ±5.0% RH; Temperature measurement accuracy: ±2.0 °C.
1	Hikari Power-30 Soldering Iron	6.84	6.84	-
1	Transparent Organizer Box	5.17	5.17	-
1	Telijia 31-Piece Precision Wrench Kit (TE-6036)	4.14	4.14	-
4	Solar Panel System (12 V-3 W)	15.57	62.26	12 V-3 W-250 mA Photovoltaic Solar Energy Board Panel Cell, with 20 cm soldered wire, dimensions 145 × 145 mm
1	Elgin 12 V Rechargeable Battery	37.41	37.41	Blister with 1 rechargeable battery 12 V 250 mAh.
3	Tin Solder Wire Cobix Tube (1 mm, 22 g)	3.26	9.79	-
1	I2C Serial Module for 16 × 2 Blue Backlight LCD Display for Arduino	8.21	8.21	The I2C module operates with a minimum supply voltage of 5 V.

Table 1. *Cont.*

Quantity	Description	Unit Amount (USD)	Total Amount (USD)	Specifications
1	Ethernet Shield W5100	24.94	24.94	Supply Voltage: 3 to 5 VDC; Communication: SPI; Operating temperature: −40 to 85 °C; Indicators: TX, RX, COL, FEX, SPD, LNK; Current: 100 mA; Support: Full-duplex and half-duplex, Auto MDI/MDIX, ADSL connection; Works directly with the official Arduino library; TX/RX RAM Buffer: 16 kBytes; Dimensions: 55.8 × 68.58 × 1.6 mm; Datasheet: W5100 Ethernet Shield Module.
1	Fiberglass Structure	124.69	124.69	-
1	Lenovo Ideapad 330 laptop	519.55	519.55	-
Total amount		835.55	888.77	

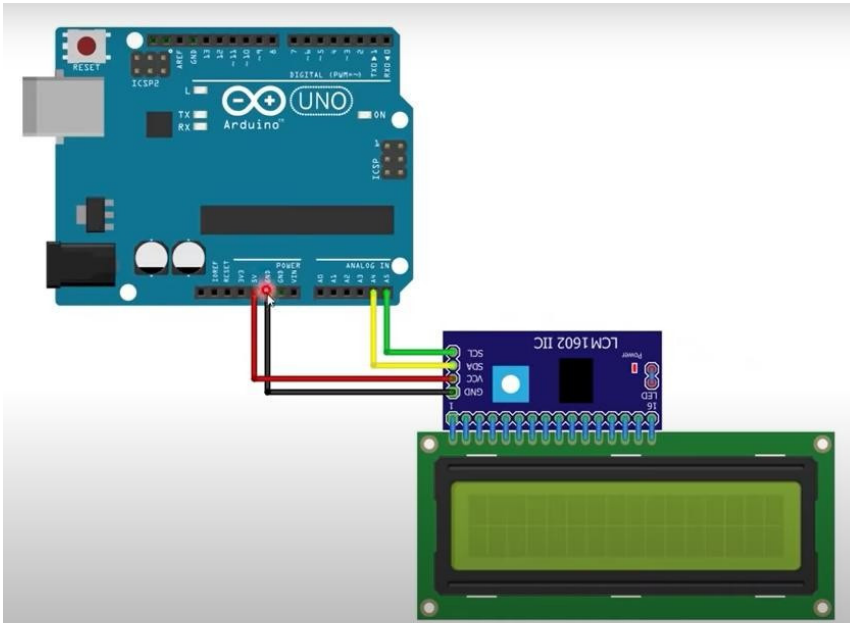

Figure 2. Connection of the LCD screen to the Arduino Mega board.

2.2.1. Arduino Board

All the sensors were calibrated and controlled using an Arduino Mega board (Figure 3), and the programming language used was C++. The software used was the Arduino IDE. The modules directly connected to the board are the soil moisture sensor, air humidity sensor, air temperature sensor, and pressure sensor.

After the testing phases, the Arduino Mega board was permanently connected to the soil moisture sensor structure, containing the programming for all the sensors and the memory for intelligent joint operation (Figure 4). All the information was displayed on the LCD screen (Figure 1).

2.2.2. Soil Moisture Sensor

The soil moisture sensor was calibrated using a potentiometer for dry and wet soil conditions. The data readings were performed in Siemens, the standard unit of electrical conductivity in the International System of Units (SI). The threshold between dry and wet soil conditions was compared and adjusted using the potentiometer present in the sensor, regulating the digital output D0.

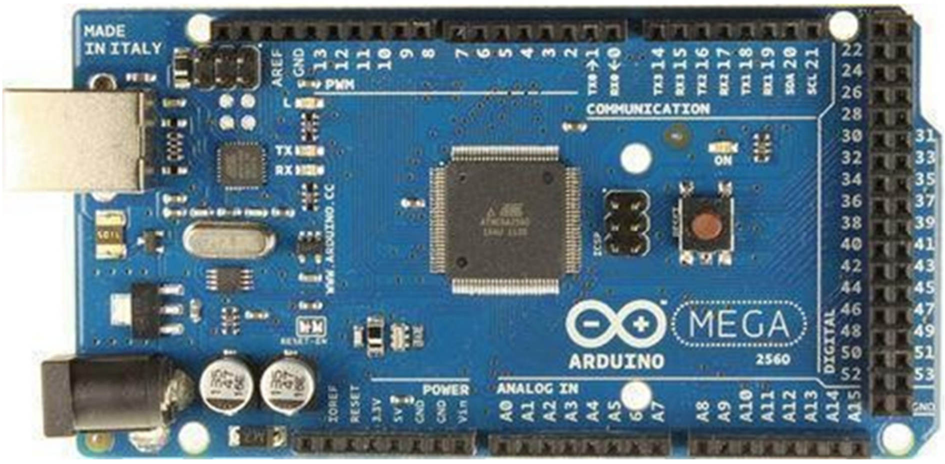

Figure 3. Arduino Mega 2560 board.

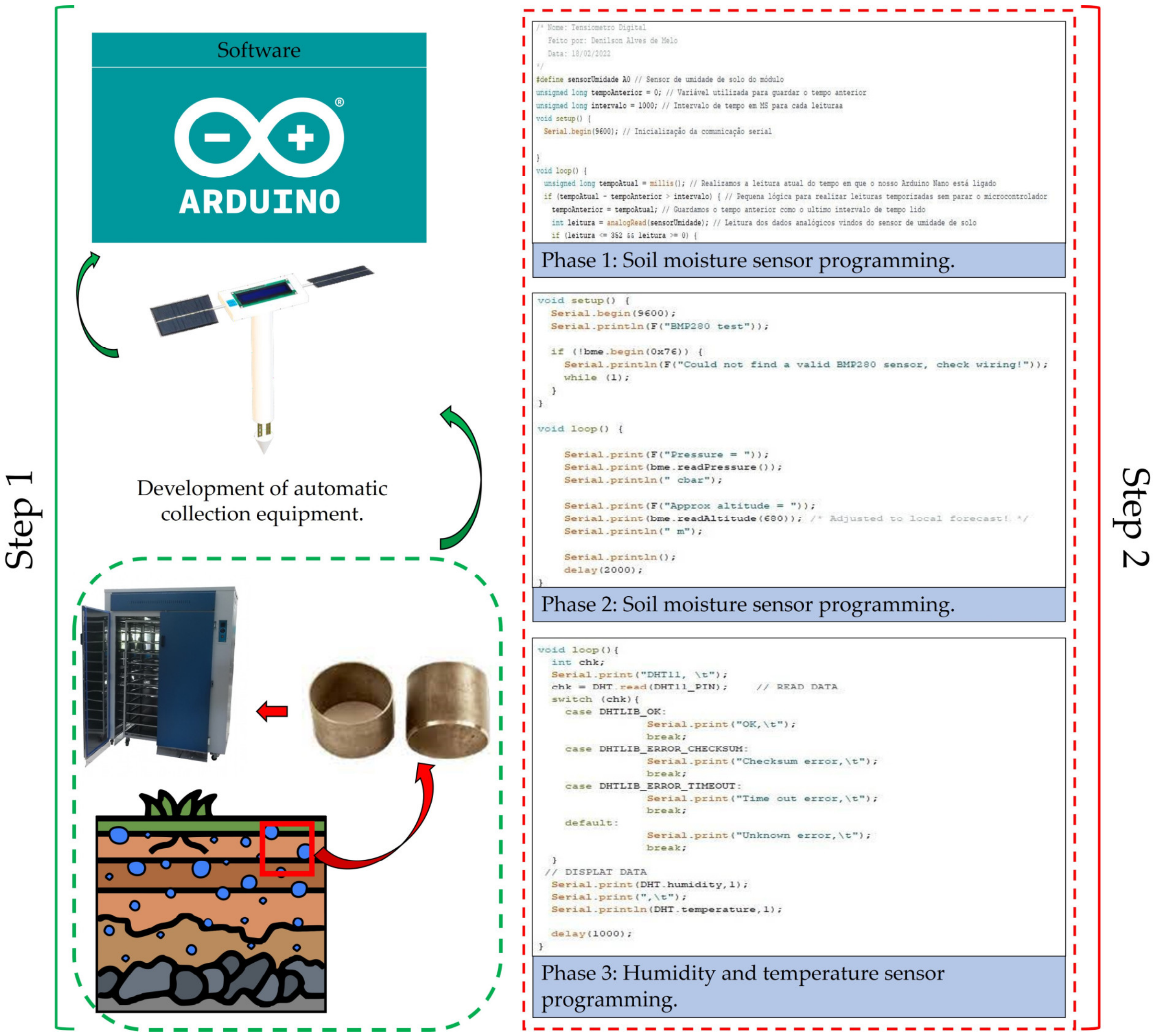

Figure 4. Soil collection flowchart, construction, and programming of the soil moisture sensor.

The soil moisture sensor was connected to a digital port of the Arduino board, providing information between high and low states, i.e., dry and wet soil, respectively. The verification limits could be adjusted through a potentiometer located on the sensor body (ELETROGATE, 201-C). The moisture sensor was positioned at the bottom in direct contact with the soil, and through electrical conductivity and the connection with the voltage sensors, it was possible to quantify the water content in the soil and assist in irrigation management.

The accuracy of the soil moisture sensor was assessed based on the gravimetric method, with readings and calibration performed using the standard oven-drying method through linear regressions.

2.2.3. BMP280 Pressure Sensor

The pressure sensor was programmed to perform negative readings to verify the pressure difference generated by water loss in the soil. The BMP280 sensor is factory-configured to read pressure data in hectopascals (hPa), so the conversion of the data is necessary since the conventional tensiometer reads in kilopascals (kPa). The sensor has a reading range of 0 to −1100 hPa.

The pressure sensor was positioned on the surface of the moisture sensor to measure air pressure data, with its lower probe in contact with the soil to measure the pressure generated by water retention in the soil and obtain a pressure result based on the difference between the two. The pressure sensor reads the pressure difference between the environment and the force of water retention in the soil. The soil moisture sensor was calibrated through analyses conducted with soil samples in the laboratory using the standard oven-drying method [46].

After converting the units of measurement, it was necessary to configure the measurement range of the pressure sensor. The Arduino Mega board was used to program the pressure sensor to work in conjunction with the moisture sensor. Both sensors were configured using a numerical scale, where a pressure of 0 kPa indicates saturated soil and a scale reaching −100 kPa means the soil is very dry. All this information was outputted by the programmed system and displayed on the LCD screen (Figure 1).

The pressure sensor was programmed to work together with the moisture sensor so that the readings would provide soil moisture information under different moisture conditions. The pressure sensor was integrated inside the PVC tube to read pressure differences between the soil and air. The soil moisture and air temperature sensors are precise sensors with low power consumption. The sensor came pre-programmed and pre-configured from the factory. Additionally, the sensor was directly connected to the Arduino Mega board to be powered by the same source as all the other sensors.

2.2.4. Photovoltaic Modules

The photovoltaic modules were connected using standard power supply cables, with connections made to the GND (power ground) and VCC (positive power supply) terminals. The cables were connected to the battery and integrated into the moisture sensor structure, allowing excess energy generated by the solar panel to be stored for future use during periods of low solar radiation. This reduced the need for battery replacement.

2.2.5. DHT11 Ambient Relative Humidity and Temperature Sensor

The DHT11 (Figure 1) consists of two sensors: a temperature sensor (NTC thermistor) and a humidity sensor (HR202). The internal circuitry reads the sensors and communicates with a microcontroller via a one-way serial signal. Its temperature readings range from 0 to 50 °C, and its humidity readings range from 20 to 90%. The DHT11 sensor for relative humidity and air temperature has a simple 3-pin connection, facilitating programming and connectivity with other sensors. It has two power supply pins and one pin for data decoding between the sensor and the Arduino board.

2.3. Statistical Modeling and Validation of Moisture Sensor

2.3.1. Descriptive Statistics

The soil moisture data from the moisture sensor and the gravimetric method were subjected to descriptive statistical analysis to obtain the mean, median, minimum, maximum, standard deviation (SD), and coefficient of variation (CV, %). The percentage value of CV was categorized as low (CV < 12%), medium (if CV = 12–24%), and high (when CV > 24%) [47]. The normality test using the Kolmogorov–Smirnov test was applied to the studied variables, with a significance level (alpha) of 0.01. Descriptive statistics were performed using R software version 4.0.3 [48].

2.3.2. Regression Analysis

To validate the developed moisture sensor, the recorded data from the device were correlated with the gravimetric method to estimate soil moisture. The coefficient of determination (R^2), Pearson correlation (r), and root mean square error (RMSE) were adopted as criteria for equipment validation. Finally, an analysis of variance (ANOVA) of the established models for pepper and okra crops was conducted, with a significant F-value at a 1% probability and a p-value less than 0.01 ($p < 0.01$) for the validation of the established model and moisture sensor. The statistical modeling was performed using R software version 4.0.3 [48].

3. Results and Discussion

Based on greenhouse measurements, linear regressions were established to validate the solar-powered moisture sensor against the gravimetric method for estimating soil moisture in the pepper crop (Figure 5). Figure 5a shows the regression for Moisture Sensor vs. Gravimetric validation, and Figure 5b shows the regression for Gravimetric vs. Moisture Sensor validation. Based on the validation components, the coefficient of determination (R^2) and the Pearson correlation coefficient (r) did not change regardless of the order of the X and Y factors. They are interpreted as the proportion of variation in Y that is explained by the variable X and vice versa, being inversely proportional and unchangeable components, as indicated by studies [9,49].

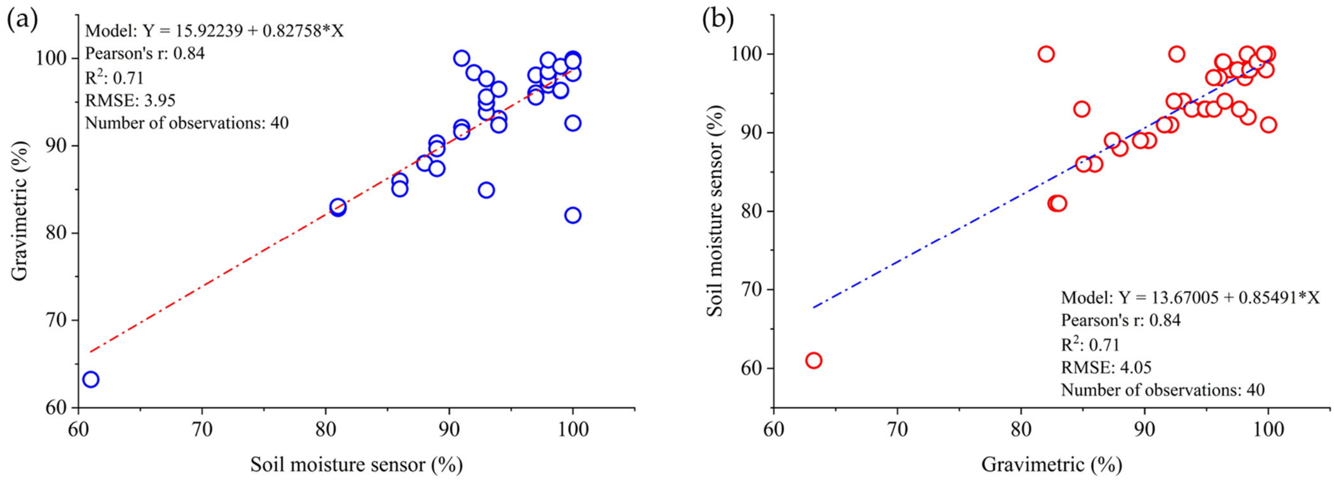

Figure 5. Regression models for Soil Moisture Sensor vs. Gravimetric validation and (**a**) Gravimetric vs. Soil Moisture Sensor validation (**b**) in the pepper crop, accompanied by their respective coefficients of determination (R^2), Pearson correlation coefficient (r), and root mean square error (RMSE).

Regarding R^2, it showed a satisfactory fit, with a value around 0.70, indicating that the accuracy of the solar-powered moisture sensor represents approximately 70.75% of the gravimetric method. On the other hand, r showed a fit of 0.84, reinforcing the accuracy of the developed moisture sensor and the reliability of its applicability in the field and the consumer market. Supporting the results of the present study, Thalheimer [50], who developed a low-cost solar-powered system for measuring soil water potential, obtained an R^2 of 1, recommending the applicability of the equipment in the field.

Furthermore, the values for the root mean square error (RMSE) were low and similar for Moisture Sensor vs. Gravimetric (Figure 5a) and Gravimetric vs. Moisture Sensor

(Figure 5b), with values around 3.95 and 4.01, respectively. Consistent with the results of this study, Sanches et al. [51], who developed and calibrated a low-cost, high-efficiency automated moisture sensor for irrigation control based on real-time monitoring, observed maximum errors of around 2.84 for the performed analyses. RMSE values are crucial for assessing the accuracy of a model, regardless of its r and R^2, as errors have a significant influence on the spatial variability of data precision.

Table 2 presents the analysis of variance (ANOVA) for the validation of the solar-powered moisture sensor against the gravimetric method in pepper crops under irrigation depths of 50, 75, 100, and 125% of crop evapotranspiration (ET_c). The generated model's F-value was found to be significant at a 1% probability level, indicating the precision and effectiveness of the developed moisture sensor and thus recommending its applicability in pepper cultivation. As for the p-value, it showed a satisfactory fit ($p < 0.01$). Silva et al. [8] emphasize the importance of exploring the components of a regression model's ANOVA (F-value and *p*-value) for validation purposes.

Table 2. Analysis of variance (ANOVA) for regression models validating the soil moisture sensor in pepper cultivation.

	[1] DF	[2] SS	[3] MS	F Value	*p*-Value
Model	1	1435.53	1435.53	91.92	<0.0001
Error	38	593.46	15.62		
Total	39	2028.99			

[1] DF—Degree of freedom; [2] SS—Sum of squares; [3] MS—Mean square.

To assess the spatial distribution of soil moisture data in the treatments of 50, 75, 100, and 125% of ET_c for the solar-powered moisture sensor and the gravimetric method, descriptive statistics were performed on the collected data, obtaining the mean, median, minimum, maximum, standard deviation (SD), and coefficient of variation (CV) (Table 3). It can be observed that the mean and median values for all treatments in both soil moisture estimation methods were close, indicating data normality, as also evidenced by the Kolmogorov–Smirnov test at a 1% probability level for the entire dataset. Supporting the results of this study, Silva et al. [49], through conventional statistical tests and geostatistical modeling, stated in their study that close mean and median values are indicative of data normality, as supported by the Kolmogorov–Smirnov test at a 1% probability level.

According to the criterion of Warrick and Nielsen [47], the CV was consistently low (<12%) for all treatments, except for the 100% ET_c treatment in the solar-powered moisture sensor. Based on the observed results, it is possible to affirm the distribution efficiency and uniformity of the subsurface drip system in pepper cultivation, which provides low spatial variability of moisture, as confirmed by the SD, which was low for all treatments. Furthermore, the values were close to the CV, substantiating the efficiency of the adopted irrigation system [52]. Supporting the results of this study, Colak [53], who evaluated leaf water potential in drip-irrigated bell pepper under various deficit irrigation strategies using surface and subsurface irrigation, highlights that the subsurface irrigation system exhibits a low CV, indicating its efficiency in water distribution and uniformity.

Figure 6a shows the regression for validating the soil moisture sensor vs. gravimetric method, and Figure 6b presents the regression for validating the gravimetric vs. soil moisture sensor method. Based on the pepper crop analyses, the observed results of R^2 and r for the okra crop were higher, with values around 0.98 and 0.99, respectively. These results indicate a greater sensitivity of the gravimetric method and the solar-powered moisture sensor in quantifying soil moisture. However, local abiotic conditions (e.g., temperature, relative humidity, wind speed, and incident solar radiation), physical and biological soil conditions, and the greater water demand sensitivity of the okra crop may have influenced the results. Supporting the observed results in this study, Aliku et al. [54], who estimated okra crop evapotranspiration using drainage lysimeters under dry season conditions, state that okra is one of the vegetables with the highest water demand.

Table 3. Descriptive statistics of the solar-powered soil moisture sensor and gravimetric method for treatments with 50, 75, 100, and 125% of crop evapotranspiration (ET_c) in pepper cultivation.

Variable	Mean	Median	Minimum	Maximum	[1] SD	[2] CV
			50%			
Soil moisture sensor	91.00	91.50	81.00	100.00	6.06	6.65
Gravimetric	91.19	90.05	82.82	99.93	6.68	7.33
			75%			
Soil moisture sensor	93.70	95.50	81.00	99.00	5.79	6.18
Gravimetric	94.22	96.17	83.04	100.02	4.94	5.24
			100%			
Soil moisture sensor	91.50	95.00	61.00	100.00	11.37	12.43
Gravimetric	91.67	95.25	63.24	98.29	10.66	11.63
			125%			
Soil moisture sensor	96.90	98.00	93.00	100.00	3.04	3.13
Gravimetric	95.38	97.07	82.04	99.82	5.40	5.67

[1] SD—Standard deviation; [2] CV—Coefficient of variation.

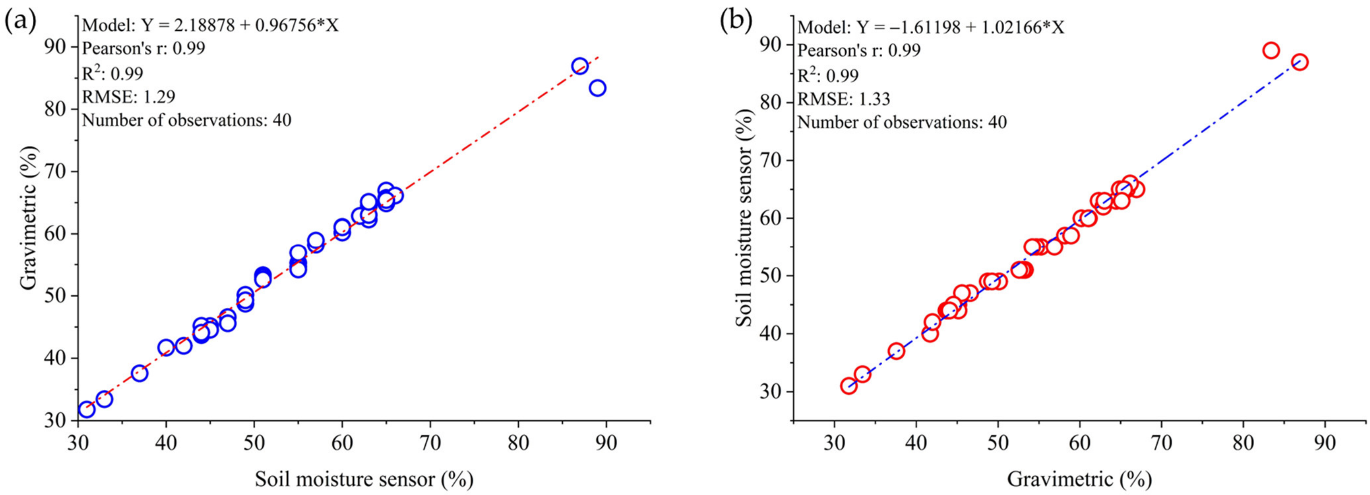

Figure 6. Regression models for validating the soil moisture sensor vs. gravimetric method and (**a**) gravimetric vs. soil moisture sensor method (**b**) in the okra crop are preceded by their respective coefficients of determination (R^2), Pearson correlation coefficient (r), and root mean square error (RMSE).

The RMSE values were lower compared to the measurements in the pepper crop. This reinforces the higher efficiency of the moisture sensor in recording soil moisture in the okra crop, making it recommended for irrigation management and accurate compared to the gravimetric method. Additionally, we emphasize that the developed moisture sensor's recording efficiency for both crop management (pepper and okra) is efficient and accurate for soil moisture between 30 and 100%.

Table 4 presents the ANOVA for validating the moisture sensor against the gravimetric method in the okra crop under irrigation depths of 50, 75, 100, 125, and 150% of ET_c. The F-value of the generated models was significant at a 1% probability level, with a value around 3269.20, indicating the precision and effectiveness of the developed moisture sensor and recommending its applicability to the okra crop. As for the *p*-value, it showed a satisfactory fit ($p < 0.01$).

Table 4. Analysis of variance (ANOVA) of regression models for validating the soil moisture sensor to okra crop.

	[1] DF	[2] SS	[3] MS	F Value	*p*-Value
Model	1	5445.47	5445.47	3269.20	<0.0001
Error	38	63.30	1.67		
Total	39	5508.76			

[1] DF—Degrees of freedom; [2] SS—Sum of squares; [3] MS—Mean square.

From the descriptive statistics (Table 5), it can be observed that the mean and median values are close, which, as discussed earlier, is indicative of data normality, as evidenced by the Kolmogorov–Smirnov test at a 1% probability level for the entire dataset. According to the criterion of Warrick and Nielsen [47], the CV ranged from moderate (CV = 12–24%) to high (CV > 24%), reinforcing the high water sensitivity of the okra crop and resulting in greater soil moisture variability.

Table 5. Descriptive statistics of the solar-powered soil moisture sensor and the gravimetric method for treatments with 50, 75, 100, 125, and 150% of crop evapotranspiration (ET_c) for the okra crop.

Variable	Mean	Median	Minimum	Maximum	[1] SD	[2] CV
			50%			
Soil moisture sensor	64.50	63.00	49.00	89.00	15.92	24.68
Gravimetric	64.52	63.37	48.74	86.92	14.40	22.31
			75%			
Soil moisture sensor	55.00	56.00	45.00	65.00	7.35	13.36
Gravimetric	55.41	56.73	45.15	65.76	7.69	13.88
			100%			
Soil moisture sensor	55.50	55.00	40.00	66.00	8.14	14.67
Gravimetric	56.31	55.79	41.69	66.15	7.65	13.58
			125%			
Soil moisture sensor	49.25	49.00	31.00	65.00	13.01	26.42
Gravimetric	49.77	49.10	31.78	65.41	13.01	26.15
			150%			
Soil moisture sensor	47.38	44.00	37.00	63.00	9.10	19.21
Gravimetric	47.75	43.99	37.58	65.13	9.79	20.50

[1] SD—Standard deviation; [2] CV—Coefficient of variation.

Regarding the minimum and maximum values, it can be observed that the okra crop requires a greater amount of water compared to the pepper crop. In the okra crop, the lowest observed soil moisture value was 31%, while the maximum was 89% (Table 5). In the pepper crop, these moisture values were higher, in the range of 61% to 100%, for the lowest and highest values, respectively. Therefore, it is evident that the okra crop requires more water than pepper.

To establish a global model for soil moisture estimation and test the sensitivity of moisture sensor estimates in both crops, Figure 7 presents the validation established for the global model. The global model proved to be more efficient than the model and validation established for the pepper crop (Figure 5), with an R^2 of 0.98 and an r of 0.99, making it the most satisfactory validation for the explored dataset. Based on these results, the use of the moisture sensor in the field is recommended for both pepper and okra crops.

Based on the RMSE, it was found to be low, indicating a satisfactory fit of the moisture sensor with the gravimetric method, with a value of around 3.00762%. With a low margin of error, good coefficient adjustments (R^2 and r), and finally, a significant F-value and *p*-value at a 1% probability level, as observed in Table 6, the use of the solar-powered moisture sensor for characterizing soil moisture in pepper and okra crops is recommended.

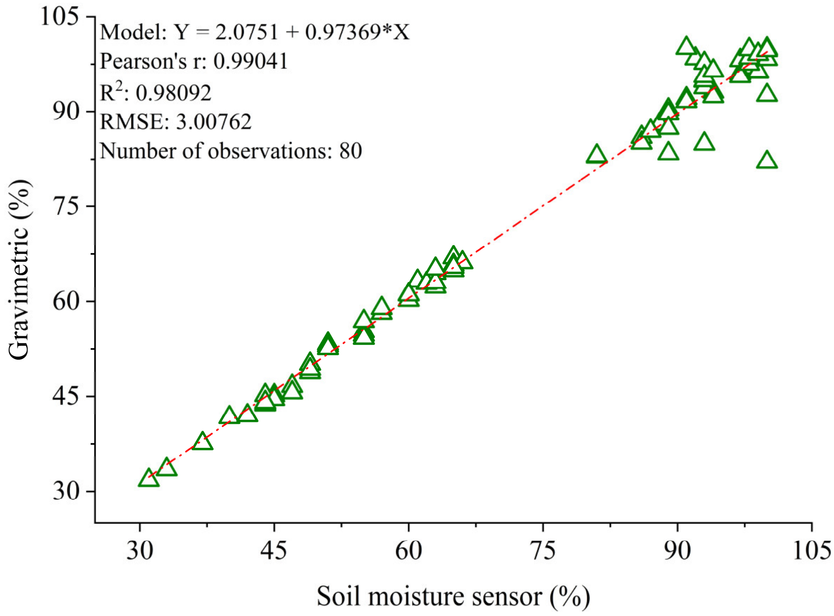

Figure 7. Global regression model for validating the soil moisture sensor vs. gravimetric method, preceded by their respective coefficients of determination (R^2), Pearson correlation coefficient (r), and root mean square error (RMSE).

Table 6. Analysis of variance (ANOVA) of the global regression model.

	[1] DF	[2] SS	[3] MS	F Value	*p*-Value
Model	1	36,268.22	36,268.22	4009.39	0.001
Error	79	705.57	9.04		
Total	80	36,973.79			

[1] DF—Degrees of freedom; [2] SS—Sum of squares; [3] MS—Mean square.

4. Conclusions

The solar-powered moisture sensor developed proved to be effective in characterizing soil moisture and was properly validated against the gravimetric method for soil moisture estimation. The parameters of coefficient of determination, Pearson correlation, and root mean square error were satisfactory for both pepper and okra crops, as well as for the global model.

The applicability of the developed moisture sensor will facilitate precise irrigation management by providing real-time and digital data, as most commonly used methods require time for moisture estimation and/or method calibration.

The automation of the soil moisture sensor emerges as a real-time alternative for irrigating at the right moment and in the right amount, thus avoiding water waste.

The solar powered soil moisture sensor is efficient and accurate. However, the present equipment has some limitations, the main one being the need for calibration, when using it in a soil with physical-chemical characteristics different from those used in this study. Therefore, it is recommended to calibrate the soil moisture photovoltaic sensor, depending on whether soils with different characteristics are used in this study.

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