Vol. 15, No. 4 (2026): 1448 - 1458 http://dx.doi.org/10.23960/jtepl.v15i4.1448-1458

JURNAL TEKNIK PERTANIAN LAMPUNG

ISSN 2302-559X (print) / 2549-0818 (online)
Journal homepage : https://jurnal.fp.unila.ac.id/index.php/JTP

Development and Validation of an ESP32-Based Multi-Sensor System for Precision Smart Greenhouse Monitoring

Muhammad Dhafir[1,✉], Muhammad Idkham[1], Safrizal[1], Khairul Anwar[2]

[1] Department of Agricultural Engineering, Faculty of Agriculture, Universitas Syiah Kuala, Darussalam, Banda Aceh, INDONESIA.

[2] Center for Agricultural Mechanization and Workshop Research (PUSMEPTAN), Universitas Syiah Kuala, Darussalam, Banda Aceh, INDONESIA.

Article History:

Received : 06 November 2025
Revised : 10 May 2026
Accepted : 01 August 2026

Keywords:

ESP32,
Multisensor,
Precision agriculture,
Real-time data acquisition,
Smart greenhouse,
Validation.

Corresponding Author:
✉ m.dhafir2001@gmail.com
(Muhammad Dhafir)

ABSTRACT

Smart greenhouse system has become one of the main technologies in precision agriculture due to its ability to control environmental parameters that influence plant growth. This study aims to perform calibration and validation of a multi-sensor system based on ESP32, which will be integrated into a smart greenhouse automation system. The sensors included DHT22 for air temperature and humidity, an analog TDS sensor for nutrient concentration, and a resistive soil moisture sensor (V1.2) for soil humidity. The testing was conducted in a real greenhouse environment with statistical parameters such as MAPE, RMSE, and R^2 were used as the basis for evaluating sensor accuracy. Results showed that the DHT22 sensor produced MAPE, RMSE, and R^2 of respectively 2.75%, 1.08%, and 0.989 for air temperature, and 6.53%, 4.80%, and 0.997 for air humidity. The TDS sensor showed a MAPE of 0.267%, RMSE of 2.760%, and R^2 of 0.875 in AB Mix solution of approximately 1000 ppm. The integrated ESP32 system operated reliably in three modes—manual, semi-automatic, and automatic—with a response time of less than two seconds. These findings confirm the potential application of multi-sensor systems in smart agriculture and highlight the importance of calibration to achieve reliability in modern greenhouse operations.

1. INTRODUCTION

The implementation of Internet of Things (IoT) sensor systems is significantly transforming the agricultural environment by offering scalable and accessible solutions for environmental monitoring. However, despite their potential to enable real-time data acquisition and improve decision-making in precision agriculture, these systems often suffer from fundamental limitations. A persistent concern is the technological fragility of low-cost sensors, which, due to their low-cost manufacturing processes, tend to degrade under fluctuating environmental conditions (Farooq *et al*., 2020).

One of the most significant issues lies in the reliability of sensor calibration. Many commercially available sensors are factory-calibrated under standard conditions that do not represent the diversity and dynamics of agricultural fields. As a result, sensors can produce biased readings that compromise the validity of the collected data (Rajan *et al*., 2018). Mansoor *et al*. (2025) argue that such data inaccuracies hinder actionable decision-making, potentially leading to inefficient resource utilization or crop failure. Despite these limitations, the ESP32 microcontroller has emerged as a promising platform for agricultural IoT due to its balance between affordability, processing power, and integrated connectivity features. Recent studies have shown that the ESP32 has been used for a variety of agricultural applications, including smart farm monitoring systems, automated irrigation, and environmental control. For example, Syahputra & Andriani (2025) developed a greenhouse monitoring system using the ESP32 in conjunction with a DHT11 sensor and soil moisture sensors, enabling real-time environmental monitoring via a mobile app. Similarly, Pereira *et al*. (2023)

utilized the ESP32 in an automated drip irrigation system and demonstrated its effectiveness in optimizing water use based on soil conditions.

The utility of the ESP32 extends beyond basic monitoring. The platform supports flexible integration of multiple sensors, cloud-based communication, and real-time control operations. This is supported by research Montillo-Balderas *et al*. (2025), which demonstrated the use of the ESP32 to design a sustainable irrigation system, highlighting the role of this microcontroller in modernizing and automating agricultural practices.

Despite their hardware advantages, ESP32-based systems are still susceptible to weaknesses in the sensors they support. In particular, factory-calibrated sensors are often poorly adapted to real-world conditions. Research Canja *et al*. (2025) notes that factory calibration fails to account for variations in soil texture and composition, particularly for moisture sensors, necessitating on-site recalibration procedures for accuracy. Sensors such as the DHT22 and DS18B20, while widely used, have been reported to exhibit delayed response times and inaccuracies under extreme conditions (Zukhri *et al*., 2025). Analog sensors such as TDS V1.2 and soil moisture probes are further limited by their susceptibility to temperature and salinity disturbances, requiring complex calibration processes to correct their readings (Rodríguez Padrón *et al*., 2022).

To overcome these limitations, the use of regression models is effective in adjusting sensor output to environmental fluctuations, as detailed by Lee *et al*. (2020). Evaluation of regression model performance is generally carried out by calculating the Average Percentage Error (APE) and Mean Absolute Percentage Error (MAPE) to assess the relative level of deviation between sensor predictions and reference values. Root Mean Square Error (RMSE) is used to measure the average absolute deviation in physical units of measurement. Furthermore, the coefficient of determination (R^2) is used to describe the level of agreement between calibration results and reference values. An R^2 value close to 1 indicates that the regression model is able to explain most of the variation in sensor data relative to actual conditions. By combining APE, MAPE, RMSE, and R^2 indicators, the effectiveness of the sensor calibration model can be quantitatively evaluated, resulting in more accurate and stable readings when applied in real time to a smart greenhouse system.

This study aims to address a methodological gap by developing a multisensor system for greenhouse monitoring using ESP32 microcontroller, with a focus on structured sensor validation. The novelty lies in the design and application of an ESP32-based modular sensor platform and sensor calibration under diverse greenhouse environmental conditions. The study emphasizes real-world applications by validating performance under field-relevant conditions, thus addressing both technological and methodological gaps in the literatures. Ultimately, this research is expected to contribute in establishing a reproducible benchmark for evaluating sensor performance systems in precision agriculture. By integrating a validated field-specific sensor calibration model with standard laboratory tools, this work lays the foundation for the implementation of robust and reliable IoT monitoring solutions tailored for smart greenhouses.

2. MATERIALS AND METHODS

2.1. Materials and Instruments

This research was conducted in the laboratory of the Agricultural Mechanization and Workshop Research Center, Universitas Syiah Kuala. The materials used to design the smart greenhouse included an ESP32 microcontroller, a DHT 22 sensor, a TDS V1.0 sensor, a water temperature sensor (DS18B20), a DS3231 RTC, a Humidity-Moisture Module V1.2, a 4-channel relay, a 220-volt AC solenoid, a male-female jumper, a 2A 12-volt adapter, and an Arduino IoT Cloud interface application. The sensor calibration instrumentation used a Dual-Function TDS (Total Dissolved Solids) and EC meter, a soil moisture meter (YIERYI), and a digital hygrometer for temperature sensor calibration.

2.2. Device Architecture

The device architecture is designed with an integrative approach, with the ESP32 serving as the central processing unit that receives data from sensors, reads digital and analog signals, converts the readings into standard units, and sends the data to the Arduino IoT Cloud via a Wi-Fi connection. This ESP32-based architecture follows the principles of modern smart greenhouse systems, which consist of a sensor layer, a processing layer, a communication layer, and a cloud layer for storage, visualization, and decision-making (Bicamumakuba *et al*., 2025; Soussi *et al*., 2024). In this study, the system was designed to acquire five main parameters from four types of sensors: air temperature, air humidity, TDS concentration, water temperature, and soil moisture.

This system was designed to obtain five parameters from four sensors: a DHT22 sensor to measure air temperature and humidity, a TDS sensor to detect dissolved substance levels in water, a DS18B20 sensor to monitor changes in water temperature, and a capacitive soil moisture sensor to monitor soil moisture content under three different conditions (dry, normal, and wet). All sensors are connected to the ESP32 via digital and analog input lines according to the characteristics of each sensor. The reading data is then calibrated internally by the ESP32 microcontroller, formatted in standard units, and sent wirelessly to the Arduino IoT Cloud platform for storage and visualization of real-time monitoring. The system is powered by a 12V 2A adapter with an external voltage regulator, while the communication interface uses Wi-Fi for IoT-based data integration. This architecture enables the acquisition, processing, and monitoring of sensor data to be carried out automatically, efficiently, and scalably in a single integrated system. The wiring diagram is shown in Figure 1 with detail modules is summarized in Table 1.

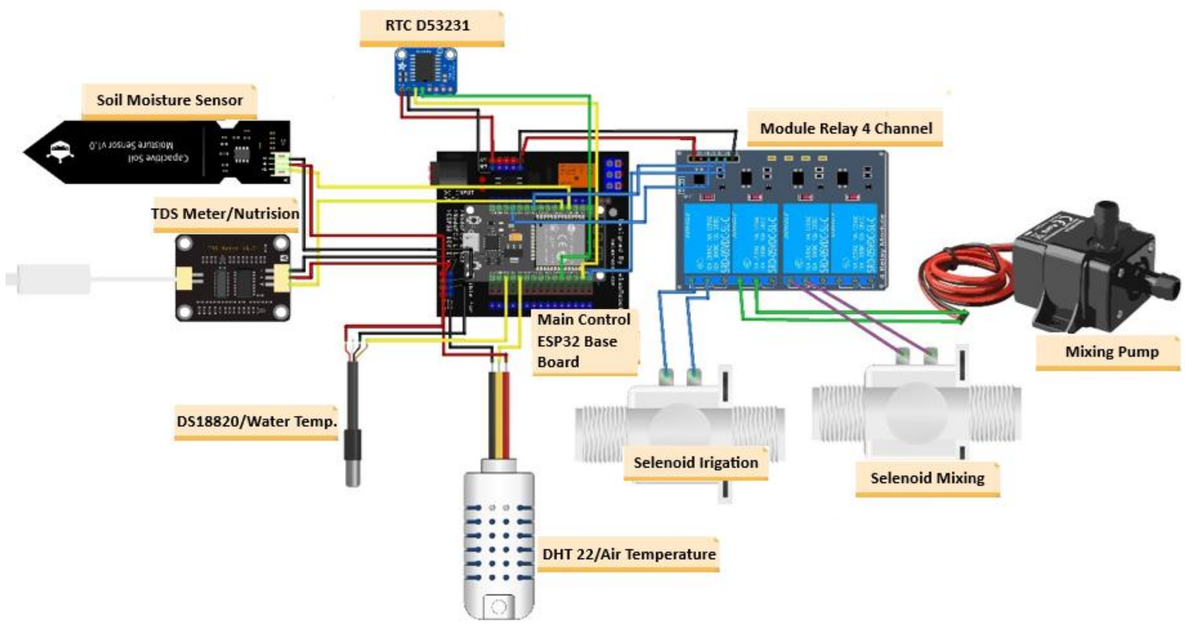


Figure 1. IoT smart greenhouse wiring diagram

Table 1. Detail description of modules for IoT smart greenhouse

Modules	Signal Line	Pin ESP32	Modules	Signal Line	Pin ESP32
DHT22	Data	GPIO4	**RTC DS3231**	SDA	GPIO21
	Vcc	3.3 V		SCL	GPIO22
	Gnd	Gnd		Vcc	3.3 V
Soil Moisture V1.2	Data	GPIO34		Gnd	Gnd
	Vcc	3.3 V	**TDS V1.0**	Data	GPIO35
	Gnd	Gnd	**DS18B20**	Vcc	3.3 V
Relay	Vcc	5 Volt		Gnd	Gnd
	Gnd	Gnd		Data	GPIO15
	CH1 – Irigasi	GPIO23		Vcc	3.3 V
	CH2 – Misting	GPIO26		Gnd	Gnd
	CH3 – Mixing	GPIO27			

2.3. Sensor Testing Protocol

Tests were conducted on five parameters: air temperature and humidity, TDS, water temperature, and soil moisture. The purpose of this test was to evaluate the accuracy and consistency of each sensor reading against reference values obtained from standard instruments. The DHT22 sensor was used to measure air temperature (°C) and relative humidity (%RH), with data collected every hour throughout the observation period. Each measurement was repeated three times to ensure reproducibility of the results. The sensor readings were compared with laboratory reference instruments using statistical analysis of APE, MAPE, RMSE, and the coefficient of determination (R^2) to assess the accuracy and linear relationship between the sensor data and the standard values.

Meanwhile, the TDS and water temperature sensors were tested using a 1000 ppm AB Mix solution. The TDS measurements were repeated five times, and the sensor measurements were compared with the TDS reference values obtained from standard instruments. Soil moisture accuracy was evaluated by calculating APE, MAPE, RMSE, and R^2 values to assess the suitability and stability of the sensor for various AB Mix solution treatments.

For the soil moisture sensor, testing was conducted under three different soil moisture conditions: dry, normal, and wet soil. These conditions were determined based on the actual soil moisture content obtained using a standardized (in-situ) instrument before the sensor was tested. Soil moisture measurement data were collected three times for each treatment. Because soil moisture values were only observed based on the soil moisture content treatment, APE, MAPE, RMSE, and R^2 calculations were not applied. Instead, sensor readings were presented as a direct comparison to theoretical soil conditions.

2.4. Sensor Accuracy Testing

Sensor accuracy was evaluated using four statistical indicators: Absolute Percentage Error (APE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and the coefficient of determination R^2. The simultaneous use of multiple metrics aims to obtain a more comprehensive picture of performance, as each metric represents a different aspect of error. RMSE is sensitive to large deviations and outliers, MAPE provides an interpretation of error as a percentage that is easily compared across parameters, while R^2 indicates the degree of agreement between sensor readings and reference values (García-Vázquez *et al*., 2023). This multi-metric approach is recommended in the evaluation of greenhouse sensors and predictive models because it can simultaneously assess absolute error, relative error, and the strength of the linear relationship (Bolandnazar *et al*., 2023). Equation (1) to (4) show calculation method for APE, MAPE, RMSE, and R^2, respectively.

$$APE_i = \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \times 100\% \tag{1}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \times 100\% \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2} \tag{3}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2)} \tag{4}$$

where Y_i is the reference value, and $\hat{Y}_i$ is the sensor reading at the $i^{\text{-th}}$ measurement point, $\bar{Y}$ is the mean of all reference values, and n is the total number of measurement data points.

3. RESULTS AND DISCUSSION

3.1. Arduino IoT Cloud Interface

This program was developed to build an automation system capable of real-time environmental monitoring and nutrient control. This confirms the findings of Farooq *et al*. (2022) and Shanto *et al*. (2023), which emphasize the importance of real-time responsiveness in agricultural automation. This program integrates various sensors, including humidity sensors, DHT22 air sensors, and TDS sensors. All sensor data is processed by the ESP32, stored, and displayed via the Arduino IoT Cloud, allowing users to remotely monitor environmental and nutrient conditions. The ESP32's capacity supports multiple sensors without data loss or latency. Supported by Maier *et al*. (2017) and Shamshiri *et al*. (2021), the ESP32's dual-core architecture and modular design are ideal for scalable IoT systems.

In addition, there are three operational modes implemented, including manual mode, where all actuators (irrigation, misting, mixing) are directly controlled by the user through the Arduino IoT Cloud interface, which provides intuitive control and monitoring, reflecting usability insights (Rezvani *et al*., 2020). This mode provides flexibility and full control in critical situations. Semi-automatic mode is activated based on a timer setting according to the user's specified time. Automatic mode allows all actuators to respond directly to sensor data without human intervention. In simulation tests such as drought and increased air temperature, the system was able to activate irrigation, misting, and mixing in less than 2 seconds from the sensor reading. The 12V 2A power supply prevented overheating, and also maintained a more consistent Wi-Fi connectivity throughout the test. This demonstrates that the ESP32 architecture is not only capable of managing multi-sensor integration but also supports scalable and reliable automation systems in precision agriculture applications. The dashboard display is presented in Figure 2.

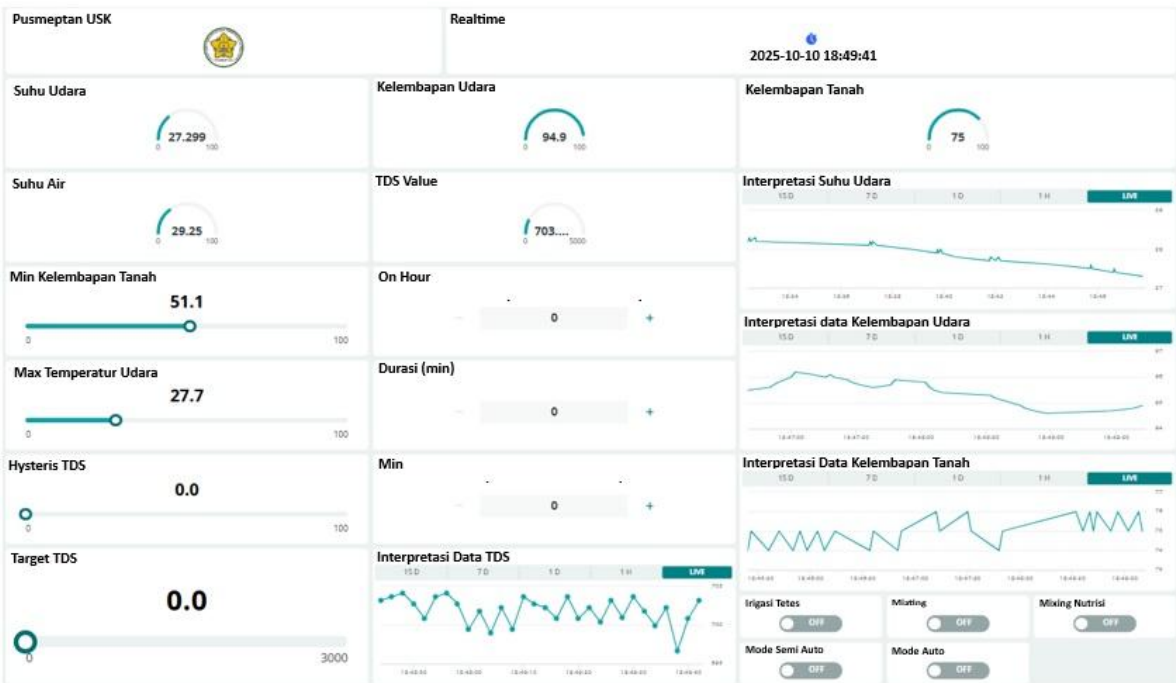


Figure 2. Arduino IoT cloud dashboard interface

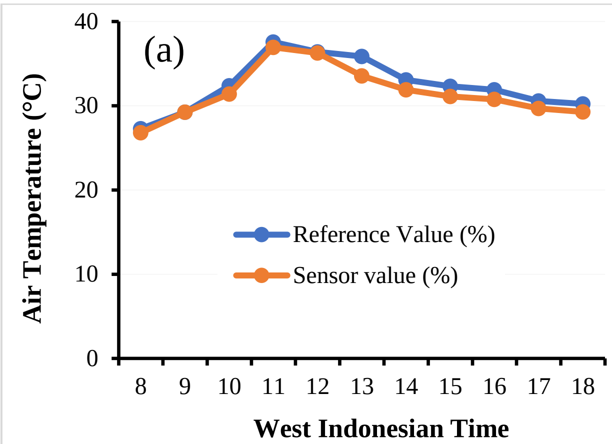
3.2. DHT22 Sensor Performance: Temperature and Humidity Accuracy

Table 1 shows the results of the DHT22 temperature sensor calibration calculations against the reference values of the comparison instrument. The APE values ranged from 0.001% to 6.515%, with an average MAPE of 2.755%. This value

Table 1. Accuracy Evaluation Results of the DHT22 Sensor for Temperature Measurements

Time	Reference Value (°C)	Sensor Value (°C)	APE (%)	MAPE (%)	RMSE (°C)	R^2
08:00 AM	27.267	26.800	1.711			
09:00 AM	29.233	29.234	0.001			
10:00 AM	32.367	31.391	3.015			
11:00 AM	37.567	36.933	1.686			
12:00 PM	36.400	36.267	0.366			
01:00 PM	35.867	33.530	6.515	2.755	1.084	0.989
02:00 PM	33.067	31.893	3.548			
03:00 PM	32.300	31.096	3.727			
04:00 PM	31.900	30.760	3.574			
05:00 PM	30.567	29.667	2.944			
06:00 PM	30.233	29.260	3.219			

indicates that the DHT22 sensor has a high level of accuracy throughout the observation period. The RMSE value of 1.084% confirms that the deviation between the sensor and reference values is relatively small. Furthermore, the coefficient of determination ($R^2 = 0.989$) shows a very strong linear relationship, indicating that the calibration model adequately represents the reference temperature data. Overall, these results indicate that the DHT22 sensor performs stably under various environmental temperature conditions, with small deviations that tend to occur during the day when temperature fluctuations are maximum. Fluctuations in air temperature data are presented in Figure 3.



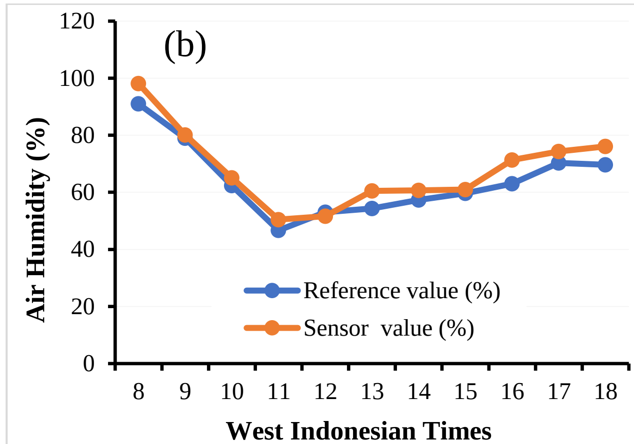


Figure 3. Fluctuations of data: (a) air temperature, (b) air humidity

Evaluation of the DHT22 sensor's performance under real-world conditions demonstrated a high level of reliability in temperature measurements, with a MAPE below 5% and an R^2 value reaching 0.98. These results align with findings Hasin *et al*. (2023), which reported similar accuracy under controlled laboratory conditions. Despite its relatively good accuracy, the DHT22 sensor exhibited a response time delay of approximately two seconds between readings, which may limit its use in real-time applications with high data acquisition frequency, as noted by Ningsih *et al*. (2023). Fluctuations in air humidity data are presented in Figure 4.

Table 2. Accuracy Evaluation Results of the DHT22 Sensor for Relative Humidity Measurements

Time	Reference Value (%)	Sensor Value (%)	APE (%)	MAPE (%)	RMSE (%)	R^2
08:00 AM	91.000	98.133	7.839			
09:00 AM	79.000	80.067	1.350			
10:00 AM	62.333	65.067	4.385			
11:00 AM	46.667	50.460	8.129			
12:00 PM	53.000	51.610	2.623			
01:00 PM	54.333	60.467	11.288	6.529	4.798	0.997
02:00 PM	57.333	60.730	5.924			
03:00 PM	59.667	60.967	2.179			
04:00 PM	63.000	71.333	13.228			
05:00 PM	70.333	74.300	5.640			
06:00 PM	69.667	76.100	9.234			

Based on Table 2, the DHT22 sensor demonstrated a good level of accuracy in measuring relative humidity, with an overall MAPE of 6.529%, an RMSE of 4.798%, and an R^2 value of 0.997, indicating a very strong correlation between the sensor readings and the reference values. The highest APE values occurred at 04.00 PM (13.228%) and 01.00 PM (11.288%), which were likely caused by rapid fluctuations in air humidity during these periods, leading to a slight lag in the sensor's response. In contrast, the smallest deviation occurred at 09.00 AM (APE of 1.350%), when relative humidity conditions were comparatively stable. Overall, these results are consistent with the pattern shown in Figure 4, in which the sensor was able to follow the trend of the reference values closely, despite small deviations during periods of sharp humidity change.

Under high humidity conditions (>90% RH), the sensor exhibited significant deviations from the reference value, consistent with the performance degradation discussed by Ansari *et al*. (2023) and Sagita *et al*. (2024). These deviations were primarily caused by saturation effects and possible condensation on the sensor element, which reduced its reliability. To address these limitations, a standard hygrometer was calibrated prior to deployment. This recalibration strategy is also recommended by Wahyu *et al*. (2024) and Siskandar *et al*. (2022) as it has proven effective in restoring measurement consistency. Overall, while the DHT22 remains an economical and reasonably accurate sensor, its use in dynamic greenhouse environments requires periodic recalibration and data filtering to maintain measurement reliability.

3.3. TDS Sensor Analysis

As seen in Figure 5, the V1.0 analog TDS sensor values show very little deviation compared to the standard values, with APE ranging from 0.202% to 0.420% and an average MAPE of only 0.267%. The RMSE value of 2.760% indicates a very small deviation between the measured data and the reference data. Furthermore, the coefficient of determination (R^2 = 0.875) indicates a strong linear correlation, meaning the sensor output closely follows the reference data. Overall, these results demonstrate that the TDS sensor has reliable and precise performance, making it suitable for real-time monitoring applications. TDS data calibration calculations are presented in Table 3.

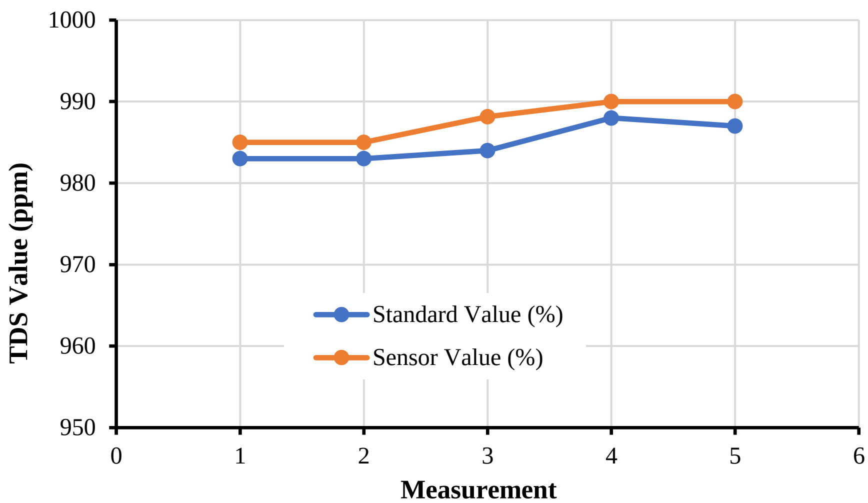


Figure 5. TDS value test results

The performance of the TDS sensor improved significantly after temperature compensation. Raw sensor readings are prone to inaccuracies due to the non-linear effect of temperature on water conductivity. These findings align with research by Bogdan *et al*. (2023), which emphasized the importance of real-time temperature correction to ensure the reliability of TDS measurements. Without such compensation, TDS data can potentially mislead nutrient management decisions and result in suboptimal or even hazardous conditions for plants. Furthermore, periodic recalibration of the standard TDS solution, as recommended by Passos *et al*. (2023), was performed to maintain accuracy across a wide concentration range. This procedure is consistent with best practices in hydroponic nutrient monitoring and confirms the practical feasibility of using TDS sensors in greenhouse systems.

Table 3. Accuracy Evaluation Results of the TDS Sensor

Replicate	Standard Value (ppm)	Sensor Value (ppm)	APE (%)	MAPE (%)	RMSE (ppm)	R^2
1	983	985	0.203	0.267	2.760	0.875
2	983	985	0.203			
3	984	988	0.420			
4	988	990	0.202			
5	987	990	0.304			

3.4. Soil Moisture Sensor Performance

Sensor performance is the sensor's ability to detect water content in three categories of soil types. Sensor measurements were repeated three times on different soil types, after which the average of the repetitions was analyzed, with the results shown in Table 4. The previously obtained sensor data was then used to analyze water content based on a calibration instrument that could only determine dry (0-30%), normal (30-60%), and wet (61-100%) soil categories. These results demonstrate the sensor's ability to effectively differentiate soil moisture levels. The test results are presented in Figure 6.

According to Table 4, the sensor produced readings of 4% in dry soil, 55% in normal soil, and 81% in wet soil. These results indicate that the sensor is able to clearly distinguish three levels of soil moisture content. This classification capability is important in automated irrigation systems because watering decisions are highly dependent on actual soil moisture conditions. In the context of agricultural IoT, soil moisture sensors are a critical input for determining when pumps or solenoids need to be activated, as demonstrated in various threshold-based and machine learning-based automated irrigation systems (Sangeetha *et al*., 2024).

Table 4. Classification of soil moisture conditions based on soil moisture sensor testing results

Calibration Instrument Classification	Sensor Reading (%)	Description
Dry	4	Low soil moisture; below field capacity and may cause water stress.
Normal	55	Optimal soil moisture; supports healthy root and plant growth.
Wet	81	High soil moisture; soil is nearly saturated and may limit oxygen availability.

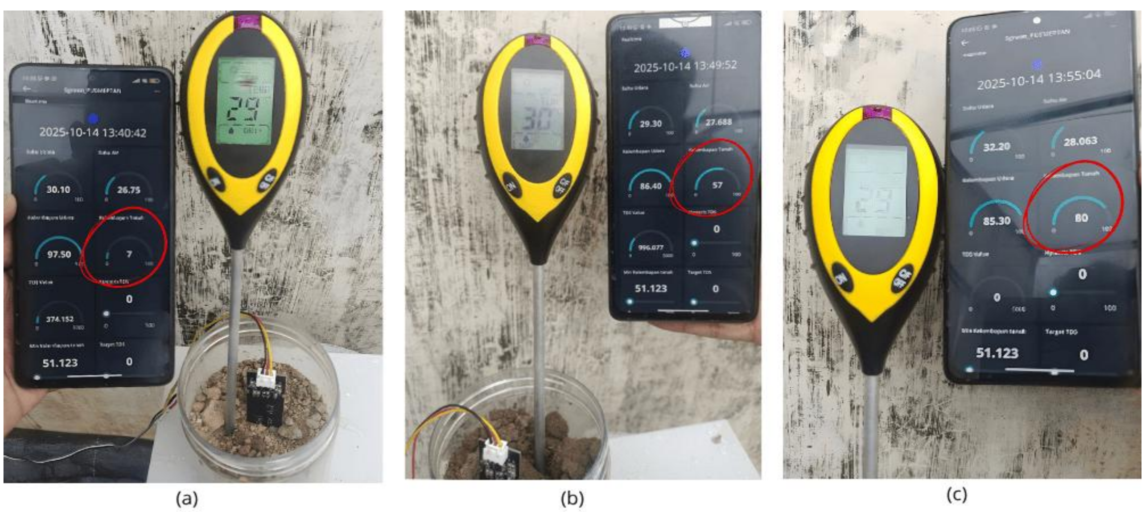


Figure 6. Soil moisture testing (a) dry, (b) normal, (c) wet

The soil moisture sensor V1.2 includes capacitive sensors, as described by González-Teruel *et al*. (2019) and Marin *et al*. (2024), offering greater stability across a wide range of conditions. However, resistive sensors have proven to be effective when properly calibrated. This study confirms the need for soil-specific calibration, as soil texture and salinity significantly impact sensor accuracy (Payero *et al*., 2017). Furthermore, environmental factors such as temperature and salinity affect sensor output, requiring additional compensation or filtering for long-term deployment. Although resistive sensors may be susceptible to drift, their affordability and clear differentiation capabilities make them suitable for general soil condition monitoring in automated systems.

The novelty of this study lies in the systematic, temperature- and soil-specific calibration approach applied to low-cost ESP32-integrated sensors—specifically the analog TDS sensor, the resistive soil moisture sensor V1.2, and the DHT22 sensor—validated directly under real greenhouse operating conditions rather than controlled laboratory settings alone. The main contribution of this research is a practical and reproducible calibration framework, supported by quantitative accuracy metrics (MAPE, RMSE, and R^2), that bridges the gap between affordable commercial sensors and the measurement reliability required for precision agriculture automation. Consequently, the findings offer a cost-effective yet scientifically validated alternative to expensive industrial-grade sensors, supporting the wider adoption of smart greenhouse systems in resource-limited agricultural settings.

4. CONCLUSIONS AND RECOMMENDATIONS

This study demonstrates the effectiveness of generating accurate and reliable environmental data, which is crucial for precision agriculture automation. This can be achieved with proper ESP32-based calibration. The temperature-compensated TDS and resistive soil moisture sensors, along with DHT22 calibration for temperature and humidity, effectively improved measurement accuracy under various environmental conditions. Sensor accuracy metrics, including MAPE values below 5% and R^2 values above 0.9%, except for the TDS value with R^2 <0.875%, confirm the multisensor's suitability for real-world agricultural applications. The integration of ESP32 with Arduino IoT Cloud allows the system to operate in manual, semi-automatic, and automatic modes, with an actuator response time of less than two seconds. These findings contribute to the body of knowledge regarding the empirical validation of low-cost sensor-based agricultural IoT systems in real-world greenhouse environments. The developed system can serve as a baseline model for the development of modular, economical, and replicable smart greenhouses. Future research is recommended to explore the integration of predictive algorithms, machine learning, automatic temperature compensation, and long-term testing to evaluate sensor stability and system reliability over one or more crop cycles.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to Universitas Syiah Kuala for the financial support provided for this research through Grant No. 730/UN11.L1/PG.01.03/15002 PTNBH/2025, dated 21 July 2025. The authors also gratefully acknowledge the Center for Agricultural Mechanization and Workshop Research (PUSMEPTAN), Universitas Syiah Kuala, for providing laboratory facilities and technical assistance.

DECLARATION OF THE USE OF GENERATIVE AI AND AI-BASED TECHNOLOGIES IN MANUSCRIPT PREPARATION

During the writing process of this article, the authors used ChatGPT (OpenAI) for spelling checks, grammar improvement, and sentence clarification. All suggestions generated by the tool were critically considered, verified for accuracy, and edited by the authors. The authors declare that no scientific content or data were entirely generated by artificial intelligence, and that the authors bear full responsibility for the content of the publication.

AUTHOR CONTRIBUTION

Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
MD	✓	✓							✓	✓				
MI	✓				✓	✓		✓	✓	✓				
Saf	✓									✓	✓	✓		
KA			✓	✓		✓								

C: Conceptualization	Fo: Formal Analysis	O: Writing – Original Draft	Fu: Funding Acquisition
M: Methodology	I: Investigation	E: Writing – Review & Editing	P: Project Administration
So: Software	D: Data Curation	Vi: Visualization	
Va: Validation	R: Resources	Su: Supervision	

REFERENCES

Ansari, S., Ansari, A., Kumar, A., Kumar, R., & Nyamasvisva, T.E. (2023). Environmental temperature and humidity monitoring at agricultural farms using internet of things & DHT22-sensor. *Journal of Independent Studies and Research - Computing*, ***21***(2), 25-31. https://doi.org/10.31645/jisrc.23.21.2.5

Bicamumakuba, E., Reza, M.N., Jin, H., Samsuzzaman, Lee, K.-H., & Chung, S.-O. (2025). Multi-sensor monitoring, intelligent control, and data processing for smart greenhouse environment management. *Sensors*, ***25***(19), 6134. https://doi.org/10.3390/s25196134

Bogdan, R., Paliuc, C., Crisan-Vida, M., Nimara, S., & Barmayoun, D. (2023). Low-cost internet-of-things water-quality monitoring system for rural areas. *Sensors*, ***23***(8), 3919. https://doi.org/10.3390/s23083919

Bolandnazar, E., Sadrnia, H., Rohani, A., Marinello, F., & Taki, M. (2023). Application of artificial intelligence for modeling the internal environment condition of polyethylene greenhouses. *Agriculture*, ***13***(8), 1583. https://doi.org/10.3390/agriculture13081583

Canja, J.F., de Azevedo, B.M., Thé, G.A.P., Mulas, M., Frazão, D.S., & de Figueredo Júnior, L.G.M. (2025). Statistical characterization of a capacitive soil moisture probe, integrated into the water balance system in agriculture in a semi-arid region. *Revista Ambiente & Água*, 20. https://doi.org/10.4136/ambi-agua.3029

Farooq, M.S., Riaz, S., Abid, A., Umer, T., & Zikria, Y.B. (2020). Role of IoT technology in agriculture: A systematic literature review. *Electronics*, ***9***(2), 319. https://doi.org/10.3390/electronics9020319

Farooq, M.S., Riaz, S., Helou, M.A., Khan, F.S., Abid, A., & Alvi, A. (2022). Internet of things in greenhouse agriculture: A survey on enabling technologies, applications, and protocols. *IEEE Access*, ***10***, 53374–53397. https://doi.org/10.1109/access.2022.3166634

García-Vázquez, F., Ponce-González, J.R., Guerrero-Osuna, H.A., Carrasco-Navarro, R., Luque-Vega, L.F., Mata-Romero, M.E., Martínez-Blanco, M.d.R., Castañeda-Miranda, C.L., & Díaz-Flórez, G. (2023). Prediction of internal temperature in greenhouses using the supervised learning techniques: Linear and support vector regressions. *Applied Sciences*, ***13***(14), 8531. https://doi.org/10.3390/app13148531

González-Teruel, J.D., Torres-Sánchez, R., Blaya-Ros, P.J., Toledo-Moreo, A.B., Jiménez-Buendía, M., & Soto-Valles, F. (2019). Design and calibration of a low-cost SDI-12 soil moisture sensor. *Sensors*, ***19***(3), 491. https://doi.org/10.3390/s19030491

Hasin, M.K., Wiranata, M.A., & Rachmat, A.N. (2023). Rancang bangun sistem monitoring iklim kerja berbasis IoT menggunakan kalman filter untuk mengurangi noise sensor. *Ijcit (Indonesian Journal on Computer and Information Technology)*, ***7***(2). https://doi.org/10.31294/ijcit.v7i2.14386

Lee, H., Kang, J., Kim, S., Im, Y., Yoo, S., & Lee, D. (2020). Long-term evaluation and calibration of low-cost particulate matter (PM) sensor. *Sensors*, ***20***(13), 3617. https://doi.org/10.3390/s20133617

Maier, A., Sharp, A., & Vagapov, Y. (2017). Comparative analysis and practical implementation of the ESP32 microcontroller module for the Internet of Things. In *2017 Internet Technologies and Applications (ITA)* (pp. 143–148). IEEE. https://doi.org/10.1109/ITECHA.2017.8101926

Mansoor, S., Iqbal, S., Popescu, S.M., Kim, S. L., Chung, Y.S., & Baek, J.-H. (2025). Integration of smart sensors and IoT in precision agriculture: Trends, challenges and future prospectives. *Frontiers in Plant Science*, ***16***, 1587869. https://doi.org/10.3389/fpls.2025.1587869

Marin, M., Elsakloul, F., Norton, G. J., Sanchez, J., Roundy, S., & Hallett, P.D. (2024). Influence of soil conditioners for enhanced water retention on the accuracy and longer-term deployment of widely used soil moisture sensors. *Soil Use and Management*, ***40***(4), e13134. https://doi.org/10.1111/sum.13134

Montillo-Balderas, M.A., Gómez-Mora, S.E., Woo-Garcia, R. M., Ovando-Rocha, M.S., Caballero-Briones, F., López-Huerta, F., & Júarez-Aguirre, R. (2025). Sustainable irrigation system design using recovered air conditioners condensate water. *IOP Conference Series: Earth and Environmental Science*, ***1524***(1), 012016. https://doi.org/10.1088/1755-1315/1524/1/012016

Ningsih, F.I.S., Irianto, B.G., Lamidi, L., & Abdulhamid, M. (2023). Monitoring baby incubator central based Raspberry Pi Zero W with temperature and skin temperature parameter based on IoT. *Indonesian Journal of Electronics, Electromedical Engineering and Medical Informatics*, ***5***(3), 116–124. https://doi.org/10.35882/ijeeemi.v5i3.183

Passos, M., Mariano, A.B.R., Andreska da Silva, D., & Oliveira de Sousa, A.B. (2023). Performance of sensors for quality analysis of irrigation water. *Revista Brasileira De Engenharia De Biossistemas*, ***16***, 1094. https://doi.org/10.18011/bioeng.2022.v16.1094

Payero, J.O., Qiao, X., Khalilian, A., Mirzakhani-Nafchi, A., & Davis, R. (2017). Evaluating the effect of soil texture on the response of three types of sensors used to monitor soil water status. *Journal of Water Resource and Protection*, ***09***(06), 566–577. https://doi.org/10.4236/jwarp.2017.96037

Pereira, G.P., Chaari, M.Z., & Daroge, F. (2023). IoT-enabled smart drip irrigation system using ESP32. *IoT*, ***4***(3), 221-243. https://doi.org/10.3390/iot4030012

Rajan, R.T., van Schaijk, R., Das, A., Romme, J., & Pasveer, F. (2018). Reference-free calibration in sensor networks. *IEEE Sensors Letters*, ***2***(3), Article 7001004, 1–4. https://doi.org/10.1109/LSENS.2018.2866627

Rezvani, S.M.-e., Abyaneh, H. Z., Shamshiri, R.R., Balasundram, S.K., Dworak, V., Goodarzi, M., Sultan, M., & Mahns, B. (2020). IoT-based sensor data fusion for determining optimality degrees of microclimate parameters in commercial greenhouse production of tomato. *Sensors*, ***20***(22), 6474. https://doi.org/10.3390/s20226474

Rodríguez Padrón, R.A., Beltramelli Gula, M.O., Bahú Ben, L.H., & Mezzomo, W. (2022). Calibration of the capacitance probe for soil moisture monitoring. *Revista Brasileira de Agricultura Irrigada*, ***16***, 131–137. https://doi.org/10.7127/rbai.v1601256

Sagita, D., Hidayat, D.D., Darmajana, D.A., Rahayuningtyas, A., & Hariadi, H. (2024). Fabrication and performance test of a multipurpose ohmic heating apparatus with a real-time data logging system based on low-cost sensors. *Research in Agricultural Engineering*, ***70***(1), 23–34. https://doi.org/10.17221/21/2023-RAE

Sangeetha, S.K.B., Immanuel, R.R., Mathivanan, S.K., Jayagopal, P., Rajendran, S., Mallik, S., & Li, A. (2024). Smart irrigation system using soil moisture prediction with deep CNN for various soil types. *Artificial Intelligence and Applications*, ***3***(2), 200–210. https://doi.org/10.47852/bonviewaia42021514

Shamshiri, R.R., Hameed, I.A., Thorp, K.R., Balasundram, S.K., Shafian, S., Fatemieh, M., Sultan, M., Mahns, B., & Samiei, S. (2021). Greenhouse automation using wireless sensors and IoT instruments integrated with artificial intelligence. In *Next-generation greenhouses for food security*. IntechOpen. https://doi.org/10.5772/intechopen.97714

Shanto, S.S., Rahman, M., Oasik, J.M., & Hossain, H. (2023). Smart greenhouse monitoring system using blynk IoT app. *Journal of Engineering Research and Reports*, ***25***(2), 94–107. https://doi.org/10.9734/jerr/2023/v25i2883

Siskandar, R., Santosa, S.H., Wiyoto, W., Kusumah, B.R., & Hidayat, A.P. (2022). Control and automation: Insmoaf (integrated smart modern agriculture and fisheries) on the greenhouse model. *Jurnal Ilmu Pertanian Indonesia*, ***27***(1), 141-152. https://doi.org/10.18343/jipi.27.1.141

Soussi, A., Zero, E., Sacile, R., Trinchero, D., & Fossa, M. (2024). Smart sensors and smart data for precision agriculture: A review. *Sensors*, ***24***(8), 2647. https://doi.org/10.3390/s24082647

Syahputra, R., & Andriani, D. (2025). Development of a smart farming monitoring system using IoT and android technology to support precision farming in the western part of Aceh. *Applied Mechanics and Materials*, ***927***, 67–79. https://doi.org/10.4028/p-bw93wr

Wahyu, S., Purwalaksana, A.Z., Ritonga, A.F., Suharmanto, P., Kusumadjati, A., Akbar, A.M., & Sujadi, T. (2024). Optimization of a smart greenhouse with a solar energy system for floating raft hydroponic cultivation: Implementation and performance evaluation. *Journal of Physics: Conference Series*, ***2866***(1), 012098. https://doi.org/10.1088/1742-6596/2866/1/012098

Zukhri, M.F., Aisyah, P.Y., Wirawan, Y., Nainggolan, T.Y., Anandhita, F., & Hermawan, M.I. (2025). Integration of liquid organic fertilizer fermentor with automated hydroponic fertilization based on IoT. *Jaree (Journal on Advanced Research in Electrical Engineering)*, ***9***(2), 146-151. https://doi.org/10.12962/jaree.v9i2.493