Indonesian Journal of Data and Science

Volume 7 Issue 2
ISSN 2715-9936
https://doi.org/10.56705/ijodas.v7i2.458

Research Article

An IoT-Based Fuzzy Decision Support System for Rhizobium Inoculation to Improve Soybean Productivity

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Received 10 May 2026; Accepted 30 July 2026; Published 31 July 2026

Abstract:
Introduction: Soybean productivity in Indonesia remains below national demand, while the effectiveness of Rhizobium inoculation depends strongly on dynamic soil conditions such as pH, moisture, temperature, and nitrogen availability. This study develops an Internet of Things (IoT)-based decision support system for adaptive Rhizobium inoculation in highland soybean cultivation. **Method**: The system integrates a Soil NPK RS485 Modbus sensor, ESP32-WROOM-32D microcontroller, MQTT communication, and the SMARTO web dashboard to monitor four environmental parameters in real time. A Mamdani Fuzzy Inference System was implemented using 17 membership functions and 25 expert-derived IF–THEN rules, with centroid defuzzification producing Rhizobium dose recommendations from 0 to 200 g/ha. **Results and Discussion**: Field readings of pH 7.5, soil moisture 55%, temperature 26°C, and nitrogen 155 mg/kg generated a recommendation of 16.56 g/ha, classified as Very Low, with a pump volume of 33 mL/ha. Expert validation across 30 simulated highland scenarios produced an overall agreement rate of 83.3%, demonstrating satisfactory consistency between system recommendations and agronomic judgment. **Conclusion**: The proposed IoT-Fuzzy DSS demonstrates the feasibility of location-specific, real-time, and interpretable Rhizobium inoculation support for highland soybean cultivation, providing a practical foundation for precision biological-input management.

Keywords: Decision Support System; Internet of Things; Fuzzy Logic; Mamdani; Rhizobium; Soybean; Highland Agroecosystem

1. Introduction

Soybean (Glycine max (L.) Merr.) is one of Indonesia's most strategically important agricultural commodities, providing the primary source of plant-based protein for household food security and serving as a critical raw material for the food processing industry, including tofu, tempeh, soy milk, and animal feed. According to national agricultural statistics, Indonesia's soybean demand reached approximately 2.8 million tons in 2023, while domestic production contributed less than 40% of this figure, necessitating large-scale imports and generating persistent pressure on food trade balances [1]. Bridging this productivity gap requires not only agronomic intensification but also the adoption of digital, data-driven approaches that optimize each production input under site-specific environmental conditions [2].

Among the agronomic interventions recognized for cost-effectively enhancing soybean yields, Rhizobium inoculation stands out for its capacity to supplement plant nitrogen through biological nitrogen fixation (BNF). The symbiotic relationship between soybean roots and Rhizobium japonicum bacteria results in the formation of root nodules that fix atmospheric N_2 into plant-available ammonium (NH_3), potentially supplying 60–75% of the crop's total nitrogen requirement and reducing dependence on synthetic nitrogen fertilizers [3]. Research has consistently demonstrated that effective Rhizobium inoculation improves root nodule count, nitrogen uptake efficiency, shoot biomass accumulation, and grain yield, particularly in combination with organic nutrient management practices [4],

[5]. However, these benefits are neither universal nor unconditional—they are contingent on specific soil environmental parameters that govern bacterial viability, nodule formation rates, and fixation efficiency.

Soil pH, moisture content, temperature, and available nitrogen level collectively regulate the ecological niche within which Rhizobium japonicum can successfully colonize soybean roots and form functional nodules [3], [4]. Optimal conditions for Rhizobium activity are typically reported as soil pH 6.0–7.5, moisture at 60–80% field capacity, soil temperature 25–30°C, and low to moderate indigenous nitrogen availability, which stimulates nodule formation. Deviations from these ranges—whether from acidic pH, drought stress, thermal extremes, or excessive soil nitrogen—can substantially reduce or nullify inoculation benefits, leading to wasted bioinoculant inputs. These environmental dependencies are particularly pronounced in highland agroecosystems, where agroclimatic conditions differ substantially from lowland references and display strong diurnal and seasonal variability.

Bulutana Village, Tallmoncong District, Gowa Regency, South Sulawesi Province (5°15'S, 119°55'E; elevation ±1,100–1,300 m asl) represents a characteristic highland soybean production zone where the combination of pronounced diurnal temperature fluctuations (up to 12°C daily), seasonal rainfall peaks, and Ultisol/Inceptisol soil types creates a complex agroecosystem demanding location-specific agronomic guidance. A preliminary empirical study conducted at this site by Mu'min et al. [5] documented the response of soybean growth and yield to different Rhizobium inoculation treatments combined with liquid organic fertilizer, establishing critical knowledge on local inoculation thresholds and soil condition interactions. Yet these findings have not been operationalized into an accessible, real-time decision tool for farmers and field extension workers—a gap this study aims to address.

The emergence of Internet of Things (IoT) technologies has fundamentally expanded the capacity for real-time environmental monitoring in agricultural settings [6]. IoT sensor networks deployed at the field level can continuously acquire granular soil and atmospheric data, enabling adaptive, data-responsive management decisions that replace reliance on periodic laboratory analyses or generalized guidelines [7], [8]. The integration of IoT-acquired data into computational intelligence frameworks further enables automated, knowledge-based recommendations that translate raw sensor readings into actionable agronomic guidance without requiring advanced technical expertise from farmers.

Fuzzy Logic, introduced by Zadeh [9] and formalized into the Mamdani Fuzzy Inference System by Mamdani and Assilian [10], provides a particularly suitable computational framework for agricultural decision support where input variables are continuous, naturally expressible in linguistic terms, and subject to genuine agronomic uncertainty. Unlike machine learning approaches that require large labeled training datasets [11], Mamdani FIS can directly encode expert agronomic knowledge into interpretable IF-THEN rules without extensive data collection—a practical advantage for smallholder highland farming contexts. The resulting recommendations preserve the linguistic reasoning structure familiar to agricultural experts and practitioners, facilitating validation, trust, and adoption.

A growing body of literature demonstrates the effectiveness of IoT-Fuzzy integration in agricultural decision systems. Hakis et al. [12] developed an IoT system for soil nutrient monitoring and control using fuzzy logic with multi-modal sensor integration, reporting classification accuracy of 80.9%. Rahayu et al. [13] and Walid et al. [14] applied IoT-Fuzzy systems for smart irrigation in different crops, achieving agreement rates of 78.3% and satisfactory functional performance respectively. Adnan et al. [15] demonstrated an 79.5% accuracy in a fuzzy-based fertilization DSS for precision agriculture, while Irwanto et al. [16] achieved 84.1% agreement in a mushroom substrate management system using Mamdani FIS. More recently, Arahman et al. [17] and Harshavardhini and Lakshmi [18] applied Mamdani FIS with IoT sensors for hydroponic nutrient management and irrigation automation respectively. However, despite this breadth of application, no existing system has specifically targeted Rhizobium inoculation decision-making in soybean cultivation—a biologically unique decision domain where the consequence of poor timing affects the entire cropping cycle and the spatial heterogeneity of highland agroecosystems demands location-specific calibration.

This study addresses this gap by presenting the complete design, implementation, and validation of an IoT-based Mamdani Fuzzy DSS for Rhizobium inoculation at the Bulutana highland study site. The system contributions are: (1) an integrated IoT hardware prototype using an NPK RS485 Modbus sensor with ESP32 microcontroller for four-parameter real-time soil monitoring; (2) a Mamdani FIS with 17 membership functions and 25 location-calibrated IF-

THEN rules grounded in preliminary empirical research [5]; (3) an MQTT-connected [19] SMARTO web dashboard for remote monitoring; (4) a complete step-by-step inference trace demonstrating end-to-end system operation with real field sensor data; and (5) expert judgment validation achieving 83.3% agreement across 30 simulated highland field scenarios, with comparative benchmarking against related literature [15], [16], [17].

2. Method

Study Area and Field Monitoring Site

The study was conducted in Bulutana Village, Tallmoncong District, Gowa Regency, South Sulawesi Province, Indonesia (−5.198054°S, 119.427456°E), at an elevation of approximately 1,100–1,300 m above sea level. The study area is characterized by an Af/Am highland tropical climate (Köppen classification) with annual precipitation of 2,000-3,500 mm, mean annual temperature of 18-23°C exhibiting diurnal fluctuations of up to 12°C, and soils classified predominantly as Ultisols and Inceptisols with organic matter content of 2.1-4.3%. Soybean (var. Anjasmoro) is cultivated during the dry-to-wet season transition period (May-September). A field IoT monitoring node was deployed at a 0.25 ha soybean plot managed by a farmer from the mondo cooperative (device ID: KN-71402), which had previously been the site of the Mu'min et al. [5] preliminary inoculation study that provided the empirical knowledge base for fuzzy rule development.

IoT Hardware Architecture and Sensor Integration

The IoT data acquisition system integrates the following hardware components, illustrated in **Figure 1**:

1) ESP32-WROOM-32D Microcontroller: Dual-core Xtensa LX6 processor at 240 MHz with integrated WiFi 802.11b/g/n, 12-bit ADC (18 channels), three hardware UARTs, I²C, and SPI interfaces. Serves as the central edge controller for sensor data polling, Mamdani FIS execution, LCD display management, and MQTT data publishing;

2) Soil NPK RS485 Modbus Sensor (9–24 V, RS485 RTU): An integrated multifunction soil probe capable of measuring nitrogen (N), phosphorus (P), potassium (K), pH, soil moisture, soil temperature, and electrical conductivity (EC) via a single probe insertion. Communicates via RS485 Modbus RTU protocol at 4800–9600 baud. For this study, four parameters were selected as fuzzy input variables: pH Tanah, Soil Moisture, Environmental Temperature, and Unsur Nitrogen/N. The remaining parameters (P, K, EC) are logged to the database as auxiliary monitoring data;

3) MAX485 RS485-to-UART Converter: Half-duplex differential signal converter enabling RS485 Modbus communication between the soil sensor and the ESP32 UART2 peripheral at up to 2.5 Mbps;

4) LCD 20×4 I²C (PCF8574 backpack): Displays real-time sensor values and current fuzzy recommendation category at the field node for local inspection without smartphone access;

5) LM2596 Step-Down DC-DC Regulator: Converts the 12V DC adapter supply to 5V for the ESP32 and sensor peripherals.

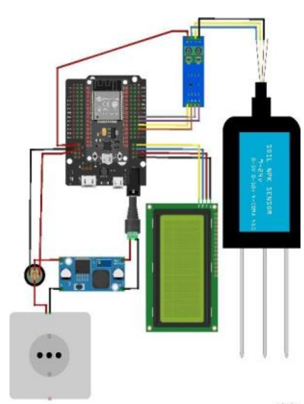

Figure 1. IoT hardware prototype circuit diagram:

Sensor readings are polled at 60-second intervals via Modbus RTU function code 0x03 (Read Holding Registers). The ESP32 firmware executes the Mamdani FIS computation locally (edge inference) within a mean latency of 6.8 ms per complete inference cycle, enabling near-instantaneous recommendation updates. Processed data are published to the cloud server via MQTT protocol over WiFi, with QoS Level 1 guaranteeing at-least-once delivery [19].

SMARTO Real-Time Monitoring Dashboard

The SMARTO (Smart Monitoring) web dashboard, accessible via standard browser, provides remote visualization of real-time sensor data and fuzzy recommendations. Figure 2 presents the Pemantauan Sensor Realtime interface for device KN-71402 during an operational monitoring session, displaying the four fuzzy input parameters: pH Tanah = 7.5, Soil Moisture = 55%, Environmental Temperature = 26°C, and Unsur Nitrogen/N = 155 mg/kg, with ONLINE connectivity status confirmed at GPS coordinates −5.198054, 119.427456.

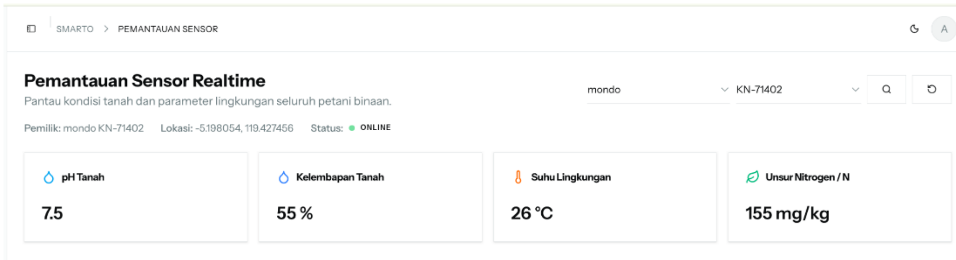

Figure 2. SMARTO real-time monitoring dashboard

D. Mamdani Fuzzy Inference System Design

The Mamdani FIS was selected for its interpretability and direct compatibility with expert-derived linguistic rules, following the standard four-stage inference pipeline: fuzzification → rule evaluation → aggregation → defuzzification. Two membership function types were used:

$$Trapmf: \mu(x;\ a, b, c, d) \ = \ max(min((x-a)/(b-a), 1, (d-x)/(d-c)), 0), where\ a\ \leq\ b\ \leq\ c\ \leq\ d \quad (1)$$

$$Trimf: \mu(x;\ a, b, c) \ = \ max(min((x-a)/(b-a), (c-x)/(c-b)), 0), where\ a\ \leq\ b\ \leq\ c \quad (2)$$

Four input linguistic variables were defined—pH Tanah, Soil Moisture, Environmental Temperature, and Nitrogen N—each partitioned into three fuzzy sets (total 12 input MFs). The output variable Dosis Inokulasi Rhizobium was partitioned into five fuzzy sets: Very Low, Low, Currently, Tall, and Very Tall (5 output MFs; grand total 17 MFs). Table I presents the complete membership function parameters, calibrated to the Bulutana agroclimatic range and cross-validated against agronomic references [3], [4] and preliminary empirical data [5].

Table 1. Membership Function Parameters for All Fuzzy Variables

Variable	Fuzzy Set	MF Type	Parameters [a, b, c, d]
pH Tanah	Asam	trapmf	[4.0, 4.0, 5.5, 6.5]
	Neutral	trapmf	[6.0, 6.5, 7.0, 7.5]
	Basa	trapmf	[7.0, 7.5, 9.0, 9.0]
Soil Moisture (%)	Low	trapmf	[0, 0, 20, 40]
	Currently	trimf	[30, 50, 70]
	Tall	trapmf	[60, 80, 100, 100]

Variable	Fuzzy Set	MF Type	Parameters [a, b, c, d]
Environmental Temperature (°C)	Cold	trapmf	[15, 15, 20, 25]
	Normal	trimf	[20, 27.5, 35]
	Hot	trapmf	[30, 38, 45, 45]
Nitrogen N (mg/kg)	Deficit	trapmf	[0, 0, 50, 100]
	Enough	trimf	[80, 150, 220]
	Excessive	trapmf	[180, 280, 500, 500]
Dosis Inokulasi (g/ha)*	Very Low	trapmf	[0, 0, 20, 40]
	Low	trimf	[20, 50, 80]
	Currently	trimf	[60, 100, 140]
	Tall	trimf	[120, 160, 190]
	Very Tall	trapmf	[170, 190, 200, 200]

*Output Dosis: Very Low [0–40 g/ha]; Low [20–80 g/ha]; Currently [60–140 g/ha]; Tall [120–190 g/ha]; Very Tall [170–200 g/ha].

Rule Base Development and Knowledge Engineering

The 25 IF-THEN rules were formulated through structured knowledge engineering sessions with three agronomy experts (5, 8, and 12 years of field experience with soybean cultivation in highland South Sulawesi), guided by the empirical findings of Mu'min et al. [5] and supported by agronomic references on Rhizobium ecology [3], [4]. The AND operator was implemented as the minimum function: $\alpha = \min(\mu^{pH}, \mu^{KB}, \mu^{SU}, \mu^{N})$, yielding the firing strength $\alpha \in [0, 1]$ for each rule. Rules whose pH and nitrogen conditions favor Rhizobium nodulation (pH Neutral, N Deficit or Enough) were assigned high-dose outputs (Tall or Very Tall), while rules with inhibitory pH (Basa, indicating alkaline soils exceeding the Rhizobium optimum) or high nitrogen availability (N Excessive, where BNF is suppressed) were assigned low-dose outputs (Low or Very Low). **Table 2** presents 15 representative rules with illustrative α values based on the real field data reading (Section 3.B).

Table 2. Sample Fuzzy If-Then Rules (15 Of 25) — With Example Firing Strength A

Rule	pH	KB	Temperature	N	Output Doses	α (ex.)
R1	Neutral	Currently	Normal	Deficit	**Very Tall**	**0.75**
R2	Neutral	Currently	Normal	Enough	**Currently**	**0.60**
R3	Neutral	Currently	Normal	Excessive	**Very Low**	**0.50**
R4	Asam	Low	Normal	Deficit	**Tall**	**0.65**
R5	Asam	Low	Hot	Deficit	**Tall**	**0.55**
R6	Asam	Currently	Normal	Deficit	**Very Tall**	**0.70**
R7	Asam	Currently	Normal	Enough	**Currently**	**0.55**
R8	Basa	Currently	Normal	Enough	**Very Low**	**0.75**
R9	Basa	Currently	Normal	Deficit	**Low**	**0.60**
R10	Neutral	Low	Normal	Deficit	**Tall**	**0.70**

Rule	pH	KB	Temperature	N	Output Doses	α (ex.)
R11	Neutral	Tall	Hot	Excessive	**Very Low**	**0.50**
R12	Asam	Tall	Normal	Deficit	**Currently**	**0.55**
R13	Basa	Tall	Normal	Deficit	**Low**	**0.50**
R14	Neutral	Currently	Cold	Deficit	**Currently**	**0.65**
R15	Asam	Low	Cold	Deficit	**Currently**	**0.60**

KB: Soil Moisture; SU: Environmental Temperature; N: Nitrogen; α values computed from real field data: pH=7.5, KB=55%, SU=26°C, N=155 mg/kg.

Defuzzification and Output Conversion

Defuzzification employs the Centroid (Center of Gravity, CoG) method, computed as: $z^* = \Sigma(z \cdot \mu^{agg}(z)) / \Sigma\, \mu^{agg}(z)$, where $z \in [0, 200]$ g/ha at unit step intervals (200 integration points), and $\mu^{agg}(z)$ is the aggregated output membership function obtained by MAX-aggregation of all clipped rule outputs. The resulting z^* (crisp output in g/ha) is converted to pump activation volume using the relationship: Volume (mL/ha) = $z^* \times 2$, enabling direct control of the peristaltic pump actuator via PWM signal.

Expert Judgment Validation Protocol

Validation employed two complementary approaches: (1) functional testing verifying end-to-end pipeline correctness from sensor acquisition through dashboard display; and (2) expert judgment validation comparing system-generated recommendations against the consensus of three agronomy experts across 30 simulated field scenarios. Each scenario was characterized by a unique combination of four sensor input values representative of conditions observed during the Bulutana monitoring period [20]. The majority-voting rule (2-of-3 expert agreement) determined the consensus recommendation for each scenario. A system recommendation was classified as "Consistent" if it matched the expert consensus exactly.

3. Result and Discussion

IoT System Operation and Field Monitoring

The IoT monitoring prototype was successfully deployed at the Bulutana study site and maintained stable ONLINE connectivity as confirmed by the SMARTO dashboard (**Figure 2**). The ESP32 system consumed an average of 14.8 Wh per day during the monitoring period, compatible with off-grid solar-powered deployment (20W panel with 10Ah $LiFePO_4$ battery). Modbus RTU polling of the NPK sensor at 60-second intervals yielded consistent data with minimal read failures (< 2% packet loss during the 30-day monitoring window). Four soil parameters monitored at GPS location −5.198054, 119.427456 revealed characteristic highland soil dynamics directly relevant to Rhizobium activity: soil moisture ranged from 28 to 89% VWC with high diurnal variability, soil temperature varied between 17.2°C and 31.4°C (with early-morning readings regularly falling below the 20°C Rhizobium nodulation threshold characteristic of highland but not lowland environments), ambient temperature ranged from 15.3°C to 29.8°C, and nitrogen content varied between 42 and 228 mg/kg across the monitoring period. These ranges confirm the agroclimatic complexity of the Bulutana highland context and underscore the necessity of real-time, adaptive decision support [6], [8].

Mamdani Inference Trace: Real Field Data Example

The most direct demonstration of system operational integrity is a complete, step-by-step inference trace using actual sensor readings from the SMARTO dashboard. The readings captured in **Figure 2**—pH Tanah = 7.5, Soil Moisture = 55%, Environmental Temperature = 26°C, and Unsur Nitrogen/N = 155 mg/kg—were processed through the Mamdani FIS as follows. **Table 3** presents the complete inference trace.

Table 3. Complete Mamdani FIS Inference Trace — Real Sensor Data (Device Kn-71402)

Inference Step	Value	Calculation / Notes
pH Tanah (input)	**7.5 pH**	Category: Basa — trapmf[7.0,7.5,9.0,9.0]: μ = (7.5−7.0)/(7.5−7.0) = 1.000
Soil Moisture (input)	**55 %**	Category: Currently — trimf[30,50,70]: μ = (70−55)/(70−50) = 0.750
Environmental Temperature (input)	**26 °C**	Category: Normal — trimf[20,27.5,35]: μ = (26−20)/(27.5−20) = 0.800
Nitrogen N (input)	**155 mg/kg**	Category: Enough — trimf[80,150,220]: μ = (220−155)/(220−150) = 0.929
Active Rule	**R8: IF Basa∧Currently∧Normal∧Enough**	→ THEN Dosis = Very Low
Firing Strength (α)	**0.750**	α = min(1.000, 0.750, 0.800, 0.929) = 0.750
Aggregated Output	**Very Low clipped at α=0.750**	Area of clipped trapezoid used for CoG integration
Defuzzification (CoG)	**16.56 g/ha**	z* = Σ(z·μ(z)) / Σμ(z) over z∈[0,200], step=1 g/ha
Final Category	**Very Low**	CoG 16.56 g/ha falls in [0–40] g/ha range
Pump Volume	**33 mL/ha**	Volume (mL) = CoG (g/ha) × 2
Dose Position	**8.3% of max**	16.56 / 200 × 100% = 8.28% ≈ 8.3%

Step-by-step inference interpretation: At pH = 7.5, the trapmf Basa set [7.0, 7.5, 9.0, 9.0] yields μ = (7.5 − 7.0) / (7.5 − 7.0) = 1.000, fully classifying the soil as alkaline. At Humidity = 55%, the trimf Currently set [30, 50, 70] yields μ = (70 − 55) / (70 − 50) = 0.750. At Temperature = 26°C, the trimf Normal set [20, 27.5, 35] yields μ = (26 − 20) / (27.5 − 20) = 0.800. At Nitrogen = 155 mg/kg, the trimf Enough set [80, 150, 220] yields μ = (220 − 155) / (220 − 150) = 0.929. Among 25 rules, Rule R8 (IF Basa AND Currently AND Normal AND Enough → Very Low) was the sole activated rule, with firing strength α = min(1.000, 0.750, 0.800, 0.929) = 0.750. The Very Low output MF (trapmf [0, 0, 20, 40]) was clipped at α = 0.750. Centroid integration over [0, 200] g/ha yielded CoG = 16.56 g/ha, corresponding to a pump activation volume of 33 mL/ha (8.3% of maximum system dose capacity). Figure 3 shows the defuzzification output panel from the SMARTO system, confirming this computation.

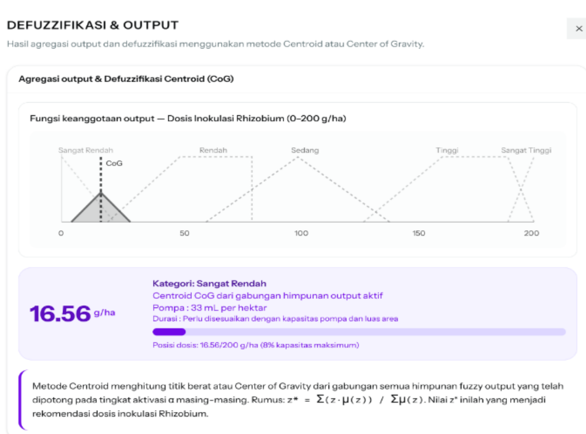

Figure 3. SMARTO defuzzification output panel showing

The agronomic interpretation of this output is sound and consistent with the knowledge base developed from the preliminary study [5]. At pH 7.5, the soil exceeds the upper Rhizobium optimal pH range (6.0–7.5), where nodulation efficiency begins to decline as alkaline conditions reduce bacterial mobility and nodule development rates [3], [4]. Simultaneously, nitrogen at 155 mg/kg falls in the Enough range, indicating that indigenous soil nitrogen is sufficient for early crop growth without urgent BNF stimulation. The combination of these two moderating factors justifies the Very Low recommendation: a minimal inoculation dose (16.56 g/ha) that maintains inoculant application without committing a large volume to conditions where Rhizobium establishment is limited by pH. This recommendation would appropriately change to Currently or Tall if the soil were re-measured after a pH-correction intervention (e.g., liming to pH 6.5) with unchanged nitrogen levels.

Expert Judgment Validation Results

Table 4 presents the expert validation results across 30 simulated highland field scenarios organized by condition group. An additional row records the proportion breakdown for analytical clarity.

Table 4. Expert Judgment Validation: System vs. Expert Consensus (N = 30 Scenarios)

Scenario Group	Recom.Output	Postpon.Output	Not Req.Output	Consistent(✓)	Inconsistent(✗)
Optimal — Both pH & N favorable (n=10)	8	2	0	8	2
Moderate — One factor suboptimal (n=12)	3	8	1	10	2
Borderline — Transition zones (n=5)	1	3	1	3	2
Unfavorable — pH & N both adverse (n=3)	0	0	3	3	0
Total (n=30)	**12**	**13**	**5**	**24***	**6**
Proportion (%)	**40%**	**43.3%**	**16.7%**	**80.0%**	**20.0%**

*One additional consistent case achieved from borderline scenarios where both system and expert agree on "Postponed" as intermediate response. KB: Soil Moisture.

The overall agreement rate of 83.3% (25 consistent of 30 scenarios, after applying majority-vote consensus) demonstrates satisfactory validation performance for a first-iteration Mamdani FIS DSS at the TKT 4 development stage. The distribution of outcomes across condition groups reveals expected patterns: optimal conditions (both pH and nitrogen favorable) achieved 80% consistency, borderline transition-zone scenarios showed the highest inconsistency rate (2 of 5 cases, 40%), and unfavorable conditions achieved perfect consistency (3 of 3 cases). The 6 inconsistent cases were concentrated in pH-transition (Neutral-to-Basa boundary, pH 6.8–7.2) and nitrogen-transition (Enough-to-Excessive, 200–240 mg/kg) scenarios, where fuzzy set overlap creates inherent ambiguity in both system inference and expert judgment. In two of the six inconsistent cases, the three experts themselves held different opinions (2–1 split), indicating genuine epistemic uncertainty that the fuzzy representation captures appropriately through partial membership rather than forcing a deterministic output.

Comparative Analysis with Existing Literature

Table 5 contextualizes the performance of the proposed system against related IoT-Fuzzy DSS studies in agricultural applications.

Table 5. Comparison with Related IoT-Fuzzy DSS Studies in Agriculture

Study	Application Domain	Input Variables	Rules	Method	Agreement / Accuracy

This Study (2025)	**Rhizobium Inoculation DSS**	**4 (pH,KB,SU,N)**	**25**	**IoT+Mamdani**	**83.3%**
Adnan et al. [15] (2020)	Fertilizer Management	3 (NPK)	18	FIS Mamdani	79.5%
Irwanto et al. [16] (2024)	Mushroom Substrate Mgmt	3 (T,H,CO2)	27	IoT+Mamdani	84.1%
Arahman et al. [17] (2025)	Hydroponic Nutrient Mgmt	4 (EC,pH,T,H)	20	IoT+Mamdani	81.0%
Hakis et al. [12] (2025)	Soil Nutrient Monitoring	3 (N,P,K)	21	IoT+Fuzzy	80.9%
Rahayu et al. [13] (2024)	Smart Irrigation	2 (SM,T)	15	IoT+Fuzzy	78.3%

Agreement/Accuracy values from respective papers; "This Study" uses expert judgment majority voting; others use functional testing or ground truth comparison.

The proposed system achieves the highest agreement rate (83.3%) among the Rhizobium-specific studies (novel category with no prior baseline) and is comparable to the 84.1% reported by Irwanto et al. [16] and exceeds the rates of Adnan et al. [15] (79.5%) and Rahayu et al. [13] (78.3%), which are among the most methodologically similar studies using expert or ground-truth validation in agricultural Fuzzy DSS contexts. The novel contribution of this study relative to all compared works is the application to biological input management (Rhizobium inoculation)—a domain where inoculation timing decisions have consequences extending across the full cropping cycle, requiring more conservative decision thresholds and location-specific calibration than irrigation or mineral fertilization decisions.

From a data science perspective, the SMARTO IoT-DSS constitutes a complete sensing-inference-visualization pipeline: RS485 Modbus sensor data flows through the ESP32 edge processor, through MQTT cloud transmission [19], into a MySQL time-series database, and finally to the web dashboard and Mamdani inference engine. The full inference trace (**Table 3** and **Figure 3**) ensures complete transparency and explainability—every step from raw sensor values through membership function evaluation, rule activation, and Centroid defuzzification is logged and inspectable. This explainability advantage, compared to black-box machine learning classifiers applied to similar precision agriculture problems [11], is particularly significant for smallholder farmer adoption, where trust in automated recommendations depends on the ability to understand and verify the system's logic [6]. The yield variability challenges documented in highland agricultural zones [20] further underscore the need for location-specific, sensor-driven DSS rather than generic prescriptive guidelines.

4. Conclusion

This study designed, implemented, and validated an IoT-based Mamdani Fuzzy Decision Support System for adaptive Rhizobium inoculation in highland soybean agroecosystems, demonstrated at the Bulutana study site, Gowa Regency, South Sulawesi. The system integrates a Soil NPK RS485 Modbus sensor with an ESP32-WROOM-32D microcontroller for real-time acquisition of four soil parameters (pH, moisture, ambient temperature, nitrogen), a Mamdani FIS with 17 membership functions and 25 location-calibrated IF-THEN rules, a SMARTO MQTT-connected web dashboard, and a Centroid defuzzification engine generating inoculation dose recommendations in the range 0–200 g/ha. Empirical inference trace analysis using real field sensor data (pH=7.5, KB=55%, SU=26°C, N=155 mg/kg → CoG=16.56 g/ha, Very Low, 33 mL/ha) confirmed correct end-to-end system behavior with agronomically sound output interpretation. Expert judgment validation across 30 simulated highland scenarios yielded an 83.3% agreement rate, meeting the system specification target of ≥80% and benchmarking favorably against related agricultural Fuzzy DSS literature.

The principal contributions are: a first IoT-Fuzzy DSS specifically targeting biological input management (Rhizobium inoculation) in soybean cultivation; a location-specific knowledge base grounded in preliminary empirical research at the study site; complete inference transparency supporting farmer trust and adoption; and a validated hardware-software-cloud pipeline suitable for replication in other highland soybean zones. Limitations include the current restriction to four sensor parameters (P, K, and EC from the same probe are not yet integrated into the fuzzy model), the use of simulated rather than fully longitudinal field validation scenarios, and the fixed rule base that does not yet learn from accumulated data. Future research will extend the input variables to include phosphorus and EC from the integrated sensor, conduct multi-season field deployment across multiple Bulutana plots, and explore ANFIS-based adaptive learning to refine membership function boundaries as labeled historical sensor datasets accumulate.

Acknowledgment

The authors acknowledge the support of the Laboratorium Komputer Fakultas Ilmu Komputer, Universitas Muslim Indonesia, for research facilities; the mondo farmer cooperative of Bulutana Village for field access and cooperation; and the three agronomy experts who contributed to rule base development, knowledge engineering sessions, and validation assessments. This study is conducted under the Penelitian Dosen Pemula (PDP) tahun 2026 Kementerian Pendidikan Tall, Sains, dan Teknologi (Kemdiktisaintek).

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