Implementation of soil fertility detection and crop recommendation system based on Geographic Information System (GIS) for precision agriculture

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Abstract. Accurate soil fertility detection and intelligent crop recommendation systems are fundamental to the advancement of precision agriculture, enabling data-driven decision-making for sustainable food production. However, many smallholder farmers still rely on intuition or traditional practices for crop selection, which often leads to mismatches between soil characteristics and crop requirements, resulting in inefficient input use and reduced productivity. To address this issue, this study implements an integrated Soil Fertility Detection and Crop Recommendation System based on Geographic Information System (GIS) technology. The system integrates real-time soil sensors (pH, temperature, and moisture) with a Fuzzy Mamdani inference model to classify fertility levels and generate crop recommendations visualized through a web-based GIS interface. Field testing was conducted in Kamal Village, Bangkalan, Indonesia, using multiple soil sampling points. Experimental validation showed high computational precision, with an average fuzzy system deviation of 0.00397% compared to MATLAB simulations. Sensor calibration yielded MAPE values of 0.0209% (temperature), 0.0481% (pH), and 0.0929% (moisture), while GPS testing using the BN220 module produced an average positional error of 4.1 cm. The recommendation subsystem accurately classified field conditions, identifying peanut for Field 1 and maize for Fields 2 and 3. GIS visualization effectively mapped spatial variations of soil parameters and crop suitability, confirming the system's reliability and applicability for data-driven precision agriculture.

1 Introduction

Accurate soil fertility detection and intelligent crop recommendation systems are fundamental to the advancement of precision agriculture, enabling data-driven decision-making for sustainable food production. Soil fertility serves as the foundation of crop productivity, determining nutrient availability, plant growth dynamics, and ecosystem stability. The ability to detect soil nutrient status in real time and generate site-specific crop recommendations is therefore crucial for optimizing fertilizer application, reducing input waste, and maintaining soil health [1][2].

However, in many agricultural practices, the selection of crop types is still predominantly based on farmers' intuition or inherited experience rather than systematic evaluation of soil characteristics. This traditional approach often neglects critical soil fertility parameters such as nutrient balance, temperature soil, pH level, and moisture content, resulting in mismatches between crop requirements and soil conditions [3]. Consequently, land productivity remains suboptimal, and agricultural inputs are often misallocated, leading to economic losses and environmental degradation [4][5].

Several recent studies have explored the integration of intelligent systems, sensor technologies, and spatial analysis for soil fertility assessment and crop recommendation. Literature [6] developed a fuzzy logic based framework using NPK sensors to monitor soil nutrients in real time, achieving accurate classification of fertility levels but lacking spatial visualization capabilities. Similarly, [7] utilized fuzzy inference and GIS mapping to generate soil fertility zonation maps, although the system relied primarily on laboratory data rather than direct in field measurements. Other research has incorporated Internet of Things (IoT) enabled sensors for nutrient monitoring and automated fertilizer suggestions [8], while [9] proposed a low-cost colorimetric sensing and cloud-based visualization system for nutrient recommendation. Moreover, [10][11] implemented a Mamdani type fuzzy inference system integrated with GIS to evaluate soil fertility through parameters such as pH, temperature, and moisture, demonstrating the potential of combining fuzzy logic and spatial modeling for precision agriculture applications.

Despite the notable progress achieved in integrating fuzzy logic, IoT, and GIS technologies for soil fertility analysis, several limitations persist in existing research. Most prior studies focus primarily on nutrient monitoring or spatial mapping, yet few provide an end to end framework that connects real time soil fertility detection with intelligent, site-specific crop recommendation [12][13]. Furthermore, several

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machine learning based models for crop recommendation rely on large datasets and static parameters, limiting their adaptability to dynamic environmental and soil conditions [14]. Many existing systems also depend on laboratory based data or lack adaptive inference mechanisms capable of handling uncertainty and variability in heterogeneous field environments.

Therefore, this study aims to implement a comprehensive, low cost, and field deployable system, soil fertility detection and crop recommendation System based on the Fuzzy Mamdani inference model combined with Geographic Information System (GIS) technology. The proposed system is designed to detect soil fertility in real time through three key parameters : soil pH, moisture, and temperature, serving as primary indicators of soil health and suitability. The fuzzy based inference mechanism classifies soil fertility levels and, through GIS spatial mapping, generates precise crop recommendations tailored to local soil conditions. In this study, the system focuses on five representative crop types : chili (*Capsicum annuum*), maize (*Zea mays*), rice (*Oryza sativa*), peanut (*Arachis hypogaea*), and watermelon (*Citrullus lanatus*), to demonstrate the model's applicability in diverse agricultural contexts.

The research contribution is threefold: (1) the development of an integrated framework combining real time sensor data acquisition, fuzzy inference, and GIS based spatial visualization for site-specific crop recommendation; (2) the design of a low cost, portable system suitable for field deployment in smallholder farming settings; and (3) the experimental validation of system accuracy and adaptability under real environmental conditions, demonstrating its effectiveness for data driven precision agriculture.

2 Design

The proposed system architecture, as illustrated in Fig. 1, integrates multi-sensor inputs, fuzzy logic processing, and GIS-based visualization to support precision agriculture. The sensing unit comprises a soil pH sensor, soil moisture sensor (SEN-00160), soil temperature sensor (DS18B20), and GPS BN-220 module, which collectively capture essential soil and location parameters in real time. These inputs are processed by an ESP32 microcontroller embedded with a Fuzzy Mamdani inference model that classifies soil fertility levels based on pH, moisture, and temperature parameters. The classified results and corresponding crop recommendations are displayed on a 16×2 LCD module for on-site feedback. In parallel, the processed data are transmitted to the ThingSpeak cloud server and subsequently mapped via a GIS-based web platform, enabling users to visualize soil fertility distribution and crop suitability zones interactively through a web browser interface.

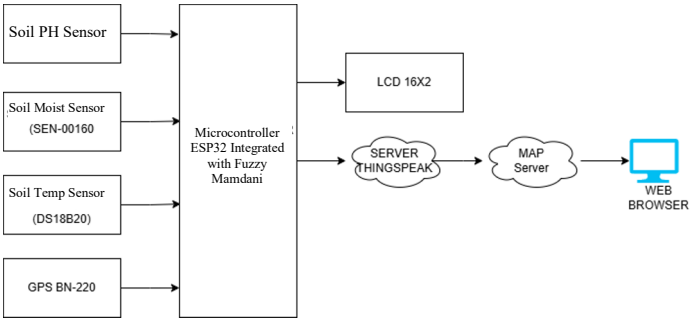


Fig. 1. The block diagram of soil fertility detection and crop recommendation system.

2.1 Hardware Design

The prototype of the proposed *Soil Fertility Detection and Crop Recommendation System* is shown in Fig. 2. The device has compact dimensions of 18.5 cm × 11.5 cm × 6.5 cm, making it portable and easy to operate in field conditions. It integrates three external soil probes pH, moisture (SEN-00160), and temperature (DS18B20), that are directly inserted into the soil during testing to capture real time fertility parameters. This configuration allows efficient data collection while maintaining practicality for field applications.

Fig. 2. The proposed system.

The circuit diagram is illustrated in Fig. 3, an ESP32 microcontroller serves as the main processing unit, managing data acquisition, fuzzy Mamdani computation, and output display via a 16×2 LCD. The system is powered by an 18650 battery regulated through an L7805CV converter to ensure a stable 5V supply. Additionally, a GPS BN-220 module provides geolocation data for GIS-based mapping and spatial analysis.

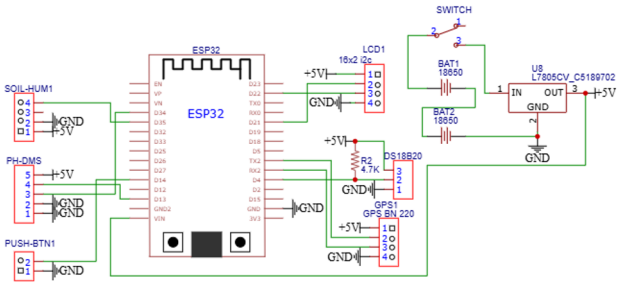


Fig. 3. Circuit diagram of the proposed system.

2.2 Software Design

The software design consists of three main stages: Fuzzy Mamdani inference, weight scoring, and GIS integration.

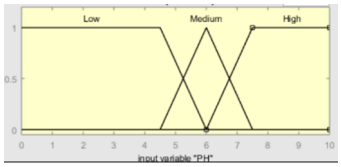
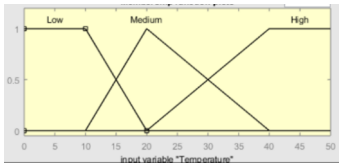
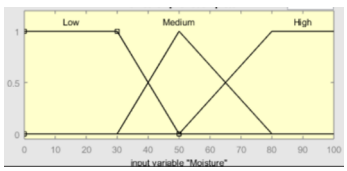
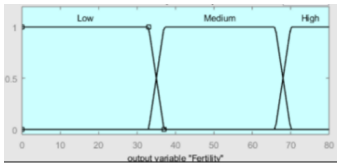
2.2.1 Fuzzy Mamdani

There are three main steps in the Fuzzy Mamdani method, namely *fuzzification*, *inference*, and *defuzzification*. In the defuzzification process, the Center of Area (CoA) method is employed, as it produces accurate numerical outputs and is widely used in control and decision-making systems [15][16].

1) Fuzzification

In this step, the input data from soil sensors are converted into fuzzy values using membership functions. There are three membership functions representing soil parameters : pH, moisture, and temperature as shown in Table 1.

Table 1. Membership function.

Membership Function of Soil PH	
	$\mu_{PHLow}(x) = \begin{cases} 1 & ,x \le 4.5 \\ \frac{6-x}{6-4.5} & ,4.5 < x < 6 \end{cases}$
	$\mu_{PHMed}(x) = \begin{cases} \frac{x-4.5}{6-4.5} & ,4.5 < x < 6 \\ 1 & ,x = 6 \\ \frac{7.5-x}{7.5-6} & ,6 < x < 7.5 \end{cases}$
	$\mu_{PHigh}(x) = \begin{cases} \frac{x-6}{7.5-6} & ,6 < x < 7.5 \\ 1 & ,x \ge 7.5 \end{cases}$
Membership Function of Soil Temperature	
	$\mu_{TempLow}(x) = \begin{cases} 1 & ,x \le 10 \\ \frac{20-x}{20-10} & ,10 < x < 20 \end{cases}$
	$\mu_{TempMed}(x) = \begin{cases} \frac{x-10}{20-10} & ,10 < x < 20 \\ 1 & ,x = 20 \\ \frac{40-x}{40-20} & ,20 < x < 40 \end{cases}$
	$\mu_{TempHigh}(x) = \begin{cases} \frac{x-20}{40-20} & ,20 < x < 40 \\ 1 & ,x \ge 40 \end{cases}$
Membership Function of Soil Moisture	
	$\mu_{MoisLow}(x) = \begin{cases} 1 & ,x \le 30 \\ \frac{50-x}{50-30} & ,30 < x < 50 \end{cases}$
	$\mu_{MoisMed}(x) = \begin{cases} \frac{x-30}{50-30} & ,30 < x < 50 \\ 1 & ,x = 50 \\ \frac{80-x}{80-50} & ,50 < x < 80 \end{cases}$
	$\mu_{MoisHigh}(x) = \begin{cases} \frac{x-50}{80-50} & ,50 < x < 80 \\ 1 & ,x \ge 80 \end{cases}$
Membership Function of Soil Fertility Levels	
	$\mu_{FerLow}(x) = \begin{cases} 1 & ,x \le 33 \\ \frac{37-x}{37-33} & ,33 < x < 37 \end{cases}$
	$\mu_{FerMed}(x) = \begin{cases} \frac{x-33}{37-33} & ,33 < x < 37 \\ 1 & ,37 \le x \le 66 \\ \frac{70-x}{70-66} & ,66 < x < 70 \end{cases}$
	$\mu_{FerHigh}(x) = \begin{cases} \frac{x-66}{70-66} & ,66 < x < 70 \\ 1 & ,x \ge 70 \end{cases}$

2) Inference

The number of rules required to determine soil fertility is 3^3 (three inputs and three fuzzy sets), resulting in a total of 27 rules, which are systematically organized as shown in Table 2.

Table 2. Rule inference.

SOIL PH	SOIL TEMP	L	M	H
L	**L**	L	M	M
L	**M**	L	M	M
L	**H**	L	M	M
M	**L**	L	M	M
M	**M**	M	M	M
M	**H**	M	M	H
H	**L**	L	M	M
H	**M**	L	M	M
H	**H**	L	M	H

L = Low, M = Medium, H = High.

3) Defuzzification

The final stage of the Fuzzy Mamdani process involves defuzzification, which is carried out using the Center of Area (CoA) method, as expressed in Equation (1) [17].

$$z^* = \frac{\int z\,\mu(z)\,dz}{\int \mu(z)\,dz} \quad (1)$$

where z^*denotes the defuzzified output value, z represents the output variable, and $\mu(z)$ is the membership function corresponding to the output fuzzy set.

2.2.2 Weight Scoring

Crop recommendations are generated using a basic fuzzy logic approach that links soil parameters to suitable crops, as shown in Table 3 [18]. When sensor readings overlap or fall outside defined ranges, an *if–*

else method combined with the Simple Additive Weighting (SAW) model and Distance-Based Similarity Function is applied to select the crop with the highest weighted score [19].

For each crop type T_i(e.g., chili, maize, rice, etc.), ideal ranges of soil pH, moisture, and temperature are defined. The score for each parameter $X$of crop T_i is calculated using the function:

Table 3. Rule crop recommendation.

Rule	Soil Moisture (%)	Soil Temperature (C)	Soil PH	Crop Recomendation
1	71 - 80	10 - 22	6.6 – 7.5	Chili
2	40 – 60	28 – 36	5.6 – 6.5	Maize
3	61 – 70	23 – 27	5.6 – 6.5	Rice
4	71 – 80	23 – 27	6.6 – 7.5	Peanut
6	61 - 70	23 - 37	5.6 – 6.5	Watermelon

$$Score_{X,i} = \frac{1}{1 + (X - T_{mid,x,i})} \quad (2)$$

where $T_{mid,X,i}$ is the midpoint of the ideal range. This score measures how close the sensor reading is to the optimal value (maximum score = 1.0). The total score for each crop is obtained by summing all parameter scores:

$$TotalScore_i = Score_{pH,i} + Score_{moisture,i} + Score_{temperature,i} \quad (3)$$

The crop with the highest total score is selected as the most suitable recommendation.

2.2.3 Geographic Information System (GIS)

The WebGIS system begins with data collection from pH, temperature, and moisture sensors equipped with GPS coordinates. The ESP32 microcontroller sends these data to the ThingSpeak cloud, which stores and visualizes them while providing a REST API for integration [20]. Using Leaflet JS, the WebGIS interface retrieves data from ThingSpeak and displays them as interactive map markers. Each marker shows detailed soil parameters and crop recommendations, supporting spatial decision-making for precision agriculture [21]. The block diagram of GIS design depicted in Fig. 4.

Fig. 4. The block diagram of GIS design.

3 Implementation and result

The implementation process involved several stages, beginning with the calibration of the pH, moisture, and temperature sensors by inserting their probes into various soil types to ensure accurate readings. This was followed by the calibration of the BN-220 GPS module to verify positional accuracy and mapping reliability. Subsequently, the Fuzzy Mamdani inference system was developed and tested in MATLAB to validate soil fertility classification and crop recommendation accuracy. These procedures were repeated until consistent results were achieved. Finally, the system was validated under real field conditions across three rice field sites in Kamal, Bangkalan, as shown in Fig. 5.

Fig. 5. Implementation the proposed system in field.

3.1 Soil PH calibration

Fig. 6 shows the comparison between soil pH values measured by the proposed system and the reference calibrator . Both data series exhibit a similar trend with very small deviations across ten measurement points, indicating strong agreement between the two methods. The obtained Mean Absolute Percentage Error (MAPE) of 0.0481% confirms the excellent accuracy and stability of the developed sensor, demonstrating its reliability and suitability for precise soil pH monitoring applications.

3.2 Soil temperature calibration

Fig. 7 presents the calibration results of soil temperature measurements between the the proposed system and the reference calibrator. The two data series exhibit a highly consistent pattern with minimal variation across all ten measurement points, indicating a strong correlation and measurement stability. The obtained Mean Absolute Percentage Error (MAPE) of 0.0209% demonstrates the excellent accuracy of the developed sensor, confirming its capability to deliver precise and reliable temperature readings comparable to the reference instrument. These results validate the sensor's effectiveness and suitability for continuous soil temperature monitoring applications.

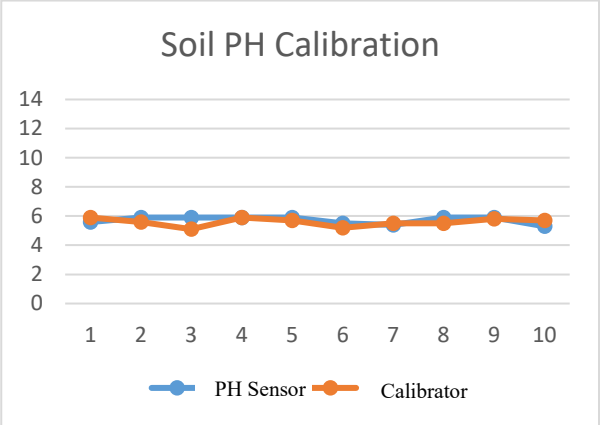


Fig. 6. PH sensor (the proposed system) vs calibrator.

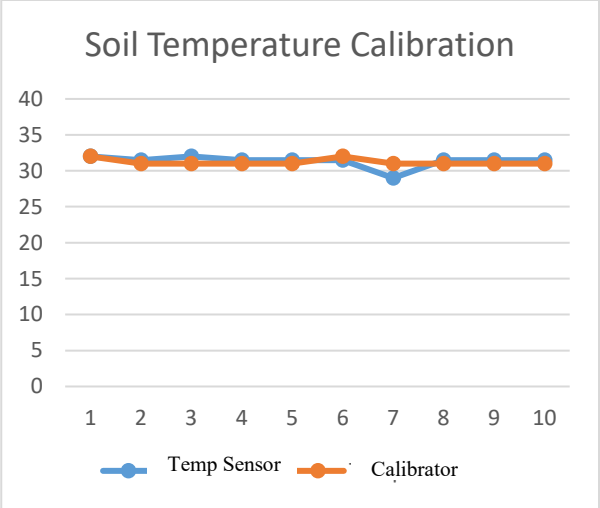


Fig. 7. Temperature sensor (the proposed system) vs calibrator.

3.3 Soil moisture calibration

Fig. 8 shows the calibration results of soil moisture measurements between the proposed system and the reference calibrator. Both data series follow a similar pattern, with slight variations observed at certain measurement points. The calculated Mean Absolute Percentage Error (MAPE) of 0.0929% indicates a high level of accuracy and consistency, confirming that the developed sensor performs reliably and is suitable for precise soil moisture monitoring applications.

3.4 GPS BN-220 calibration

Table 4 presents the calibration comparison between the BN-220 GPS module and Google Maps reference coordinates. Each test point includes latitude and longitude readings from both sources, followed by the calculated positional difference in centimeters. The results show small deviations ranging from 1.4 to 7.5 cm, with an average distance difference of 4.1 cm. This indicates that the BN-220 GPS module provides relatively high positional accuracy suitable for small-scale navigation and localization applications.

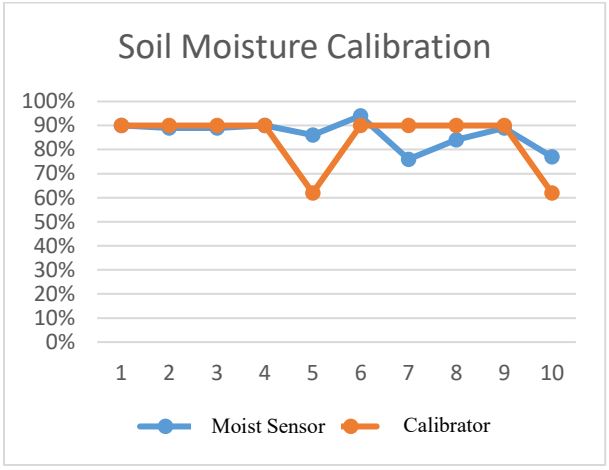


Fig. 8. Moisture sensor (the proposed system) vs calibrator.

Table 4. GPS BN-220 calibration.

No	GPS BN-220		GOOGLE MAPS		Distance Difference (cm)
	Lat	Long	Lat	Long	
1	-7.1257	112.7244	-7.1257	112.7244	2.6
2	-7.1257	112.7247	-7.1258	112.7247	4.9
3	-7.1257	112.7250	-7.1257	112.7251	4.9
4	-7.1258	112.7251	-7.1258	112.7251	3.2
5	-7.1261	112.7251	-7.1262	112.7251	3.1
6	-7.1265	112.725151	-7.126624	112.725125	4.2
7	-7.126574	112.724739	-7.126641	112.724744	7.5
8	-7.126599	112.724365	-7.126550	112.724387	6.0
9	-7.126112	112.724419	-7.126103	112.724450	3.6
10	-7.125824	112.724403	-7.125812	112.724401	1.4
AVERAGE DISTANCE DIFFERENCE (Centimeter)					**4.1**

3.5 Fuzzy mamdani calibration

Table 5 compares the output of the proposed Fuzzy Mamdani system with the reference results obtained from MATLAB under varying pH, temperature, and soil moisture conditions. The comparison includes the absolute percentage error for each test case. The results show minimal deviations between the proposed system and MATLAB, with a Mean Absolute Percentage Error (MAPE) of 0.00397%, indicating that the proposed fuzzy system achieves high accuracy and strong consistency with the MATLAB model. Therefore, the system is ready to be implemented in paddy fields for real-time environmental monitoring and control.

Compared with previous works, the proposed system demonstrates superior computational accuracy and robustness in real time soil parameter processing. Earlier studies on fuzzy logic based agricultural systems reported higher deviation values between simulation and hardware implementation. For example, study [22] developed a fuzzy logic controller for tomato irrigation and obtained a Mean Absolute Percentage Error (MAPE) of 0.24 %, indicating good performance but

with notable variation during temperature fluctuations. Similarly, [23] implemented a MATLAB Simulink based soil moisture regulation model with a deviation of 0.12 %, emphasizing the challenge of achieving consistency across diverse field conditions. Another study in [24] designed a fuzzy inference model for nitrogen estimation that achieved deviations ranging between 0.08 % and 0.15 % depending on soil texture and calibration quality. In addition, [25] utilized a Fuzzy Mamdani inference system for real time soil nutrient monitoring and achieved MAPE values between 0.10 %–0.15 %, while [26] integrated Mamdani logic in an IoT based nutrient recommendation platform, obtaining a deviation of 0.11 % under controlled environments. Another relevant study in [27] employed a Mamdani fuzzy decision model for paddy irrigation scheduling, yielding an accuracy of 98.7 % but requiring manual calibration during extreme humidity variation.

Table 5. Fuzzy Mamdani calibration.

No	PH	Temp (°C)	Moist (%)	Running Matlab	Proposed System	Absolute Percentage Error (%)
1	6.2	29.5	60	55.4	55.17	0.00415
2	5.8	28.1	59	54.7	54.52	0.00329
3	6.4	30	60	55.5	55.31	0.00342
4	5.9	35.2	60	54.7	54.53	0.00311
5	6.1	28	59	54.7	54.5	0.00366
6	6.8	26.5	71	55.3	55.05	0.00452
7	5.6	26.4	68	54.9	54.68	0.00401
8	6	28	65	56.3	55.96	0.00604
9	6.1	29	58	54.6	54.39	0.00385
10	6.3	28	60	55	54.8	0.00364
MAPE						**0,00397 %**

In contrast, the MAPE of 0.00397 % achieved in the present work signifies a substantial improvement, confirming that the optimized membership function parameters and refined rule base in the proposed Fuzzy Mamdani framework yield higher precision and better inference stability. The improvement can also be attributed to the direct integration of real time sensor data and adaptive fuzzification logic, which minimizes data latency and signal noise during field measurements. Overall, the proposed model outperforms previously reported fuzzy and IoT based frameworks in terms of computational fidelity and environmental adaptability, even when implemented on a low cost microcontroller platform.

The findings of this research confirm that combining Fuzzy Mamdani inference with real time soil sensing and GIS based visualization provides a robust, field deployable system for soil fertility analysis and crop recommendation. The negligible deviation from MATLAB validation underscores the computational efficiency of the embedded fuzzy inference system, while the GIS integration enhances spatial understanding of soil variability, an essential aspect of precision agriculture. When compared to existing fuzzy-IoT frameworks for irrigation and nutrient monitoring [22][23][24][25][26][27], the proposed system achieves not only higher accuracy but also improved operational flexibility. This can be attributed to the system's design, which focuses on in situ sensor calibration and real time data acquisition rather than dependence on laboratory based or static datasets. Such an approach allows the model to adapt dynamically to heterogeneous soil environments commonly found in tropical regions like Indonesia.

The implications of these results are twofold. First, the achieved computational precision demonstrates that a low cost, microcontroller based fuzzy inference device can reliably support decision making in smallholder precision agriculture. Second, the successful alignment of fuzzy system outputs with MATLAB simulation validates the feasibility of scaling this approach to larger farm management platforms. Nevertheless, the study's current limitation lies in its focus on only three soil parameters : pH, moisture, and temperature, while excluding major nutrient elements such as nitrogen, phosphorus, and potassium. These macronutrients are essential for a comprehensive fertility assessment. Therefore, future work should integrate multi parameter sensing and hybrid inference models, such as adaptive neuro fuzzy or deep fuzzy systems, to enhance predictive accuracy and system scalability. The present study thus contributes a technically validated, field oriented, and computationally efficient fuzzy GIS framework that advances the state of smart farming for sustainable agricultural productivity.

3.6 Implementation in field 1

According to Table 6, 78.89% of the area was classified as suitable for peanut, while 14.44% and 6.67% were recommended for chili (*Capsicum annuum*) and maize (*Zea mays*), respectively. The predominance of peanut suitability demonstrates a strong agroecological alignment, making it the most viable and sustainable crop option for the analyzed location, as illustrated in Fig. 9.

Table 6. Crop recommendation in Field 1.

Crop Recommendation	Sum	Percentage
Maize	6	6.67%
Peanut	71	78.89%
Chili	13	14.44%

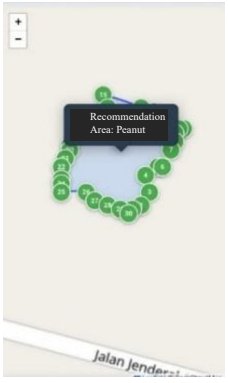


Fig. 9. GIS based crop recommendation in field 1.

3.7 Implementation in field 2

Table 7 presents the crop recommendation results derived from the suitability analysis in Paddy Field 1. The results indicate that 66.67% of the area is classified as suitable for maize (Zea mays), while 33.33% is recommended for peanut (Arachis hypogaea). This distribution suggests that the environmental conditions, such as soil fertility, texture, and moisture availability, are more favorable for maize cultivation, reflecting a strong correspondence between the site's agroecological characteristics and the crop's growth requirements.

Table 7. Crop recommendation in Field 2.

Crop Recommendation	Sum	Percentage
Maize	20	66.67%
Peanut	10	33.33%

As illustrated in Fig. 10, the GIS-based spatial visualization highlights the dominant recommendation area for maize. Each numbered marker represents a sampling point used in the suitability assessment, forming a polygon that delineates the field boundary. The concentration of maize recommendations within the area confirms the analytical results presented in Table 1, emphasizing maize as the most viable and sustainable crop option for this site.

Fig. 10. GIS based **c**rop recommendation in field 2.

3.8 Implementation in Field 3

Table 8. Crop recommendation in Field 3.

Crop Recommendation	Sum	Percentage
Maize	19	63.33%
Peanut	5	16.67%
Rice	2	6.67%
Watermelon	4	13.37

Table 8 presents the crop suitability results for the analyzed area, showing that maize (Zea mays) dominates with 63.33%, followed by peanut (Arachis hypogaea) at 16.67%, watermelon (Citrullus lanatus) at 13.33%, and rice (Oryza sativa) at 6.67%. As illustrated in Fig. 11, the GIS-based spatial visualization identifies maize as the most suitable crop within the field, where clustered sampling points delineate the recommended cultivation zone. This spatial pattern confirms that the environmental characteristics of the area are highly compatible with maize growth requirements.

Fig. 11. GIS based **c**rop recommendation in field 3

4 Conclusion

This study presents the implement of an integrated soil fertility detection and crop recommendation system combining the Fuzzy Mamdani inference model with GIS technology to advance precision agriculture. The system achieved high computational precision, with sensor calibration errors below 0.1%, a GPS positional deviation of 4.1 cm, and a mean absolute percentage error (MAPE) of 0.00397% compared to MATLAB simulations. Field validation in Kamal, Bangkalan, demonstrated its reliability, as GIS-based visualization accurately identified crop suitability : peanut for Field 1 and maize for Fields 2 and 3. Theoretically, this research contributes a validated framework for embedding fuzzy inference into low cost, real time, and spatially adaptive decision support systems. The findings highlight the system's potential to enhance site-specific agricultural management through data-driven recommendations. However, the current model is limited to three soil parameters (pH, moisture, and temperature). Future work will incorporate macro nutrient sensors and hybrid inference models, such as neuro fuzzy systems, to improve scalability, predictive accuracy, and applicability across diverse agroecological conditions.

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