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Design Of Fuzzy Mamdani in The Soil Fertility Monitoring System for Corn Crops

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Abstract

.Soil fertility is an important factor that affects the growth and productivity of corn plants. Soil fertility assessments that are still carried out manually often produce different interpretations because they are influenced by the subjectivity of the observer. This study aims to design a soil fertility monitoring system using the Mamdani fuzzy logic method implemented through the MATLAB Fuzzy Logic Toolbox. The system uses three input parameters, namely soil pH, soil moisture, and soil temperature, with the output being the level of soil fertility. The data processing stages include fuzzification, application of IF–THEN-based rules, aggregation, and defuzzification using the centroid method to produce a definite output value. Simulation results show that the system is able to classify soil conditions into infertile, moderately fertile, and fertile categories consistently. The developed system can help users understand soil conditions more objectively and support decision-making in corn field management. Thus, the Mamdani fuzzy method is effective in processing uncertain environmental parameters into measurable information.

Keywords: soil fertility; fuzzy Mamdani; soil monitoring; corn plants; MATLAB

INTRODUCTION

Soil fertility is a major factor that determines the success of plant growth and productivity because it is related to the soil's ability to provide the nutrients needed by plants. Intensive land use without proper management can cause a decline in soil nutrient content, which in turn affects agricultural production. Therefore, evaluating soil fertility is an important step in supporting sustainable agricultural land management (Sriwahyuni et al., 2025).

In corn cultivation, soil fertility is a key indicator in determining land suitability and potential crop yields. Corn is a strategic food commodity that plays an important role in food security, so proper land management is essential. Land suitability evaluation is conducted to determine the actual condition of the soil and limiting factors that affect plant growth, such as nutrient availability and soil acidity (Suryawijaya et al., 2024).

Previous studies have analyzed soil fertility using conventional approaches, such as laboratory testing, field surveys, and geographic information system-based mapping. These methods provide detailed information on soil conditions, but they still have limitations in processing complex and uncertain parameters simultaneously (Sriwahyuni et al., 2025).

With the development of precision agriculture technology, artificial intelligence-based methods are beginning to be applied to assist in the decision-making process in evaluating soil conditions. One of the most widely used methods is fuzzy logic because it is capable of processing uncertain data and uses a linguistic approach that approximates real conditions in the field. Recent research shows that the fuzzy approach can improve the accuracy of soil fertility mapping and support precision agriculture systems in land nutrient management (Navalakhe et al., 2025).

However, most previous studies still focus on partial soil fertility analysis and have not integrated key environmental parameters that can be measured directly in the field. Parameters such as soil pH, soil moisture, and soil temperature are strongly correlated in determining soil fertility levels, but are rarely analyzed simultaneously in a fuzzy-based monitoring system. This indicates a research gap that needs to be further developed.

Based on these issues, this study aims to design a corn soil fertility monitoring system using the Mamdani fuzzy logic method by utilizing soil pH, soil moisture, and soil temperature as input variables, and soil fertility level as output. The novelty of this study lies in the integration of several key environmental parameters into a single fuzzy-based decision-making system that is capable of producing soil fertility classifications that are more objective, rapid, and consistent.

METHODS

This study uses a quantitative approach with the Mamdani fuzzy logic-based system modeling method to design a soil fertility monitoring system for corn crops. This method was chosen because it is capable of processing uncertain data and accommodating environmental variables that have unclear value limits. The study focused on developing a simulation model using MATLAB Fuzzy Logic Toolbox as the main tool in system design.

The research objects are soil environmental parameters that affect soil fertility levels, namely soil pH, soil moisture, and soil temperature as input variables, and soil fertility levels as output variables. The data used in this study is secondary data obtained from a literature review of various scientific journals related to soil fertility and optimal corn growth conditions. The range of values for each parameter is determined based on agronomic standards and previous research results.

The research procedure begins with the identification of research variables and the determination of the range of values for each parameter. The next stage is the design of membership functions for each variable using triangular and trapezoidal curves that are adjusted to the characteristics of the data. After that, a rule base is compiled in the form of IF-THEN rules that represent the relationship between input and output variables based on expert knowledge and previous research references.

The data processing stages in the Mamdani fuzzy system include the fuzzification process, which converts input values into degrees of membership in each fuzzy set. Next, the inference process is carried out using the MIN logic operator on rule implications and the MAX operator on rule result aggregation. The final stage is defuzzification using the centroid method to produce definite output values in the form of soil fertility levels.

Data analysis was performed through system simulation using MATLAB Fuzzy Logic Toolbox to test the model's performance in classifying soil fertility levels based on input value combinations. The simulation results were then analyzed descriptively to determine the system's ability to produce consistent and representative decisions regarding actual conditions in the field. The Mamdani fuzzy logic method used in this study refers to the concept developed by Zadeh (1965) and the implementation of fuzzy inference systems described by Ross (2010).

The soil fertility monitoring system in this study was designed using an ESP32 microcontroller as the data processing center. The ESP32 was chosen based on its ability to process digital and analog signals simultaneously, making it suitable for sensor-based monitoring systems. This system uses three main types of sensors, namely soil pH sensors, soil moisture sensors, and DHT22 sensors. Soil pH sensors function to measure soil acidity levels, which play an important role in the availability of nutrients for plants. Soil moisture sensors are used to determine the water content in the soil, which is related to plant growth conditions. Meanwhile, the DHT22 sensor is used to measure the ambient temperature, which affects root activity and biological processes in the soil. All sensors are connected to the ESP32 via the appropriate digital and analog pins to ensure stable data acquisition. The combination of these

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components allows the system to obtain key soil parameters, which are then used to determine soil fertility status using fuzzy logic.

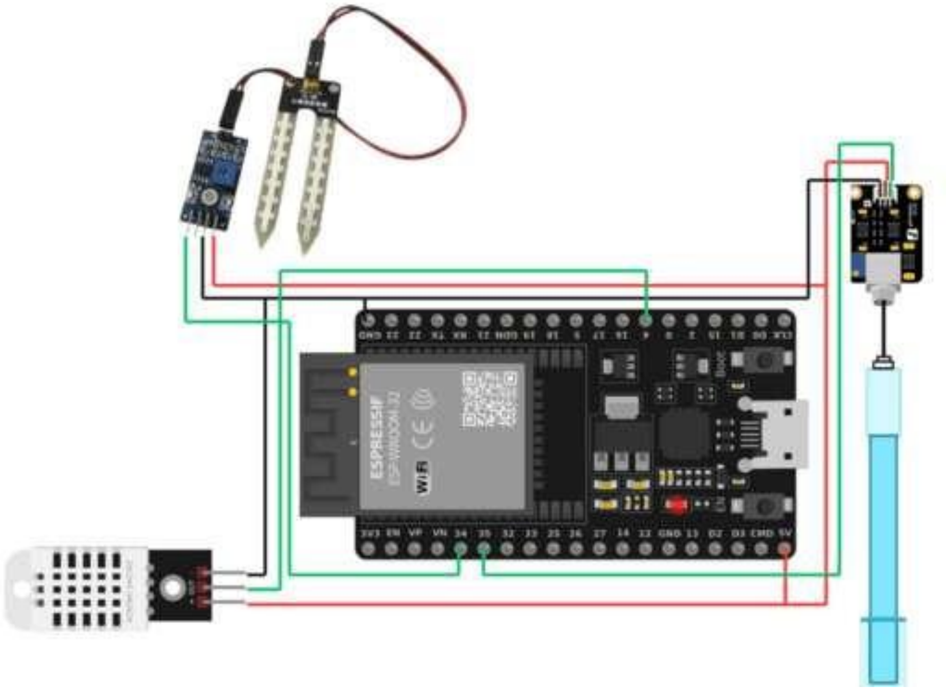

Figure 1. Hardware Wiring Configuration of Soil Fertility Monitoring System Using ESP32

Table 1. ESP32 Pin Configuration for Soil Fertility Monitoring System

No.	Component	Sensor Pin	ESP32 Pin	Pin Type	Description
1	ESP32 Dev Module	—	—	—	Main control unit
2	DHT22	VCC	3V3	Power	Sensor power supply
		DATA	GPIO 4	Digital Input	Temperature & humidity data
		GND	GND	Ground	Common ground
3	Soil Moisture Sensor Y-69	VCC	3V3	Power	Sensor power supply
		AO	GPIO 34	Analog Input (ADC)	Soil moisture analog value
		GND	GND	Ground	Common ground
4	Soil pH Sensor	VCC	3V3	Power	Sensor power supply
		AO	GPIO 35	Analog Input (ADC)	Soil pH analog value
		GND	GND	Ground	Common ground

1. Formation of Fuzzy Sets and Input Variables

In the initial stage of system design, all input and output variables are represented in the form of fuzzy sets. The input variables used in this study include soil pH, soil moisture (%), and soil temperature (°C), each of which is expressed using specific linguistic terms. Soil pH variables are classified into Acidic, Neutral, and Alkaline sets; soil moisture is grouped into Dry, Moist, and Wet; while soil temperature is divided into Low, Normal, and High categories. Meanwhile, the output variable in the form of soil fertility status is defined using fuzzy sets of Not Fertile, Less Fertile, Fertile, and Very Fertile. The definition of these fuzzy sets aims to accommodate uncertainty and variation in sensor measurement values, so that the fuzzy inference system is able to produce decisions that are more adaptive and closer to human assessment methods.

Table 2. Variable Input Membership Function

Type	**Variabel**	**Fuzzy Set**	**Conversation Universe**	**Domain [a, b, c, d]**
Input	pH	Acid	4 – 8,5	[4.0, 4.0, 5.0, 6.0]
		Neutral		[5.5, 6.5, 6.5, 7.5]
		Base		[7.0, 7.8, 7.8, 8.5]
	Humidity (%)	Dry	0 – 100	[0, 0, 25, 50]
		Valley		[40, 60, 60, 75]
		wet		[70, 85, 85, 100]
	Temperature(°C)	Low	15 – 40	[15, 15, 20, 25]
		Normal		[24, 28, 28, 32]
		High		[30, 35, 35, 40]

Table 3. Variable Output Membership Function

Type	Variabel	Fuzzy Set	Conversation Universe	Domain [a, b, c, d]
Output	Fertility	Infertile	0 – 100	[0, 25, 50]
		Fertile		[40, 60, 80]
		Very Fertile		[70, 85, 100]

Soil fertility in agriculture can be determined through several key parameters, particularly soil pH and soil moisture (Putera et al., 2023). Soil acidity affects nutrient availability, with plants growing optimally at a pH of 6.5–7.5 because nutrients are easily absorbed under these conditions (Ikhtiar et al., 2020; Morseleno, 2021). In addition, soil moisture also plays an important role in supporting plant growth and determining agricultural soil conditions. Therefore, soil pH and moisture parameters can be used as input variables in a fuzzy logic system to produce output in the form of soil fertility status.

Table 4. Fuzzy System Input–Output Rules

No	pH	Humidity	Tempera ture	Fertility
1	Acid	Dry	Low	Infertile
2	Acid	Dry	Normal	Infertile
3	Acid	Dry	High	Infertile
4	Acid	Damp	Low	Infertile
5	Acid	Damp	Normal	Infertile
6	Acid	Damp	High	Infertile
7	Acid	Wet	Low	Infertile
8	Acid	Wet	Normal	Infertile
9	Acid	Wet	High	Infertile
10	Neutral	Dry	Low	Infertile
11	Neutral	Dry	Normal	Infertile
12	Neutral	Dry	High	Infertile
13	Neutral	Damp	Low	Fertile
14	Neutral	Damp	Normal	Very Fertile
15	Neutral	Damp	High	Fertile
16	Neutral	Wet	Low	Fertile
17	Neutral	Wet	Normal	Fertile
18	Neutral	Wet	High	Infertile
19	Base	Dry	Low	Infertile
20	Base	Dry	Normal	Infertile
21	Base	Dry	High	Infertile
22	Base	Damp	Low	Fertile
23	Base	Damp	Normal	Fertile
24	Base	Damp	High	Infertile
25	Base	Wet	Low	Infertile
26	Base	Wet	Normal	Infertile
27	Base	Wet	High	Infertile

RESULTS AND DISCUSSION

Based on these issues, this study aims to design a corn soil fertility monitoring system using the Mamdani fuzzy logic method by utilizing soil pH, soil moisture, and soil temperature as input variables, and soil fertility level as output. The novelty of this study lies in the integration of several key environmental parameters into a single fuzzy-based decision-making system that is capable of producing soil fertility classifications that are more objective, rapid, and consistent.

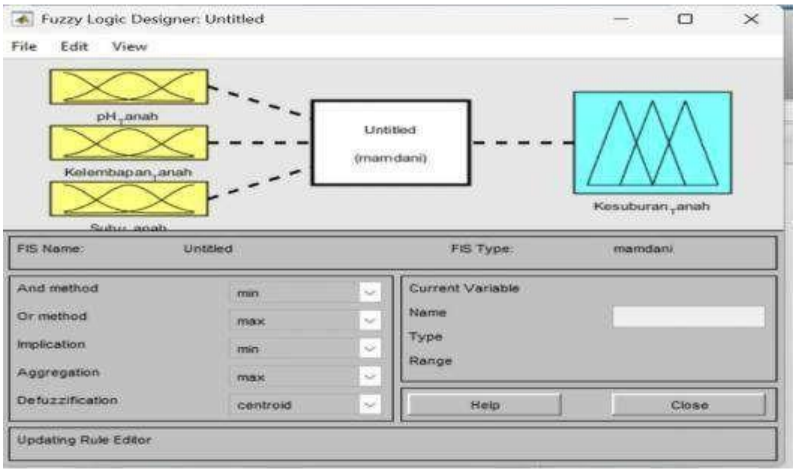

Figure 2. Structure of the Mamdani Fuzzy Inference System (FIS) for Determining Soil Fertility

A. Fuzzification of Input Variables

1) Soil pH

The soil pH membership function plot defines three fuzzy sets, namely Acid, Neutral, and Base. The Neutral set is represented as a central set that covers the optimal pH range for plant growth, where pH values in that range have the highest membership degree. The pH values measured by the sensor are mapped to the fuzzy membership function so that each pH value can have a membership degree in one or more linguistic sets gradually. For example, a soil pH value of 6.8 is in the dominant area of the Neutral set, resulting in a μ(Neutral) value close to 1, while the membership degree in the Acid and Base sets is smaller. The membership curve shows that pH values below the optimal range will gradually transition towards the Acid set, while pH values above that range will shift towards the Base set. This fuzzification approach allows for a more flexible and realistic representation of soil pH conditions, in line with the fuzzy membership concept which states that the optimal pH value has high membership in the Neutral category and gradually decreases towards the Acid or Base categories for more extreme values (Baskoro, 2008).

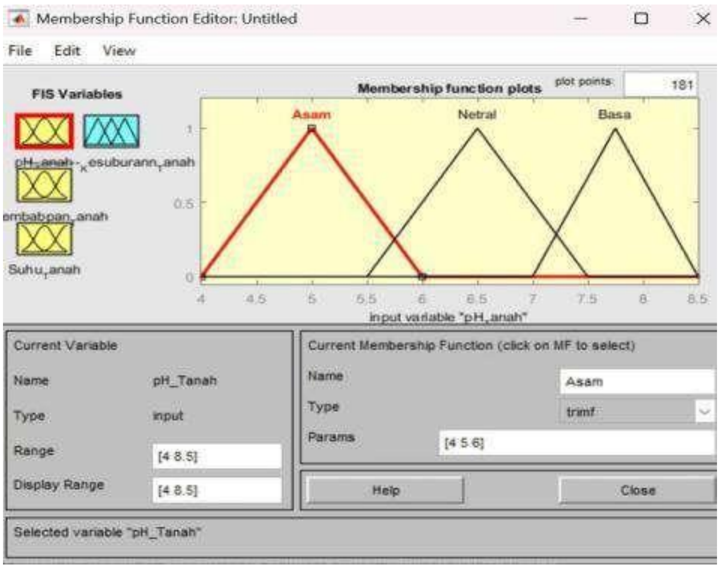

Figure 3. Membership function graph for the variable input "pH"

2) Soil Moisture (%)

The soil moisture membership function plot defines three fuzzy sets, namely Dry, Moist, and Wet. The Moist set is represented as a middle category that covers the optimal moisture range for corn growth, where the soil conditions are neither deficient nor excessive in water. The soil moisture values obtained from the sensor are then mapped to the fuzzy membership function so that each value can have a membership degree in more than one set gradually. For example, if the soil moisture value is 65%, then that value is in the dominant range of the Moist set, resulting in a high μ(Moist), while the membership degree in the Dry and Wet sets is relatively smaller. The membership curve shows that lower moisture values will gradually transition to the Dry category, while higher values move towards the Wet category. This approach allows the fuzzy system to represent variations in soil moisture content continuously, which is important in evaluating agricultural conditions because soil moisture greatly affects plant growth and productivity (Putera et al., 2023).

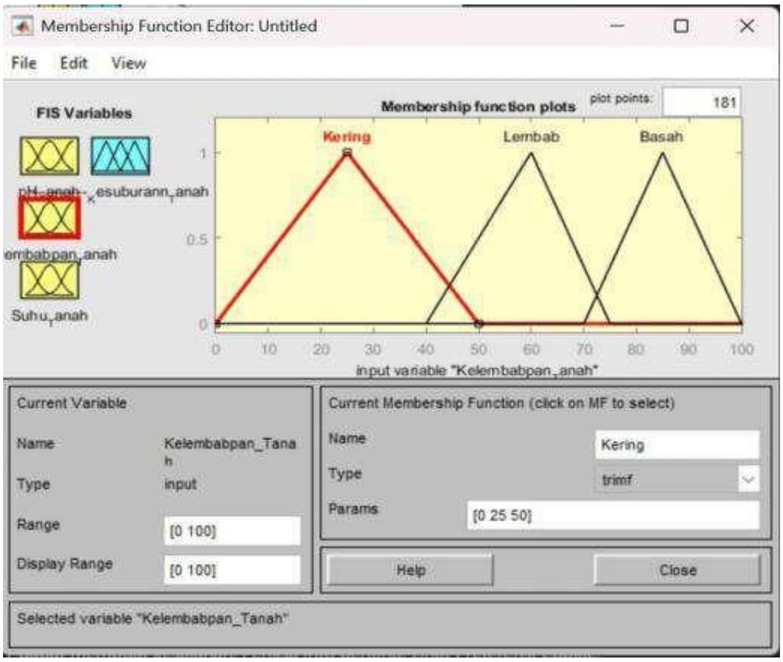

Figure 4. Membership function graph for the variable input "Moisture"

3) Soil Temperature (°C)

The soil temperature membership function plot defines three fuzzy sets, namely Low, Normal, and High. The Normal set is the central set that represents the optimal soil temperature range for corn growth, where plant physiological activity and nutrient absorption can occur optimally. The measured soil temperature values are then mapped to the fuzzy membership function so that each temperature value has a certain degree of membership in one or more linguistic sets. For example, a soil temperature of 27 °C is in the dominant area of the Normal set, resulting in a high μ(Normal) value, while the degrees of membership in the Low and High sets are smaller. The membership curve shows that temperatures below the optimal range will gradually transition to the Low category, while temperatures exceeding the optimal limit will shift to the High category. This fuzzification approach allows for a more realistic and flexible representation of soil temperature conditions, in line with the agronomic concept that soil temperature is an important factor affecting root growth, soil microorganism activity, and nutrient availability for plants (Hillel, 2004).

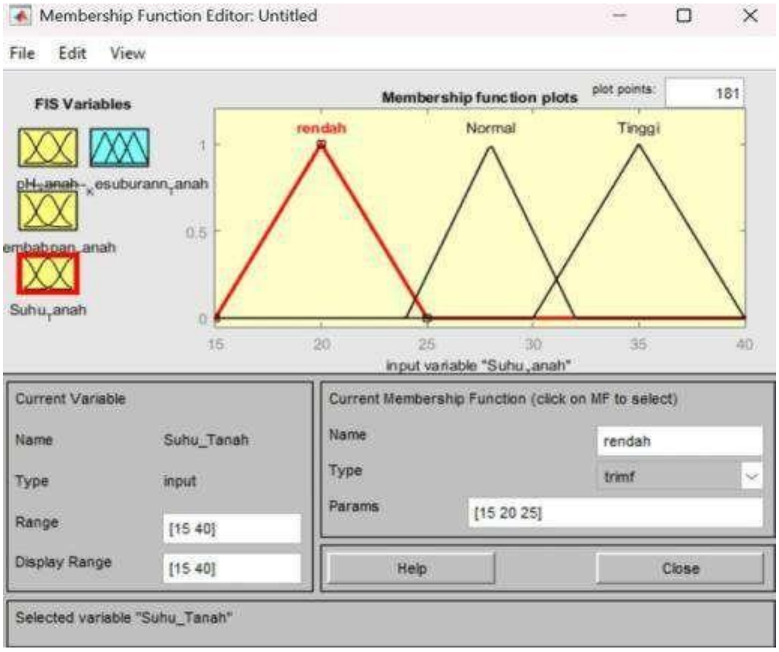

Figure 5. Membership function graph for the variable input "Temperature"

4) Output Aggregation

The set of soil fertility status outputs in the Mamdani fuzzy system is defined into three categories, namely Unfertile [0, 25, 50], Fertile [40, 60, 80], and Very Fertile [70, 85, 100]. Each active fuzzy rule produces a membership degree in one of these output sets based on the minimum operator (MIN). Furthermore, all inference results are combined using the maximum operator (MAX) to form a single aggregate fuzzy set that represents the overall soil fertility condition before the defuzzification process is carried out (Putera et al., 2023).

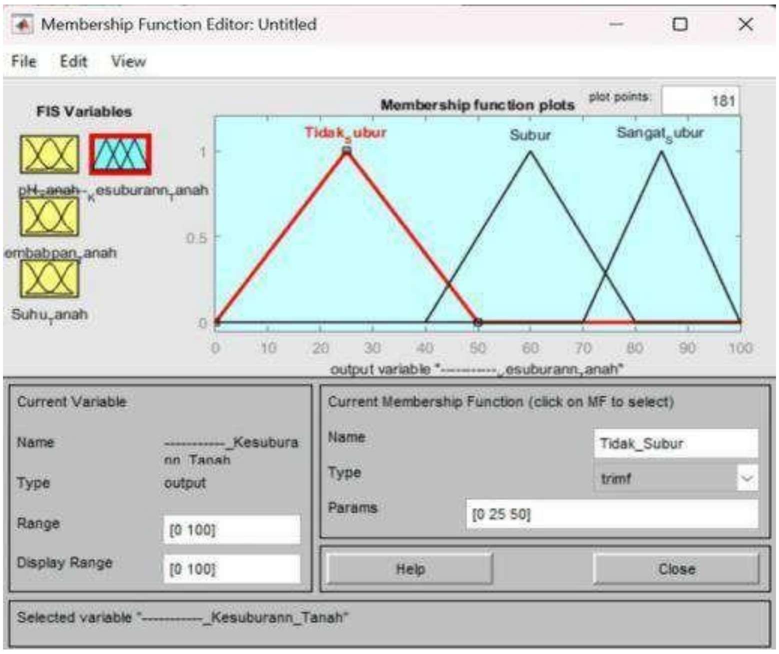

Figure 6. Membership function graph for the variable output "Fertility"

5) Defuzzification (Centroid Method)

Defuzzification is the final stage in a fuzzy inference system that aims to convert fuzzy aggregation results into a single crisp value. This study uses the Center of Gravity (Centroid) method because it considers the entire area of the aggregation curve, thereby producing a more representative value. Mathematically, the centroid value is formulated as:

B. Calculation

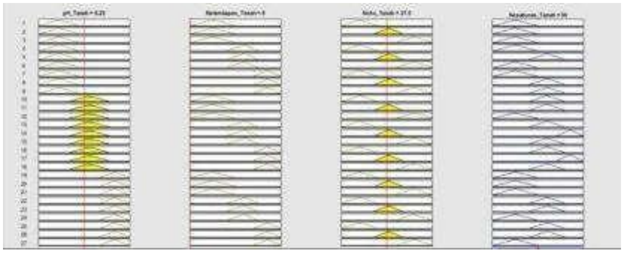

Figure 7. Fuzzy Rule Viewer Showing Input–Output Mapping for Soil Fertility

In the simulation with the following inputs:

[6.25; 0; 27.5]

MATLAB produces soil fertility:

Z* = 50

1) Fuzzification
   a. Soil pH (6.25°C)
      Neutral Domain :

      [5.5,6.5,7.5]

      Since 6.25 is on the rising side of the Neutral triangle function, then:

$$\mu Netral(6.25) = \frac{6.25 - 5.5}{6.5 - 5.5}$$
$$= \frac{0.75}{1}$$
$$= 0.75$$

   b. Soil Moisture (0°C)
      Dry Domain:

      [0,0,40]

      Since 0 is at the maximum value of the left shoulder function, then:

$$\mu Dry(0) = 1$$

   c. Soil Temperature (27.5°C)
      Low Domain:

      [20,25,30]

      Since 27.5 is on the descending side of the Normal triangle function, then:

$$\mu Netral(6.25) = \frac{30-27.5}{30-25}$$
$$= \frac{2.5}{5}$$
$$= 0.5$$

2) Inference (MIN Operator)
Active rules:
IF pH is neutral AND humidity is dry AND temperature is normal
THEN fertility is moderate

With the MIN operator:

$$\alpha = \min(0.75, 1, 0.5)$$

$$\alpha = 0.5$$

This means that the membership function is truncated at a height of 0.5.

3) Determining the Output Area
Medium Domain:

[40,50,60]

Ascending side intersection point:

$$0.5 = \frac{Z - 40}{50 - 50}$$

$$0.5 = \frac{Z - 40}{10}$$

$$Z - 40 = 5$$

$$Z = 45$$

Downward side intersection point:

$$0.5 = \frac{60 - Z}{60 - 50}$$

$$0.5 = \frac{60 - Z}{10}$$

$$60 - Z = 5$$

$$Z = 55$$

So the active areas are:

$$45 \le Z \le 55$$

with a height of 0.5.

Centroid Calculation
Using the centroid formula :

$$Z* = \frac{\int z\mu(z)\,dz}{\int \mu(z)dz}$$

Since the shape of the inference function is symmetric about the point 50, the center point is:

$$Z*=50$$

C. Analysis

Based on manual calculations and simulations using MATLAB, a defuzzification value of Z*=50 was obtained. This value is at the center of the Medium fertility domain ([40, 50, 60]), indicating that soil conditions are at a medium level of fertility. This result is supported by the Surface Viewer visualization, where the combination of pH 6.25, very low moisture, and temperature 27.5 °C is located in the surface area with moderate elevation.

Although the pH value is close to neutral, which theoretically contributes positively to soil fertility, the extremely low moisture conditions prevent the output value from reaching the high category. This is due to the Mamdani inference mechanism using the MIN operator, which results in an α-predicate value of 0.5 and cuts the output membership function at that level. As a result, the surface elevation on the graph decreases.

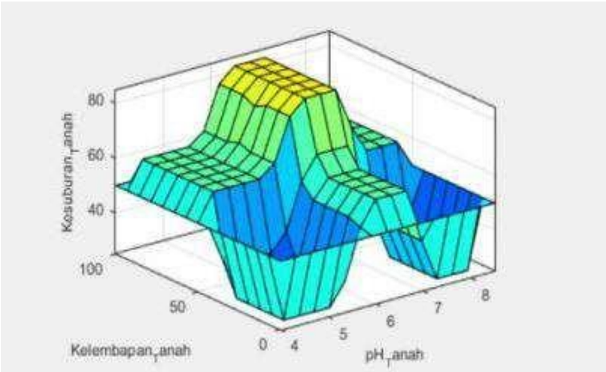

Figure 8. Fuzzy Surface Mapping of Soil Fertility Using pH and Soil Moisture Variables

Because the membership function is symmetric, the defuzzification process produces values that are exactly in the middle of the domain. Thus, the numerical results and surface visualization show consistency, confirming that the fuzzy inference system has worked logically and in accordance with the theory and computational implementation in MATLAB.

The determination of soil fertility status in this study was carried out through a process of inference and defuzzification in the Mamdani fuzzy logic system. After the soil pH, soil moisture, and soil temperature values were defuzzified into their respective linguistic sets, the system applied fuzzy rules to produce membership degrees in the output variables. Three output categories were used: Not Fertile, Fertile, and Very Fertile, each represented by the value domains [0, 25, 50], [40, 60, 80], and [70, 85, 100], respectively.

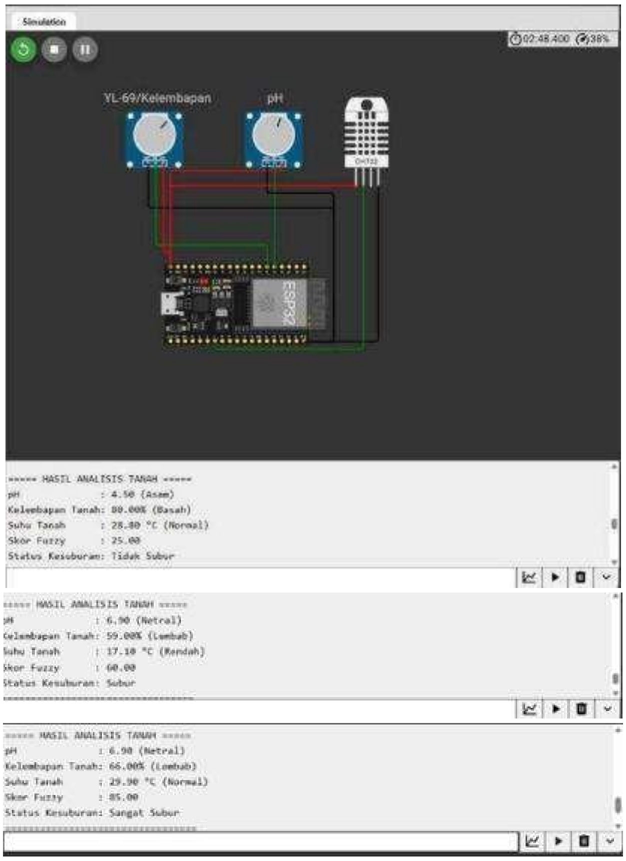

Figure 9. Hardware Simulation of ESP32-Based Soil Fertility Monitoring System in Wokwi

The Unfertile output value is obtained when soil conditions show extreme parameters, such as pH that is too acidic or alkaline and soil moisture that is either too dry or too wet. Conversely, the Fertile status is obtained when most parameters are in fairly good condition but not yet fully optimal. The Very Fertile status is obtained when the pH value is in the neutral range, soil moisture is moist, and soil temperature is within the normal range simultaneously. The degree of activity of each rule is then combined using the maximum (MAX) operator to form an aggregate fuzzy set.

The defuzzification process is carried out using the centroid method to produce crisp values that represent the level of soil fertility. The crisp value is calculated as the weighted average of the midpoint of each output domain based on its membership degree. The defuzzification results are then used to determine the final soil fertility status, where values below 50 are classified as Not Fertile, values between 50 and 74 as Fertile, and values above or equal to 75 as Very Fertile.

ACKNOWLEDGEMENT

Based on the design and simulation results, a soil fertility monitoring system for corn crops using the Mamdani fuzzy logic method has been successfully developed by utilizing three main parameters as input variables, namely soil pH, soil moisture, and soil temperature. The data processing process consists of several stages, including fuzzification, the application of IF–THEN rule-based inference, aggregation, and defuzzification using the centroid method to produce an output value representing the level of soil fertility. The simulation results show that the system is capable of consistently classifying soil conditions into several fertility categories, namely infertile, fertile, and very fertile, based on the combination of environmental parameter values obtained from the sensors. The integration of the system with an ESP32 microcontroller and environmental sensors also enables soil monitoring to be performed more objectively and automatically. Therefore, the Mamdani fuzzy method proves to be effective in processing uncertain environmental parameters into measurable information that can support decision-making in agricultural land management, particularly in corn cultivation.

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