Jurnal Mandiri IT
Vol. 15 No. 1, July (2026), pp. 71-79

ISSN 2301-8984 (Print), 2809-1884 (Online)
Published by Institute of Computer Science

Development of a multi-parameter based agricultural land condition monitoring system

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ARTICLE INFO

Article history:

Received May 19, 2026
Revised Jun 10, 2026
Accepted Jul 20, 2026

Keywords:

Agriculture;
Decision support systems;
Expert knowledge rules;
Multi-parameter;
Soil monitoring.

ABSTRACT

Regular soil monitoring is essential to support agricultural land management and maintain crop productivity. Conventional methods generally require separate analyses to obtain information on several soil parameters, necessitating a system capable of integrating soil condition measurements and interpretation in a more practical manner. This research aims to develop Farm Thrive, a multi-parameter soil monitoring system based on expert knowledge rules. The system processes pH, humidity, temperature, nitrogen (N), phosphorus (P), potassium (K), electrical conductivity (EC), and rainfall as additional parameters. Measurement values are validated and compared against target ranges based on the selected crop. Each parameter is classified as low, optimal, or high and scored based on its proximity to the target range. Parameter scores are then aggregated using a weighted average to generate a soil condition score and categorized as Ready for Planting, Needs Improvement, or Not Ready for Planting. Implementation results demonstrate that the system is capable of integrating multi-parameter measurements, classifying soil conditions, identifying parameters requiring attention, and providing improvement recommendations based on the rules used. The system also stores measurement history to support monitoring changes in soil conditions over time. Farm Thrive can be a tool for monitoring and initial interpretation of agricultural soil conditions.

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1. INTRODUCTION

Soil is a crucial component of agricultural systems because it provides a growing medium, water, nutrients, and various ecosystem functions that support agricultural productivity and sustainability. The concept of soil health is not only related to fertility but also encompasses the soil's ability to sustainably maintain its physical, chemical, and biological functions (Toor et al., 2021; Wade et al., 2022; Fausak et al., 2024). Therefore, assessing soil condition requires a number of indicators that can represent soil characteristics and functions in an integrated manner (Ros et al., 2022; Chang et al., 2022; Cao et al., 2023; Zeng et al., 2025).

Various methods have been developed to assess soil condition and health, ranging from laboratory analysis and soil health indices to sensor-based approaches. Index methods integrate multiple indicators into a composite score, but indicator selection, weighting, scoring functions, and appropriateness to site characteristics remain challenges (Wade et al., 2022; Ros et al., 2022; McCarty et al., 2023; Cao et al., 2023). Recent studies have also shown that soil health indicators and scores can vary based on cropping system, soil type, and environmental conditions, so overly general approaches can potentially reduce assessment sensitivity (Das et al., 2023; Hughes et al., 2023; Zhang et al., 2024; Zeng et al., 2025).

Advances in sensor technology offer opportunities for faster, in-situ soil condition information. Sensors have been used to measure soil moisture, temperature, pH, electrical conductivity, and various nutrients (Yin et al., 2021; Silvero et al., 2023; Faqir et al., 2024). Studies on portable sensors have shown that this approach can mitigate the limitations of conventional methods, which require more time and expense, although calibration, accuracy, and environmental impacts remain challenges (Najdenko et al., 2024; Pal et al., 2024; Mane et al., 2024). Temporal monitoring studies have also demonstrated the potential of multi-parameter sensors to repeatedly obtain soil condition information in the field (Dhamu et al., 2025; Thingujam et al., 2025).

However, data acquisition alone is not enough to produce usable information for decision-making. Multi-parameter data needs to be translated into user-understandable condition statuses, scores, and recommendations. The expert knowledge rules approach can be an alternative when the relationships between parameters have interpretable boundaries that can be explicitly formulated. This approach also has the advantage of decision traceability because results can be traced back to the parameters, ranges, weights, and rules used. In the context of intelligent systems, the integration of data acquisition and decision-making mechanisms is crucial for building systems that can be used in real-world environments (Riandari & Panjaitan, 2025).

Based on these developments, there is still a need for a system that integrates multi-parameter measurements, condition analysis, weighting, classification, and recommendations in a single, simple platform for field use. This research developed Farm Thrive, a multi-parameter soil condition monitoring system based on expert knowledge rules. The system processes pH, moisture, temperature, nitrogen, phosphorus, potassium, and additional parameters such as EC and rainfall to generate a soil condition score and improvement recommendations. The system also stores measurement results so that land conditions can be monitored over time. This approach provides the basis for the development of more connected monitoring systems with smart devices and the IoT in the future, including the implementation of lightweight computing models on devices with limited resources (Riandari & Sihotang, 2024).

Thus, the novelty of this research lies in the integration of multi-parameter measurements with expert knowledge rules, which transform sensor data into condition classifications, aggregate scores, parameter priorities, and action recommendations within a single Farm Thrive system. This research aims to develop and test this system based on its functionality and the suitability of the analysis output to established rules.

2. RESEARCH METHOD

This research uses a Research and Development (R&D) approach to develop the Farm Thrive system as a measurement and analysis system for agricultural soil conditions. The system receives data from the SOIL-001 device in the form of pH, humidity, temperature, nitrogen (N), phosphorus (P), potassium (K), as well as optional parameters such as electrical conductivity (EC) and rainfall. The measurement data is validated, analyzed using expert knowledge rules, and then stored as a measurement history.

2.1 Data and Expert Knowledge Rules

The validation limits and parameter weights used by the system are shown in Table 1. The validation range is used to reject invalid sensor values, while the target range is used in determining parameter status and scores.

Table 1. Parameters and rules for soil condition analysis

Parameter	Unit	Validation	Basic target range	Weight
pH	–	0–14	5.5–6.5	20%
Humidity	%	0–100	30–60	15%
Temperature	°C	−10–70	24–32	10%
N	mg/kg	0–2,000	40–60	17%
P	mg/kg	0–2,000	20–40	17%
K	mg/kg	0–2,000	30–50	17%
EC	mS/cm	0–20	0.2–1.2	4%

The target range is then adjusted based on the target crop. For example, the rice profile uses pH 5.5–6.5, humidity 60–85%, temperature 24–32 °C, N 40–60 mg/kg, P 20–40 mg/kg, K 30–50 mg/kg, and EC 0.2–1.2 mS/cm; while the corn profile uses pH 5.8–7.0, humidity 40–60%, temperature 20–30 °C, N 45–70 mg/kg, P 25–45 mg/kg, K 35–55 mg/kg, and EC 0.2–1.2 mS/cm.

2.2 Soil Condition Analysis

For each parameter, the measured value is compared with the lower limit $x_i L_i$ and upper limit U_i:

$$Status_i = \begin{cases} Rendah, & x_i < L_i \\ Optimal, & L_i \le x_i \le U_i \\ Tinggi, & x_i > U_i \end{cases} \tag{1}$$

The parameter score is calculated based on the distance of the value to the target range:

$$S_i = \max\left(0, \mathrm{round}\left[100\left(1 - \frac{d_i}{U_i - L_i}\right)\right]\right) \tag{2}$$

with for values below target, for values above target, and if the value is within the optimal range $d_i = L_i - x_i d_i = x_i - U_i d_i = 0$

The soil condition score is calculated using a weighted average:

$$S_{soil} = \mathrm{round}\left(\frac{\sum_{i=1}^{n} w_i S_i}{\sum_{i=1}^{n} w_i}\right) \tag{3}$$

where is the parameter score and is its weight $S_i w_i$

Table 2. Classification of soil conditions

Score	Category
≥80	Ready to Plant
60–79	Needs Improvement
<60	Not Ready to Plant

The classification is used to produce the final status of the soil condition.

2.3 Recommendations and System Evaluation

Parameters with a Low or High status generate rule-based recommendations. High priority is given if the parameter score is <60, while a score ≥60 receives Medium priority. Each recommendation stores the parameter, actual value, target range, rule, and corresponding action so that results can be traced back to the knowledge base. Testing was conducted through functional testing and scenario-based analytical testing. Scenarios included optimal conditions, parameters below/above range, invalid sensor values, and changes to the target crop. System testing showed that optimal conditions resulted in a score of 100 and a Ready to Plant category, low N values resulted in a high-priority recommendation, values outside the validation limits were rejected, and changes to the target crop altered the evaluation range and score.

3. RESULTS AND DISCUSSIONS

3.1 Implementation of the Farm Thrive System

The development resulted in the Farm Thrive application, which integrates measurement processes, soil condition analysis, improvement recommendations, and measurement history storage in a single system. The data used includes pH, humidity, temperature, nitrogen, phosphorus, potassium, EC, and rainfall as additional parameters. The system also allows users to specify target crops so that the parameter evaluation range can be tailored to the selected crop.

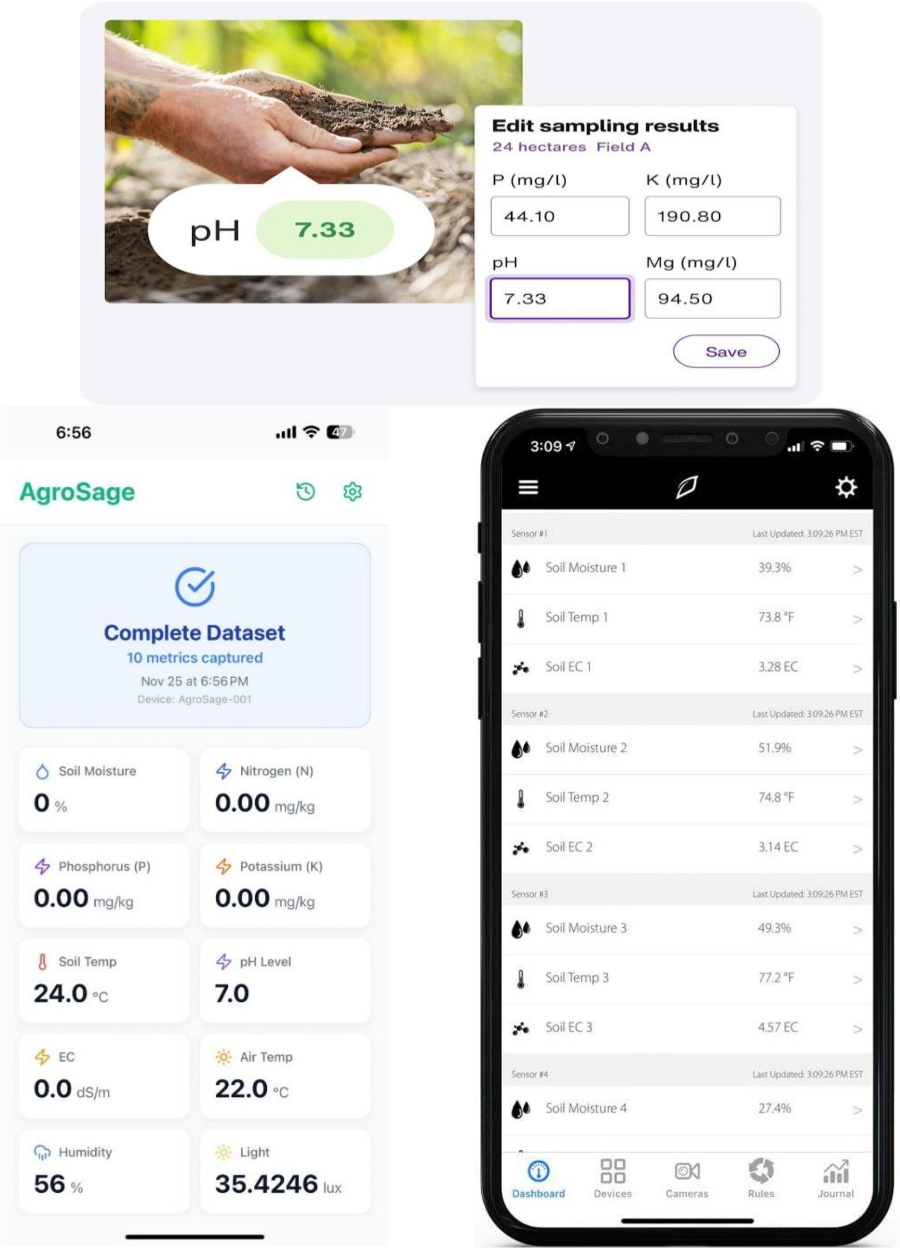

Figure 1. Display of the soil preparation and measurement process at Farm Thrive.

Figure 1 shows the measurement flow, from device connection, plant selection, field identification, sensor parameter preview, and the measurement process. The system provides a reading stabilization indicator before the user completes the measurement. This implementation reduces the possibility of data being processed before the device and sensor readings are ready.

3.2 Results of Soil Condition Analysis

After the measurements are complete, the system displays the value of each parameter and its status based on the crop's target range. Implementation results show that each parameter can be classified as Optimal, Low, or High and then used to calculate the soil condition score.

For example, in the scenario displayed in the system, the obtained pH is 5.42, humidity is 38%, N is 24 mg/kg, P is 12 mg/kg, K is 18 mg/kg, and temperature is 29.40 °C. Based on the target range for rice, pH, humidity, N, P, and K are categorized as Needs Improvement, while temperature is at optimal conditions. The aggregation results produce a soil condition score of 55/100 with the category Not Ready for Planting.

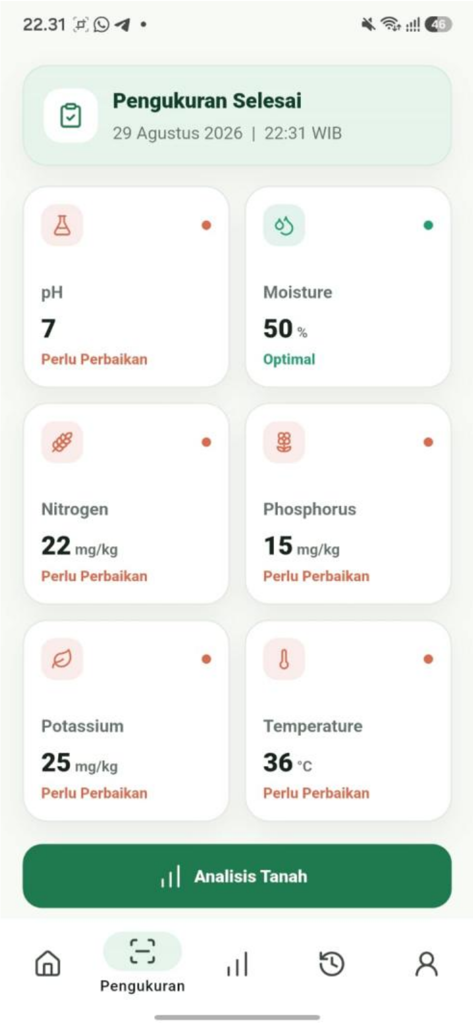

Figure 2. Summary of Farm Thrive soil condition analysis results

These results demonstrate that the expert knowledge rules method can transform multi-parameter numerical data into more interpretable information. Aggregate scores also allow users to prioritize land conditions without having to interpret each parameter separately.

3.3 Parameter Analysis and Improvement Recommendations

The analysis results are then displayed as parameter cards containing actual values, recommendation ranges, and parameter status. The system also displays the target crop context and the crop recommendation model output separately.

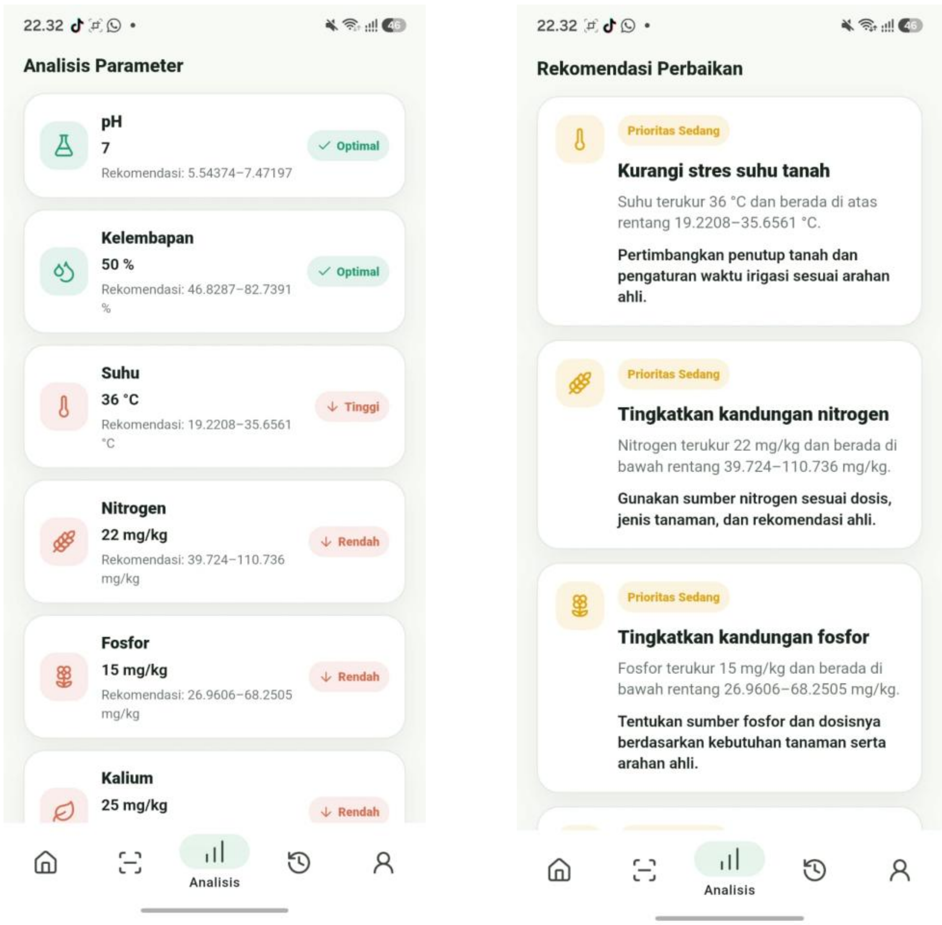

Figure 3. Parameter analysis and improvement recommendations on Farm Thrive

Parameters outside the target range automatically generate recommendations. In this scenario, moisture, nitrogen, and potassium generate high-priority recommendations because their values fall significantly below the target range. Each recommendation includes the detected condition, the measured value, the rationale, and general actions to consider.

This approach provides a direct link between measurement results → parameter conditions → priorities → corrective actions. Thus, the system serves not only as a tool for recording measurement results, but also as an initial interpretation aid.

3.4 Monitoring Soil Conditions through Measurement History

Farm Thrive stores measurement results so you can compare soil conditions over time. The history feature displays a graph of soil condition score development and a list of measurements that you can revisit for detailed analysis.

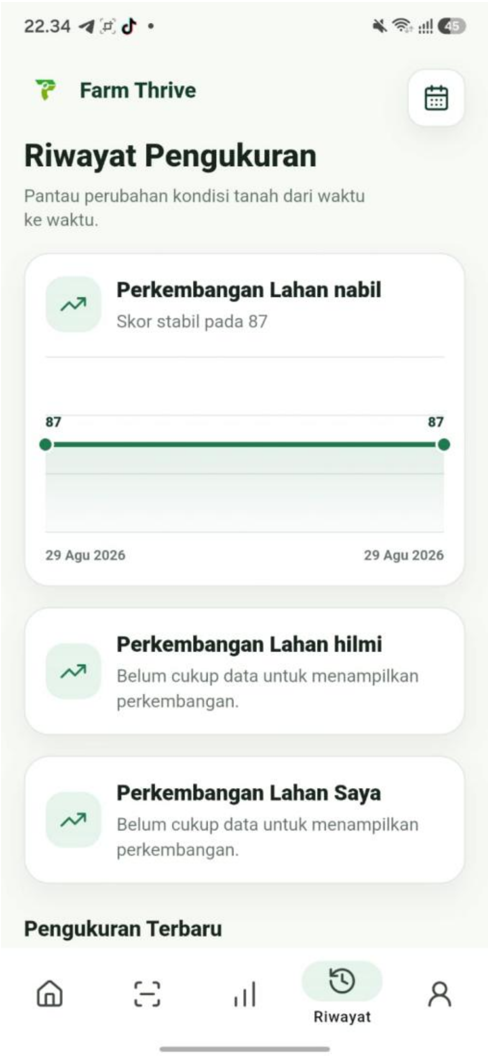

Figure 4. Display of history and development of soil conditions

This feature is a crucial component for temporal monitoring. The example display shows scores of 54, 62, and 71 for three consecutive measurements, allowing users to visually observe changes in soil conditions. However, the graphs in the current version of the system still function primarily as trend visualizations, not as baseline-based change detection algorithms. Therefore, these results support the monitoring function, while developing baseline-based early detection could be a future development step.

3.5 Discussion of Development Results

Implementation results show that Farm Thrive has integrated multi-parameter measurements with a rules-based analysis mechanism into a single workflow. The system's key advantages lie in its ability to link sensor values to target crop ranges, generate soil condition scores, identify parameters requiring attention, and provide trackable recommendations based on measurement results. The system also maintains historical data so that changes in conditions can be monitored during subsequent measurements.

However, these results also highlight the system's limitations. Expert knowledge rules rely on predefined target ranges and do not fully represent the variations in specific conditions of each field. Furthermore, the resulting recommendations are preliminary guidelines and do not automatically determine fertilizer dosages; management decisions still require field verification or laboratory testing, if necessary.

Thus, Farm Thrive at this stage of development can be positioned as a support system for monitoring and early decision-making of soil conditions, while the development of land-specific baselines and quantitative change detection mechanisms represents an opportunity for further development.

4. CONCLUSION

This research has produced Farm Thrive, a multi-parameter, expert knowledge rules-based agricultural soil monitoring and analysis system. The system integrates measurements of pH, humidity, temperature, nitrogen, phosphorus, and potassium, as well as additional parameters such as EC and rainfall. Measurement data is processed through validation, classification of the condition of each parameter, score weighting, and aggregation into a soil condition score categorized as Ready for Planting, Needs Improvement, or Not Ready for Planting. Implementation results demonstrate that the system can link measurement results to identify parameters requiring attention and recommend corrective actions, as well as store measurement results for monitoring land conditions over time. The history feature also allows users to observe the development of soil condition scores over multiple measurement periods. Thus, Farm Thrive can be used as a tool for monitoring and initial interpretation of soil conditions before users undertake further management actions. However, the system at this stage still relies on a predetermined range of parameters and expert knowledge rules, so it does not fully represent the variations in specific conditions of each land area. Further development will focus on establishing land-specific baselines, quantitative analysis of changes, and early detection and warning mechanisms for changes in soil conditions based on historical data. Real-time sensor and IoT integration can also be developed at a later stage to improve monitoring continuity and data availability.

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