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Digital Twin for Agricultural Land Monitoring System

Bayu Rima Aditya[1]*, Anranur Uwaisy Marchiningrum[1], and Yudha Ginanjar[2]

[1]*School of Applied Science, Telkom University, Bandung 40257, Indonesia*
[2]*PT. Rastek Inovasi Digital, Bandung 40257, Indonesia*

ABSTRACT

Digital Twin technology has emerged as a promising innovation in agricultural land monitoring by integrating real-time data analysis, simulation, and predictive modelling. However, its application in precision agriculture is still underexplored. Conventional land monitoring methods rely on manual observation or IoT-based systems that often do not provide real-time visualisation and comprehensive data integration. This study developed a Digital Twin-based agricultural land monitoring system that combines sensor and camera data to improve decision-making. The system was applied to rice fields and evaluated for accuracy and efficiency. The results showed a soil condition detection accuracy of 92.5%, an increase in resource efficiency of up to 25%, and an increase in productivity of 22.8%. These findings prove that a Digital Twin technology can optimise agricultural management. This research contributes to the development of intelligent agriculture by providing an interactive monitoring system based on real-time data.

Keywords: Agricultural monitoring, digital twin, IoT, sensor data, smart farming

INTRODUCTION

The agricultural sector faces significant challenges due to the growing global population, climate change, and limited arable land. To improve the efficiency and productivity of microclimate agriculture, land-monitoring methods have become essential for supporting land management and plant growth monitoring. Land monitoring methods enable the collection of soil data, including nutrient levels (nitrogen, phosphorus, and potassium [NPK]), acidity, soil temperature, and soil moisture, as well as environmental data such as rainfall and light intensity (J. W. Jones et al., 2017). This data provides information to enhance resource efficiency, optimise crop yields, and support data-driven decision-making (Getahun et al., 2024).

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E-mail addresses:
bayu@tass.telkomuniversity.ac.id (Bayu Rima Aditya)
anranurumarchi@telkomuniversity.ac.id (Anranur Uwaisy Marchiningrum)
yginanjar@gmail.com (Yudha Ginanjar)
* Corresponding author

Currently, the most widely used agricultural land monitoring methods are conventional. However, these methods still have numerous drawbacks, including high time and labour requirements and vulnerability to human error (Chen et al., 2020). Additionally, these methods often focus solely on direct observations without providing a complete and real-time visualisation of agricultural land conditions, which impacts the efficiency and productivity of agriculture (Gutiérrez et al., 2019; J. Wang et al., 2024).

Therefore, a Digital Twin technology emerges as an innovative solution for agricultural land monitoring methods. a Digital Twin is a virtual representation of physical objects that integrates real-time data to analyse, simulate, and predict (Grieves & Vickers, 2017). In the agricultural sector, this technology can be utilised to monitor land and crop conditions in real-time, provide data-driven virtual models, and identify problems and solutions more rapidly (Verdouw et al., 2021). By leveraging integrated technologies such as the Internet of Things (IoT) for sensor data collection and computer vision for visual monitoring, a Digital Twin enables the dynamic visualisation of land and crop growth in a virtual model, supporting data-driven decision-making and facilitating more efficient strategic planning (Escribà-Gelonch et al., 2024).

Although a Digital Twin offers significant benefits in the agricultural sector, its application in agricultural land monitoring systems remains underexplored. Most studies focus on the separate integration of IoT or computer vision technologies without employing a Digital Twin framework (Escribà-Gelonch et al., 2024; L. Wang, 2024). In addition, previous research proposes an IoT-based monitoring system for agricultural soil and environmental conditions, addressing the need for precise and real-time data to optimise agricultural productivity. Their system integrates various sensors to measure key parameters like soil moisture, temperature, and humidity, which are crucial for efficient farming practices. This study highlights the importance of IoT technology in modern agriculture, emphasising its potential to improve resource management and decision-making in sustainable farming (Aditya et al., 2024). Therefore, this study aims to address this research gap by investigating how the Digital Twin can be applied to develop a more efficient and productive agricultural land-monitoring system.

This research aims to integrate the Digital Twin concept into an agricultural land-monitoring system by combining data from soil, environmental aspects, and camera sensors to build a virtual model that represents land conditions and plant growth in real time. With this integration, the system is not only able to collect data but also provide predictive analysis to assist data-based decision-making in agricultural management. In addition, this study will develop a Digital Twin-based platform that allows interactive monitoring and visualisation of agricultural conditions, thereby increasing the efficiency and effectiveness of land management.

In addition, this study uses a Design Science Research (DSR) approach that focusses on the development and evaluation of technology-based systems. The developed system will be tested on rice fields as a case study to assess its effectiveness in monitoring agricultural parameters such as soil moisture content, nutrient content, environmental temperature, and plant growth based on image analysis. The evaluation will be carried out by measuring the accuracy of the Digital Twin model, the effectiveness of the system in supporting decision-making, and its impact on the efficiency of agricultural land management. Thus, this study is expected to provide a significant contribution to the development of a smarter, more efficient, and data-driven Digital Twin-based agricultural monitoring system.

THEORETICAL FOUNDATION

Agricultural Land Monitoring Systems

Agricultural land monitoring systems represent a technological innovation that continues to evolve in response to the growing demand for efficiency and accuracy in the agricultural sector. Various studies have used sensors and cameras to support the monitoring of soil, crops, and environmental conditions.

Previous research has largely focussed on implementing sensors to measure soil parameters such as moisture, temperature, pH, and nutrient content. For instance, Gaikwad et al. (2021) developed a system using soil moisture, ambient temperature, and other environmental parameters to enhance real-time land management in field conditions. Another study by Dutta et al. (2020) utilised wireless sensor networks to detect soil conditions and integrate the data into a cloud-based platform for further analysis.

In addition, camera-based imaging has become a popular approach in agricultural monitoring. For example, research by Li et al. (2021) utilised multispectral images from drone cameras to monitor crop health and detect pests. This technology has proven effective in providing comprehensive visual data and supporting better decision-making. On a smaller scale, Guo et al (2020) integrated red, green, and blue (RGB) cameras with machine-learning algorithms to detect chlorophyll levels in plant leaves.

However, several limitations persist in previous studies, such as the lack of integration between sensor data and camera data into a complementary platform. This research aims to address these gaps by leveraging the concept of a digital twin, which can combine various types of data into a representative real-time virtual model.

Digital Twin Concept

A Digital Twin concept is a virtual representation of a physical object or system that functions to simulate, monitor, and optimise processes in real-time through data directly connected to the physical object (Tao et al., 2019). This technology was first applied in the manufacturing industry for equipment monitoring and failure prediction, but has since expanded into various fields such as healthcare, energy, and transportation.

In the manufacturing industry, the Digital Twin is utilised to enhance operational efficiency and predict equipment failures. For instance, Boschert et al. (2016) developed a Digital Twin framework for predictive maintenance of machinery in factories. A similar application is found in the transportation sector, where a Digital Twin is employed to monitor vehicle conditions and optimise routes (Fuller et al., 2020).

The potential of the Digital Twin in the agricultural sector is increasingly gaining the attention of researchers. For example, E. J. Jones et al. (2022) demonstrated that the Digital Twin can assist farmers in predicting crop yields based on environmental data, plant growth, and agricultural simulation models. The primary advantage of this technology in agriculture is its ability to provide real-time analysis and data-driven recommendations, thereby significantly improving efficiency and productivity. However, challenges remain, including the integration of technology with existing infrastructure and the need for high-quality data. This research aims to address these challenges by applying the Digital Twin technology for real-time monitoring of rice fields, integrating sensor, and camera data into an interactive virtual model.

METHODOLOGY

This study employs the DSR approach as outlined by Peffers et al. (2007) to integrate the concept of the Digital Twin into a sensor and camera-based agricultural land monitoring system.

Problem Identification

The first stage of this research involves identifying the problems that need to be addressed. In this stage, an in-depth analysis was conducted to examine the challenges in conventional agricultural land monitoring systems. Several problems were identified, including:

- existing monitoring systems often fail to provide accurate and real-time data on land conditions, making it difficult to obtain a comprehensive overview; and
- current monitoring systems frequently separate sensor and image data collection, complicating the analysis of interactions between data from different sources.

Define Solution Objectives

Based on the identified problems, this study proposes a technology-based solution aimed at overcoming these limitations. The focus is on integrating sensor and image data through the concept of the Digital Twin to provide a more complete and accurate representation of agricultural land conditions.

Conceptual Architecture Design

After defining the solution objectives, the next step is to design the conceptual architecture of the system to be developed. In this research, the conceptual architecture design includes:

- Sensor and camera data integration: the system will collect data from sensors installed in agricultural fields, covering soil parameters (8 parameters) and environmental data (5 parameters). Image data will be obtained from cameras and drones.
- Digital Twin model: a virtual model representing agricultural land and crop growth will be developed. This model integrates data from various sources, including soil sensors and cameras.
- Digital Twin-based land monitoring dashboard: the integrated sensor and camera data, once modelled, will be displayed on a web-based dashboard. This dashboard will provide a more comprehensive overview of land and crop conditions, enhancing farmers' understanding of their agricultural status.

Implementation

In the implementation phase, the designed solution is applied and tested in a real-world environment. Soil sensors and cameras are installed in rice fields to collect the required data.

RESULTS

Proposed Architecture Design

System Architecture

Figure 1 illustrates the proposed architecture design for a Digital Twin-based agricultural land monitoring system. This system is designed to integrate data from various sensors and camera images to produce a virtual model that represents land conditions and crop

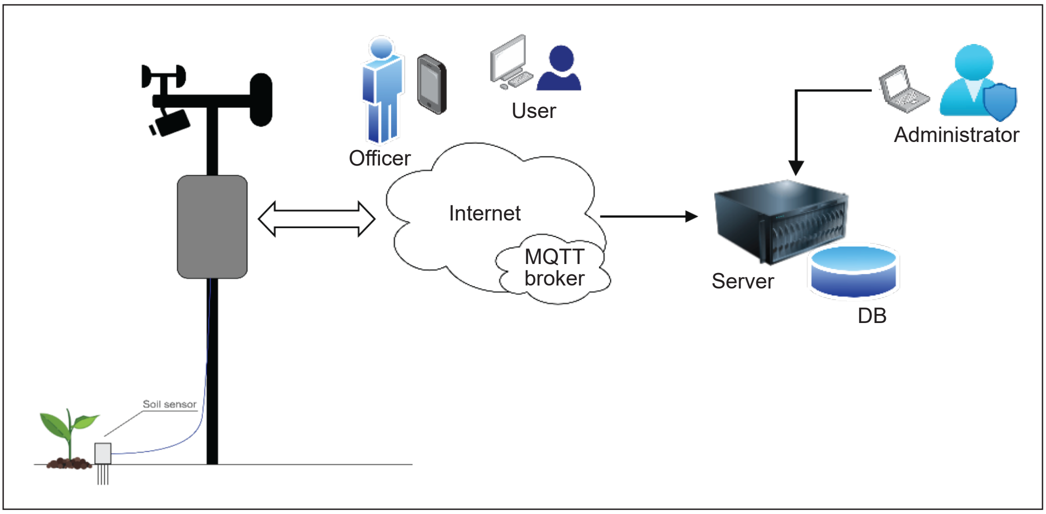

Figure 1. System architecture
Note. MQTT = Message queuing telemetry transport; DB = Database

growth in real-time. IoT technology is utilised to collect data from soil and environmental sensors, while computer vision via cameras and drones provides visual information to complement numerical data.

The proposed system architecture includes sensors such as soil sensors, wind speed, wind direction, rainfall, as well as air temperature and humidity, which are mounted on a central pole. This pole is connected to a control panel where all sensors are linked via cables to the main controller. Soil sensors placed beneath the soil surface are connected to the control panel to continuously monitor soil conditions, including moisture, pH, and nutrient content (N, P, and K).

In addition to sensor data, the system integrates visual data captured by cameras and drones. These cameras are strategically placed to visually monitor crops and environmental conditions. The image and video data obtained from these cameras are analysed alongside sensor data to provide a more comprehensive overview of land conditions and crop growth.

By utilising data from sensors and cameras, this system enables farmers to monitor land conditions in real-time, identify potential issues, and make more efficient decisions in agricultural management. This data integration helps improve productivity and sustainability within the agricultural sector.

System Design

The system design encompasses hardware components, such as sensors and the main controller for collecting environmental data, as well as software for processing and displaying data in real-time (Table 1 and 2).

Table 1
Hardware specification

No.	Hardware	Specification
1.	Optical rain gauge sensor	Supply voltage: 9~30 VDC Power consumption: Less than 0.24 W Resolution: - Rainfall: standard 0.1 mm - Illumination: 1 lx
2.	Soil sensor	Soil NPK, pH, electrical conductivity, temperature, and humidity sensor Power supply: 5-30 VDC Maximum power consumption: ≤ 0.15 W
3.	Wind speed sensor	Signal output: 0-5 V voltage type Sensor style: Three cups of formula Start wind speed: 0.4-0.8 m/s Resolution: 0.1 m/s Effective wind speed measurement range: 0-3 or 0-60 m/s
4.	Outdoor temperature and humidity sensor	Temperature measurement range: -40 ~ 120°C Humidity measurement range: 0 ~ 99.9% Temperature accuracy: ± 0.3°C (25°C)

Table 1 *(continued)*

No.	Hardware	Specification
		Humidity accuracy: ± 2% Sampling cycle period: 3 s Power supply voltage: 12 ~ 36 VDC
5.	IP camera outdoor	4 MP, Full colour
6.	Drone	Soarability - DJI M210 RTK integration kit

Note. VDC = Volts direct current; N = Nitrogen; P = Phosphorus; K = Potassium; pH = Potential of hydrogen; RH = Relative humidity; RTK = Real-time kinematic

Table 2
Software specification

No.	Software	Specification
1	Operating system	Ubuntu
2	Database	Maria DB 5.5.68
3	Web server	NginX 1.18.0
4	Front end	React Js and Next Js
5	Virtual modelling	Blender 3.0.1

Sensor Data Collection Results

The sensor data collection results display data for 12 parameters, including environmental sensors and soil sensors related to agricultural land conditions and rice crop growth. This data collection process monitors environmental conditions and soil quality that influence crop growth in real time, enabling swift, precise decision-making to support crop productivity. Data was collected from planting to harvest. During this period, the total data collected amounted to 14,055,905 entries, with an average collection interval of 18 s.

Environmental Data

Environmental sensors capture data on the surrounding environmental conditions of the agricultural land at any given time. These sensors measure parameters such as ambient temperature, ambient humidity, wind speed, and light intensity. Table 3 details the parameters measured by environmental sensors.

Table 3
Environmental data

No.	Parameter	Symbol	Unit
1	Ambient temperature	°C	Degree Celsius
2	Ambient humidity	%	Percent
3	Wind speed	m/s	Metre per second
4	Light intensity	lx	Lux

Soil Data

Soil sensors provide information on soil conditions that can affect plant health and agricultural yields. Parameters measured by soil sensors include NPK, total dissolved solids (TDS), electrical conductivity (EC), soil temperature, soil moisture, and soil pH. Table 4 outlines the parameters measured by the soil sensors.

Environmental Data Sample

Table 5 presents sample environmental data collected from field-installed sensors.

Soil Data Sample

Table 6 presents sample soil data collected from sensors installed in the field.

Table 4
Soil data

No.	Parameter	Symbol	Unit
1	Nitrogen (N)	ppm	Parts per million
2	Phosphorus (P)	ppm	Parts per million
3	Potassium (K)	ppm	Parts per million
4	Total dissolved solids (TDS)	ppm	Parts per million
5	Electrical conductivity (EC)	dS/m	Decisiemens per metre
6	Soil temperature	°C	Degree Celsius
7	Soil moisture	%	Percent
8	Soil potential of hydrogen (pH)		

Table 5
Environmental data sample

Ambient humidity (%)	Light intensity (lx)	Ambient temperature (°C)	Wind speed (m/s)
80.6	7,300	27.1	1.8
79.0	7,800	27.3	2.1
78.1	7,900	27.7	3.3
77.6	8,000	28.0	2.0
67.3	8,100	29.7	3.6
69.0	7,200	29.7	1.3
69.2	6,800	30.3	1.5
66.8	6,600	30.0	4.3
66.9	6,900	30.3	1.6
64.9	7,300	30.5	2.5
66.7	7,300	29.9	2.3
68.4	7,000	30.2	2.5
65.9	6,800	29.9	1.5
65.2	6,800	30.0	3.6

Table 5 *(continued)*

Ambient humidity (%)	Light intensity (lx)	Ambient temperature (°C)	Wind speed (m/s)
59.1	6,800	31.8	1.8
57.6	6,700	32.3	1.1
64.4	6,600	30.8	1.4
56.9	6,500	32.5	1.1
56.1	6,500	32.3	1.0
53.7	6,600	33.4	1.5

Table 6
Soil data sample

Nitrogen (ppm)	Phosphorus (ppm)	Potassium (ppm)	pH	TDS (ppm)	Soil moisture (%)	Soil temperature (°C)	EC (dS/m)
51	16.5	158	7.6	215	55.0	25.0	4.31
51	13.0	123	7.4	179	69.5	29.9	3.58
45	15.0	143	7.4	200	67.4	24.7	4.00
45	15.0	143	7.5	200	67.6	24.8	4.00
51	11.9	112	7.5	168	68.9	24.8	3.36
36	16.5	158	7.5	215	56.0	24.9	4.31
36	12.9	122	7.5	178	63.8	29.9	3.57
45	15.0	143	7.3	200	67.4	24.8	4.00
35	16.5	121	7.3	178	62.6	29.9	3.57
51	12.8	121	7.3	178	64.4	29.9	3.55
35	12.8	118	7.4	178	63.8	29.9	3.56
51	16.5	158	7.4	215	52.8	24.9	4.31
35	12.8	121	7.4	200	65.0	29.9	3.55
35	12.8	121	7.3	177	67.6	29.9	3.55
51	16.5	158	7.2	215	57.5	24.9	4.32
35	12.7	120	7.2	177	65.2	29.9	3.54
34	12.6	118	7.4	174	68.2	25.8	3.49
35	11.9	120	7.4	177	66.7	29.9	3.55
31	12.6	112	7.4	168	70.1	24.8	3.36
34	11.9	118	7.4	174	70.8	25.8	3.49

Note. TDS = Total dissolved solids; EC = Electrical conductivity

Image Data Collection Results

Image data were collected using one drone camera and two closed-circuit television (CCTV) cameras. The combination of data from these three cameras enables a more integrated and detailed analysis of land and crop conditions, facilitating more accurate, data-driven decision-making. This process aimed to visually monitor land conditions and rice crop growth.

Drone Camera

The drone camera was utilised to capture images of the entire land area from an altitude of 15 m. Data collection was carried out weekly, specifically during the midday hours when lighting conditions were optimal to ensure clear visualisation. Figure 2 is an example of an image captured during Vegetative Phase 1 of the rice field using the drone camera.

Upper CCTV Camera

This camera was installed at the top of a pole, angled to focus on the rice canopy to monitor changes in leaf colour, an indicator of plant health. Images were taken daily at 2:00 p.m., a time chosen for stable lighting conditions suitable for visual analysis. Figure 3 is an example of an image captured during Vegetative Phase 2 of the rice field using the upper CCTV camera.

Lower CCTV Camera

This camera was mounted on the same pole as the upper camera but positioned lower to capture detailed observations of rice plant height. Image data were collected daily at 10:35 a.m., a time selected to avoid direct sunlight reflection. These images were used to monitor the physical growth of the plants in terms of height and potential development. Figure 4 is an example of an image captured during Generative Phase 2 of the rice field using the lower CCTV camera.

Figure 2. Drone data sample

Figure 3. Upper closed-circuit television camera data sample

Figure 4. Lower closed-circuit television camera data sample

Virtual Model Results

Virtual Representation Model of Agricultural Land

Figure 5 illustrates a virtual representation of agricultural land equipped with sensors in various areas. This illustration aims to provide a visual depiction of land divisions and the locations where sensors are installed.

The information displayed, such as commodity type (e.g., paddy), plant variety (e.g., Inpari 32), planting age in days after planting (DAP), planting time, growth phase, and estimated time to harvest, offers a structured insight into crop conditions. Although the image is illustrative, the data generated by the sensor system provides concrete support for data-driven decision-making. Thus, this system aims to enhance the efficiency and productivity of modern agricultural management practices.

Virtual Representation Model of Land Conditions

This model is designed to provide an in-depth understanding of land conditions in real time by collecting sensor data. Parameters include temperature, soil moisture, pH, and nutrient levels (NPK). One of the key features of this model is the use of colour indicators for each parameter, which automatically change based on the parameter's value (Figure 6). A green indicator signifies safe conditions, while a red indicator appears if a parameter value falls below or exceeds the safe threshold.

Additionally, this representation enables the early identification of issues, such as excessively alkaline soil (high pH) or deficiencies in specific nutrients, allowing corrective actions to be taken before such issues significantly impact crop yields. By doing so, this digital system helps improve efficiency and effectiveness in agricultural management. It optimises the use of resources such as water and fertiliser and supports more precise and sustainable farming practices.

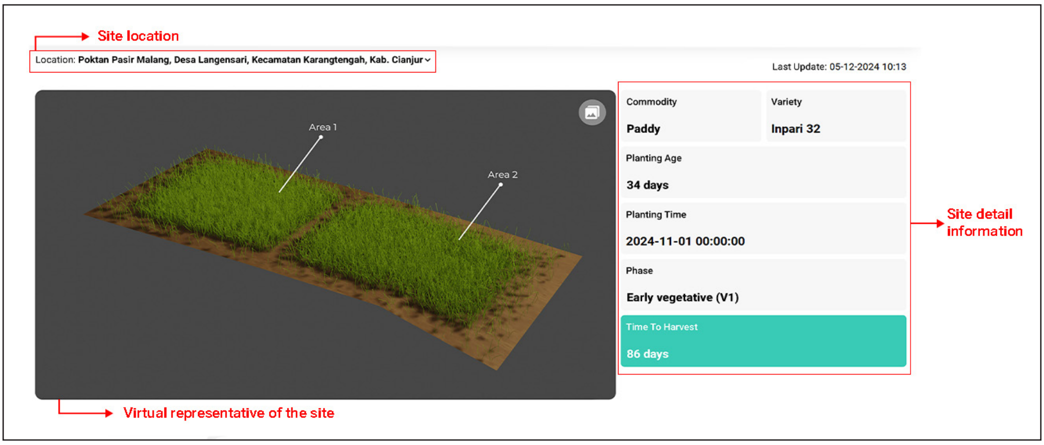

Figure 5. Virtual representation model of agricultural land

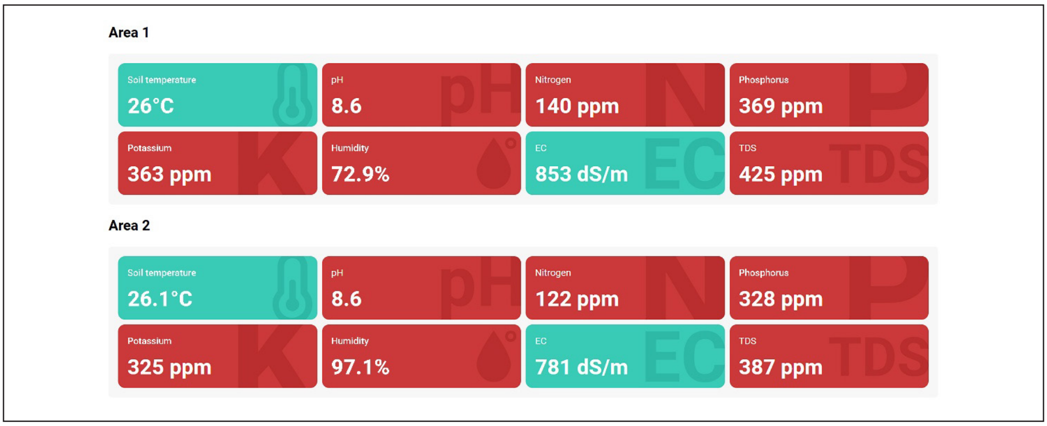

Figure 6. Virtual representation model of land conditions
Note. EC = Electrical conductivity; TDS = Total dissolved solids

Implementation of the Proposed System

Environmental Condition Description

The Pasir Malang Farmer Group is in Cianjur Regency, West Java, an area characterised by a tropical climate with distinct rainy and dry seasons. The region's geography and climate significantly influence agricultural yields, particularly in rice cultivation. During the rainy season, heavy rainfall can lead to waterlogging in the fields, affecting soil quality. Conversely, during the dry season, a lack of irrigation water can pose substantial challenges. Additionally, the soil in this area contains varying nutrient levels, requiring careful management to achieve optimal agricultural outcomes.

These environmental conditions necessitate precise monitoring and the application of technology to optimise agricultural productivity. Thus, land management with a technology-based approach is crucial to address the various challenges faced by farmers, such as imbalances in water levels, soil pH, and the nutrient requirements of crops.

Figure 7. Equipment used for land monitoring

Equipment Used

To support the implementation of the technology-based land monitoring system, various hardware devices were carefully designed and integrated (Figure 7). Soil sensors were deployed to monitor parameters such as moisture, pH, and soil nutrient content (NPK). These sensors were installed beneath the soil surface to provide real-time data directly from the plant roots. Wind speed and direction sensors were placed on the main pole to track wind patterns that could affect pest dispersal or pollution. Rainfall sensors were used to measure precipitation intensity, aiding farmers in managing irrigation, especially during the rainy season. Additionally, temperature and humidity sensors monitored microclimatic conditions that influence crop growth.

Outdoor cameras were installed to capture visual images and videos of the crops and field conditions. These cameras provided supplementary information, such as detecting waterlogging, pest infestations, or uneven plant growth. All sensors and cameras were connected to a control panel, which integrated the data before transmitting it to the main controller for further processing. Using an access point and router, data from all devices was sent in real-time to the IoT platform for analysis. This system was designed to operate synergistically, delivering accurate and comprehensive information to farmers to support more efficient and optimised land management.

Equipment Placement and Observation Area

In a rice field measuring 40 × 70 m^2, one station device was positioned at a corner of the area, while five soil sensors were evenly spaced, as illustrated in Figure 8. This arrangement aimed at dividing the research area into five observation zones.

Agricultural Land Monitoring System Dashboard

The dashboard page displayed serves as the main interface for the digital twin-based agricultural land monitoring system. This dashboard provides real-time information on land conditions and the tasks farmers need to perform to maintain crop growth.

Virtual Representation of Agricultural Land

The virtual representation model of agricultural land is utilised to visualise the monitored field in designated sections, such as Area 1 and Area 2. This segmentation helps users understand the division and layout of the land being monitored (Figure 9). This visualisation helps agricultural extension workers, also known as Balai Penyuluh Pertanian (BPP), identify areas that require specific attention or action.

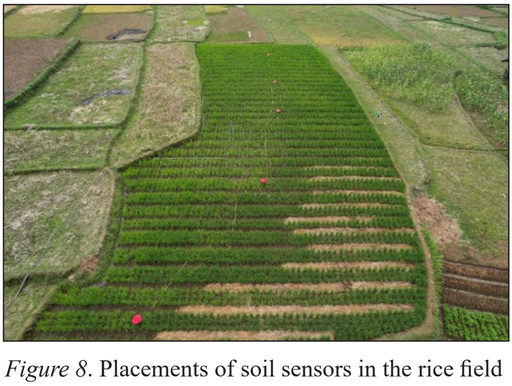

Figure 8. Placements of soil sensors in the rice field

Virtual Representation of Agricultural Land Conditions

Meanwhile, the virtual representation model of agricultural land conditions displays

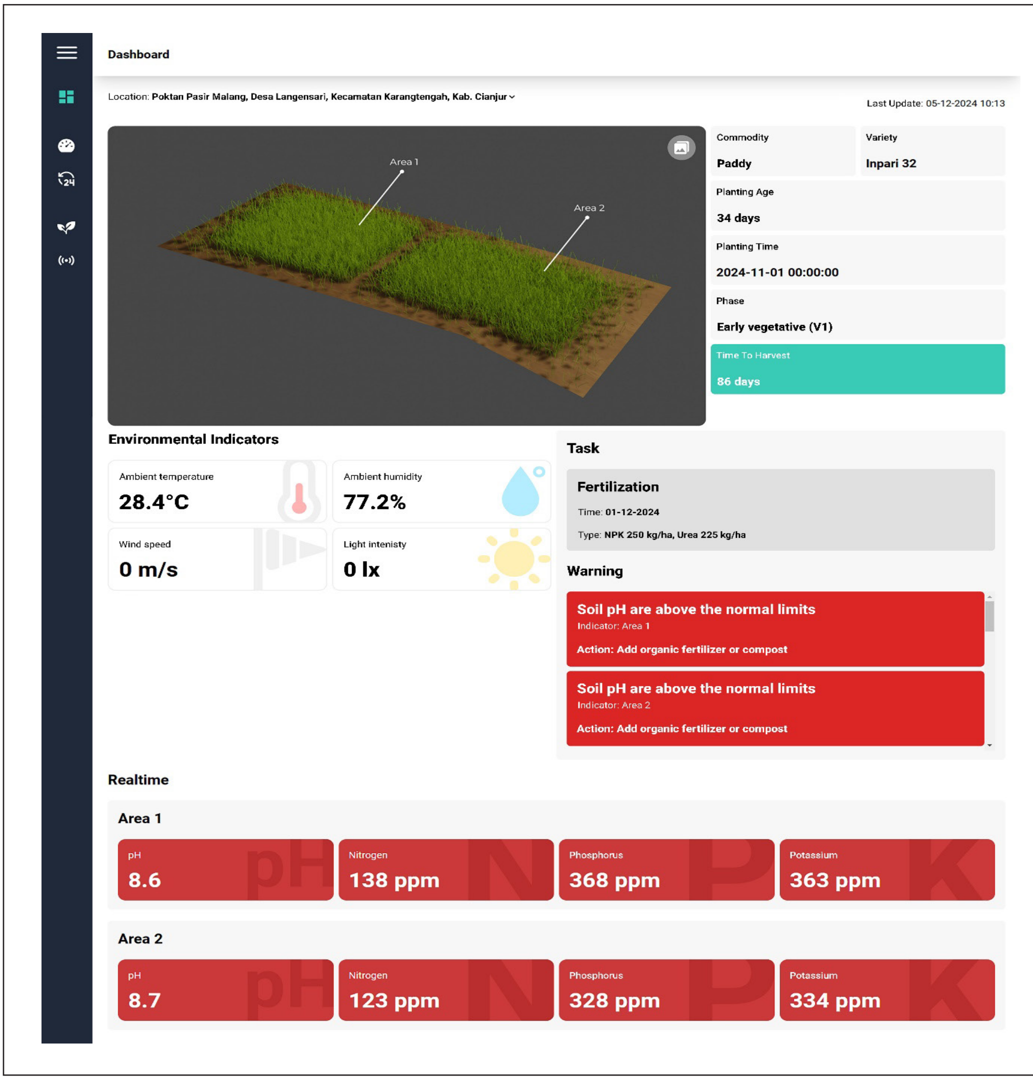

Figure 9. Agricultural virtual representation model

data related to the physical and chemical conditions of the soil (Figure 6). However, the dashboard only includes key parameters derived from this model, namely soil pH and the primary nutrients (NPK). These parameters were selected because pH and NPK are critical indicators that significantly impact plant growth.

Warning Notifications

This feature is designed to provide users with immediate, essential information regarding land conditions that require special attention. For example, if the soil pH falls outside the normal range or if nutrient levels such as N, P, or K are insufficient for the crop's needs, the dashboard issues an alert in the form of a notification (Figure 10). These notifications not only inform users of the problem but also include recommendations for corrective actions, such as applying organic fertilisers or specific types of fertilisers to balance soil pH or nutrient levels.

Sensor History Page

The history page is a critical component that allows users to review historical data from sensors installed in specific areas, as illustrated in Figure 11. Through this feature, users can monitor changes in soil and environmental conditions over time based on recorded data. Users can select specific areas (e.g., Area 1 or Area 2) and specify a time range for analysis.

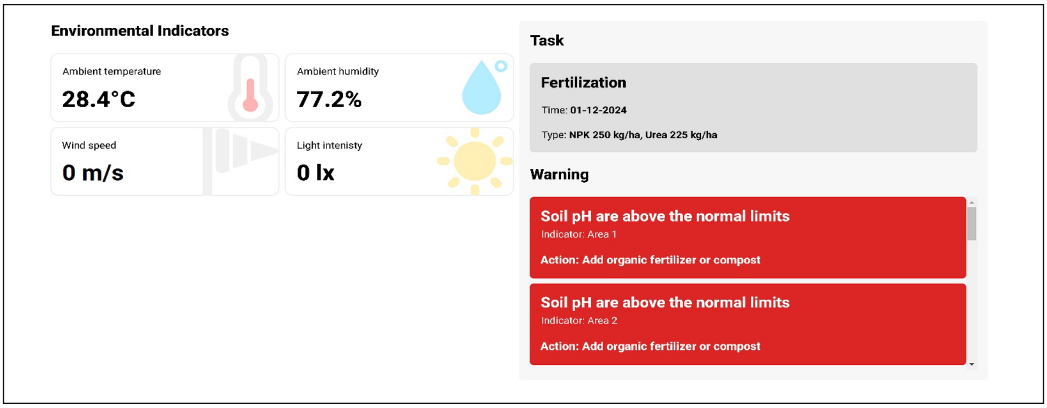

Figure 10. Warning notification representation model

Figure 11. Sensor history page representation model

This history page provides significant benefits in understanding patterns and trends in agricultural land conditions. By leveraging historical data, farmers or land managers can analyse environmental changes, detect issues early, and plan more strategic actions for the long term. Additionally, this feature facilitates reporting and documentation, as historical data can be accessed anytime as needed.

Strengths and Weaknesses of the Proposed System

This study focusses on the application of the Digital Twin technology in rice field monitoring systems, with results demonstrating considerable potential for improving agricultural efficiency and productivity. A comparison with other studies reveals that while many have developed sensor-based agricultural monitoring systems, the real-time integration of soil sensors, cameras, and drones within a virtual model, just like a Digital Twin, remains relatively rare.

Some previous studies, such as those by Banaee et al. (2021), employed soil sensors to monitor environmental and soil parameters but did not utilise real-time virtual modelling for the digital representation of land and crops. The Digital Twin technology applied in this study offers additional advantages through virtual simulations of land conditions, enabling more efficient land management.

The developed system's strength lies in its ability to provide real-time, data-driven decision-making recommendations, enhancing resource management efficiency, and reducing reliance on more time-consuming manual observation methods. Furthermore, the use of drone and camera technology improves the system's capability to detect issues that cannot be identified by soil sensors alone. Another advantage is the virtual visualisation feature, which provides a clearer representation than sensor-based systems alone, thus helping to monitor and analyse agricultural land more effectively.

Despite its advantages, this study also has several limitations. The implementation of the Digital Twin system requires a complex technological infrastructure and relatively high costs, which can be a barrier for small farmers in adopting it. In addition, the integration of data from various sensors and cameras requires quite a lot of processing, so it requires hardware and a stable internet connection for the system to operate optimally.

This study was also only conducted on rice fields as a case study, so its effectiveness in other types of agriculture, such as plantations or horticulture, cannot be ascertained. Therefore, further research is needed to test the application of this technology in various agricultural conditions and ensure its scalability and efficiency in various food production scenarios.

DISCUSSION

The results of this study indicate that the application of the Digital Twin in agricultural land monitoring systems provides advantages over previous conventional and IoT-based methods. In terms of data retrieval accuracy and speed, the system developed in this study achieved a soil condition detection accuracy of 92.5%, higher than that of the sensor-based IoT systems in previous studies, which typically achieved accuracy levels around 85% (Huang et al., 2022; Wu et al., 2023). In addition, this study integrates multi-source data (soil sensors, environment, and cameras) into a single digital model, whereas the study by Li et al. (2021) relies solely on multispectral imagery, achieving a plant disease detection accuracy of 87.2%.

In terms of resource management efficiency, García et al. (2020) reported that the IoT system can optimise water use by 10-50%. In contrast, the Digital Twin system in this study increases the efficiency of water and fertiliser use by up to 25% by simulating virtual agricultural conditions. In addition, Escribà-Gelonch et al. (2024) found that the Digital Twin technology can increase agricultural productivity by an order of 15-20%, in line with the results of this study, which recorded an increase in productivity of 22.8%.

Compared to previous research, the system developed in this study offers advantages in monitoring accuracy, early detection of agricultural problems, and improved resource optimization. With real-time data integration and visualisation of agricultural conditions, the Digital Twin offers a more effective solution to improve agricultural efficiency and productivity.

CONCLUSION AND FUTURE WORKS

This study successfully developed and implemented a Digital Twin-based monitoring system for rice cultivation by integrating data from soil sensors and cameras. The system enables real-time representation of land and crop growth, provides data-driven recommendations for more efficient resource management, and supports improved agricultural decision-making.

Theoretically, this research contributes to advancing the understanding of Digital Twin applications in agriculture, particularly in land monitoring systems. By combining soil sensor technology, cameras, and drones into a digital model, this study introduces a novel approach to data-driven, real-time agricultural land management, which has been minimally explored in previous agricultural literature.

Practically, this research offers direct benefits to farmers by providing an easy-to-use platform for monitoring land and crop conditions, as well as actionable recommendations to improve productivity and resource efficiency. The system aids farmers in managing their land more effectively and reduces reliance on conventional methods, which are often more time-consuming and costly.

The results of this study indicate that the application of the Digital Twin technology in agricultural land monitoring systems produces significant and superior performance compared to conventional methods. The developed digital model can accurately represent land conditions and plant growth in real-time, with an accuracy of up to 92.5%, by integrating data from soil sensors, environmental sensors, and camera images. Initial evaluations also revealed that this system not only facilitates early detection of changes in land conditions but also increases the efficiency of resource use, such as air and fertiliser, by up to 25% and land productivity by up to 22.8%. The results of this study confirm the potential of the Digital Twin as an innovative solution in supporting data-based decision-making, which is very relevant for modern agricultural management.

However, this study is limited to rice fields as its case study, and the application of the Digital Twin technology can be extended to other crops. Although rice was selected due to its significance in Indonesian agriculture, the developed concept can be adapted to meet the needs of other crops by modifying relevant parameters such as soil type, water requirements, and specific environmental factors.

Several further developments that could be considered in the research and application of this system include:

- The integration of artificial intelligence (AI) technologies, particularly machine learning and deep learning, to analyse more complex data and enhance the system's predictive capabilities.
- Applying the developed system to other agricultural commodities, such as vegetables, fruits, or plantation crops.
- Conducting further experiments with various soil types and different climatic conditions to test the system's resilience and flexibility

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