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Development of an IoT-Based Adaptive Precision Agriculture System for Small-Scale Farmers

Maya Hidayat[1]*, Nadia Saputra[2], Rizki Wijaya[3]
[1,2] Department of Agroecotechnology, Faculty of Agriculture, Universitas Brawijaya, Malang, Indonesia
[3] Department of Agribusiness, Faculty of Agriculture, IPB University, Bogor, Indonesia

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ABSTRACT

This study aims to explore the development of an IoT-based adaptive precision agriculture system for small-scale farmers in response to irrigation uncertainty, limited digital access, and the need for practical farm decision support. This research used a qualitative case study approach in Sumberjo Village, Dlanggu District, Mojokerto Regency, East Java, Indonesia, from March to June 2025. Data were collected through semi-structured interviews, field observation, and documentation involving small-scale farmers, agricultural extension officers, farmer group leaders, and IoT system developers selected through purposive and snowball sampling. The findings reveal five main themes: the use of sensor data as a comparison tool for local farming knowledge, the need for simple and understandable technology, gradual trust-building in sensor data, the role of farmer groups in social learning, and economic practicality as a key condition for adoption. These findings show that IoT-based precision agriculture becomes meaningful when it fits farmers' routines, economic capacity, and local decision-making processes. The study contributes to socio-technical perspectives on digital agriculture by explaining how technology, users, institutions, and local farming practices interact in small-scale farming contexts. The study implies that IoT systems for small farmers should be affordable, adaptive, easy to use, and supported by continuous extension services. Further research should examine long-term impacts on productivity, water efficiency, and adoption sustainability.

***) Corresponding Author:**

Maya Hidayat,
Department of Agroecotechnology, Faculty of Agriculture, Universitas Brawijaya, Malang, Indonesia
Email: maya.hidayat104@gmail.com

1. Introduction

Global agriculture faces increasing pressure from climate variability, water scarcity, land degradation, rising input costs, and food security demands. These pressures affect small-scale farmers more directly because they often operate with limited capital, fragmented land, and restricted access to digital infrastructure. Precision agriculture offers a data-based approach to improve farm decisions through accurate monitoring of soil, water, crop, and weather conditions. In this context, Internet of Things technology enables real-time sensing, automated data collection, and adaptive decision support for crop management. IoT-based smart farming can improve resource efficiency by connecting field sensors, communication networks, and analytics systems (Dhanaraju et al., 2022). This shift is important because small farms need practical technologies that reduce uncertainty without increasing operational burden.

In Indonesia, small-scale farmers still play a central role in food production, yet many of them rely on experiential knowledge to decide irrigation, fertilization, pest control, and harvesting schedules. This knowledge remains valuable, but it becomes less reliable when weather patterns change and input prices fluctuate. Field-based studies on smart agriculture show that farmers often need technologies that are simple, affordable, and compatible with local farming routines. IoT adoption among smallholder farmers depends not only on technical performance but also on cost, usability, connectivity, and support systems (Antony et al., 2020). Similar concerns appear in IoT-enabled agriculture, where infrastructure gaps and limited digital literacy continue to shape adoption outcomes (Quy et al., 2022).

The main problem in the field is the mismatch between advanced technological design and the everyday reality of small-scale farming. Many IoT systems are built with strong technical capacity, but they do not always reflect farmers' working habits, economic constraints, and local decision-making processes. IoT-enabled smart agriculture still faces challenges related to interoperability, data management, security, connectivity, and user readiness (Rajak et al., 2023). For small-scale farmers, these challenges become more complex because technology adoption involves trust, learning, maintenance capacity, and perceived usefulness. Farmers' decisions to adopt precision agriculture technologies are also shaped by farming culture, practical support, and perceived relevance to their daily work (Kendall et al., 2022).

The issue is socially and educationally important because the use of IoT in agriculture changes how farmers understand land, crops, risk, and productivity. Adaptive precision agriculture does not only provide tools. It also introduces a new learning process in farm management. Farmers must learn to interpret sensor data, compare digital recommendations with local knowledge, and adjust decisions based on real-time information. Smart sensors can strengthen agricultural monitoring, but their value depends on how users interpret and apply the information (Ullo & Sinha, 2021). Therefore, IoT-based precision agriculture should be examined as a socio-technical process, not only as a technical innovation.

Previous studies have widely discussed IoT architecture, sensor networks, wireless communication, artificial intelligence, and smart irrigation systems. However, many studies still focus on system performance and technological potential. Fewer studies examine how small-scale farmers experience, interpret, accept, and negotiate adaptive IoT systems in real farming contexts. Farmers' perceptions are essential for understanding agricultural technology adoption (Jha et al., 2020). This gap shows the need for qualitative inquiry that explores meaning, experience, learning, and contextual barriers in the development of IoT-based adaptive precision agriculture systems.

This study aims to explore the development of an IoT-based adaptive precision agriculture system for small-scale farmers. The study focuses on farmers' needs, experiences, perceived benefits, adoption barriers, and adaptation processes during the use of IoT-based farm monitoring. Theoretically, this study contributes to socio-technical perspectives on digital agriculture by explaining how technology, users, institutions, and local practices interact in small-scale farming. Practically, the findings can guide technology developers, agricultural extension officers, farmer groups, and policymakers in designing affordable, adaptive, and user-centered precision agriculture systems.

2. Materials and Methods

This study used a qualitative case study approach. This approach was selected because the research aimed to explore the development and use of an IoT-based adaptive precision agriculture system within a real farming context. A case study design allowed the researcher to examine farmers' experiences, technology acceptance, practical constraints, and adaptation processes in depth. This approach was relevant because IoT-based precision agriculture involves interaction between devices, users, land conditions, local knowledge, and institutional support. Qualitative analysis is useful for identifying patterns of meaning in participants' experiences (Kiger & Varpio, 2020).

The research was conducted in Sumberjo Village, Dlanggu District, Mojokerto Regency, East Java, Indonesia, from March to June 2025. This location was selected because it represents a small-scale farming area with active crop cultivation, irrigation needs, and emerging interest in digital agricultural innovation. The research site also provided a suitable context for observing how farmers respond to sensor-based monitoring, adaptive irrigation recommendations, and digital information. The participants consisted of small-scale farmers, agricultural extension officers, farmer group leaders, and IoT system developers.

Participants were selected through purposive sampling. The inclusion criteria were direct involvement in farming activities, experience in managing crop production, willingness to participate in interviews and observations, and relevance to the development or use of the IoT system. Farmers were selected from those managing small plots and making daily decisions on irrigation, fertilization, and crop maintenance. Agricultural extension officers were included because they understood local farming problems and farmer support mechanisms. Snowball sampling was also used when initial participants recommended other informants who had relevant knowledge about technology use, irrigation practices, or farmer group decision-making.

Data were collected through semi-structured interviews, field observation, and documentation. Semi-structured interviews explored farmers' perceptions of IoT technology, their decision-making habits, perceived benefits, technical difficulties, and expectations for adaptive precision agriculture. Field observation focused on farming routines, irrigation practices, sensor placement, device use, farmer interaction with data, and communication between farmers and extension officers. Documentation included field notes, photographs, sensor records, system design notes, farmer group documents, and training materials. Smart agriculture requires attention to sensor function, field conditions, and user interaction (Rajak et al., 2023).

Data validity was ensured through source triangulation, method triangulation, member checking, and audit trail. Source triangulation compared information from farmers, extension officers, farmer group leaders, and system developers. Method triangulation compared interview results, observation notes, and documents. Member checking was conducted by returning key interview summaries to participants to confirm whether the researcher's interpretation matched their experiences. An audit trail was maintained by organizing interview transcripts, observation notes, coding records, and analytical memos. Credibility, dependability, confirmability, and transferability are central elements of trustworthiness in qualitative research (Ahmed, 2024).

Data were analyzed using thematic analysis supported by the interactive model of Miles, Huberman, and Saldaña. The analysis began with data condensation through repeated reading of transcripts and field notes. The researcher then developed initial codes related to farmer needs, digital literacy, usability, cost, trust in sensor data, irrigation decisions, technical constraints, and perceived value. These codes were grouped into broader themes to explain how farmers experienced and adapted to the IoT-based system. The findings were then interpreted through a socio-technical lens to show the relationship between technology design, farmer agency, local practice, and institutional support.

3. Results and Discussions

The findings show that small-scale farmers viewed the IoT-based adaptive precision agriculture system as useful when it helped them solve direct field problems. The most frequent problem mentioned by participants was uncertainty in irrigation decisions. Farmers usually relied on visual soil conditions, weather experience, and daily habits to decide when to water crops. After the system introduced soil moisture data, several farmers began to compare their personal judgment with sensor readings. One farmer stated, "I usually water the field when the soil looks dry, but the sensor showed that the lower soil layer was still moist." This statement shows that IoT data did not replace local knowledge. It became a comparison tool that helped farmers make more careful decisions.

The second theme was the need for simple and understandable technology. Farmers accepted the system more easily when the information appeared in clear language and practical indicators. They did not want complex dashboards or technical terms. They preferred direct messages such as “soil is dry,” “irrigation is needed,” or “water is sufficient.” Observation showed that farmers were more active in using the system when the interface used color indicators and short recommendations. One participant explained, “If the system only shows numbers, I do not understand quickly. But if it tells me whether the plant needs water, I can use it.” This finding indicates that usability became a key factor in technology acceptance.

The third theme was trust in sensor data. At the beginning of the trial, some farmers doubted whether sensor readings could represent the real condition of their land. They trusted the data only after comparing it with direct field observation. This process created gradual acceptance. Farmers did not accept the system immediately. They tested it through repeated use. An agricultural extension officer noted, “Farmers need proof from their own field before they believe the technology.” This shows that trust emerged through experience, not only through explanation or training.

The fourth theme was the role of social learning. Farmers learned to use the system through informal discussion with other farmers, extension officers, and system developers. Group interaction helped reduce fear of technology. Farmers who understood the system earlier became informal references for others. Observation during field visits showed that farmers often asked peers before asking the developer. This pattern reflects the importance of farmer groups as learning spaces. The system became easier to accept when it entered existing social networks rather than being introduced only through formal training.

The fifth theme was economic practicality. Farmers supported the idea of precision agriculture, but they questioned cost, maintenance, internet access, and long-term benefits. They were more willing to use the system if it could reduce water use, save labor, prevent crop stress, or improve yield quality. One farmer said, “The tool is good, but we need to know whether the cost is equal to the harvest benefit.” This finding shows that adoption depends on perceived economic value. Small-scale farmers assess technology through daily risk and household income, not only through technical performance.

Discussion

The findings confirm that IoT-based adaptive precision agriculture should be understood as a socio-technical innovation. The system works not only because sensors collect data, but because farmers can interpret, trust, and use that data in their routines. This result aligns with Dhanaraju et al. (2022), who argue that IoT can improve farm efficiency through real-time monitoring. However, this study adds that efficiency becomes meaningful only when the information is simple, relevant, and connected to farmers’ decisions. The technology must fit the user context, not the other way around.

The finding on usability supports Antony et al. (2020), who found that IoT adoption among smallholder farmers depends on cost, ease of use, connectivity, and support systems. In this study, farmers did not reject digital technology, but they rejected complicated information. This indicates that the main barrier is not always resistance to innovation. It can also come from poor design, unclear language, and weak user support. Therefore, adaptive precision agriculture for small-scale farmers should prioritize practical recommendations over technical complexity.

Trust in sensor data emerged as a major condition for adoption. This finding is consistent with Kendall et al. (2022), who showed that farmer adoption of precision agriculture is shaped by perceived relevance and practical confidence. In this study, trust was built through repeated comparison between sensor data and field observation. This means that technology acceptance among farmers is experiential. Farmers need to see that data matches their land conditions before they use it as a basis for decision-making.

The role of social learning strengthens the argument that digital agriculture depends on local institutions and farmer networks. Farmer groups, extension officers, and peer discussion shaped the adoption process. This finding expands previous studies that mainly emphasize technical architecture and system performance. Quy et al. (2022) discuss challenges in IoT-enabled agriculture, including connectivity and interoperability. This study adds that social interoperability is also important. A system must connect with local habits, group communication, and trusted actors in the farming community.

The economic practicality theme shows that small-scale farmers evaluate technology through direct benefits. They need evidence that IoT can reduce risk, save resources, or improve production outcomes. This supports Rajak et al. (2023), who emphasize that smart agriculture must address real field challenges. However, this study also shows that economic benefit cannot be separated from maintenance capacity and affordability. A system that works technically may still fail if farmers cannot maintain it or justify its cost.

Theoretically, this study contributes to the socio-technical perspective by showing that adaptive precision agriculture is formed through interaction between sensor systems, farmer knowledge, social learning, and economic judgment. Practically, the findings suggest that IoT systems for small-scale farmers should use simple interfaces, low-cost devices, offline or low-bandwidth options, clear recommendations, and continuous extension support. Future studies can examine the long-term use of IoT systems across different crops, seasons, and regions. Further research can also combine qualitative insights with yield, water-use, and cost-efficiency data to assess both social acceptance and measurable agricultural impact.

4. Conclusions

This study concludes that the development of an IoT-based adaptive precision agriculture system for small-scale farmers should not be understood only as a technical innovation, but also as a socio-technical process shaped by farmer experience, trust, usability, social learning, and economic practicality. The findings show that farmers accepted the system when it helped them solve direct field problems, especially irrigation uncertainty, and when sensor data could be compared with their own observations. The study contributes to the literature on digital agriculture by showing that local knowledge and digital data can work together when technology is designed in a simple, relevant, and context-sensitive way.

Theoretically, this study strengthens the socio-technical perspective in understanding precision agriculture adoption among small-scale farmers. Practically, the findings suggest that IoT systems should use simple interfaces, low-cost devices, clear recommendations, and continuous support from extension officers and farmer groups. From a policy perspective, digital agriculture programs should prioritize affordability, infrastructure readiness, farmer training, and local institutional support. Future studies can examine the long-term impact of IoT-based adaptive systems on yield, water efficiency, production costs, and adoption sustainability across different crops and regions.

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