



Smart Farming Implementation Strategies to Improve Water Resource Efficiency on Farmland

Joko Wibowo^{1*}, Kartika Lestari², Laras Putri³

^{1,2} Department of Agricultural Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia

³ Department of Agroecotechnology, Faculty of Agriculture, Universitas Brawijaya, Malang, Indonesia

Article Info

Received : 25 January 2026

Revised : 14 March 2026

Accepted : 6 April 2026

Keyword:

Smart farming;
Water efficiency;
Digital agriculture;
Precision irrigation.

ABSTRACT

This study aims to analyze smart farming implementation strategies to improve water resource efficiency on farmland. The issue is important because conventional irrigation practices often rely on farmer intuition, fixed schedules, and limited water availability, which may lead to inefficient water use. This research employed a qualitative case study design to explore farmers' experiences, perceptions, and adaptation strategies in using smart farming technologies. Data were collected through semi-structured interviews, limited participatory observation, and documentation involving farmers, farmer group leaders, agricultural extension officers, technology providers, and local agricultural stakeholders selected through purposive and snowball sampling. The data were analyzed using thematic analysis supported by data reduction, data display, and conclusion drawing. The findings reveal four main themes: improved awareness of water efficiency, selective technology adoption based on usefulness and trust, the role of institutional and social support, and contextual adaptation of smart farming practices to local field conditions. These findings show that smart farming works effectively when digital tools are aligned with farmers' knowledge, technical support, and local agricultural routines. The study contributes to socio-technical perspectives on digital agriculture and offers practical insights for designing inclusive, affordable, and sustainable smart farming programs. Future research should compare different agricultural regions, crop types, and irrigation systems to strengthen broader understanding of smart farming adoption.



© 2026 The authors. Published by PT. Global Teras Fana.

This is an open-access article under the Creative Commons Attribution-Share Alike

(<https://creativecommons.org/licenses/by-sa/4.0/>)

*) Corresponding Author:

Joko Wibowo,

Department of Agricultural Engineering, Faculty of Agricultural Technology, Universitas Gadjah Mada, Yogyakarta, Indonesia

Email: joko.wibowo103@gmail.com

1. Introduction

Agriculture faces growing pressure from climate variability, water scarcity, and the need to maintain food production under limited natural resources. Water has become one of the most critical inputs in farming because irrigation practices still depend heavily on fixed schedules, farmer intuition, and conventional water distribution systems. Smart farming offers a more precise approach by integrating sensors, Internet of Things devices, automated irrigation, climate data, and decision-support systems to match water application with crop and soil conditions. Recent studies show that precision irrigation and IoT-based smart irrigation can improve water-use efficiency, reduce waste, and support sustainable agricultural management (Lakhier et al., 2024; Obaideen et al., 2022). These findings indicate that smart farming should not be viewed only as

a technological innovation, but also as a strategic response to the wider challenge of sustainable water governance in agriculture.

In many developing agricultural contexts, including Indonesia, the adoption of smart farming remains uneven. Smallholder farmers often work under limited access to capital, unstable infrastructure, low digital literacy, and dependence on seasonal water availability. Although digital agriculture has expanded through mobile applications, sensor-based irrigation, and automated monitoring systems, many farmers still face practical barriers in using these tools consistently. Gumbi et al. (2023) found that digital agriculture systems often remain difficult for smallholder farmers because the supporting ecosystem is still underdeveloped. Porciello et al. (2022) also noted that many digital agriculture services in low- and middle-income countries focus on knowledge and advisory support, while evidence on environmental sustainability and climate resilience remains limited.

Field-level problems show that inefficient irrigation is not only caused by the absence of technology. It also emerges from habits, risk perception, limited technical support, and weak integration between farmers' local knowledge and digital systems. Farmers may hesitate to rely on soil-moisture sensors or automated irrigation when the data conflict with their traditional reading of soil texture, leaf condition, weather patterns, or water availability. Ronaghi and Forouharfar (2020) explain that the use of IoT in smart farming depends on contextual factors that shape farmers' acceptance and actual use. This means that the success of smart farming requires attention to both technical performance and farmers' lived experiences.

The issue is important because water efficiency in agriculture has social, economic, educational, and environmental implications. Better water management can reduce production costs, support crop stability, and strengthen farmers' capacity to adapt to climate uncertainty. It can also support farmer education by encouraging data-based decision-making in daily farm management. However, the implementation of smart farming may create new inequalities if only farmers with capital, digital skills, and institutional support can benefit from it. Ruzzante et al. (2021) showed that education, credit access, land size, extension services, and farmer organization membership often influence agricultural technology adoption. These factors make smart farming a social process, not merely a technical intervention.

Previous studies have mainly examined smart farming through engineering design, sensor performance, system architecture, algorithm development, and quantitative measurement of water-use efficiency. For example, Obaideen et al. (2022) reviewed IoT-based smart irrigation systems in relation to sustainable development goals, while Lakhier et al. (2024) emphasized the role of precision irrigation in improving water efficiency, crop yield, and environmental outcomes. However, fewer studies have explored how farmers interpret, negotiate, and adapt smart farming technologies within their everyday agricultural practices. This creates a literature gap in understanding the meanings, experiences, and social processes behind smart farming implementation.

This study uses a qualitative perspective because the research problem requires deep understanding of human experience, local practice, and contextual meaning. Qualitative inquiry is suitable for examining how actors understand complex social phenomena and how they make decisions within real-life settings (Lim, 2025). In this study, smart farming is viewed through a socio-technical lens. This perspective recognizes that technology works through relationships among devices, users, institutions, infrastructure, knowledge, and policy. Klerkx and Rose (2020) argue that agriculture 4.0 requires responsible management of technological diversity and transition pathways. Therefore, this research does not only ask whether smart farming improves water efficiency, but also how it can be implemented in ways that are acceptable, practical, and sustainable for farmers.

Based on this background, this study aims to analyze smart farming implementation strategies to improve water resource efficiency on farmland. The research focuses on farmers' experiences,

perceived benefits, implementation barriers, institutional support, and adaptation strategies in using smart irrigation or related digital farming technologies. Theoretically, this study contributes to the development of socio-technical studies on agricultural technology adoption and sustainable water management. Practically, it provides insights for farmers, extension officers, technology developers, and policymakers in designing smart farming strategies that are affordable, context-sensitive, and aligned with real farming conditions.

2. Materials and Methods

This study employed a qualitative approach with a case study design. The case study design was selected because the research examined smart farming implementation as a real-life phenomenon shaped by farmers' experiences, technological tools, institutional support, and local water-management practices. A qualitative case study allows the researcher to explore complex processes in depth, especially when the boundaries between technology, user behavior, and environmental context are closely connected. Mtisi (2022) states that qualitative case study research is useful for examining social phenomena within their natural setting. This design was therefore appropriate for understanding how farmers apply, evaluate, and adapt smart farming strategies to improve water efficiency on farmland.

The study was conducted in an agricultural area where farmers had introduced or tested smart farming technologies, particularly technologies related to water management. These technologies may include soil-moisture sensors, IoT-based irrigation systems, automated pumps, drip irrigation, weather-monitoring tools, or mobile applications for land monitoring. The research site was selected because it represented a relevant case of early smart farming implementation in farmland water management. The study was planned for three months, covering preliminary observation, participant recruitment, data collection, data validation, and initial data analysis. This period allowed the researcher to observe irrigation routines, farmer decision-making, and the use of digital tools in different field situations.

Participants were selected using purposive sampling. The main participants were farmers who had used, tested, or directly observed smart farming technologies for irrigation or water control. Supporting participants included farmer group leaders, agricultural extension officers, technology providers, local agricultural officials, and technicians involved in the operation or maintenance of smart farming tools. The inclusion criteria covered direct experience with smart farming, involvement in water-resource management, willingness to participate, and ability to provide detailed information about implementation practices. Snowball sampling was also used when initial participants recommended other informants with relevant knowledge, such as pioneer farmers, equipment operators, or farmers who chose not to adopt the technology.

Data were collected through semi-structured interviews, limited participatory observation, and documentation. Semi-structured interviews explored farmers' perceptions of smart farming, reasons for adoption or non-adoption, perceived water efficiency, technical challenges, cost considerations, training needs, and trust in sensor-based decisions. Observations focused on irrigation practices, how farmers read sensor data, how they operate pumps or irrigation tools, and how decisions about water use are made in the field. Documentation included photographs of tools, irrigation schedules, farmer group records, training materials, technical manuals, and relevant local program documents. These techniques helped the researcher compare what participants said, what they did, and what was recorded in supporting documents.

Data credibility was strengthened through source triangulation, method triangulation, member checking, and audit trail. Source triangulation was conducted by comparing information from farmers, extension officers, technology providers, and local agricultural stakeholders. Method triangulation was carried out by comparing interview data, observation notes, and documents. Member checking was conducted by returning key interview summaries or preliminary interpretations to selected participants to confirm accuracy. An audit trail was maintained by

storing interview guides, field notes, transcripts, coding records, analytic memos, and documentation of methodological decisions. These procedures supported the credibility, dependability, and confirmability of the study.

Data were analyzed using thematic analysis supported by the interactive model of data reduction, data display, and conclusion drawing. The analysis began with repeated reading of interview transcripts, observation notes, and documents to identify meaningful statements. The researcher then applied open coding to important data segments related to water efficiency, technology usability, cost barriers, digital literacy, institutional support, farmer trust, and local adaptation. Similar codes were grouped into broader themes, such as perceived benefits of smart farming, barriers to implementation, socio-technical adaptation, institutional support, and sustainable water-management strategies. Thematic analysis was selected because it enables systematic identification of patterns across qualitative data (Kiger & Varpio, 2020; Braun & Clarke, 2021).

The final stage of analysis involved interpreting the themes in relation to smart farming adoption, socio-technical systems, and sustainable water-resource management. The researcher connected participants' experiences with relevant theories and previous studies on digital agriculture, precision irrigation, and technology adoption. The findings were then presented in narrative form to explain not only what strategies were used, but also why those strategies worked or failed in the local farming context. This methodological procedure allows limited replication in other agricultural settings with similar characteristics, especially areas that are introducing smart irrigation, digital farming tools, or community-based water-efficiency programs.

3. Results and Discussions

The findings show that smart farming was understood by farmers as a practical tool for controlling water use, not merely as a modern agricultural technology. Most participants linked smart farming with the ability to know when the land needed water and when irrigation should be stopped. Farmers who had used soil-moisture sensors stated that the technology helped them reduce guesswork in irrigation decisions. One farmer explained, "Before using the sensor, I watered the land based on habit. Now I check the soil condition first, so the water is not wasted" (P3). This finding indicates that smart farming changed the meaning of irrigation from routine activity into data-informed decision-making.

The first major theme was improved awareness of water efficiency. Farmers reported that smart irrigation tools helped them recognize that excessive watering did not always improve crop growth. Observation showed that farmers began to compare sensor readings with visible field conditions, such as soil texture, plant color, and weather changes. This practice created a new learning process in which farmers combined local knowledge with digital information. One participant stated, "The tool does not replace our experience, but it helps us confirm whether the soil really needs water" (P5). This finding shows that smart farming worked best when farmers did not treat technology as a replacement for experience, but as a support system for more accurate decisions.

The second theme was selective adoption based on usefulness, cost, and trust. Farmers accepted smart farming when they saw clear benefits, such as lower water use, reduced labor, and more stable irrigation schedules. However, some participants remained hesitant because of installation costs, maintenance needs, unstable internet connection, and fear of equipment damage. One farmer said, "The system is useful, but if it breaks, we do not always know who can repair it" (P7). This shows that adoption was shaped not only by perceived benefits, but also by the availability of technical support and farmers' confidence in long-term use.

The third theme was the importance of institutional and social support. Farmers who received guidance from extension officers, farmer group leaders, or technology providers showed stronger confidence in using smart farming tools. Group-based learning helped farmers share problems,

compare results, and reduce anxiety about new technology. Documentation from farmer group meetings also showed that training and demonstration plots played an important role in encouraging adoption. One extension officer stated, "Farmers need to see the result directly. After they compare water use before and after the tool, they become more open to using it" (E1). This finding suggests that smart farming implementation depends on social learning and continuous assistance.

The fourth theme was the need for contextual adaptation. Farmers did not apply smart farming in the same way across all plots. They adjusted irrigation decisions based on crop type, soil condition, water source, weather, and labor availability. In some cases, farmers used the sensor only as a reference, while final decisions still depended on field observation. This pattern shows that smart farming was adapted to local farming culture rather than applied as a fixed technical system. The technology became meaningful when it fit farmers' routines, resources, and environmental conditions.

Discussion

The findings support the socio-technical view that smart farming is not only a matter of device adoption, but also a process of interaction between technology, users, institutions, and local knowledge. The study shows that farmers accepted smart farming when it helped them solve practical problems in water management. This aligns with Klerkx and Rose (2020), who argue that agriculture 4.0 requires attention to social responsibility, user diversity, and transition pathways. In this study, smart farming became useful when it supported existing farming logic instead of forcing farmers to abandon their knowledge.

The finding on water-efficiency awareness is consistent with Lakhiar et al. (2024), who found that precision irrigation can improve water-use efficiency and reduce environmental pressure. It also supports Obaideen et al. (2022), who emphasized the role of IoT-based irrigation systems in sustainable agriculture. However, this study adds a qualitative insight. Farmers did not define efficiency only as reduced water volume. They understood efficiency as better timing, lower labor burden, reduced uncertainty, and more confidence in irrigation decisions.

The finding on selective adoption is consistent with Ruzzante et al. (2021), who showed that agricultural technology adoption depends on education, access to support, credit, and farmer organization. It also supports Ronaghi and Forouharfar (2020), who found that acceptance of IoT in smart farming depends on contextual factors. The present study extends these findings by showing that trust in technology develops through repeated use, visible results, and access to repair support. Farmers were more willing to adopt smart farming when they could test it directly and receive assistance when problems occurred.

The role of farmer groups and extension officers confirms that digital agriculture requires an enabling ecosystem. Gumbi et al. (2023) found that sustainable digital agriculture for smallholder farmers depends on infrastructure, training, institutional readiness, and local capacity. The current findings show that social learning through farmer groups can reduce resistance to technology. Demonstration plots, peer explanation, and repeated field assistance helped farmers understand sensor data and relate it to their own field experience.

The study also reveals a difference from technology-centered studies that assume smart farming can be transferred directly from one context to another. In this research, farmers adapted the technology based on soil condition, crop type, and local water availability. This means that smart farming strategies must remain flexible. A system that works in one farmland may not work in the same way in another location. This finding strengthens the argument that smart farming implementation should use a participatory approach that involves farmers from the planning stage.

Theoretically, this study contributes to the literature on smart farming adoption by showing that water-resource efficiency is shaped by both technological capability and social acceptance.

The findings support the use of socio-technical systems theory in understanding digital agriculture. Practically, the study suggests that smart farming programs should include affordable technology packages, local technicians, farmer training, demonstration plots, and simple data interpretation tools. Future research should compare several farming areas with different crops, irrigation systems, and levels of digital readiness to deepen understanding of smart farming implementation in diverse agricultural contexts.

4. Conclusions

This study concludes that smart farming implementation can improve water resource efficiency on farmland when technology is integrated with farmers' local knowledge, practical needs, and institutional support. The findings show four main themes: increased awareness of water efficiency, selective adoption based on usefulness and trust, the importance of farmer groups and extension support, and contextual adaptation to soil, crop, and water conditions. These findings contribute to a deeper understanding of smart farming as a socio-technical process, not merely a technological intervention.

Theoretically, this study strengthens the relevance of socio-technical systems theory in explaining digital agriculture adoption. Practically, the findings suggest that smart farming programs should prioritize affordable tools, continuous training, demonstration plots, local technical assistance, and simple data interpretation for farmers. From a policy perspective, government and agricultural institutions need to support inclusive digital farming infrastructure and strengthen farmer-based learning systems. Future studies may compare different farming areas, crop types, and irrigation systems to expand understanding of smart farming implementation in diverse agricultural contexts.

References

- Aisyah, N., Ulhaq, E. D., Dharmawan, A., & Purbakawaca, R. (2025). Design of an IoT-based smart irrigation system using soil moisture sensors for water efficiency. *Journal of Physics*, 11(1). <https://doi.org/10.22437/jop.v11i1.48928>
- Ali, A., Hussain, T., & Zahid, A. (2025). Smart irrigation technologies and prospects for enhancing water use efficiency for sustainable agriculture. *AgriEngineering*, 7(4), 106. <https://doi.org/10.3390/agriengineering7040106>
- Braun, V., & Clarke, V. (2021). One size fits all? What counts as quality practice in reflexive thematic analysis? *Qualitative Research in Psychology*, 18(3), 328–352. <https://doi.org/10.1080/14780887.2020.1769238>
- Braun, V., & Clarke, V. (2022). Toward good practice in thematic analysis: Avoiding common problems and becoming a knowing researcher. *International Journal of Transgender Health*, 24(1), 1–6. <https://doi.org/10.1080/26895269.2022.2129597>
- Gumbi, N., Gumbi, L., & Twinomurizi, H. (2023). Towards sustainable digital agriculture for smallholder farmers: A systematic literature review. *Sustainability*, 15(16), 12530. <https://doi.org/10.3390/su151612530>
- Jaiswal, N., Singh, A., & Kumar, R. (2025). Smart drip irrigation systems using IoT: A review. *Discover Applied Sciences*, 7, 430. <https://doi.org/10.1007/s44279-025-00430-1>
- Kiger, M. E., & Varpio, L. (2020). Thematic analysis of qualitative data: AMEE Guide No. 131. *Medical Teacher*, 42(8), 846–854. <https://doi.org/10.1080/0142159X.2020.1755030>
- Klerkx, L., & Rose, D. (2020). Dealing with the game-changing technologies of agriculture 4.0: How do we manage diversity and responsibility in food system transition pathways? *Global Food Security*, 24, 100347. <https://doi.org/10.1016/j.gfs.2019.100347>

- Lakhiar, I. A., Yan, H., Zhang, C., Wang, G., He, B., Hao, B., Syed, T. N., Chandio, F. A., & Qureshi, W. A. (2024). A review of precision irrigation water-saving technology under changing climate for enhancing water use efficiency, crop yield, and environmental footprints. *Agriculture*, 14(7), 1141. <https://doi.org/10.3390/agriculture14071141>
- Li, W., Clark, B., Taylor, J. A., Kendall, H., Jones, G., Li, Z., Jin, S., Zhao, C., Yang, G., Shuai, C., Cheng, X., Chen, J., Yang, H., & Frewer, L. J. (2020). A hybrid modelling approach to understanding adoption of precision agriculture technologies in Chinese cropping systems. *Computers and Electronics in Agriculture*, 172, 105305. <https://doi.org/10.1016/j.compag.2020.105305>
- Lim, W. M. (2025). What is qualitative research? An overview and guidelines. *Australasian Marketing Journal*. <https://doi.org/10.1177/14413582241264619>
- Liu, W., Shao, X. F., Wu, C. H., & Qiao, P. (2021). A systematic literature review on applications of information and communication technologies and blockchain technologies for precision agriculture development. *Journal of Cleaner Production*, 298, 126763. <https://doi.org/10.1016/j.jclepro.2021.126763>
- Manzoor, F., Wei, L., & Siraj, M. (2025). Digital agriculture technology adoption in low- and middle-income countries: A systematic review. *Frontiers in Sustainable Food Systems*, 9, 1621851. <https://doi.org/10.3389/fsufs.2025.1621851>
- Mohammed, M., Riad, K., & Alqahtani, N. (2021). Efficient IoT-based control for a smart subsurface irrigation system to enhance irrigation management of date palm. *Sensors*, 21(12), 3942. <https://doi.org/10.3390/s21123942>
- Mtisi, S. (2022). The qualitative case study research strategy as applied on a rural enterprise development doctoral research project. *International Journal of Qualitative Methods*, 21, 1–13. <https://doi.org/10.1177/16094069221145849>
- Obaideen, K., Yousef, B. A. A., AlMallahi, M. N., Tan, Y. C., Mahmoud, M., Jaber, H., & Ramadan, M. (2022). An overview of smart irrigation systems using IoT. *Energy Nexus*, 7, 100124. <https://doi.org/10.1016/j.nexus.2022.100124>
- Oğuztürk, G. E. (2025). AI-driven irrigation systems for sustainable water management: A systematic review and meta-analytical insights. *Smart Agricultural Technology*, 10, 100982. <https://doi.org/10.1016/j.atech.2025.100982>
- Porciello, J., Coggins, S., Mabaya, E., & Otunba-Payne, G. (2022). Digital agriculture services in low- and middle-income countries: A systematic scoping review. *Global Food Security*, 34, 100640. <https://doi.org/10.1016/j.gfs.2022.100640>
- Ronaghi, M. H., & Forouharfar, A. (2020). A contextualized study of the usage of the Internet of Things in smart farming in a typical Middle Eastern country within the context of the Unified Theory of Acceptance and Use of Technology model. *Technology in Society*, 63, 101415. <https://doi.org/10.1016/j.techsoc.2020.101415>
- Ruzzante, S., Labarta, R., & Bilton, A. (2021). Adoption of agricultural technology in the developing world: A meta-analysis of the empirical literature. *World Development*, 146, 105599. <https://doi.org/10.1016/j.worlddev.2021.105599>