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Review Article

Sensor-Based Smart Irrigation Management for Rice Production: A Systematic Review

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ABSTRACT

Despite advances in sensor-based smart irrigation, existing research often examines sensing, Internet of Things (IoT), and artificial intelligence (AI) approaches separately, with limited synthesis of their combined roles in precision water management for rice production. This review addresses this gap by systematically evaluating soil moisture sensors, IoT-enabled irrigation, and AI approaches to improve irrigation precision, water use efficiency, and rice productivity. A structured major database search identified 210 records, with 80 studies meeting the inclusion criteria. The studies were grouped into four themes: soil moisture sensors and calibration, IoT and automated irrigation, sensor-based water management, rice production and machine learning and AI-based decision making. Soil moisture sensors, including resistive, capacitive, Time Domain Reflectometry, Frequency Domain Reflectometry and neutron probe sensors, provide different capabilities for real-time monitoring. The performance of all those sensors is influenced by soil conditions, calibration procedures and sensor placement. IoT systems enabled continuous monitoring, automated irrigation and cloud-based decision support, while AI support soil moisture forecasting and

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predictive scheduling. Quantitative evidence indicates that sensor-based smart irrigation reduces water use, improves water use efficiency, and maintains or enhances rice yield. However, sensor reliability, calibration, implementation cost, infrastructure, maintenance and scalability remain important barriers to adaptive irrigation under diverse rice-growing conditions. Future research should address gaps in affordable, validated systems that integrate sensing, IoT, and AI technologies for precise and sustainable rice water management.

Keywords: Internet of Things (IoT), irrigation, moisture content, rice, soil moisture sensor, water use efficiency, yield

INTRODUCTION

Rice (*Oryza sativa* L.) is a vital cereal crop worldwide, serving as a staple food for over half the global population, with Asia producing 90% of the total global yield (Fukagawa & Ziska, 2019). It is highly water-dependent and consumes approximately 24-30% freshwater resources in the world (Nandan et al., 2020). The amount of fresh water that is available for human use is less than 0.01% of the total amount of water on Earth, highlighting its scarcity despite being crucial for sustaining biodiversity (Potharaju & Aruna, 2024). Rapid population growth has increased water scarcity across many regions. Agriculture consumes nearly 70% of global freshwater withdrawals, while 15-35% of irrigation water use remains unsustainable, highlighting the need for improved water use efficiency (Ingrao et al., 2023).

Overwatering, nutrient leaching, and water wastage might result from using conventional irrigation techniques. With the growing need to conserve water resources and improve crop yields, precision irrigation technologies have gained prominence in rice farming (Loconsole et al., 2025). Smart farming allows farmers to remotely monitor the plants, including harvesting and crop yields, as well as automation of the sensors and machinery in order to optimise the quantity and quality of product (O'Grady et al., 2017). Local rural economies are greatly impacted by irrigation since it influences crop output and encourages economic growth. Soil type significantly influences water holding capacity and crop productivity, with clay loam soils having higher field capacity than sandy soils (Ma et al., 2016).

Organic matter enhances soil structure and moisture retention, especially in sandy and loamy soils, improving crop resilience under water stress (Cachipuendo et. al., 2025). Ensuring the soil has a suitable amount of moisture in critical stages for maintaining good crop growth because of varying requirements for soil moisture content at different periods and its impact on crop yields (Nangia et. al., 2018). According to several studies, during the mid-to-late grain filling stage, moderate soil drying enhances the activity of key enzymes involved in the synthesis of starch, significantly increasing the grain-filling rate and grain weight, thereby improving rice yield (Wang et al., 2019). Evidence suggests that after drought, rehydration can recover the metabolism of rice source and sink organs, facilitating

normal growth and development (Lawas et al., 2019). A proven technique for controlling agricultural water requirements during the growing season is irrigation scheduling. Various irrigation scheduling techniques, including evapotranspiration (ET), soil moisture sensing and artificial intelligence (AI)-based methods have been previously demonstrated (Kelley et al., 2023). Today's agricultural technology has changed the way farming is carried out, and the Internet of Things has revolutionised traditional methods (Quy et al., 2022).

Internet of Things (IoT) technologies in farm management can provide real-time monitoring of soil moisture, temperature and other critical environmental variables, allowing more precise and automated irrigation practices. Using IoT and microcontroller devices with solar panels, a smart irrigation system for rice cultivation was developed. It can automate irrigation by minimising physical labour through proper monitoring (Binayao et al., 2024). This Internet of Things (IoT) information helps farmers in rice fields by monitoring them remotely. Among these, soil moisture sensors provide real-time data on soil water availability, which forms the foundation of water management decision-making systems (Placidi et al., 2020). In order to guarantee ideal levels of moisture for crops and avoid excess irrigation, using IT-based soil moisture sensing irrigation scheduling helps to maintain proper moisture content in the plant's root zone (Bryant et al., 2023). Therefore, when compared to traditional techniques of irrigation, sensor-based irrigation scheduling improved the efficiency of water consumption. IoT-based irrigation using soil moisture sensors enables precise water application, significantly enhancing water use efficiency and crop yields in diverse cropping systems (Gopal et al., 2025). Despite the fact that a number of studies on soil sensors have been conducted, users of soil sensors continue to face many difficulties because of diverse concepts, types and production requirements, in addition to the characteristics of soil moisture sensors.

Even with the increasing application of soil moisture sensors and IoT technologies in agricultural water management, several research gaps remain. Previous review articles have discussed soil moisture sensing technologies, smart irrigation systems and IoT-based agricultural applications. However, most have focused on general irrigation practices, individual sensor technology or broad precision agriculture applications. Limited attention has been given to the integration of recent advances in soil moisture sensing, sensor calibration, field capacity-based irrigation threshold, IoT-enabled irrigation control, artificial intelligence (AI) and water use efficiency specifically for rice production. Furthermore, previous reviews have generally provided descriptive overviews with limited critical comparison of sensing performance, calibration requirements, irrigation scheduling strategies and the practical challenges associated with sensor deployment under diverse rice growing conditions. Rapid developments in low-cost sensors, wireless communication, edge computing and AI-driven decision support systems have also generated substantial recent evidence that needs systematic and critical analysis.

Therefore, the present review focuses especially on sensor-based smart irrigation management for rice production. It provides a comprehensive synthesis of soil moisture sensing technologies, sensor calibration, field capacity threshold, IoT integration, AI-assisted irrigation scheduling, water use efficiency, sensor deployment, yield improvement and emerging research direction. In contrast to earlier reviews, this study integrates recent literature published during 2015-2026, with particular emphasis on rice-specific smart irrigation applications and a critical comparison of sensor technologies, AI and IoT-driven precision irrigation strategies. The principal contribution of the reviews is to establish a holistic framework that links soil moisture sensing, calibration, automated irrigation control, efficient water management, and sustainable rice production. Also, identifying technological and practical research priorities for improving irrigation efficiency under increasing climate variability and water scarcity. This review further examines the fundamental working principles of major types of soil moisture sensors and their applications in rice irrigation management to assess their integration with Internet of Things (IoT) technologies and automation systems. Also identify the current challenges, research gap and future opportunities for smart irrigation management.

LITERATURE SEARCH AND SELECTION CRITERIA

The literature search was carried out comprehensively following the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) to make the process of literature selection transparent and reproducible. Five scientific databases (Scopus, Web of Science, ScienceDirect, IEEE Xplore and SpringerLink) were used to identify relevant publications published between 2015 and 2026. The reference lists of the selected articles were manually searched for additional relevant publications to make sure that the topic was covered in as comprehensive a way as possible. Literature search was done using keywords, machine learning, sensor calibration, precision irrigation, soil moisture monitoring, irrigation scheduling, smart irrigation, soil moisture sensor, Internet of Things (IoT), rice, water use efficiency and combinations of these with Boolean operators (AND, OR). Records were regularly assessed for relevance during the review process because the literature search was carried out manually in phases. Table 1 provides a summary of the inclusion and exclusion criteria utilised in the selection of the literature.

Potentially relevant articles were assessed using abstracts and titles, and after removal of duplicate publications, full-text evaluation was performed. The studies were chosen because they are relevant to soil moisture sensing technologies, smart irrigation systems, irrigation scheduling, Internet of Things (IoT) applications, artificial intelligence, sensor calibration and water use efficiency in rice production. Lastly, 80 articles were selected to participate in the qualitative synthesis, which was then grouped into thematic categories such as soil moisture sensing technologies, calibration and sensor performance, irrigation systems with IoT support, irrigation scheduling, water use efficiency, irrigation decision support using AI, and future research directions. The process of study identification,

screening, eligibility assessment and final inclusion is summarised following the PRISMA 2020 framework in Figure 1.

Table 1
Criteria for inclusion and exclusion in the selection of literature

Criterion	Inclusion Criteria	Exclusion Criteria
Publication period	From 2015 to 2026	Published prior to 2015
Language	English	Publications written in languages other than English
Publication type	Selected conference proceedings and peer-reviewed journal articles	Newsletters, theses, patents, editorials and short communications
Study focus	Water use efficiency, rice production, IoT, AI, smart irrigation, precision agriculture, soil moisture sensors and irrigation scheduling	Research unrelated to soil moisture monitoring or irrigation technologies
Crop	The main focus is rice; specific studies on other crops are utilised to compare technologies.	Other crop studies without relevance to rice irrigation technology
Accessibility	Articles in full text	Publications with only abstracts
Scientific relevance	Experimental investigations, field trials, greenhouse studies, modelling studies and review papers relevant to smart irrigation	Research with insufficient technical details or applicability

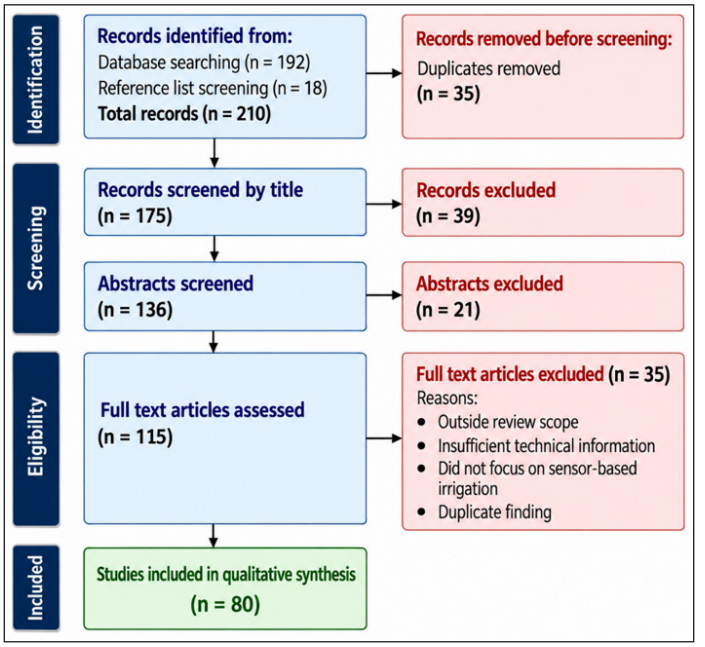

Figure 1. PRISMA 2020 flow diagram showing how studies were identified via database screening in this systematic review

The bibliographic distribution of selected articles by year of publication is shown in Figure 2. The overall trend of the number of publications is an increasing one, especially after 2021, reaching the highest in 2024 (14 publications), followed by 2025 (13 publications) and 2023 (13 publications). The rising publications reflect the growing research interest in sensor-based smart irrigation, IoT-based agricultural systems, and data-driven water management for rice production.

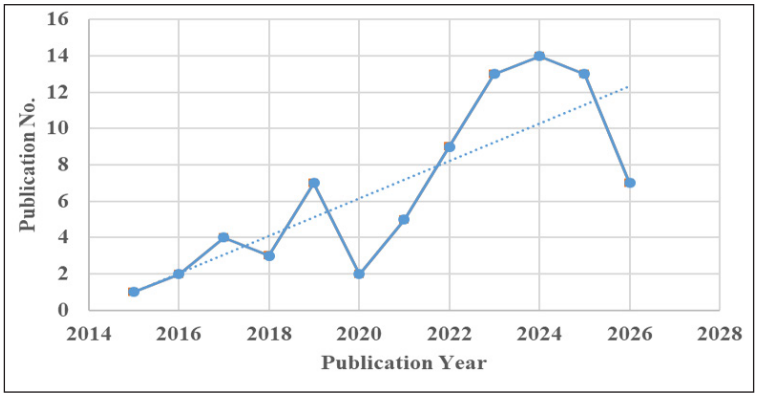

Figure 2. Annual publication trend of the studies included in the systematic review (2015-2026)

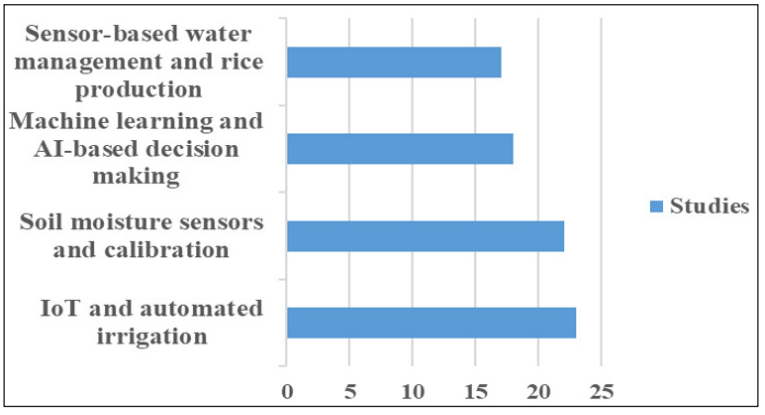

Figure 3. Distribution of the 80 chosen studies among the primary research themes

The selected studies are also grouped into four main research themes, defined by their principal research focus (Figure 3). The largest thematic category was IoT and automated irrigation, with 23 studies, followed by soil moisture sensors and calibration (22 studies), machine learning and AI-based decision-making (18 studies), and sensor-based water management and rice production (17 studies). This thematic distribution illustrates the high focus on irrigation using the IoT and the sensing of soil moisture, as well as growing integration of AI-based irrigation approaches in rice water management.

OVERVIEW OF SOIL MOISTURE SENSING TECHNOLOGIES

Comparative Analysis of Different Types of Soil Moisture Sensors

The soil moisture sensor is a critical part of smart irrigation systems, aiding in the effective irrigation scheduling and water resource management. These sensors are based on different principles and thus have different levels of accuracy, response time, cost and applicability to agricultural uses (Mahmud et al., 2026). A comparative outline of the main categories of soil moisture sensors is given in Table 2, which summarises the working principle, main advantages, limitations, applications and references for them.

Overall, sensor accuracy is highly dependent on soil texture, bulk density, salinity, temperature, sensor configuration, and calibration method. Capacitive, TDR and FDR sensors are generally more accurate than low-cost resistive sensors and neutron probes, which need accurate calibration. However, site-specific calibration is still relevant, especially in the case of dielectric sensors, since there may be inconsistencies in the calibration relationships from one soil to another.

To further illustrate the practical characteristics of the mentioned five sensor categories, representative commercial models are presented in Figure 4. These include (a) resistive sensors (SparkFun Soil Moisture Sensor), (b) capacitive sensors (DFRobot Gravity Capacitive Soil Moisture Sensor), (c) TDR sensors (TDR-150), (d) FDR sensors (BND-MS10) and (e) neutron probe sensors (Schematic hydroprobe). These demonstrate the different sensor configurations used for soil-moisture monitoring in agricultural and smart irrigation applications.

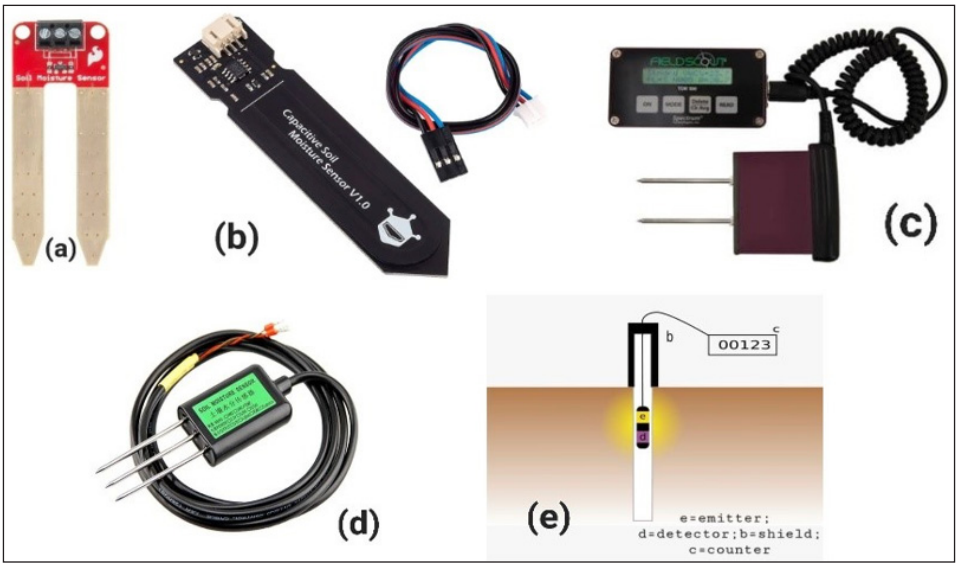

Figure 4. Representative models of five soil moisture sensor types: (a) resistive; (b) capacitive; (c) time domain reflectometry (TDR); (d) frequency domain reflectometry (FDR); and (e) neutron probe sensors

Table 2
Comparison of soil moisture sensor types used in a smart irrigation system

Sensor Type	Working Principle	Advantages	Limitations	Measurement Accuracy/ Error Range*	Typical Application	Key References
Resistive Sensor	Measure the electrical resistance between two electrodes inserted in the soil	Low cost, simple design, easy installation, suitable for basic irrigation monitoring	Sensitive to soil salinity, temperature and electrode corrosion, reducing long-term measurement accuracy	≈4-12.5% VWC error	Small-scale irrigation, educational project	Nandi & Shrestha, 2024
Capacitive Sensor	Estimates the moisture of soil by measuring the changes in soil dielectric constants caused by varying water content	Provide real-time data measurements, low maintenance, minimal calibration requirements, and less affected by salinity than resistive sensors	Accuracy may vary with soil texture and bulk density; periodic calibration is recommended for different soil types	≈1-8.5% VWC error	Precision irrigation, IoT-based smart farming, greenhouse and field monitoring	Escriba et al., 2020; Mahmud et al., 2026; Nandi & Shrestha, 2024
Time Domain Reflectometry (TDR)	Uses electromagnetic pulse travel time to estimate soil moisture	High accuracy, reliable long-term performance, continuous monitoring at multiple soil depths, less affected by salinity	High equipment cost, complex calibration, requires technical expertise for installation and data interpretation	≈2-4% VWC error under calibrated conditions	Scientific research, precision agriculture, and soil water dynamics studies	Zhu et al., 2019; Datta & Taghvaeian, 2023
Frequency Domain Reflectometry (FDR)	Measures changes in resonant frequency or capacitance associated with the soil dielectric constant	Rapid responses, continuous monitoring, lower cost than TDR, suitable for automation	Overestimate moisture in high saline soils; accuracy depends on conductivity and calibration	≈1-4% VWC error under calibrated conditions	Smart irrigation systems, commercial agriculture, and real-time moisture monitoring	Qi et al., 2024; Zhu et al., 2019; Qin et al., 2021; Datta & Taghvaeian, 2023

Table 2 *(continued)*

Sensor Type	Working Principle	Advantages	Limitations	Measurement Accuracy/ Error Range*	Typical Application	Key References
Neutron Probe Sensor	Determine the water content of soil by measuring the scattering of fast neutrons by hydrogen atoms present in soil water	Very high accuracy, suitable for long-term assessment, capable of measuring moisture at multiple soil depths	Expensive, required licensed radioactive sources with safety procedures, not suitable for routine field application	<1% VWC RMSE under well-calibrated conditions	Agricultural research, hydrological studies, and soil water balance investigation	Channuie et al., 2017

Note. Measurement accuracy/error range is an approximate value reported in recent literature and may vary with sensor model, soil texture, bulk density, salinity, temperature, installation condition and calibration method. VWC = Volumetric Water Content

Calibration and Accuracy of Soil Moisture Sensor for Reliable Irrigation Scheduling

Irrigation scheduling in the context of soil moisture estimates is particularly important, as in puddled paddy and direct-seeded. Sensors' accuracy will vary with soil texture, bulk density, temperature, salinity, sensor type and calibration method. These effects can be particularly important in clay-rich soils commonly associated with rice production (Awais et al., 2026; Datta & Taghvaeian, 2023; Zhu et al., 2019). Recent evaluations of TDR and FDR-type sensors have demonstrated that measurement errors can differ substantially across sensor models and soil textures, highlighting the importance of evaluating sensors under representative soil conditions (Zhu et al., 2019). For example, Zhu et al. (2019) also reported RMSE values ranging from approximately 0.014 to 0.041 $m^3\ m^{-3}$ among different TDR/FDR-type sensors and soil textures, demonstrating that sensor performance is strongly soil-dependent.

High precision is often required for irrigation scheduling, and site-specific calibration is therefore recommended, particularly in fine-textured or clay-rich soils (Awais et al., 2026). The calibration of dielectric sensors based on local soil texture and salinity is important for obtaining reliable measurements from sensors such as the ThetaProbe, HydraProbe, and TDR (Mane et al., 2025). A systematic review by Datta and Taghvaeian (2023) reported that the average RMSE under factory calibration was approximately three times higher than that obtained following site-specific calibration, emphasising the importance of calibration for irrigation applications. The general sensing workflow for obtaining reliable soil moisture estimates is illustrated in Figure 5.

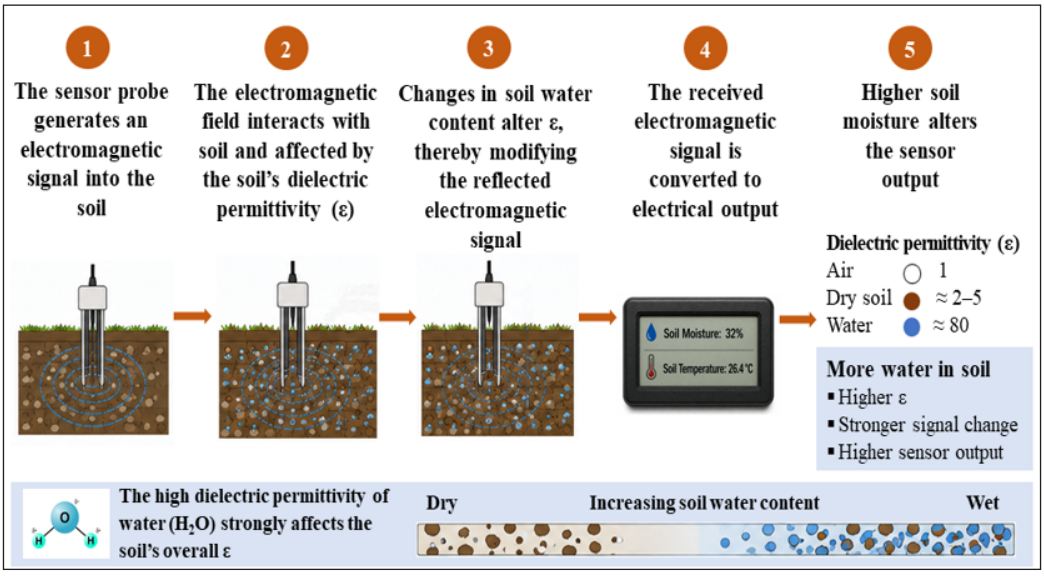

Figure 5. Working principle of dielectric soil moisture sensors for reliable irrigation scheduling

Generalised calibration curves may be inaccurate from one location to another, and soil moisture sensors based on dielectric properties should be calibrated according to soil type and relevant environmental conditions, including temperature and salinity (Mane et al., 2024). Recent studies provide quantitative evidence of this effect. For example, Qin et al. (2021) reported RMSE values of approximately 0.89-1.04% VWC under laboratory conditions and 1.44-1.93% VWC under field conditions for an FDR sensor, demonstrating that accuracy can change between controlled and field environments. Similarly, empirical in-situ recalibration of FDR sensors has been shown to substantially improve soil water content estimation compared with manufacturer calibration, particularly across heterogeneous soil profiles (Qin et al., 2021). A general calibration process for obtaining accurate soil moisture estimates is shown in Figure 6

The two-phase calibration approach can further improve sensor performance by establishing a site-specific relationship between dielectric permittivity and soil water content. Domínguez-Niño et al. (2019) reported an RMSE of 1.03 vol.% following two-phase calibration compared with 5.33 vol.% for factory calibration, demonstrating the substantial improvement achievable through soil-specific calibration. Similar findings have been reported for other dielectric sensors, where calibration performance differed according to soil texture and bulk density (Domínguez-Niño et al., 2019; Zhu et al., 2019). Therefore, the use of factory calibration alone may introduce substantial uncertainty when sensors are transferred to soils that differ from the conditions under which the original calibration was developed.

Sensor performance may also gradually deteriorate due to sensor drift, environmental exposure, and changes in soil conditions, making periodic verification and recalibration

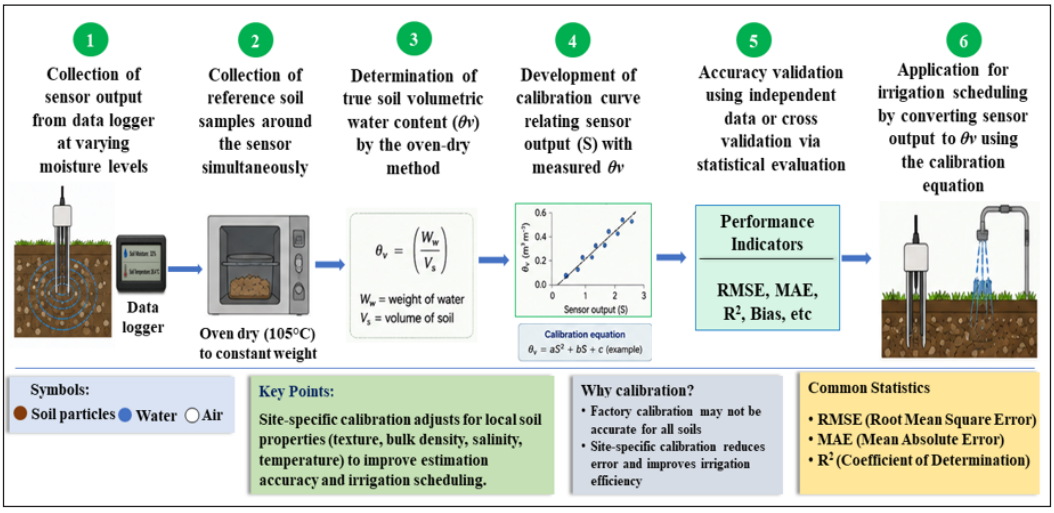

Figure 6. Process workflow for site-specific soil moisture sensor calibration and irrigation scheduling

important for maintaining measurement reliability. Probabilistic drift-correction techniques have been shown to reduce mean square error (MSE) and improve the reliability of long-term sensor observations (Domínguez-Niño et al., 2019). For water-sensitive crops, even relatively small measurement errors can influence irrigation timing and the amount of water applied; therefore, calibration uncertainty should be considered when developing soil-moisture-based irrigation thresholds (Chowdhury et al., 2022). Overall, the available evidence indicates that soil-specific calibration, periodic sensor verification and appropriate correction for environmental effects are essential for obtaining reliable soil moisture estimates and improving irrigation scheduling and water use efficiency.

Sensor Placement and Deployment Strategies for Accurate Soil Moisture Monitoring

Sensors can be used in controlled pot trials to gain a more accurate idea of the impact of varying irrigation levels on rice growth. Sensors are deployed in different field capacity zones in field applications to provide information for irrigation decision-making (Vadivu et al., 2023). The accuracy of moisture estimation can be improved significantly by the optimal placement of the sensors. A study with 42 sensors at different depths demonstrated that optimally placed sensors significantly improve the accuracy of moisture field estimation using an extended Kalman filter, reducing the average root mean square error (RMSE) by approximately 30% compared with random placement (Orouskhani et al., 2023). In addition, watermark tensiometers and TDR-type probes were more accurate in alternating wet-dry conditions than simpler and cheaper devices such as SM150 or PR2 sensors in clay soils (Mahmud et al., 2026).

INTEGRATION OF IOT TECHNOLOGY IN SMART IRRIGATION SYSTEMS

IoT Implementation in Agriculture

The Internet of Things (IoT) has transformed the agriculture industry by allowing for the monitoring of agriculture in real-time and data-driven decisions for automation. In agriculture, IoT solutions cover a wide range of application areas, such as wireless sensor networks (WSNs), GPS, remote sensing, cloud platforms and data analytics, all in pursuit of improving productivity and resource efficiency (Wolfert et al., 2017). Recent findings indicate that precision agriculture with the support of cloud-connected IoT technology can enhance water management by using real-time soil moisture data for automated irrigation systems (Baladevaguru et al., 2025). A smart irrigation method has been developed by implementing IoT sensors and actuators, which enable efficient irrigation scheduling based on evapotranspiration and crop demands (Ahmed et al., 2018). Furthermore, AI-powered platforms are crucial for monitoring as well as forecasting yield, which are all critical functions of IoT (Obaideen et al., 2022). Notably, cloud-based IoT architectures such as

ThingsBoard and FIWARE offer scalable and secure data management in smart farming (Hitiris et al., 2026). For system setup, ThingsBoard is an open-source IoT platform that aggregates and visualises data to optimise irrigation and fertilisation and alerts/notifies farmers when conditions require attention. The increasing adoption of edge computing and the introduction of new technologies like LoRa and NB-IoT have also made real-time responsiveness and energy efficiency more efficient in agricultural IoT systems (Manono et al., 2026). Further, IoT has been applied along with a machine learning approach for forecasting of diseases and intelligent decision support systems (Nawaz & Babar, 2025). There is also a growing emphasis on IoT applications in smallholder farming contexts as a result of the availability of low-cost microcontroller-based mobile integration systems (Kaushik, 2023). The climate variability and sustainability challenges have made IoT a potential solution for resilient and smart agricultural systems (Sarkar et al., 2024). These innovations demonstrate the transformative power of IoT applications in contemporary agriculture. A detailed smart sensor system architecture in precision farming is illustrated in Figure 7, which describes how several sensor nodes that gather information on soil moisture, ambient temperature, and nutrient levels communicate with a central processing hub using reliable wireless communication protocols. A data-driven approach to farm management is made possible by this system architecture, which enables accurate resource application and automated irrigation modifications to increase crop yields, reduce waste, and assure long-term environmental sustainability.

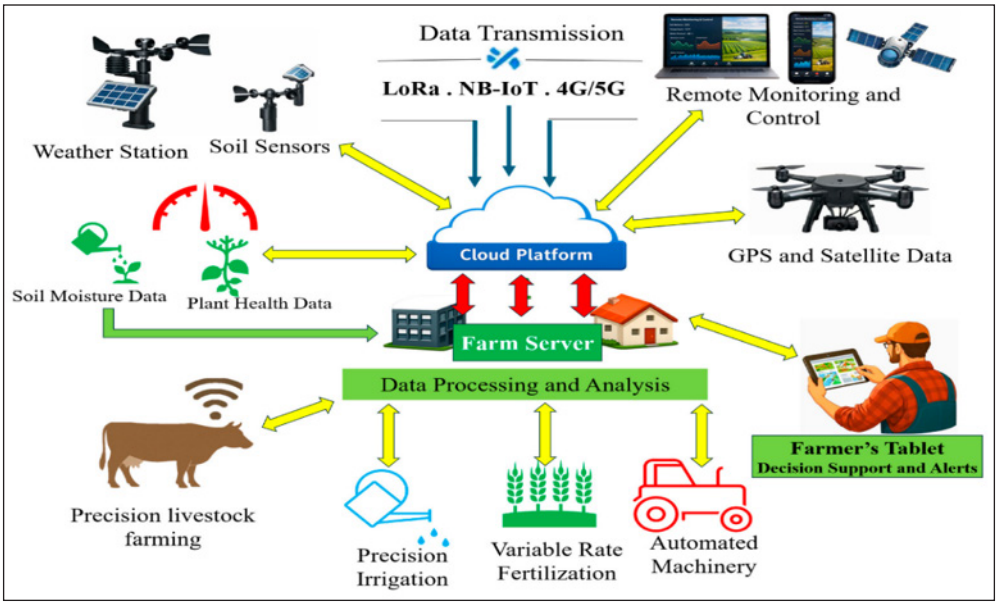

Figure 7. Precision farming with smart sensor architecture (Manono et al., 2026)

Architecture and Components of IoT-Based Smart Irrigation System

A typical smart irrigation system using IoT technology consists of several components, including soil moisture sensors, microcontrollers (such as Arduino or ESP32), wireless communication modules (Wi-Fi, LoRa, etc.), cloud platforms (ThingSpeak, Blynk, Arduino IoT Cloud), and irrigation actuators. The system integrates a soil moisture sensor with a user-defined irrigation threshold to automate irrigation and improve water use efficiency (Gopal et al., 2025). In recent years, rice farming has started using IoT sensors such as soil moisture sensors (SMC) (sometimes capacitive type, with low-cost microcontroller like ESP8266 or Arduino) and communication technologies like Wi-Fi, LoRa communication and a mobile-cloud platform (Mahmud et al., 2026). Optimised irrigation scheduling and automated alerts in applications, achieving water savings up to 30 % and an increase in upland rice yield by 15-20 % (Sutomo et al., 2025).

Real-Time IoT-Based Soil Moisture Monitoring and Decision Support

Real-time data transmission allows farmers to access the field data through mobile applications for irrigation management. The integration with decision support systems (DSS) and machine learning can further improve the predictive capabilities (Vadivu et al., 2023). Emerging technologies in soil moisture monitoring have improved irrigation efficiencies by combining real-time data analytics, cloud computing and wireless sensors (Rajani et al., 2023). They use a variety of hardware platforms and communication technologies to monitor, predict and automatically manage for irrigation. Table 3 lists the main soil moisture monitoring systems based on IoT technology, along with their technology stacks, main results and supporting references.

Table 3
Comparison of recent IoT-based soil moisture monitoring and smart irrigation systems for precision agriculture

System / Study	Tech Stack & Approach	Key Outcomes	Key References
Biswas model + wireless sensors	Sensor network + region-specific modelling	Real-time moisture tracking, $R^2 > 0.97$, error reduction ~15-25%	Zhang et al., 2025
IoT-assisted soil moisture & temperature monitoring system	Raspberry Pi + IoT + wireless sensor network (WSN)	real-time visualisation, RMSE ≈ 3.1%	Rajani et al., 2023
IoT-integrated soil moisture detection & prediction system	ESP8266 IoT nodes + time-series prediction model	High prediction accuracy with a very low RMSE (1.175682×10^{-5})	Setiawan et al., 2022
IoT-driven soil moisture monitoring system	Arduino + Wi-Fi + ThingSpeak cloud alerts	Real-time alerts, cost-effective, and irrigation optimised	Osanaiye et al., 2022
IoT enable Smart Drip Irrigation System (SIS)	Wireless sensor network + ThingSpeak + Android/ web application + Machine learning	Achieved 89% classification accuracy (up to 98% with KNN), reliable automated water management	Ndunagu et al., 2022

APPLICATIONS OF MOISTURE SENSORS IN RICE PRODUCTION

Irrigation Practices and Water Saving Strategies for Sustainable Rice Production

Crop production, resource utilisation, and sustainability are directly affected by irrigation, which is an integral part of modern farming. Alternate wetting and drying (AWD) is a newly developed alternative to continuous flooding of fields that was appreciated in rice farming because it saves water for the crop without reducing yield (Lampayan et al., 2015). In addition, Hendrawati et al. (2025) reviewed and discussed smart irrigation systems that combine IoT and sensor technologies, reporting their increasing use in data-driven irrigation management for all types of irrigation systems. Irrigation scheduling with a soil moisture sensor can reduce water use and increase yield stability as compared to irrigation according to a given schedule, thus providing substantial savings in water (Pushparani et al., 2025). Alternate Wetting and Drying (AWD) is one of the water-saving irrigation methods that is widely promoted as a water-saving option that will reduce water use by ~38 % and improve productivity by ~17 % without a yield penalty (Carrijo et al., 2017). Research has demonstrated that sensor-based irrigation can save up to 30% water without affecting the yields of rice crops (Kishore et al., 2025). Other equipment, such as soil moisture monitoring and sub-surface water level monitoring, is also required, as traditional ultrasonic sensors monitoring above-ground water are not effective under AWD dynamics (Mahmud et al., 2026). However, the study revealed that ultrasonic sensors were not suitable for AWD because of the wave distortion and interference of floating debris in the water, suggesting that the irrigation gate control system be automated using water-level telemetry and soil moisture probes in AWD fields (Pereira et al., 2022). Last but not least, Carrijo et al. (2017) showed that selection of the most suitable irrigation method, based on crop type, soil texture and climate conditions, is important to ensure the best water use efficiency and ensure agricultural production is more resilient to climate variability.

Field Capacity Threshold and Soil Moisture-Based Irrigation Scheduling in Rice Cultivation

Field Capacity (FC) is the moisture-holding capacity of soil after drainage, and it is crucial for smart irrigation because accurate field capacity enhances irrigation efficiency in agriculture (Kan et al., 2025). The knowledge and definition of this threshold are crucial to sustainable water use, particularly in water-intensive crops, such as rice. Soil water balance models are important tools in precision irrigation, and accurate identification of FC threshold levels can make a big difference in these models (Radheshyam et al., 2024). Likewise, Bihon et al. (2024) pointed out that it has a significant impact on hydrological modelling, as different FC values will result in different estimates of evapotranspiration and deep percolation. Furthermore, Awais et al. (2026) pointed out that the threshold values vary depending on soil texture, composition and depth, so calibration needs to be done

on a site-specific basis in precision agriculture applications. Meena et al. (2022) findings showed that maintaining irrigation at around 80-100% of the field capacity threshold is a good practice for enhancing yield and water productivity in the rice and wheat rotations. Mougare et al. (2025) investigated machine learning techniques for estimating threshold capacity levels in field conditions, utilising soil and environmental data to support automated irrigation systems in smart farming. Additionally, Abd El Baki et al. (2024) showed that the adjustment of these thresholds throughout the phenological stage of crops improves the moisture status in the root zone for better nutrient uptake and crop growth.

Water Use Efficiency Optimisation through Smart Irrigation Technologies

With growing water scarcity and climate variability, water use efficiency (WUE) has become a key measure of sustainable agriculture. The goal of water utilisation optimisation strategies is to enhance WUE by matching irrigation with the crop physiological requirements and environment. Recent research has shown that precision irrigation technologies contribute to the optimisation of water use. For instance, Pereira et al. (2022) highlight the advantages of deficit irrigation with regard to the maintenance of crop productivity with lower water inputs. In the case of rice farming that adopts a smart irrigation system incorporating real-time soil moisture conditions and crop performance data, it improves WUE and reduces water usage by 20% (Kulkarni et al., 2025). In a similar way, Agase & Tiwari (2025) reported that the use of soil moisture sensors based on Internet of Things (IoT) in paddy fields resulted in a 30-50% increase in the effectiveness of water use. According to the study, midstream farmers in the Philippines benefited from the alternate wetting and drying approach without reducing the yields, emphasising its potential to alleviate water constraints in rice agriculture (Chandra et al., 2026). Meng et al. (2024) emphasised the implementation and improvement of remote sensing and modelling applications for measuring and optimising water use efficiency in different cropping systems. These Optimised irrigation schedules also helps to save a considerable amount of water and improve water productivity. The findings of Meng et al. (2024) also highlight the importance of applying deep learning algorithms to predict irrigation schedules for maximising WUE. Finally, Gopal et al. (2025) pointed out that the use of weather-based irrigation scheduling and IoT platforms had enhanced water governance and water efficiency at the farm level. To further synthesise the quantitative findings reported in the reviewed studies on improvements in water use, water use efficiency (WUE), crop productivity and sensor/system performance are summarised in Table 4.

The quantitative evidence indicates that sensor-based and IoT-enabled irrigation technologies can improve water management, sensor performance and crop productivity. Reported water savings generally ranged from approximately 20% to 38%, while improvements in water-use efficiency reached 25-50% in selected studies. Yield or

Table 4
Quantitative evidence from previous studies on sensor-based irrigation, soil moisture monitoring and smart irrigation performance

Evidence Category	Quantitative Evidence Reported	Representative Studies
Sensor calibration accuracy	RMSE decreased from 5.33 to 1.03 vol.%	Domínguez-Niño et al., 2019
Sensor placement accuracy	RMSE reduction: ≈30%	Orouskhani et al., 2023
Water saving through AWD/ sensor irrigation	20-38% water reduction; up to 30% in sensor-based systems	Carrijo et al., 2017; Kishore et al., 2025; Kulkarni et al., 2025; Sarkar et al., 2024
WUE improvement	25-50% improvement	Agase & Tiwari, 2025; Munyaradzi et al., 2022
Yield/productivity improvement	15-20% improvement	Carrijo et al., 2017; Sutomo et al., 2025
IoT/model prediction performance	R^2 >0.97; RMSE ≈3.1% and 1.175682×10^{-5}; error reduction ≈15-25%	Zhang et al., 2025; Rajani et al., 2023; Setiawan et al., 2022
Machine-learning classification accuracy	Up to 89-98%	Ndunagu et al., 2022
IoT-enabled irrigation performance	Water saving up to 30%; water use reduction 30%	Sutomo et al., 2025; Chintamaneni et al., 2024

productivity improvements of approximately 15-20% were also reported. Sensor-related studies further demonstrated improvements in measurement and prediction performance, including reductions in RMSE, high R^2 values and machine-learning classification accuracies of up to 98%. However, the magnitude of these improvements varied among studies because of differences in sensor types, calibration procedures, soil characteristics, irrigation strategies, environmental conditions and experimental designs. Therefore, these values represent study-specific findings rather than a pooled statistical effect.

Impact of Sensor-Based Irrigation Scheduling on Water Use Efficiency and Crop Productivity

The adoption of sensor-based irrigation scheduling has proven to be a game-changing method that allows for more precise irrigation timing and water application based on the current soil moisture status. Korlepara et al. (2024) pointed out that integrating soil moisture sensors with a central monitoring system improves decision-making through real-time data to ensure optimal irrigation supply as crop demand. Later, Chintamaneni et al. (2024) showed that the use of soil moisture sensors enabled by the Internet of Things made 30% reduction in the use of water in crops, without adversely affecting yields. Likewise, Munyaradzi et al. (2022) reported that cotton water use efficiency (WUE) was improved by up to 25% with the use of sensor-based irrigation systems indicating their cross-crop

applicability. For rice systems, a low-cost sensor network was employed, and the results showed a 30% reduction in irrigation water use, provided that sensors can work in a paddy environment (Sarkar et al., 2024). Ejofodomi and Ofualagba (2019) emphasised that soil moisture feedback loops should be used for automated irrigation systems to significantly minimise the excess irrigation by utilising real-time data from a moisture sensor. Kaushik (2023) also discovered that the use of ThingsBoard-based IoT platforms greatly improved water use monitoring and control. According to Singh et al. (2024), there were socio-economic benefits of using sensor-based irrigation, such as savings in labour and improved yields. Finally, Kulkarni et al. (2025) discuss how IoT and machine learning enable the prediction of water-yield dynamics in order to support real-time irrigation decision-making.

Relationship Between Water Management, Yield Components, and Rice Productivity

The knowledge of the yield components and their linkages with water use and yield response in rice is essential to improve agricultural productivity in the context of limited water availability. Smart water management, such as deficit and alternate wetting and drying irrigation, has emerged as an effective option for optimising the use of limited water resources without reducing yields (Loconsole et al., 2025). Water application based on soil moisture sensors proved to be an effective way to manage the tillering and flowering stages to improve water productivity, as described by Kumar et al. (2024). Nangia et al. (2018) reported that the timing of irrigation has a positive effect on biomass accumulation and harvest index, which enhances the yield response. Furthermore, the IoT-based monitoring systems have enhanced water use efficiency in real-time, resulting in positive water yield in precision rice cultivation (Agase & Tiwari, 2025). In the meantime, Meng et al. (2024) studied the response in yield to different irrigation amounts in smart farming contexts, revealing that the water-yield curve can be optimised through precision water management, based on real-time information. Habib et al. (2024) showed that there were genotype-environment interactions, meaning that their study rice cultivars had differential responses in terms of yield under different water regimes, which play an important role in rice water-efficient cultivation. These empirical results have been confirmed by more recent modelling studies, which have indicated that the dynamic irrigation scheduling leads to optimum production parameters (Gopal et al., 2025).

FORECASTING AND AI-BASED IRRIGATION MANAGEMENT

Soil Moisture and Crop Water Requirement Forecasting

Moving from a reactive to a predictive approach to irrigation management will require accurate forecasts of soil moisture and crop water demand. Historical observations from sensors can be combined with weather and irrigation data to practice soil moisture forecasting to help in irrigation decision-making. According to a recent systematic

review, there are 60 studies published from 2014-2024, and machine-learning approaches are an important route to predicting soil moisture from sensor, weather and irrigation observations (Ivanova, 2025). Likewise, the ability to estimate water needs, based on data, has increasingly been aided by the observations of IoT technologies, which have provided high-resolution water measurements to predict when, where and how much water should be used in irrigation systems (Togneri et al., 2023). In rice growing, machine-learning models have also been shown to have the potential to predict crop water needs. Nasir et al. (2025) modelled reference evapotranspiration (ETR) and rice irrigation water requirement (IWR) based on climatic variables using Support Vector Regression (SVR) and Random Forest (RF) in the Kerian Irrigation Scheme (KIS), Malaysia. The predictive performance of the SVR model was very good, with R2 of 0.971 and 0.988, respectively, for the testing-phase data for reference evapotranspiration and rice irrigation requirement. AI-based forecasting has also been developed to predict root-zone soil moisture and to schedule and manage the amount of irrigation water, which reflects AI-based potential forecasting techniques for water-saving irrigation scheduling (Gu et al., 2021).

AI and Machine Learning for Irrigation Scheduling

Artificial intelligence (AI) and machine learning can offer the chance to learn nonlinear relationships of soil, weather, crop and irrigation variables, thereby improving irrigation scheduling. According to a review by Umutoni and Samadi (2024), machine-learning (ML) models are increasingly being adopted for irrigation scheduling and crop-water-demand prediction, highlighting data availability, uncertainty quantification and model transferability as key limitations. Similarly, Gao et al. (2023) reviewed the use of ML for irrigation applications, including water-demand forecasting, irrigation decision-making and proposing an intelligent irrigation framework based on machine learning. Neural-network models can be used directly to assist irrigation scheduling by forecasting soil-water conditions and using these forecasts to make irrigation decisions. Gu et al. (2021) created a neural network soil moisture model that can be used for root-zone soil moisture prediction and produce irrigation schedules. Furthermore, for practical agricultural applications, AI can be considered as a technology to support the decision-making process based on sensor observations and agronomic knowledge rather than a technology that replaces traditional irrigation rules.

Predictive and Intelligent Irrigation Management

Forecasting models, IoT sensing and intelligent control are moving irrigation systems into them of predictive and adaptive management in future. Recent studies have shown that intelligent irrigation can utilise soil moisture data that is continuously updated, as well as optimise irrigation decisions, not just based on threshold conditions. A soil moisture

prediction model, which used deep reinforcement learning and a sequence-to-sequence structure, was used to reduce irrigation water by 42.4% with the most optimised reward design while retaining the soil moisture at a field capacity level, as reported by Mukti et al. (2026). Intelligent decision-making for irrigation is also the subject of research using deep learning techniques. According to Yu et al. (2025), a deep learning approach can be used for soil-water prediction, long-term forecasting and irrigation optimisation. Also, hybrid models and edge-cloud architectures can be applied to make real time decision. Another route to adaptive irrigation is through the use of Model Predictive Control (MPC), which permits the use of future soil-water conditions and environmental variables in repeated irrigation decisions. In addition, recent innovations in Malaysia on the application of RNN-LSTM in soil-moisture prediction coupled with real-time smart irrigation management have shown the promise of the integration of sensor networks and AI forecasting in practical agricultural systems (Maniam et al., 2026). These recent developments demonstrate the progression towards predictive and intelligent irrigation management. Table 5 summarises some of the recent uses of AI and machine learning applications in predictive irrigation management.

Table 5
Recent application of AI and machine learning approaches for predictive irrigation management

Study	Crop/ System	Input Variables	AI/ML Approach	Prediction/ Decision Target	Main Outcome
Gu et al., 2021	Agricultural crop	Soil moisture, environmental variables	Neural network	Root-zone soil moisture and irrigation scheduling	Improved irrigation decision
Togneri et al., 2023	Various crops	IoT, weather, soil and crop data	Machine learning (ML)	Crop water requirement	Water-need estimation
Nasir et al., 2025	Rice	Climatic variables	SVR and Random Forest	ETo and rice irrigation requirement	High prediction accuracy
Yu et al., 2025	Various crops	Soil, weather and crop data	Deep learning	Irrigation decision-making	Improved predictive capability
Mukti et al., 2026	Agricultural system	Soil moisture, environmental data	Seq. to Seq. + deep reinforcement learning	Irrigation optimisation	Reduced irrigation water
Maniam et al., 2026	Precision agriculture	IoT-based soil moisture data	RNN-LSTM	Soil moisture prediction	Real-time prediction

With the integration of forecasting models, IoT sensing and intelligent control, irrigation systems are shifting towards predictive and adaptive management. Table 5 highlights

the recent applications of AI and machine learning to forecast soil moisture, crop water requirement estimation, irrigation scheduling and predictive irrigation management. The studies illustrate the transition from traditional machine learning methods, like Random Forest and Support Vector Regression, to deep learning as well as reinforcement learning. Specifically, by combining the data from the sensors provided by IoT devices with AI models, the system can predict irrigation needs in real time and make decisions accordingly. Most of the current studies, however, are crop and site specific, and there is a need for more comprehensive crop models that can take different soil properties, meteorological conditions, crop growth stages and irrigation methods. More research is needed to confirm the use of AI-based predictive irrigation systems across a range of field conditions for rice production and their impacts on water use efficiency and yield.

CHALLENGES AND FUTURE RESEARCH DIRECTIONS

Smart irrigation using sensors has been shown to achieve substantial water use efficiency and sustainable rice production, but has not yet been well adopted on a large scale due to some technical, economic and operational challenges. There are still significant concerns regarding the accuracy and reliability of the soil moisture sensors, as they are affected by soil texture, organic matter content, temperature, salinity and changing soil field conditions. Hence, there is a need for site-specific calibration to get reliable soil moisture data, especially in heterogeneous rice cultivation areas (Mane et al., 2024; Awais et al., 2026). Long-term exposure to the field can also cause sensor drift, fouling, corrosion and degradation, leading to lower measurement accuracy and higher maintenance needs. Therefore, self-calibrating sensors that automatically correct for drift and increase sensor durability are needed to enable long-term, reliable irrigation management (Domínguez-Niño et al., 2019).

Energy supply, communication reliability and system maintenance are also limitations on the sustainability of IoT irrigation systems. The battery lifetime is a critical problem of wireless sensor networks in rice fields, especially in remote fields where battery replacement/recharging is difficult, in contrast to that of large-scale sensor networks. Low power sensor networks, energy efficient communications, energy auto-powering sensor nodes (e.g. solar) and system autonomy should be undertaken in future research (Manono et al., 2026). Furthermore, in rural areas, network connections may not be reliable, communications may be missed, and network access may be low, which can reduce the value of monitoring tools that can be done in real-time and automatic irrigation in these areas. The use of advanced communication technologies such as LoRa, NB-IoT and edge computing can improve the reliability of data transmission and reduce the need for frequent connections to the cloud (Quy et al., 2022).

Other important issues include the interoperability of IoT-based agri-systems, cybersecurity and privacy management of these systems. Different manufacturers' sensors,

micro controls, communication devices, decision supporting systems, cloud systems and others must be able to communicate with each other, and the same protocols need to be used to ensure seamless data exchanges and system compatibility. Additionally, increasing dependence on cloud-based agricultural platforms raises issues over privacy, data security and illegal access to farm information (Nawaz & Babar, 2025; Obaideen et al., 2022).

Economic viability and farmers' adaptation are still major constraints, especially for smallholder farmers. The initial costs associated with implementing irrigation sensors, communication networks, automation systems and technical support could discourage some farmers from adopting this technology to achieve large water savings and productivity benefits (Quy et al., 2022; Nawaz & Babar, 2025).

So, future research should continue to investigate how to combine advanced digital technologies to create autonomous and scalable irrigation systems. Edge AI can facilitate real-time analysis of sensor data at the farm level to minimise latency and aid in decision-making in areas of poor internet connectivity. AI can be used to optimise the performance of smart irrigation systems, which can be integrated with IoT sensors to forecast soil moisture, predict weather conditions, and model crop water requirements, thereby improving the efficiency of water use in irrigation systems (Kulkarni et al., 2025).

The integration of remote sensing, UAV-assisted monitoring and irrigation scheduling based on satellite data is another promising research direction. UAV-based thermal and multispectral imaging can provide high-resolution data on crop water stress and spatial variability. While satellite observations can be used in conjunction with other meteorological and soil moisture estimation equipment to provide guidance for irrigation management in large areas (Haokip et al., 2025; Meng et al., 2024). Moreover, a multisensory fusion approach that combines soil moisture, soil temperature, weather, crop growth parameters, remote sensing data and machine learning models for irrigation prediction can result in more accurate predictions, especially in environments with fluctuating conditions (Meng et al., 2024; Vadivu et al., 2023).

New possibilities for smart irrigation systems will rely on the development of integrated digital agriculture platforms that aggregate IoT sensors, cloud computing, artificial intelligence, remote sensing and farm management tools. Cloud-based monitoring and decision-support systems can enable real-time visualisation, automatic alerts, and data-driven irrigation decisions (Hitiris et al., 2026). The incorporation of new technologies and sophisticated digital solutions will continue to drive future advancements in intelligent, automatic and sustainable irrigation systems. In Figure 8, a roadmap for future research is presented, indicating major technological directions for smart irrigation management using sensors in rice production.

In general, future research should be aimed at developing low-cost, energy-efficient, self-calibrating AI-enabled sensor networks supported by long-term field validation. These

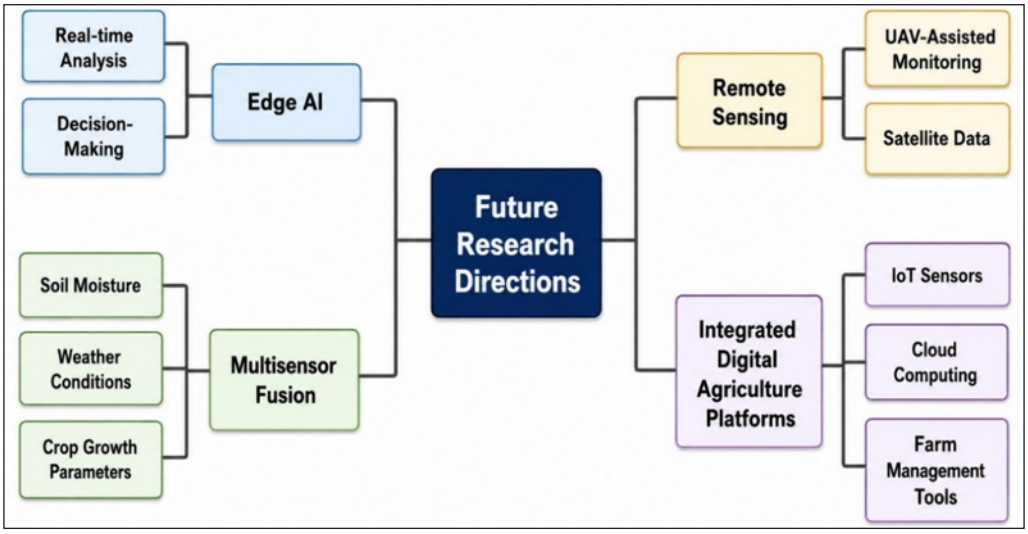

Figure 8. Future research directions for emerging technologies in smart irrigation management for sustainable rice production

innovations will speed up the shift to smart irrigation systems that are sustainable, efficient, resistant to climate change, and economically viable.

CONCLUSION

Sensor-based smart irrigation has become a promising approach for improving irrigation precision, water use efficiency and sustainable rice production. Integration of soil moisture sensors with IoT can enable timely and efficient irrigation management. This systematic review identifies that capacitive, FDR and TDR sensors are particularly suitable for real-time soil moisture monitoring, supported by rapid measurements, IoT integration with proper calibration and placement. However, their effectiveness depends on soil properties, environmental conditions and calibration. Resistive sensors are less suitable for long-term monitoring because salinity, electrode polarisation, and corrosion can affect measurement stability. Neutron probes are reliable but less practical for routine IoT applications because of radioactive sources, specialised operation and regulatory requirements. The reviewed studies further indicate that IoT-enabled irrigation improves monitoring, scheduling, water savings, and water-use efficiency. Additionally, AI and Machine learning support soil moisture forecasting and intelligent irrigation decisions. However, calibration, maintenance, energy use, cybersecurity, adaptation and cost remain key challenges. Overall, future research should focus on low-cost sensors, Edge AI, multi-sensor fusion and energy-efficient IoT networks. Emphasis should also be placed on standardisation, calibration, economic feasibility and farmer-oriented solutions.

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