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Review

A Review of Precision Irrigation Water-Saving Technology under Changing Climate for Enhancing Water Use Efficiency, Crop Yield, and Environmental Footprints

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Abstract: Water is considered one of the vital natural resources and factors for performing short- and long-term agricultural practices on Earth. Meanwhile, globally, most of the available freshwater resources are utilized for irrigation purposes in agriculture. Currently, many world regions are facing extreme water shortage problems, which can worsen if not managed properly. In the literature, numerous methods and remedies are used to cope with the increasing global water crises. The use of precision irrigation water-saving systems (PISs) for efficient water management under climate change is one of them and is a highly recommended approach by researchers. It can mitigate the adverse effects of changing climate and help enhance water use efficiency, crop yield, and environmental footprints. Thus, the present study aimed to comprehensively examine and review PISs, focusing on their development, implementation, and positive impacts on sustainable water management. In addition, we searched the literature using different online search engines and reviewed and summarized the main results of the previously published papers on PISs. We discussed the traditional irrigation method and its modernization for enhancing water use efficiency, PIS monitoring and controlling, architecture, data sharing communication technologies, the role of artificial intelligence for irrigation water-saving, and the future prospects of the PIS. Based on the brief literature review, the present study concluded that the future of PISs seems bright, driven by the need for efficient irrigation water management systems, technological advancements, and increasing environmental awareness. As the water scarcity problem intensifies due to climate change and population growth, the PIS is poised to play a critical role in optimizing and modernizing water usage, increasing water use efficiency, and reducing environmental footprints, thus ensuring sustainable agriculture development.

Keywords: smart irrigation; Internet of Things; artificial intelligence; water scarcity; wireless sensors network; agriculture; irrigation methods; irrigation scheduling

1. Introduction

Compared to other natural resources (such as soil), water is one of the most critical resources and factors considered for performing agricultural activities. Studies have reported that globally, the agriculture sector utilizes around 70% of available freshwater annually to irrigate only 25% of the arable land [1,2]. Also, water is essential for many other agricultural activities, such as livestock and aquaculture development. Both sectors have significant contributions to the gross domestic product of several countries and are necessary for manufacturing several value-added products; thus, water availability is often a limiting factor in agricultural production [3,4]. He et al. [5] stated that water resources are fundamental natural and strategic economic sources that can retain the sustainable development of agriculture. Climate change further increases water stress issues, making water availability less predictable by changing world weather patterns. Now, the annual temperature and precipitation trends are changing, and several regions are facing unpredictable weather patterns. For example, some regions are experiencing more extreme rainfall events and frequent flooding scenarios, while other areas are experiencing frequent droughts and heat waves. Therefore, working on more sustainably managing the available natural resources (soil, water, and air) to produce more food is an essential topic [6]. Water is considered a finite and essential reserve, and its sustainable management is crucial for tackling the challenges caused by climate change, population growth, and the increasing demand for agricultural and industrial activities. Therefore, the proper use and optimal management of water resources for food production is still one of the critical issues worldwide. It is a prime reason why researchers reported alarm that there may be a rising threat that food production and water availability may not be enough to feed the population.

With the advancement of people from a hunter civilization to an agricultural civilization, efforts have been made to improve the efficiency of the agriculture systems and efficient management of the available water resources. Researchers have begun investigating new possibilities for efficient water management in the last decades by implementing diverse precision and advanced methods and tools in the traditional agriculture sector. Li et al. [7] reported that adopting precision farming tools and water management methods can significantly uplift the production of traditional agricultural systems. Also, it can ensure long-term sustainability and help mitigate the concerns people raise about global food and water shortage issues. In addition, several studies have reported that precision farming is a modern farm management and plant-growing technique in which various advanced technology tools are used to efficiently distribute and manage available natural resources. Precision farming tools help the crops and soils to receive the correct amount of nutrients and water for healthy growth and production and provide higher water use efficiency (WUE). It is a center for solving the overarching problems of traditional agriculture [8–12].

In recent years, digital transformation has influenced several aspects of our society. It has also positively impacted the traditional agriculture sector by integrating innovative technologies and solutions and evolving towards the digital agriculture paradigm. Precision irrigation methods have appeared as game-changers in the traditional agriculture sector for efficient water utilization and management [13,14]. Precision irrigation methods are also known as smart or digital irrigation methods. It represents a paradigm shift in the age-old application of irrigating crops. It comprises multiple weather and soil parameter-based monitoring and control sensors and actuators (such as water valves and pumps). In the precision irrigation system, the sensors monitor and record the real-time field data of the climate and soil parameters and continuously update the controllers to open or close the actuators. Precision irrigation methods integrate different tools to monitor and control the irrigation water supply to the plants and deliver precise water supply (where and when irrigation is needed) based on real-time field collected data according to the requirement of the plant. Studies have reported that in an era where water resources are increasingly stressed and sustainability paramount, precision irrigation presents a promising solution for significantly optimizing water use efficiency and raising crop yield by decreasing environmental footprints [15–17]. Section 2 reports the methodology of the review, including literature search criteria, study keywords, and article inclusion and exclusion criteria. Section 3 presents the results and discussion, including irrigation applications, their modernization for enhancing water use efficiency, and why we need smart irrigation water-saving systems, the current work on smart irrigation water-saving systems, the precision irrigation water-saving monitoring and controlling systems, and wireless communication technologies used for smart irrigation water-saving, the role of artificial intelligence in irrigation water saving, and the future application prospectus. Finally, the paper ends with the study's conclusion in Section 4.

2. Review Methodology

This review paper structures the scientific information related to smart irrigation water-saving systems that enhance water use efficiency, crop growth, and environmental footprints. We posed the following specific questions to analyze the irrigation water footprint concepts and considerations in agriculture:

(1) What irrigation systems are used to provide water to crops?
(2) How does a water-intensive system impact irrigation water use efficiency, crop growth, and environmental footprints?
(3) Can modernizing traditional irrigation systems help enhance water use efficiency, crop growth, and environmental footprints?
(4) What is the current status of smart/precision irrigation water-saving systems in agriculture?
(5) How can the irrigation sector benefit from modern irrigation water-saving tools?

Therefore, we sought to answer the mentioned questions by (1) discussing the current traditional irrigation method and its modernization for enhancing water use efficiency, (2) linking precision irrigation scheduling tools with the traditional irrigation sector for efficient water management, (3) analyzing the status of the current research work on the precision irrigation water-saving systems, and (4) briefly discussing the concept and system procedure of smart/precision irrigation water-saving systems tools and their importance.

In addition, the information reported in this study was gathered from previously published research papers. Previously, a massive amount of scholarly literature and material on the use of precision irrigation water-saving systems in the disciplines of agriculture and engineering have been available. Thus, systematically productive approaches were considered to assess the advanced knowledge on the mentioned topic. For the literature search (see Figure 1), 'precision irrigation', 'smart irrigation', 'IoT-based irrigation', 'modern irrigation tools', 'smart irrigation monitoring tools', smart irrigation control tools', 'smart irrigation architecture', and 'irrigation water management' were selected as the keywords for the online search. However, to achieve a speedy review, core studies were comprehensively searched using online scholar databases, including China National Knowledge Infrastructure, Google Scholar PubMed, Web of Science, Scopus, ResearchGate, AGRO, MDPI, Cambridge Journals, IEEE Xplore, Taylor & Francis, Wiley Online Library, ScienceDirect, Hindawi, and Springer, reviewing 225 articles from different countries. Published research work (articles, dissertation theses, and proceedings articles) included in this analysis were open-access papers and those from journals to which Jiangsu University Library subscribes. After searching the keywords, the literature was carefully read and further screened according to the criteria to include or exclude literature for review proceedings. The literature was directly considered if the article significantly related to the study-selected keywords. The data, such as titles, keywords, abstracts, authors, and references, obtained by extracting and exporting the literature, were considered the original dataset for this study. However, the research articles published in languages other than English were excluded from the analysis. The articles selected for the review were discussed in thematically relevant sections of the manuscript.

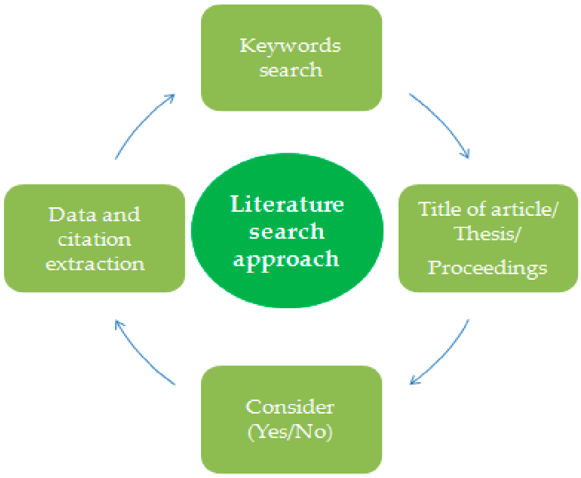


Figure 1. Literature search approach.

3. Results and Discussion

This section briefly discusses and analyzes the results of the previously published research studies considered for summarizing their results. These studies were selected following a brief literature search on different online search engines, focusing on precision/smart irrigation water-saving systems.

3.1. Traditional Irrigation Method and Its Modernization for Enhancing Water Use Efficiency

The traditional irrigation sector has significantly changed over the last 50 years. The reason behind this change is the rise in climate change, drought issues, urbanization, and population. This trend has increased researcher's interest in searching for and developing modern methods of optimizing irrigation to get higher WUE and crop yield [2,11]. Generally, two irrigation methods are included (see Figure 2): (1) gravity-driven (traditional method) and (2) pressure-driven (modern methods) [18]. A study by Olamide et al. [19] said that in gravity-driven practices, farmers apply uniform irrigation water across the entire farm, disregarding field variability and crop water needs. Also, this approach does not use external pressure or pumps to supply the water. It only relies on the water velocity or slope of the field. In contrast, the pressure-driven system supplies water with pressure using external pressure or pumps rather than gravity force. Compared to gravity-driven methods, the pressure-driven system achieves higher WUE and enhances crop yield more than gravity-driven methods.

In addition, gravity-driven practices have lesser water-saving abilities than pressure-driven systems. They can also increase the possibilities of non-uniform water distribution. This non-uniform water distribution can lead to undesired water stress for crops. However, pressure-driven systems are highly water-use efficient methods without adhering to the plant, soil, and environment. Previously, several studies have reported the significance of pressure-driven systems. These systems are the best irrigation water-saving methods compared to gravity-driven practices. They can help to maximize crop yield and increase WUE by providing water at the desired location based on the plant's water needs [20]. Also, studies have stated that pressure-driven systems can efficiently achieve a specific target by directly delivering applied nutrients and water to plant roots in various forms (such as drop-by-drop or spray mist-like rain). The main benefits of pressure-driven systems are that they can keep the soil moisture at optimal levels to reduce surface runoff and deep percolation water losses [21]. In addition, Anjum et al. [22] reported that surface irrigation (basin, border, and furrow) accounts for nearly 84–85% of the world's irrigated land and is one of the most common irrigation water supply applications globally. This study further reported the water application efficiency of various irrigation methods, including surface irrigation (50–70% for furrow, 40–60% for border, and 40% for basin) and pressure irrigation

(65–95% for drip and 50–90% for sprinkler). However, overall, surface irrigation systems provide an efficiency of 40–70%, and pressure irrigation offers up to 95% efficiency.

In conclusion, all irrigation applications have their benefits and drawbacks. Integrating smart technology tools and updating irrigation systems with contemporary infrastructure can further improve water consumption efficiency. Thus, renovating currently accessible irrigation systems through new technologies is essential for advancing water management practices [23].

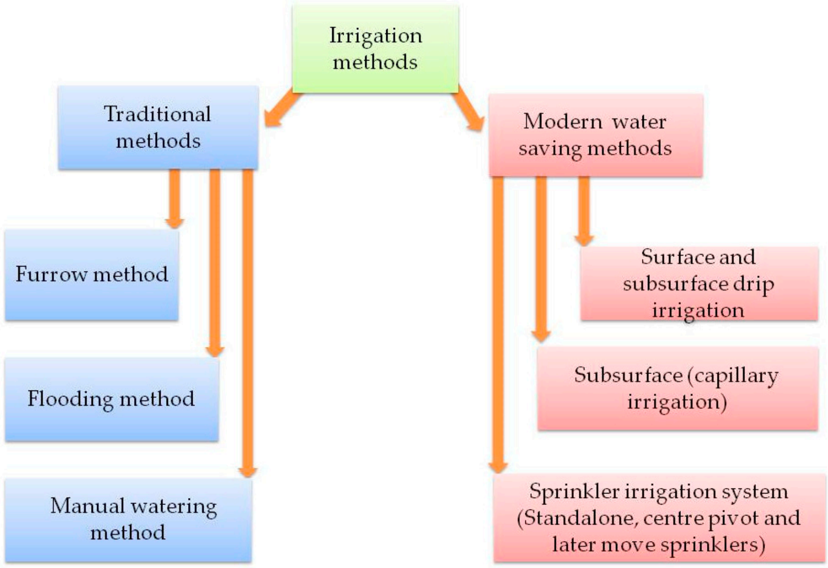


Figure 2. Different irrigation methods.

3.1.1. Precision Irrigation Scheduling (PS) for Efficient Water Management

Irrigation scheduling is the application that determines the duration and quantity of irrigation water to be applied to a field to attain complete plant water requirements. Its unmanaged patterns can significantly affect WUE and plant yield [24,25]. Also, unmanaged irrigation scheduling can increase the chances of under-watering or water-logging conditions in the field. Both conditions can raise the possibility of nutrients leaching below the root zone, decrease growth, waste inputs, cause losses (water, energy, and nutrients), and contribute to adverse environmental issues [26]. Thus, understanding the active role of plant water use is vital for the efficient irrigation system to fill the crop water need; getting real-time information on soil properties, weather, and plant physiology is essential [27,28]. Furthermore, understanding soil moisture status and its patterns is also essential for various other fields, including hydrology, meteorology, and climate change-based studies. At present, several methods have been developed and used to evaluate soil moisture levels in the field. However, traditionally, farmers visually monitor soil moisture from their fields using traditional techniques (such as lifting, kicking, and handling the soil with a shovel) to determine irrigation scheduling. In addition, Rasheed et al. [29] reported that direct and indirect soil moisture measuring methods are the two main types used for laboratory and field conditions.

In addition, PS is an advanced irrigation practice that uses various modern technology tools to optimize water use for plant growth. The goal of PS is to efficiently apply the correct quantity of water at the right time to maximize crop yield while minimizing water waste and environmental impact. A PS represents a significant advancement in modern agriculture, promising more efficient water use, higher productivity, and enhanced sustainability. The key components of the PS are soil moisture and plant water uptake sensors, weather sensors, variable rate irrigation techniques, geographic information systems, remote sensing, and decision support system tools. Furthermore, the main benefits of the PS are water conservation, improved crop yield, cost savings, and environmental protection.

However, the issues associated with adopting PS are the initial settlement cost, the technical expertise required to operate the system, and data management.

3.1.2. Why Do We Need Precision Agriculture and Irrigation Water-Saving Systems?

Precision/smart irrigation water-saving systems (PISs/SISs) are essential for several reasons: they help manage and utilize the available water resources efficiently, increasing crop yield and reducing environmental footprints. Efficient water management methods can significantly decrease the volume of water applied to agricultural fields and enhance crop production [30,31]. Previous research findings have suggested that enhancements in irrigation efficiency alone can fulfil 50% of the anticipated rise in water demand [32]. In addition, efficient water management (EWM) is a key solution to the long-term viability of global food production and processing. EWM is essential for equitable water allocation, enhancing resilience to climate change and other shocks, especially addressing water scarcity. Also, it is considered one of the fundamental components for achieving sustainable development because its development intersects with multiple Sustainable Development Goals set by the United Nations, including clean water and sanitation (SDG 6), climate action (SDG 13), and sustainable cities and communities (SDG 11) [33].

Olatunde et al. [34] stated that historically, water management has been a critical component of human civilizations for millennia, evolving from simple agricultural irrigation systems in ancient times to complex networks of dams, canals, and water treatment facilities today. In the modern era, powered pumps, efficient water supply systems, filtration systems, and chemical treatment have vastly improved water quality and accessibility. However, challenges remain in equitable distribution and sustainable management. Additionally, EWM requires deep knowledge and modern problem-solving methods to enhance the WUE in agriculture. More likely is the modernization of existing irrigation systems to improve efficiency and to cater to the new technology. Sinwar et al. [35] reported that global water shortage problems can be solved by adopting EWM systems to irrigate more crops per area with low water consumption. Sprinkler and drip irrigation systems are low-water consumption-based irrigation techniques compared to surface irrigation methods. The main issue with these systems is that they need continuous human involvement to operate the methods (ON and OFF of valves and water pumps). Unlike traditional irrigation methods, sprinkler and drip irrigation systems are highly efficient and water-saving but require operators to run, control, and monitor them. The efficiency of these systems can increase by adding modern features or existing systems (precision technologies) to develop them as intelligent systems. Also, implementing these systems with surface irrigation methods can improve their efficiency and help manage equal water distribution among farmers (Such as water cards). Smart methods can help these systems perform their work without human intervention. The smart tools continuously monitor the water level in a field by predicting and comparing the available water content in soil and plants with ordinary water needs. If the plant needs water, the system will automatically send commands to sprinklers or drips to start working until the crop water needs are fulfilled.

In addition, the digital transformation of nearly every sector has been seen in recent years as the grand aim to get maximum output using minimum input. However, this digital transformation has positively influenced traditional agriculture and enhanced efficiency. The results showed that we have now spoken about transforming traditional agriculture to digital agriculture or Agriculture 4.0. The flagship of modern technologies linked with digital transformation is to guarantee the capability to obtain in situ measurements remotely and in real-time without using extra-human efforts. This modern technology flagship shifts the grower's interest towards using precision agricultural tools for solving problems and considering agriculture in the context of cyber-physical systems to support a better understanding and modeling of physical processes. However, the main goal of introducing precision technologies in traditional agriculture is (1) to support the decision-making process and (2) to incorporate green energy sources into smart agriculture farms. As for achieving these goals, the combined use of various modern technology tools (such as wireless sensors, Internet of Things, global positioning systems, remote sensing and other automation, and monitoring, controlling, and management information systems) is essential to implement with the traditional agriculture sector [36].

The PIS is grounded in various interdisciplinary theories and concepts that span environmental science, technology, and socio-economic policy. At their core, these systems utilize the principles of cyber-physical systems, where physical water infrastructure is monitored and controlled by computer-based algorithms, integrating the dynamics of the physical environment with software to achieve more efficient, reliable, and sustainable water management [37,38]. This technological innovation can be vital for advancing the water management sector, offering solutions to enhance WUE, monitoring, treatment, and equal water distribution among farmers. Thus, PIS leveraging technologies are at the forefront of transforming traditional water management approaches (see Figure 3). These technologies enable real-time monitoring of water systems, predictive analytics for demand and supply management, and efficient leak detection and water quality assessment, thereby improving the sustainability and resilience of water resources [39].

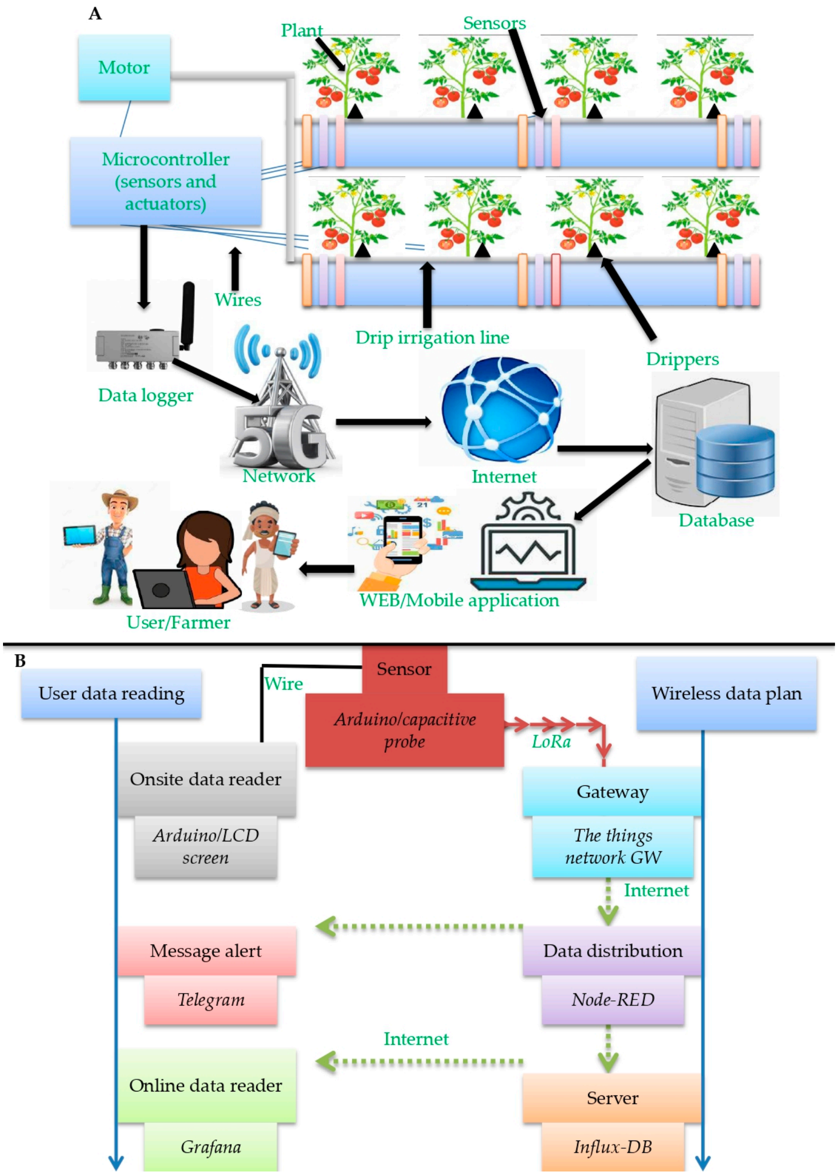


Figure 3. Working protocol (**A**) and flow chart (**B**) of precision irrigation water-saving system (flow chart (**B**) redrawn from [40]).

Previously, several studies accounted for the possible advantages of PISs/SISs, i.e., Gabuya et al. [41] stated that compared to the manual irrigation method, SISs significantly saved water (19%) and improved growth rate and increased the number of leaves of coffee seedlings. Zeng et al. [42] proposed an SIS for rice crops. This study reported that using modern technology tools to manage available water resources efficiently has gained increasing attention among researchers. The proposed SIS combined the monitoring, control, and cloud-based systems to optimize the efficiency and decrease the grower's workload. It also can perform automated irrigation processes to save water consumption and improve WUE. Lakshmi et al. [43] found a 46% decrease in water consumption and higher crop yield using an SIS compared to a conventional watering system. Laphatphakkhanut et al. [44] used an IoT-based SIS and found water usages were decreased by 40.29% (alternating wet and dry) and 29.22% (basin irrigation) compared to the traditional irrigation method. Barkunan et al. [45] reported a 41.5% (conventional flood) and 13% (drip irrigation) reduction in water usage for paddy cultivation using an automated drip irrigation system. Mason et al. [46] simulated (using CROPWAT 8.0 version software to arrange different field scenarios) how an SIS could manage and shrink water consumption without affecting tomato plant production. The simulated results showed that the SIS reduces water use by 59% on average without affecting the yield of tomato plants. Gonz'alez-Briones et al. [47] reported a significant water reduction (reducing water consumption by 15.06%) compared to traditional automotive irrigation to optimize irrigation in a potato crop. However, previous studies on proposing smart irrigation water-saving systems are presented in Table 1.

In summary, precision irrigation water-saving systems represent a sustainable approach to water management in the face of growing water scarcity and changing climatic conditions. PISs can include and integrate all of the challenges and improvements to deliver new and improved solutions and services to all of the stakeholders. Therefore, traditional irrigation water application and management practices must be improved to meet the increasing demands. The farmers must adopt the latest irrigation water application and management advancements to serve this growing demand. The primary purpose of using precision irrigation water-saving technologies in agriculture is to improve water conservation using advanced tools such as soil moisture sensors, irrigation controllers, and real-time climate data collecting and analyzing tools. This technology offers several advantages in smart irrigation water saving:

(1) SISs can provide real-time and nonstop observation of several field parameters (climate, soil, water, and plant). They let farmers be updated about field situations and make real-time decisions about IS, nutrient, and pest management applications.
(2) SISs can eliminate the requirement for the manual data collection of several variables. They can help reduce the labor engaged in field data collection, data collection errors, and the entire operational efficiency of the system.
(3) SISs can save several input costs by decreasing water consumption, significantly saving water utility bills.
(4) SISs can help prevent over- or under-watering and allow plants to get the desired water and nutrients as they need them.
(5) SISs are an environmentally friendly technology. Their implementation with current irrigation systems can reduce the water losses caused by over-irrigation (runoff and seepage). These losses are the primary carriers of applied fertilizers and pesticides into nearby water bodies.

Table 1. Some of the studies published on proposing smart IWS systems.

Study Object	Crop/Factor	Input Parameters	Smart Tool	Outcome
SIS [48].	Maize	SM, CD, and IM	DRL	DRL tools are a potential method of IS.
Soil moisture [49].	Citrus	CD	RS	Tool exhibited the highest accuracy in predicting SM, with R^2 of 0.635–0.921 and RRMSE of 7.214–18.564%.
Automation of drip system [50].	Agricultural fields	CD and SM	FL and WSAN	The tool can calculate crops' water needs and provide a scientific basis for water-saving irrigation to optimize fertilizer use.
Irrigation water quality [51].	Water resources	Water	FL	The system helps farmers identify polluted water and decide on reliable IS.
SIS [52].	Olive grove parcels	SM and CD	IoT	The proposed tool can be employed as a support service tool for SISs.
SIS [53].	Corn	SM and CD	IoT	Earlier harvesting and higher yield were found under the smart IWS system.
SIM [54].	Rice	SM and water height	IoT	A total of 82–88% and 57% labor savings were observed during the flush-irrigation and ponding period.
SIM [55].	Soilless crops	SM, CD, and IM	GCS	The new MCP system significantly reduced input cost by 50% compared to other commercial smart systems.
SIM [56].	Agricultural field	CD and SM	FL and IoT	The proposed SIM significantly conserved and saved water and energy.
SIS [57].	Tomato	SM, CD, and IM	DQN	Improve yield by 11% and decrease WC by 20–30%.
SIM [58].	Agricultural field	SM, CD, and IM	FL	The second mode is more efficient and saves WC by 70%.
Smart irrigation system [59].	Agricultural field	SM and CD	IoT	The proposed approach reduced water utilization and labor engaged for irrigation.
SIM [60].	Agricultural field	SM and CD	FL	The system achieved WC by 94.74% more than the conventional manual system.
Irrigation requirement forecasting [61].	Grass, farm, and arable land	CD and SM	DLNN	The proposed model showed high IWSs compared to others.

Table 1. *Cont.*

Study Object	Crop/Factor	Input Parameters	Smart Tool	Outcome
IoT-based SIS [62].	Agricultural field	CD	AI & PM	The SIS presented as the superior system with 11% water saving compared to the traditional method.
SIM [63].	Agricultural field	SM and CD	FL	The approach reduced irrigation costs by 30% and WC by 45% compared to the traditional method.
SIM [64].	Agricultural field	CD and SM	WSAN	Conserved water up to 81% of WC.
Predicting the occurrence of irrigation events [65].	Tomato, maize rice	CD and IM	DT	Developed models have been able to predict between 68% and 100% of the positive irrigation events and between 93% and 100% of the negative irrigation events.
Predicting irrigation scheduling [66].	Potato	SM, CD, and IM	LSTM	The system attains an IWSs ranging from 20 to 46%.
CIMIS [67].	145 automated weather stations	CD	-	CIMIS helps farmers manage their water resources more efficiently and provides the data to determine when and how much to irrigate.
Benefits of CIMIS [68].	Agricultural field	CD	-	CIMIS demonstrates the high value of public information that enhances water conservation and increases water-use efficiency.
ECOSTRESS and CIMIS [69].	Heterogeneous environments	CD	-	ET_o measured with ECOSTRESS and CIMIS showed good agreement, and methods have significant implications for regional water utilities.
Implementing CIMIS [70].	Walnuts	CD	-	Increased water use, production, and profits were experienced.
IRRISAT [71].	Agricultural field	CD	RS	It uses remote sensing data and provides site-specific crop management information at a relatively low cost across large scales.
RS-SWB [72].	Maize and wheat	CD	RS	The tool offers reproducible and reliable mapped estimations, and time series data allows irrigation land monitoring.
IrriSatSMS [73].	Agricultural field	CD	SMS	A total of 80% of irrigators found the system helpful and easy to use. The tool can be used as a very cheap bi-directional communication channel.
IrriSatSMS [74].	Agricultural field	CD	SMS	The tool helped farmers determine how much water plants needed and how long they needed to run the pump daily.
Bluleaf [75].	Agricultural field	CD	-	The tool can monitor, plan, and manage agricultural processes, particularly irrigation and fertigation.

Table 1. *Cont.*

Study Object	Crop/Factor	Input Parameters	Smart Tool	Outcome
CoAgMET [76].	Weather stations	CD	-	The data gathered from various stations helps to calculate ET values to model water use for different crops.
IRMA_SYS [77].	Agricultural field	CD	-	The tool utilizes weather stations and flowmeter data and calculates daily water requirements, considering parameters of soil, cultivation, and irrigation practices.
Modelling with IRMA_SYS [78].	Agricultural field	CD	-	IRMA_SYS is open, fully customizable, modular software that estimates field-specific crop WC and SIS at multiple scales, from farm to water basin level.

Note: California irrigation management information system (CIMIS), climate data (CD), decision trees (DT), deep Q-learning (DQN), deep learning neural network (DLNN), deep reinforcement learning (DRL), reference evapotranspiration (ET), fuzzy logic (FL), Internet of Things (IoT), irrigation amount (IM), irrigation water saving (IWS), the Italian On-line Satellite Irrigation Advisory Service (IRRISAT), gravimetric control system (GCS), long short-term memory network (LSTM), Modbus-RTU communication protocols (MCP), remote sensing (RS), remote sensing-based soil water balance (RS-SWB), soil moisture (SM), smart irrigation scheduling (SIS), smart irrigation method (SIM), short messaging service (SMS), water consumption/usage (WC), wireless sensor and actuator network (WSAN), artificial intelligence (AI) and prediction models (PM).

3.2. Related Work on the Precision Irrigation Water-Saving Systems

This section summarizes the existing literature work published on PISs/SISs. Moreover, researchers' interest in exploring the various SIS approaches is growing, intending to decrease water use without disturbing crop growth and environmental footprints. The technological advancements drive SISs, and they can hold great promise for efficiently optimizing water usage, crop productivity, and ecological footprints [79,80]. Previously, several studies have been published using several aspects of SISs/PISs.

For example, in 2024, Hassan et al. [81] said that accurately determining the location and position of sensor nodes is crucial in intelligent irrigation. Thus, they presented a new localization tool for localizing unidentified sensor nodes. The process was based on the Levenberg–Marquardt optimization algorithm. This study mentioned that the suggested method attained 19% and 58% perfection in assessment accuracy compared to the other two methods. Another work by Benameur et al. [82] presented a low-cost, full-featured fog-IoT/AI SIS. The proposed scheme was integrated with anomaly detection using an autoencoder. The results demonstrated higher performance than the GANs method. However, the accuracy rates were 90% (soil moisture), 95% (air temperature), and 97% (humidity). Al Mashhadany et al. [83] used the IoT-coupled sensors method to remotely examine the variation in agro-metrological parameters by assessing their daily and long-term trend changes. They used artificial intelligence (AI) tools to regulate IS, crop pests, disease detection, and management. The proposed system significantly optimized water use efficiency by monitoring the plant status in real-time and regulating correct irrigation intervals. Alce et al. [84] created an SIS for rice irrigation scheduling using a low-cost WAN technology (LoRa module). This study reported that adopting an SIS for rice crops can significantly reduce water consumption by providing real-time information to the local farmer using an intelligent message service. Morchid et al. [85] presented a smart irrigation system using cloud computing, embedded systems, and IoT tools to monitor and control water consumption. This study demonstrated a striking 70% reduction in water consumption for irrigation when utilizing the proposed SIS. The farmers can easily access comprehensive farm data anywhere in the world through the ThingSpeak cloud and the ThingView platforms. Manocha et al. [86] designed an IoT-digital twin-inspired SIS. They concluded that the projected method could provide a promising solution for creating an SIS that can significantly increase crop growth and development, increase water use efficiency, and minimize misuse. Abbas et al. [87] developed an intelligent control and monitoring algorithm for various plants. They reported that the new algorithm showed a high accuracy and found a 5.46% average absolute relative deviation. Singh et al. [88] concluded that IoT-based greenhouse monitoring and control systems can assist growers in adopting cost-effective, user-friendly, and durable modern problem–solution systems. These IoT-based systems accurately monitor and regulate temperature, humidity, light intensity, CO_2 levels, and soil moisture. Therefore, selecting a suitable sensor networking system is crucial while creating an efficient greenhouse parameter monitoring and control system.

In 2023, Vandôme et al. [40] designed a low-cost, low-tech, low-energy, open-source IoT-based wireless sensors network (WSN) for drip irrigation. The proposed tool can be a decision-support tool for real-time irrigation water management. Vakula Rani et al. [89] presented an SIS for plant growth monitoring using unmanned aircraft systems (UAVs) and IoT technology. This study reported that the system can monitor several parameters (soil moisture, climate data, water level, and plant health status). Also, it can efficiently control and make in situ IS decisions on when and how much water to supply to the plants. Seyar and Ahamed [90] developed an IoT-based (LoRaWAN-based) SIS for tomato plants using two surface and subsurface drip methods. This study recommended integrating the SIS with surface and subsurface drip methods. The SIS provides many opportunities with easy operation and robust monitoring and controlling capabilities for cultivating tomatoes in outdoor conditions.

In 2022, Dahane et al. [91] proposed an Edge-IoT-Cloud method for SISs. Their process was based on a deep learning methodology. The proposed method can efficiently monitor and predict the IS intervals. Shahidi et al. [92] designed an SIS system using the IoT technique. They used temperature, humidity, and soil moisture sensors to collect the in situ field information. Their system can analyze real-time field data collected via sensors and online weather forecasts. Based on the collected data, the planned tool can decide the appropriate irrigation water required for the plant's growth. Chithra et al. [93] presented an SIS for sprinkler systems. In the design, they used a Raspberry Pi and wireless sensor techniques. They reported that the developed system can help farmers better understand their field's conditions smartly. The farmers can efficiently utilize the input resources and get significant benefits. Also, it provides an opportunity to automate the sprinkler irrigation systems. Cheema et al. [94] developed an SIS by proposing an Android application called "Kistan Pakistan" in their native language. The proposed application can allow farmers to remotely monitor their fields by providing data on real-time soil moisture, pH, and climate parameters. This system can help farmers remotely understand the variations in soil quality, environmental factors, and cropping pattern analysis. Also, its adoption can automate irrigation systems and provide guidelines about timely harvesting schedules, pests, diseases, and weed control. Pham and team [95] presented an economical and full edge-IoT/AI-based SIS. They named the system the SIS method in the box. The proposed system was specially designed for smallholder growers. The authors reported that without internet access, cloud servers, or lockdown with proprietary software platforms, intelligent irrigation in the box can quickly be deployed with a minimum of technological infrastructure, even in very remote and rural areas. Chakraborty et al. [96] proposed an IoT-based SIS to provide an opportunity to monitor environmental parameters and control irrigation decisions remotely. The authors used the BLYNK application with Arduino and ESP32 microcontrollers in this study. The authors concluded that the BLYNK app is a user-friendly interface and provides a simpler way of managing IoT systems. The proposed system is developed using cheap apparatus to implement an affordable mid-range IoT system for increasing water use efficiency and crop growth. Sahoo et al. [97] developed the SIS for the center-pivot sprinkler irrigation system. In addition, the developed tool was tested under three situations involving diverse soil kinds, crops, and climate uncertainties. They said the proposed system accurately predicted the IS intervals under all of the scenarios and could keep the plants stress-free, resulting in maximum crop yield, crop water use efficiency, and irrigation events. Xie et al. [98] presented an SIS system for the Litchi orchard using soil moisture and climate data as input parameters to an improved particle swarm optimization algorithm. The authors reported that the system is highly accurate, easy to utilize, and appropriate for monitoring and controlling the real-time environment of the Litchi orchard.

In 2021, Chen et al. [99] used a deep Q-learning algorithm and short-term weather prediction data to make paddy farming irrigation intervals. The authors reported that the proposed technique is newly introduced and tested in several flooded irrigation fields. The tested results showed the reliability of the daily predictions and the effectiveness of the deep Q-Learning strategy for irrigation water saving in several areas. Gimpel et al. [100] developed an SIS for urban trees using IoT. The authors used data on agro-climatic parameters as input and achieved excellent results. The system correctly made the irrigation decisions and significantly reduced irrigation water usage. Zia et al. [101] compared the efficiency of an IoT-based gadget and an agriculture-based decision system to optimize crop WUE. The authors found impressive results that saved water usage by 50% and increased crop yield by 35% than the traditional scheduling method. Mohammed et al. [102] developed an IoT-based cloud SIS integrated with a subsurface drip irrigation system to monitor and control the IS of date palms. The authors compared the efficiency of the subsurface drip system integrated with SIS and traditional surface irrigation systems. The study reported that the IoT-based cloud SIS integrated with a subsurface drip system reduced irrigation water consumption by 61–64.1% compared with the traditional method. Nath et al. [103] used a sensor system to monitor the inside greenhouse climate parameters and soil moisture to see and control the soil water level status for automatic irrigation. The proposed system collects temperature and soil moisture information from the field via an IoT system by automatically sending the real-time monitoring data to a web server.

In 2020, Mousavi et al. [104] proposed a hybrid cryptographic tool based on elliptic-curve cryptography, secure hash algorithm, and rivest cipher approaches to collect real-time information in IoT-based SISs. The authors concluded that the scheme coped or secured to diverse hidden and unknown attacks, such as the Man-in-the-middle attack, performed superior to other cryptographic tools. Fraga-Lamas et al. [105] presented a design of an SIS based on a LoRaWAN-based architecture for those locations where SIS-IoT gadgets have no direct reach to the internet. The study results showed good accuracy, and the proposed system can be used in areas where remote IoT apparatus has no direct reach to the internet. Another study by [106] developed an SIS using LoRa and LoRaWAN. They concluded that regarding water consumption, the proposed system reduced 23% of the water usage by considering climate projections. In addition, the study's result presents valuable suggestions and guidelines for developing the SIS in the future. Guillén-Navarro et al. [107] proposed an IoT-based SIS for sprinkler irrigation systems. The system was designed using a multivariate long short-term memory model to forecast the temperature variations. This study reported that the proposed method accurately predicted temperature variations (R^2 greater than 0.97), which helped us save a significant amount of water used for anti-frost practices.

In conclusion, the studies above have recommended adopting or integrating several SIS schemes into traditional irrigation systems, such as drip or sprinkler. SIS scheme adoption can considerably help improve and increase crops' water-use efficiency, increase crop yield, and reduce environmental footprints. In addition, the SIS schemes are particularly suitable for those areas with extreme water shortage issues.

3.3. Precision Irrigation Water-Saving Monitoring and Control Systems

Precision irrigation is described as applying technologies integrating sensors, information systems, and skilled management to optimize water use efficiency within sustainable farming operations. In addition, economic profitability, environmental preservation, and sustainability are the primary objectives of precision irrigation. Monitoring and controlling irrigation water usage for efficient water resources management is one of the key characteristics of precision irrigation, which has acquired considerable curiosity in recent years. The advancement of this novel concept to boost the efficiency of applied water and irrigation methods is mainly due to the current evolution in communication technologies, especially the IoT and wireless sensor network (WSN). The technological advances pave the way for reducing redundant burdens in extremely challenging circumstances such as work, regular monitoring and controlling, and the reduction of input resources. These techniques involve many embedded electronic devices coupled with software that can generate numerous chances for combining the physical world into computer-based real-time monitoring and control systems. Ultimately, this combination improves effectiveness and accuracy and eases input costs with minimum human involvement [108–110].

In addition, smart irrigation system architecture consists of several key components (such as devices, network structure, and cloud technology) that work together to collect, observe processes, monitor, transmit data, and allow devices to communicate. Basic smart irrigation system architecture can consist of three layers: (1) perception, (2) network, and (3) application. These three layers support smart gadgets through data collection and processing. Abioye et al. [20] defined advanced control strategies as a wide range of modern techniques. These technologies used in the process and industrial control systems fall under the subfield of control theory in electrical engineering and mathematics. However, an irrigation controller is a central part of the irrigation system. It helps manage the required irrigation water volume for a particular period, leading to high water use and fertilizer use efficiency [111].

Moreover, irrigation control strategies are divided into two main (open-loop and closed-loop systems) systems. The research conducted by Bwambale et al. [112] emphasized that smart irrigation monitoring includes real-time data collection on soil, plants, and climate parameters utilizing advanced communication technologies. The establishment of a real-time monitoring system necessitates the integration of various sensors with accessible data transfer technology. Smart irrigation monitoring methods can be grounded on soil-, weather-, or plant-based methods (see Figure 4). Meseguer and Quevedo [113] reported that control and monitoring are essential to a successful smart watering system. The control systems of the network exhibit high sensitivity to faults impacting sensors (e.g., flow meters and pressure meters), actuators (e.g., pumps and valves), and components (e.g., pipes and reservoirs). As a result, implementing a monitoring module is essential for diagnosing faulty situations and averting abnormal network performance stemming from the control system. Therefore, the monitoring, control theory, and decision support technologies must be carefully considered in an efficient irrigation system to provide a precision irrigation setup [114].

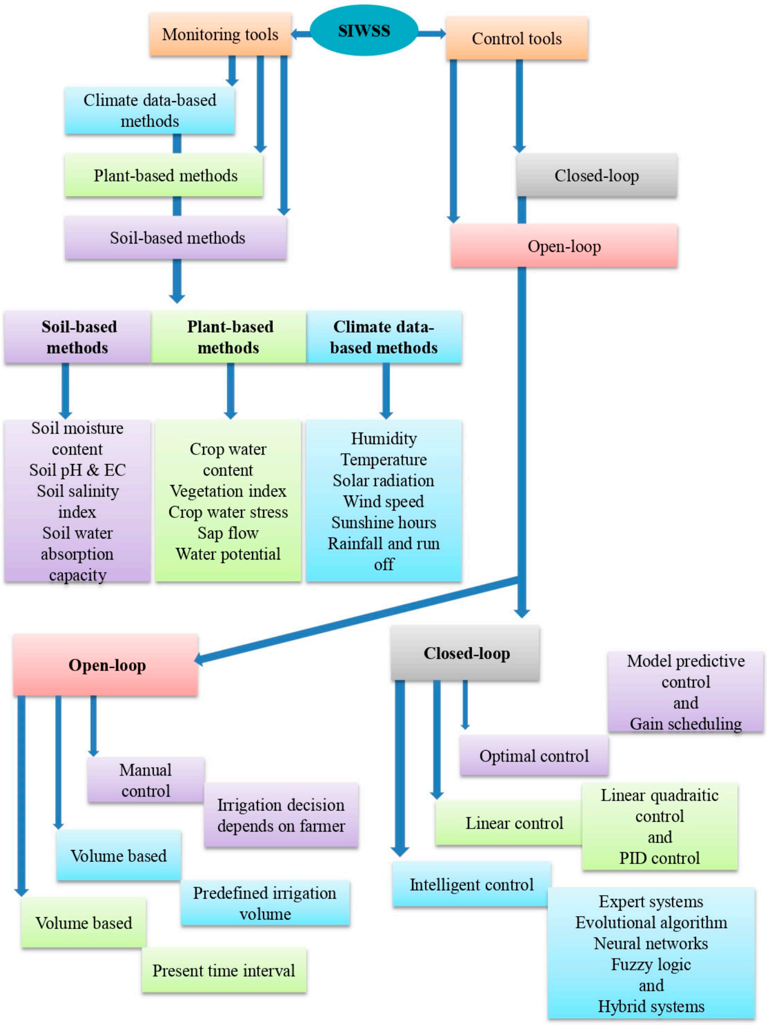


Figure 4. Smart irrigation water-saving (SIWSS) monitoring and control systems (redraw from [20,112]).

3.3.1. Smart Irrigation Water-Saving Controlling Tools

(a) Open-loop control system (OCS)

OCS is the control system with no feedback system and is a one-way signal flow system without input [115]. Christ and Wernli Sr. [116] informed that an OCS represents a condition on a functioning machine with two fundamental states: "On" or "Off". This system is crucial for the proper operation of the equipment. An example of OCS feedback is a simple light switch that, upon activation, remains in the "On" or "Off" position until manually changed. It is easy to design and implement. It is economical compared to several other control systems. Their maintenance is simple and easy to construct and use. However, it has some disadvantages. Its bandwidth is less, and due to the one-signal system, it does not allow or facilitate the automation process [117–119].

Moreover, the farmer makes decisions using irrigation timers in the OCS irrigation control system. However, the volume and time of the irrigation water delivered to the crop are judged according to the traditional scheduling method. Its advantage is that it is simple to install, operate, and maintain because no sensors and actuators are required to implement or manage the system [120].

(b) Closed-loop control (CLS)

A CLS, called a feedback control system, employs an open loop system in its forward path, with one or more feedback loops or paths between its output and input. The term "feedback" denotes that a portion of the output is returned to the input, contributing to the system excitation. It eliminates the shortcomings of open-loop control [121]. CLS is designed to automatically achieve and maintain the desired output condition by comparing it with the actual condition. In the control system, the operator manually or automatically defines and sets the point/control value, representing a higher level of automation than the envelope protection system [122]. In other words, a CLS is a fully automatic control system whose control action is somehow dependent on the output. CLS plays a significant role in a broad application range, from production machinery via automated vehicles to robots. CLS robustly operates the actual values of a process to match pre-determined set points, typically in in situ conditions and with significant precision [123].

Zacher [124] stated that the whole cycle of the CLS is separated into two stages: (1) engineering (such as conception, planning, the supply of components, assembly, commission, testing, measurements, experiments, the identification of plants, the tuning of controllers, and the simulation of control) and (2) implementation (such as control, the supervision of control, and maintenance). In addition, the engineering and the implementation are carried out in two domains: (1) the real world (the world of real devices and physical signals) and (2) the virtual world (the world of mathematical descriptions and simulation). CLS is further classified as linear control (such as linear quadratic proportional integral derivative controller, intelligent, optimal/adaptive control schemes), intelligent control (fuzzy logic-based, artificial neural network based, expert system based, genetic algorithm based, particle swarm optimization-based, and hybrid intelligent systems), and model predictive [20].

A study by Bwambale et al. [11,112] reported that linear control, intelligent control, and model predictive-based irrigation controllers are extensively used in irrigation research and various industrial applications due to their simplicity, cost-effectiveness, and extensive control algorithms. These methods can address complex, multivariate, non-linear, and time-variant issues affecting irrigation systems. Moreover, CLS algorithms can simulate human decision-making when applied to specific problem domains. Klein et al. [125] and Patil and Desai [126] reported that CLS fully automates irrigation delivery and calculates the plant's water requirement. The operator creates a general control approach in closed-loop systems. Once the overall strategy is formulated, the control system takes over the time and frequency of water supply to plants. Previously, many research works have been published (see Section 3.2 related works) on monitoring, controlling, and automatic irrigation integrated with CLS irrigation control principles. They used a CLS control approach, combining soil, plant, and weather variables to measure the crop's water demand and optimize irrigation scheduling.

3.3.2. Smart Irrigation Water-Saving Monitoring Techniques

(a) Climate/Weather data-based monitoring system (WBMS)

Irrigation applications enable the maintenance of plant health, particularly in severe drought conditions. Nevertheless, unsustainable irrigation practices may lead to erosion and the pollution or depletion of natural resources. Furthermore, changing climate conditions determine the rate at which water evaporates and transpires from the plant and soil (ET) [127]. Plant growth, development, and water requirements mainly rely on the surrounding climate factors, especially thermal performance. Therefore, it is important to understand the amounts of solar and thermal radiation converted into sensible (SHF) and latent heat fluxes (LHF) and the characteristics of energy partition. In addition, the SHF and LHF are key variables in energy and water vapor exchanges between the crop surface and the atmospheric conditions, and their information is essential for planning the irrigation scheduling. In addition, over 90% of water losses in agriculture are caused by the action of the above two parameters [128].

In addition, WBMS monitors all of the climate-related parameters that cause quick or slow water release into the atmosphere and makes real-time decisions. WBMS involves local weather data and soil conditions to tailor real-time watering schedules. WBMS controllers can determine when and how much water is needed [129]. WBMS monitors five major climate components (rainfall, relative humidity, temperature, and solar radiation) to compute daily ET variations and regulate the irrigation schedules to replenish water lost since the previous irrigation event. It ensures that watering happens only when the plant and soil need it. A WBMS is also called an ET system [130]. The United States Environmental Protection Agency [131] mentioned that WBMS is a new generation of smart irrigation systems using weather data to adapt irrigation schedules appropriately. A WBMS can automatically reduce the watering times or days when less water is needed, typically during the cooler months. As outdoor temperatures increase or rainfall decreases, programmed controllers adjust the irrigation system's watering run times or schedules to compensate for the fluctuation. They can automatically alter their irrigation schedules daily or weekly based on site-specific variables, such as soil type, sprinkler or drip irrigation application rate, and local weather changes. Generally, there are three basic types of WBMS: stand-alone controllers, add-on devices, and plug-in devices. All three types of WBMS are available in various sizes appropriate for small residential and large commercial applications. In addition, two primary technologies are employed by WBMS: (1) on-site sensor-based control and (2) signal-based control. WBMS are alternative techniques for those areas where soil or plant measurements are impossible [132].

A recent study by Akshath et al. [133] proposed an IoT-based weather monitoring system with a NodeMCU reporting system. This study reported that with this system, anyone can collect data, process it for analysis, and show measured data on a Web server. Singh et al. [134] designed a soil data and real-time weather conditions-based SIS monitoring system. This study concluded that the proposed IoT-based system is based on low-cost sensors. It can be used for the precise monitoring of weather parameters in the field. However, there are particular concerns in deploying low-cost sensors, especially requiring frequent calibration to test their field applicability and performance consistency. Velmurugan et al. [135] presented an open-source SIS to predict irrigation requirements. The authors used soil moisture, climate conditions, and weather forecast data from the internet as input data sources. They concluded that the proposed algorithm uses the sensors' collected recent and past data and the weather-predicted data to forecast soil moisture in the upcoming days. Keswani et al. [136] designed a real-time weather conditions monitoring system using an IoT-enabled SIS. They reported that the irrigation valve control commands were generated successfully with a fuzzy logic climate model to fulfill uniform farm irrigation requirements in almost all weather conditions. Wasson et al. [137] presented an IoT-based weather monitoring system that monitors and analyzes the soil's agro-metrology data and moisture content, using different weather-based sensors interfaced with wireless communication standards for real-time data transfer and web-based services.

In addition, the greenhouse gas (GHG) effect is the natural process of radiation trapping, where the Earth absorbs short-wave radiations and emits long-wave radiations. GHG absorbs most of this thermal radiation, increasing the Earth's climate parameters over time [138]. Solar energy naturally warms the earth's surface as it receives it directly. However, many GHGs are emitted annually into the atmosphere due to industrial activities, fossil fuel combustion, widespread deforestation, biomass burning, land-use change, and land management practices. The rise in GHG concentrations concerns the global scientific community due to its potential to increase the Earth's average climate parameters, such as surface temperature. CO_2 gas is the main GHG contributing to global warming and is mainly emitted due to anthropogenic activity. The global atmospheric concentrations of temperature, CO_2, CH_4, and N_2O have increased markedly due to human activities [139]. Estimating the net warming potential of GHG emissions from agriculture is important [140–142]. An eddy covariance flux and Bowen ratio towers could be useful in this context. The Bowen ratio and eddy covariance are key concepts in meteorology and climatology. Both methods use several sensors to monitor climate parameter variations (see Figure 5). Besides, eddy covariance-based climate data flux towers give continuous measurements over a larger area with detailed information on short-term flux variation. The towers are precise, efficient, and have a high sampling rate within a short response time [138]. However, the Bowen ratio method determines latent heat flux and land surface evaporation by measuring vertical air temperature and vapor pressure gradients to partition a region's energy balance and water cycle dynamics [143]. The eddy covariance and Bowen ratio are valuable tools in environmental science for understanding and monitoring the interactions between the land surface and the atmosphere. These tools are important in managing natural resources and predicting environmental changes.

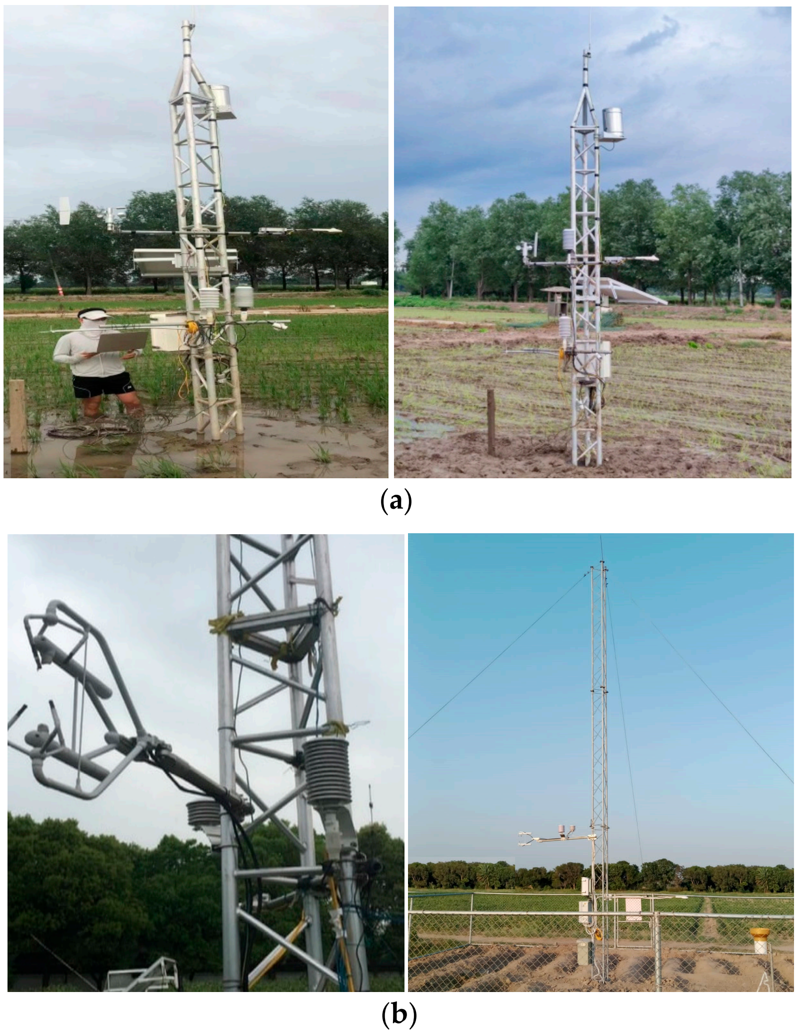


Figure 5. Climate/Weather data-based monitoring system. (**a**) Bowen ratio and (**b**) eddy covariance (EC) system (adopted from [144]).

(b) Plant water-status indices-based monitoring system (PBMS)

Non-destructive monitoring of plant water status is vital for precision irrigation practices [145]. Monitoring the real-time plant water status enables the precise control of the irrigation schedule, thereby preventing plant water stresses and losses (see Table 2). A direct relationship exists between plant biomass production and water consumption through transpiration [146,147]. Various standard techniques are used to know plant–water relations and to measure and understand plants' water needs. These techniques include the relative water content method and pressure chamber to determine half-day or pre-dawn leaf or stem water potential.

Moreover, substitute testing methods are used to calculate plant water requirements in real-world conditions. These substitute analysis methods encompass diurnal sap flow, relative growth rates, tissue expansion, and stomatal conductance measurements [20,148]. In addition, a study by Quemada et al. [146] reported that various passive (PSs) and active (ASs) sensors are employed to examine the real-time water status of the crops. The PS computes radiation and emission imitated by the tested point coming from a source diverse from the instrument or emitted by another point. However, sunlight is the most common radiation resource detected by this instrument. The typical PS comprises radiometers and spectrometers mounted on satellites and aircraft, sensor cameras, and portable spectrometers.

In contrast, the AS illuminates the object with its electromagnetic radiation and then computes the radiation reflected, backscattered, or transmitted through it. Various plant-based water status monitoring ASs have been developed and evaluated to assess plant water status automatically. The most frequently used ASs included volumetric soil water content probes, scatterometers, radars, ZIM-probe, lasers, coaxial probes or portable dielectric probes, sap-flow rate and sap-flux density gauges, and some kinds of spectroscopy techniques. Figure 6 shows the plant-wearable sensor to monitor the online water transport status.

(c) Soil data-based monitoring system (SBMS)

Soil water content is typically measured or estimated for on-farm irrigation water delivery [149]. According to Thompson et al. [150], the soil water content is predicated on the idea that plant water status and soil water content are correlated. It is frequently employed for irrigation scheduling and entails measuring the water content or soil water potential. Understanding the dynamics of soil moisture and how it relates to the water provided for irrigation and plant uptake makes monitoring the soil's moisture content in plants' root regions crucial [151]. Soil moisture content can be measured directly or indirectly using various methods and tools. Gravimetric sampling directly measures soil moisture content, and indirect approaches include heat conductivity, water potential, electrical resistance, electromagnetic properties, and neutron count [152]. In addition, studies reported that several other techniques, such as satellite, aerial, and ground-based water sensors, are used to monitor soil moisture. These techniques are becoming more popular in the irrigation sector [153]. Islam et al. [154] stated that smart soil monitoring systems have gained considerable attention recently (see Figure 7 and Table 2). The data collected by these systems is gathered using various sensors to monitor real-time soil conditions. This information is then transmitted to a central hub for analysis and decision-making, which allows for optimizing irrigation schedules and fertilizer applications, ultimately resulting in enhanced plant yield and water use efficiency.

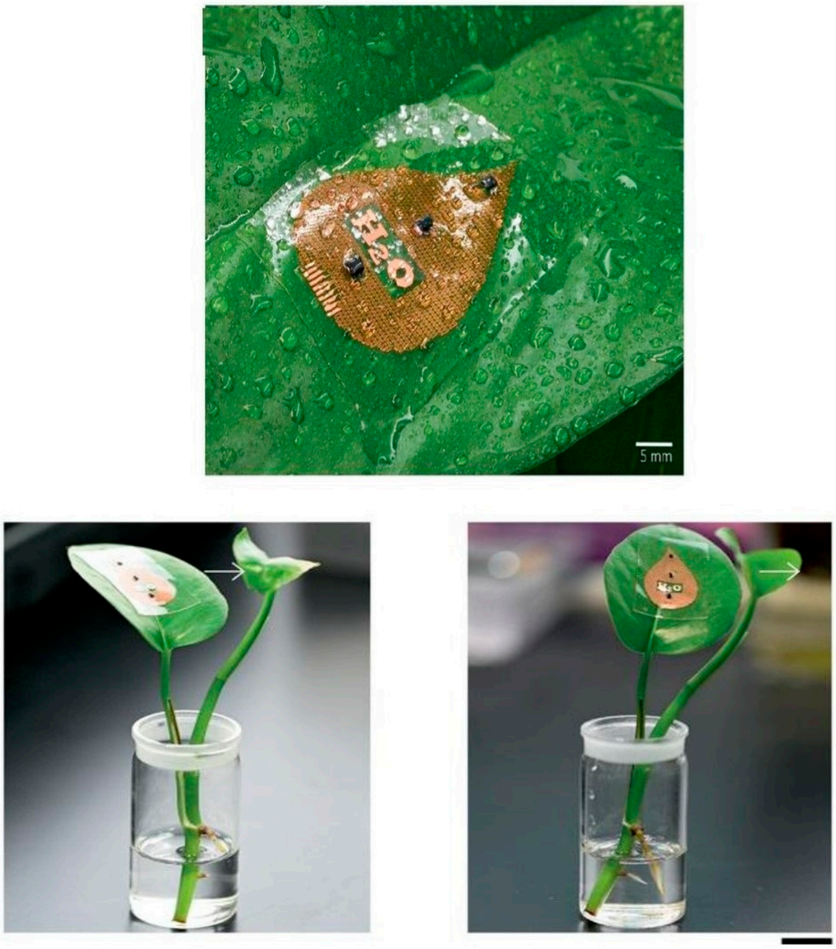
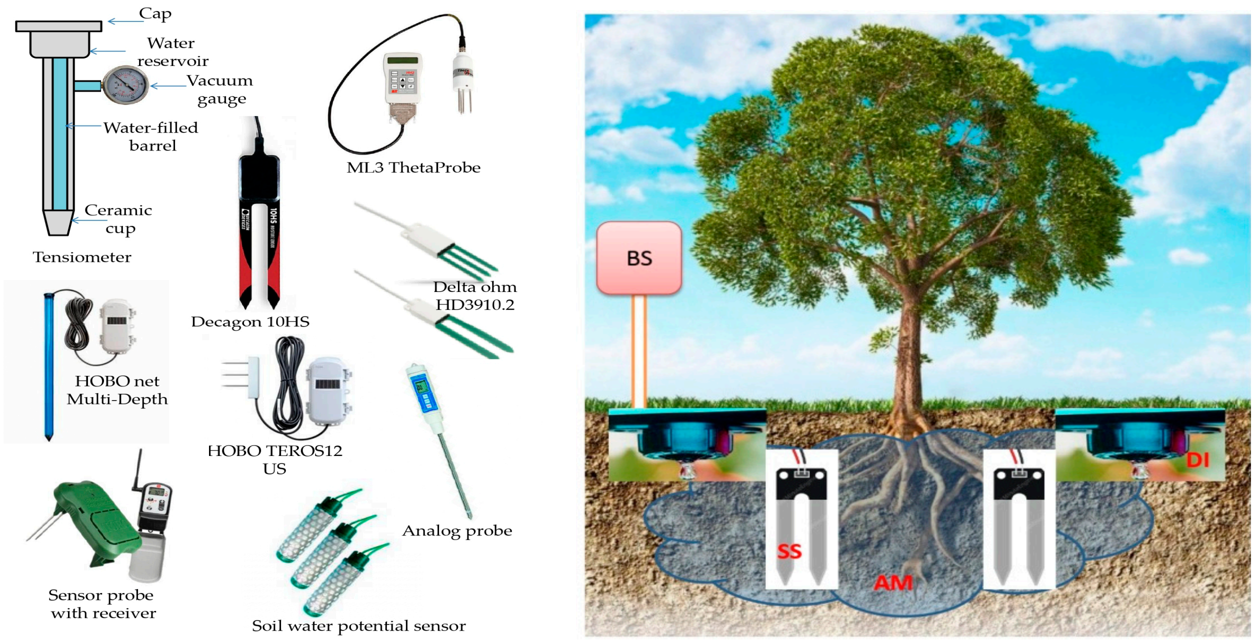


Figure 6. Plant water-status indices-based monitoring system [147].



(**a**) (**b**)

Figure 7. Soil data-based monitoring system: (**a**) soil moisture measuring sensors and (**b**) layout of soil moisture monitoring system (BS—base station; DI—drip irrigation line; SS—soil moisture sensors; and AM—available soil moisture).

In 2024, Comegna et al. [155] introduced a novel multi-parameter sensor-tailored method to assess soil moisture at various depths. The study highlighted that the developed monitoring system consistently exhibited strong performance over prolonged data collection periods and is well-suited for the continual monitoring of soil water status. Lloret et al. [156] presented an economical sensor for soil water status measurement to aid growers in optimizing irrigation processes. The research concluded that prototype 1, operating at 93 kHz, was the top-performing sensor. Furthermore, a power circuit based on ICM7555 was developed to produce the biphase signal for powering the soil moisture sensor, which can measure the water content percentage in the soil at the desired depth. In 2013, DeRouin et al. [157] developed an integrated passive wireless sensor to track moisture levels in sand. The sensor featured a printed spiral inductor embedded within the sand and housed an inductive-capacitive resonant circuit.

Similarly, Kizito et al. [158] conducted a study using ECH20 sensors to assess soil moisture content, bulk electrical conductivity, and temperature across different soils at various measurement frequencies. Shamshiri et al. [159] reported sensors are made of multiple raw materials. However, low-cost sensors are not highly resistant to harsh environmental conditions like sunlight, strong winds, and wildlife. Consequently, integrating systems on farms presents challenges due to these natural obstacles. The maintenance of sensor components in a proximal network is expensive, resulting in higher producer expenses. Therefore, the cost-effective soil volumetric water content analysis is crucial for advancing sustainable agriculture through computerized machines and IoT development, particularly for smallholder farmers. This is due to the fundamental aspect of agricultural operations, which involves the experimental determination of soil moisture.

(d) Irrigation water management using remote sensing (RS)

RS systems employing information and communication technologies can produce enormous amounts of spectrum data due to the high spatial, temporal, and radiometric resolutions necessary for applications in precision agriculture. Besides, irrigation water management using RS is an advanced approach that leverages satellite imagery and other RS tools to optimize water usage in agriculture. Studies have recognized RS as a powerful tool for monitoring crop development and assessing spatial and temporal variability in crop water use [160]. The use of RS tools can increase the efficiency of irrigation systems by providing accurate and timely data on various factors, including the characterization of surface water bodies, the forecasting of climate parameters and soil surface characteristics, and the estimation of soil moisture and evapotranspiration. With high-resolution satellite data, it is now feasible to monitor flood, drought, and irrigation management events in close to real-time [161].

RS is a cutting-edge technique; its offshoots have grown significantly in recent decades for natural resource management [162]. Various RS tools are currently developed to support operational irrigation water management by computing actual crop evapotranspiration and irrigation water requirements. This computation is possible due to the increasing availability of the high-resolution Normalized Difference Vegetation Index (NDVI) time series, which allows the operational use of remotely sensed crop coefficients coupled with a soil water balance model based on FAO56 methodology [163–165]. In addition, some other examples of RS tools for water management include the TOPS-SIMS model, the SPIDER system, the HYDROMORE, and the SAMIR tool (Satellite Monitoring of Irrigation) [166–168]. These models are designed to compute spatialized estimates of evapotranspiration, the mapping of crop growth conditions, and crop water budget assessment at a regional scale based on the FAO56 method and the NDVI time series.

(e) Water meters and prepaid water units in participatory irrigation management (PIM)

The term PIM refers to the participation of users—the farmers—in managing the irrigation system. PIM can be defined as the involvement of the irrigation users in all aspects of irrigation management (planning, operation and maintenance, financing, decision, rules, and monitoring and evaluation) and at all levels (the primary, secondary, and tertiary levels) [169]. PIM is internationally well known as a principle management concept that reforms the agricultural water sector and transfers irrigation management to farmers. Worldwide PIM policies draw on economic liberalization and the privatization of services, emphasizing decentralizing irrigation management responsibilities to local governments and user-based associations [170]. In addition, water user associations, local multipurpose development authorities, prepaid metering systems, and smart cards (see Figure 8) are some of the main components of PIM. These components are essential in promoting agriculture water reform at the community level and help create an efficient and equitable policy environment for farmers' water use [171].

Figure 8. Water meters.

A study by Zaman [169] reported that the prepaid metering system provides every farmer with a user card containing the user's photo ID, name, and ID number). The card is loaded with credit by paying cash at any government office or to an accredited dealer. The card is then inserted in a slot at the pump station, and water is pumped automatically with the charge levied against the credit on the card. Welsien and Lazar [172] said pre-paid water meter technology could help increase water access by reducing lost revenue and receiving excess water. The technology is simple and user-friendly, and there are several global manufacturers, including Lorentz, eWATERservices, Grundfos, and Nairobi-based Maji Milele (using SUSTEQ); all of these manufacturers are proposing several easy-to-use instruments for efficient water management.

Table 2. Studies recommending, proposing, and validating the different smart tools for monitoring and supplying irrigation water to crops for enhancing crop yield, WUE, and environmental footprints.

Object	Tool	Compared	Data	Outcome
SW data management system [173].	AI and BD	MS	WD	The system provided significant results (R^2 = 0.96 and RMSE = 0.04) and offered diverse services such as visualization and analysis of meteorological data and weather time series forecasts.
Climate data perdition with smart tool [174].	Eight ANN models	Eight GEP	WD	ANN models provide significant results (R^2 = 97.6–99.8% and RMSE = 0.20 to 2.95 mm d^{-1}) and GEP models performed slightly worse than the ANN models.
SW station [175].	IoT	MS	WD	The system successfully executed and fetched data accurately with an accuracy of 95%. The system is pocket-friendly and very easy to use and set up.
Smart irrigation system based on weather data [176].	WSN	N.M	SM and WD	This system is a value-effective device to optimize and save water for future generation agricultural requirements by analyzing the field's temperature, humidity, and soil moisture.
Portable SW station [177].	IoT and DL	OPD	WD	The device is a small effort for farmers and is operated without the internet. It can predict the atmospheric parameters and sky status.
Wearable crop sensor [178].	GBS	PS	PP	Provides a new method to monitor crop water status. It holds great potential in studying and monitoring crop physiological information and individual plant biology.
Plant vapor pressure deficit monitoring [179].	OET	N.M	PP	It is a novel tool for monitoring the changes occurring in the plant sap following changes in VPD conditions to achieve increased water use efficiency and yield.
Plant water stress monitoring system [180].	WSN	N.M	PWU	Designed a clip-shaped temperature sensor to solve issues related to the leaf structure and actuate an IIS, resulting in water resource and plant health protection measures.
Water content measuring sensor [181].	THM	LWM	PWU	The device was subsequently used to monitor the real-time water content of leaves in situ under water stress conditions.
Real-time water delivery control [182].	LRE	HHDS	SM	On-farm SM maps could be generated (RMSE of 0.044 cm^3/cm^3), which can then be passed to the irrigation software to adjust the flow to meet the plant water requirements.
Monitoring moisture conditions with sensors [183].	5TE	NM	SM and DHC	The results indicated that using TDR instrumentation is a cost-effective and time-saving technique to construct a system for saving irrigation water.
In situ soil sensors for the wireless network [184].	LoRaWAN	TDR	SM	The device is designed to be autonomous in operation, communication, and energy for over a year. Data are available in real-time on a web-accessed database.
Soil moisture smart monitoring system [185].	IoT	NM	SM	The proposed tool using Thingspeak shows that the system is dynamic and efficient. It is also cost-effective, eliminating the vast budget for hiring farm workers.
In-field precision irrigation management system [186].	IoT	LM	SM	The result showed that the IoT-based sensor irrigation strategy can save up to 30% on irrigation while maintaining the same product yields and quality.
Smart SM monitoring system [187].	IoT	NM	SM and temperature	The tool showed expected results, and when the temperature is high and soil moisture is low, the automatic irrigation system can be triggered and send a notification to the user via email.

Note: Smart weather (SW), weather data (WD), soil moisture (SM), plant water status based on temperature differences (PWU), physiological parameter (PP), artificial intelligence (AI), big data (BD), Internet of Things (IoT), wireless sensor networks (WSN), deep learning (DL), artificial neural network (ANN); not mentioned (NM), meteorological station (MS); long-range wide area network (LoRaWAN), time-domain reflectometry technique (TDR), gene expression programming (GEP), other portable devices (OPD), graphene oxide-based noninvasive crop water sensor (GBS), photosynthesis system (PS), organic electrochemical transistor (OET), density and hydraulic conductivity (DHC); leaf weight method (LWM); Handheld Hydraprobe Data Acquisition System (HHDS), manually controlled system (MCS), vapor pressure depict (VPD), laboratory method (LM); L-band radiometer ELBARA (LRE); 5TE sensors, employing TDR and Em50 data logger (5TE); thin-film micro-heater (TMH); and intelligent irrigation system (IIS).

3.4. Smart Irrigation Water-Saving Architecture and Data-Sharing Communication Technologies

3.4.1. IoT Architecture

The IoT is built around IoT devices, such as sensors and actuators, that can exchange information and manage with some other external system, usually an IoT platform. The IoT system is a network wherein physical devices, machinery, sensors, and objects communicate seamlessly without requiring human intervention via the presently accessible information and communication technologies. In addition, IoT architecture encompasses several critical segments, including sensors and devices, connectivity, action and automation, and user interface and interaction [188,189]. The equipment collects data from the field and is connected at different levels of IoT architectures for smart irrigation water applications. However, challenges arise in determining the architecture for smart irrigation water due to the extensive potential scale and specific requirements, such as soil conditions, weather dynamics, and geographical variations. Therefore, meticulous efforts are necessary to integrate IoT devices and systems into agricultural practices. These efforts entail acquiring IoT devices and employing diverse protocols and standards to guarantee seamless compatibility and integration [190]. In agricultural IoT setups, sensors and devices generate a substantial volume of data, heightening the intricacy of real-time data management, processing, and analysis. The designated framework facilitates structured data storage, efficient processing, and robust analytical capabilities [191,192]. A study by Mowla et al. [193] reported that the architecture of IoT technologies is employed based on various methodologies, varying from application to application. Typically, architecture is structured in a framework comprising three, four, and five layers (including the perception layer, connectivity layer, application layer, middleware, and processing layer) for smart agriculture applications. Table 3 shows the studies proposing, and validating the smart tools (IoT and WSN) for monitoring and supplying irrigation water to crops to enhance crop yield, WUE, and environmental footprints.

Table 3. Different authors propose smart drip and sprinkler irrigation system tools.

Object	Tool	Controller	Communication Tool	Sensors Data	Result Display	Recommendation
Automation of drip irrigation [194].	IoT	WeMos D1 board	Wi-Fi and BH	SM	Android app	The tool is cost-efficient and uses real-time SM data to apply water in an automated way by switching the drip service ON/OFF using an Android app.
Automation of drip irrigation [195].	Big data	Raspberry Pi	Wi-Fi	Climate and pH	Android app	The tool allows farmers to stay connected and make any changes online.
Smart system for drip irrigation [196].	WSAN	End-device (slave node) board	LoRaWAN	-	GUI app	The tool is simpler, cost-effective, and designed to control drip irrigation systems.
Smart irrigation system [197].	IoT (Fuzzy logic)	Arduino	GSM	Climate	Android app	The system proved that water and power conservation was more efficient than the local system.
Smart system for drip irrigation [198].	IoT	Arduino YUN	Wi-Fi	Climate	Mobile app	An intelligent system will permit farmers and gardeners to observe and nurture the crop's yield and water use and improve overall production.
Smart drip irrigation system [199].	IoT	Raspberry Pi	Wi-Fi and BH	Climate and leakages	Webpage	The tool decreases overall water wastage and human intervention, and the user can monitor and manage the system using a mobile app.
Controlled sprinkler system [200].	IoT (*Blynk* Platform)	Arduino Uno	Wi-Fi	Climate	Mobile app	The Blynk tool could read the value of climate parameters and water discharge and carry out watering according to the desired SM level.
Smart sprinkler system [201].	IoT	AVR-RISC-based ATMEGA 328	Wi-Fi	SM & climate	Website	The smart system improves water savings by 55% and decreases fertilizer wastage by 25%.
Smart sprinkler system [202].	IoT	Arduino UNO	GSM	SM	Mobile	The tool is cost-effective for optimizing water inputs and can be used to switch on/off based on real-time data.
Hybrid sprinkler system [203].	IoT	Arduino UNO	Wi-Fi	SM and climate	Website/App	The present tool gives farmers access to monitoring and control irrigation fields remotely.
Smart sprinkler [204].	WSAN	ZigBee	GPRS	Climate and pH	LCD display	The proposed system can monitor and control various parameters with acceptable water over-supply levels.
Smart sprinkler system [205].	IoT	Arduino platform/ ATMEGA328	BH	SM	Mobile app	The proposed system is cost-effective and significantly more efficient than traditional methods.

Note: Internet of Things (IoT), soil moisture (SM), wireless sensor and actuator network (WSAN), global system for mobile communications (GSM), wireless fidelity (Wi-Fi); Bluetooth (BH), and long-range wide area network (LoRaWAN).

3.4.2. Wireless Sensor Network Architecture

A wireless sensor network (WSN) comprises large or small, low-power, tinny, and autonomous devices, also known as sensor nodes. These sensor nodes are randomly deployed in a given environment, either inside, near, or outside the area of interest, to measure and monitor various parameters (such as temperature, humidity, air quality, and soil moisture). These nodes are interconnected and can communicate with each other either directly or indirectly. The data collected by these sensors is then transmitted to a central node, known as a base station, which collects and processes the data [206]. The base station can then transmit the data to a remote server, which can be used for further analysis and processing. A wireless sensor network consists of three main components: nodes, gateways, and a base station. The architecture of a WSN is typically divided into the physical layer, the data link layer, the network layer, the transport layer, and the application layer [190,193,207].

3.4.3. Data Sharing and Communication Technologies (DSCT)

DSCT plays a crucial role in irrigation management. They are utilized in central control, field monitoring, control terminals, and pressure sensing systems. Data such as soil moisture and climate variations are collected by sensors and transmitted to the central control system through DSCT (see Figure 9). Integrating these technologies allows for remote monitoring and managing irrigation systems and system early warnings [208]. Lalle et al. [209] reported that integrating information and communication technologies into the current water delivery systems is one feasible solution to access water-related real-time data. This innovative infrastructure incorporating information and communication technologies into the water supply system is called the smart water grid and emerges as the next generation of smart water management.

In addition, in existing SIS applications, data sharing and communication technologies typically use wired and wireless networks. Wired technologies depend on cables and have drawbacks, such as high power consumption, cost, complexity, and maintenance issues. Consequently, wireless communication technologies have become indispensable for transmitting data from sensing devices. Obaideen et al. [210] stated that communication technologies are considered a vital and imperative point to attain successful system operations concerning the implementation of smart devices. The essential communication technologies employed in SIS are classified into two types (short- and long-range communication technologies): (1) the devices that function as sensor nodes and lead to transmitting data at small distances and have low energy consumption, and (2) the other devices are the ones that can forward massive data over long distances, having high-energy consumption [193]. Examples of short-range wireless communication technologies are Bluetooth, ZigBee, Z-wave, and Wi-Fi, which have transmission ranges between 1 and 500 m. These technologies are utilized in smart irrigation systems due to their low power consumption and short distance coverage, making them unsuitable. Examples of long-range communication technologies are cellular networks such as 1G, 2G (e.g., GSM and GPRS), 3G (e.g., UMTS), 4G (e.g., LTE), and 5G are widely used despite their high energy consumption. However, these cellular networks are greedy regarding energy consumption and could be more efficient regarding infrastructure costs [209]. Furthermore, low-power wide area networks (LPWAN) are other long-range communication networks that offer solutions to the challenges the above communication technologies face in WSN and IoT applications. Generally, there are two categories of LPWAN: unlicensed (such as LoRa and Sigfox) and licensed (including long-term evolution machine-type communications and narrow-band IoT) [211].

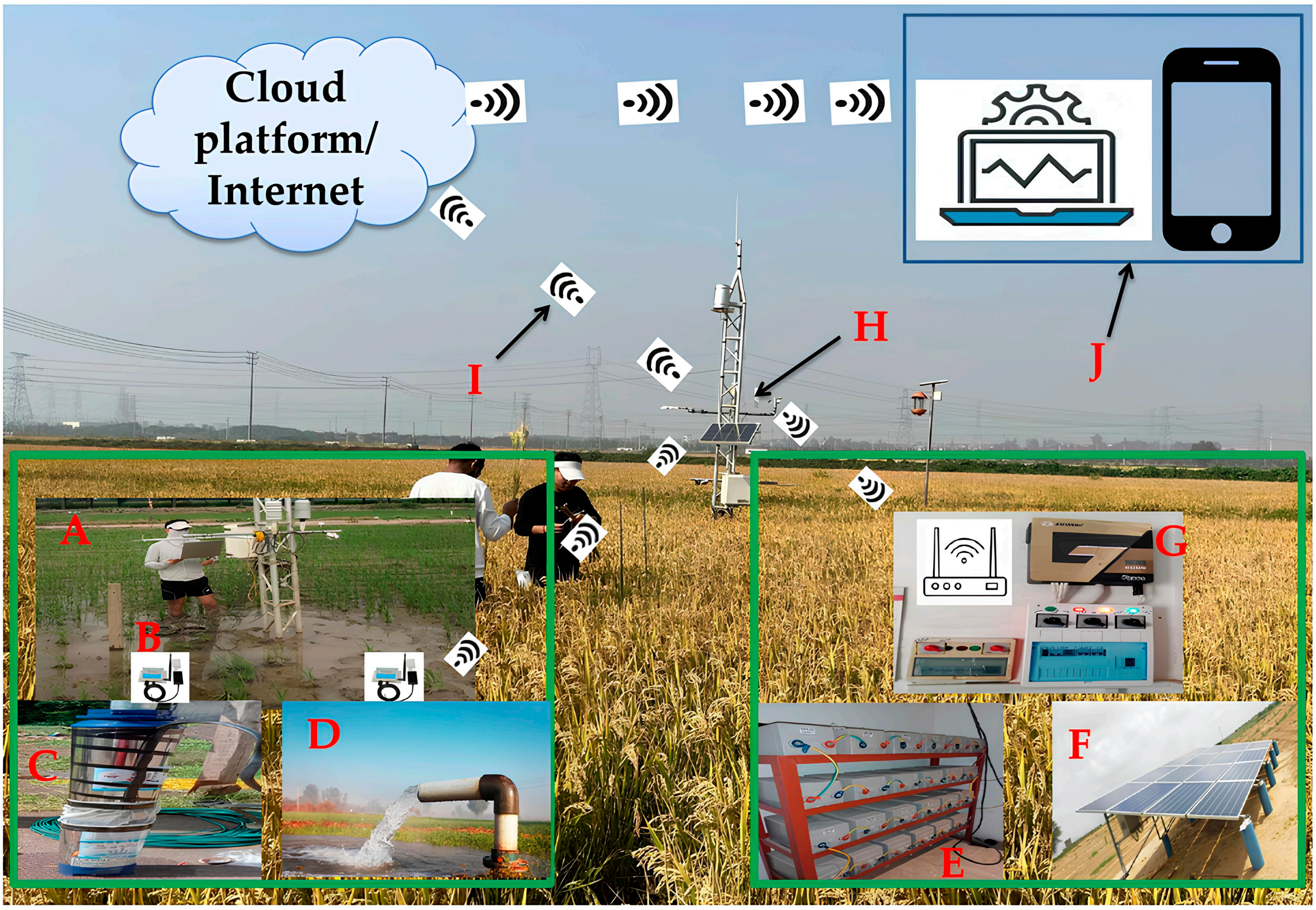


Figure 9. Role of data communication systems in smart irrigation technology (A: field; B: soil moisture sensors; C: water pump; D: water delivery system, i.e., filter, flow meter, and automatic valves for different zones; E: power storage system; F: solar panels; G: control system; H: data communication and sharing tower; and I: incoming and outgoing signals; and J: end user/farmer via computer and mobile application).

3.5. Role of Artificial Intelligence (AI) in Irrigation Water Saving

In this modern era, AI has revolutionized almost every industry and is becoming a game-changer in irrigation, offering a variety of ways to save water and improve efficiency. AI systems can help expedite and refine irrigation decision-making, particularly in response to climate change. The application of AI in agriculture, particularly to improve the efficiency of irrigation water use, is an increasingly important area of research and development [212–215]. AI has already engendered digital transformation in the water management sector by providing insights and synthesis of real-time data analytics to make informed decisions. With AI-based predictions, applications (See Section 3) have been developed to monitor crop health, detect disease proliferation, and optimize resource utilization. Such data-driven approaches allow users to make more timely decisions on when plants should be planted and how to irrigate, fertilize, or apply pesticides, aiming to improve crop productivity and cost efficiency by reducing environmental impact [216–219]. Pandey et al. [220] reported that many features in programming languages like MATLAB and FORTRAN are mathematical functions. These mathematical functions are needed to study water variable forecasting (such as sediment, dam or lake water levels, water velocity, stream flow, rainfall-runoff, *ET*, and other factors). These mathematical functions and hybrid models often use AI algorithms to process the data. AI algorithms can offer an opportunity to analyze historical and real-time data sets to predict the water demand for present and future irrigation scenarios. This prediction can help with the more precise planning of the water supply.

Additionally, intelligent irrigation systems can precisely adjust the amount of water supplied based on various variables such as soil moisture, crop status, vegetation index, and irrigation strategy, automatically acting on automation elements. It can allow for exact irrigation scheduling, delivering the precise amount of water the plants need at the right time by reducing under-watering or over-watering. AI algorithms can predict future climate change patterns and water requirements. They can help farmers plan irrigation schedules proactively, ensuring they have enough water during dry periods and avoiding unnecessary watering during the wet season. AI algorithms can monitor irrigation infrastructure for leaks and inefficiencies, preventing significant water loss. AI algorithms can schedule irrigation to avoid peak electricity hours, reducing energy use.

In conclusion, AI is revolutionizing irrigation practices by enabling a shift from traditional, static irrigation schedules to dynamic, data-driven irrigation management. This transformation leads to significant water savings, improved crop yields, and increased sustainability in the agricultural sector. AI algorithms enable automated production processes, optimize resource utilization, and reduce human intervention. The potential of AI applications to significantly improve water resource management, help to enhance soil fertility, protect biodiversity, and optimize water management for sustainable agriculture is evident. AI tools can efficiently optimize soil productivity and water resources by recording and forecasting water demands, installing infrastructure, and monitoring and predicting coming disasters. Also, these efficient natural resources monitoring capabilities help to attain the proposed task of the Goals for Water—2030 [221–225].

3.6. Future Prospects of PISs/SISs

The future of PISs seems bright, driven by the need for efficient irrigation water management systems, technological advancements, and increasing environmental awareness. As the water scarcity problem intensifies due to climate variation and population increase, PISs are poised to be critical in optimizing and modernizing water usage and increasing water use efficiency, thus ensuring sustainable agriculture development.

Smart irrigation systems increasingly use intelligent sensors and actuators to monitor and control soil moisture, weather conditions, and plant health in real-time. This data will help optimize watering schedules, reducing water waste. However, imagine sensors that go beyond monitoring essential soil moisture to analyzing nutrient levels, pest infestation, and even plant health. This real-time data will enable systems to tailor irrigation to water needs and a plant's specific requirements at each growth stage. In addition, adopting AI-powered decision-making algorithms can improve predictive analytics, allowing systems to anticipate weather change forecasts and adjust irrigation schedules accordingly. These algorithms refine irrigation patterns based on historical data and real-time inputs and enable users to control and monitor irrigation remotely via smartphones or computers, providing greater flexibility and efficiency. Also, they can allow users to share data with other farm management systems for a holistic view of agricultural operations. The vast amount of data collected by sensors and actuators can be harnessed through big data analytics. It will allow farmers to identify patterns, predict future water needs, and make data-driven decisions for improved water management practices.

Traditional irrigation methods require manual adjustments and frequent monitoring, consuming time and effort. SISs automate watering, allowing farmers to set customized schedules and preferences through intuitive control panels or mobile apps. This hands-free operation means farmers can spend less time tending to crops. SISs provide practical tools and methods for conserving water and enhancing soil health. Irrigation adjustments based on soil properties, crop varieties, weather conditions, and field layouts prevent runoff, under-watering, excess watering, and soil erosion, thus mitigating the impact of climate change and boosting agricultural productivity. With climate change bringing more erratic weather patterns, SISs will become essential for building drought resilience. They will help farmers adapt to changing conditions by optimizing water use during the dry and wet periods. While the initial settlement and investment cost in an intelligent irrigation system may seem daunting, the long-term savings make it a wise financial decision. By optimizing water usage and minimizing wastage, it can significantly reduce water and electricity bills over time.

In conclusion, the future of smart irrigation water-saving systems is bright, with significant potential for technological innovation, environmental impact, and economic benefits. As these systems evolve, they will be crucial in addressing global water challenges and promoting sustainable water use. However, educating farmers and homeowners about the benefits and operation of smart irrigation systems is vital for their wider adoption and applicability in the field.

4. Conclusions

This study concluded that traditional irrigation is experiencing a change motivated by modern technologies (such as precision automatic monitoring and control systems). This transformation looks promising regarding the efficient utilization of available water resources and enables this area to shift to the next level of the water management sector. Modern irrigation is based on precision/smart irrigation principles, with producers using systems that generate data in their farms, which will be processed in such a way as to make proper strategic and operational decisions.

In the traditional irrigation scheduling method, farmers visit the fields to check the status of their soil and crops. Later, he makes decisions based on their visual experience. In addition, traditional techniques are time and resource-consuming and no longer sustainable. Therefore, SISs provide valuable solutions within the context of intelligent farming. Also, despite some growers having long-time knowledge collected after many years of work in agriculture, modern tools may present an organized means to identify unexpected or unseen field problems that are hard to examine by the visual assessment on occasional checks. The smart irrigation system provides a promising solution for improving plant growth and crop yields by efficiently managing water resources. It has the potential to increase the productivity of agricultural systems while reducing water waste and environmental footprints, which is a critical issue in areas with water scarcity.

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