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Review

Smart Irrigation Systems from Cyber–Physical Perspective: State of Art and Future Directions

Mian Qian [1,*], Cheng Qian [2], Guobin Xu [3], Pu Tian [4] and Wei Yu [1,*]

[1] Department of Computer and Information Sciences, Towson University, Towson, MD 21252, USA
[2] Department of Computer Science & Information Technology, Hood College, Frederick, MD 21701, USA; qian@hood.edu
[3] Department of Computer Science, Morgan State University, Baltimore, MD 21251, USA; guobin.xu@morgan.edu
[4] Division of Computer and Science, Stockton University, Galloway, NJ 08205, USA; pu.tian@stockton.edu
* Correspondence: mqian2@students.towson.edu (M.Q.); wyu@towson.edu (W.Y.)

Abstract: Irrigation refers to supplying water to soil through pipes, pumps, and spraying systems to ensure even distribution across the field. In traditional farming or gardening, the setup and usage of an agricultural irrigation system solely rely on the personal experience of farmers. The Food and Agriculture Organization of the United Nations (UN) has projected that by 2030, developing countries will expand their irrigated areas by 34%, while water consumption will only be up 14%. This discrepancy highlights the importance of accurately monitoring water flow and volume rather than people's rough estimations. The smart irrigation systems, a key subsystem of smart agriculture known as the cyber–physical system (CPS) in the agriculture domain, automate the administration of water flow, volume, and timing via using cutting-edge technologies, especially the Internet of Things (IoT) technology, to solve the challenges. This study explores a comprehensive three-dimensional problem space to thoroughly analyze the IoT's applications in irrigation systems. Our framework encompasses several critical domains in smart irrigation systems. These domains include soil science, sensor technology, communication protocols, data analysis techniques, and the practical implementations of automated irrigation systems, such as remote monitoring, autonomous operation, and intelligent decision-making processes. Finally, we discuss a few challenges and outline future research directions in this promising field.

Keywords: Internet of Things; smart agriculture; smart irrigation system; sensors

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1. Introduction

1.1. Motivation and Contributions

As the Food and Agriculture Organization (FAO) of the United Nations projected, the global population will reach nine billion by 2050 [1]. A report from the U.S. Geological Survey underscores agriculture's substantial consumption of ground and surface water in the US [2]. In 2015, irrigation alone accounted for a staggering 42% of the nation's total freshwater withdrawals. To accommodate the surging 60% increase in food demand, securing supplementary water resources becomes necessary in the agricultural application domain [1]. However, the wide use of chemical fertilizers has caused excessive nutrient loading, soil degradation, and surface and groundwater contamination. The impacts of climate change (e.g., floods, droughts, and heat waves) also disrupted water supplies. Over the period from 2000 to 2019, available land per capita dwindled by 22% [1].

The Internet of Things (IoT) has been widely deployed into numerous smart systems, including irrigation systems, to optimize water utilization. The benefits of adopting IoT irrigation systems include but are not limited to the following. (i) Cost Efficiency: most sensors used in smart irrigation systems are relatively small and cheap. (ii) Mobility and Flexibility: The integration of interconnected sensors and devices enables remote access and data retrieval, thereby enhancing the irrigation system's mobility and adaptability. (iii) Rapid Responsiveness: The majority of data consists of numerical values within the context of irrigation. The rapid transmission of these data across networks facilitates timely responses to inquiries.

An assessment of seventeen survey articles [3–19] within the smart agriculture system revealed that although smart irrigation constitutes a subset, it remains under-represented in the literature. Most publications focus on technological aspects within the IoT system, often sidestepping user-centric evaluations. In contrast, our study aims to formulate a generic problem space and evaluate the most recent research works related to IoT irrigation systems, highlighting the contributions and drawbacks of existing research works while pointing out the challenges and future trends.

We make three key contributions: (i) a comprehensive and systematic review of irrigation technology, history, and irrigation methods; (ii) a generic problem space to review IoT technologies in irrigation systems in three aspects: "*IoT layers dimension*", "*Environment factors dimension*" and "*Cost efficiency dimension*", since a well-designed system should incorporate cutting-edge technologies, adapt to external environmental factors, and remain cost-effective; and (iii) proposed future study trends on how to develop an advanced and comprehensive irrigation system.

1.2. Comparison to Other Survey Articles

In the literature review, we conducted a comprehensive system research review based on the Cochrane research method [20,21]. The Cochrane reporting methodology was adopted to mitigate bias risks during the literature review process. This approach enables the construction of a 3D problem space, facilitating a robust evaluation of the reviewed papers. The following research question guided our study: "What are the latest technologies used in current irrigation systems, including physical sensors and applications?" We selected papers published between 2018 and 2023, using the keywords "smart farm" and "smart agriculture" to focus on agriculture systems. We then narrowed the scope with the keywords "IoT" and "Internet of Things". Further, we refined it with "irrigation" and "water", filtering out 92 papers that focused on irrigation systems or included a chapter discussing irrigation systems. Of these, 17 papers were classified as surveys. Table 1 summarizes the comparison results between our work with the other 17 survey works.

Some research papers narrow their focus to specific technologies when evaluating irrigation systems. For instance, Pagano et al. [3] reviewed LoRa applications without covering other technologies, such as NB-IoT applications in smart irrigation systems. Elbasi et al. [6] concentrated on artificial intelligence (AI) in smart farming. Sharma et al. [15] and Farooq et al. [10] reviewed machine learning in smart farming. Alharbi et al. [7] focused on applications related to energy-saving technologies, and Kassim [12] discussed IoT applications used in smart agriculture. Likewise, Chen et al. [8] used the Jinsha River Basin's data, including temperature, humidity, and sunlight, as an input for their experiment lab setup to evaluate technologies such as RFID recognition.

While specific research papers delve into advanced technologies within smart irrigation systems, they often overlook essential factors such as overall cost, which is vital for a comprehensive evaluation. For instance, Farooq et al. [4] divided the IoT system into four components, physical structure, data acquisition, processing, and analytics, to review the latest technologies and trends. Likewise, Hassan et al. [5] divided the IoT system into components (the physical layer, network layer, decision layer, and application layer) and then identified four factors that could heavily affect smart farming performance, which are soil erosion, chemical pesticides, climate change, and water usage. Neither of them consider cost-effective factors in their survey.

Table 1. Related survey on smart irrigation systems.

Survey ID	IoT Layers			Environment Factors			Business Dimension	Others	Year
	Perception	Network	App.	Field Cond.	Natural Var.	Crops	Cost/Energy/Water Util.		
[3]	LoRa	LoRaWAN	Monitoring	No	No	No	partial	No	2023
[4]	Yes	Yes	Yes	Partial	Partial	Yes	No	4 layers (physical structure, data acquisition, processing, and analytics)	2019
[5]	Yes	Yes	Yes	Partial	Yes	Yes	No	4 layers (physical, network, decision, app)	2021
[6]	Partial	Partial	AI	No	No	No	Partial	AI tech	2019
[7]	Yes	Yes	Partial	No	No	No	Partial	4 layers (IoT, Edge, Fog, Cloud)	2021
[8]	No	No	Yes	No	Yes	No	No	4 layers (perception, transport, processing, app)	2019
[9]	Yes	Yes	Yes	No	No	Partial	No	5 layers (physical, network, middleware, service, app)	2019
[10]	Yes	Yes	Yes	No	No	No	Yes	Greenhouse	2022
[11]	Yes	partial	Yes	No	No	No	Yes	Smart agriculture	2019
[12]	No	No	Monitoring	No	No	No	Partial	Application layer	2020
[13]	Yes	Yes	Yes	Yes	No	No	Partial	Water management	2022
[14]	Yes	Yes	Yes	No	No	No	Yes	Smart agriculture	2022
[15]	No	No	ML	No	No	No	Partial	ML	2021
[16]	Yes	Yes	Yes	No	Partial	Partial	Partial	IoT in agriculture, including irrigation	2020
[17]	Sensor	Partial	Partial	No	No	Partial	Partial	Sensors	2022
[18]	Yes	Yes	Yes	No	No	Partial	Yes	Smart farm	2023
[19]	Partial	No	No	No	No	No	Yes	Water management	2020
Ours	Yes	Yes	Yes	Yes	Yes	Yes	Yes	3D problem space	-

1.3. Organization of Remaining Paper

The remainder of this paper is organized as follows. Section 2 introduces the background of the irrigation system. Section 3 explores the defined problem space consisting of IoT layers, environment factors, and cost-effective dimensions. Section 4 presents several challenges and future research directions along with final remarks in Section 5.

2. Overview of Irrigation Technology

Irrigation water can be sourced from diverse sources, including groundwater obtained from springs or wells, surface water drawn from rivers and lakes, treated wastewater, drainage water, or even collected fog. Since 2017, with the rapid advancements in IoT and AI technologies, agriculture has developed into Agriculture 4.0, also called Smart Agriculture, which includes smart irrigation systems.

There are four major types of irrigation systems: (i) *Surface irrigation*, the oldest form of irrigation, is also called "gravity irrigation", which uses the gravity of water to design the irrigation system. Surface irrigation is the first engineering innovation humans have. (ii) *Sprinkler irrigation* refers to how water is pushed to the central locations and distributed to different places through high-pressure water devices. (iii) *Micro-irrigation* refers to the one that distributes water under low pressure via prearranged networks to each plant. (iv) *Drip irrigation* sends water to the root zone of plants directly with various dripping methods [22,23].

Among the four primary types of irrigation systems, surface irrigation is the least efficient, with an efficiency rate of 60%, whereas drip irrigation is the most efficient, achieving a rate of 90% [24]. Despite its inefficiency, surface irrigation remains the predominant method, constituting 85% of all irrigation techniques. This method results in nearly 40% of water wastage, especially in countries such as India and China [1]. Conversely, although micro-irrigation and drip irrigation systems are more efficient, they have been less studied, which is primarily due to their higher setup and maintenance requirements. As a result, most of the literature focuses on surface and sprinkler irrigation systems rather than drip or micro-irrigation systems.

3. Problem Space

To better understand and comprehensively review the identified papers, we propose a three-dimensional problem space for the smart irrigation system:

- *IoT Layers Dimension:* This dimension explores the contribution of each layer to the efficiency, scalability, and reliability of IoT-driven irrigation solutions.
- *Environmental Factors Dimension:* This dimension assesses environmental variables to determine their effects on the efficacy of IoT irrigation systems, providing insights into adaptability across various agricultural contexts and geographic areas.
- *Cost-Effectiveness Dimension:* This dimension evaluates the economic feasibility of IoT-driven irrigation systems. It includes an analysis of the impact of green energy on smart irrigation systems, integrating this factor into the overall cost assessment.

By employing this 3D problem space in Figure 1, we tend to offer a complete view of the examined papers. Accordingly, the overall layout and topics discussed in our 3D problem space are shown in Figure 2.

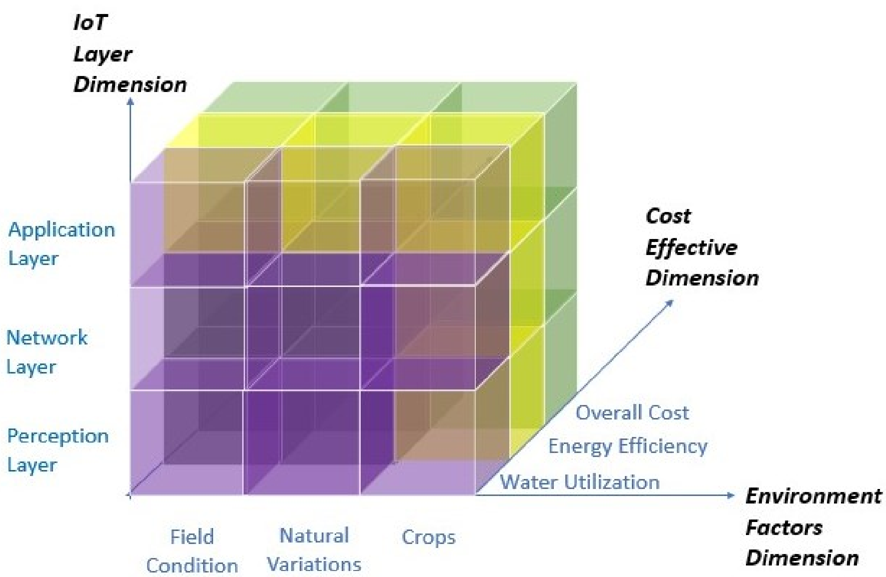

Figure 1. Three-dimensional (3D) problem space overview.

3.1. IoT Layer Dimension

The IoT layers dimension provides a technological perspective, focusing on the vertical layers that constitute the framework of typical IoT systems. These layers support various smart-world applications [25–29]. (i) *Perception Layer:* Also known as the physical layer, it includes all hardware components like sensors, nodes, actuators, controllers, and other devices responsible for data collection. Our review will focus on key devices such as sensors and microcontrollers, comparing their implementations in 34 complete system proposals. (ii) *Network Layer:* Often referred to as the communication layer, it enables connectivity among physical devices and between devices and applications through both wired and wireless means. Most proposals favor wireless technologies for their ease of setup, with prevalent technologies including Low-Power Wide Area Networks (LPWANs), Bluetooth, and WiFi. We will evaluate several pivotal edge technologies in this layer for their effectiveness. (iii) *Application Layer:* This layer includes user interfaces and backend data management applications. Our analysis will concentrate on studies integrating AI, aiming to assess their performance. Although IoT platforms are well documented in the literature, we will discuss the most prominent platforms.

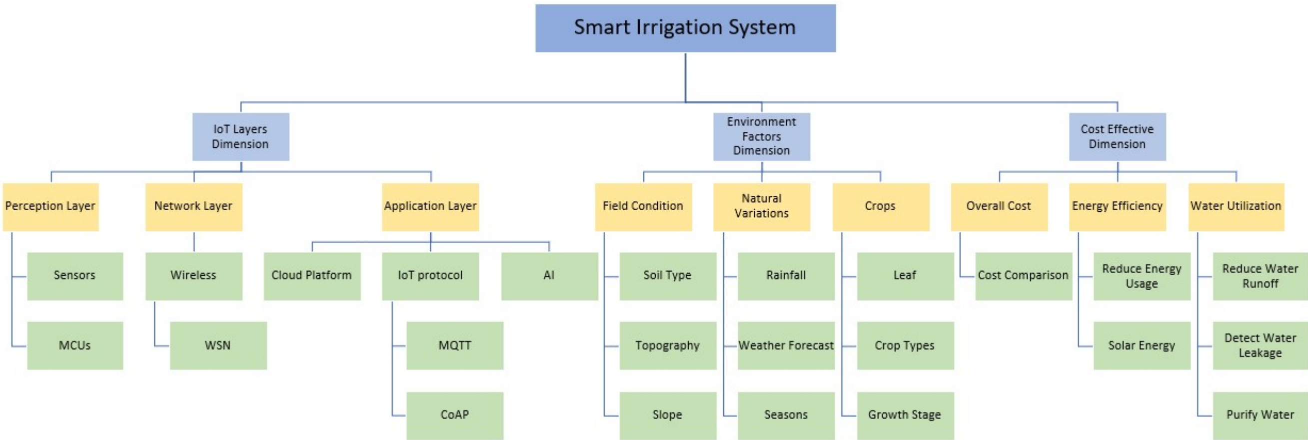

Figure 2. Smart irrigation system overview.

Through the IoT Layers Dimension, our objective is to highlight the technologies, devices, and methodologies utilized in designing and implementing IoT-driven irrigation systems. This approach offers a thorough insight into how these interconnected layers contribute to system effectiveness. Figure 3 illustrates the architecture of a typical IoT system.

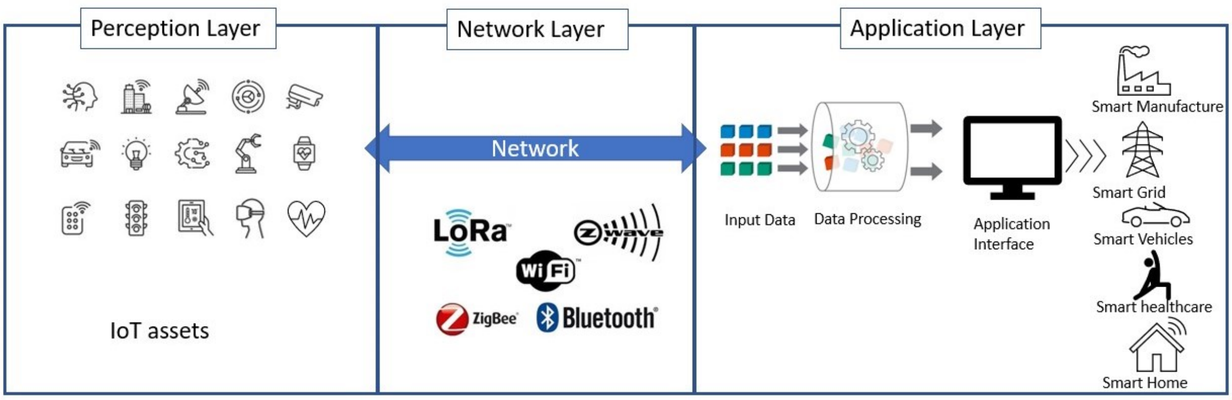

Figure 3. IoT system architecture.

3.1.1. Perception Layer

Sensors play a critical role in data collection and signal transmission, thus shaping the efficacy of IoT systems [29,30]. Table 2 provides an overview of the various types of sensors in smart irrigation systems. These sensors enable comprehensive data gathering, foster informed decision-making processes, and facilitate real-time adjustments to optimize irrigation efficiency. The table offers a valuable snapshot of the Perception Layer in a smart irrigation system.

Table 2. Sensors in IoT irrigation systems.

Purpose	Sensor Type	Paper IDs	Remarks
Soil Moisture	Soil Moisture Sensor	[31–58]	Two types: resistive and capacitive
Soil Condition	Ultrasonic Sensor	[31,45,46,50,58,59]	Determines soil type
Soil Temperature	Temperature Sensor	[31,33,47,49,50]	Such as DS18B20 to measure the soil temperature
Soil pH Value	Soil pH Sensor	[31,33,42,43,49]	Measures soil pH
Rain Detection	Rain Sensor	[37,41,42,44,46,47,49,55]	Detects rain presence
Freshwater Measurement	Water Meter, Water pH Sensor, Water Flow Sensor	[31,37,48,55–57]	Measures water flow, pH, and volume
Surrounding Environment	Humidity and Temperature Sensor	[31,33,35,37,42–44,46,49–51,53–55,57,58,60]	Such as DHT11 or DHT22 sensors to measure the air temperature and humidity
Surrounding Environment	Light Sensor	[31,51,57,58]	Measures light strength (e.g., in greenhouses)
Surrounding Environment	Wind Speed Sensor	[31,49]	Monitors wind speed
Surrounding Environment	Solar Radiation Sensor	[31,49,58]	Measures solar radiation levels

The workflow, as shown in Figure 4, illustrates the crucial facet of smart irrigation systems. This data-driven approach ensures that irrigation is initiated only when necessary, minimizing water wastage while maintaining optimal soil conditions for plant growth [32,34,38–40,52,60–62].

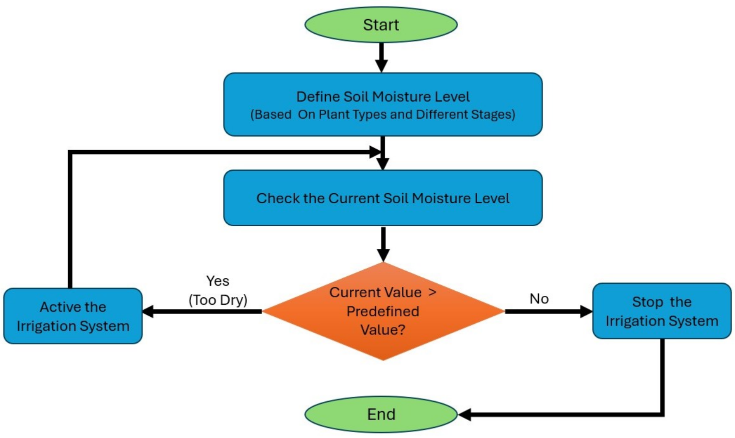

Figure 4. Workflow of current smart irrigation systems.

While soil moisture sensors are invaluable tools for gauging soil dryness, there are some concerns to address.

- *Suitability of Soil Moisture Alone*: Relying solely on soil moisture data might not provide a comprehensive understanding of the irrigation needs. How much water to use is affected by soil composition, organic matter content, soil type, soil and air temperature, wind speed, and evaporation rates. Only using the soil moisture value without considering the potential impact from other resources might cause over-watering or under-watering.
- *Reliability of Soil Moisture Data*: While soil moisture sensors provide valuable insights, their reliability relies on factors such as sensor accuracy and placement.

- *Comprehensive Irrigation Management*: The distribution of plant roots can also lead to varied moisture levels even within the same soil at a given time. Moreover, a plant's water requirement varies with its growth stage. Using over-watering as an example, Sehler et al. [63] explained that over-watering could be as harmful as under-watering. One of the common reasons for over-watering is ignoring weather forecasts and watering fields.

Thus, combining soil moisture sensors with other sensors (temperature, humidity, etc.), implementing predictive models, and adopting real-time adjustments can enhance system reliability.

Temperature sensors are another widely adopted sensor used in irrigation systems. There are two types of temperature sensors: *waterproof temperature sensors* (i.e., *DS18B20*) and *air temperature and humidity sensors* (i.e., *DHT11* or *DHT22*). The rain sensor, also called *Rain Switch*, is used to shut down the irrigation system when detecting rainfall to save water. Using a rain sensor [36,42,44,46,47,49] can utilize natural water resources to reduce water usage. Reza et al. [41] even recommended using a rain sensor to stop unwanted rain. According to the performance test by Islam et al. [47], a rain sensor can save around 27% of the water. In addition to these three types of sensors, other sensors (e.g., pH, water flow, light, wind, and pressure sensors) can be used in smart irrigation systems to gather more data for precise purposes.

To connect with the sensors, extract measurement reading data from the sensor, and send it to the user application/API, it is necessary to select either a microcontroller or microprocessor. A microcontroller (also called MCU) consists of one or multiple CPUs (processor cores) and memory and IO peripherals. In the investigated irrigation systems, except for [43], which used a Pycon LoPy4 microcontroller, and [49], which used an Atmega 328 SOC Nano, 40% of the papers chose the Arduino Uno R3. NodeMCU (ESP32) is another smaller and cheaper option that can be a good choice when only three to four sensors are used. Table 3 summarized the microcontroller chosen for the IoT irrigation system.

Table 3. Microcontroller for IoT irrigation system.

Brand	Model	Open Source	Paper ID	Embedded Wireless Module	Strengths	Limitations
Arduino	Uno	Yes	[33,35,36,39–41,44,45,47,50,51,54,56,57]	WiFi	Expandable I/O pins. Wide range of code libraries. Cost-effective.	Only WiFi module embedded.
Raspberry Pi	Pi	No	[32,37,46,52,58,64]	WiFi	Expandable I/O pins including memory. Can function as edge computer for data storage.	Only WiFi module embedded. Pricier than Arduino Uno.
Espressif	NodeMCU (ESP8266 or ESP32)	Yes	[41,42,51,55,59]	WiFi and Bluetooth	Expandable I/O pins. Compatible with Arduino platform. Compact and the most affordable.	Limited I/O pins.
Pycom	LoPy4	Yes	[43]	LoRaWAN, Sigfox, WiFi, Bluetooth	Expandable I/O pins. Compatible with the Arduino platform. Compact and supports multiple wireless technologies.	Limited I/O pins.

3.1.2. Network Layer

The network layer establishes communication between IoT devices or devices to servers or from devices to clouds. According to our findings, WiFi has been widely adopted into embedded systems such as Arduino Uno or NodeMCU, providing a seamless foundation for direct utilization. The use of Wireless Sensor Networks (WSNs) in rural areas is highlighted by several studies [53,65,66]. WSNs consist of three primary topologies: star, cluster tree, and mesh. With a range of up to 4000 m and low-power consumption, WSNs are particularly suitable for smart irrigation systems [67,68]. Depending on the deployment environment, WSNs can be classified into terrestrial, underwater, mobile, and other types [67]. In smart irrigation, terrestrial, underground, and mobile WSNs are preferred for their cost-effectiveness, ease of implementation, and straightforward management. Table 4 compares different types of wireless technologies used in irrigation systems.

Table 4. Wireless technology overview.

Range	Technology	Data Rate	Power Consumption	Distance Range	Security
Short	WiFi	High (1.2 Mbps–6.75 Gbps)	High (1 W)	Up to 100 m	High (WPA2/WPA3)
Short	Bluetooth	Medium (1–3 Mbps)	High (1 W)	Up to 100 m	Medium (AES-128)
Short	Bluetooth LE	Medium (1 Mbps)	Low (10–500 mW)	Up to 100 m	Medium (AES-128)
Short	ZigBee	Low (250 Kbps)	Low (1 mW)	Up to 20 m	Medium (AES-128)
Short	RFID	Low (423 Kbps)	Low (1 mW)	Up to 1 m	Very Low (N/A)
Long	LoRaWAN	Very Low (0.3–50 Kbps)	Low (up to 25 mW)	Up to 10 km	Medium (AES-128)
Long	NB-IoT	Low (200 Kbps)	Low (up to 17 mW)	Up to 15 km	Medium (AES-128)
Cellular	GPRS	Low (171–384 Kbps)	High (1–3 W)	Up to 26 km	Low (GEA2/3/4, A5/3/4)
Cellular	5G	High (20 Gbps)	High (1–5 W)	Up to 28 km	High (256-bit)

One challenge with Wireless Sensor Networks (WSNs) is their limited energy, which can lead to network malfunctions [67]. While power banks can alleviate this issue, they require frequent replacements or recharges, which compromises system flexibility and portability. Alternatively, setting up charging stations offers a solution but involves additional investments and maintenance, adding complexity [67]. Utilizing natural energy sources such as solar panels is a viable approach to overcome these challenges, supporting WSN sustainability [44,45,47].

LoRa, a low-power Wide Area Network (LPWAN) standard, is particularly suited for large-scale irrigation on farms due to its cost-effectiveness, long-range capabilities, no-operator infrastructure, and use of unlicensed spectrum [3]. In urban areas, LoRa coverage reaches up to 3 miles, extending to 10 miles in rural settings, making it ideal for transmitting small data packets like text messages. Comparatively, another WAN technology, NB-IoT, also provides long-distance coverage and offers quality of service (QoS) and reliable message delivery. However, LoRaWAN has enhanced battery life in comparative tests [3,37,69].

Table 5 illustrates the paper related to wireless technology in the irrigation system.

3.1.3. Application Layer

A smart irrigation system is a blend of hardware and software technologies. We have covered hardware in the perception layer. The application layer emphasizes the software side. Several protocols are widely employed in smart irrigation systems within the application layer, such as HTTP (Hypertext Transfer Protocol), MQTT (Message Queue Telemetry Transport), and CoAP (Constrained Application Protocol). Our study focuses on the MQTT and CoAP, which are widely used in typical IoT systems [70,71].

MQTT is a protocol that leverages message publishing and message subscription between IoT devices and brokers to establish communication among devices and users [72]. The benefits of using MQTT include but are not limited to the following. (i) *Lightweight and Efficiency:* In the initial design of MQTT, it targets the use of minimal battery loss and bandwidth usage when communicating with the satellite [73]. That is why it can be widely used in small microcontrollers. (ii) *Scalability*: MQTT has built-in features that support communication for IoT devices because of its low energy consumption and minimizing data size during transmission. Hence, the MQTT protocol can be used to connect a large number of devices, improving scalability. (iii) *Security*: To secure IoT systems, MQTT makes it easy for developers to implement encryption mechanisms like OAuth, TLS1.3, Customer Managed Certificates, etc. (iv) *Robust*: Python and others widely support MQTT protocol implementation. It is also commonly used in open-source because of good MQTT maintenance. Figure 5 demonstrates how to send soil moisture value through MQTT in a typical irrigation system.

Table 5. Wireless technology for IoT irrigation systems.

Range	Technology	Paper IDs	Strength	Weakness
Short	WiFi	[31,38,41,44,45,49,50,55,57,58,60,64]	High data rate suitable for large message sizes. Embedded modules in Arduino Uno and Raspberry Pi. No need for additional modules. High security with WPA2.	High power consumption (1 W) and limited range (up to 100 m).
Short	Bluetooth LE	[31,58]	Moderate data rate compared to WiFi. Suitable for messages like sound. Embedded modules in Arduino Uno and Raspberry Pi. No additional modules are needed. Cost-effective.	Moderate power consumption (up to 500 mW) with a range of up to 100 m. Lower security (AES-128).
Short	ZigBee	[32,34,53]	Energy efficient (1 mW), potentially increasing battery life. Cost-effective.	Moderate security (AES-128). Limited range (up to 20 m).
Long	LoRaWAN	[39,43,52]	Low power consumption (25 mW) with a long range (up to 10 km).	Moderate security (AES-128). Narrow frequency bandwidth; potential interference issues.
Long	NB-IoT	[37]	Low power consumption (17 mW). Extensive range (up to 15 km).	Moderate security (AES-128). Narrow bandwidth; potentially complex and costly to implement.
Cellular	GPRS	[32]	Extensive range (up to 26 km). Compatibility with existing cellular plans. Broad bandwidth (850–1900 MHz).	High power consumption (1 W to 3 W). Dependency on cellular provider's infrastructure.
Cellular	5G	[46,54,56,57]	Long range (up to 28 km). Compatibility with current cellular plans. Extensive bandwidth (700 MHz–72 GHz). High data rates (20 Gbps) and enhanced security (256 bits).	High power consumption (1 W to 3 W). Requires cellular provider's infrastructure.

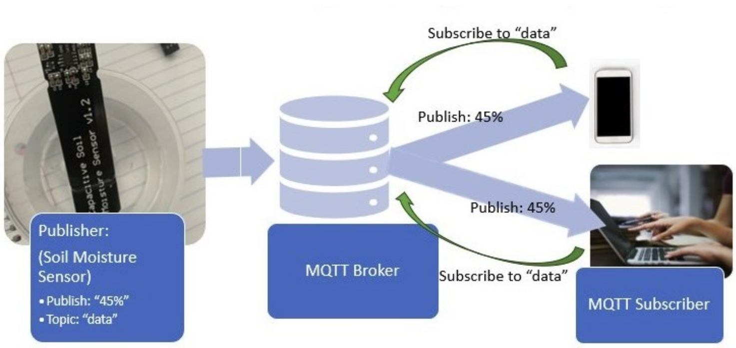

Figure 5. MQTT flow of messages with soil moisture sensor.

Another prominent IoT protocol is CoAP [74]. While MQTT relies on message passing via an intermediary MQTT broker using a publish/subscribe model, CoAP facilitates state information transmission between a client and a server. CoAP is developed primarily for constrained devices.

Constrained devices are characterized by their restricted resources, including limited memory, storage, computational capabilities, constrained battery power, and restricted bandwidth [75]. Using the soil moisture sensor data as an example, the message between clients and sensors via CoAP can be shown in Figure 6.

CoAP facilitates direct device-to-device interaction. It empowers devices to uncover and negotiate compatible content formats autonomously. CoAP uses UDP (User Datagram Protocol). However, UDP does not guarantee message delivery or the preservation of message order.

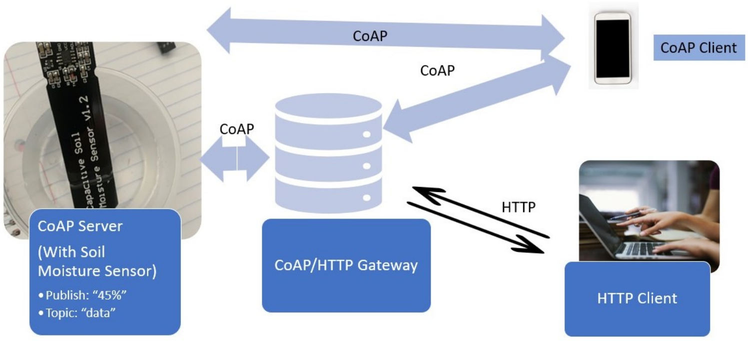

Figure 6. CoAP protocol.

The choice between MQTT and CoAP depends on the precise demands of the IoT application. When devices need to exchange data adhering to fixed formats while ensuring reliable message delivery, MQTT could be a better choice. Conversely, if devices necessitate the ability to negotiate content formats and the application directly tolerates a degree of message loss or non-sequential arrival, CoAP becomes a more fitting selection.

Throughout our study, as shown in Table 6, various platforms can be used to support IoT irrigation systems. For example, Blynk and ThingSpeak are cloud-based platforms that use the MQTT IoT protocol. The Android API is popular for developing codes to facilitate communication with various sensors and establish connections with cloud platforms such as ThingSpeak [42,64] or Blynk [41]. Notably, the preference has tilted toward open-source platforms over conventional IoT cloud platforms, including AWS IoT, Microsoft Azure IoT, and Google Cloud. The choice between ThingSpeak and Blynk hinges on the IoT application's specific requirements and intended functionalities.

Table 6. Platform of IoT irrigation system.

Name	Type	IoT Protocol	Open Source	Mobile App Support	Device Management	Security	Paper ID
ThingSpeak	Cloud Platform	HTTP and MQTT	Yes	No	No	TLS	[42,58,64]
Blynk	Cloud Platform	HTTP and MQTT	Yes	Yes	Yes	TLS	[41,50,59]
Chirpstack	Standalone (LoRaWAN Network Server)	MQTT	Yes	Yes	Yes	OTAA	[64]
Amazon EC2	Cloud Platform	MQTT	No	Yes	Yes	AWS Secure	[33]
Website	Custom Development	HTTP and MQTT	Yes	No	No	None	[38,49,55,56,60]

The recent surge in AI and big data technologies has led to enhanced decision making through AI-based predictors. Leveraging massive datasets and discernible trends, these predictors hold the potential to refine and fine-tune the accuracy of various processes. Some examples of AI include Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI) [31,64,76,77]. Most AI used in smart irrigation systems are ANI, since they focus on handling one task such as predicting water usage.

Machine learning (ML) is a subset of AI, which relies on two types of data: the training and test sets. The training data are used to develop the initial model, while the test data are employed to validate the model's accuracy and subsequently refine it. More data enhance the model's accuracy but have the potential to uncover latent trends inherent within the data itself, as highlighted by [78].

Numerous machine learning algorithms have been proposed using data collected from IoT sensors. For instance, Chen et al. [79] introduced the utilization of a support vector machine (SVM) to rectify biased recursive data. Swetha et al. [80] combined SVM, Decision Tree, and K-Nearest Neighbour (KNN) algorithms for data classification. Similarly, Madelon et al. [81] employed binary SVM to ascertain the optimal timing for irrigation. These algorithms empower accurate predictions, thereby mitigating errors associated with arbitrary guessing.

Deep learning represents the recent and growing development of machine learning that leverages principles from artificial neural networks [82,83]. Unlike conventional machine learning, deep learning automates a significant portion of feature extraction, thereby reducing the necessity for extensive manual human intervention, as elucidated by Zeynep Ünal [84]. By identifying patterns within data, deep learning models proficiently group inputs, enhancing their ability to comprehend intricate relationships [76].

Kashyap et al. [85] propounded an innovative approach termed "DLiSA", featuring a long short-term memory network (LSTM) to prognosticate volumetric soil moisture content for the forthcoming day. This model incorporates predictions regarding irrigation periods and spatial water distribution. Simulation results indicate that DLiSA outperforms contemporary models in prudent water resource utilization within experimental farming areas. Ding and Du [86] introduced a deep reinforcement learning-based approach to improve the intelligence of irrigation systems, deploying neural networks to learn optimal control policies. These networks decode "raw" observations to articulate irrigation decisions for subsequent days, delineating a forward-looking approach to irrigation management. Vrishti et al. [87] employed Recurrent Neural Networks (RNNs), Gated Recurrent Units (GRUs), and LSTM architectures to forecast approximate temperature and moisture levels.

3.2. Environment Factors Dimension

The environmental factors dimension acknowledges that the surrounding environment or field conditions influence the design of an irrigation system. Within our survey, we have identified three factors within this dimension. (i) *Field Conditions*: Several terms are used to describe field conditions. These conditions combined will affect the water flows and water absorption. (ii) *Natural Variations:* Variations in weather patterns, temperature, and precipitation will impact irrigation scheduling and water requirements. (iii) *Crops*: A robust irrigation system must be adept at accommodating the evolving water requirements of different crop types, considering growth stages, crop types, and targeted water distribution. Through the environmental factors dimension, our survey strives to comprehensively analyze the interaction between field conditions, natural variations, and crop specifics in shaping irrigation systems. Through understanding how these factors interact and impact irrigation design, we aim to provide insights into the adaptability, efficiency, and customization of IoT-driven irrigation solutions.

3.2.1. Field Condition

Several key terms are used to describe a field condition:

Soil types: The soil texture triangle, a fundamental concept in soil science, introduced the three primary types of isolated soils: sand, silt, and clay. Sand particles are typically the largest grains visible to the naked eye. It exhibits rapid water infiltration and drainage due to its inability to retain water. Clay (size is less than 0.002 mm) retains water efficiently but impedes water infiltration. Silt sits between sand and clay with a size in the range of 0.002–0.05 mm. According to the USDA (United States of Agriculture), the ideal soil, which favors nearby waters, consists of 20% clay, 40% sand, and 40% silt on a flat surface [88].

Soil texture: It refers to the ratio of sand, silt, and clay in a sample. Soil texture profoundly influences water retention and availability, directly impacting irrigation strategies. For example, Jahnavi et al. [89] investigated the correlation between soil texture and irrigation effectiveness. The team employed soil moisture and humidity sensors to collect data for analysis. The findings indicated that silt soil demonstrated superior water retention capabilities compared to peat soil, which is a type of organic mixture soil under similar conditions.

Other Terms: The field's topography means the direction of surface and underground water flows. Topography is an elevation measurement, and the slope is the ratio change in that elevation over a certain distance. A perfect topography in agriculture is a flat field. However, almost all fields have slopes, while water always runs off and collects in low-lying areas. Slopes and elevation variations can affect water distribution and drainage. For example, Ismail et al. [90] used a thermal camera to obtain RGB images of the surface of the ground to conduct the learning model training; then, they used the thermal pictures and the machine learning model to estimate the slope and flatness of the ground.

An advanced irrigation management system is urgently needed to monitor water reserves, safeguard plants from overwatering, and detect leaks within the system.

Sensors such as water meters and water flow sensors can be used to obtain information about water size areas and water leakage. For instance, Jani et al. [31] proposed over 10 types of sensor data, including water meters and water flow sensors, to detect water leakage. Mustika et al. [59] used an ultrasonic sensor to monitor the water tank's level status and send alerts to users with water shortages or water exceeding. Likewise, Owaga et al. [91] implemented a prototype system for landslide detection. The designed system leveraged different sensors (inclination sensor, soil moisture sensor, and camera sensor) to collect data to edge nodes that evaluate the risk of landslide.

Unmanned Aerial Systems (UASs) have emerged as a transformative technology for real-time crop monitoring and management. This shift is exemplified by seminal survey papers like [17,18,92]. Gallay et al. [93] demonstrated the potential of UASs for comprehensive data collection. The deployment of an autonomous unmanned helicopter equipped with hyperspectral, visible, and laser sensors yielded valuable insights into phenomena like landslides, flooding, erosion, and phenology. Also, Caruso et al. [94] explored using drones equipped with LoRa radios to assess the optimal drone-sensor proximity for effective data collection. In this scenario, sensors are programmed to record data in their memory when the drone flies over, subsequently transmitting these data. To maintain quality data collection, sensors need to be organized in a grid along a predefined route. This methodology, while promising, necessitates further exploration for scenarios involving diverse field shapes, varied drone flight plans, and alternative sensor deployments. Incorporating UASs marks an advancement in the smart agriculture system.

3.2.2. Natural Variations

Natural variations, encompassing weather patterns, temperature fluctuations, and precipitation levels over the year, play a significant role in irrigation scheduling and water demand estimation. The dynamic interplay between these factors and the chosen crop types affects water requirements. Particularly during dry periods, the necessity for increased irrigation becomes pronounced. Water reservoirs or storage tanks must be adequately provisioned to cater to these enhanced needs.

In response to these natural variations, innovative irrigation systems have been developed. For example, Mustica et al. [59] devised a water discharge scheduling strategy based on diverse factors such as rainfall, hydrology, soil characteristics, plant species, and climatic data. Once the water reservoir reaches its maximum capacity, the system triggers alerts to halt irrigation. Conversely, users are notified to refill the reservoir if water levels drop below a designated minimum threshold. Udit Shandilya and Vidhi Khanduja et al. [40] proposed an intelligent farming system using weather forecasts and history data to estimate the water in need. It added a manual option to turn the irrigation system from automatic to manually controlled. During the rainy season, once the data meet the maximum level, the irrigation system is turned off until the user manually turns it on. Also, Gupta et al. [56]

designed an irrigation system that automatically starts sucking out the excess water with the pump when the water level exceeds the ideal point for the crop.

Maize is one essential grain crop in China. Yu et al. [95] designed a machine learning-based model to predict soil moisture level at various depths with different locations for maize during the summer growth period. Likewise, Chen et al. [79] used data collected by synthetic aperture radar (SAR) for winter wheat fields in Canada. The winter wheat region is generally sown in October and then starts its regrowth in April of the following year. Winter wheat harvest commonly happens near end of July or early August, depending on the area. The study recorded the soil moisture data through SAR during the whole growth period to develop several machine learning models. Based on their research, it is possible to estimate the soil moisture value with the machine learning model if the environmental conditions can be controlled.

Interestingly, irrigation systems are not solely dedicated to water provision. They can also be harnessed to regulate soil temperature [31,33,43]. Soil temperature sensors can monitor thermal conditions. When temperatures rise excessively, the irrigation system can be triggered to mitigate the heat by supplying water, thereby preserving optimal growing conditions.

Overall, accounting for natural variations is crucial in smart irrigation systems. Advances in data-driven techniques, sensor integration, and machine learning facilitate accurately estimating irrigation needs based on weather patterns, temperature changes, and crop types. Moreover, irrigation systems can serve multifunctional roles, such as soil temperature regulation.

3.2.3. Crops

IoT-driven systems are increasingly being used to monitor crop growth stages and modulate irrigation practices. For instance, DB et al. [57] combined soil moisture sensors to obtain the soil moisture value, a temperature sensor to obtain the air temperature and light sensors, and leaf wetness sensors to obtain the crop growth status. The system adopts an Arduino board as the central control unit, which is used to recognize the growth rate of crops and extract the insights from the data, leading to the crops' health and yield. Once the water exceeds the volume, it will activate the pump to suck out the water.

Shandilya and Khanduja [40] used real-time data via sensors like soil moisture, temperature, humidity sensors with historical crop data, and weather API information. These integrated data empower the system to recommend suitable crops for specific growth stages. Kushal et al. [42] used machine learning models, including Decision Tree, K-Neighbor, and Random Forest, to predict crop yield. They leveraged measured data from sensors like soil moisture, temperature, and humidity sensors (DHT11) and a Random Forest classifier for this purpose. Also, Peraka et al. [48] designed a mobile app-driven system based on crop type and growth stage, which divides five types of crops (rice, sugar cane, wheat, potato, and corn) into five stages: 1–30 days, 31–60 days, 61–90 days, 91–120 days, and 121–150 days. Since different crops require different volumes of water, the system predetermines the water usage for each crop and then distributes the water based on predefined water usage. Once the irrigation system is activated, real-time data from sensors are compared with a predefined threshold to ensure the proper volume of water will be provided.

These examples underscore the importance of IoT technologies in crop growth stage monitoring and adaptive irrigation. By collecting data from various types of sensors, leveraging machine learning, and integrating historical and real-time information, these systems contribute to precise and efficient irrigation practices throughout different growth phases.

3.3. Cost-Effective Dimension

The cost-effective dimension acknowledges the transition from design to practical product development within the business landscape. Within this dimension, we have identified three significant pivotal factors for users. (i) *Overall Cost*: Affordability is a paramount consideration for any system implementation. However, the cost is associated with the features and the system's reliability. Finding the optimal balance point between cost, reliability, and feature richness is required during the design phase. (ii) *Energy Efficiency*: Beyond cost, minimizing energy consumption is a crucial concern. Leveraging contemporary advancements like solar energy offers a sustainable approach to curbing energy usage. Similarly, the integration of low-power technologies can substantially reduce energy consumption. Within our review, we linked various edge technologies related to energy efficiency, outlining their advantages and limitations for users' informed consideration. (iii) *Water Utilization:* At the core of any irrigation system lies efficient water resource management to minimize waste. This encompasses precise water distribution aligned with varying crop requirements, optimizing usage efficiency, and reducing unnecessary water loss.

Our survey bridges the gap between design and practical application. Recognizing the significance of cost, energy efficiency, and water utilization not only aids in developing economically viable solutions but also ensures that the resultant systems align with sustainable practices and environmental responsibility.

3.3.1. Overall Cost

Considering the large size of the farm, it is desirable that the hardware expenses associated with IoT implementation, particularly those for solar panels and sensors, be regulated at a reasonable level in order to encourage farmers to adopt the system. Therefore, cost must be considered while designing an irrigation system.

Only using soil moisture sensors is the most economical way to control the cost [32,34,38–40,52,60]. However, as discussed for the perception layer in Section 3.1, solely relying on soil moisture sensors cannot guarantee reliability. A water meter sensor should be used to monitor the overall water changes [37,55–57], but it cannot reflect the soil moisture situation. In addition, we need services such as calibration to ensure data reliability.

Zyrianoff et al. [96] designed an open-source application called "SWAMP Kali", which collects real data from all types of soil moisture sensors in real time to provide calibration services. "SWAMP Kali" uses stateless behavior, which does not store data in the application or a dedicated database. It uses data managed by Orion. Likewise, Lin et al. [97] designed a tool called "CalibrationTalk" to handle incorrect placement or aging sensor issues. The tool has a special sensor called "Wildcard" to match sensors and provide calibration service.

Sensors are normally put above the ground to receive signals. Sensors buried underground purposely avoid interfering with farm machinery [52]. Hossain et al. [52] proposed using an assisted IoT system to solve the problem. They put a Raspberry Pi on top of the sensor to convert it to a LoRa-enabled sensor and then bury it under the ground. The new sensor will receive the LoRa signal and store data on the Raspberry Pi to communicate with the drone. Once the drone flies over the farm in a predefined route, it can communicate with the LoRa-enabled sensor to collect soil moisture data. However, this proposal has increased the buried LoRa-enabled sensor price with the added microcontroller price, plus a drone in need, which will make the whole system cost extremely high.

In addition to sensor types, the quantity of sensors also significantly affects the overall cost. In the network layer section, we mentioned LPWAN technology, which can be used to reduce the overall quantity used in the sensors. Nonetheless, so far, the LPWAN technology is still in the lab testing stage. Alongside security concerns (AES-128 bit, in the cybersecurity area, is considered a low security level), narrow bandwidth means the same radio frequencies are required for the connected gateways. Thus, the coexistence of multiple gateways can create interference that affects performance. In addition, the farms are not flat; some even have steep slopes, which will also lower the performance of the LPWAN. However, if we use short-range protocols, such as WiFi, Bluetooth, or ZigBee, we need to add more sensors, since the range can cover up to 100 m.

Table 7 lists the cost range for the user to choose from. The cost is based on ten sets of installed sensors plus the microcontroller. The base station, solar energy, or the user's mobile device are not included.

Table 7. Cost overview.

Cost Range	Features	Hardware	Strengths	Limitations	Paper ID
<$500	WiFi/ZigBee, soil moisture	Soil moisture sensor, NodeMCU/Arduino Uno	<$30/unit, simple setup	Limited range (<100 m), single sensor	[34,38,40,52,59,60,62]
<$500	WiFi/ZigBee, soil moisture, environmental metrics	Up to 4 sensors, NodeMCU/Arduino Uno	<$40/unit, multi-sensor data	Limited range (<100 m)	[35,36,41,44,45,48,50,54,56,59,98]
$500–$2000	LoRaWAN/NB-IoT, soil moisture	LoRa sensors, Pycom LoPy4, Arduino/Raspberry Pi	Extended range	Reliability of LPWAN	[37,39,43,51,53]
$500–$2000	WiFi/BLE/ZigBee, environmental metrics	6 sensors, camera, NodeMCU/Arduino/Pi	Crop-monitoring capability	Limited range (<100 m)	[32,52,64]
>$2000	LPWAN/WiFi/BLE/ZigBee, field	Multiple sensors, UASs	Real-time field data	Extended range, but less efficient	[31,52]

3.3.2. Energy Efficiency

IoT devices need continuous power to work properly. One way to extend the battery's lifetime is to turn the system into sleep mode once we do not need it. Such kind of scheduling assumes sensors have two operation modes [99]: (i) *Active Mode*, in which sensing, communication, and computation can be carried out; and (ii) *Sleep Mode*, which refers to the energy-saving mode with a small amount of energy being used. To this end, Patel et al. [100] suggested irrigating different types of crops in turns. That means that even during the active time, only partial sensors will be activated to save more energy. The risk associated with the sleep mode is the possibility of losing data when turning off the node. In addition, activation might consume time and extend the data transmission time. Haseeb et al. [101] proposed clustering schemes similar to sleep mode to increase the network lifetime and efficiency of data transmission. Each cluster has its cluster head in the clustering schemes, which gathers and forwards the data collected from its sensors to the base station or access point as a data collector.

Another way is to use green energy, such as solar energy, which is a renewable energy source that can eliminate the process of changing or charging a battery. It can also reduce the emission of carbon dioxide and improve the overall environment. Chen et al. proposed a photovoltaic pumping irrigation system with solar energy [102]. The solar photovoltaic pump module provides the partial solar energy to the device for operations, and the remainder is stored in the battery. Thus, even in the evening, with the saved battery, there are no concerns about resource shortage without the sun. Sinugo and Omowunmi [45] proposed connecting a solar panel with a solar charger with a 12 V Direct Current (DC), which can shut down the system for 4 h to save energy once it detects wet soil. The total solar energy generated depends on the solar panel power, efficiency, number of daily sunlight hours, and losses. Thus, it is unstable in providing stable and non-stop energy.

Innovative approaches are explored to enhance solar energy utilization. For instance, Palniladevi et al. [58] designed a system attaching one servo motor to one side of a solar panel and placed two LDR sensors on the other side to detect the sunlight. These devices are attached to an Arduino microcontroller. When the sunlight is within LDR sensor 1's measurement range, 90 clock degrees will be moved. When the sunlight is within LDR sensor 2's measurement range, 90 reverse clock degrees will be performed. In this way, the solar panel can turn in the direction of sunlight to absorb more energy, similar to a sunflower. Islam et al. [47] compared the water savings with an irrigation system with a solar panel. According to their test result, it saves 64% of the water and 50% of the energy.

As technology and implementation methods evolve, solar-powered irrigation is likely to become an increasingly viable and attractive option for farmers and agricultural enterprises.

3.3.3. Water Utilization

Water resources for irrigation mainly come from the following two sources: surface water and groundwater. After a rain, the actual amount of water that remains in the soil is affected by several factors. (i) *Water Runoff*: Because of the slide of the ground and the type of soil texture, water might run off from the soil and move to nearby lakes. The type of irrigation method can also affect the water runoff rate. For instance, surface watering has the lowest utilization because of the runoff water and poisoned water by fertilization. On the contrary, the dripping method has the highest water utilization, because all the water is applied in the root zone, which can have up to a 95% utilization rate [89,102]. (ii) *Water Gravity*: Water gravity will let water go down to the deep underground, which reduces the surface water and increases the groundwater amount. (iii) *Evaporation*: Heat can increase the speed of evaporation. Water changes from liquid in the ground to vapor in the air. Evaporation is part of the three steps of the water cycle: evaporation, condensation, and precipitation. In addition to heat, wind also increases the evaporation process. (iv) *Absorption*: Plant roots, the type of soil texture, such as clay, organisms such as bacteria, fungi (such as mushrooms), earthworms, small animals, and organic matter will absorb the water in the soil as well. Thus, even for the same plant with different evaporation and absorption rates, the soil moisture value will differ when we utilize different depths.

In vertical farms, water gravity is paramount to water collection and circulation. IoT devices such as soil moisture sensors, pH sensors, CO_2 sensors, acoustic sensors, and light sensors are employed to gather data related to plants and their environment [6,14,16,18]. By analyzing these data and designing efficient input and output water flows, vertical farming systems can minimize water usage while also saving land area [103].

Integrating natural resources, like rainwater, further enhances water utilization in smart irrigation systems. Rain sensors provide real-time rain status information, enabling irrigation systems to halt operations during rainy periods [36,42,44]. However, these approaches often overlook the effects of runoff water from rainfall. Shandilya and Khanduja [40] used the weather forecast to estimate the soil moisture and then activate or stop the irrigation system based on the actual soil moisture data plus the weather forecast rainfall status. However, it still ignores the facts related to runoff water's impact on the soil and various soil textures with different absorption rates from rainfalls [104]. The traditional way to hold the runoff water is to use a water tank or build a dam to keep the runoff water. Thus, water level sensors send alerts to the user once the water reserved is under the minimum level or exceeds the maximum level. Tubes are used to guide water to the water tank or dam; leakage of the tube or tunnel will cause water loss during transportation. Aggarwal and Sehgal [105] used water flow sensors to collect real-time water flow speeds at different interfaces with users, sending the data to the server to perform data mining to ensure the data processed are accurate, nothing is missed, and errors are removed before entering it into the machine learning models. Then, a neural network will be used to detect leakage and water consumption prediction.

Water gravity will affect the underground water level. Unfortunately, urbanization development has already overdrawn underground water, which has caused the shrinkage of underground water levels. With increased wastewater, polluted rivers, and runoff water from contaminated soil merging into the groundwater, according to the WHO, 80% groundwater is contaminated, and 40% of the US stream river water is not suitable for livestock anymore [104]. IoT can be used to test the water quality before irrigation. Jani and Chaubey [31] proposed to use pH sensors, ultrasonic sensors, soil temperature sensors, air temperature sensors and humidity sensors, and water pH sensors to obtain the irrigation water quality index, aiming to measure the water quality for crop irrigation. A separate purifying process can be added to the irrigation system to clean the water before it goes into the irrigation system.

4. Challenges and Future Directions

As a result of our investigation into smart irrigation systems, we found that none of the proposed solutions meet all of our specified problem space requirements. For instance, relying solely on soil moisture sensors will bring in unreliable inputs, which will cause biased or wrong results. In contrast, integrating many sensors into one system will increase cost, energy consumption, hardware, and maintenance costs. Thus, practitioners need to balance the three dimensions to make a choice. The following summarizes the discussions about the current challenges and potential research directions.

- *Hardware and Sofware Failure*: One of the key challenges in IoT irrigation systems is hardware and software failure. For example, while most sensors are small and affordable, they are also prone to damage, especially in harsh operational environments. This can lead to inaccurate data, posing a significant challenge. To address this, it is crucial to design novel technical solutions to detect hardware and software failures, automatically troubleshoot the root cause of failures, and implement a cost-effective failure-tolerant plan for recovery, ensuring data accuracy and system reliability.
- *High Cost*: The installation of an IoT irrigation system needs investment, such as power supply, sensors, base stations, and application development. Thus, the overall cost for a complete irrigation system is not cheap, especially for a system that integrates various types of sensors for individual plants. As one solution, LPWAN technologies can solve a range of concerns and will be a future trend in IoT irrigation systems. However, the high installation costs of LPWAN base stations, plus the complex field conditions affecting the communication performance, need further study to reduce costs and improve the performance.
- *User Training*: After the installation, farmers need to be trained on how to use the application, how to control the irrigation system, how to identify potential risks, how to detect failures, and how to charge the battery, which needs continuous training with the farmers to ensure data reliability. Farmers in developing countries lack access to network or computer systems. Thus, how to ensure that farmers receive ongoing training to adapt to these rapid changes in the IoT world is another challenge we are facing. To this end, related curriculum and training materials need to be developed for farms with real-world practice and assist farms in accessing state-of-the-art technology.
- *Data Transmission*: LPWAN is suitable for its long coverage range. However, the bandwidth is so narrow that only text messages can be transmitted. When using drones to collect data from sensors to solve the data size problem, sensors should add a data storage feature function to save the data until the drone flies by [31,52]. Microcontrollers need to be added on top of sensors to meet the requirement, increasing the unit cost for the sensor system. New network technology needs to be developed to provide more bandwidth with long-distance coverage. Additionally, the state-of-the-art AI technology can be leveraged to the smart irrigation systems to tune network settings to optimize the required network performance.
- *Water Utilization*: Even with efficient data collection and analysis, there is a risk that new pollution events may occur between monitoring intervals, leading to the contamination of irrigation water. Developing sensors that can rapidly and accurately detect various types of water pollution is an ongoing challenge. New sensor technologies and techniques may be needed to address emerging contaminants. Integrating additional sensors and technologies to enhance water quality monitoring can increase the overall cost of the irrigation system, potentially impacting its affordability for users. It is essential to balance the need for rapid detection and the solution's cost-effectiveness all while ensuring the long-term sustainability of agriculture practices.
- *Security*: It is an essential issue in irrigation systems, because any damage to the irrigation system will influence crops' growth rate or cause water contamination. Blockchain technology has been widely used in the farming industry. However, if we apply blockchain to our irrigation system, its lack of scalability and high energy consumption will burden the irrigation system. In addition, the massive volume of

data collected by the sensors must be passed to the cloud server for further analysis. Physical device protection also needs to be considered, such as adding lockers to protect sensors. We can design mechanisms on the server to collect data only sent from trusted sensors. The continuous adaptation of security methodologies is essential to meet the evolving needs of these systems.

These challenges underline the multifaceted nature of implementing smart irrigation systems. Solutions will likely involve interdisciplinary collaborations, technological advancements, and a deep understanding of local agricultural contexts. The path forward lies in continuous research and innovation to overcome these challenges and create sustainable, efficient, and reliable irrigation systems.

5. Conclusions

In this paper, we have systematically assessed the landscape of smart irrigation systems by leveraging IoT technology. The study engages with a comprehensive analysis using the Cochrane research method to filter out scholarly works concentrated on the smart irrigation system design or the survey overview for the smart irrigation system. Our analysis aligns with a three-dimensional problem space: IoT layers, environmental factors, and cost-effective dimensions. This study has achieved a comprehensive view of the evolving smart irrigation landscape, thus enhancing the scholarly value of the present work. The synthesis of the review has culminated in identifying six critical challenges that smart irrigation systems face, encompassing aspects such as hardware durability, cost implications, user training, seamless data transmission, optimal water usage, and security and privacy concerns. Moreover, the paper has offered informed insights into forthcoming trends in smart irrigation, highlighting avenues for growth, which will be invaluable sources for researchers, practitioners, and users in advancing smart irrigation systems.

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