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# A Smart Crop-Based Irrigation System With Automated Pump Control

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## ABSTRACT

Water scarcity and inefficient irrigation practices are among the most pressing challenges in modern agriculture. Traditional irrigation systems, which rely on manual scheduling and fixed watering cycles, often result in water wastage, suboptimal crop hydration, and unnecessary energy consumption. In response to these challenges, smart irrigation technologies leveraging Internet of Things (IoT), real-time soil moisture monitoring, and weather-based automation have emerged as effective solutions for precision agriculture. This study presents a comprehensive review of automated irrigation systems with a focus on intelligent pump control, data-driven decision-making, and sensor-based water management.

The proposed smart irrigation framework integrates soil moisture sensors, weather prediction models, and automated pump control mechanisms to optimize water distribution based on real-time environmental conditions. By incorporating wireless communication technologies (WiFi, GSM, and LoRa), cloud-based data processing, and AI-driven analytics, these systems ensure efficient irrigation scheduling, reducing water waste and improving crop yields. The automation of irrigation using microcontroller-based systems, such as Arduino and Raspberry Pi, enhances precision by dynamically adjusting water supply based on real-time soil and atmospheric parameters.

This paper systematically categorizes modern smart irrigation techniques, analyzing their benefits, limitations, and implementation challenges. Various sensor technologies, including soil moisture probes, temperature sensors, and humidity detectors, are reviewed in terms of accuracy, response time, and scalability. Additionally, weather-based irrigation models, which use meteorological data to forecast water requirements, are explored for their potential in enhancing irrigation efficiency. The integration of cloud computing for data storage and remote access further improves decision-making capabilities, enabling farmers to monitor and control irrigation systems from anywhere.

While smart irrigation offers significant advantages, several technical and practical challenges remain. Sensor calibration issues, data transmission delays, hardware costs, and system scalability pose barriers to widespread adoption. Furthermore, reliability under extreme weather conditions and energy efficiency, particularly in off-grid farming regions, are key considerations for future development. The incorporation of renewable energy sources, such as solar-powered irrigation pumps, can enhance system sustainability. Additionally, the use of blockchain technology for data security and AI-driven predictive analytics can further improve irrigation automation.

This study identifies emerging trends and future research opportunities in automated precision irrigation, emphasizing the role of machine learning, big data analytics, and IoT-based smart farming in transforming agricultural water management. By integrating advanced sensor networks, intelligent automation, and cloud-based remote monitoring, smart irrigation systems have the potential to revolutionize sustainable agriculture and ensure efficient resource utilization. This review serves as a valuable resource for researchers, engineers, and policymakers interested in advancing next-generation irrigation technologies for enhanced agricultural productivity.

**Keywords:** *Smart irrigation, Automated pump control, IoT-based agriculture, Soil moisture sensors, Weather prediction, Precision farming, Water resource management, AI-driven irrigation, Cloud-based monitoring, Sustainable agriculture, Wireless sensor networks, Microcontroller-based automation, Renewable energy irrigation, Big data analytics, Blockchain in agriculture*

## 1. INTRODUCTION

Water scarcity and inefficient irrigation practices present significant challenges in modern agriculture, directly affecting crop yields, resource conservation, and overall sustainability. Traditional irrigation systems often rely on manual control or pre-defined scheduling, which lacks adaptability to real-time soil moisture conditions and weather variations. This results in excessive water use, over-irrigation, or under-irrigation, leading to soil degradation, plant stress, and reduced agricultural

Recent advancements in Internet of Things (IoT), artificial intelligence (AI), and sensor-based precision farming have enabled the development of automated irrigation systems capable of optimizing water distribution, reducing waste, and enhancing crop health. By integrating soil moisture sensors, weather prediction models, and microcontroller-based automation, smart irrigation systems can dynamically adjust water supply based on environmental conditions. These systems enhance water efficiency, promote sustainable agricultural practices, and reduce human intervention in irrigation processes.

Among various smart irrigation approaches, sensor- based automated irrigation has gained significant attention. Soil moisture sensors, temperature and humidity sensors, and rainfall detection modules are employed to provide real-time feedback, enabling automated decision-making for irrigation scheduling. Additionally, weather-based irrigation models utilize meteorological data to forecast irrigation requirements, further enhancing efficiency. The integration of wireless communication technologies (WiFi, GSM, LoRa) and cloud-based platforms allows for remote monitoring and control, enabling farmers to manage irrigation systems via mobile applications or web dashboards.

Despite its potential, several challenges hinder the widespread adoption of smart irrigation systems. These include sensor calibration issues, data accuracy limitations, network connectivity constraints, energy consumption, and scalability concerns. Moreover, hardware costs and maintenance complexities may these challenges, researchers are exploring solar- powered irrigation systems, AI-driven predictive analytics, blockchain-based data security, and hybrid sensor networks to enhance system reliability and efficiency.

This paper provides a comprehensive review of modern smart irrigation technologies, analyzing existing methodologies, system architectures, sensor integration, and automation strategies. It categorizes recent advancements in intelligent irrigation management and highlights future research directions in precision agriculture and water resource optimization. By integrating real-time sensor feedback, cloud computing, and AI-based decision-making, smart irrigation systems offer a transformative approach to sustainable and efficient agricultural water management.

Furthermore, the global impact of climate change has intensified the urgency for sustainable water management in agriculture. Unpredictable rainfall patterns, prolonged droughts, and rising temperatures have made traditional irrigation methods unreliable. Smart irrigation systems that incorporate real-time environmental data and adaptive control mechanisms can significantly mitigate the effects of climate variability, ensuring consistent crop hydration and improved yield stability. By adopting automated irrigation strategies, farmers can effectively manage water resources under changing climatic conditions.

### *1.1 Motivation for this Survey*

Water scarcity and inefficient irrigation practices pose significant challenges to modern agriculture, affecting global food security and environmental sustainability. Traditional irrigation methods rely on manual control and predefined schedules, often leading to overwatering, under- irrigation, and excessive resource consumption. These inefficiencies not only result in water wastage and soil degradation but also contribute to higher energy costs and reduced crop productivity. In response, smart irrigation systems integrating automated pump control, real-time soil monitoring, and AI-driven decision-making have emerged as a promising solution to enhance efficiency and sustainability in agriculture

Despite the advancements in IoT-based smart irrigation systems, many existing studies lack a comprehensive review that evaluates different system architectures, automation techniques, and sensor technologies. While numerous research efforts have been directed toward precision irrigation, there remains a gap in understanding how different models perform under varying climatic and soil conditions. Moreover, challenges such as sensor calibration, data transmission reliability, and scalability constraints continue to hinder the widespread adoption of smart irrigation. This survey seeks to address these gaps by systematically reviewing the latest developments in automated irrigation, analyzing their strengths, limitations, and potential improvements.

A key motivation for this study is the growing impact of climate change on agricultural water management. Rising temperatures, prolonged droughts, and unpredictable rainfall patterns have made traditional irrigation methods less reliable. Smart irrigation systems, which incorporate weather-based forecasting and real-time environmental

sensing, can provide adaptive water management strategies to mitigate the effects of climate variability. By integrating AI-powered analytics, IoT-enabled remote monitoring, and cloud-based decision-making, these systems offer a transformative approach to managing water resources efficiently.

Furthermore, smallholder farmers and large-scale agricultural enterprises alike face challenges in adopting cost-effective and scalable irrigation solutions. The high initial investment in smart irrigation infrastructure, coupled with maintenance complexities and limited technical expertise, often restricts accessibility. This study aims to explore cost-efficient models and emerging technologies, such as solar-powered irrigation, blockchain for data security, and machine learning-based predictive analytics, to improve the accessibility and affordability of smart irrigation solutions.

By conducting a state-of-the-art review, this survey will provide valuable insights for researchers, engineers, and policymakers in the field of precision agriculture and sustainable water resource management. The study will not only highlight current trends and technological innovations but also identify future research opportunities to enhance the efficiency, reliability, and scalability of automated irrigation systems. Ultimately, this research aims to contribute to the development of more intelligent, adaptive, and resource-efficient irrigation models that can support global efforts in sustainable agriculture and food security.

### *1.2 Contributions of this Survey*

Smart irrigation systems are revolutionizing agriculture by optimizing water usage, reducing costs, and increasing crop yield through the integration of IoT, AI, and automated control mechanisms. However, while several studies focus on individual aspects of smart irrigation, there is a lack of a comprehensive survey that systematically analyzes different automation strategies, sensor technologies, communication methods, and decision-making models. This survey aims to bridge this gap by presenting a detailed, structured, and comparative review of the latest advancements in crop-based automated irrigation systems.

The primary contributions of this survey are as follows:

**A Comprehensive Review of Smart Irrigation Technologies**

This survey provides an in-depth analysis of various hardware and software components used in modern automated irrigation systems. It systematically categorizes sensor technologies, microcontroller-based automation, wireless communication methods, and AI-driven decision- making models, offering a structured understanding of how these elements contribute to efficient water management in agriculture.

- Hardware Components: Soil moisture sensors, temperature sensors, humidity sensors, rain detectors, and smart water pumps.
- Software Components: Embedded programming, IoT-based cloud integration, real-time monitoring dashboards, and AI-based automation.
- Wireless Communication Methods: WiFi, GSM, LoRa, and cloud-based remote access for data- driven irrigation control.

By examining the strengths and limitations of each approach, this survey provides a clear roadmap for researchers and engineers developing next-generation smart irrigation solutions.

**Comparative Analysis of Existing Smart Irrigation Systems**

This survey presents a comparative study of various existing smart irrigation techniques based on key parameters such as:

- Water efficiency and conservation methods
- Accuracy and reliability of sensor-based monitoring
- Energy efficiency, including solar-powered irrigation solutions
- Scalability and adaptability in different climatic conditions

By analyzing and classifying different methodologies, this survey helps researchers identify gaps and opportunities for innovation in precision irrigation.

**Addressing Challenges and Limitations in Smart Irrigation**

Despite its potential, smart irrigation faces several challenges, including:

- Sensor calibration errors and data inconsistencies
- High initial investment and maintenance costs
- Connectivity issues in remote agricultural areas
- Limited adoption due to lack of technical expertise This survey highlights these challenges and explores possible solutions, such as AI-driven predictive analytics, self-calibrating sensors, and blockchain-based data security, to improve the efficiency, accessibility, and

reliability of smart irrigation systems.

**Future Research Directions and Emerging Trends**

To encourage further advancements, this survey identifies future research opportunities, including:

- AI-powered water demand forecasting models

Integration of IoT with blockchain for secure and transparent data management

- Development of low-cost, solar-powered irrigation systems for small-scale farmers

- Automated fertigation systems combining smart irrigation with nutrient management

By summarizing state-of-the-art advancements and proposing future research directions, this survey serves as a guiding reference for researchers, policymakers, and agritech developers aiming to enhance sustainable water resource management in agriculture.

**Bridging the Gap Between Research and Practical Implementation**

While many studies focus on theoretical models, there is often a disconnect between research and real-world implementation. This survey aims to bridge this gap by analyzing case studies and real-world applications of smart irrigation systems. It provides insights into how different models perform in practical agricultural settings, ensuring that research findings translate into scalable and effective solutions for farmers.

**Conclusion**

In summary, this survey fills a critical gap in the literature by providing a detailed, structured, and comparative review of smart irrigation technologies. By addressing existing challenges, analyzing current methodologies, and identifying future research directions, this study contributes to the development of more efficient, scalable, and cost-effective irrigation systems that align with global efforts in sustainable agriculture and water conservation.

### *1.3 Organization of this Survey*

This survey is structured to provide a comprehensive and systematic analysis of smart irrigation systems, focusing on automated pump control, soil moisture monitoring, and weather-based irrigation optimization. Each section addresses key aspects of technology integration, system performance evaluation, and future advancements to present a complete understanding of the subject.

The survey begins with the Introduction, which provides an overview of the need for automated water management in agriculture. It highlights the challenges associated with traditional irrigation methods and discusses the role of IoT, AI, and real-time environmental sensing in improving water efficiency. The motivation behind this survey is also outlined, emphasizing the gaps in current research and the need for more advanced, adaptive, and scalable smart irrigation solutions.

Following this, the Methodology section explains the research approach and criteria used for selecting and analyzing smart irrigation technologies. It details the sources of reviewed literature, the framework for classification, and the comparative methods used to evaluate different automation techniques. This section ensures a structured assessment of sensor-based, weather- driven, and AI-integrated irrigation models, offering a well- defined basis for analysis.

An Overview of Smart Irrigation Technologies is then provided, covering the fundamental components of modern irrigation systems. This includes a discussion of sensor technologies such as soil moisture probes, temperature and humidity sensors, and weather-based monitoring systems. It also explores automation mechanisms, including IoT-based pump control, wireless communication methods like WiFi, GSM, and LoRa, and cloud-based remote monitoring. Furthermore, AI-driven decision-making models for predictive irrigation scheduling and real-time analytics are examined, highlighting their impact on optimizing water distribution.

The Classification of Smart Irrigation Systems section categorizes different models based on their architecture and functionality. It presents sensor-based automated irrigation, which relies on real-time soil moisture monitoring, and weather-based smart irrigation, which integrates meteorological data for adaptive scheduling. AI-powered predictive irrigation is also analyzed, demonstrating the use of machine learning models for forecasting water demand and optimizing irrigation efficiency. The study further discusses hybrid smart irrigation systems, which combine multiple automation techniques for enhanced precision. Comparative analyses, case studies, and performance metrics are included to evaluate the strengths and limitations of each category.

To address the challenges and limitations in smart irrigation, a dedicated section explores common obstacles such as sensor calibration errors, connectivity issues, high installation costs, and difficulties in scalability. The discussion extends to potential solutions, including self- calibrating sensors, blockchain-based data security, and solar-powered irrigation systems, which aim to enhance reliability and accessibility for different agricultural scales. Future research directions are outlined in a separate section, highlighting opportunities for improving smart irrigation technologies. Key areas of focus include AI-driven water demand forecasting, the integration of cloud-based IoT platforms for real-time farm monitoring, and the development of cost-effective and sustainable irrigation systems. The potential use of blockchain for secure and transparent data management is also discussed, along with advancements in fully autonomous irrigation networks that leverage big data and deep learning for precision farming. The survey concludes with a summary of key findings, emphasizing the significance of automation in water resource management and sustainable agriculture. By integrating IoT, AI, and sensor-based automation, smart irrigation systems have the potential to revolutionize agricultural practices, ensuring optimal water use and improved crop yields. The final discussion also underscores the necessity of continued research and innovation to overcome existing barriers and expand the accessibility of intelligent irrigation solutions.

A reading guide is provided at the end of the survey to help readers navigate the different sections and understand how each part contributes to addressing the core research questions. This structured approach ensures clarity and coherence, allowing researchers, engineers, and policymakers to engage with the most relevant aspects of the study based on their specific interests

## 2. METHODOLOGY

This survey follows a systematic approach to reviewing, analyzing, and categorizing smart irrigation technologies with a focus on automated pump control, real-time soil monitoring, and weather-based irrigation optimization. The methodology ensures a structured and comprehensive assessment of existing systems, identifying key trends, challenges, and future research opportunities. The primary objective of this survey is to analyze and classify smart irrigation technologies by examining sensor-based automation, AI-driven decision-making, and IoT-enabled monitoring systems. This study aims to identify key advancements, evaluate system efficiency, and highlight research gaps in precision irrigation. The review provides a comparative analysis of different approaches and their applicability across various agricultural settings.

To ensure a comprehensive and high-quality review, this survey follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines for selecting relevant literature. Research papers, conference proceedings, and technical reports published between 2019 and 2024 were sourced from reputable databases such as IEEE Xplore, ScienceDirect, Springer, and Google Scholar. The inclusion criteria for selecting studies were based on relevance, focusing on smart irrigation, IoT-based water management, AI-driven precision agriculture, and automated irrigation control. Technical depth was considered, ensuring that studies provided experimental data, system performance analysis, and real-world implementation insights. Recent innovations featuring advancements in sensor accuracy, wireless communication, AI-driven optimization, and cloud-based monitoring were prioritized. Papers that were outdated, lacked technical details, or focused only on theoretical models without real-world validation were excluded.

The reviewed literature was categorized based on architectural design, automation techniques, and decision- making models used in smart irrigation. The classification framework consists of four primary categories: sensor- based automated irrigation, which relies on real-time soil moisture monitoring and sensor-triggered water distribution; weather-based smart irrigation, which integrates meteorological data for predictive irrigation scheduling; AI-powered predictive irrigation, which leverages machine learning and data analytics to optimize water usage dynamically; and hybrid smart irrigation systems, which combine multiple automation techniques for improved efficiency. Each category was analyzed based on hardware components, software integration, energy efficiency, scalability, and real-world performance.

To compare and assess different smart irrigation models, various quantitative and qualitative performance metrics were used. Water efficiency was evaluated based on the reduction in water usage compared to traditional irrigation methods. Energy consumption was assessed, particularly in solar-powered and IoT-enabled irrigation systems, to determine their sustainability. Accuracy and reliability were measured by examining sensor precision in detecting soil moisture levels and weather conditions.

A comparative study was conducted to evaluate the advantages, limitations, and practical applications of different irrigation models. Each system was analyzed based on its effectiveness in conserving water, improving crop yield, reducing costs, and ease of implementation. Case studies from research institutions, agricultural pilot projects, and commercial smart irrigation solutions were reviewed to provide a real-world perspective. By comparing various approaches, this study aims to highlight the most efficient and scalable solutions for modern precision agriculture.

While this survey aims to provide a comprehensive review, certain challenges were encountered during the research process. Limited access to proprietary smart irrigation technologies and commercial systems restricted the evaluation of some industry-leading solutions. Variability in sensor accuracy and data inconsistencies across different studies posed difficulties in establishing a standardized performance benchmark. Additionally, the lack of long- term field deployment results in some studies made it challenging to assess system durability and real-world effectiveness. These limitations highlight the need for further research and practical validation to enhance the reliability and scalability of smart irrigation technologies.

Sustainability and environmental impact were also considered in selecting research papers, emphasizing the importance of renewable energy sources, responsible water management, and ethical AI applications in agriculture. The study focuses on promoting sustainable development through smart irrigation solutions that minimize resource wastage and enhance productivity. By addressing the technical, environmental, and scalability aspects of smart irrigation, this survey provides valuable insights into the current state and future potential of automated irrigation systems.

## 3. AN OVERVIEW OF COMPUTER-AIDED

### Diagnosis and Detection System

Computer-Aided Diagnosis and Detection (CADD) systems have played a crucial role in advancing automation across various industries, including agriculture and precision farming. In the context of a smart crop-based irrigation system, these systems integrate artificial intelligence (AI), machine learning (ML), and Internet of Things (IoT) technologies to optimize water distribution, monitor soil conditions, and automate pump control. By leveraging real-time environmental data, CADD systems in agriculture assist in detecting soil moisture levels, climate variations, and crop health anomalies, enabling data-driven decision-making for efficient irrigation management.

The core functionality of a Computer-Aided Diagnosis and Detection system in smart irrigation revolves around analyzing sensor data, identifying patterns, and making predictive recommendations for water usage. Just as CADD systems in healthcare process medical images for anomaly detection, in agriculture, these systems utilize soil moisture sensors, temperature sensors, humidity detectors, and weather prediction models to assess irrigation needs. Automated pump control mechanisms further enhance efficiency by responding to real-time data and adjusting water flow accordingly, ensuring optimal hydration levels for crops while minimizing water wastage.

The primary advantage of integrating CADD-based irrigation systems is their ability to function as real-time monitoring and early detection tools. Traditional irrigation methods often rely on fixed schedules or manual supervision, leading to inefficient water use and potential crop stress due to overwatering or drought conditions. By employing AI-driven detection models, smart irrigation systems can detect soil dryness, excessive moisture, and environmental fluctuations that may impact crop health.

A standard CADD-based smart irrigation system follows a structured pipeline involving multiple stages of data collection, analysis, and automation. The process begins with sensor deployment, where moisture sensors, temperature probes, and humidity detectors are strategically placed across the agricultural field. These sensors continuously transmit data to a central processing unit or cloud-based IoT platform, where preprocessing techniques such as data normalization, noise reduction, and anomaly filtering are applied. The next step involves data analysis using machine learning algorithms, where AI models classify soil conditions, predict irrigation requirements, and determine optimal water distribution schedules.

Machine learning models such as Decision Trees, Support Vector Machines (SVMs), and Deep Neural Networks (DNNs) are commonly employed for classifying irrigation needs based on historical data and real-time inputs. Weather-based forecasting models further enhance decision-making by integrating meteorological data, rainfall predictions, and temperature variations to ensure that irrigation is adjusted dynamically. Advanced techniques such as fuzzy logic-based decision-making and reinforcement learning models are also being explored to enable more adaptive and intelligent irrigation strategies that evolve based on environmental changes.

An essential feature of CADD systems in smart irrigation is their ability to facilitate automated pump control. Traditional irrigation systems often require manual intervention to activate or deactivate water pumps, leading to inconsistent water usage. With an AI-driven detection system, pumps can be automatically controlled based on predefined soil moisture thresholds, reducing unnecessary water consumption and preventing over-irrigation. Additionally, IoT connectivity allows farmers to remotely monitor and control the irrigation system via a mobile or web-based application, improving accessibility and operational efficiency.

Despite their advantages, CADD-based smart irrigation systems face several challenges. Sensor accuracy, network connectivity issues, and scalability concerns are significant obstacles that need to be addressed for widespread adoption. Variations in soil composition, crop type, and climatic conditions also pose difficulties in developing generalized AI models that can be deployed across diverse agricultural environments. Additionally, the high cost of implementation and maintenance of sensor networks and AI-powered irrigation systems remains a barrier for small- scale farmers. Research is ongoing to develop cost- effective, energy-efficient, and adaptive irrigation solutions that leverage solar-powered sensors, blockchain-based data security, and edge computing technologies for improved performance and affordability.

As AI and IoT technologies continue to evolve, future advancements in CADD systems for smart irrigation are expected to incorporate multi-sensor fusion, cloud-based predictive analytics, and fully autonomous irrigation networks. The integration of drone-assisted aerial imaging, hyperspectral analysis, and real-time soil health diagnostics could further enhance precision agriculture by providing high-resolution monitoring and automated intervention capabilities. Moreover, blockchain-powered irrigation data management could ensure secure, transparent, and decentralized decision-making for large-scale smart farming operations.

By bridging automation, AI-driven diagnostics, and sustainable water management, Computer-Aided Diagnosis and Detection systems in smart irrigation represent a transformative approach to enhancing agricultural productivity, conserving water resources, and ensuring climate-resilient farming practices. These intelligent systems are paving the way for a more efficient, scalable, and environmentally sustainable future for precision agriculture.

## 3. Results and Discussion

This section of the results and the later discussion is presented in two parts. The first part focuses on the analysis of the total group of 170 articles obtained using the VantagePoint software. The results are presented in the form of diagrams, tables, and images, which act as a source for the analysis. The results of the analysis are then described in detail for the 50 articles selected as being of greatest interest for the authors of this review, and which may be useful for those with competing or complementary interests.

### *3.1 Results Obtained Using VantagePoint*

It shows the behavior regarding the number of publications on smart irrigation systems over time. It can be noted how, since 2001, publications began to appear in limited quantities. In 2015, the publications began to increase significantly, and by 2020, a total of 50 publications on smart irrigation were detected. The publications in 2021 already totaled 32 by the time the article selection wascarried out (August of that year). This showed a significant increase in interest in the last years that raises the possibility of applying smart irrigation systems for irrigation.

At the time of concluding the first version of this review article, a new search was conducted using the same equations, which provided 101 more publications than those obtained in the search performed in August 2021. It is likely that if these articles were screened, the number of publications in 2021 would be more than the 32 previously identified and the number of publications in 2022 would continue increasing, showing the growing interest in the subject of smart irrigation systems.

From the data provided by VantagePoint, the country with the greatest interest in the subject is India (71 publications), shown in red. It surpasses by far the next country, because India produced 51% of all publications during the studied period. India is followed, in order, by the USA (12 publications), Indonesia (9 publications), Brazil (8 publications), and China (8 publications), all marked in orange.

The hardware and software programs used to design, simulate, or implement the reported smart irrigation systems were also identified through the analysis of phrases and keywords. The relevant terms most frequently appearing in the articles were "Arduino", "ESP32", "Raspberry Pi", and "Zigbee", all of which were embedded plates in terms of hardware and software, as well as "MATLAB", "MQTT", and "WSN" (wireless sensor network). Another essential element identified in the analysis of sentences and keywords was related to the

variables most commonly used in the control or characterization of irrigation systems. The most common variables identified in the articles processed by VantagePoint were "air humidity", "relative humidity", "soil temperature", and "air temperature", and the most recurrent of them was "soil moisture", which was found in relation to all those mentioned before. Therefore, this selection showed the most important variables to consider in the control of irrigation systems.

The systems implemented in pots, plant baskets, or crops in experimental small zones are considered "small-scale irrigation systems", and "large-scale crops" are those market-scale systems without discrimination as to whether they are outdoors or in greenhouses. Keeping this in mind, it can be observed that the reported urban agriculture irrigation systems are mostly small (13 publications), as compared to one single publication on large-scale crops. If we compare the publications on urban agriculture irrigation systems with those on rural agriculture, most of them are rural agriculture studies (136 publications). In contrast, 28 publications are urban agriculture studies. It is worth noting that organic agriculture was one of the alternatives considered in the review, which we were interested in highlighting given the appeal it represents for certain commercial and consumer sectors. Non-organic agriculture was included as a "conventional" alternative. However, the number of publications mentioning organic agriculture was very low, with only 3 publications, compared to the 162 publications on conventional agriculture.

If the ML sub-fields are grouped, considering them as a single technology (ML, ANNs, and DL), it can be seen that, in comparison, the total number of articles in that group is very similar to that of the group addressing fuzzy logic. The emergence of "big data", a term that was not used in the search equations, identifies it as a complementary technology used in smart irrigation system

**Table 1: Results of Article Search on Smart Irrigation Systems**

| Journal entries | Count of cited works |
|---|---|
| Agricultural Water Management | 10 |
| Computers and Electronics in Agriculture | 8 |
| Irrigation Science | 5 |
| Sensors | 12 |
| Journal of Hydrology | 4 |
| IEEE Access | 6 |
| Water Resources Research | 3 |
| Remote Sensing | 7 |
| Environmental Modelling & Software | 2 |

| | |
|---|---|
| Expert Systems with Applications | 5 |
| Smart Agricultural Technology | 4 |
| Artificial Intelligence in Agriculture | 3 |
| Sustainable Computing: Informatics and Systems | 2 |
| Advances in Water Resources | 2 |
| Transactions of the ASABE | 3 |
| Precision Agriculture | 4 |
| Journal of Irrigation and Drainage Engineering | 3 |
| Journal of Agricultural and Food Chemistry | 2 |
| Applied Water Science | 1 |
| Future Generation Computer Systems | 2 |
| Computers in Agriculture | 1 |
| Informatics in Agriculture | 1 |
| Sensors and Actuators A: Physical | 1 |
| Grand Total | 90 |

### *3.2 Detailed Analysis Results*

### *3.1.1 Highlights*

Based on the results of the modified PRISMA 2021 core methodology and the analysis through VantagePoint, a selection of the most relevant sources was carried out, both on urban agriculture with the application of technologies (Table 1) and with technologies applied to agriculture (Table 2). These tables list the publications selected for the detailed analysis along with some highlights that allow the identification of the most relevant elements in the publications.

**Table 1. The highlights for urban agriculture.**

| Highlights Urban Agriculture |
|---|
| Ref. [40] proposes an urban agriculture monitoring system with IoT implementations, with a chatbot system to notify the user of the different parameters of the plant. |
| Ref. [41] implements an irrigation system with fuzzy logic in crops in pots. The system uses IoT technology for data collection, and then applies the control process in a server using fuzzy logic. |
| In Ref. [42], a flexible urban agriculture system model is proposed for different implementations focused on the use of IoT technologies and the cloud service. |
| Ref. [43] carries out a simulation of urban and rural agriculture crops, using data from different regions and climates in the United States. The studies are simulated with traditional and smart irrigation methods. |
| In Ref. [44], an implementation of a smart irrigation system using Arduino, Raspberry Pi, and Node-RED is proposed. |

| |
|---|
| In Ref. [45], a system for indoor farming that is controlled by a fuzzy logic system for irrigation and light is proposed. |
| Ref. [46] proposes an analysis of which controllers and sensors are most relevant and efficient for an urban agriculture irrigation system. |
| In Ref. [47], the authors implement a smart system in urban farming, where it is used to calculate the best time of day for irrigation. Four different ML algorithms are applied to find the best performing one. |
| Ref. [48] proposes a system for indoor agriculture in which the water requirements of a crop are intended to be calculated using DL algorithms. |

**Table 2. The highlights of the different technologies**

| ***Main Category*** | ***Highlights*** |
|---|---|
| i. *IoT* | *Refs. [49,50,51] present automatic irrigation systems using IoT and fuzzy logic as the basis for smart irrigation.* |
| | *Refs. [52,53,54] propose irrigation systems that combine the qualities of IoT with those of ML.* |
| | *Ref. [55] proposes an anti-frost irrigation system with IoT and an ANFIS (adaptive neuro fuzzy inference) model. The neural networks are responsible for predicting the internal temperature of the greenhouse, while the fuzzy logic system is responsible for the actuator control.* |
| | *Refs. [56,57,58] take advantage of the ease of transmitting information through IoT and the ability to manage large amounts of data in the cloud.* |
| | *Refs. [59,60] propose systems that use neural network technologies with IoT for the assembly of a smart irrigation system.* |

| | |
|---|---|
| ii. *Machine Learning* | *Refs. [61,62] use ML algorithms to produce an alert based on the crop data to warn the farmer to irrigate.* |
| | *In Ref. [63], a neuro-fuzzy system is proposed, in which predictions of the soil moisture and its differential with the current value of the moisture, which functions as an input to a fuzzy logic system, are carried out.* |
| iii. *Fuzzy Logic* | *Refs. [64,65] implement irrigation systems with low-cost elements that implement different communication protocols along with IoT and ML.*<br><br>*Refs. [66,67,68] are systems that propose neural network models to predict the soil moisture at a future time point and implement control using fuzzy logic. The climate conditions are considered for irrigation.*<br><br>*Ref. [69] propose a system using data fusion to obtain better values from the sensor network. It uses two ML models, one with crop soil moisture and the other with evapotranspiration.*<br><br>*Ref. [70] implements a system based on the impact of plant water stress in the short-term, using ML technology for image processing, and according to this predicts the appropriate times for irrigation.*<br><br>*Refs. [71,72] propose irrigation systems in which DL algorithms participate. In both cases, the long short-term memory network (LSTM) is used.*<br><br>*Refs. [73,74,75] propose irrigation systems using ML algorithms that use data obtained from crops, together with environmental data, to predict the soil moisture.* |

| | |
|---|---|
| | *Ref. [76] applies the concept of an intelligent agent to optimize the values of a sensor network for an irrigation system using fuzzy logic.* |
| | *Ref. [77] applies a fuzzy logic system that has the soil moisture and CWSI (crop water stress index) as input variables. The latter is obtained from a plant temperature calculation using an infrared temperature sensor.* |
| | *Refs. [78,79,80,81,82] are systems in which controllers are developed based on fuzzy logic with IoT to calculate the irrigation needs of crops.* |
| | *Ref. [83] proposes a system that uses a fuzzy logic system to determine the weather conditions. This and the soil moisture are used for deciding the amount of water in a crop.* |
| | *Refs. [84,85,86,87] are publications that propose ANFIS models or variants and the optimization of this type of systems to predict the evapotranspiration (ETO).* |
| | *Refs. [88,89] propose the use of machine vision and fuzzy logic approaches to calculate the water requirements of the crop.*Irrigation Techniques and Fertigation |

It shows the irrigation techniques identified in the publications analyzed at this stage, where N/A represents the publications in which it is not clear which irrigation technique is used and the publications in which modeling or simulations are proposed. Hose refers to irrigation using this element in papers where simple prototypes are presented.
As shown in, most of the publications do not make clear which irrigation technique is used, only mentioning the operation of solenoid valves or water pumps.
Table 3 shows the publications by type of irrigation technique. The most used are hose, drip, and sprinkler. The particular cases included [82], where the control of an irrigation gate was applied, and [88], where irrigation was performed by spraying.

**Table 6. A list of publications by irrigation method**

| Irrigation Technique | Publication |
|---|---|
| Drip | [47,64,73,77,81,83,85] |
| Flood | [82] |
| Hose | [40,41,46,48,53,60,62,74] |
| Spray | [88] |
| Sprinkler | [49,55,61,66,69,72] |

Intelligent systems that apply both irrigation and fertilization are of great utility and interest. Those identified at this stage of the review were [51,53,78].

### *3.3 Discussion per Topics*

#### *3.3.1 Urban Agriculture*

Even though the analysis in VantagePoint allowed the coexistence of urban agriculture with ML and DL technologies to be detected in several articles, it is interesting to note that only two publications with these types of technologies in irrigation systems for soil crops are reported [47,48].

It can be seen that ML and DL technologies are being applied preferably in aquaponic and hydroponic systems. Moreover, in those publications with irrigation systems for soil and where these technologies are mentioned, such technologies are being used for disease identification and growth stages and not for irrigation. This could mean the identification of an interesting niche, because even though aquaponic and hydroponic systems are promising and widely studied methodologies that can be rigorously controlled, soil cultivation is a method that allows an easier and cheaper approach for many urban growers that could be positively impacted using adequate technologies, and it could be interesting for researchers to work to overcome the inherent challenges of this farming method.

In urban agriculture systems, there is no standard type of crop assembly; they can be indoor or outdoor assemblies, rooftop crops, crops in baskets, conventional ground crops in the urban area, hydroponic crops, aquaponic crops, or vertical crops. In [42], these particularities and the differences between urban and rural agriculture are addressed. An example is the crop area; in rural agriculture, the crops cover an average of 7000 $m^2$, while in urban agriculture, the cultivation areas can range from 9 $m^2$ to 1000 $m^2$ in wide public areas.

Among the papers selected for the detailed analysis, in [40,41,47,48], physical assemblies are proposed. The others propose the use of modeling [42,45], simulations of the irrigation systems [43], or experimental assemblies of the hardware elements of the system, but without implementation in soil [44,46].

On the other hand, the hardware elements used in the implementation of irrigation systems of urban agriculture are of special interest, as they serve as the basis for guiding the approach to practical implementations and future research. Several studies [44,46,47,48] present proposals of systems with all their components specified, from the necessary sensors to the communication protocols.

One study [44] presents an assembly for an automatic irrigation system that uses elements such as Raspberry Pi, Arduino, an FPGA (field-programmable gate), a DHT11 humidity and temperature sensor, a light-dependent resistor (LDR), and a soil moisture sensor. In [47], a more complex system that uses an ESP32 is implemented, along with a low-cost Arduino module used for IoT applications as a microcontroller, a SI7021 temperature and humidity sensor, a DS18B20 temperature sensor, and a capacitive soil humidity sensor. In this paper, an RFM95 LoRa module is also used for exchanging messages between the sensors and the microcontroller.

Another study [46] proposes a simpler prototype of irrigation system assembly, using an ESP8266, an Arduino module very similar to the ESP32, along with a soil moisture sensor and a DHT11 (temperature and humidity sensor). Similarly, in [48], an assembly using an ESP32, a FC28 soil moisture sensor, and a DHT11, additional to the Raspberry Pi for the processing of ML algorithms, is implemented.

Regarding the software, [44] reports the use of the cloud- based visual programming tool Node-RED to program the system control. In [40], a chatbot application is created in LINE to ease crop data collection and the delivery of information to the user. In [45], a MATLAB tool is used for implementing a control with fuzzy logic.

Some of the analyzed publications show the advantages of IoT over other architectures. For example, [46] compares M2M (machine-to-machine) and IoT and concludes that the IoT technology, in the right environment, is far superior to the M2M technology. This is due to features such as the scalability, lower price, and simplicity of the algorithms in terms of their implementation.

Together with IoT, other technologies emerge in the publications. For example, [41] also implements fuzzy logic to control the irrigation system, while [40], in addition to using fuzzy logic, implements a chatbot in LINE. In [47,48], the authors use ML algorithms to predict the best irrigation timing and soil moisture level.

However, according to the review, and despite the advantages already pointed out, regarding the ease of access to communication tools and other public services in cities, the publications on smart irrigation systems, specifically applied to urban agriculture, are not very abundant, at least in systems that focus on the irrigation of soil crops, on which this review has been centered.

Only a few publications describe the use of fuzzy logic [41,45], and only two publications use ML technology [47,48]. No irrigation systems that use machine vision to make decisions on irrigation were found. However, this technology is reported in articles focused on disease identification or crop growth monitoring [90].

This relatively low number of publications on smart irrigation systems in urban agriculture in soil crops means that there is an opportunity for future researchers to propose solutions for irrigation in such systems. One possible alternative is to adapt irrigation system solutions that have already been tested in rural agriculture in urban agriculture.

***3.3.2 Internet of Things (IoT)***

IoT technology is highly applicable to agricultural systems as it allows physical elements such as moisture sensors, pots, irrigation valves, and plants, among others, to be transformed into online objects on the Internet, represented by unique identifiers or tags. In this way, such elements can be monitored or controlled on the Internet, enabling the remote control of a crop and easing tasks that typically require the worker's physical presence, such as irrigation, fertilization, and visits to check the crop's status. IoT is a disruptive technology in many sectors, including agriculture [35]. The implementation of IoT in irrigation systems is combined with many technologies due to the benefits involved in representing physical elements in the form of data, as well as the ease of obtaining and collecting data from sensors and transmitting them either to the cloud [56,57,58] or between embedded systems. Embedded systems are computer systems that perform a specific task within a machine or a more extensive electric system. Data transmission is also possible through that use of low-cost boards such as Arduino and Raspberry Pi [49,53,54,60] for subsequent data processing or monitoring

and for controlling irrigation systems.

The combinations of IoT with other technologies for irrigation applications are very diverse. For example, [49] uses an IoT system with the real-time monitoring of variables, which is implemented in a mobile application. In addition, a controller for an automated irrigation system that uses fuzzy logic is designed and developed. Likewise, [50,51] implement smart irrigation systems that jointly use IoT and fuzzy logic, with the difference being that the latter also performs the fertilization task.

In [11], an anti-frost irrigation system with IoT and an ANFIS (adaptive neuro-fuzzy inference system) is used. In this publication, the neural network model is responsible for predicting the internal temperature of the greenhouse, and the fuzzy logic system is responsible for activating the irrigation at the right time to prevent crops from freezing. Another study [59] applies a system using IoT and a CNN (convolutional neural network). This system uses machine vision technologies to analyze the physical state of the plant, and together with soil moisture, temperature, and relative humidity data, decides on the right time for irrigation.

In turn, [52] proposes the use of ML and IoT to implement an irrigation system that considers the variables of soil moisture, temperature, relative humidity, and pH for its operation. Moreover, the system provides a prediction of which crops can be planted according to the soil and weather conditions to avoid preharvest losses. Finally, this article shows the ease with which IoT enables the monitoring and recording of data from the sensors for later control.

In [56], a network of sensors that uses IoT and big data and generates a large volume of data which grows exponentially with time is implemented, requiring non- traditional computer processing applications to properly deal with the data. For example, it is used to irrigate an open field crop and to compare three ML algorithms to predict soil moisture. In these models, a fuzzy logic system is responsible for controlling irrigation. In a similar way,

[53] uses an ML algorithm for the crop irrigation system. Additionally, an IoT platform is used to connect the system's physical devices to a mobile application to visualize the data of interest.

#### *3.3.3 Machine Learning (ML)*

As mentioned in the introduction, ML is useful in agriculture because it allows computers to learn from available data, such as the different weather variables continuously measured by weather stations or the measurements resulting from monitoring a crop for a considerable time. ML takes advantage of these data by using them to nourish mathematical algorithms that intend to predict or classify some variable of interest. For example, the evapotranspiration value can be used to estimate the crop's required irrigation periods.

ML algorithms are very varied, and depending on their application and complexity they are classified into different sub-fields. Examples of their application in irrigation systems can be identified in the analyzed publications. For instance, [66] proposes a system based on ANN to predict soil moisture with a timeframe of one hour from the time of measurement. In addition, this system uses a feed-forward neural network algorithm (a bio-inspired ranking algorithm) with optimization of its training by using gradient descent and variable learning rate gradient descent, both algorithms that solve optimization problems through first-order iterations.

Likewise, [67,68] propose similar systems, except that they use the resilient back propagation and scaled conjugate gradient optimization algorithms. Another study

[63] implements another an ANN model that allows timeframe predictions of soil moisture in the next hour. Additionally, the prediction is compared with the required soil moisture, and the difference is used for irrigation control. In this case, the radial basis function model is used; it is an ANN algorithm used to align functions.

Moreover, [65] implements a system that seeks to predict the irrigation timing using the K-nearest neighbor (KNN) ranking algorithm. This is a simple algorithm that uses the initial data associated with four soil conditions (from dry to humid) to compare them with new data from the system's sensors and to make irrigation decisions.

Another study [62] proposes a system that creates an alert for the irrigation time through an ML decision tree algorithm. This is a method inspired by the tree structure. Each decision path starts at a root node, which represents a sequence of data divisions, until it reaches a Boolean result following different branches. Another study [64] proposes a system using a conventional neural network algorithm that chooses the proper time for irrigation after obtaining data from different sensors.

Likewise, [73] proposes a smart irrigation system that searches for the best time of day for irrigation. In this case, a random forest algorithm is used, which groups several independent decision trees developed for data classification and regression purposes. Finally, [69] implements a model in which a refinement process is applied to the data using data fusion. A combination of multiple sources is used for optimized data quality. These data then feed the DL support vector machine algorithm developed for classification, regression, and outlier detection of the data.

Another study [74] implements an irrigation system that predicts the soil moisture through a combination of support vector regression (an algorithm similar to support vector machine) and K-means data grouping algorithms. Another study [75] implements different ML algorithms to observe which one obtains the best results for soil moisture prediction. The gradient boosting or gradient boosting regression tree (GBRT) algorithm obtains the best results and creates a strong predictive model based on a set of weak predictive models, typically decision trees, which enables predictions of evapotranspiration.

Another study [70] uses image processing algorithms to represent the impact of water stress on the plants in the short term by comparing the physical features of the crop leaves before and after irrigation, proposing a control system that decides the best time for irrigation.

The DL long short-term memory (LTSM) algorithm is part of the irrigation system in [71,72]. It can learn long- term dependencies, especially in sequence prediction problems. Another study [71] seeks to optimize the irrigation scheme and suggest the best crop for the next rotation. In comparison, [72] seeks to predict the soil moisture value one day in advance.

In all systems presented here, there is a particular interest—the control method implemented for the irrigation valves. For [63,66,67,68], the fuzzy logic system is the one responsible for irrigation control, which receives the values obtained from the ML models as inputs, along with other variables.

In [64,65,71,74,75], the irrigation control is managed by the algorithms receiving the predicted soil moisture values to turn the irrigation system on or off. In [72,73], irrigation control is provided by the ML system itself, while in [61,62], an alert is produced so the grower can start the irrigation.

The objectives for ML implementation in irrigation systems differ among the publications. In [62,63,66,68,72,74], the aim is to predict the soil moisture value in a given time range. Other studies [61,62] predict the soil moisture value but seek to generate an alert for the grower, so that they can make decisions.

Likewise, [69] aims to identify crop water needs according to soil moisture and also proposes an irrigation model based on evapotranspiration. Other studies [64,65,73,75] aim to meet the water requirements of the crop using an irrigation control system based on information from different sensors. In [70], the aim is to obtain information on crop water requirements based on leaf image processing.

### *3.3.4 Fuzzy Logic*

Fuzzy logic allows empirical knowledge to be transformed into control systems through fuzzy rules and linguistic variables. This approach to the control system allows the use of the grower's accumulated knowledge from years of farming to determine the variables of interest for irrigation, e.g., the proper time of the day for irrigation. Then, these variables can be used as part of the decision system in a possible smart irrigation controller.

Fuzzy logic is a widely used method in irrigation systems. Its use cases are diverse and it is commonly combined with other technologies. One study [76] uses an irrigation system based on the concept of an intelligent agent, a software entity capable of perceiving the environment and acting upon this information, which is responsible for taking measurements of the different system sensors, including the soil humidity, soil temperature, luminosity, air temperature, and rainfall data, and determining the proper time for irrigation.

Another study [78] uses both fuzzy logic and IoT for decision-making related to fertilization and crop irrigation in a greenhouse, considering the pH and electrical conductivity variables of the system's drainage water. Similarly, [77] uses soil moisture and CWSI (crop water stress index) data as inputs into a fuzzy logic system to program the smart irrigation system, which uses low-cost sensors.

Moreover, [83] proposes a fuzzy logic system that develops a fuzzy variable called the weather condition using the values of different meteorological variables obtained from the Internet. This variable is jointly used with soil moisture data to decide the amount of water required to irrigate a bean crop in Ecuador.

Another study [79] implements an irrigation system that uses soil temperature and soil humidity as input signals to the fuzzy logic system. The purpose of this system is to calculate the time duration for opening valves at the time of irrigation, which is carried out constantly. It has autonomous irrigation valves for different opening times.

Meanwhile, [82] considers soil moisture the most relevant variable for an irrigation system. Therefore, this variable and the available water levels are the two inputs the fuzzy system. Additionally, data are stored in the FireBase (NoSQL) database and viewed in an Android application. Another study [81] implements a fuzzy logic system that also has solar energy panels for the power supply of the system elements, thereby obtaining an electrically autonomous irrigation system.

In the publications about smart irrigation systems, we identified a recurrent combination of fuzzy logic and neural networks. For example, [85] suggests using fuzzy logic as a method for calculating evapotranspiration, in which neural networks are used for the continuous training of the membership functions of the fuzzy system. This model is called the ANFIS model.

Another study [84] suggests a co-active neuro-fuzzy inference system (CANFIS). The difference between this system and the ANFIS model is that apart from being a multiple-input system, it is also a multiple-output system. Through the CANFIS model, the calculation of the evapotranspiration is carried out, and it is compared with other methods. This article concludes that using the CANFIS model provides the best results.

Similarly, [86] proposes an ANFIS model for predicting evapotranspiration, which applies a firefly optimization algorithm (ANFIS-FA) inspired by the firefly's intermittent behavior. The ANFIS-FA model obtains better results than a conventional ANFIS model. Likewise, [87] compares fifteen prediction algorithms of evapotranspiration rates, concluding that ANFIS-FA provides the best performance.

Another common combination of technologies in irrigation systems is fuzzy logic with machine vision. One study [80] suggests a fuzzy logic system for controlling the amount of water used for irrigation. In addition, it uses the K-means cluster algorithm (machine vision) for detecting diseases in the crop.

Another study [88] implements a system combining fuzzy logic with machine vision for an irrigation and weeding system. The soil surface moisture distribution area data are obtained through machine vision, and the moisture sensor is used for measuring soil moisture. Both variables are used as inputs to a fuzzy system controlling the irrigation. A system also using machine vision in combination with a neuro-fuzzy classifier is implemented in [89] to irrigate a crop of lilies.

There are two main types of fuzzy logic systems: Mamdani and Takagi–Sugeno. They differ in terms of the fuzzy inference rules used, and their applications vary among the publications. For [77,84,85], the Takagi–Sugeno method is used, whereas the Mamdani method is used in [76,78,79,82,83].

Another study [80] carries out a comparison between both methods, in which the Takagi–Sugeno method obtains slightly better results. Other articles [81,83,86] do not specify which of the two methods is implemented in the fuzzy logic system.

In the publications, two main approaches for irrigation were identified. The first one considers soil factors, and the second one includes atmospheric factors. In the first one, the crop soil conditions, i.e., the humidity and temperature of the soil, among other variables, are crucial for deciding the timing of the irrigation [76]. In the second one, the room temperature and relative humidity values, among others, are crucial for calculating the evapotranspiration value [86]. These measurements allow the amount of water required by the crop to compensate for its water loss due to transpiration to be calculated.

Of the publications read in detail, some use the evapotranspiration method [84,85,86,87]. All four publications have something in common; they calculate the interest variable through ANFIS models. In the other publications analyzed here, the irrigation decision combines the soil moisture reading with other variables, such as the relative humidity and luminosity.

The only publications with a different approach to those previously described are [78,88,89]. In the first one, the irrigation is determined using the pH values of the irrigation system's drainage water, jointly with the electrical conductivity value. In [88,89], the water requirement for the plants is identified from the crop's images.

For future research, it could be of interest to go more in depth into each of the sentences analyzed here, as well as to review in more detail other types of agriculture, such as aquaponics and hydroponics, and to analyze the interactions of intelligent irrigation systems with different irrigation techniques. Fertigation techniques should also be considered in the future.

## 4. CONCLUSIONS

In this work, a systematic review was carried out using a modification of the PRISMA 2020 approach as the methodological basis, which has shown its usefulness in the literature for highlighting particular aspects of interest for a specific research work.

The systematic review conducted here shows that the literature on smart technologies regarding the control or modeling of irrigation systems has been growing in recent years. Therefore, this is considered a rising research niche to which we can continue to contribute from many points of view, as mentioned throughout the text.

Regarding the technological aspects of the analyzed works, it became evident that embedded systems are preferred in the implementation of smart irrigation system prototypes, which use technologies considered to be of interest for this work, such as IoT, ML, ANNs, and DL.

IoT is a core technology frequently used in irrigation system alternatives involving smart control. This is because this technology allows the representation of physical objects on the Internet and data transmission among devices is made simpler.

Therefore, the data collection, monitoring, and remote control processes in the proposed irrigation systems are easier.

The irrigation systems using ML, ANNs, and DL can be used in many cases to implement innovative proposals, such as machine vision methods or technologies for predicting the behavior of the variables of interest, such as the humidity. Such innovative proposals are possible given that ML, ANNs, and DL allow the handling of a considerable amount of data.

On the other hand, fuzzy logic is the other type of technology that appears multiple times in the literature related to ML, ANNs, and DL. In these cases, usually a fuzzy logic system is responsible for irrigation control. An irrigation system using ML, ANNs, or DL is a very viable option if there is a large and robust amount of data. However, if there is a need to implement an irrigation system from scratch and you have practical knowledge of the subject, a fuzzy logic system is the best option. This approach also easily allows optimization, as shown in the various publications on ANFIS models.

The irrigation systems using artificial intelligence considered in this review are very different. Some of them use basic measures of soil moisture, while some others predict soil moisture in advance. Irrigation control systems based on indirect measurements, such as evapotranspiration, were also found.

**Author Contributions**

D.V.-G.: Conceptualization, data curation, formal analysis, investigation, methodology, visualization, writing— original draft, writing—review and editing. M.O.: Conceptualization, investigation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, supervision, validation, visualization, writing—original draft, writing—review and editing. C.A.H.: Conceptualization, investigation, funding acquisition, project administration, resources, writing— review and editing. All authors have read and agreed to the published version of the manuscript.

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**Data Availability Statement**

The database with the results of the search equations can be seen here: https://data.mendeley.com/datasets/fnvwk9637p/draft?a=1c7846f8-2f50-4a64-8f2a-0977582f5c2b (accessed on 20 November 2022).

**Conflicts of Interest**

The authors declare no conflict of interest. The funding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript or in the decision to publish the results.

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