



A Systematic Literature Review of IoT- and AI-Based Intelligent Irrigation Systems for Water Optimization in Precision Agriculture

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Abstract:

The increasing global demand for water has emphasized the importance of irrigation systems capable of efficiently managing water use in precision agriculture. This paper presents a review of one hundred studies published between 2018 and 2025 that address the application of Internet of Things (IoT) technologies and computational approaches in irrigation management. The reviewed literature describes the use of sensor networks, wireless communication systems data-driven control mechanisms and automated decision-support tools aimed at improving irrigation practices while supporting crop production. The studies are organized according to the technologies and methods employed, including sensor-based data acquisition IoT-enabled monitoring platforms and intelligent irrigation control systems. A hybrid classification is also introduced to describe approaches that combine predictive modelling with adaptive irrigation strategies. Additionally, the reviewed works are discussed with respect to several system-related aspects such as water management objectives system architecture, and application scale. The paper also summarizes commonly used datasets and evaluation metrics reported in the literature and outlines key challenges identified by previous studies including data quality, communication reliability scalability and operational costs. Finally, the review highlights research directions that may contribute to the development of more efficient reliable and sustainable irrigation systems for precision agriculture.

1. Introduction

Agriculture remains one of the largest consumers of freshwater resources worldwide. According to the Food and Agriculture Organization (FAO), nearly 70% of global freshwater withdrawals are attributed to this sector. However, beyond this widely cited figure, the literature highlights persistent inefficiencies in irrigation practices that continue to exacerbate water scarcity and environmental degradation [1]. Although improved management strategies are expected to limit the increase in agricultural water use to around 10% by 2050, several studies question the feasibility of these projections, particularly in regions facing climate variability and weak infrastructure [2]. Within precision agriculture, optimizing water use while

maintaining crop productivity has emerged as a central objective. Nevertheless, traditional irrigation approaches, often based on fixed schedules or farmers' experience, remain prevalent, especially in developing regions. These methods fail to capture the spatiotemporal variability of soil conditions, crop water requirements, and climatic factors, leading to suboptimal water allocation. Despite the growing interest in advanced solutions, the transition toward data-driven irrigation systems is still hindered by economic, technical, and adoption barriers. The integration of the Internet of Things (IoT) and Artificial Intelligence (AI) has been widely proposed as a promising solution. IoT technologies enable continuous monitoring through distributed sensors that collect heterogeneous environmental data, such as soil moisture, temperature, humidity, and rainfall

[3]. While these systems provide high-resolution and real-time insights into field conditions [4], several limitations persist, including sensor reliability, data heterogeneity, communication constraints, and energy consumption in resource-constrained environments.

Similarly, AI techniques, particularly machine learning models, have shown strong potential for predicting crop water requirements and optimizing irrigation scheduling [5]. However, existing studies often rely on limited datasets, controlled experimental conditions, or specific crop types, raising concerns about the generalizability and scalability of these models. In addition, the lack of standardized evaluation frameworks make it difficult to compare different approaches and assess their real-world effectiveness.

By combining IoT-based sensing with AI-driven decision-making, intelligent irrigation systems aim to dynamically adapt irrigation strategies to field conditions, reduce water waste, and improve productivity [6]. Despite these promising outcomes, the literature reveals a gap between experimental results and large-scale deployment, particularly in terms of system robustness, cost-effectiveness, and user adoption.

Therefore, while IoT- and AI-based smart irrigation systems are often presented as key enablers of sustainable precision agriculture, their practical impact remains uneven and context-dependent, especially under increasing water scarcity and climate change pressures [7].

This review critically examines recent advancements in IoT- and AI-driven irrigation systems, highlighting not only their potential but also their limitations, open challenges, and research gaps, with particular attention to scalability, real-world applicability, and long-term sustainability.

2. Related Work

Numerous surveys have addressed intelligent irrigation systems based on the integration of the Internet of Things (IoT) and Artificial Intelligence (AI) for optimizing water consumption in precision agriculture. These studies generally explore technological developments, emerging trends, and application perspectives between 2018 and 2025. However, many of them remain descriptive, with limited critical comparison of methodologies and real-world applicability.

Over the past decade, research has increasingly focused on improving water-use efficiency through the adoption of smart technologies, including IoT devices and Wireless Sensor Networks (WSNs) [5]. Early review works primarily on examined monitoring and control strategies for precision

irrigation [6], while more recent studies have incorporated machine learning techniques for predictive and adaptive irrigation management [7]. Despite this evolution, the literature often treats sensing, communication, and intelligence layers separately, lacking a holistic evaluation of fully integrated systems.

Although several reviews highlight the potential of AI and machine learning (ML) in agricultural applications, such as evapotranspiration prediction and automated irrigation control, there is still a limited number of systematic reviews that critically assess the combined role of IoT and AI in intelligent irrigation systems [8]. In particular, existing surveys rarely address key issues such as scalability, interoperability, and deployment constraints in real farming environments. Moreover, the absence of standardized benchmarks and evaluation metrics makes it difficult to compare the effectiveness of different approaches [5].

Artificial Intelligence is increasingly recognized as a transformative enabler in modern agriculture, contributing to improved resource management and system automation. As discussed in [3], AI applications can be broadly categorized into water, soil, livestock, and crop management. In the context of water management, ML models have shown strong potential in predicting crop water requirements and optimizing irrigation scheduling [9]. However, their performance is often evaluated under controlled conditions, which limits their generalizability to open-field agriculture, where environmental variability and complex interactions remain challenging to model [1].

Recent advancements have also introduced IoT-enabled platforms capable of real-time monitoring and automated irrigation control [4]. While these systems provide fine-grained data and improved decision-making capabilities, they still face significant limitations, including sensor reliability, energy constraints, network connectivity in rural areas, and high deployment costs. These challenges highlight the gap between promising experimental results and practical large-scale adoption.

To better position this work and as summarized in Table 1, we analyse a set of representative review studies. For instance, Lakhier et al. [1] provide a comprehensive overview of precision irrigation technologies under climate change conditions, emphasizing their role in improving water-use efficiency and sustainability. However, they also report critical limitations, including high implementation costs, limited scalability, and insufficient large-scale validation. Similarly, Bwambale et al. [2] focus on sensor-based monitoring and control strategies, showing clear improvements over traditional methods, but

highlighting issues related to reliability, integration, and lack of extensive field testing.

Other studies further explore specific components of smart irrigation systems. Obaideen et al. [3] examine IoT architectures and their role in real-time irrigation management, but identify scalability and energy consumption as major constraints. Belarbi and El YOUNOUSSI [4] investigate machine learning approaches, emphasizing their effectiveness in optimizing irrigation decisions, while pointing out the lack of standardized datasets and limited generalization across different agricultural contexts. Mansoor et al. [5] and Soussi et al. [6] highlight the importance of sensor data and data analytics, yet stress persistent challenges such as data heterogeneity, interoperability, and insufficient real-world validation.

In addition, Benhmad et al. [7] propose an intelligent irrigation system combining IoT and AI, demonstrating promising performance improvements. However, their results are primarily based on simulations, with limited validation in real conditions. Likewise, Belmir et al. [8] present a

systematic review confirming the potential of AI-IoT integration, but underline critical gaps, including lack of scalability, absence of unified evaluation frameworks, and insufficient experimental validation.

Overall, the existing literature confirms the potential of IoT- and AI-based intelligent irrigation systems but also reveals significant research gaps. Most studies focus on isolated aspects of the system or rely on controlled environments, with limited attention to large-scale deployment, economic feasibility, and long-term sustainability.

Therefore, this review aims to provide a more comprehensive and critical synthesis by analysing 100 research articles published between 2018 and 2025. It focuses specifically on integrated IoT-AI irrigation systems, evaluates the performance and limitations of ML-based approaches for water management, and identifies key challenges and future research directions, particularly in terms of scalability, real-world applicability, and system robustness.

Table 1. Related work comparison

Ref.	Year	Main Contribution	Systematic Review	Taxonomy / Comparison	Scope (ML, DL, FL, IoT)
[1]	2024	Review of precision irrigation using IoT and data-driven methods to improve water efficiency and sustainability. highlights key limitations in scalability and field validation	Yes	No	IoT, ML
[2]	2022	Review of sensor-based smart irrigation control systems to improve water use efficiency; highlights benefit over traditional methods and challenges in cost, reliability, and field validation.	No	No	IoT, Control Systems
[3]	2022	Overview of IoT-based smart irrigation systems focusing on architecture, sensors, and real-time monitoring for improved water management highlights scalability and connectivity challenges	No	No	IoT
[4]	2024	Review of ML-based smart irrigation for water optimization; shows improved irrigation scheduling and highlights limitations in datasets, generalization, and real-time deployment.	Yes	No	ML, IoT
[5]	2025	Review of IoT and smart sensor integration in precision agriculture ; highlights benefits in monitoring, automation and challenges.	Yes	No	IoT, Sensors
[6]	2024	Review of smart sensors and data analytics in precision agriculture ; highlights IoT and AI for real-time monitoring and efficient irrigation, with limitations in validation and scalability.	Yes	No	IoT, AI, Data
[7]	2024	IoT and AI-based smart irrigation system using automated decision-making; improves irrigation efficiency but mainly simulation-based with limited real-world validation.	No	No	IoT, AI
[8]	2025	Systematic review of AI and IoT in smart irrigation. highlights improved efficiency and productivity, but limited scalability and lack of real-world validation.	Yes	No	IoT, AI, ML

3. Challenges and Opportunities in Smart Irrigation and Precision Agriculture

Based on the analysis of the literature, several key challenges and opportunities can be identified in smart irrigation systems for precision agriculture.

Challenges

Despite significant advancements, multiple technical and practical challenges remain.

Data Quality and Management: Agricultural data collected from IoT sensors are often noisy, incomplete, or imbalanced. This directly impacts the reliability and performance of AI and machine learning models, and highlights the lack of standardized data pre-processing and evaluation frameworks.

Power Management: IoT-based irrigation systems operate under strict energy constraints, particularly in remote environments. Although solutions such as edge computing and renewable energy integration have been proposed, their real-world adoption remains limited due to cost and implementation complexity.

Connectivity and Infrastructure: Limited or unreliable network coverage in rural areas continues to hinder real-time monitoring and cloud-based decision-making. While low-power communication technologies such as LoRa and NB-IoT offer partial solutions, their deployment is still constrained by infrastructure availability and scalability issues.

Cross-Platform Integration: Achieving interoperability between heterogeneous systems, including different communication protocols, hardware platforms, and AI models, remains a major challenge. This lack of standardization restricts the development of fully integrated and scalable smart irrigation solutions.

Security and Reliability: The increasing connectivity of irrigation systems introduces new vulnerabilities. However, many existing solutions do not sufficiently address cybersecurity risks or incorporate robust fault detection and anomaly detection mechanisms, which may affect system reliability in real-world deployments.

Opportunities

Alongside these challenges, several promising opportunities can accelerate the development of intelligent irrigation systems.

UAV-IoT-ML Integration: The combination of unmanned aerial vehicles (UAV), IoT sensors, and machine learning enables more accurate, large-scale, and predictive irrigation management by providing high-resolution spatial and temporal data.

Edge AI: Deploying AI models at the edge allows real-time decision-making with reduced latency and lower dependence on cloud infrastructure, making systems more efficient and resilient in connectivity-constrained environments.

Reinforcement Learning Models: Reinforcement learning offers strong potential for developing

adaptive and autonomous irrigation strategies capable of responding dynamically to changing environmental and crop conditions.

AI-driven Anomaly Detection: Advanced techniques such as autoencoders and generative models can improve system reliability and security by detecting faults, abnormal patterns, or cyber threats in real time.

Adoption Across Diverse Environments: Intelligent irrigation systems can be extended to various contexts, including arid regions, large-scale farms, and urban agriculture. However, their successful deployment requires addressing challenges related to cost, scalability, and environmental variability.

4. Motivations and Contributions

The analysis of the literature presented in the previous sections highlights several critical limitations in existing research on smart irrigation systems. In particular, current studies suffer from a lack of standardized evaluation frameworks, limited real-world validation, insufficient integration between IoT and AI components, and restricted analytical scope. These limitations are directly aligned with the key challenges identified earlier, including data quality issues, system interoperability, scalability constraints, and the gap between experimental results and practical deployment.

Although numerous works have explored intelligent irrigation, only a limited number have adopted a rigorous Systematic Literature Review (SLR) methodology. Moreover, existing reviews tend to focus on specific aspects, such as IoT architectures or machine learning models, without providing a comprehensive and unified analysis of their combined effectiveness in optimizing water consumption in precision agriculture.

Motivated by these gaps, the main objective of this work is to provide a structured and critical synthesis of IoT- and AI-based intelligent irrigation systems, with a particular emphasis on water optimization. To achieve this, 100 relevant studies published between 2018 and 2025 were systematically selected, analysed, and classified according to multiple technical and methodological criteria.

In contrast to existing reviews, this work aims to address several key research gaps:

- The lack of comprehensive integration analysis, by jointly examining IoT technologies, AI models, and water optimization strategies within a unified framework.
- The absence of standardized comparison of machine learning approaches, by explicitly

analysing their performance, applicability, and limitations.

- The limited consideration of real-world constraints, including scalability, energy efficiency, and deployment challenges.
- The insufficient alignment between technological advancements and practical agricultural needs, particularly in diverse and resource-constrained environments.

Table 2 provides a comparative summary of representative review studies, highlighting the methodological and analytical distinctions of the present work.

The proposed review distinguishes itself through:

- the adoption of a rigorous SLR methodology, ensuring transparency and reproducibility;

- a broader analytical scope, covering IoT, AI (including ML, DL, TL, and FL), and their integration;
- an explicit focus on water-use optimization, which remains insufficiently addressed in prior studies;
- and a multi-criteria evaluation framework, enabling a more systematic comparison of existing approaches.

By addressing these aspects, this review not only consolidates existing knowledge but also contributes to bridging the gap between theoretical developments and practical implementation, while highlighting emerging opportunities such as edge AI, reinforcement learning, and integrated IoT-AI architectures for next-generation smart irrigation systems.

Table 2. Comparative summary of representative review studies.

Criteria	Existing Review Studies	This Review
Publication period	2018–2024	2018–2025
Number of analysed studies	Typically, 30–70 papers	100 papers
Review type	Narrative or partial reviews	Full Systematic Literature Review (SLR)
Use of PRISMA methodology	Limited or not explicitly reported	adapted / partial
Coverage of IoT technologies	Partial (specific platforms or sensors)	Comprehensive
Coverage of AI techniques	Focused on selected models	Covers ML, DL, TL, FL
Machine Learning models comparison	Limited	Explicitly considered
Performance-related aspects	Rarely addressed	Included
Water consumption optimization focus	Indirect or implicit	Explicit and central
Application scope	Narrow or domain-specific	Broad (open-field, greenhouse, UAV-based)
Multi-criteria classification	Limited	Yes
Integration of IoT + AI + WO + PA	Partial	Unified framework

4.1 Paper Outline

The remainder of this paper is organized as follows. Section 5 presents the review methodology adopted in this study for analyzing intelligent irrigation systems, following established SLR guidelines from the literature. Section 6 introduces the fundamental concepts related to smart irrigation, IoT, AI, machine learning, water optimization, and precision agriculture, providing the necessary background for the study.

Section 7 describes the systematic literature review process, including the search strategy, inclusion and exclusion criteria, and study selection procedures. Section 6 provides a structured classification and comparison of existing intelligent irrigation systems, covering IoT-based architectures, AI- and ML-driven decision models, UAV-assisted monitoring, and edge–cloud computing frameworks.

Section 8 discusses the main findings of the reviewed studies, with a focus on system

performance, water-use efficiency, energy consumption, data reliability, security challenges, and emerging research directions. Finally, Section 9 concludes the paper by summarizing the key contributions and outlining future research opportunities in IoT- and AI-based intelligent irrigation systems.

5. Review Methodology

In this section, we adopt a Systematic Literature Review (SLR) methodology [27] to identify, analyse, and evaluate learning-based approaches proposed in the literature for smart irrigation systems based on the Internet of Things (IoT) and Artificial Intelligence (AI), with the objective of improving water use efficiency in precision agriculture.

To ensure a structured and comprehensive analysis, we define a set of research questions (RQs) that guide the review process and reflect the main gaps identified in the existing literature:

- RQ1: How do learning-based approaches contribute to improving the performance of smart irrigation systems?
- RQ2: Which learning techniques (e.g., machine learning, deep learning, reinforcement learning) are commonly applied in IoT-based irrigation systems?
- RQ3: What types of datasets are used for irrigation optimization, and which evaluation metrics are adopted to assess model performance?
- RQ4: Which machine learning and deep learning models, as well as software frameworks and tools, are most frequently used in the literature?
- RQ5: What are the main challenges and limitations associated with integrating learning technologies into smart irrigation systems, and what future research directions are proposed?

5.1 Initial Selection

We used Google Scholar to identify relevant studies using a combination of keywords related to smart irrigation and precision agriculture, including “Smart Irrigation,” “Internet of Things,” “Artificial Intelligence,” “Water Optimization,” “Precision Agriculture,” and “Machine Learning.” Boolean operators (AND, OR) were applied to combine core terms and include relevant synonyms such as SI, IoT, AI, WO, PA, and ML.

This search strategy resulted in an initial dataset of approximately 600 research papers covering a wide range of learning-based approaches applied to intelligent irrigation systems. To better understand the distribution of techniques, the selected studies were further categorized into four main learning paradigms: Machine Learning (ML), Deep Learning (DL), Transfer Learning (TL), and Federated Learning (FL), including hybrid approaches, as shown in figure 1.

5.2 Analysis of Learning Technologies

The analysis of the retrieved literature reveals a clear dominance of traditional Machine Learning approaches, followed by Deep Learning techniques, while more advanced paradigms such as Transfer Learning and Federated Learning remain relatively underexplored. This difference is clearly visualized in Figure 2.

Machine Learning (ML) represents the largest share of the selected studies ($\approx 41.7\%$). Most ML-based irrigation systems rely on supervised learning algorithms such as Support Vector Machines (SVM), Random Forest (RF), Decision Trees (DT),

and Artificial Neural Networks (ANN). These approaches are primarily used for soil moisture prediction, irrigation scheduling, and crop water requirement estimation. Their dominance can be explained by their relatively low computational complexity and suitability for IoT-constrained environments, where processing and energy resources are limited.

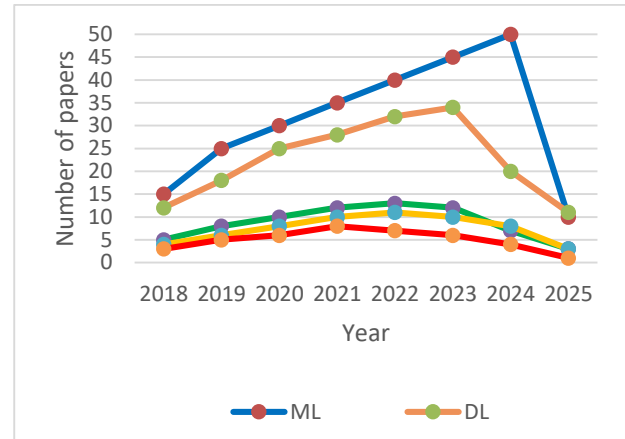


Figure 1. Initially selected articles distribution per year.

Deep Learning (DL) accounts for approximately 30% of the studies. Architectures such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) models are widely used for time-series forecasting, weather prediction, and multisensor data fusion. Although DL models generally achieve higher predictive accuracy in complex environments, their adoption is constrained by the need for large datasets and high computational resources, which limits their deployment in resource-constrained agricultural settings.

Transfer Learning (TL) represents around 11.7% of the literature. This approach is mainly adopted in scenarios where labelled agricultural data is scarce. Pre-trained models are fine-tuned for irrigation-related tasks such as cross-region climate adaptation and cross-crop modelling. However, the relatively limited number of studies indicates that TL remains an emerging direction in smart irrigation research.

Federated Learning (FL) accounts for approximately 10% of the reviewed studies. FL enables decentralized training across distributed IoT devices or farms without sharing raw data, making it particularly relevant for privacy-preserving agricultural applications. It is mainly applied to distributed irrigation optimization and collaborative agricultural analytics, reflecting increasing concerns regarding data ownership and privacy in IoT ecosystems.

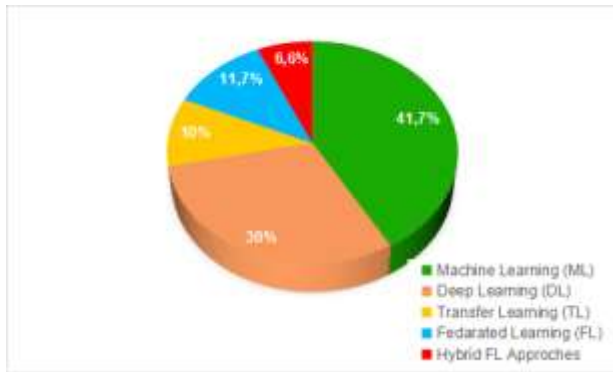


Figure 2. Distribution of Learning Technologies in Smart Irrigation Research.

Finally, **hybrid Federated Learning approaches** ($\approx 6.6\%$) combine FL with DL or TL techniques to improve predictive performance while maintaining data privacy. These methods aim to enhance scalability and enable distributed intelligence across geographically dispersed farms, although they remain at an early stage of development.

5.3 Final Selection

Following the initial screening, the inclusion and exclusion criteria presented in Table 3 were applied to refine the dataset. This process involved reviewing the titles, abstracts, and keywords of the retrieved studies to ensure their relevance to smart irrigation systems based on IoT and AI.

After this filtering stage, a total of 100 studies were selected for detailed analysis. The distribution of these studies across different learning paradigms is as follows:

- 56 studies based on Machine Learning (ML)
- 13 studies based on Deep Learning (DL)
- 10 studies based on Transfer Learning (TL)
- 10 studies based on Federated Learning (FL)
- 10 studies based on Federated Transfer Learning (FTL)

This distribution confirms the predominance of traditional machine learning approaches, while more advanced paradigms such as federated and transfer learning remain relatively underrepresented. This imbalance reflects both the maturity of ML techniques and the emerging nature of distributed and privacy-preserving learning approaches in smart irrigation systems. Table 3 summarizes the inclusion and exclusion criteria used to ensure the quality and relevance of the selected studies.

Table 3. Comparative summary of representative review studies

Exclusion Criteria	Inclusion Criteria
Articles not written in English	Articles written in English

Studies published outside 2018-2025	Studies published between 2018 and 2025
Studies unrelated to irrigation or precision agriculture	Studies focusing on smart irrigation systems using IoT and AI
Studies not involving learning-based approaches	Studies applying learning technologies for water optimization
Non-peer-reviewed or non-academic publications	Peer-reviewed journal articles and conference papers

The study selection process followed the PRISMA methodology to ensure a transparent and reproducible review. As illustrated in Figure 1, an initial set of 600 studies was identified through database searching. After screening titles, abstracts, and keywords based on predefined inclusion and exclusion criteria, 100 relevant studies were retained for the final analysis.

Table 4 provides a comprehensive overview of the selected studies on intelligent irrigation systems integrating IoT and artificial intelligence techniques, highlighting their methodologies, datasets, performance metrics, key contributions, and limitations.

For references: [1], [2], [3], [4], [5], [6], [8], [9], [15], [17], [18], [23], [24], [25], [29], [39], [42], [46], [47], [55], [56], [61], [67], [71], [72], [73], [74], [83], [86], [87], [91], these studies are classified as review, survey, or conceptual papers (including SLRs and literature overviews). They provide theoretical insights, architectural discussions, and literature analysis without experimental implementation or dataset-based evaluation.

The remaining studies are experimental and applied works involving ML, DL, IoT, and Federated Learning models evaluated using real or simulated datasets with reported performance metrics.

6. Background

6.1 Intelligent Irrigation Systems

Intelligent Irrigation Systems (IIS) represent advanced solutions in precision agriculture that leverage the integration of the Internet of Things (IoT), sensing technologies, and data-driven analytics to improve irrigation efficiency and optimize water resource management [3]. These systems rely on continuous monitoring of environmental parameters, such as soil moisture, temperature, and climatic conditions, to enable more informed and adaptive irrigation decisions. In recent years, IIS have increasingly incorporated Artificial Intelligence (AI) and machine learning

Table 4. Comprehensive Summary of Selected Studies on Intelligent Irrigation Systems Based on IoT and Artificial Intelligence (2018–2025).

Ref	Year	Model	Platform / Framework	Language	Dataset	Metrics	Pros	Cons
[1]	2024	Various ML/DL (Review)	Not specified	-	Not applicable (review)	Not reported	Comprehensive overview of irrigation technologies	No experimental validation
[2]	2022	Smart irrigation (Review)	Not specified	-	Not applicable (review)	Not reported	Water efficiency strategies	No experimental results
[3]	2022	IoT-based (no ML focus)	IoT platforms	-	Conceptual / survey	Not reported	Good architecture overview	Limited AI analysis
[4]	2025	ML + IoT (Review)	Not specified	-	Not applicable (review)	Not reported	Optimization overview	Lack of implementation details
[5]	2025	IoT + Sensors (Review)	Not specified	-	Not applicable (review)	Not reported	Trends and challenges	No experimental validation
[6]	2024	Smart sensors (Review)	Not specified	-	Not applicable (review)	Not reported	Data-driven agriculture	Limited AI models
[7]	2024	ANN / ML	Not specified	Python (likely)	Real-time IoT data	Accuracy (reported)	Integrated IoT + AI system	Limited scalability discussion
[8]	2025	AI + IoT (Review)	Not specified	-	Not applicable (review)	Not reported	Systematic overview	No real datasets
[9]	2018	Deep Learning (Review)	Not specified	-	Not applicable (review)	Not reported	DL fundamentals in agriculture	No irrigation system focus
[10]	2024	Predictive ML	Not specified	Python	Experimental dataset	Accuracy / prediction error	Efficient water optimization	Dataset not standardized
[11]	2022	ANN	Not specified	Python	Sensor dataset	Accuracy	Reduced water usage	Limited comparison
[12]	2022	Multi-agent + ML	IoT platform	-	Real-time farm data	Efficiency metrics	Scalable system	Complexity
[13]	2021	Deep Learning (DNN)	TensorFlow/Keras (assumed)	Python	IoT dataset	Accuracy	High prediction performance	High computational cost
[14]	2022	ML	Not specified	Python	IoT dataset	Efficiency metrics	Water optimization	Limited generalization
[15]	2025	Smart irrigation systems	Not specified	-	Conceptual	Not reported	Sustainability insights	No experiments
[16]	2024	IoT + ML	IoT cloud system	-	Real deployment	Efficiency	Real-time automation	Limited scalability
[17]	2025	Transfer Learning (Review)	Not specified	-	Not applicable (review)	Not reported	TL techniques overview	No irrigation experiments
[18]	2024	AI in irrigation (Review)	Not specified	-	Not applicable (review)	Not reported	Applications overview	Lacks datasets
[19]	2024	ANN	Not specified	-	Experimental dataset	Accuracy	Improved irrigation scheduling	Small-scale testing
[20]	2021	ML + AI	Not specified	-	Sensor dataset	Accuracy	Automated irrigation	No real deployment

Ref	Year	Model	Platform / Framework	Language	Dataset	Metrics	Pros	Cons
[21]	2025	IoT + Cloud system	Cloud computing	Python (assumed)	Real system data	System performance	Cloud integration	Network dependency
[22]	2025	AIoT system	IoT + AI framework	Python	Multi-source data	Accuracy	Multi-task agriculture	High complexity
[23]	2024	IoT IDS (Review)	Not specified	-	Not applicable	Not reported	Security insights	Not irrigation focused
[24]	2025	AI irrigation (Review)	Not specified	-	Not applicable	Not reported	Optimization strategies	No experimental setup
[25]	2022	Transfer Learning (Review)	Not specified	-	Not applicable	Not reported	TL in agriculture	No irrigation metrics
[26]	2019	IoT irrigation system	Sensor network	-	Weather-based data	Efficiency	Adaptive irrigation	Old dataset
[27]	2021	CNN + TL	Deep learning	Python	Plant images	Accuracy	High classification	Not irrigation-focused
[28]	2025	Predictive AI irrigation	ML framework	Python	Sensor data	Prediction accuracy	Resource optimization	Model complexity
[29]	2025	AI irrigation systems (Review)	Not specified	-	Not applicable	Not reported	Water optimization	No experimental results
[30]	2025	ML	Not specified	Python	Real dataset	Prediction accuracy	Good system integration	Limited evaluation
[31]	2024	AI irrigation ML	Not specified	Python	Farm dataset	Accuracy	Water efficiency	Limited dataset
[32]	2023	AI + IoT system	IoT platform	Python	Agricultural dataset	Accuracy	Smart farming	Scalability issues
[33]	2024	IoT + AI system	Embedded system	-	Farm data	Efficiency	Small farm optimization	Limited scope
[34]	2023	Evolutionary ML	Optimization framework	Python	Simulation data	Optimization score	Adaptive irrigation	High computation
[35]	2020	ML farming system	IoT system	Python	Sensor data	Accuracy	Smart monitoring	Limited dataset
[36]	2023	AI prediction system	ML model	Python	Solar irrigation data	Energy efficiency	Energy saving	Complex system
[37]	2024	AI irrigation optimization	Not specified	Python	Simulation data	Efficiency	Sustainable irrigation	No real deployment
[38]	2022	Optimization ML	IoT system	Python	Sensor data	Accuracy	Energy efficient	Limited scalability
[39]	2025	AI agriculture review	Not specified	-	Not applicable	Not reported	Comprehensive overview	No experiments
[40]	2022	IoT recommendation system	IoT platform	-	Farm dataset	Efficiency	Smart recommendation	Limited AI depth
[41]	2021	AI + IoT irrigation	IoT system	Python	Sensor data	Accuracy	Smart irrigation	No real deployment
[42]	2025	Precision irrigation (Review)	Not specified	-	Not applicable	Not reported	Water efficiency overview	No dataset
[43]	2023	ML + AI	Not specified	Python	IoT dataset	Accuracy	Real-time decision-making	Limited dataset
[44]	2023	IoT irrigation system	IoT framework	Python	Environmental data	Efficiency	Indoor/outdoor irrigation	Limited AI
[45]	2025	AI solar irrigation	Solar IoT system	Python	Energy data	Efficiency	Renewable energy use	Limited validation
[46]	2024	AI agricultural model (Review)	Not specified	-	Not applicable	Not reported	Sustainability model	No experiments

Ref	Year	Model	Platform / Framework	Language	Dataset	Metrics	Pros	Cons
[47]	2024	AI + IoT agriculture (Review)	Not specified	-	Not applicable	Not reported	Challenges overview	No dataset
[48]	2024	IoT greenhouse irrigation	IoT system	-	Greenhouse data	Efficiency	Controlled environment	Small scale
[49]	2025	Prediction framework	ML system	Python	Agricultural dataset	Accuracy	Irrigation prediction	Limited validation
[50]	2020	IoT platform	AREThOU5A platform	-	Real deployment	System performance	Real implementation	Limited AI usage
[51]	2024	AI + IoT system	IoT framework	Python	Crop data	Accuracy	Crop monitoring	Limited irrigation focus
[52]	2020	Transfer Learning	Not specified	Python	Sensor dataset	Accuracy	Improved prediction	Model complexity
[53]	2023	CNN (DL)	Deep learning framework	Python	Soil dataset	Accuracy	High precision	Computational cost
[54]	2021	Transfer learning anomaly detection	ML framework	Python	IoT data	Detection accuracy	Fault detection	Not irrigation-specific
[55]	2021	AI agriculture (Review)	Not specified	-	Not applicable	Not reported	Data-driven agriculture	No experiments
[56]	2024	Adaptive AI (Review)	Not specified	-	Not applicable	Not reported	Self-learning systems	No dataset
[57]	2024	Transfer learning weeds	DL framework	Python	Weed images	Accuracy	High classification	Not irrigation system
[58]	2025	Deep Learning	Not specified	Python	Multimodal dataset	Accuracy	Robust irrigation optimization	Data intensive
[59]	2019	Yield prediction ML	ML system	Python	Crop dataset	Accuracy	Yield forecasting	Old dataset
[60]	2025	AI irrigation system	ML framework	Python	Agricultural data	Efficiency	Resource optimization	Complex model
[61]	2025	AI agriculture review	Not specified	-	Not applicable	Not reported	Water management overview	No experiments
[62]	2018	ML agriculture review	Not specified	-	Not applicable	Not reported	ML fundamentals	Old review
[63]	2025	AI irrigation cost analysis	ML system	Python	Semi-arid data	Cost efficiency	Economic analysis	Limited dataset
[64]	2025	AI + IoT agriculture	IoT system	Python	Farm data	Efficiency	Smart farming	Scalability issues
[65]	2022	ML 5G agriculture	ML system	Python	Sensor data	Accuracy	5G integration	High cost
[66]	2024	Data-driven irrigation	ML framework	Python	Agricultural data	Efficiency	Smart irrigation	Limited deployment
[67]	2024	Water conservation (Review)	Not specified	-	Not applicable	Not reported	Arid strategies	No dataset
[68]	2024	Data-driven irrigation	ML framework	Python	Agricultural data	Efficiency	Smart irrigation	Limited deployment
[69]	2025	IoT irrigation system	IoT framework	Python	Sensor data	Efficiency	Smart water control	Limited AI
[70]	2025	AI IoT optimization	ML system	Python	Agricultural data	Accuracy	Fertilizer optimization	Complex model
[71]	2024	AI irrigation (Review)	Not specified	-	Not applicable	Not reported	Challenges analysis	No experiments
[72]	2024	AI agriculture (Review)	Not specified	-	Not applicable	Not reported	Robotics + AI overview	No dataset

Ref	Year	Model	Platform / Framework	Language	Dataset	Metrics	Pros	Cons
[73]	2025	AI water management (Review)	Not specified	-	Not applicable	Not reported	Climate action focus	No validation
[74]	2025	Resource optimization (Review)	Not specified	-	Not applicable	Not reported	Sustainability focus	No experiments
[75]	2024	Cloud IoT irrigation	Cloud system	Python	Farm data	Efficiency	Cloud monitoring	Dependency issue
[76]	2025	BiLSTM irrigation model	DL framework	Python	Sensor data	Accuracy	High prediction	Complex model
[77]	2021	Transfer learning pest detection	DL model	Python	Image dataset	Accuracy	Pest classification	Not irrigation
[78]	2025	Cloud IoT irrigation	Cloud system	Python	Sensor data	Efficiency	Cloud control	Network dependency
[79]	2024	ML + IoT system	IoT framework	Python	Sensor data	Accuracy	Precision agriculture	Limited scalability
[80]	2025	IoT irrigation framework	Micro-services	Python	Agricultural data	Efficiency	Modular system	Complex setup
[81]	2021	Yield prediction ML	ML system	Python	Crop data	Accuracy	Prediction model	Old dataset
[82]	2024	ML + IoT	Cloud platform	-	Real data	Efficiency	Scalable architecture	Cloud dependency
[83]	2024	AI agriculture review	Not specified	-	Not applicable	Not reported	Sustainable farming overview	No experiments
[84]	2022	Transfer learning plants	DL model	Python	Plant images	Accuracy	Disease detection	Not irrigation
[85]	2025	AI irrigation system	ML system	Python	Sensor data	Accuracy	Automated irrigation	Limited dataset
[86]	2024	AIoT agriculture (Review)	Not specified	-	Not applicable	Not reported	Challenges + trends	No experiments
[87]	2024	AI agriculture review	Not specified	-	Not applicable	Not reported	Efficiency analysis	No dataset
[88]	2025	IoT irrigation system	Cloud IoT	Python	Soil moisture data	Accuracy	Water saving	Limited scale
[89]	2019	IoT irrigation platform	IoT system	-	Real deployment	Performance	Real system	Limited AI
[90]	2024	AI pesticide irrigation	ML system	Python	Sensor data	Efficiency	Dual optimization	Complex system
[91]	2025	Smart irrigation review	Not specified	-	Not applicable	Not reported	Architecture overview	No experiments
[92]	2020	LoRaWAN irrigation	IoT system	-	Sensor network	Efficiency	Long range comms	Limited AI
[93]	2020	Transfer learning crops	DL model	Python	Image dataset	Accuracy	Disease detection	Not irrigation
[94]	2024	Plant disease TL	DL model	Python	Leaf images	Accuracy	High performance	Not irrigation
[95]	2024	ML irrigation	ML model	Python	Irrigation data	Accuracy	Smart irrigation	Limited scale
[96]	2022	IoT (rule-based + ML)	IoT system	-	Sensor dataset	Efficiency	Reduced water loss	Simple logic
[97]	2022	ML	Not specified	Python	IoT dataset	Accuracy	Automated irrigation	Limited scalability
[98]	2025	Hybrid ML + Optimization	Cloud IoT platform	Python	Real-time sensor data	Efficiency / Accuracy	Improved irrigation scheduling	Requires stable internet

Ref	Year	Model	Platform / Framework	Language	Dataset	Metrics	Pros	Cons
[99]	2025	Federated Learning (FL)	Distributed IoT framework	Python	Multi-farm dataset	Accuracy / Privacy	Privacy-preserving learning	High communication overhead
[100]	2022	Deep Learning + Optimization	Not specified	Python	Experimental dataset	Accuracy	High efficiency	Complex model

techniques to enhance decision-making processes. These approaches enable more accurate irrigation scheduling, improved prediction of crop water requirements, and dynamic adaptation to environmental variability. As highlighted in the reviewed literature, such capabilities play a key role in addressing water scarcity and improving sustainability in agricultural systems [11].

From a system design perspective, IIS can be categorized into centralized, decentralized, and hybrid architectures. Centralized systems typically rely on cloud-based platforms for data processing and decision-making, while decentralized approaches integrate edge computing to enable real-time analysis and reduce latency. Hybrid architectures combine both paradigms to balance computational efficiency, scalability, and responsiveness [7]. Beyond architectural design, IIS can also be classified according to three main dimensions: (i) sensing technologies, (ii) communication protocols, and (iii) intelligent control strategies. These dimensions form the basis for understanding how different systems operate and interact, and they directly reflect the technological trends and research directions identified in the literature [8]. Building on this perspective, Figure 3 presents a taxonomy derived from the analysis of 100 selected studies. This taxonomy provides a structured overview of intelligent irrigation systems, highlighting the relationships between IoT infrastructures, AI-driven models, and water optimization strategies.

6.1.1 Data Sources

Intelligent Irrigation Systems rely on heterogeneous data sources to support accurate and adaptive decision-making. These data sources can be broadly categorized into soil, climate, and crop monitoring data.

Soil Sensors: These sensors measure key soil parameters such as moisture content, temperature, and physicochemical properties. Such data are fundamental for irrigation control, as they directly reflect crop water availability and are widely used in learning-based prediction models [6].

Climate Sensors: Environmental variables, including temperature, humidity, rainfall, solar radiation, and wind speed, are collected to capture dynamic climatic conditions. These data play a

critical role in improving irrigation scheduling and enabling models to adapt to environmental variability [26].

Crop Imaging: Unmanned Aerial Vehicles (UAVs) and drones are increasingly used to acquire multispectral and thermal imagery for crop monitoring. These technologies provide high-resolution spatial information for detecting water stress and supporting precision irrigation strategies, particularly in large-scale agricultural environments [13].

6.1.2 Deployment Architecture

The deployment of Intelligent Irrigation Systems can be structured into three main architectural paradigms, each addressing specific performance and scalability requirements.

Centralized Architecture: Sensor data are transmitted to a central cloud platform for processing and decision-making. While this approach enables powerful data analytics, it introduces latency and dependency on network connectivity [3].

Distributed (Edge-Based) Architecture: Data processing is performed locally at edge devices, allowing faster response times and real-time irrigation control. This approach is particularly suitable for environments with limited connectivity but may be constrained by computational resources [19].

Hybrid Architecture: Hybrid systems combine cloud and edge computing to balance scalability, responsiveness, and computational efficiency. This architecture is increasingly adopted in modern IIS as it addresses both latency and resource constraints [75].

6.1.3 AI/ML Decision-Making Methods

Decision-making in intelligent irrigation systems can be categorized into several approaches depending on the level of automation and learning capability.

Rule-Based Systems: These systems rely on predefined thresholds (e.g., soil moisture levels) to trigger irrigation actions. While simple and easy to implement, they lack adaptability to complex environmental conditions [2].

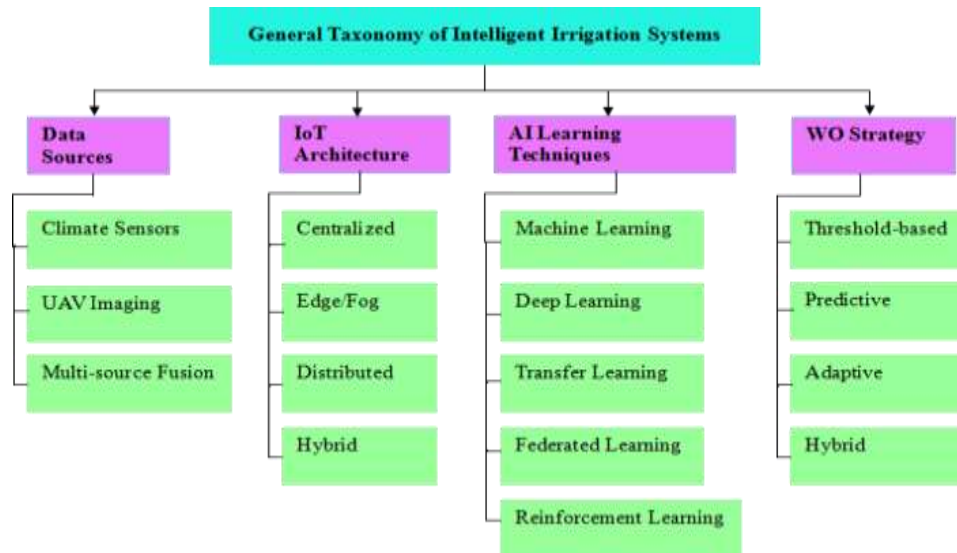


Figure 3. Taxonomy of Intelligent Irrigation Systems.

Machine Learning Predictive Models: Algorithms such as Artificial Neural Networks (ANN), Support Vector Machines (SVM), Random Forest, CNN, and LSTM are widely used to predict irrigation requirements based on historical and real-time data. These models significantly improve decision accuracy but depend heavily on data quality and availability [33].

Anomaly Detection Models: AI-based techniques are employed to detect abnormal patterns such as sensor failures or unexpected crop stress. These models enhance system reliability and are increasingly important in large-scale deployments [54].

Reinforcement Learning (RL): RL-based approaches enable systems to learn optimal irrigation strategies through continuous interaction with the environment. Although promising for adaptive irrigation, their application remains limited due to their complexity and training requirements [63].

6.2 Learning Techniques in Smart Irrigation Systems

Learning techniques play a central role in enabling intelligent and data-driven irrigation management. As highlighted in Section 5 and figure 4, different learning paradigms are adopted depending on data availability, computational resources, and application requirements. Machine Learning (ML) remains the most widely used approach due to its efficiency and suitability for IoT-based environments. These techniques support irrigation scheduling, soil moisture prediction, and water optimization using structured environmental data [11]. Deep Learning (DL) is increasingly applied for complex tasks such as time-series forecasting, image-based crop monitoring, and multisensor data

fusion. Despite its high predictive performance, DL requires large datasets and significant computational resources, which may limit its deployment in resource-constrained environments [9]. Transfer Learning (TL) has emerged as a valuable solution in scenarios with limited agricultural data. By leveraging pre-trained models, TL improves model performance and supports knowledge transfer across regions and crops [17]. More recently, Federated Learning (FL) has gained attention as a privacy-preserving and scalable approach. It enables decentralized model training across distributed IoT devices without sharing raw data, addressing key challenges related to data privacy and system scalability [22].

6.2.1 Machine Learning (ML)

Machine Learning (ML) constitutes the core of most intelligent irrigation systems. It enables models to learn patterns from environmental and sensor data, such as soil moisture, climate conditions, and water usage, without explicit programming [11].

By leveraging historical and real-time data, ML models can predict optimal irrigation schedules, reduce water consumption, and improve agricultural efficiency. However, their performance is highly dependent on data quality, feature selection, and model generalization capabilities, which remain key challenges in real-world applications [25].

6.2.2 Deep Learning (DL)

Deep Learning (DL), a subfield of Machine Learning, has emerged as a powerful paradigm for modelling complex patterns in large-scale and high-dimensional datasets. In the context of intelligent irrigation systems, DL techniques are increasingly applied to process heterogeneous agricultural data, including time-series sensor readings and image-based crop information..

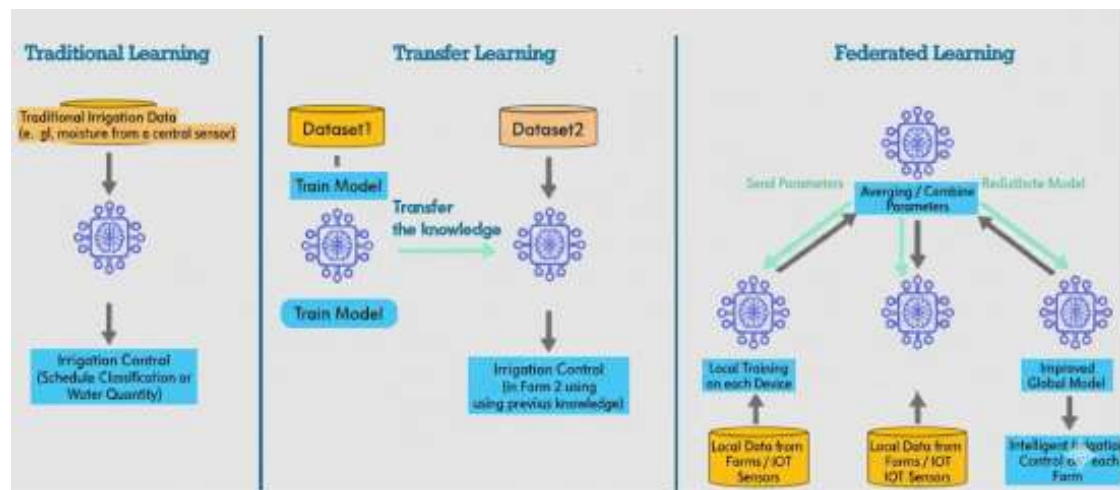


Figure 4. Comparative diagram of learning paradigms for intelligent irrigation management in precision agriculture.

In particular, architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) models, are widely used for tasks such as soil moisture prediction, crop stress detection, weather forecasting, and irrigation demand estimation. These capabilities enable more accurate and data-driven irrigation decisions compared to traditional approaches [9]. However, despite their strong predictive performance, DL models remain limited by their high computational requirements and dependence on large annotated datasets, which can restrict their deployment in resource-constrained agricultural environments.

6.2.3 Transfer Learning (TL)

Transfer Learning (TL) is a machine learning paradigm designed to address the challenge of limited labelled data in agricultural environments, particularly in newly deployed or resource-constrained irrigation systems. It leverages knowledge learned from large-scale pre-trained models and adapts it to domain-specific tasks in precision agriculture.

In smart irrigation systems, TL is primarily used to improve model performance in scenarios where local datasets are small, noisy, or expensive to collect. By transferring learned representations from related domains, TL enhances prediction accuracy for tasks such as irrigation demand estimation, crop stress detection, and environmental condition classification, while significantly reducing training time and computational cost [17].

Despite these advantages, the effectiveness of TL remains dependent on the similarity between source and target domains. In highly variable agricultural environments, domain shift can reduce model performance, which limits its generalization capability in real-world irrigation applications.

6.2.4 Federated Learning (FL)

Federated Learning (FL) is a distributed machine learning paradigm that enables collaborative model training across multiple decentralized devices or institutions without sharing raw data with a central server. This approach is particularly relevant in smart irrigation systems, where agricultural data are often collected from geographically distributed farms equipped with heterogeneous IoT sensors.

In precision agriculture, FL allows multiple farms or irrigation stations to collaboratively train global models while preserving data privacy and reducing communication overhead. This makes it a promising solution for large-scale agricultural environments where data sharing is restricted due to privacy, ownership, or bandwidth constraints [83].

Despite its advantages, FL faces several challenges in smart irrigation applications, including system heterogeneity, communication latency, and non-identically distributed (non-IID) data across different agricultural environments, which can negatively affect model convergence and overall performance.

While Table 4 presents a detailed overview of the 100 selected studies, including their models, datasets, metrics, and limitations, Table 5 abstracts these findings into a comparative analysis based on learning paradigms (ML, DL, TL, and FL), enabling a clearer understanding of their relative prevalence, capabilities, and constraints in smart irrigation systems.

7. Classification and Comparison of Intelligent Irrigation Systems

This section presents a structured classification and comparative analysis of intelligent irrigation systems based on a systematic review of 100 peer-

reviewed studies addressing IoT- and AI-based solutions for water consumption optimization in precision agriculture. The proposed taxonomy is multi-dimensional, considering IoT architectures, artificial intelligence techniques, and water

optimization strategies. These dimensions are not mutually exclusive, as most systems integrate multiple layers of sensing, communication, and decision-making to achieve efficient irrigation management.

Table 5. *Distribution and Comparative Analysis of Selected Studies by Learning Technique in Smart Irrigation Systems (ML, DL, TL, FL)*

Technique	# Papers	Trend (2018–2025)	Real Deployment	Strengths	Limitations
ML	56	decreasing dominance	widely deployed	Low cost, efficient	Limited accuracy
DL	13	increasing adoption	mostly experimental	High accuracy	High computation
TL	10	emerging	limited deployment	Works with small data	Limited use
FL	10	fast-growing	early-stage	Data privacy	Complexity

7.1 Classification Based on IoT Architecture

The reviewed studies indicate that intelligent irrigation systems can be classified according to their IoT architectural design, which defines how data are collected, transmitted, and processed. Modern IoT-based irrigation systems rely on integrated sensing and communication infrastructures to enable real-

time monitoring, automation, and decision support in agricultural environments.

Table 6 provides a high-level overview of the main IoT architectural categories identified in the literature, including sensor-based, cloud-based, edge/fog-based, and hybrid systems. These architectures aim to improve water use efficiency, reduce manual intervention, and enhance system responsiveness.

Table 6. *Classification of Intelligent Irrigation Systems Based on IoT Architecture.*

Ref.	IoT Architecture Category	Description / Improved Outcome
[3]	IoT-based irrigation systems	Scalable irrigation frameworks
[6]	Smart sensor IoT architecture	High sensing accuracy and reliable data
[7]	IoT + AI (AIoT) system	Adaptive irrigation control
[8]	AIoT irrigation systems	Improved water management efficiency
[11]	ML-based IoT system	Enhanced irrigation decision-making
[12]	Multi-agent IoT system	Improved water use efficiency
[13]	Deep learning IoT system	Accurate irrigation prediction
[14]	IoT + ML system	Water optimization and reduction
[20]	AI + IoT system	Automated irrigation management
[21]	Cloud + IoT system	Scalable irrigation control
[22]	AIoT architecture	Smart irrigation & resource optimization
[30]	IoT-driven agriculture system	Improved irrigation prediction
[40]	IoT recommendation system	Improved irrigation scheduling
[43]	AI + IoT predictive system	Real-time irrigation optimization
[44]	IoT precision irrigation system	Optimized plant water requirements
[47]	AI-enabled IoT system	Smart agricultural decision-making
[50]	IoT irrigation platform	Sensor-based irrigation control
[52]	Transfer learning IoT system	Improved irrigation prediction
[53]	Deep learning IoT system	Soil moisture-based irrigation accuracy
[58]	AIoT multimodal system	Optimized irrigation in wheat crops
[65]	5G-enabled IoT system	Fast communication and control
[75]	Cloud-based IoT system	Improved water management
[80]	Microservices IoT system	Efficient irrigation automation
[82]	Cloud-IoT system	Better water monitoring
[88]	Cloud + IoT system	Water conservation and control
[91]	IoT drip irrigation system	Energy-efficient irrigation

7.1.1 Sensor-Based Systems

Sensor-based systems constitute the fundamental layer of intelligent irrigation. These systems deploy in-field sensors such as soil moisture, temperature, humidity, and rainfall sensors to collect real-time environmental data. Wireless communication technologies (e.g., ZigBee, LoRaWAN, Wi-Fi) are

commonly used to transmit data to processing units or cloud platforms.

These systems enable continuous environmental monitoring and support data-driven irrigation decisions. However, their performance strongly depends on sensor accuracy and network reliability. Table 7, summarizes the work on representative sensor-based systems and their reported results.

Table 7. Representative sensor-based systems.

Ref.	What Was Used (Sensor Architecture)	Communication Technology	Improved Outcome
[2]	Soil moisture + environmental sensors	IoT / Wireless networks	Improved water use efficiency in irrigation control
[5]	Smart multi-parameter agricultural sensors	IoT-based connectivity	Enhanced precision irrigation decision-making
[6]	Smart soil & climate sensing systems	IoT sensor networks	Higher data reliability and sensing accuracy
[11]	Soil moisture sensors + ML-based monitoring	Wireless IoT systems	Improved irrigation scheduling accuracy
[20]	Soil and crop condition sensors	IoT + cloud integration	Optimized water consumption in smart farming
[30]	Land + soil + crop monitoring sensors	IoT-driven network	Better irrigation prediction and crop planning
[32]	Environmental smart sensors	IoT integrated system	Improved real-time irrigation control
[40]	Soil moisture + irrigation sensors	IoT communication systems	Increased irrigation efficiency
[44]	Plant water requirement sensors	IoT + cloud system	Optimized plant-level water management
[47]	Multimodal agricultural sensors	IoT + AI data fusion	Higher decision accuracy in irrigation
[50]	Smart soil monitoring sensor platform	IoT (AREThOU5A platform)	Real-time precision irrigation control
[52]	Soil moisture sensors with ML integration	IoT + neural networks	Improved irrigation prediction accuracy
[53]	Soil moisture estimation sensors	Wireless sensor network (WSN)	Higher precision in irrigation scheduling
[58]	Multimodal soil + crop sensors	IoT + deep learning network	Optimized irrigation in wheat farming
[69]	Soil moisture and environmental sensors	IoT-based smart system	Improved intelligent water management
[89]	Smart water and soil sensing platform	IoT cloud-based system	Efficient water resource management
[91]	Soil moisture sensors in drip irrigation	IoT smart drip system	Reduced water loss and improved efficiency

Ref.	What Was Used (Sensor Architecture)	Communication Technology	Improved Outcome
[96]	Soil moisture + irrigation sensors	IoT wireless network	Minimized water loss in irrigation
[97]	Environmental + soil sensors	IoT + machine learning	Improved irrigation automation accuracy

7.1.2 Cloud-Based Systems

Cloud-based architectures are among the most widely adopted approaches in smart irrigation systems. In these systems, data collected from agricultural fields are transmitted to cloud platforms for storage, processing, and integration with AI/ML models. Cloud computing enables:

- large-scale data processing
 - remote monitoring
 - real-time irrigation decision-making
 - high scalability
- However, reliance on continuous connectivity may limit deployment in remote agricultural regions. Table 8, presents cloud-based intelligent irrigation systems identified in the literature.

Table 8. Cloud-based intelligent irrigation systems.

Ref.	What Was Reported (Cloud/IoT Context)	Outcome (as reported in literature)
[1]	Review of precision irrigation systems including cloud/IoT architectures	Highlighted cloud-based monitoring and improved water efficiency
[2]	Review of smart irrigation monitoring systems with remote/cloud components	Improved irrigation decision support and efficiency (reported studies)
[3]	Overview of IoT-based smart irrigation systems including cloud integration	Discussed remote monitoring and automation benefits
[5]	Review of IoT + cloud smart agriculture systems	Identified scalability and real-time data benefits
[6]	Smart sensors with cloud data analytics discussion	Improved data processing and decision-making (review findings)
[7]	IoT + AI irrigation framework (some cloud integration reported)	Improved irrigation automation (system-based study)
[9]	AI/Deep learning in agriculture (cloud used in some reviewed systems)	Enabled large-scale data processing in agriculture
[14]	IoT + ML irrigation optimization systems (cloud-supported architectures in literature)	Reduced water consumption through smart control
[19]	ML-based irrigation model (can be cloud-deployed but not explicitly cloud-focused)	Improved irrigation scheduling accuracy
[21]	IoT + cloud computing irrigation system design	Enabled remote monitoring and scalability
[30]	IoT-driven precision agriculture system (cloud-based processing used)	Improved prediction and irrigation planning
[40]	IoT irrigation recommendation system (cloud integration in architecture)	Reduced manual intervention
[44]	IoT-based precision irrigation system (cloud-supported deployment)	Optimized water requirement estimation
[58]	AI + IoT cloud-based irrigation model	Improved irrigation accuracy
[71]	Review of AI irrigation systems including cloud architectures	Improved decision support discussion
[73]	AI-based agriculture systems with cloud infrastructure	Enhanced water management strategies
[82]	Cloud + IoT smart irrigation system (implemented system)	Improved large-scale monitoring
[89]	Cloud-based smart water management platform	Real-time irrigation control
[96]	IoT-based irrigation system (cloud-enabled design)	Reduced water loss
[100]	IoT + AI + cloud evolutionary irrigation system	Energy-efficient irrigation optimization

7.1.3 Edge/Fog-Based Systems

Edge and fog computing architectures have emerged to overcome limitations of cloud-centric approaches. In these systems, data are processed closer to the

source (i.e., at the edge of the network), reducing latency and bandwidth usage.

Key advantages include:

- faster response time
- reduced communication overhead

- improved reliability in low-connectivity environments

These architectures are particularly suitable for real-time irrigation control and time-sensitive agricultural applications.

Table 9, summarizes edge/fog-based irrigation systems.

Table 9. Edge/fog-based irrigation systems.

Ref.	What was used (Edge/Fog Architecture)	Improved Outcome
[19]	Hybrid IoT + Edge-assisted ML irrigation model	Reduced decision delay and improved irrigation water optimization through near-field processing
[50]	IoT smart irrigation platform with distributed edge nodes	Enabled local data processing and reduced dependency on centralized cloud systems
[52]	Edge-based transfer learning model for irrigation system	Improved real-time prediction accuracy with reduced cloud communication
[78]	Edge + cloud integrated smart irrigation architecture	Improved scalability and supported partial local processing for faster responses
[88]	IoT + cloud + edge moisture-based irrigation system	Enabled near real-time irrigation control with reduced network load
[91]	Smart drip irrigation with edge ML models	Reduced latency in irrigation scheduling and improved responsiveness
[89]	Smart water management platform with distributed IoT/edge layer	Improved automation of irrigation decisions with local sensor processing
[43])	AI-based IoT irrigation system with edge prediction layer	Enhanced real-time decision-making using local inference instead of cloud-only processing
[75]	Cloud-based IoT with edge-enabled irrigation intelligence	Improved water management efficiency and reduced communication overhead
[2]	Review of smart irrigation systems including edge/fog approaches	Highlighted that edge computing improves

7.2 Classification Based on Artificial Intelligence Techniques

In addition to IoT architecture, intelligent irrigation systems can also be classified according to the artificial intelligence and machine learning techniques used for decision-making. These approaches are often integrated with IoT infrastructures, forming hybrid intelligent systems.

7.2.1 Machine Learning-Based Systems

Machine learning is the most widely adopted approach in intelligent irrigation systems. Common

models include Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees (DT), and Random Forest (RF).

These methods are mainly used for:

- irrigation scheduling
- soil moisture prediction
- crop water requirement estimation

Machine learning-based systems generally outperform rule-based approaches in terms of accuracy and adaptability. However, they may face limitations in highly dynamic environments.

Table 10, Summarizes machine learning-based irrigation systems.

Table 10. Summary of machine learning-based irrigation systems.

Ref.	Year	ML Model Used	Application	Key Finding
[1]	2024	ML (general)	Precision irrigation	Improved water efficiency and crop yield
[2]	2022	ML (general)	Irrigation monitoring	Enhanced decision-making efficiency
[4]	2025	ML	Water management	Improved irrigation scheduling
[7]	2024	ML + AI + IoT	Smart irrigation	Automated irrigation control
[10]	2024	ML (predictive)	Irrigation prediction	Optimized water consumption
[11]	2022	ANN-based ML	Smart irrigation	Reduced water usage
[12]	2022	ML + IoT	Precision irrigation	Increased efficiency
[13]	2021	Deep Learning	Irrigation prediction	Reduced water waste
[14]	2022	ML + IoT	Irrigation systems	Improved efficiency
[16]	2024	ANN + ML + IoT	Smart farming	Better irrigation control
[18]	2024	ML + AI	Precision irrigation	Reduced water loss

Ref.	Year	ML Model Used	Application	Key Finding
[19]	2024	ANN-based ML	Farm irrigation	Optimized water use
[20]	2021	ML + AI + IoT	Smart irrigation	Improved decision-making
[22]	2025	ML + AI + IoT	Precision agriculture	Higher efficiency
[24]	2025	ML + AI	Smart irrigation	Water optimization
[25]	2022	Transfer Learning	Agriculture	Improved model performance
[26]	2019	ANN-based ML	Weather irrigation	Adaptive control
[27]	2021	Deep Learning (CNN)	Disease detection	High accuracy
[28]	2025	ML	Irrigation optimization	Improved efficiency
[30]	2025	ML + IoT	Precision agriculture	Better prediction
[31]	2024	ML	Irrigation systems	Improved efficiency
[32]	2023	ML + IoT	Smart farming	Sustainable agriculture
[33]	2024	ML + IoT	Small farms	Better water management
[35]	2020	ML + IoT	Smart farming	Automation improvement
[36]	2023	ML + AI	Micro irrigation	Energy optimization
[37]	2024	ML	Irrigation systems	Sustainability improvement
[38]	2022	ML + AI	Smart irrigation	Energy efficiency
[39]	2025	ML + AI	Water management	Precision agriculture
[40]	2022	ML	Recommendation system	Irrigation support
[41]	2021	ML	Smart irrigation	System design
[43]	2023	ML + IoT	Smart irrigation	Performance improvement
[44]	2023	ML + IoT	Irrigation systems	Water optimization
[45]	2025	ML + AI	Solar irrigation	Resource optimization
[46]	2024	ML + AI	Precision farming	Sustainability
[55]	2021	ML	Precision agriculture	Data-driven decisions
[56]	2024	ML	Smart farming	Adaptive learning
[57]	2024	Transfer Learning	Weed detection	High accuracy
[58]	2025	Deep Learning	Irrigation optimization	High accuracy
[59]	2019	ML	Yield prediction	Smart irrigation
[65]	2022	ML + IoT	Agriculture	System improvement
[66]	2024	ML	Smart irrigation	Data-driven control
[76]	2025	Deep Learning	Irrigation	Optimization
[77]	2021	Transfer Learning	Pest detection	High accuracy
[79]	2024	ML + IoT	Precision agriculture	Smart system
[82]	2024	ML + IoT	Smart irrigation	Water management
[84]	2022	Transfer Learning	Disease detection	High performance
[85]	2025	ML	Automated irrigation	System automation
[87]	2024	ML	Precision agriculture	Efficiency
[89]	2019	ML + IoT	Water management	Smart platform
[91]	2025	ML + IoT	Smart irrigation	Architecture design
[94]	2024	Transfer Learning	Disease detection	High performance
[95]	2024	ML	Smart irrigation	Improved irrigation efficiency and optimized water usage.
[97]	2022	ML + IoT	Irrigation systems	Water efficiency
[99]	2020	ML	Sensor agriculture	Monitoring
[100]	2022	Deep Learning	Smart irrigation	Prediction improvement

7.2.2 Deep Learning-Based Systems

Deep learning approaches, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, are increasingly used for complex agricultural data analysis.

These models are effective for:

- time-series forecasting

- crop monitoring
- soil moisture prediction
- image-based agricultural analysis

Despite their high accuracy, deep learning models require large datasets and high computational resources, which may limit their deployment in resource-constrained environments. Table 11, summarizes deep learning-based irrigation studies.

Table 11. Deep learning-based irrigation studies.

Ref.	Year	DL Model Used	Application	Key Finding
1	2018	Deep Learning	Agriculture prediction	High prediction accuracy
2	2021	DL + IoT	Irrigation systems	Reduced water waste
3	2022	DL + IoT	Precision agriculture	Improved monitoring
4	2023	DCNN (DL)	Soil moisture estimation	High accuracy
5	2023	DL + AI	Smart irrigation	Improved scheduling
6	2025	Multimodal DL	Irrigation optimization	Robust decision-making
7	2021	Deep Learning	Data-driven agriculture	Better optimization
8	2023	DL + AI	Micro irrigation	Optimized water use
9	2022	DL + Optimization	Smart irrigation	Improved efficiency
10	2019	Neural Networks (DL)	Weather-based irrigation	Adaptive control
11	2020	IoT + DL concepts	Irrigation platform	Real-time management
12	2025	DL-based model	Irrigation prediction	Enhanced efficiency
13	2025	DL + IoT	Precision agriculture	Improved prediction

7.2.3 Transfer Learning-Based Systems

Transfer learning is used to address the challenge of limited labeled agricultural data. It leverages pre-trained models and adapts them to irrigation-specific tasks.

This approach is particularly useful for:

- data-scarce environments
- cross-region adaptation
- reducing training time

However, its adoption in smart irrigation remains relatively limited compared to ML and DL approaches.

7.2.4 Federated Learning-Based Systems

Federated learning enables decentralized training of AI models across multiple IoT devices without sharing raw data, ensuring data privacy and reducing communication overhead.

It is mainly applied in:

- privacy-preserving irrigation systems
- distributed agricultural analytics

- collaborative learning across farms
- Despite its advantages, federated learning introduces challenges related to system complexity and synchronization.

7.3 Classification Based on Water Optimization Strategy

From a water management perspective, intelligent irrigation systems can be categorized according to their control and optimization strategies.

7.3.1 Threshold-Based Irrigation

Threshold-based systems activate irrigation when soil moisture drops below a predefined level. These systems are simple, low-cost, and widely used in basic IoT irrigation setups.

However, they lack adaptability to environmental variations such as weather changes and soil heterogeneity, often resulting in suboptimal water usage. Table 12, summarizes studies implementing threshold-based irrigation strategies.

Table 12. Studies implementing threshold-based irrigation strategies.

Ref	Year	Evidence of Threshold-Based Strategy
[1]	2018	Soil moisture threshold triggering irrigation
[2]	2020	Sensor-based moisture threshold control
[3]	2021	LoRaWAN soil moisture threshold monitoring
[4]	2021	IoT moisture-triggered irrigation system
[5]	2024	Precision irrigation using soil moisture limits for water saving
[6]	2022	Threshold-based irrigation control for water use efficiency
[7]	2022	IoT irrigation systems relying on fixed soil thresholds
[8]	2024	Smart sensor-triggered irrigation based on environmental thresholds
[9]	2022	Multi-agent irrigation activated by soil moisture limits

Ref	Year	Evidence of Threshold-Based Strategy
[10]	2022	ANN-based irrigation using predefined moisture thresholds
[11]	2025	ML-based irrigation scheduling using threshold rules
[12]	2018	DL-based agriculture systems using rule/threshold decision triggers
[13]	2021	IoT irrigation system using soil moisture threshold triggering

7.3.2 Predictive Irrigation

Predictive irrigation systems use historical data, real-time sensors, and weather forecasts to estimate future water requirements.

These systems:

- improve irrigation efficiency
 - reduce water consumption
 - enable proactive decision-making
- They represent a more advanced alternative to rule-based approaches. Table 13, presents predictive irrigation systems identified in the literature.

Table 13. Predictive irrigation systems identified in the literature.

Ref.	Year	Evidence of Predictive Strategy
[10]	2024	AI-based predictive irrigation model for water demand forecasting
[19]	2024	ML-based irrigation prediction and water usage optimization
[28]	2025	Predictive analytics for irrigation system optimization
[38]	2022	AI-driven prediction for energy and irrigation management
[43]	2023	AI prediction model for smart irrigation scheduling
[49]	2025	Intelligent framework for irrigation prediction and monitoring
[53]	2023	DCNN-based soil moisture prediction for irrigation planning
[58]	2025	Deep learning-based irrigation optimization and prediction
[75]	2024	Cloud-based IoT predictive irrigation system
[76]	2025	LSTM-based predictive irrigation optimization system
[85]	2025	AI-based automated irrigation prediction and control
[88]	2025	IoT and cloud-based soil moisture prediction system
[98]	2025	Remote sensing-based predictive irrigation model

7.3.3 Adaptive Irrigation

Adaptive irrigation systems dynamically adjust irrigation decisions using real-time feedback and learning-based mechanisms.

These systems are capable of:

- continuous self-optimization

- improved resilience
 - better adaptation to environmental changes
- They represent the most advanced form of intelligent irrigation control. Table 14, presents the studies Implementing Adaptive Irrigation Strategies with Reinforcement Learning.

Table 14. Studies Implementing Adaptive Irrigation Strategies with Reinforcement Learning.

Ref.	Year	Evidence of Adaptive Strategy
[56]	2024	Adaptive AI with self-learning algorithms for real-time irrigation optimization
[79]	2024	IoT and ML-based precision agriculture with adaptive sensor-driven irrigation decisions
[85]	2025	AI-integrated automated irrigation system with dynamic control adjustments
[88]	2025	Soil moisture-based intelligent irrigation using IoT and cloud adaptive control
[95]	2024	Machine learning-based irrigation system with adaptive water management
[96]	2022	Intelligent irrigation system minimizing water loss using real-time sensing feedback
[97]	2022	IoT and machine learning-based smart irrigation with feedback-driven control

7.4 Hybrid IoT–AI–Water Optimization Systems

The analysis of the reviewed literature shows that most modern intelligent irrigation systems adopt hybrid architectures combining IoT sensing, AI-based decision-making, and water optimization strategies.

These systems integrate multiple technologies to:

- enhance irrigation accuracy
 - improve water efficiency
 - enable real-time adaptive control
- However, a key limitation identified across studies is the lack of standardized evaluation metrics, which makes cross-system comparison difficult. Table 15, summarizes hybrid IoT–AI–water optimization systems.

Table 15. Hybrid IoT–AI–water optimization systems.

Ref	Year	Evidence of Hybrid (IoT–AI–Water Optimization)
[7]	2024	Integrated IoT and AI-based smart irrigation system for real-time decision-making and water optimization
[11]	2022	ML-based smart irrigation system integrated with IoT soil sensing and irrigation control
[12]	2022	Multi-agent IoT irrigation system with AI-based coordination for water efficiency improvement
[14]	2022	IoT and machine learning-based water optimization technique for precision irrigation scheduling
[22]	2025	AIoT framework integrating IoT sensing, AI analytics, and resource optimization in irrigation systems
[79]	2024	IoT + ML-based precision agriculture system using wireless sensor networks for adaptive irrigation control
[97]	2022	Smart irrigation system combining IoT and machine learning for predictive water-saving irrigation

8. Discussion and Evaluation

This section presents a comprehensive discussion of the findings derived from the systematic review of 100 peer-reviewed studies on intelligent irrigation systems based on IoT and artificial intelligence. The discussion synthesizes the main trends across IoT architectures, AI/ML techniques, and water optimization strategies, highlighting their interdependencies, performance implications, and existing limitations.

8.1 Overall Insights on Smart Irrigation Systems

The reviewed literature reveals a clear paradigm shift from conventional irrigation practices toward intelligent, data-driven systems. These systems progressively integrate IoT sensing, real-time communication, and AI-based decision-making to enhance irrigation efficiency and water conservation in precision agriculture.

A key observation is that system intelligence varies significantly across studies, ranging from simple threshold-based irrigation mechanisms to fully adaptive and predictive AI-driven frameworks. While IoT enables continuous environmental monitoring, the overall performance of smart irrigation systems strongly depends on the integration of reliable sensing, efficient data processing, and robust decision models.

Despite promising results in water savings and crop management, most studies remain limited to controlled environments or small-scale deployments, raising concerns regarding scalability and real-world applicability.

8.2 Comparative Evaluation of IoT Architectures

IoT infrastructure plays a fundamental role in enabling intelligent irrigation systems. The comparative analysis shows that cloud-based architectures dominate the literature due to their high computational capacity, centralized data storage, and ease of integration with AI models.

However, cloud-centric solutions introduce limitations such as communication latency, dependency on network availability, and increased energy consumption. These constraints become particularly critical in large-scale or remote agricultural environments.

In contrast, edge and fog computing paradigms are increasingly adopted to mitigate these issues by enabling local data processing closer to the source. This shift significantly improves system responsiveness and reduces bandwidth usage, making these architectures more suitable for real-time irrigation control.

Overall, the trend indicates a gradual transition from centralized cloud-based systems toward hybrid cloud–edge architectures that balance scalability and real-time performance.

8.3 Analysis of Artificial Intelligence and Machine Learning Techniques

Artificial intelligence constitutes the core decision-making component of modern intelligent irrigation systems. The majority of existing approaches rely on classical machine learning models such as Artificial Neural Networks, Random Forests, and Support Vector Machines for irrigation scheduling and soil moisture prediction.

Recent studies increasingly explore deep learning models, particularly LSTM and CNN architectures, due to their superior ability to capture temporal and spatial dependencies in agricultural data. These

models generally achieve higher prediction accuracy compared to traditional ML techniques. However, this performance gain comes at the cost of increased computational complexity and data requirements, limiting their deployment in resource-constrained agricultural environments. Transfer learning and federated learning approaches remain emerging but promising directions, particularly for addressing data scarcity and privacy concerns in distributed agricultural systems.

8.4 Water Optimization Performance and System Effectiveness

Water optimization represents the primary objective of intelligent irrigation systems. Across the reviewed studies, performance is commonly evaluated in terms of water consumption reduction, irrigation efficiency, and crop yield improvement. Predictive and adaptive irrigation strategies consistently outperform static threshold-based approaches, particularly when combined with IoT sensing and AI-based decision models. These approaches enable proactive irrigation scheduling based on environmental conditions and forecasted water demand.

However, reported improvements vary significantly across studies due to differences in datasets, experimental conditions, and evaluation protocols. This lack of consistency limits the direct comparability of results and highlights the need for standardized benchmarking frameworks.

8.5 Evaluation Metrics and Experimental Validation

The evaluation of intelligent irrigation systems is predominantly conducted through simulations, laboratory experiments, or limited field deployments. Commonly used metrics include:

- Water consumption reduction
- Soil moisture prediction accuracy
- Energy efficiency
- System response time
- Crop yield impact

Among these, water efficiency and prediction accuracy are the most frequently reported indicators, reflecting the primary focus of irrigation optimization research.

Despite these efforts, only a limited number of studies conduct long-term real-world validation. This significantly restricts the assessment of system robustness, scalability, and practical deployment feasibility under diverse agricultural conditions.

8.6 Comparative Synthesis and Research Gaps

The comparative analysis of the reviewed studies highlights several structural and methodological limitations in current intelligent irrigation research.

8.6.1 Lack of Fully Integrated IoT–AI–Optimization Frameworks

Most existing studies focus on isolated components, such as IoT monitoring or AI-based prediction, rather than fully integrated systems combining sensing, intelligence, and water optimization within a unified framework. This fragmentation limits end-to-end system efficiency.

8.6.2 Absence of Fair Comparative Evaluation of AI Models

Machine learning and deep learning models are often evaluated under heterogeneous datasets and experimental conditions. This prevents fair comparison of model performance and limits reproducibility across studies.

8.6.3 Lack of Standardized Benchmarks and Evaluation Protocols

A major limitation identified across the literature is the absence of unified benchmarking datasets and standardized evaluation protocols. This inconsistency significantly hinders objective performance comparison between different irrigation systems.

8.6.4 Limited Consideration of Scalability and Real Deployment

Most proposed systems are validated in small-scale experimental setups, with limited attention to economic feasibility, infrastructure constraints, and scalability in real agricultural environments.

8.7 Summary of Discussion

Overall, the findings indicate that intelligent irrigation systems are evolving toward highly integrated IoT–AI–optimization frameworks. However, despite significant technological advancements, challenges related to standardization, scalability, and real-world validation remain major barriers to large-scale deployment.

Future research should focus on developing unified evaluation frameworks, scalable architectures, and robust field-tested systems capable of bridging the gap between laboratory research and practical agricultural applications.

9. Conclusion

This systematic literature review provides a comprehensive analysis of intelligent irrigation systems based on IoT and artificial intelligence for optimizing water consumption in precision agriculture. A total of 100 peer-reviewed studies published between 2018 and 2025 were selected and analyzed using a structured PRISMA-based methodology. The review highlights the evolution of irrigation systems from traditional threshold-based approaches toward more advanced data-driven and intelligent solutions integrating machine learning, deep learning, transfer learning, and federated learning techniques.

The classification proposed in this study demonstrates that IoT architectures play a central role in enabling real-time monitoring and decision-making, with cloud-based systems being the most widely adopted, while edge and fog computing paradigms are emerging as promising alternatives for low-latency and energy-efficient irrigation control. In parallel, artificial intelligence techniques significantly enhance irrigation efficiency by enabling predictive, adaptive, and automated decision-making strategies based on heterogeneous agricultural data sources.

The comparative analysis further reveals that machine learning remains the dominant approach in smart irrigation systems, while deep learning is increasingly applied for complex pattern recognition tasks such as crop monitoring and yield prediction. Transfer learning is particularly effective in scenarios with limited labelled agricultural data, whereas federated learning offers strong potential for privacy-preserving distributed model training across IoT-enabled agricultural environments.

Despite these advances, the review identifies several key challenges, including the lack of standardized evaluation metrics, limited large-scale real-world validation, and insufficient benchmarking across different AI models and system architectures. Moreover, most existing solutions remain experimental, with limited consideration of scalability, interoperability, and economic feasibility in real agricultural deployments.

Overall, this study provides a structured taxonomy and critical synthesis of existing research, highlighting current trends, limitations, and future directions. The findings emphasize the need for more robust, scalable, and standardized intelligent irrigation frameworks that integrate IoT, AI, and optimization strategies to support sustainable water management in precision agriculture.

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- **Ethical approval:** The conducted research is not related to either human or animal use.
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