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Smart Irrigation Systems: A Comprehensive Review of IoT, AI, and Sustainable Agriculture Technologies. A Review Article

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ABSTRACT

Smart irrigation systems have become essential for mitigating water scarcity, climate variability, and rising energy costs in modern agriculture. This review synthesizes recent advances in multi-source sensing, IoT/LPWAN connectivity, and hybrid edge–cloud AI frameworks that enable real-time irrigation and fertigation optimisation. A PRISMA-based methodology was applied to over 150 studies, focusing on high-impact contributions from 2017–2025. Results show that AI- and sensor-driven scheduling commonly reduces water use by 15–40% while maintaining or improving yield and nutrient-use efficiency across open-field, orchard, and greenhouse systems. Machine-learning models (RF, XGB, LSTM, CNN–LSTM, Transformer) and control strategies (MPC, RL, fuzzy logic) significantly enhance ET estimation, soil-moisture forecasting, anomaly detection, and automated valve control. Commercial platforms such as Netafim NetBeat®, Rivulis Manna, Jain AquaSphere, Rain Bird IQ4, and Toro IntelliDash demonstrate scalable field deployment, integrating IoT diagnostics, hydraulic monitoring, and interoperable APIs. Key barriers include sensor drift, connectivity limitations, proprietary architectures, and the limited explainability of deep-learning models. Future directions emphasize interoperable data standards, trustworthy and uncertainty-aware AI, self-calibrating sensing systems, high-fidelity digital twins, and energy-autonomous edge hardware. Collectively, these innovations position smart irrigation as a core enabler of climate-resilient, resource-efficient agricultural water management.

***Keywords*:** Smart irrigation; Precision irrigation; IoT and LPWAN connectivity; Model predictive control; LSTM-based forecasting; Fertigation management; Digital twin; Explainable AI.

INTRODUCTION

Agriculture remains the dominant global consumer of freshwater, accounting for approximately 70% of all withdrawals [1,2]. Climatic instability, recurrent droughts (**Figure 1**), shifting precipitation patterns, and accelerating groundwater depletion have tightened water constraints in many production regions. At the same time, rising energy costs for pumping and distribution, expanding urban demand, and deterioration in soil and water quality compound the challenge of meeting crop water requirements sustainably [1,19]. In many water basins, the combined effects of excessive water extraction and climate-induced variability are already causing groundwater levels to fall and environmental degradation to occur.

Traditional irrigation methods, typically based on fixed schedules or manual operator judgment, lack the adaptive capacity to respond to real-time soil moisture fluctuations, plant stress indicators, and microclimate variations. Such approaches rarely incorporate real-time information on soil moisture, plant water status, or short-term weather forecasts. The resulting mismatch between crop water demand and irrigation supply often manifests as over-irrigation during stable periods (**Figure 2**) and under-irrigation during sensitive phenological stages, reducing yield potential, diminishing fertilizer-use efficiency, and increasing leaching losses [3,4,10].

Over the past decade, precision agriculture, IoT/LPWAN communication, cloud analytics, and AI/ML have converged to form what is now widely recognized as smart irrigation systems [3–6,11,13]. These systems integrate multi-layer sensing of soil, plant, atmospheric, and hydraulic states with distributed computation and optimization. Time-series models predict evapotranspiration and soil moisture; fuzzy, Model Predictive Control (MPC), and Reinforcement Learning (RL) controllers generate adaptive schedules; anomaly detectors identify leaks, clogging, or sensor drift; and user interfaces translate complex system states into actionable insights [5–7,23,24,29]. As deployments scale from research plots to commercial orchards, greenhouses, and smallholder systems, smart irrigation is reshaping how water and nutrients are managed across diverse landscapes [3,8,11,12]. Despite a rapidly growing literature, existing reviews often examine sensing technologies, communication protocols, or AI algorithms in isolation [4-7,13,29], creating a fragmented understanding. Few studies integrate these components into a cohesive architecture and systematically connect technical advances with real-world hydraulic design, fertigation practices, and commercial platforms. Moreover, recent developments in digital twins, explainable AI, and energy-autonomous edge systems are only partially reflected in current syntheses [7,27,31,32,48,52].

This review addresses these gaps by providing an integrated analysis of sensing, communication, edge–cloud orchestration, and AI-driven control, alongside a quantitative synthesis of performance outcomes. It also outlines a research roadmap toward interoperable, trustworthy, and scalable smart irrigation ecosystems.

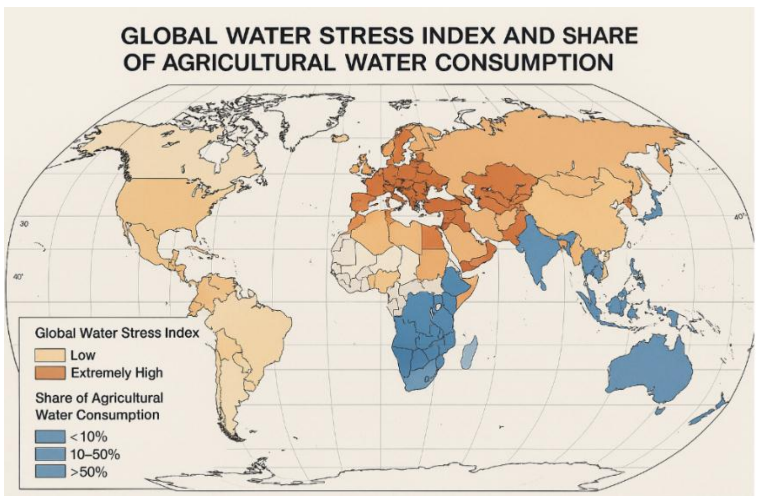

Fig.1. World map illustrating the global water stress index and the share of agricultural water consumption

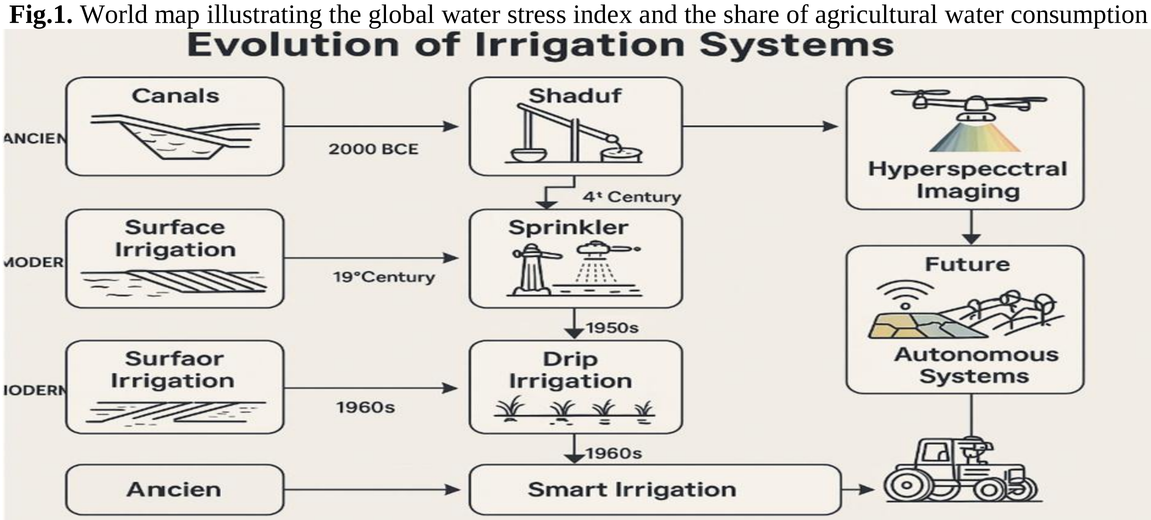

Fig.2. Evolution of irrigation systems

2. Scope and Review Methodology

This review follows a structured protocol aligned with PRISMA 2020 guidelines [18] and recent methodologies employed in smart irrigation and digital agriculture reviews [4,5,13,29]. **Figure 3** presents the PRISMA flow diagram illustrating the screening and selection process. The objective was to capture the technical, agronomic, and socioeconomic dimensions of smart irrigation while maintaining coherence across sensing, connectivity, computation, and control components.

Databases and Sources: Searches were conducted in Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink, MDPI, Wiley Online Library, and Taylor & Francis Online, complemented by open repositories and industry documentation. This ensured adequate coverage of agricultural engineering, computer science, water resources, AI/ML, hydraulics, and commercial practice.

Time Horizon: The primary window (2017–2025) reflects the period of rapid advancement in IoT/LPWAN and deep learning applications in agriculture. Foundational works such as FAO-56 were included to provide conceptual anchors for evapotranspiration modelling [1,2,19,20]. For emergent domains including digital twins and explainable AI, earlier sources were incorporated as needed [31,32,47,62].

Search Terms: Boolean strings combined keywords related to smart irrigation, IoT architectures, connectivity technologies, AI/ML forecasting and control, fertigation, anomaly detection, digital twins, and decision-support systems.

Inclusion Criteria: Studies were included if they provided:

- Experimental or modelling evidence on IoT/AI-enabled irrigation or fertigation with quantitative metrics [3–7,10–17,21–24].
- Syntheses of architectures, sensing systems, communication technologies, or AI components [4–7,11,13–15,29,30,61].
- Industry reports or case studies relevant to operating commercial smart irrigation platforms at scale [40–45].

Exclusion Criteria: Excluded materials included purely conceptual works without validation, non-agricultural IoT/AI applications without clear transferability to irrigation, and generic precision-agriculture reviews without irrigation-specific analysis.

Screening and Selection: Initial searches returned several hundred records. After screening, a corpus of over 150 relevant documents was compiled. A representative subset of more than 60 high-impact sources was selected for detailed synthesis, with emphasis on the most recent contributions (2024–2025) [6,7,23,29,37,61–63].

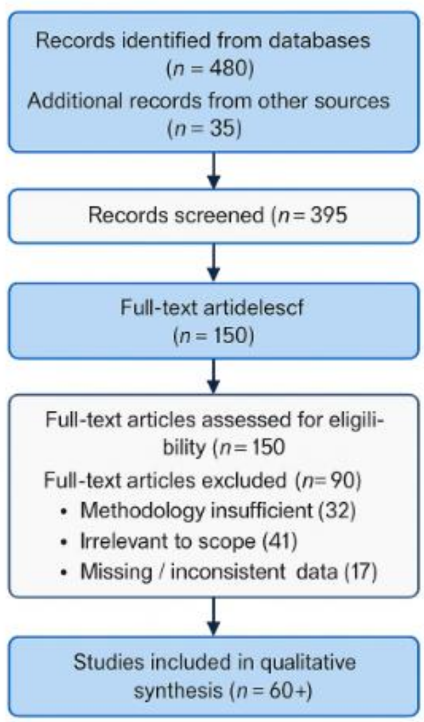

Fig.3. PRISMA diagram

3. Smart Irrigation Architecture: Layers, Functions, and Data Flows

Smart irrigation systems operate through tightly coupled sensing, communication, intelligence, and actuation layers that convert environmental data into real-time water-management decisions. A fully integrated architecture typically includes: sensing and perception, connectivity and networking, edge/cloud intelligence, actuation and hydraulic control, and supervisory management interfaces as illustrated .

3.1. Sensing Layer

The sensing layer quantifies soil–plant–atmosphere dynamics to support irrigation scheduling. Soil moisture remains the cornerstone parameter, monitored by probes such as Time Domain Reflectometry (TDR), Frequency Domain Reflectometry (FDR), capacitance sensors, tensiometers, and impedance devices [10,33]. Recent studies highlight the variability in sensor performance under field conditions, with low-cost sensors requiring systematic calibration to achieve acceptable accuracy [21]. Complementary measurements include soil temperature, electrical conductivity (EC), canopy temperature, sap flow, leaf turgor, NDVI-based vegetation indices, and microclimate variables such as air temperature, humidity, solar radiation, and wind speed [34].

Plant-based indicators have gained traction because they directly capture crop stress responses. Continuous canopy temperature measurement, dendrometry, and stem water potential sensing help refine crop water status estimation in orchards and specialty crops [34]. When integrated with remote sensing (satellite, UAV, multispectral imagery), the sensing layer expands its spatial coverage, enabling multi-scale decision making that is particularly useful for heterogeneous fields [9,35].

3.2. Communication Layer

This layer transmits sensor data to edge gateways and cloud servers. Connectivity options range from local radio (Wi-Fi, Bluetooth, ZigBee), long-range low-power networks (LoRaWAN, Sigfox), cellular networks (4G/5G/NB-IoT), and hybrid architectures [25,26]. In large fields, LoRaWAN remains the dominant choice because of its low-power operation, kilometer-scale range, and low operational cost.

Communication reliability is a critical determinant of system performance. High packet loss or latency can disrupt decision-making workflows, particularly in feedback-based MPC or AI-driven systems. To mitigate these risks, multi-channel redundancy, adaptive data-rate control, and gateway health monitoring are increasingly adopted in modern installations [27].

3.3. Edge–Cloud Intelligence Layer

AI and machine learning algorithms transform raw data into actionable irrigation recommendations. This layer typically hosts:

- ET estimation models including FAO-56 PM, hybrid feature-engineered ML models, and deep-learning architectures such as Long Short-Term Memory (LSTM), CNN-LSTM, and Transformer networks [1,2,19,20,39,64].
- Soil moisture forecasting using time-series ML and state-space models.
- Crop water stress classification leveraging thermal imagery and vegetation indices.
- Optimization and control algorithms, including model predictive control (MPC), fuzzy control, and reinforcement learning (RL) [37,53,54].

While cloud-based AI facilitates scalability through integration with extensive datasets (satellite imagery, weather reanalysis, multi-farm analytics), edge computing is critical for ensuring low-latency decision-making during time-sensitive irrigation cycles [27]. Several studies demonstrate that AI-enhanced models improve water-use efficiency by 10–40% and enhance yield stability under variable climate conditions [5,6,7,14,56].

3.4. Actuation and Hydraulic Control Layer

This layer executes irrigation decisions using pumps, solenoid valves, pressure regulators, fertigation injectors, and filtration units. Intelligent fertigation systems increasingly rely on variable-rate injection, real-time EC/pH monitoring, and inline flow sensing to maintain precise nutrient delivery [16,17,23,36]. The performance of this layer depends on robust hydraulic modeling, fault detection (e.g., pressure drops, clogged emitters), and automated shutdown protocols to prevent system failures.

3.5. Supervisory Management Layer

Farm managers interact with the irrigation system through dashboards, mobile applications, and SCADA-like interfaces. These platforms visualize soil moisture trends, ET forecasts, hydraulic parameters, alarms, and recommended actions [40–45]. Multi-site management, language localization, role-based access, and integration with ERP/FMS platforms are emerging requirements for commercial adoption.

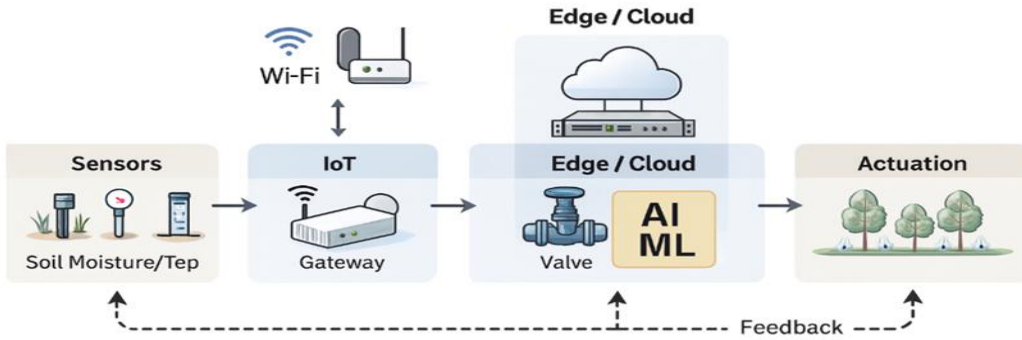

Fig.4 System Overview & Dataflow

4. Components, Placement, and Calibration

Effective smart irrigation depends fundamentally on the correct selection, installation, and calibration of system components. A typical sensor suite is shown in **Figure 7**. Even advanced AI or optimisation algorithms cannot compensate for poor sensing quality, inappropriate placement, or misaligned hydraulic infrastructure.

4.1 Soil Sensors

Capacitance and TDR sensors estimate volumetric water content by measuring dielectric properties. Their accuracy is influenced by soil salinity, bulk density, and organic matter, often making manufacturer calibrations insufficient in heterogeneous soils. Field calibration using gravimetric sampling or laboratory-derived moisture curves improves accuracy. Multi-depth installation (e.g., 10–30–60 cm) helps distinguish shallow wetting, root-zone extraction, and deep percolation patterns [10,21].

4.2 Plant-Based Indicators

Dendrometers capture diurnal stem diameter fluctuations, which correlate strongly with plant water status. Sap-flow sensors quantify transpiration directly, while infrared thermometry and thermal cameras detect early signs of stomatal closure. These measurements complement soil moisture data by integrating physiological responses to microclimatic and soil conditions [22,34].

4.3 Hydraulic Sensors

Flowmeters and pressure transducers ensure that system hydraulics remain within design specifications. Monitoring pressure at key nodes validates the operating range of pressure-compensating emitters, while differential-pressure sensors across filters provide early warnings of clogging. Hydraulic data are also essential inputs for anomaly detection and predictive maintenance algorithms [21,22,28].

4.4 Fertigation Sensors

Inline EC and pH sensors regulate nutrient dosing, especially in high-frequency drip and greenhouse systems. These sensors require frequent cleaning, calibration, and drift compensation. Emerging nitrate-specific sensors show promise but still face stability challenges under field conditions [16,17,23,36].

4.5 Placement Strategy

Sensor placement must capture spatial heterogeneity in soil texture, topography, and management zones. In drip irrigation, soil sensors positioned between emitters avoid edge effects while accurately tracking root-zone dynamics. Orchards benefit from placement near the fringe of the wetted bulb, where both stress signals and deep percolation can be more effectively identified [3,4,10,22].

4.6 Calibration and Maintenance

Calibration remains one of the most persistent bottlenecks in adoption. Soil probes should be validated regularly, particularly after soil disturbance or seasonal transitions. EC/pH probes require two- or three-point calibration to correct for drift. Periodic firmware updates, connectivity checks, and cross-validation against manual measurements preserve long-term data integrity. Research into self-calibrating sensors using embedded machine learning for drift detection represents a promising direction [27,55].

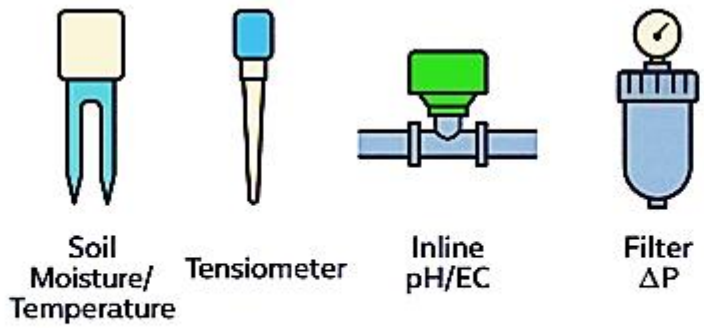

Fig.5 Sensor Suite: soil moisture/temperature, tensiometer, inline pH/EC, filter ΔP

5. Connectivity and Edge–Cloud Orchestration

Reliable connectivity is essential for transforming sensor data into timely and accurate irrigation decisions. **Figure 8** illustrates a typical connectivity topology for an orchard deployment using LoRaWAN/NB-IoT, while **Figure 9** shows an edge/AI cabinet housing the local computation and communication hardware. Agricultural environments, however, introduce challenges such as sparse cellular coverage, terrain variability, radio interference, and strict energy constraints on field devices. Smart irrigation systems therefore rely on robust communication architectures and careful allocation of computational workloads between edge and cloud layers.

5.1 LPWAN Technologies

Low-power wide-area networks (LPWAN) form the backbone of many field-scale deployments:

- **LoRaWAN** provides long-range, low-energy communication ideal for battery–solar sensor nodes in orchards and open fields [3,11,25].
- **NB-IoT and LTE-M** operate on licensed cellular spectrum, offering reliable quality of service and broad coverage, though at the cost of higher energy consumption and subscription fees [26,37].

These technologies enable scalable sensing networks but must comply with duty-cycle restrictions and variable signal penetration in rural landscapes.

5.2 Short-Range Technologies

Short-range protocols are preferred in high-density or high-data-rate scenarios:

- **Zigbee/Thread and BLE** support greenhouse and compact-field deployments [11,25].
- **Wi-Fi** enables image-based and high-frequency sensing but is energy-intensive and sensitive to interference [27].

Mesh topologies can extend range but may increase latency and reduce reliability for time-critical irrigation decisions.

5.3 Protocols and Interoperability

Data exchange depends on lightweight and interoperable communication protocols:

- **MQTT** supports publish–subscribe telemetry and efficient command distribution [3,25,27].
- **REST/JSON APIs** provide compatibility with cloud services, weather platforms, and farm management applications [27,29].
- **OPC UA**, increasingly used in industrial contexts, enhances interoperability and semantic consistency across diverse devices [27,29,46].

Open standards are critical to avoid vendor lock-in and support modular system expansion.

5.4 Edge–Cloud Workload Allocation

Smart irrigation performance depends on a balanced task distribution between **edge** and **cloud**, a pattern increasingly emphasized in IoT, smart agriculture and cloud-computing reviews [11,25–27].

Edge Layer Responsibilities

The edge executes time-critical and reliability-focused tasks:

- Local rule-based or fuzzy-logic control algorithms for immediate irrigation decisions [53].
- Rapid anomaly detection for flow, pressure or sensor drift, where latency must be minimal [28,60].
- Fallback irrigation schedules ensuring safety during connectivity loss [11,25].

- Data filtering, compression and temporary buffering to reduce transmission loads and energy consumption [27].

Edge computing ensures that irrigation continues safely even when cloud access is intermittent.

Cloud Layer Responsibilities

The cloud hosts computationally intensive and long-horizon functions:

- Training of ML/AI forecasting models (soil moisture, ET, demand prediction) [5,6,23,29,30].
- Simulation and optimisation workflows, including digital-twin-based scenario testing [31,32].
- Multi-field or multi-farm resource allocation and cross-season analytics [7,27].
- Deployment of updated model parameters, firmware, or optimisation rules back to edge devices [27].

Hybrid orchestration reduces communication overhead, increases operational resilience and enables more advanced decision-support under real-world conditions.

5.5 Resilience and Fail-Safe Operation

Connectivity gaps are unavoidable in agricultural landscapes. Robust smart irrigation platforms therefore include:

- Local data buffering and automatic cloud resynchronisation [11,25].
- Scheduled fallback irrigation to prevent crop stress during communication outages [28].
- Routine integrity checks for sensor drift and actuator condition [10,21,60].
- Safety interlocks preventing pump overload, emitter malfunction or pressure loss [22,28].

These mechanisms ensure that irrigation remains stable and secure even when individual sensors, nodes, or communication channels fail [70]. Having established the critical role of reliable data flow, the following section examines how machine learning transforms this data into intelligent irrigation decisions.

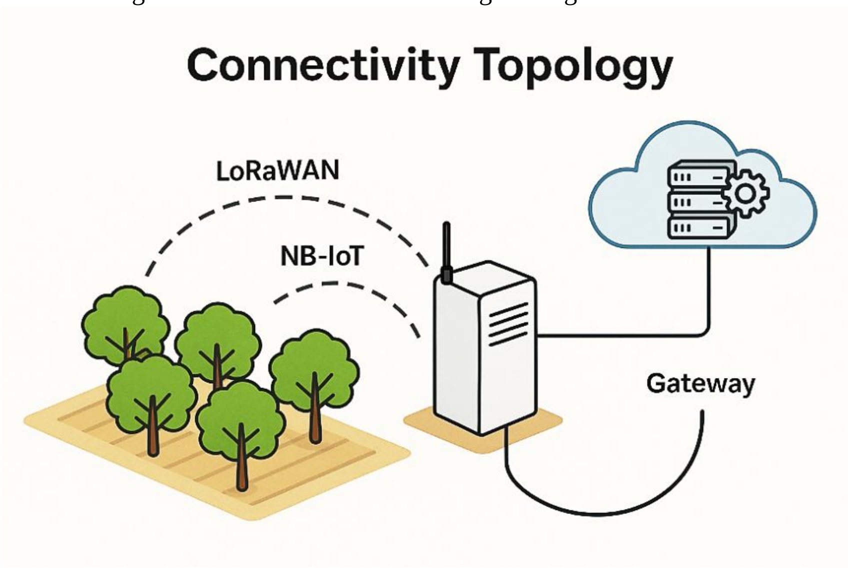

Fig.6 Connectivity Topology: LoRaWAN / NB-IoT orchard deployment

6. Machine Learning Methods for Smart Irrigation

Machine learning (ML) has become a structural pillar of next-generation irrigation systems, enabling predictive, self-optimizing, and adaptive decision-making far beyond static rule-based approaches. **Figure 10** outlines a typical AI pipeline from training to inference, and **Figure 11** depicts a hybrid control logic combining fuzzy logic, MPC, and constraint-based alerts. **Figure 12** illustrates a closed-loop fertigation control system integrating pH and EC feedback for automated nutrient dosing. Recent systematic reviews confirm a rapid expansion of ML applications, including ET estimation, soil-moisture forecasting, crop stress detection, and fully autonomous irrigation scheduling [5,6,14,30,37,68].

6.1. ET and Soil-Moisture Prediction Models

Accurate evapotranspiration (ET) estimation remains the core of data-driven irrigation planning. While FAO-56 Penman–Monteith remains the agronomic benchmark [1,2,19], its reliance on full meteorological datasets limits applicability in data-scarce regions. To mitigate this, deep-learning models such as LSTM, CNN-LSTM, and Transformer architectures integrate limited weather data with historical ET patterns to achieve high predictive accuracy [20,39,64].

Feature-engineering approaches, such as those reported by Považanová et al. (2023), demonstrate that hybrid ML models can outperform classical ET equations when trained on region-specific environmental variables [20].
For soil-moisture prediction, state-space models, sequence networks (e.g., LSTMs), and Gaussian process regressors are employed to forecast short-term dynamics. This capability supports proactive irrigation scheduling. Time-series ML frameworks have demonstrated accuracy improvements of 10–25% over physics-based moisture balance models in field deployments [6,37].

6.2. AI-Based Irrigation Recommendation Systems

Integrated ML controllers translate predicted ET, soil moisture and crop stress into irrigation recommendations or automated valve operations. Major categories include:

- **Model Predictive Control (MPC):** Uses soil–plant–hydrology dynamic models and constraints to determine optimal watering sequences. Demonstrated in sweet corn and greenhouse vegetable systems with significant water-use efficiency (WUE) gains [22,37,54].
- **Reinforcement Learning (RL):** Enables agents to discover irrigation strategies that maximize yield or minimize water use through exploration of dynamic environments. RL is increasingly adopted in multi-objective scenarios where trade-offs involve WUE, energy consumption, and nutrient leaching [30,37].
- **Fuzzy logic controllers:** Effective in systems requiring interpretability and low computational load, especially for smallholder farms [53].
- **Hybrid methods:** Integration of ML predictions with agronomic rules, MPC constraints and remote-sensing indices to create robust, transferable decision engines [5,14,23].

6.3. Challenges in Model Deployment

Despite progress, several limitations persist:

- **Generalization gaps:** Models trained in one agro-ecological region fail when transferred to others due to soil-structure, canopy, and microclimate differences [14,68].
- **Data scarcity:** High-frequency labeled datasets remain limited, especially for plant-based stress indicators.
- **Explainability:** Deep-learning models often lack interpretability, restricting adoption by practitioners.
- **Infrastructure constraints:** Reliable connectivity and edge-computation capacity are essential for real-time ML-based scheduling [26,27].

These issues highlight the need for adaptive, transferable, and interpretable ML frameworks to support widespread adoption.

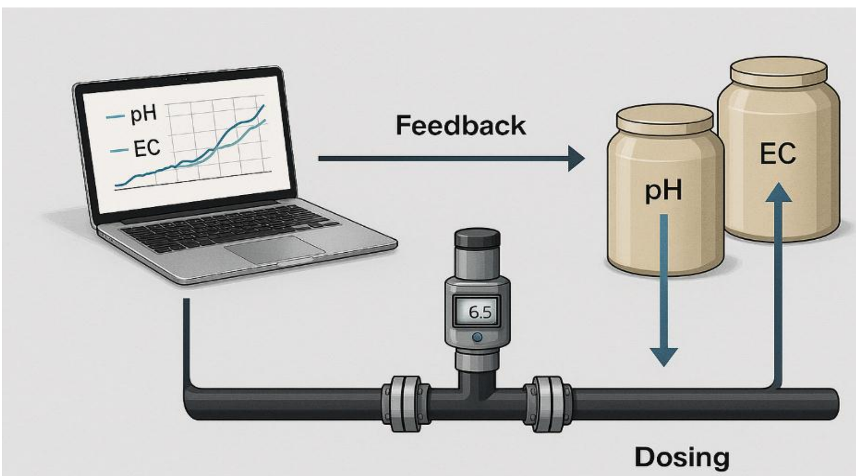

Fig7 Closed-loop fertigation control system integrating pH and EC feedback for automated nutrient dosing.

7. Digital Twins in Smart Irrigation

Digital twins (DTs) represent a transformative paradigm that integrates real-time data, predictive modeling, and automated control. Predictive simulation models and control algorithms converge into a continuously updated virtual representation of fields, crops, and hydraulic systems. In agriculture, DTs extend beyond monitoring to encompass predictive diagnostics, scenario evaluation, and automated control [31,32].

7.1. Digital Twin Architecture for Irrigation

- **Real-time sensor streams** (soil moisture, microclimate, canopy temperature, flow/pressure).
- **Crop and hydrological simulation models** (FAO-based ET, soil-water balance, root dynamics).
- **Predictive analytics and ML layers** for forecasting crop stress, yield responses, and water consumption.
- **Control interface** linking virtual recommendations to physical actuators (valves, pumps, fertigation units).

These structures mirror industrial IoT paradigms but require substantial calibration and computational consistency when applied to biological systems [31].

7.2. Applications and Advantages

Recent studies demonstrate major advancements:

- **Dynamic irrigation optimization:** DTs evaluate hypothetical irrigation strategies before deployment, improving WUE and yield stability [31,46].
- **Failure detection:** Hydraulic anomalies (leaks, clogging, pump inefficiencies) are detected earlier through virtual–physical mismatch analytics.
- **Scenario simulation:** DTs assess effects of extreme weather, salinity shifts, and fertigation strategies in virtual environments, thus reducing economic risk.
- **Training and decision-support:** DTs support agronomists by revealing system behavior over multi-season horizons.

7.3. Current Limitations

Despite strong potential, barriers remain:

- **High data requirement:** Digital twins require dense, calibrated sensor networks and historical datasets [32,62].
- **Lack of standardization:** Interoperability across vendors and platforms remains limited.
- **High computational load:** Real-time simulation of soil–plant–atmosphere processes remains expensive.
- **Adoption gap:** Smallholders lack financial and technical capacity for DT deployment [52].

Continued advances in edge computing, low-cost sensors, and unified data standards are likely to accelerate adoption.

8. IoT-Based Smart Irrigation Infrastructures

IoT infrastructures provide the backbone for data acquisition, communication, and automated control within smart irrigation ecosystems. The shift from isolated sensor networks to fully integrated IoT platforms mirrors developments in other industrial cyber–physical systems. **Figure 13** presents a hydraulics map showing pressure/flow monitoring and pressure-compensating laterals, while **Figure 14** exemplifies user-interface dashboards for zone-based management and trend visualization.

8.1. Network Architectures

Smart irrigation deployments typically use multi-tier IoT architectures consisting of:

- **Device layer:** Battery-powered soil sensors, weather stations, flow meters, fertigation injectors, UAVs, and camera nodes [9,11,21].
- **Gateway layer:** Aggregates data via LoRaWAN, Wi-Fi, NB-IoT, or hybrid configurations [25,26].
- **Cloud/edge layer:** Performs ML-based analytics, hydraulic modeling, and decision algorithms [27].
- **Actuation layer:** Executes irrigation commands with remote valve control, pump automation, and fertigation dosing.

8.2. Communication Technologies

Communication reliability is critical for continuous irrigation scheduling:

- **LoRaWAN:** Most widely adopted for large farms due to its long range and low battery consumption [25].
- **NB-IoT / LTE-M:** Provides higher bandwidth and reliability for dense sensor deployments [26].
- **Hybrid networks:** Combine satellite-backed communication with LoRaWAN for remote regions with limited terrestrial coverage.

IoT fault-tolerance remains an issue: node dropouts, gateway overloads, and radio interference can degrade system performance. Robust IoT deployments therefore include redundancy, self-healing routing, and adaptive transmission strategies.

8.3. IoT–AI Fusion for Autonomous Irrigation

Emerging IoT frameworks embed AI at multiple layers:

- **Edge AI for real-time scheduling** in latency-sensitive irrigation cycles [27].
- **Cloud-based predictive analytics,** integrating remote-sensing imagery and multi-field datasets [11,30].
- **Anomaly detection systems** identify irrigation failures using deep-learning pipelines trained on flow, pressure, and soil-moisture patterns [60].

8.4. Adoption Barriers and Practical Considerations

Widespread adoption faces:

- **Cost constraints,** especially in low-income agricultural regions.
- **Maintenance challenges,** including sensor recalibration, battery replacement, and connectivity troubleshooting.
- **Digital literacy gaps,** limiting effective use of dashboards and configuration tools [52].

These issues necessitate simplified UIs, reliable vendor support, and scalable pricing models.

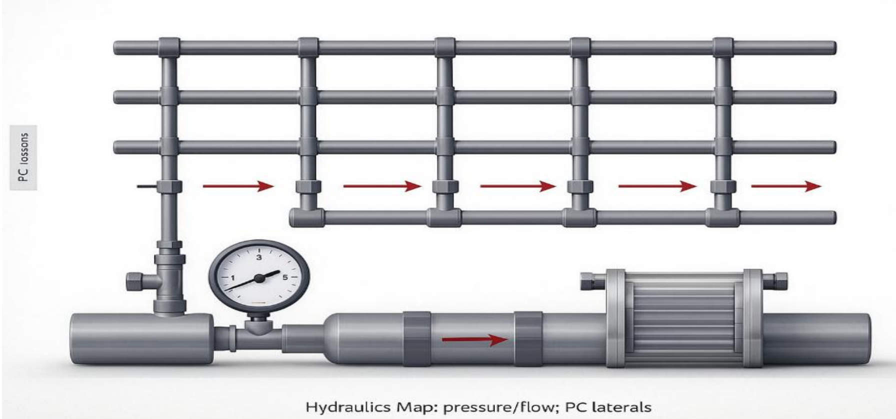

Fig.8 Hydraulics Map (pressure/flow; PC laterals)

9. Performance Synthesis: Water, Yield and Economic Outcomes

A growing body of empirical evidence demonstrates that the integration of sensor networks, IoT/LPWAN connectivity, and AI-driven decision-support substantially improves irrigation and fertigation performance across diverse production systems. **Figure 15** summarizes the reported water savings and yield deltas across multiple studies. Results converge on three main outcomes: **reduced water use**, **greater yield stability**, and **enhanced resource-use efficiency** [3,4,10,17,22,28,69].

9.1 Water Use

Across open-field crops, orchards, and greenhouse operations, AI or sensor-guided irrigation typically reduces water application by **15–40%**, with higher reductions reported when the baseline practice is flood or furrow irrigation. When farms also transition from surface irrigation to pressurised systems (drip or micro-sprinkler), total water savings may reach **25–60%**, depending on crop type, climate, and soil properties. These savings are primarily attributed to more precise irrigation timing, reduced deep percolation, improved spatial water distribution uniformity, and the avoidance of unnecessary irrigation during periods of low evapotranspiration demand.

9.2 Yield and Quality

Yield responses vary by crop sensitivity and environmental conditions. Many studies document **5–20% yield gains**, especially in crops where water stress during critical phenological stages impacts fruit set or biomass accumulation. Even when yields remain stable, water-use efficiency (WUE) improves substantially. Enhanced fruit quality—size, firmness, soluble solids, and uniformity—is frequently attributed to tighter control of soil moisture dynamics [16,17,22,28,69].

9.3 Nutrient Use and Environmental Impact

Closed-loop fertigation strategies often maintain or increase yields with **lower fertilizer inputs**, improving nutrient-use efficiency (NUE). Optimised nutrient timing reduces nitrate leaching, mitigates salinity accumulation, and limits off-site nutrient transport, especially in drip and greenhouse systems where root-zone salinity is a critical constraint

[16,17,23,36].

9.4 Economic Feasibility

Economic benefits are strongest in high-value horticulture and protected cultivation, where water, labour, and fertilizer savings shorten payback periods to **2–4 years**. For smallholders, economic constraints remain significant, underscoring the need for subscription-based, cooperative, or subsidised models to broaden adoption [48,52].

10. Industrial State-of-Practice

Commercial smart irrigation platforms have advanced rapidly, integrating multi-source sensing, hydraulic monitoring, and AI-driven analytics into unified systems. **Figure 16** provides an industry mapping that aligns leading platforms (NetBeat, Manna, IQ4, IntelliDash) with the component stack described in Sections 3–5. These platforms operationalise research concepts at scale and highlight industry priorities such as **reliability**, **remote diagnostics**, **alarm workflows**, and **system interoperability**.

Netafim NetBeat®

NetBeat integrates soil probes (e.g., Sentek), weather-analytics tools (e.g., Arable), and crop-specific models to generate irrigation and fertigation recommendations. It supports cloud dashboards, mobile interfaces, hydraulic monitoring, and API-based integration with farm-management tools [40,41].

Rivulis Manna

Manna is positioned as a "sensor-less" irrigation intelligence system by relying on satellite imagery, local weather, and crop models instead of large in-field sensor deployments. This makes it suitable for regions where hardware installation is challenging [42].

Jain AquaSphere

AquaSphere combines sensor networks, remote sensing, and agronomic advisory services, emphasising multi-zone irrigation and fertigation in high-value horticulture [43].

Rain Bird IQ4

Originally developed for turf/golf irrigation, IQ4 offers centralised hydraulic modelling, multi-site management, and robust industrial control. Its SCADA-like capabilities are increasingly used in agricultural settings [44].

Toro IntelliDash & Lynx

These systems integrate hydraulic modelling with analytics and scheduling logic, originally for landscaped assets but now expanding into intensive agriculture [45].

Industrial Trend

Despite architectural differences, these platforms share common design principles: modularity, high uptime, diagnostics, multi-language user interfaces, and open APIs. Ongoing mergers and acquisitions suggest further consolidation and increased emphasis on interoperability across systems.

Across these leading platforms, system architectures closely parallel the layered framework described in **Sections 3–5**. Common design principles include robust IoT/LPWAN connectivity, hybrid edge–cloud computation, comprehensive alarm workflows, predictive diagnostics, multi-language user interfaces, and growing emphasis on SCADA/ERP interoperability. The rapid consolidation occurring within the irrigation industry indicates that **interoperability, open standards, and modular integration** will become defining characteristics of next-generation smart irrigation ecosystems.

11. Digital Twins, Explainable AI and Energy-Autonomous Edge Systems

11.1 Digital Twins

Digital twins (DTs) provide dynamic representations of soil–plant–atmosphere–irrigation systems, continuously updated using sensor data. Unlike static models, DTs enable scenario testing (e.g., deficit irrigation), allow safe training of MPC or reinforcement learning (RL) agents, and provide benchmarking of real-time performance [31,32,46]. Key challenges include uncertainty propagation, multi-scale coupling, and validation against independent field measurements. **Figure 17** highlights security and power considerations, showing a typical weather-resistant enclosure and power-management practices for field deployments.

11.2 Explainable and Trustworthy AI

As ML-based systems influence operational decisions, transparency becomes essential. Explainable AI (XAI) tools—SHAP, LIME, rule extraction, and attention maps—help users understand how recommendations are generated. These tools support model debugging, agronomic validation, and user trust while enabling compliance with emerging ethical guidelines for agricultural AI [47].

11.3 Energy-Autonomous Edge

Field devices depend on small solar panels and batteries; thus energy autonomy is a core design constraint. Approaches include low-power electronics, adaptive sampling, event-driven communication, compressed telemetry, and hybrid solar-wind harvesting [27]. These strategies reduce maintenance needs and support long-term reliability in remote deployments.

12. Challenges and Adoption Barriers

Despite promising technical progress, several barriers hinder widespread adoption:

12.1 Sensor Reliability

Sensor drift, fouling, salinity sensitivity, and calibration requirements limit long-term accuracy. Inconsistent data reduces model performance and erodes user confidence [21].

12.2 Connectivity Limitations

Coverage gaps, radio interference, and LPWAN duty-cycle restrictions can disrupt time-critical communication. Hybrid connectivity and edge-first logic help manage outages but do not eliminate them entirely [70].

12.3 Economic & Operational Constraints

High upfront investment, subscription fees, and technical complexity reduce adoption among smallholders. Systems requiring specialised installation or maintenance face stronger resistance [48,52].

12.4 Interoperability & Lock-In

Closed protocols and proprietary hardware limit the ability to integrate third-party sensors or controllers. Standardised data models and open APIs are essential to avoid vendor lock-in.

12.5 Data Governance & Trust

Concerns about ownership, privacy, monetisation, and cloud dependence influence adoption. Transparent data policies and user control over data sharing are critical.

13. Research Roadmap 2025–2030

Emerging scientific trajectories and industry needs suggest the following priorities for the next decade:

Interoperability & Open Data Standards

Widespread adoption of MQTT/JSON, OPC UA, shared ontologies, and plug-and-play sensor standards.

Trustworthy, Explainable AI

Models with explicit uncertainty quantification, interpretable structures, and farm-centric explanation interfaces.

Self-Calibrating Sensor Systems

Embedded ML for drift detection, auto-calibration, and cross-validation with reference sensors.

High-Fidelity Digital Twins

Field-to-basin scale DTs integrating mechanistic, data-driven, and remote-sensing components with multi-objective optimisation capability.

Energy-Autonomous Edge Hardware

Ultra-low-power processors, intelligent duty cycling, and hybrid energy harvesting for multi-year operation without manual maintenance.

Socioeconomic & Policy Innovation

New business models (Irrigation-as-a-Service), cooperative sensor ownership, capacity building, and targeted subsidies for smallholders.

Integrated Water–Nutrient–Energy Management

Unified platforms that coordinate irrigation, fertigation, and renewable-energy-driven pumping.

Conclusions

Smart irrigation has evolved from isolated experimental systems into a mature technological domain capable of delivering significant water savings, stabilising or enhancing yield, and reducing environmental impacts. These advances stem from the convergence of multi-source sensing, IoT/LPWAN connectivity, edge–cloud analytics, and AI-driven control.

The next generation of systems will depend on:

- improved sensor robustness,
- open and interoperable data ecosystems,
- trustworthy and explainable AI,
- validated digital twins,
- energy-autonomous field hardware,
- inclusive and financially accessible deployment models.

As climate variability intensifies and water scarcity deepens, smart irrigation will become a foundational element of sustainable intensification—enhancing productivity while reducing environmental pressure and strengthening agricultural resilience.

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أنظمة الري الذكية: مراجعة شاملة لتقنيات إنترنت الأشياء والذكاء الاصطناعي والزراعة المستدامة

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الخلاصة

أصبحت أنظمة الري الذكية ضرورية للتخفيف من ندرة المياه، وتقلبات المناخ، وارتفاع تكاليف الطاقة في الزراعة الحديثة. يستعرض هذا البحث أحدث التطورات في مجال الاستشعار متعدد المصادر، وربط إنترنت الأشياء/شبكات***LPWAN*** ، وأطر الذكاء الاصطناعي الهجينة بين الحوسبة الطرفية والسحابية، والتي تُمكّن من تحسين الري والتسميد في الوقت الفعلي. طُبقت منهجية ***PRISMA*** على أكثر من 150 دراسة، مع التركيز على المساهمات ذات الأثر الكبير خلال الفترة من 2017 إلى 2025. تُظهر النتائج أن الجدولة المدعومة بالذكاء الاصطناعي وأجهزة الاستشعار تُقلل عادةً من استهلاك المياه بنسبة 15-40% مع الحفاظ على المحصول وكفاءة استخدام العناصر الغذائية أو تحسينهما في أنظمة الحقول المفتوحة والبساتين والبيوت الزجاجية. تُحسّن نماذج التعلم الآلي***RF)*** ، ***XGB***، ***LSTM***، ***CNN-LSTM***، ***Transformer)*** واستراتيجيات التحكم***MPC)*** ، ***RL***، المنطق الضبابي) بشكل كبير من تقدير التبخر النتحي، والتنبؤ برطوبة التربة، واكتشاف الحالات الشاذة، والتحكم الآلي في الصمامات. تُظهر منصات تجارية مثل ***Netafim NetBeat®*** و ***Rivulis Manna***و ***Jain AquaSphere***و ***Rain Bird IQ4***و ***Toro IntelliDash*** إمكانية نشرها ميدانيًا على نطاق واسع، حيث تدمج تشخيصات إنترنت الأشياء، والمراقبة الهيدروليكية، وواجهات برمجة التطبيقات المتوافقة. تشمل العوائق الرئيسية انحراف المستشعرات، ومحدودية الاتصال، والبنى الاحتكارية، ومحدودية تفسير نماذج التعلم العميق. تركز التوجهات المستقبلية على معايير البيانات المتوافقة، والذكاء الاصطناعي الموثوق والواعي بالشكوك، وأنظمة الاستشعار ذاتية المعايرة، والتوائم الرقمية عالية الدقة، والأجهزة الطرفية المستقلة عن الطاقة. مجتمعةً، تُرسّخ هذه الابتكارات مكانة الري الذكي كعامل تمكين أساسي لإدارة المياه الزراعية بكفاءة عالية ومرونة في استخدام الموارد، بما يتناسب مع تغير المناخ.

الكلمات المفتاحية: الري الذكي؛ الري الدقيق ، اتصال إنترنت الأشياء وشبكات ***LPWAN***، التحكم التنبؤي القائم على النموذج، التنبؤ القائم على ***LSTM***، إدارة التسميد بالري، التوأم الرقمي، الذكاء الاصطناعي القابل للتفسير.