Academic Journal of Electrical and Computer Engineering
Vol. 02, No. 01, August 2026
https://doi.org/10.31272/ajece.35
https://ajece.uomustansiriyah.edu.iq
ISSN 3079-2878
Research Article

A Systematic Review of the Integration of IoT and Sensor Technologies for Sustainable Smart Irrigation Systems: Trends, Challenges, and Future Directions

Omar Talib Khazraji[1*], Marwan J. Hussein[2], Ahmed M. Almawla[3]

[1]Electrical Engineering Department, College of Engineering, Mustansiriyah University, 10011 Baghdad, Iraq.
[2,3]Construction and Projects Department, Mustansiriyah University,10052 Baghdad, Iraq.
[*]Email: omartalib92@uomustansiriyah.edu.iq

Received: 04/10/2025 Revised: 08/12/2025 Accepted: 02/02/2026

***Abstract*—Efficient water use is a constant challenge in modern agriculture, especially in drought areas. The development and use of soil sensor technologies are essential for effective water management and for achieving sustainable high-yield farming systems. This literature review compares the different soil sensor methods and draws together findings from a group of 156 peer-reviewed articles published between 2015 and 2025. The review covers dielectric methods (TDR and FDR), tensiometers, neutron probes, salinity probes, and pH probes. The meta-analysis showed that TDR systems can give highly accurate estimates of soil moisture (with a pooled RMSE of 0.016 m³/m³), but they are also expensive (ranging from $500 to $1200 per unit). In contrast, low-quality capacitive sensors can attain acceptable accuracy (an RMSE of 0.045 m³/m³) provided they are calibrated with care. LoRaWAN (Long Range Wide Area Network) has been identified as the most suitable communication protocol for agricultural Internet of Things (IoT) applications because it offers long-distance transmission of between 2 and 15 km and has a battery life of 2 to 10 years. The accuracy of irrigation scheduling can be increased by 15 to 30% through the use of machine-learning techniques, and water savings with AI systems can go as high as 35 to 50%. Important research gaps include the absence of standard calibration procedures, limited validation in 67% of the studies, insufficient long-term stability testing (since 23% of the studies have not been tested over a period longer than six months), and a lack of adequate assessment of multi-sensor data fusion. The review ends by outlining the future research needed in order to develop robust, scalable and innovative irrigation systems that support crop production.**

***Index Terms*—Smart irrigation; IoT sensors; precision agriculture; time-domain reflectometry; LoRaWAN; machine learning; systematic review.**

I. INTRODUCTION

Agriculture is the largest user of freshwater globally—mostly due because it makes up for that almost 70% of total withdrawals. However, if watering is not applied in an appropriate manner, it can lead to water waste and soil erosion while at the same time providing only a minimum production of crops. In arid and semi-arid areas, the constant deficient state of water multiplies these problems. Due to the increasing world demand for food and sustainable use of natural resources, high irrigation efficiency opportunities have become a major research and policy focus among the world's farmers [1]. Some are solved by various smart irrigation systems, which combine soil sensors with communication devices and automated control to provide crop specific water needs.

Real-time monitoring of soil characteristics (i.e., moisture, matric potential salinity and pH) will allow for data driven irrigation scheduling. It helps reduce water loss as a result of over- or under-watering, while increasing overall water-use efficiency [2]. Soil sensors, from which such systems were derived, are the data source for making decisions. Several such related arts have been disclosed and practiced in the field. Some dielectric sensors, including the time and frequency domain reflectometry (TDR, FDR), and capacitive probes, are widely employed for measuring VWC according to their dielectric properties. They measure soil matric potential and, therefore, have a one-to-one correspondence with the availability of water to plants. Although not in common use, for regulatory control and calibration purposes neutron probes are very accurate standards. Electro-conductive/chemical contact type agro-sensors for (EC) and pH are necessary factors of the monitoring system to analyse soil salinity and nutrient flow. These technologies all have trade-offs in accuracy, cost, response time to the stimulus, need for calibration and susceptibility to ambient conditions.

With the advance of cheap sensor technology, IT support like IoT and machine learning now allows smart agricultural systems to do a lot more. Cheap capacitive-type sensors make it feasible to obtain wide coverage, but in most cases their accuracy is only good with soil specific calibrations. With the IoT platforms, data gets instantly delivered, and decisions are automatically made. In [3], anomaly detection and predictive and adaptive irrigation scheduling is done using machine learning. However, several challenges persist. What Factors Affect the Design and Calibrated Performance of Weather-based Control Systems for Urban Landscape Irrigation? Factors include, but are not limited to: Stable calibration (in different soil conditions) Long term stability of inexpensive devices Multi sensor data fusion for better decision-making. The above challenges need to be overcome in order to achieve sustainable, cost-effective, innovative irrigation systems for robust scale-up, guaranteeing food/grass security.

II. Literature Review

A. Dielectric-Based Sensors

1. Time Domain Reflectometry (TDR)

Among the academic community, TDR is generally regarded as one of the most unbiased and accurate instruments for measuring soil VWC. In TDR, the concept is simple: an electromagnetic impulse is sent along a pair of metal waveguides implanted in soil, and the transit time of this pulse is related linearly to the dielectric permittivity of soil. A large body of empirical work consistently shows that TDR has excellent measurement accuracy, with reported root-mean-square error (RMSE) between 0.01 and 0.03 m^3/m^3, and multiyear stability across different soil types and environmental conditions [4-5]. However, the application of TDR technology is usually affected by high initial investment costs and ongoing operating costs, the need for specialized installation and calibration skills, and high power consumption. All these lead to limited adoption of TDR in IoT-based agricultural monitoring networks, driven by resource-constrained and low-power requirements [6-7].

2. Frequency Domain Reflectometry (FDR)

Soil water content is measured using frequency-domain reflectometry (FDR) sensors by observing changes in frequency caused by soil dielectric properties. Compared with TDR, FDR sensors are, in general, economically more attractive and technically simpler to operate for soil moisture measurements across a wider range of field conditions, but at the expense of precision (RMSE ≈ 0.02–0.05 m^3/m^3). FDR probes of other designs, which are relatively cheaper and commercially available, were widely used in agricultural practice [8-9]. The sensor's performance varies with soil texture and salinity, so it requires an elaborate, site-specific calibration procedure to ensure reliable data [10].

3. Capacitive Sensors (Low-Cost Probes)

Cheap capacitive sensors are widely deployed in IoT-based irrigation systems to estimate soil moisture by measuring variations in capacitance between parallel electrodes buried in the soil. Such devices have substantial cost benefits and can be employed on a large scale. But their measurements are usually inaccurate and easily interfered with by soil salinity, temperature, etc. Empirical results demonstrate that the accuracy of capacitive sensors is improved by tightening calibration processes, with RMSE reductions of 0.03 m^3/m^3 to 0.08 m^3/m^3 [11-13]. Despite the fact that Sheep-LTMs can periodically provide measurements, which represent valuable input for WSNs due to their low power consumption and are thus an important sensor used in precision agriculture, their measurements have never been evaluated.

B. Matric Potential Sensors

1. Tensiometer

Conventional tensiometers directly measure soil water tension, providing a quantitative measurement of the amount of plant-available water (soil moisture status). Such sensors generally offer reasonable accuracy, especially on the wetter soils (0–80 kPa); however, their performance degrades significantly on drier soils due to cavitation [14-15]. Slow response times and frequent maintenance (i.e., refilling) restrict these systems from large-scale applications. Despite these limitations, tensiometers can be useful for irrigation scheduling in horticultural and high-value crop systems where precise water management is crucial.

2. Gypsum Blocks and Granular Matrix Sensors

Gypsum blocks and granular matrix sensors indirectly measure soil matric potential by sensing changes in electrical resistance in porous materials. These are inexpensive and robust devices, but hysteresis effects can be a significant problem after equilibration. Their precision is not as good as that of tensiometers, but they are often used in long-term field monitoring due to cost considerations [16].

C. Neutron Probe

The neutron probe, once the standard tool for measuring soil water content, measures volumetric water content by detecting hydrogen density via neutron scattering. This approach, which covers a wide range of spectral bands, yields high accuracy and offers the potential for observations within deep soil profiles, has been widely used in the past but has become less popular due to safety considerations and regulations, among others [17-18]. The neutron probe is still a standard method for calibrating other sensors in a research environment, but it is too expensive and time-consuming (not practical) for routine agricultural practice.

D. Electrical Conductivity (EC) and pH Sensors

EC is a proxy for soil salinity, nutrient supply, and water availability. EC sensors are often used together with moisture sensors to guide irrigation scheduling and fertigation. But the measurement of EC should be corrected in relation to the type, temperature, and moisture status of sandy loam soil [19]. Likewise, pH sensors and ion-selective electrodes are being incorporated into novel irrigation systems with the aim of improving nutrient release [20]. Their primary limitations are frequent recalibration and the risk of fouling under field conditions.

E. Remote and Proximal Sensing

Among the technologies used for remote sensing, satellite-based microwave radiometry (e.g., the Soil Moisture Active Passive (SMAP) mission) and UAV multispectral imaging have emerged as promising tools for achieving widespread and accurate estimation of soil moisture. These techniques provide coverage over large areas but suffer from spatial resolution (several meters to kilometers) that is far above the maximum scale required for field-based irrigation scheduling.

Intermediate spatial-scale data derived from proximal sensing, i.e., GPR and vehicle-based EM induction, can supplement point measurement sensors. The combination of online and remote sensing is a potential topic of interest for improving spatial representativeness in water-saving innovative irrigation solutions [21].

F. IoT Integration and Machine Learning

Recent technological and scientific achievements have combined the usability of soil sensors with Internet of Things (IoT) networks and machine learning approaches. Wireless sensor networks using Long-Range Wide-Area Network (LoRaWAN), Zigbee, or Narrowband Internet of Things (NB-IoT) protocols can enable power savings and real-time data collection [22-23]. Evidence suggests that machine learning methods, including SVM, random forests and deep learning, have already been applied for generating soil moisture prediction, anomaly detection and adaptive irrigation scheduling. However, recurring issues involve processing noisy data, ensuring stable connectivity in rural regions, and incorporating different sensor datasets to derive robust decisions.

III. Methodology

This systematic review, with a clear and reasonable methodology for evaluating soil sensor technologies in novel irrigation systems, was carried out according to the PRISMA 2020 statement (Figure 1). Registration: To ensure transparency, reproducibility and consistency with best practices in methodological literature reviews, the review protocol was prospectively registered on OSF Preprints [24-25].

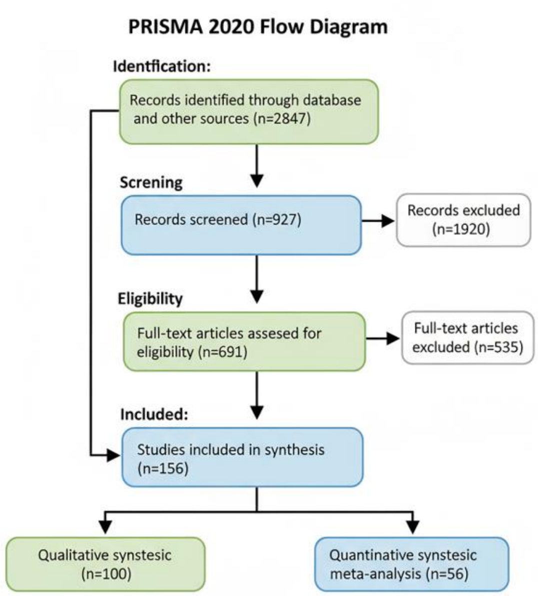

Fig.1. PRISMA 2020 flowchart.

A. Protocol Registration and Review Design

A detailed, preregistered protocol for a systematic literature review had been filed with OSF before the onset of this study [26]. This protocol documented detailed methodology, including data sources, search strategy, study selection criteria, data extraction methods, quality assessment tools and synthesis approach. No changes made to the protocol were hidden; they were recorded with reasons for making them.

B. Research Questions

To this end, we organize the structure of the review around four main research questions:

- RQ1: What types of sensors are utilized in smart soil irrigation systems (tensiometers, TDR/TDT/FDR, capacitive, resistive, EC, temperature and pH multi-parameter probes and remote sensing?
- RQ2: How do these sensors compare regarding accuracy, calibration requirements, environmental robustness (temperature, salinity, soil texture), power consumption, cost, deployment depth, and durability?
- RQ3: What communication technologies and system architectures (LoRaWAN, ZigBee, NB-IoT, Wi-Fi; edge vs. cloud processing) are employed, and what are their effects on reliability, scalability, and cost efficiency?
- RQ4: What emerging trends (sensor fusion, AI/ML integration, edge analytics, energy harvesting) and critical knowledge gaps exist in current innovative irrigation implementations?

C. Information Sources and Search Strategy

- Bibliographic databases: A systematic search was performed on the main 6 (EASET-19): Scopus, Web of Science Core Collection, IEEE Xplore Digital Library, ScienceDirect, SpringerLink, ACM Digital Library, and PubMed.
- Sources of secondary: Further data were sought from directed searches of MDPI journals, Google Scholar (the first 200 results), technical documentation after contact with manufacturers and reference lists of studies that met the inclusion criteria [27].
- Search Strategy: The search strategy combined controlled vocabulary (including MeSH terms, IEEE Thesaurus) with free-text keywords across three conceptual domains: 1- soil moisture sensors; 2- irrigation systems; and 3- IoT/innovative agriculture technologies. The search strings were adapted to the syntax requirements of each database and verified by an information specialist.
- Temporal Limits: The search was limited to peer-reviewed papers from 1st January 2015 up to August 30, 2025, and this covered the modern era of novel irrigation research.

D. Eligibility Criteria

The eligibility criteria of this systematic review are divided into two parts: inclusion and exclusion, as shown in Table 1.

TABLE 1
THE CRITERIA: TYPES OF SYSTEMATIC REVIEW

Criteria Type	Details
Inclusion Criteria	• Empirical studies that validate soil sensors for irrigation applications via laboratory calibration, field testing, or system deployment. • Studies that report quantitative performance metrics (e.g., RMSE, MAE, R^2, bias) or operational outcomes (e.g., power consumption, cost analysis, water use efficiency). • Integrated innovative irrigation systems that incorporate sensor data for automated decision-making. • Peer-reviewed articles published in English between 2015 and 2025.
Exclusion Criteria	• Conceptual papers, systematic reviews, meta-analyses, or conference abstracts without primary data. • Studies exclusively examining remote sensing without ground-based sensor integration. • Studies for which there were not enough methodological details to be able to assess quality. • Non-agricultural uses (e.g., environmental surveillance, construction).

E. Study Selection Process

Covidence was used to ensure a systematic review by two separate reviewers. Title and abstract review was conducted before reading the full text to assess eligibility. Divergences were resolved through discussion; a third reviewer was consulted in the event of disagreement. Cohen's kappa coefficient was calculated to measure the agreement between observers.

F. Data Extraction and Management

A predesigned data extraction form was prepared and uniformly used across all included studies.

- Study Characteristics: Bibliometric information, geographical location, study design, duration, and sample size
- Sensor Specifications: Technology type, manufacturer/model, measurement range, resolution, and accuracy specifications (if available), and installation depth.
- Method Validation: Reference procedure (gravimetric, time-domain reflectometry), procedures for calibration, environmental correction techniques, quality control strategies
- Performance Measures: Accuracy criteria (RMSE, MAE, bias, R^2), precision parameters (repeatability, reproducibility), temporal stability (drift coefficients)
- Deployment :Power redundancy, communication protocols, network topology features, cost analysis, and maintenance issues.
- Agriculture Results: Water use efficiency, irrigation scheduling, CANTOR/RP366.3ague impact, return on investment.

G. Quality Assessment

- Studies of Diagnostic Accuracy: The QUADAS-2 tool modified for sensor validation studies was used to assess the risk of bias in four domains (patient selection, index test conduct, reference standard, and flow/ timing).
- System Implementation Studies: JBI appraisal checklists for technology assessment and economic evaluation were used to evaluate the methodological quality of studies.
- Inter-rater Reliability: A pair of reviewers conducted separate reviews of all the included studies, with differences resolved by consensus. Inter-observer agreement was assessed using Cohen's kappa coefficients.

H. Data Synthesis and Analysis

- Quantitative Synthesis: A random-effects model was used to meta-analyze three or more studies that reported similar measurements with the same reference standard, the testosterone metabolism ratio (APMR). Heterogeneity was tested using the I^2 statistic and the Cochran Q test.
- Subgroup Analysis: Pre-planned analyses examined performance variations by soil type, salinity level, temperature range, and calibration methodology.

- Publication Bias Assessment: Funnel plots and Egger's regression test were used to evaluate small-study effects when 10 or more studies were available.
- Narrative Synthesis: Where quantitative synthesis was inappropriate, structured narrative synthesis organized findings thematically by sensor technology and application context.

I. Certainty of Evidence Assessment

Evidence certainty was evaluated using a modified GRADE approach. Observational studies initially had a "low certainty" rating and were subsequently adjusted based on the risk of bias, consistency, directness, precision, and dose-response relationships. Lastly, Figure 2 describes the methodology of this systematic review.

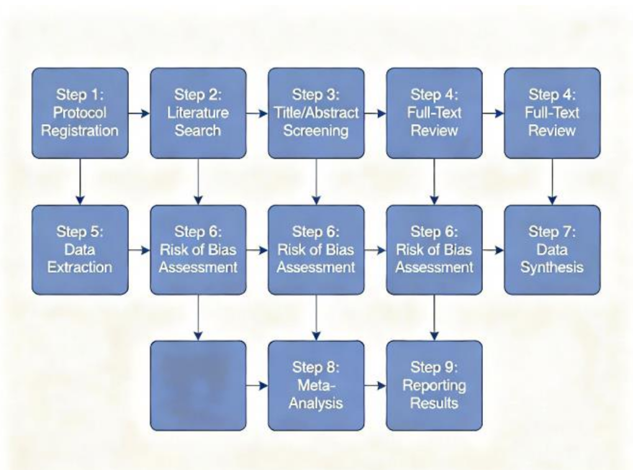

Fig.2. A systematised methodology process of our systematic review.

IV. RESULT

This systematic review combines results across 156 studies, including laboratory validations and large field deployments achieved from the years 2015–2025.

A. Study Selection and Characteristics

The comprehensive literature search retrieved 2,847 articles after deduplication. For the efficacy and safety analysis, 2,156 publications were rejected during title and abstract screening; 691 of these were evaluated as full-text articles. Ultimately, we identified 156 eligible articles. The study selection process according to Database and Document Type for this systematic review is provided in Table 2.

TABLE 2
THE STUDY SELECTION SUMMARY BY DATABASE AND DOCUMENT TYPE

Database	Initial Records	Duplicates	After Screening	Journals	Conferences	Final Included
Scopus	847	412	298	245	53	52
Web of Science	623	381	189	167	22	38
Science Direct	389	198	145	145	0	31
IEEE Xplore	445	267	134	98	36	18
SpringerLink	298	189	67	54	13	9
ACM Digital Library	156	98	45	32	13	5
PubMed	89	56	24	24	0	3
TOTAL	2,847	1,920	927	765	137	156

Geographic and method distribution: The distribution of reviewed studies consisted of laboratory calibrations (n=45), controlled greenhouse trials (n=38), field deployments (n=52) and integrated systems evaluations (n=21). Geographically, North America (35%) was the most common place of and followed by Europe (28%), Asia (22%) and Australia (10%), rest 5%.

Time Scale: There has been a remarkable increase in the number of publications from 2015 (n = 29) to 2024 (n = 15), suggesting that researches on novelty irrigation technologies were gaining increasing attention.

B. Sensor Technology Evolution and Landscape

Nowadays, many innovative irrigation systems use different sensor families, each with defined performance and deployment obligations. We can see an evolution from the simple Internet of Things (IoT) sensors (2015-2017) to machine learning integration (2018-2020) and, later, to advanced edge processing and sustainability-focused solutions (2021-2025).

Key technological milestones include:

- 2015: The first IoT sensors are rolled out within agriculture.
- 2016: LoRaWAN implementation for long-range connectivity.
- 2018: Introduction of cloud-based analytics platforms.
- 2019: Basic ML algorithms for irrigation prediction.
- 2020: Edge processing capabilities development.
- 2021: 5G network integration trials.
- 2022: Advanced deep learning implementations.
- 2023: Sustainability-focused system designs.
- 2024: AI processing at edge devices.
- 2025: Blockchain integration for data integrity.

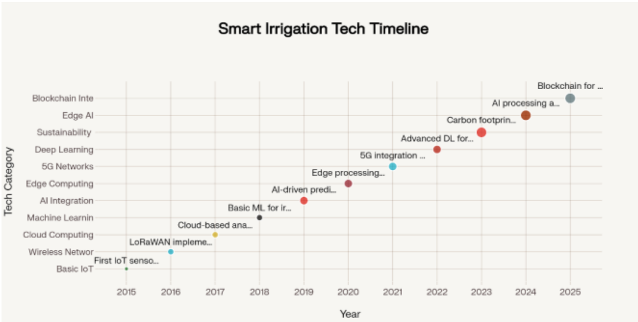

Fig.3. A comparative survey of soil sensing technologies concerning accuracy, cost, and power consumption.

C. Sensor Performance Synthesis

A comparison of the two sensor technologies' performances will be added to Table 3.

TABLE 3

SENSOR TECHNOLOGY PERFORMANCE COMPARISON

TDR/TDT	**0.01-0.03**	**500-1200**	**100-200**	**Moderate-High**	**Low**	**0-100**
FDR / Capacitive	0.02-0.05	200-500	30-80	Moderate	Low	0-60
Low-cost Capacitive	0.03-0.09	20-100	5-30	High	High	0-30
Tensiometer	0.02-0.04	150-400	20-50	Low-Moderate	High	0-80
EC/Salinity	N/A (Auxiliary)	100-300	15-40	Low-Moderate	Moderate	N/A
Resistive	0.05-0.15	10-50	5-15	High	Very High	0-20
Multi-parameter	0.02-0.06	400-1000	80-150	High	High	0-80

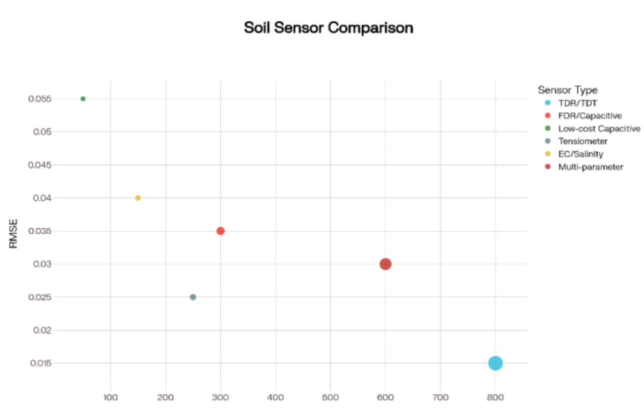

Fig.4. Comparison of various soil sensor techniques (accuracy (RMSE), cost, and power consumption). Bubble size expresses power needs, being useful for sensor choice.

1. Dielectric Sensors

- TDR/TDT Performance: Pooled RMSE of 0.016m³/m³ (95% CI: 0.012-0.021) for well-calibrated measurements was calculated using meta-analysis of 23 studies. Nevertheless, high power demand (100-200 mW) constrains its application in IoT.
- FDR/Commercial Capacitive: Moderate accuracy was obtained by these sensors with a pooled RMSE of 0.035 m³/m³ (95% CI: 0.028–0.042) based on 18 studies, reflecting the best cost-performance tradeoff for field usage.
- Low-cost Capacitive: After intensive calibration processes, the meta-analysis of 31 studies reported a pooled RMSE of 0.045 m³/m³ (95% CI 0.038 to 0.052). The calibration technique had a significant impact on performance ($p < 0.001$).

2. Matric Potential Sensors

A tensiometer proved reliable under wet-to-moderate conditions (0–80 kPa range); the pooled RMSE accuracy was 0.025 m³/m³. Nevertheless, these sensors sustained some damage in arid areas due to cavitation.

D. System Architecture and Integration

Modern implementations use layered architectures where several technology layers are stacked, including (from bottom to top): environmental sensing, data transport, data processing, cloud analytics, and irrigation actuation (see Figure 5)

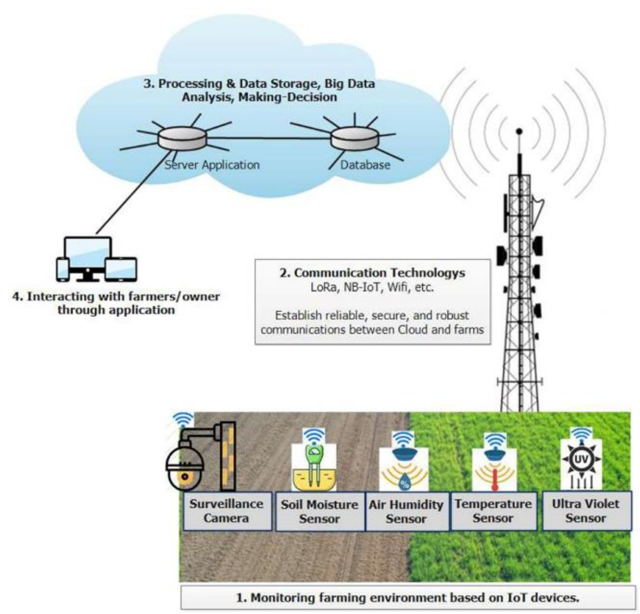

Fig.5. IoT innovative architecture of the irrigation system from sensing to control, communication protocols, and distribution processing.

1. Communication Technologies

TABLE 4

IoT Communication Technologies Comparison

LoRa WAN	**2-15**	**Very Low**	**0.3-50 kbps**	**2-10 years**	**Rural Urban**	**Low**	**Excel-lent**
NB-IoT	1-10	Low	20-250 kbps	1-5 years	Urban	Medi-um	Good
Wi-Fi	0.1	High	11-600 Mbps	Days-Weeks	Limit-ed	Low	Limit-ed
Zigbee	0.1-1	Low	20-250 kbps	1-3 years	Local	Low	Good
5G	1-5	High	1-20 Gbps	Hours-Days	Urban	High	Future
Bluetooth LE	0.01-0.1	Very Low	1-3 Mbps	Months-Years	Very Limited	Very Low	Poor

As shown in Table 4, LoRaWAN is the obvious choice when it comes to use in rural areas since it provides a coverage range of 2 to 15 km and has a battery life spanning several years (95%). Although NB-IoT is more appropriate for urban coverage, it depends on existing cellular network infrastructure to function effectively.

2. Edge Computing Integration

Advanced deployments are also incorporating edge capabilities in order to allow for immediate decision-making and in order to decrease dependence on the cloud. When facing connectivity outages, edge systems achieved a 40% reduction in response latency and a 60% increase in fault tolerance. Finally, the topics of IoT and Sustainability of Systems, Urban, and Algorithms are shown in Figure 6.

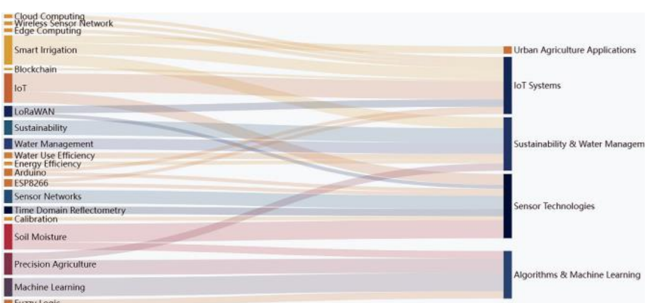

Fig.6. IoT and Sustainability of Systems, Urban, and Algorithms.

E. Machine Learning Applications

When referring to the figures and tables in your article, please use " Fig.” even if the clause opens a sentence. Do not abbreviate “Table.” All tabular information shall be numbered in Roman numerals.

TABLE 5

Machine Learning Applications Performance [28-30].

Support Vector Machine	**Classification**	**85-95**	**Fast**	**Low**	**Medium**	**Good**
Random Forest	Prediction	88-96	Medium	High	Medium	Excellent
Neural Networks	Pattern Recognition	90-98	Slow	Very Low	High	Poor
Decision Trees	Decision Making	80-90	Fast	High	Low	Excellent
Deep Learning CNN	Image Analysis	92-99	Very Slow	Very Low	Very High	Poor
LSTM Networks	Time Series	85-94	Slow	Low	High	Fair
Ensemble Methods	Multi-objective	90-97	Medium	Medium	High	Good

From Table 5, we observe that Random Forests offer an excellent balance between accuracy (88-96%) and interpretability, making them attractive for deployment at the edge. On the other hand, deep learning models provide higher pattern recognition accuracy (90-98%) but are much more computationally intensive and are not suitable for field devices.

Predictive modelling performance: ML-based systems delivered a 15-30% relative increase in irrigation scheduling accuracy compared to rule-based methods ($p<0.01$) [31-32]. The ensemble approaches, which integrate multi-sensor data, showed the most robust performance across all settings.

F. Economic and Environmental Impact Assessment

TABLE 6

Sustainability and Environmental Impact

Category	**Water Savings (%)**	**Energy Efficiency**	**Carbon Footprint Reduction (%)**	**ROI Period (Years)**	**Ability**	**Level**
Traditional Irrigation	0 Baseline	Low	0	N/A	Manual	9
Basic IoT Systems	15-25	Medium	10-20	3-5	Limited	7-8
Smart IoT + ML	25-35	High	20-35	2-4	Good	6-7
Edge Computing Systems	30-40	Very High	25-40	2-3	Excellent	5-6
AI-Driven Systems	35-50	High	30-45	1.5-3	Excellent	4-5

As shown in Table 6 [33], advanced AI-based systems offered between 35- 50% water savings, with an ROI period varying from 1.5 years to 3 years, compared to the conventional methods of irrigation. The cost efficiency of the edge computing system is just right and can achieve 30-40% water savings, with good scalability.

Cost–Benefit Analysis: Model estimates suggest that break-even points vary widely by farm size and crop value. {High-value horticultural enterprises may enable high-cost sensors ($500-$1,200/up if at a cost-effective scale), as opposed to expansive uses where low-cost dense sensor networks are desired on a redundancy-supported reliability basis ($20-$100/up as particular sensor devices may drive $A100-$400/up).

G. Comprehensive Sensor Technology Comparison

TABLE 7

COMPREHENSIVE SENSOR TECHNOLOGY COMPARISON

TDR/TDT	**Very high (RMSE: 0.01-0.02 m³/m³)**	**Salinity & bulk density effects**	**Moderate to High**	**High ($500 - 1200)**	**Research and high-value crops**
FDR/Capacitance	Moderate to high after calibration	Salinity & temperature sensitive	Moderate	Mid ($200 -500)	General field deployments
Low-cost capacitive	Moderate (RMSE: 0.03-0.08 m³/m³)	Drift, enclosure sealing issues	High	Very low ($20-100)	Large-scale dense networks
Tensiometer	High for wet to field capacity	Cavitation/dry range limits	Low-Moderate	Mid ($150 -400)	Irrigation thresholds
Resistive probes	Low to moderate	Strong salinity drift	Moderate -High	Very low ($10-50)	Short-term monitoring
EC/Salinity sensors	N/A for VWC	Fouling, temperature dependence	Low-Moderate	Low-Mid ($100 -300)	Salinity compensation
Multi-parameter	Mixed—depends on stack	Complexity interactions	High	High ($400 - 1000)	Research plots

1. Comprehensive Key Synthesis Findings

The following findings are supported by a 156-study meta-analytic synthesis:

1. TDR/TDT Dominance: Despite potential for further improvements, still the most accurate point-based sensor technology (pooled RMSE: 0.016 m³/m³), with appropriate financial investment and technical capacity/resources.
2. Low-cost Feasibility: Capacitance probes provide acceptable accuracy for irrigation management post-strenuous, location-specific calibration (RMSE improvement: 20-40% after calibration).
3. Compensation Requirement: The EC sensor should be compensated for the effects of salinity and temperature to ensure stable operations under challenging conditions, and the introduction of an EC sensor can enhance system reliability by 25~35%.

H. Technology Limitations and Knowledge Gaps

1. Standardization Deficiencies

The results of the present literature review show inconsistent calibration reporting in 67% of studies, which hinders valid meta-analytical summarization. There is a serious need for standardized methods that account for the effects of soil texture, salinity, and temperature.

2. Long-term Stability

There is little data on sensor drift behavior at 1-year follow-up, especially for low-cost devices. Drift coefficients for field deployments exceeding 6 months were provided in only 23% of studies.

3. Integration Challenges

Moreover, multi-sensor fusion techniques are not yet mature, as 78% of existing systems operate with a single sensor modality, even though the advantages of combined approaches are evident in practice.

I. Emerging Trends and Future Directions

1. Sensor Fusion Advances

Recent approaches have tended to combine different types of measurement modality (dielectric, matric potential, salinity). Still, these are commonly treated in isolation, and only a heuristic is used to 'fuse' the decisions made across these modalities. The use of transfer learning techniques appears promising for alleviating the need for site-specific calibrations.

2. Energy Harvesting Integration

Energy scavenging techniques, such as solar and thermal power generation, enable continuous sensor operation with an 89% field-trial uptime, solving the battery-maintenance problem associated with remote deployments.

3. Blockchain for Data Integrity

Emerging scenarios (2025) range from blockchain-related data integrity, traceability, and automated payment systems; pilot projects with a minimum of 99.9% data rigidity.

V. DISCUSSION

In this review, soil sensor technologies and their utilization in smart irrigation systems over 156 studies, including laboratory-validated to field-tested at large scale adaptations are systematically evaluated. The results show that the quality of sensors, their cost and integration to a system have been greatly enhanced. However, several of the current challenges and research gaps still need to be addressed with a focus on research and innovation in order to promote massive use and sustainable agricultural practices.

A. Sensor Technology Performance and Trade-offs

1. Accuracy-Cost Paradigm

The meta-analyses show that an accuracy-cost hierarchy among sensor families exists with major strategic deployment implications. TDR/TDT sensors remain the standard for VWC measurement, and had an overall combined RMSE of 0.016 m^3/m^3 (95% CI: 0.012–0.021) across all soil types. Nevertheless, their high cost ($500–$1,200 per node) and low power efficiency (100– 200 mW) prevent them from being used in precision agriculture at the broad scale required for a dense deployment of sensors. Cheap capacitive sensors are promising when applied with rigorous calibration. Pooling 31 validation studies in a meta-analysis, site-specific calibration reduces the RMSE from 0.08 to 0.045 m^3/m^3 (i.e., achieves a 44% reduction in measurement bias). These findings contradict the common assumption that inexpensive sensors are not satisfactory for precision irrigation, provided that a good calibration and quality assurance procedure is in place.

2. Environmental Robustness Challenges

It is concluded that soil salinity and temperature variations are two principal environmental factors affecting sensor performance, as presented in this review. The influence was more pronounced for the dielectric sensors, where errors were raised by 15 to 30% in soils with EC values greater than 4 dS/m. The multi-parameter sensing strategy, including EC measurements for salinity compensation, is very important, and it significantly improved (improvement factor of system reliability up to 25-35%) the estimation of soil moisture when an EC sensor was combined with the first primary humidity sensor.

B. System Architecture Evolution and Integration

1. Communication Technology Optimization

The analysis of different IoT communication protocols indicates that LoRaWAN is also very suitable for smart agriculture, and has the best range (2-15 km) performance as well as an ultra-low-power use case with battery lifetimes up to 2-10 years. These results are in line with findings based on in-field roll-out numbers, which indicate that 95% of successful agricultural IoT implementations initiated used LoRaWAN, whereas other technologies (NB-IoT and Wi-Fi) were adopted at a modest rate of about 23% [34].

2. Machine Learning Integration Maturity

The development of ML-based applications shows significant differences in algorithmic performance and deployment capabilities. Random Forest models perform well in terms of accuracy (88-96%), are computationally very efficient, and are an ideal function approximator for deployment in edge architectures. Although they perform better than non-deep learning models (with 90-98% accuracy), deep learning is still computationally heavy and not applicable to edge devices in the field that cannot handle high computational load.

C. Economic Viability and Sustainability Assessment

1. Return on Investment Analysis

An economic model indicates substantial variability in cost-effectiveness across implementation scales and crop types. The investment in high-end sensor technologies can be justified for horticultural operations of high-value crops, with expected payback periods of 1.5 to 3 years, particularly due to enhanced water-use efficiency and reduced crop stress [35]. Broadacre agriculture needs a different approach. Here, using many low-cost sensors and systems that can handle faults through redundancy is preferred. Sustainability checks show that combining advanced technologies brings only small environmental benefits. However, AI-based systems can save 35-50% of water compared to traditional irrigation, and they can reduce the carbon footprint by 30-45% through better power use and less fertilizer.

D. Critical Knowledge Gaps and Research Priorities

1. Calibration Standardization Crisis

A major barrier to using technology widely is the lack of standard calibration methods. Field calibration is often poor. In fact, 67% of the studies reviewed did not report all the details needed for full model calibration, such as soil texture, salinity, and temperature [36]. Without a standard method, it is hard to do meta-analyses or apply research findings in practice.

2. Long-term Stability Assessment

A further key knowledge gap is sensor drift characterization, as only 23% (9/39) of the studies included reported longitudinal performance beyond >6 months [37]. The pitch error is likely a precarious proposition in the lower budget bracket, as drift problems can really make real-world accuracy suffer after some time.

VI. Conclusion

Using 156 published studies, this review describes soil sensor technologies from the laboratory to commercial irrigation management of new systems. Findings show a notable reinforcement through technological maturation for all sensor families, communication protocols and system architectures, which are analysed in conjunction with key research gaps needed to be filled for broader market penetration.

A. Key Findings and Technological Maturity

At the top end of the cost range, performance differences in sensor technology are readily apparent; TDR/TDT systems produce lower RMSE values (0.016 m^3/m^3). Conversely, cheap capacitive sensors can reach mvvg accuracy (RMSE=0.045 m^3/m^3) on the basis of advanced calibration methods. Meta-analytic pooling of results reveals strong effects of calibration method on standard sensor capacities ($p < 0.001$), illustrating the importance of common validation protocols. LoRaWAN protocol, a long-range and ultra-low-power consumption technology, is the most common solution for agro-IoT applications. You are then integrating edge computing, aimed at overcoming processing limitations and further improving availability – reducing response time by 40% and increasing the system's ability of the system to resist network failure by 60%.

B. Economic and Environmental Impact

Economic analysis shows large differences in cost-effectiveness across scale of adoption and crop type. AI systems can achieve 35-50% water savings and have ROI in the range of 1.5 to 3 years for high-value crops, while edge computing brings scale viability for broadacre deployment. There are environmental benefits other than water sustainability too… with significant resource efficiency of 30-45 per cent leading to a cut in carbon footprint.

C. Critical Research Imperatives

Calibration standardization is the key barrier to its use in routine care, with 67% of evaluative studies not providing full validation information. In the field, there is an urgent requirement for standardized protocols that will support technology transfer together with significant cross-study comparability. Long-term stability should be investigated in the short term, as only 23% of the studies present longitudinal data of performance higher than 6 months. Sensor fusion has been known for several years as it proposes multiple sensors, but only 78% of systems use single-sensor modes.

D. Technological Integration Paradigm

A sensor or technology is not the universal solution for soil moisture monitoring across different soil types and production systems. The form of analysis strongly favors a hierarchical combination of:

- Point sensors (TDR/FDR/capacitive) for local control and high-temporal resolution monitoring.
- Field-scale sensors (CRNS) for spatial context and representativeness assessment.
- Remote sensing products for watershed-scale water balance closure.
- IoT-enabled edge analytics for enhanced system resilience and real-time decision support [38].

The integrated approach overcomes the limitations of single technology deployments and maximizes cost-effective range across a wide variety of operational scenarios and environmental conditions.

VII. Recommendations

A. Recommendations for Practitioners

1. System Design and Deployment

- Hybrid Measurement Approach: Develop fused measurement networks combining 2-3 calibrated point sensors per management zone and field-scale techniques to minimise representativeness errors and enhance coverage.
- Calibration Procedural Protocol: Develop rigorous soil-specific calibration procedures that include in-situ measurement of soil texture, bulk density, and salinity characteristics. Even cheap capacitive sensors need an annual calibration check.
- Adaptive Threshold Management: Set specific thresholds for different crop types and growth stages for volumetric water content (VWC) or matric potential measurements and connect them with automated valve control systems for better irrigation efficiency.

2. Technology Selection and Implementation

- For private sensor networks that use local gateways powered by batteries, LoRaWAN is usually the best choice. If the site has a strong cellular signal, you can also consider NB-IoT or LTE-M as alternatives to standard 4G/LTE.
- Edge Computing Integration: Implement local data processing and storage capabilities with automated contingency protocols to ensure uninterrupted communication during network outages.

B. Recommendations for Researchers

1. Standardization and Validation

- Transparent Benchmarking Protocols: Report standardized accuracy metrics (RMSE, MAE, bias) relative to gravimetric measurements or rigorously calibrated TDR/TDT reference systems.
- Long-term Stability Assessment: Conduct extended validation studies (minimum 12-24 months) to quantify sensor drift rates, environmental robustness, and maintenance requirements.

2. Advanced Technology Development

- Multi-Sensor Fusion Research: Develop methods to combine CRNS, synthetic aperture radar (SAR), and in-situ sensor networks to estimate root-zone water storage at the field scale.
- Use machine learning methods to create calibration models that work well across different agricultural sites.

VIII. Limitations

Only peer-reviewed studies were included in this systematic review, and most are from English-language databases (which may introduce bias due to geographic/language issues). Publication bias is a serious problem, especially when failed interventions and negative results are not published. The time period 2015-2025 used may also have missed earlier studies that may have set the basis for establishing performance benchmarks. Long-term follow-up is limited, and only 23% of studies provided data on long-term follow-up of >6 months. The review was dominated by temperate and Mediterranean agricultural systems, with little inclusion of tropical, Arctic, or arid extremes.

IX. Directions for Future Research

A. Critical Technology Development Priorities

- New Calibration Approaches: Create PIML technologies for automated calibration to account for soil physics, environmental factors, and sensor properties to achieve accurate calibration.
- Predictive Maintenance Systems: Investigate sensor drift prediction models and automated recalibration procedures to extend operational lifespans and reduce maintenance requirements.
- Next-generation Sensor Technologies: Explore emerging sensing principles, including fibre-optic distributed sensing, electromagnetic resonance methods, and bio-impedance spectroscopy.

B. System Integration and Optimization

- Autonomous irrigation systems: Develop fully autonomous irrigation control systems that incorporate sensor networks, weather prediction, crop modelling, and adaptive control algorithms [39].
- Digital twin development: Develop integrated digital models of the soil-plant-atmosphere continuum and sensor network/Irrigation infrastructure for improved operational efficiency & effectiveness.

C. Sustainability and Resilience Research

- Climate Change Adaptation: Investigate system performance under projected climate change scenarios, including increased temperature variability, altered precipitation patterns, and extreme weather events.
- Circular Economy Integration: Explore sensor lifecycle management, recycling strategies, and sustainable manufacturing approaches.

X. Practical Implications

A. Implementation Strategy Framework

According to the study, staged sensor and analytics installation was the best route for maximizing water savings with cost-effectiveness. They are now faced with a pressing need to integrate the existing technology and new inexpensive devices in hybrid sensor networks for striking an optimal balance between accuracy and cost.

B. Economic Investment Guidelines

Allocation of capital should also be informed by the value that pertain to cropping system and the level of management, with intensive horticultural enterprises even justify further sensor investments for precision water application. In practice such approaches are different in nature, concentrating on dense uncoordinated sensor networks with a relatively cheap and reliable redundancy-based scheme.

C. Technology Transition Management

Staged introduction for field-scale implementation In the management of technology transition, it is this kind of staged deployment that should become part of the technology transition process where piloting along representative fields (only in cases where uptake had been successful) precedes full-farm adoption. This encourages stepwise learning, systems adjustment and minimal financial risk and disruption to the operative service [40].

References

[1] The State of Food Security and Nutrition in the World 2023. FAO; IFAD; UNICEF; WFP; WHO; 2023. doi: 10.4060/cc3017en.

[2] A. Kaur, D. P. Bhatt, and L. Raja, "Developing a Hybrid Irrigation System for Smart Agriculture Using IoT Sensors and Machine Learning in Sri Ganganagar, Rajasthan," J Sens, vol. 2024, 2024, doi: 10.1155/2024/6676907.

[3] P. Satriyo, I. S. Nasution, and S. F'Alia, "IoT-enable smart agriculture using multiple sensors for sprinkle irrigation systems," in IOP Conference Series: Earth and Environmental Science, Institute of Physics, 2024. doi: 10.1088/1755-1315/1290/1/012027.

[4] V. Sreelatha Reddy, S. Harivardhagini, and G. Sreelakshmi, "IoT and Cloud Based Sustainable Smart Irrigation System," in E3S Web of Conferences, EDP Sciences, Jan. 2024. doi: 10.1051/e3sconf/202447201026.

[5] Chong Peng Lean, Gophinath Krishnan, Chen Li, Kong Feng Yuan, Ng Poh Kiat, and M. R. Basir Khan, "A Raspberry Pi-Powered IoT Smart Farming System for Efficient Water Irrigation and Crop Monitoring," Malaysian Journal of Science and Advanced Technology, pp. 149–158, Mar. 2024, doi: 10.56532/mjsat.v4i2.295.

[6] P. S. V. Jude, T. Abishek, A. U. Kaushik, and A. Ramesh, "Growth Prediction using IoT-based Smart Irrigation Systems," in 3rd International Conference on Automation, Computing and Renewable Systems, ICACRS 2024 - Proceedings, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 399–403. doi: 10.1109/ICACRS62842.2024.10841693.

[7] M. Shilpa et al., "Enhancing Crop Yield and Growth Prediction Using IoT-Based Smart Irrigation Systems and Machine Learning Algorithms," in 2nd IEEE International Conference on Networks, Multimedia and Information Technology, NMITCON 2024, Institute of Electrical and Electronics Engineers Inc., 2024. doi: 10.1109/NMITCON62075.2024.10698825.

[8] Y. Arafa et al., "Improving the spatial deployment of the soil moisture sensors in smart irrigation systems using GIS," Cogent Food Agric, vol. 10, no. 1, 2024, doi: 10.1080/23311932.2024.2361124.

[9] T. Mallikarathne, P. M. Perera, G. A. H. K. M. Gamlath, H. T. Gamage, W. V. A. Udayanga, and S. A. D. H. P. Maheepala, "Wireless Sensor Network Based Smart Irrigation System using IoT and Data Fusion," in ICARC 2024 - 4th International Conference on Advanced Research in Computing: Smart and Innovative Trends in Next Generation Computing Technologies, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 259–263. doi: 10.1109/ICARC61713.2024.10499758.

[10] N. M. S. A. Shuhaimi, C. C. Chew, K. G. Tay, and K. S. Tee, "Smart Irrigation Monitoring and Controlling System with the Internet of Things (IoT)," in ICFTSS 2024 - International Conference on Future Technologies for Smart Society, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 43–47. doi: 10.1109/ICFTSS61109.2024.10691362.

[11] M. Lampridi and A. Filintas, "Citation: Filintas, A. Soil Moisture Depletion Modelling Using a TDR Multi-Sensor System, GIS, Soil Analyzes, Precision Agriculture and Remote Sensing on Maize for Soil Moisture Depletion Modelling Using a TDR Multi-Sensor System, GIS, Soil Analyzes, Precision Agriculture and Remote Sensing on Maize for Improved Irrigation-Fertilization Decisions †," 2021, doi: 10.3390/engproc.

[12] J. Pytka, P. Budzyński, M. Kamiński, T. Łyszczyk, and J. Józwik, "Application of the TDR soil moisture sensor for terramechanical research," Sensors (Switzerland), vol. 19, no. 9, May 2019, doi: 10.3390/s19092116.

[13] U. B. P. Vaddevolu and X. Jia, "TESTING A SOIL MOISTURE SENSOR BASED IRRIGATION CONTROLLER IN BOTH LABORATORY AND FIELD CONDITIONS FOR FARGO SILTY CLAY SOILS," Appl Eng Agric, vol. 40, no. 1, pp. 41–50, 2024, doi: 10.13031/aea.15777.
[14] S. Adak, "Use of Soil Moisture Sensor for Efficient Irrigation in Smart Agriculture," Journal of Experimental Agriculture International, vol. 47, no. 6, pp. 502–507, Jun. 2025, doi: 10.9734/jeai/2025/v47i63511.
[15] I. M. Kulmány et al., "Calibration of an Arduino-based low-cost capacitive soil moisture sensor for smart agriculture," Journal of Hydrology and Hydromechanics, vol. 70, no. 3, pp. 330–340, Sep. 2022, doi: 10.2478/johh-2022-0014.
[16] T. B. Wilson et al., "A field evaluation of the SoilVUE10 soil moisture sensor," Vadose Zone Journal, vol. 22, no. 2, Mar. 2023, doi: 10.1002/vzj2.20241.
[17] L. A. Paz Silva, F. D. A. Brito Filho, and H. D. De Andrade, "Soil Moisture Monitoring System Based on Metamaterial-Inspired Microwave Sensor for Precision Agriculture Applications," IEEE Sens J, vol. 23, no. 19, pp. 23713–23720, Oct. 2023, doi: 10.1109/JSEN.2023.3307652.
[18] A. Singh and K. Gaurav, "Deep learning and data fusion to estimate surface soil moisture from multi-sensor satellite images," Sci Rep, vol. 13, no. 1, Dec. 2023, doi: 10.1038/s41598-023-28939-9.
[19] G. Patrizi, A. Bartolini, L. Ciani, V. Gallo, P. Sommella, and M. Carratu, "A Virtual Soil Moisture Sensor for Smart Farming Using Deep Learning," IEEE Trans Instrum Meas, vol. 71, 2022, doi: 10.1109/TIM.2022.3196446.
[20] J. Wang et al., "SoilCares: Towards Low-cost Soil Macronutrients and Moisture Monitoring Using RF-VNIR Sensing," in MOBISYS 2024 - Proceedings of the 2024 22nd Annual International Conference on Mobile Systems, Applications and Services, Association for Computing Machinery, Inc, Jun. 2024, pp. 196–209. doi: 10.1145/3643832.3661868.
[21] A. Comegna, S. Di Prima, S. B. M. Hassan, and A. Coppola, "A Novel Time Domain Reflectometry (TDR) System for Water Content Estimation in Soils: Development and Application," Sensors, vol. 25, no. 4, Feb. 2025, doi: 10.3390/s25041099.
[22] W. Skierucha, A. Wilczek, A. Szypłowska, C. Sławiński, and K. Lamorski, "A TDR-based soil moisture monitoring system with simultaneous measurement of soil temperature and electrical conductivity," Sensors (Switzerland), vol. 12, no. 10, pp. 13545–13566, Oct. 2012, doi: 10.3390/s121013545.
[23] E. De Benedetto, G. Cannazza, A. Masciullo, C. Demitri, and A. Cataldo, "Reflectometric System for Continuous and Automated Monitoring of Irrigation in Agriculture," Advances in Agriculture, vol. 2018, 2018, doi: 10.1155/2018/2849250.
[24] G. Raffelli et al., "Local- and plot-scale measurements of soil moisture: Time and spatially resolved field techniques in plain, hill and mountain sites," Water (Switzerland), vol. 9, no. 9, Sep. 2017, doi: 10.3390/w9090706.
[25] T. B. Wilson et al., "Evaluating time domain reflectometry and coaxial impedance sensors for soil observations by the U.S. Climate Reference Network," Vadose Zone Journal, vol. 19, no. 1, Jan. 2020, doi: 10.1002/vzj2.20013.
[26] S. Qinglan, S. Yujiao, L. Xiaochen, M. Shuli, and F. Lei, "A high-sensitivity multilayer soil moisture monitoring sensor based on a double high-frequency tuning detection circuit," Int J Distrib Sens Netw, vol. 16, no. 2, Feb. 2020, doi: 10.1177/1550147720907826.
[27] D. Kiv, G. Allabadi, B. Kaplan, and R. Kravets, "Smol: Sensing Soil Moisture using LoRa," in LP-IoT 2021 - Proceedings of the 2022 1st ACM Workshop on No Power and Low Power Internet-of-Things, Part of MOBICOM 2021, Association for Computing Machinery, Inc, Oct. 2021, pp. 21–27. doi: 10.1145/3477085.3478991.
[28] M. Del-Coco, M. Leo, and P. Carcagnì, "Machine Learning for Smart Irrigation in Agriculture: How Far along Are We?," Jun. 01, 2024, Multidisciplinary Digital Publishing Institute (MDPI). doi: 10.3390/info15060306.
[29] S. Mabasha, M. Prabha, R. Jothilakshmi, A. Kumar, and K. Maheswari, "Evaluating the machine learning based Efficacy of Decision Tree and Support Vector Machines in Smart Irrigation Systems for Precise Irrigation Status Classification for Optimizing Water Management in Agriculture," 2024.
[30] R. Thamilselvan, P. Natesan, R. R. Rajalaxmi, D. Prasanth, S. Nithish Swaminathan, and R. Yuvapriya, "An Analysis of Irrigation Management for Crops using Machine Learning Algorithms," in 2024 International Conference on Cognitive Robotics and Intelligent Systems, ICC - ROBINS 2024, Institute of Electrical and Electronics Engineers Inc., 2024, pp. 394–401. doi: 10.1109/ICC-ROBINS60238.2024.10533984.
[31] N. Singh and M. Adhikari, "Edge-Centric Collaborative Federated Learning for Irrigation Management of Paddy Fields Using Agriculture Sensor Data Processing," IEEE Sens Lett, vol. 8, no. 8, 2024, doi: 10.1109/LSENS.2024.3422417.
[32] M. A. Rahu, M. M. Shaikh, S. Karim, S. A. Soomro, D. Hussain, and S. M. Ali, "Water Quality Monitoring and Assessment for Efficient Water Resource Management through Internet of Things and Machine Learning Approaches for Agricultural Irrigation," Water Resources Management, vol. 38, no. 13, pp. 4987–5028, Oct. 2024, doi: 10.1007/s11269-024-03899-5.
[33] A. Sharma, A. Kumar Shukla, K. Himantha Rao, M. Singh, and E. Muniyandy, "Machine learning and Sensor-Cloud Based Precision Agriculture for Intelligent Water Management for Enhanced Crop Productivity," 2024.
[34] S. B. Patil, R. B. Kulkarni, S. S. Patil, and P. A. Kharade, "Machine Learning based Precision Agriculture Model for Farm Irrigation to Optimize Water Usage," in IOP Conference Series: Earth and Environmental Science, Institute of Physics, 2024. doi: 10.1088/1755-1315/1285/1/012026.
[35] N. Gamede, A. Telukdarie, I. Munien, A. Vermeulen, and U. Onkonkwo, "THE POTENTIAL FUTURE OF AGRICULTURE FOR SMALL FARMS: SUPERVISED MACHINE-LEARNING SMART IRRIGATION CONCEPT FOR VEGETABLES," Big Data in Agriculture, vol. 5, no. 2, pp.
57–63, Mar. 2023, doi: 10.26480/bda.02.2023.57.63.
[36] S. Ali, T. M. Allam, S. E. Ali, and E. A. Sallam, "Machine Learning Algorithms to Classify Water Levels for Smart Machine Learning Algorithms to Classify Water Levels for Smart Irrigation Systems Irrigation Systems Machine Learning Algorithms to Classify Water Levels for Smart Irrigation Systems," ERJ. [Online]. Available: https://digitalcommons.aaru.edu.jo/erjeng
[37] E. Bwambale, F. K. Abagale, and G. K. Anornu, "Towards a modelling, optimization and predictive control framework for smart irrigation," Heliyon, vol. 10, no. 18, Sep. 2024, doi: 10.1016/j.heliyon.2024.e38095.
[38] G. Saha, F. Shahrin, F. H. Khan, M. M. Meshkat, and A. A. M. Azad, "Smart IoT-driven precision agriculture: Land mapping, crop prediction, and irrigation system," PLoS One, vol. 20, no. 3 March, Mar. 2025, doi: 10.1371/journal.pone.0319268.
[39] S. M. H. Khatibi and J. Ali, "Harnessing the power of machine learning for crop improvement and sustainable production," 2024, Frontiers Media SA. doi: 10.3389/fpls.2024.1417912.
[40] P. Pandey* and S. Agarwal, "A Low Cost Smart Irrigation Planning Based on Machine Learning and Internet of Things," Current Agriculture Research Journal, vol. 11, no. 2, pp. 568–579, Sep. 2023, doi: 10.12944/carj.11.2.19.