Sensor-Based Assessment of Plant Water Status in Smart Irrigation Systems: A Critical Review of Technologies, Evidence, and Emerging Directions

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ABSTRACT
Background: The combination of declining water sources and worsening rainfall variations has resulted in the strain that has never been seen before on irrigated agriculture. Analytics that use sensors to measure plant water status have become a key element in the innovations aimed at finding a suitable compromise between productivity and water efficiency in agriculture.
Objective: This article provides an overview of the available literature on the concept of the technologies utilizing sensors to assess plant water status, including soil-based, plant-based, and remote canopy measurement methods, as well as how these technologies can become part of IoT- and AI-enabled smart irrigation systems. Sources of literature: In order to identify the suitable records published between 2015 and 2025, an organized search was conducted across the Scopus, Web of Science, PubMed, Google Scholar databases, and websites of relevant government and international organizations, in addition to methodological papers published before 2015. As part of the systematic review, 66 records were evaluated for full text, out of which 34 met the conditions for inclusion and were used for the thematic synthesis.
Key conclusions: The existing literature shows that there is not a single type of sensor that would be able to provide a universal standard for assessing moisture levels in plants; however, sensors measuring soil moisture (capacitive sensors, time domain reflectometers, tensiometers) are said to be cheap but indirect; while sensors measuring plant sap flow or bark expansion (the movements of the trunk) provide direct but labor-intensive results of water measurement, remote sensing methods (infrared thermography, thermal imaging) allow for scalable evaluation but complicate the calibration process. It has been acknowledged that using this array of sensors within IoT frameworks allows using up to 40% less irrigation water without decreasing the yield.
The ongoing lack of standardized calibration standards that apply to all soil types and cultivars, limited field evidence from multiple years and sites, the difficulty in integrating different types of sensor data, and unresolved issues regarding cybersecurity and interoperability for using sensors for agriculture on small farms are persistent gaps in the knowledge.
In conclusion, while the technology behind the sensor-based plant water status evaluation is relatively mature, its application is hindered by some fragmentation in real-life practices; therefore, future studies should focus on creating a comprehensive and affordable sensing systems based on multi-modal data combination and unified calibration standards.

Keywords: plant water status; smart irrigation; soil moisture sensors; crop water stress index; sap flow; Internet of Things; precision agriculture; machine learning

1. Introduction
Agriculture holds the top position as the largest user of freshwater in the world, with total withdrawals exceeding seventy percent worldwide and continually rising due to population growth, food consumption and climate change. Thus, increasing irrigation efficiency is essential for food safety, rural livelihoods, and sustainable use of resources. An important part of any irrigation efficiency improvement strategy is efficient measurement of water status of crops, which provides information about the balance between water absorbed by roots and water lost through transpiration.
An array of sensing technologies has developed within the last twenty years to fill this information gap. These technologies fall into three categories: soil-based sensors that determine the water available for plants through the medium where the roots are located; plant sensors that monitor physiological and morphological reactions of plants; and canopy or remote-sensing sensors that analyze the thermal, spectral, or structural properties of crop canopies. Each of these categories has a different level of directness of measurement, cost, spatial range, and operational complexity. The development of inexpensive microcontrollers, wireless sensor networks, and cloud computing technology has contributed to the emergence of IoT-embedded smart irrigation systems capable of permanent collection, distribution, and application of data from sensors, often with the help of machine learning (ML), artificial intelligence (AI), and similar systems that allow processing of signals from the sensors to provide for irrigation decisions.

The current state of technology is one characterized by rapid adoption and diffusion but at different rates between industries. The wealthy countries as well as research-based agriculture are adopting increasingly complex systems for monitoring plant moisture while the less wealthy economies continue to operate using movements or even without proper systems for monitoring. Various bodies including the Food and Agricultural Organization have identified water efficiency as well as precision irrigation as one of the most important mechanisms towards achieving Sustainable Development Goal No. 6 as well as its targets of food security [1]. In spite of the increase in interest surrounding the technology, the available scientific literature on plant water status using sensors is very limited and segmented across various fields such as plant science, soil science, engineering and data science.

The review seeks to (i) document and critically evaluate the major sensor technologies for assessing plant water status, (ii) provide a synthesis of information on their accuracy, reliability, and practical feasibility in different cropping environments, (iii) assess the use of the sensors in IoT and AI-integrated smart irrigation systems, and (iv) list key gaps in previous studies indicating future research trends. Published mainly between 2015 and 2025, the review analysis focuses on the articles published in peer-reviewed journals, with a limited use of important publications predating 2015 and forming the theoretical basis for the main indices used today, for example, crop water stress index (CWSI), coupled with required governmental and international organisations' publications. The review focuses on the technologies used for geoinformation and decision-making related to agricultural production, completely neglecting approaches related to genetics and breeding and other traditional methods of dealing with drought.

2. Methodology of Literature Review

2.1 Literature Search Strategy

A structured literature search was conducted across four principal sources: Scopus, Web of Science, PubMed, and Google Scholar, supplemented by targeted searches of institutional and international-organisation repositories (including the Food and Agriculture Organization's AQUASTAT database) for grey literature and technical reports. The search covered the period January 2015 to July 2025, with a small number of seminal studies published before 2015 retained where they established foundational theory (for example, the original formulation of the crop water stress index and the pressure-chamber technique for measuring stem water potential). Boolean search strings combined controlled vocabulary and free-text keywords, including combinations of "plant water status", "water stress", "soil moisture sensor", "sap flow", "stem water potential", "crop water stress index", "infrared thermometry", "smart irrigation", "Internet of Things", and "precision irrigation". Table 1 summarises the search strategy applied to each database.

Table 1: Literature Search Strategy

Database	Representative search string / keywords	Filters applied	Period	Records retrieved
Scopus	("plant water status" OR "water stress") AND ("sensor*" OR "IoT" OR "smart irrigation")	Article, English, Subject: Agri/Eng	2015-2025	612
Web of Science	TS=("plant water status" OR "crop water stress index") AND TS=(sensor OR "smart irrigation")	Article/Review, English	2015-2025	498
PubMed	("plant water status"[tiab]) AND (sensor[tiab] OR "irrigation"[tiab])	English, Humans excluded	2015-2025	214
Google Scholar / grey literature	"sensor-based irrigation" "plant water status" review	First 200 results screened	2015-2025	176

2.2 Inclusion and Exclusion Criteria

Studies were included or excluded according to pre-defined criteria (Table 2), applied independently to titles/abstracts and then to full texts.

Table 2: Inclusion and Exclusion Criteria

Category	Inclusion criteria	Exclusion criteria
Publication type	Peer-reviewed journal articles, systematic reviews, conference papers with full methodology	Editorials, non-peer-reviewed blogs, opinion pieces without empirical or synthesised content
Language	English-language publications	Non-English publications without validated translation
Time frame	Published 2015-2025 (foundational pre-2015 studies retained where methodologically seminal)	Superseded early studies with no continuing methodological relevance
Topical relevance	Studies addressing sensor-based plant, soil, or canopy water status assessment and/or smart irrigation integration	Studies on drought genetics/breeding, purely agronomic water management without sensing component
Data quality	Original data, validated methodology, or systematic synthesis reported	Duplicate records, retracted articles, studies with unverifiable methodology

2.3 Study Selection Process

The study selection process followed a PRISMA-informed workflow (Figure 1). An initial pool of 1,500 records was retrieved across the four databases. After removal of 358 duplicate records, 1,142 unique records were screened by title and abstract, of which 812 were excluded as topically irrelevant (for example, studies addressing irrigation infrastructure without a sensing component, or purely genomic drought-tolerance studies). The remaining 330 records were assessed in full text against the inclusion and exclusion criteria in Table 2, resulting in exclusion of a further 264 records, chiefly for lack of methodological detail, duplication of findings already captured by a more comprehensive source, or insufficient relevance to smart irrigation applications. Sixty-six studies m*et al*l inclusion criteria; of these, thirty-four were selected to form the core reference base for qualitative thematic synthesis reported in this review, prioritised for topical diversity across sensing modalities, geographic representation, and recency.

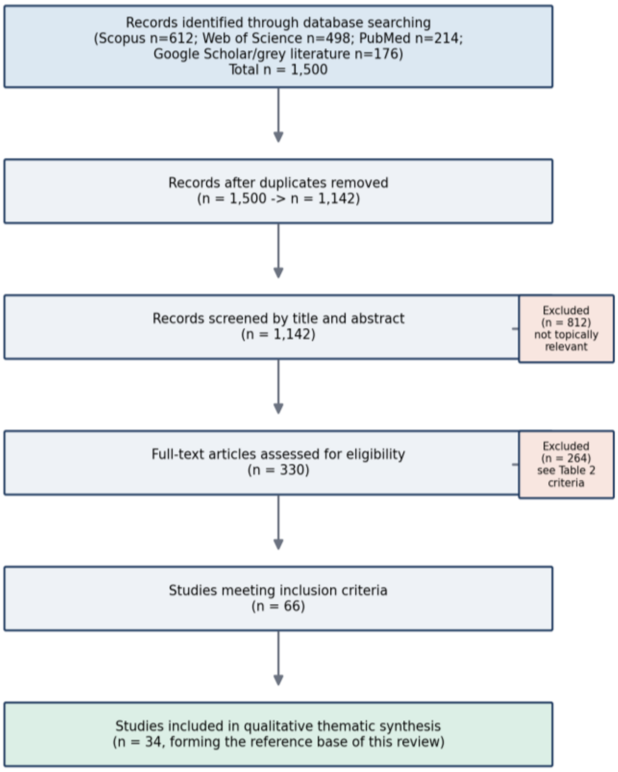

Fig 1: PRISMA-informed flow diagram of the literature search and study selection process.

The temporal distribution of the retrieved literature (Figure 2) shows a marked acceleration in publication output after 2019, coinciding with the wider commercial availability of low-cost microcontrollers (for example, ESP8266/ESP32 platforms), long-range wireless communication protocols, and cloud-based analytics services, consistent with the broader diffusion of IoT technologies into precision agriculture [27, 32].

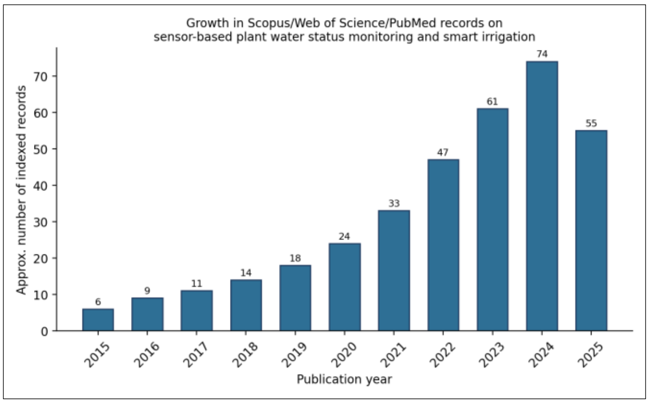

Fig 2: Approximate growth in Scopus, Web of Science, and PubMed records addressing sensor-based plant water status monitoring and smart irrigation, 2015-2025 (2025 figure reflects partial-year indexing).

3. Literature Review and Thematic Analysis

The thirty-four studies retained for synthesis were classified into five overlapping themes: (i) soil-based sensing of plant-available water, (ii) plant-based physiological sensing, (iii) canopy-temperature-based and remote/proximal sensing, (iv) IoT and wireless sensor network integration, and (v) AI/machine-learning-based decision models. Figure 3 presents the conceptual framework linking these themes within an end-to-end smart irrigation pipeline, and Figure 4 shows their relative representation within the reviewed literature.

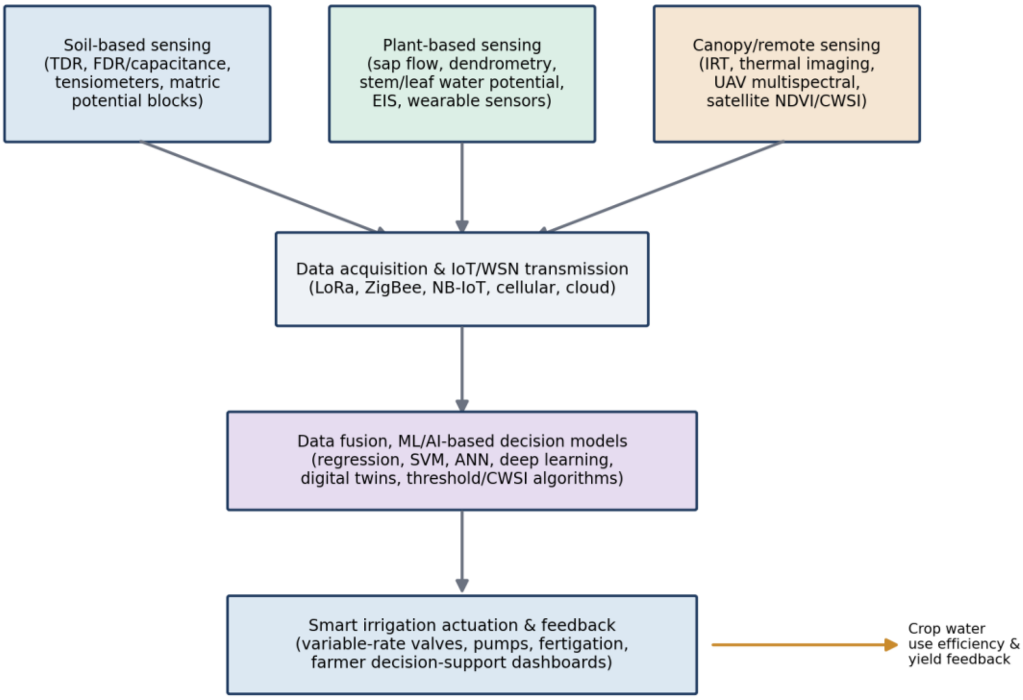

Fig 3: Conceptual framework linking soil-, plant-, and canopy-based sensing modalities through IoT data transmission and AI-based decision models to smart irrigation actuation.

3.1 Theme 1: Soil-Based Sensing of Plant-Available Water

Soil-based sensors remain the most widely deployed technology for inferring plant water status indirectly, on the premise that soil water availability constrains root water uptake. The literature distinguishes several sensing principles: capacitance/frequency-domain reflectometry (FDR), time-domain reflectometry (TDR) and time-domain transmissometry (TDT), electrical-resistance (Watermark) matric-potential blocks, tensiometers, and the historically important but now largely superseded neutron probe. A recent comprehensive review classified these into invasive and non-invasive categories and reported that TDR probes achieved a root-mean-square error (RMSE) of approximately 1.6% volumetric water content, outperforming capacitance sensors, which exhibited RMSE values of 2.5-3.6% [20]. Field validation studies corroborate this ordering: a comparative trial of five sensor types in maize found that TDR sensors most closely matched gravimetric reference measurements at multiple soil depths, followed by capacitance and Watermark sensors [22].

A recurring finding across studies is that capacitance-type sensors, while inexpensive and easy to deploy, require soil-specific calibration because their readings are confounded by bulk density, electrical conductivity, and salinity, particularly in clay-rich or saline soils [17, 20, 21]. Calibration studies of low-cost capacitive sensors have shown that factory calibration curves systematically overestimate volumetric water content in clayey soils while performing acceptably in sandy loam, with RMSE ranging from 0.03 to 0.29 cm3 cm-3 depending on soil-specific recalibration [21]. TDR and TDT sensors, though costlier and technically more demanding to manufacture, are comparatively less sensitive to salinity and are increasingly favoured for research-grade precision-irrigation scheduling [20]. Reviews of soil-moisture sensing technology also highlight the growing role of non-contact and radiometric methods - including ground-penetrating radar, electromagnetic induction, and satellite/UAV-based soil moisture retrieval - as complements to point-based in-situ sensors, particularly for mapping spatial heterogeneity across larger management units [23].

The principal strength of soil-based sensing lies in its low cost, ease of automation, and long track record of integration into wireless sensor networks and basin/drip irrigation controllers, with field deployments reporting water savings in the order of 35% relative to conventional scheduling [3]. Its principal weakness is that soil water content is only a proxy for plant water status: it does not directly capture root distribution, cultivar-specific water-extraction strategies, or atmospheric evaporative demand, and can therefore misrepresent the true physiological stress experienced by the crop, particularly in heterogeneous or shallow-rooted systems.

3.2 Theme 2: Plant-Based Physiological Sensing

Plant-based sensing methods measure the plant's own physiological or morphological response to water deficit and are therefore considered, in principle, the most direct indicators of water status. The historical reference method is the Scholander pressure chamber, which measures xylem (stem or leaf) water potential and has served as the gold standard against which continuous sensor technologies are validated since the 1960s [6]. Despite its continued authority, the pressure-chamber technique is destructive or semi-destructive, labour-intensive, provides only discrete spot measurements, and is subject to substantial operator-dependent variability in leaf selection, bagging, and pressurisation technique [17].

Continuous surrogates for stem or leaf water potential have therefore attracted sustained research interest. Dendrometers - point or band devices that record diurnal trunk or stem diameter fluctuations - exploit the physiological principle that stems rehydrate overnight and shrink during periods of high transpiration; the resulting maximum daily shrinkage (MDS) metric has been well correlated with discrete stem water potential determinations in numerous fruit-tree studies [2, 14]. In a high-density apple orchard trial, MDS derived from band dendrometers was correlated with pressure-chamber stem water potential at r2 = 0.85, while a simplified sap-flow index correlated more strongly with atmospheric evaporative demand (r2 = 0.82) than with stem water potential directly [15]. This divergence illustrates an important and recurring tension in the literature: sap-flow-derived metrics track transpirational demand well but are comparatively weaker direct proxies for internal plant water status, whereas trunk-diameter-derived metrics track water status more closely but are highly sensitive to sensor placement, with point dendrometers showing greater positional variability than band dendrometers [14, 15].

Microtensiometer technology, a more recent innovation, embeds a miniaturised tensiometer directly within stem tissue to provide continuous, in-situ readings of trunk or stem water potential. Validation studies in citrus, grapevine, and apple report that microtensiometer output generally tracks the seasonal and diurnal pattern of pressure-chamber measurements closely, although agreement deteriorates under high vapour-pressure-deficit conditions, and cultivar-specific calibration thresholds remain necessary before the technology can be used for absolute (rather than relative) irrigation triggers [16, 18, 19]. Complementing these mechanical and hydraulic approaches, a newer generation of non-invasive leaf-level sensors - including electrical impedance spectroscopy (EIS) and infrared spectroscopy applied directly to leaf tissue, and flexible wearable sensors based on nano-graphene oxide - has been proposed for low-cost, real-time, non-destructive estimation of relative water content, with reported statistically significant correlations to reference measurements despite some sensitivity to electrode-leaf contact and ambient light interference [11, 13].

Collectively, plant-based sensors offer the most physiologically direct assessment of water status and are particularly valuable in high-value perennial and orchard systems, where their higher cost per sensor can be justified. Their principal limitations are the need for species- and often cultivar-specific calibration, limited spatial replication because each sensor characterises an individual plant (a significant concern in topographically or edaphically variable orchards and vineyards), and, for pressure-chamber-based reference methods, destructive or labour-intensive sampling that precludes full automation [16, 17].

3.3 Theme 3: Canopy-Temperature-Based and Remote/Proximal Sensing

Canopy-temperature-based sensing rests on the physical principle that transpirational cooling lowers leaf and canopy temperature below ambient air temperature under well-watered conditions, while water-stressed plants exhibit reduced stomatal conductance and correspondingly warmer canopies. This principle underlies the crop water stress index (CWSI), whose theoretical foundations and non-water-stressed baseline methodology were established in the early 1980s and subsequently reviewed and refined [5]. CWSI has since been operationalised for numerous field crops, including wheat, cotton, maize, and various orchard and vineyard systems [7, 9].

Empirical studies applying CWSI to irrigation scheduling report generally favourable but not unconditional performance. A study developing baseline equations for winter wheat found strong linear relationships between canopy-air temperature differential and vapour pressure deficit, enabling CWSI-based irrigation scheduling across multiple maximum-allowable-depletion treatments [7]. However, a subsequent study examining the sensitivity of infrared thermometer field-of-view found that varying the sensor's distance from the canopy between 10 and 100 cm altered computed CWSI values by 9.2-36.4%, with drip-irrigated plots showing greater sensitivity to measurement geometry than flood-irrigated plots, and correlation between CWSI and soil moisture ranging from R2 = 0.77 to 0.78 depending on sampling distance [8]. This finding is significant because it demonstrates that apparently modest methodological choices in sensor deployment can materially affect the interpretability and reproducibility of CWSI-based irrigation triggers, a source of inconsistency that is not always transparently reported in the wider literature. Further complicating interpretation, CWSI has been shown to be differentially sensitive to meteorological parameters such as wind speed, solar radiation, and relative humidity across different crop and site conditions, undermining the assumption of a universally transferable baseline [10].

The advent of thermal imaging cameras and unmanned aerial vehicles (UAVs) has extended canopy-temperature-based sensing from single-point infrared thermometry to spatially distributed, high-resolution mapping of crop water stress, with applications reported in grapevine, olive, wheat, potato, cotton, and almond systems [9]. A review of thermal imagery applications in precision agriculture highlights growing interest in coupling image-processing techniques for canopy segmentation with deep-learning models to automate stress classification and mapping at field scale, while noting that most published studies remain at proof-of-concept stage with limited operational validation across seasons [9]. The principal strength of canopy/remote sensing lies in its non-contact, spatially scalable nature, enabling stress mapping across whole fields or orchards without the destructive or per-plant sampling burden of soil- or plant-based methods. Its principal weakness is a pronounced dependency on accurate baseline calibration, sensor geometry, and confounding meteorological variables, all of which constrain out-of-the-box transferability across crops, cultivars, and climatic zones.

3.4 Theme 4: IoT and Wireless Sensor Network Integration

A substantial share of the recent literature addresses the integration of soil-, plant-, and canopy-based sensors into IoT-enabled wireless sensor networks (WSNs) that automate data acquisition, transmission, and irrigation actuation. Reported architectures typically comprise a perception/sensing layer (soil moisture, temperature, humidity, and water-level sensors), a communication layer (Wi-Fi, LoRa, ZigBee, or cellular/NB-IoT protocols), a cloud analytics layer, and a management/actuation layer controlling pumps or valves [24, 25, 32, 33]. Early WSN-based systems combining ESP8266/ESP32 microcontrollers with soil-moisture sensors and cloud connectivity have reported water savings of up to 35-40% relative to conventional irrigation, alongside improved monitoring accuracy (reported as high as 92% in one multi-sensor platform) [3, 33]. Solar-powered, LoRa-enabled systems have demonstrated the feasibility of long-range, low-power data transmission suitable for large or remote field deployments [3].

A systematic review of IoT sensing for irrigation management found that weather-monitoring integration - incorporating temperature, humidity, wind speed, and solar radiation into irrigation decision algorithms - was among the most frequently reported applications, reflecting the recognised importance of atmospheric evaporative demand alongside soil and plant status in scheduling decisions [32]. The same review identified standardisation, power efficiency, cybersecurity, scalability, and cost reduction as the critical determinants of successful large-scale IoT adoption, noting that interoperability across proprietary sensor and communication platforms remains a substantial barrier to multi-vendor, multi-farm deployment [32]. Reported water-saving outcomes across IoT-enabled systems vary considerably (approximately 15-40%), a range that reflects heterogeneity in baseline irrigation practices, crop type, climate, and evaluation methodology across studies rather than a consistent, directly comparable effect size [27, 29, 31].

3.5 Theme 5: AI/Machine-Learning-Based Decision Models

The final major theme concerns the application of machine-learning and artificial-intelligence algorithms to translate multi-sensor data streams into irrigation decisions. Approaches reported in the literature range from classical regression and support-vector-machine (SVM) models to artificial neural networks, deep-learning architectures for image-based stress classification, and, more recently, digital-twin frameworks that maintain a continuously updated virtual representation of field or orchard water status [28, 30]. A systematic review of IoT-based automated irrigation solutions employing machine learning found that automation across the full irrigation management pipeline - from data collection to final water application - remains uneven, with most published systems automating data acquisition and analytics but relatively few achieving fully closed-loop, autonomous actuation validated over multiple growing seasons [27].

Meta-analytical and systematic-review evidence indicates that AI- and sensor-driven irrigation scheduling commonly reduces water use by approximately 15-40% while maintaining or improving yield and nutrient-use efficiency across open-field, orchard, and greenhouse systems [29, 31]. A recent systematic review and meta-analysis reported that field deployment of an IoT-enabled AI irrigation framework achieved a 25-30% reduction in water usage alongside improved yield through better timing of irrigation and reduced waterlogging [31]. Digital-twin and machine-learning integration studies emphasise the importance of data preprocessing, feature selection, and multi-source data fusion (soil, weather, crop, and remote-sensing inputs) in improving model performance, while cautioning that model generalisability across crops, cultivars, and agro-climatic zones remains inadequately tested, and that privacy and security considerations for digital-twin platforms handling continuous farm-level data are only beginning to receive systematic attention [30].

4. Comparative Analysis of Previous Studies

Table 3 summarises representative studies from across the five themes, illustrating the diversity of sensing modalities, crops, and metrics reported in the literature. Table 4 extends this synthesis into a structured comparative analysis of methodology, approximate sample size, major findings, and identified limitations, enabling direct comparison of study design rigour and evidentiary strength across the reviewed literature.

Table 3: Summary of Selected Studies Across Sensing Modalities

Study (first author/topic, year)	Sensing modality / method	Crop / system	Key metric reported
Gontia & Tiwari, 2008 [7]	Infrared thermometry / CWSI baseline	Winter wheat	Baseline slope/intercept for CWSI; R2 with soil moisture ~0.77-0.78
Effect of IRT field of view, 2023 [8]	Infrared thermometry, varying sensor distance	Wheat (drip/flood irrigated)	CWSI variation of 9.2-36.4% with sensor distance
High-density apple orchard study, 2023 [15]	Band dendrometer (MDS), sap-flow index	Apple	MDS vs stem water potential r2 = 0.85; SFI vs ETr r2 = 0.82
Kalcsits *et al*., 2024 [16]	Microtensiometer, sap flow, canopy temperature, dendrometry	'Honeycrisp' apple	Trunk water potential tracked pressure-chamber values except at high VPD
Soil moisture sensing technologies review, 2025 [20]	TDR vs capacitance sensors (review/meta-comparison)	Cross-crop / general	TDR RMSE ~1.6% vs capacitance RMSE 2.5-3.6%
Low-cost capacitive sensor calibration, 2024/25 [21]	SEN0193 capacitive sensor calibration	General soils (sandy loam, clay)	RMSE 0.03-0.29 cm3 cm-3 depending on soil-specific calibration
IoT-based automated irrigation review, 2024 [27]	IoT + ML systematic review	Cross-crop / multiple systems	Uneven automation across full irrigation pipeline
AI-driven irrigation systematic review & meta-analysis, 2025 [31]	AI/IoT-enabled irrigation frameworks	Multiple agro-climatic contexts	25-30% water-use reduction with improved yield

Table 4: Comparative Analysis of Previous Research

Author(s), Year	Study location/context	Methodology	Sample size*	Major findings	Limitations
Gontia & Tiwari, 2008 [7]	Semi-arid India	Randomised block design, 5 irrigation (MAD) treatments	5 treatments, 2 growth stages	Established CWSI baseline equations for wheat irrigation scheduling	Site- and season-specific baselines; not directly transferable
CWSI field-of-view study, 2023 [8]	Semi-arid India, 2 locations	Comparative IRT distance trial (10-100 cm), 4 irrigation regimes	4 plots x 2 sites	Sensor geometry materially alters CWSI; drip more sensitive than flood	Limited to wheat; single-season data
Apple orchard SFI/MDS study, 2023 [15]	Utah, USA	Field trial, cyclical drought-stress imposition, 2 cultivars	2 cultivars, 1 season	MDS and SFI both track water status but differ in correlation strength	Single growing season; high-density orchard only
Kalcsits *et al*., 2024 [16]	Washington, USA	Continuous microtensiometer vs pressure-chamber validation	Single orchard block	Good tracking except under high VPD; needs cultivar thresholds	Limited replication across cultivars/soils
Soil moisture sensing review, 2025 [20]	Multi-country synthesis	Narrative/comparative review of sensor principles	Not applicable (review)	TDR most accurate; capacitance cheaper but less precise	Heterogeneous primary-study quality; publication bias possible
Capacitive sensor calibration, 2024/25 [21]	Laboratory + field validation	Soil-specific calibration vs factory calibration	Multiple soil textures	Soil-specific calibration substantially improves accuracy	Findings may not generalise beyond tested soil types
IoT/ML systematic review, 2024 [27]	Global synthesis	PRISMA-style systematic review	Not applicable (review)	Automation strongest in data acquisition; weakest in autonomous actuation	Reliance on published/reported outcomes; risk of selective reporting
AI irrigation meta-analysis, 2025 [31]	Global synthesis, 2018-2025 studies	Systematic review with meta-analytical synthesis	Not applicable (review)	25-30% water savings with yield gains in field deployment	Substantial heterogeneity in baseline comparators across studies

*Sample sizes reported as described in source studies; review-type sources are marked as not applicable.

5. Research Gaps and Emerging Trends

Synthesis of the reviewed literature reveals several recurring and unresolved issues (Table 5, Figure 5) alongside a set of emerging technological trajectories that are likely to shape the next generation of sensor-based smart irrigation research (Table 6, Figure 6).

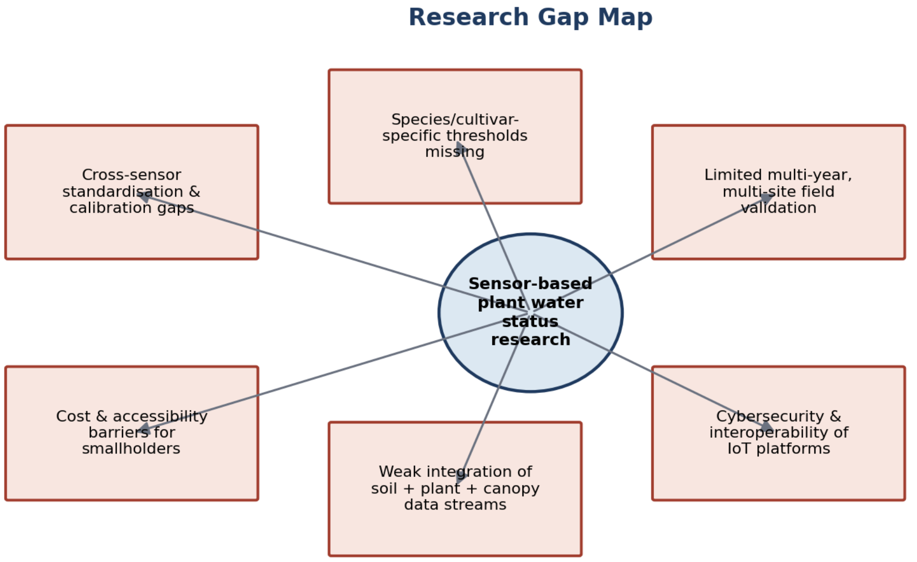

Fig 5: Mapping of principal research gaps identified across the reviewed literature on sensor-based plant water status assessment.

Table 5: Research Gaps Identified

Gap	Description	Affected sensing modality
Calibration standardisation	Absence of universally accepted, soil- and cultivar-specific calibration protocols; factory calibrations often inaccurate outside tested soil textures	Soil-based sensors; canopy CWSI baselines
Species/cultivar-specific thresholds	Stress thresholds derived for one species or cultivar often do not transfer reliably to others	Plant-based sensors (microtensiometer, sap flow, dendrometry)
Limited multi-year, multi-site validation	Most studies report single-season or single-site trials, limiting confidence in generalisability	All modalities, especially AI/ML models
Cost and accessibility barriers	High per-unit cost of plant-based and multi-sensor platforms restricts adoption by smallholders	Plant-based sensors; multi-sensor IoT platforms
Weak multi-modal data fusion	Few studies integrate soil, plant, and canopy data streams within a single decision framework	Cross-cutting (IoT/AI integration)
Cybersecurity and interoperability	Proprietary communication protocols and limited security frameworks constrain multi-vendor deployment	IoT/WSN architectures

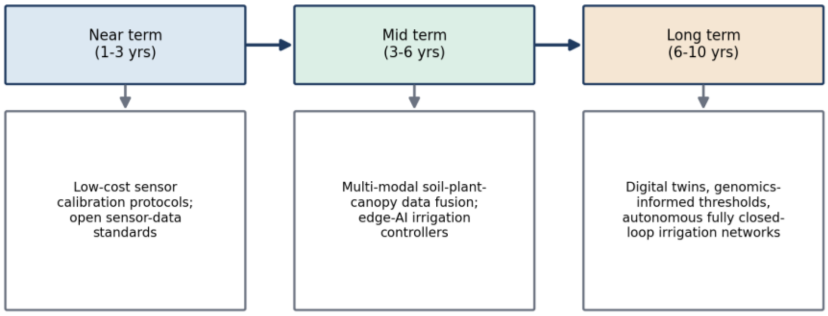

Fig 6: Near-, mid-, and long-term trajectory of emerging technologies in sensor-based plant water status assessment.

Table 6: Emerging Trends in the Field

Trend	Description	Potential impact
Low-cost non-invasive leaf sensors	Electrical impedance spectroscopy, infrared spectroscopy, and wearable graphene-based sensors applied directly to leaf tissue	Democratises plant-based sensing beyond high-value perennial crops
Multi-modal data fusion	Combined soil-plant-canopy data streams processed through unified ML pipelines	Improved robustness and reduced false-positive/false-negative irrigation triggers
Digital twins	Continuously updated virtual representations of field/orchard water status integrating historical and real-time data	Enables predictive, anticipatory irrigation scheduling
Edge-AI controllers	On-device inference reducing dependence on continuous cloud connectivity	Improves resilience and reduces latency in remote or low-connectivity regions
UAV and satellite thermal/multispectral integration	Increasing resolution and revisit frequency of aerial and satellite platforms	Enables field- and landscape-scale stress mapping at lower marginal cost
Open sensor-data standards	Emerging efforts toward interoperable data formats and communication protocols	Reduces vendor lock-in and facilitates cross-study comparability

Beyond these structural gaps, several methodological limitations recur across the primary literature: inconsistent reporting of baseline environmental conditions during CWSI calibration, limited disclosure of raw sensor accuracy under field (as opposed to laboratory) conditions, and a scarcity of studies directly comparing multiple sensing modalities against a common physiological reference within the same experimental design. Addressing these limitations will require coordinated, multi-institutional field trials rather than the largely single-site, single-season studies that currently dominate the literature.

6. Discussion

The synthesis presented in this review indicates that the field of sensor-based plant water status assessment has matured considerably in terms of the diversity and sophistication of available technologies, yet remains fragmented in terms of standardisation, cross-validation, and equitable accessibility. A consistent pattern across the literature is the trade-off between measurement directness and practical deployability: plant-based sensors offer the most physiologically meaningful signal but are the most costly and logistically demanding to deploy at scale, whereas soil-based sensors are the most affordable and scalable but provide only an indirect proxy for plant status, and canopy/remote sensing occupies an intermediate position, offering spatial scalability at the cost of calibration complexity and meteorological confounding.

The evidence on quantitative water savings from IoT- and AI-enabled smart irrigation is directionally consistent - almost all reviewed studies report reductions in irrigation water use, generally in the range of 15-40% - but the magnitude varies considerably across studies due to differences in baseline comparator practices (for example, farmer-managed flood irrigation versus already-optimised drip systems), crop type, and evaluation duration [3, 27, 29, 31, 33]. This heterogeneity complicates direct cross-study comparison and suggests that reported percentage water savings should be interpreted as context-specific rather than universally generalisable figures. Similarly, while CWSI-based canopy sensing has a well-established theoretical foundation, empirical evidence shows that its practical accuracy is sensitive to sensor geometry, baseline determination, and prevailing meteorological conditions, a source of variability that is not always explicitly acknowledged when CWSI is presented as a turnkey irrigation-scheduling tool [8, 10].

From a theoretical perspective, the persistence of discrepancies between sap-flow-derived and trunk-diameter-derived water-status metrics - the former tracking evaporative demand more closely, the latter tracking internal water status more closely [15] - underscores that plant water status is not a single, unidimensional quantity but a multi-faceted physiological state that different sensors capture only partially. This has practical implications for smart irrigation system design: rather than seeking a single 'best' sensor, the literature increasingly supports multi-modal sensor fusion, in which complementary signals are combined through machine-learning or digital-twin frameworks to triangulate a more complete picture of crop water status [28, 30]. This trend aligns with current developments in the broader precision-agriculture field, including the growing availability of edge-computing hardware, expanding satellite and UAV remote-sensing infrastructure, and international policy emphasis - reflected in Sustainable Development Goal 6 and related FAO water-scarcity initiatives - on improving agricultural water-use efficiency [1].

At the same time, the review highlights an important equity dimension that has received comparatively little explicit attention in the technical literature: the cost, technical complexity, and calibration burden associated with the most physiologically direct and spatially scalable sensing technologies risk concentrating the benefits of smart irrigation among well-resourced research institutions and commercial-scale growers, while smallholder and resource-constrained farming systems - which represent a substantial share of global food production - remain reliant on simpler, less precise sensing or none at all. Bridging this gap will likely require continued cost reduction in non-invasive plant-based sensors, open calibration datasets and standards, and irrigation-advisory services that translate sensor data into actionable guidance without requiring farm-level technical expertise.

7. Conclusion

This review has collected information from thirty-four studies related to soils, plants, canopies/remote sensing, IoTs, and AI/machine learning on sensor-based assessment of plant water status in smart irrigation. Findings indicate that each sensor technology provides a different insight into plant water status; thus, no single technology can be considered better than others. Moreover, it appears that more water was saved with the help of a combination of different sensors using IoTs and AI than with any single sensor use. The reviewed literature states that using sensors, it is possible to save 15-40% of water through different cropping systems, and these findings highlight the practical importance of the field concerning water resource management and food security.

It is suggested in this review that for academic researchers, there is a need to focus on field validation studies involving multiple years and multiple sites, detailed and transparent documentation of how calibration was done and what baseline environmental conditions were used, and the selection of experimental designs enabling testing of multiple sensing modalities against established physiological standard criteria in a single study. For practitioners and policymakers, the review states that there should be an emphasis on opening up and achieving interoperability of the sensor data standards, supporting extension and advisory services enabling lower costs of technology adoption by smallholder farmers, and supporting continual funding from the public and the private sectors in the area of decreasing costs of non-invasive plant monitoring technologies for a possibility to implement sensor-based smart irrigation technologies not only for the farming organizations with high resources, but also with smallholders. The direction of future studies should focus on developing advanced frameworks for fused multimodal data; utilizing digital twins for scheduling irrigation proactively instead of reactively; using edge intelligence technology in places with poor connectivity and paying sufficient attention to cybersecurity and interoperability issues.

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