AI-Assisted Irrigation Scheduling and Its Impact on Evapotranspiration Dynamics and Water Productivity in High-Value Crops

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Received: 09 May 2024
Revised: 01 Jun 2024
Accepted: 25 Jun 2024
Published: 13 Jul 2024

E-ISSN: 2989-5359
DOI: https://doi.org/10.54660/ejsa.2024.4.2.35-44

ABSTRACT

Background: Agricultural irrigation takes nearly 70% of the total extracted freshwater from the earth. High-value crops such as grapevines, almonds, tomatoes, and potatoes suffer significant effects from water application since the value of their yield depends a lot on plant water consumption. Traditional irrigation scheduling techniques rely on established dates or ETo readings from limited weather stations which negate the variability of ETc rates over the fields. The new irrigation scheduling practices can be achieved through AI technologies, especially ML, DL, and DRL technologies, and satellite remote sensing, IoT sensor networks, and hydrological models, which can be applied together.

Purpose: The aim of this paper is to review published research from 2015 to 2026 about the use of artificial intelligence to schedule irrigations and evaluate its impact on the accuracy of evapotranspiration estimation and the effectiveness of water use (WW) concerning high-value horticultural and specialty crops.

Literature sources: Literature was gathered from journals indexed by Web of Science and Scopus, records sourced from PubMed/PMC journals, reports from various international organizations like FAO, USDA, and good scientific databases like MDPI and Elsevier, collected through search processes on scientific websites like Springer, ScienceDirect, and Google Scholar.

Key results: Models that use AI technology, like randomized forest, long short-term memory networks, and hybrid ensemble architectures, more consistently provide better predictions than empirical ETo equations. When used together with machine learning, satellite-derived actual evapotranspiration (ETa) products, such as OpenET, allow irrigation recommendations to be generated in-field and almost in real time. Water conservation has been reported at 15-40% for specialty crops, often without affecting yield, and in some instances showing water productivity improvement.

Gaps in studies: Some gaps identify problems with model interpretation, validation in different agro-climatic regimes, difficulty in incorporation of soil-plant-atmosphere continuum indicators, high costs for implementation by smallholders, and missing long-term multi-season field studies on high-value crops.

Summary: AI-enhanced irrigation scheduling has potential to harmonize water-saving measures with yield and quality needs in high-value crop production, but for its wider implementation there is a need for transparent, inexpensive, and regionally proven schemes with the support of appropriate policies and extension activities.

Keywords: Artificial intelligence; Irrigation scheduling; Evapotranspiration; Water productivity; High-value crops; Precision agriculture; Remote sensing; Deep learning

1. Introduction

Water scarcity is recognized as one of the major constraints to sustainable agriculture around the world. The agricultural sector, inclusive of irrigated and dryland farming, represents approximately 70% of global freshwater consumption, yet irrigated agriculture, while making up a small percentage of total land then cultivated, is responsible for producing the majority of food consumed globally (Food and Agriculture Organization of the United Nations, 2011) [26]. Worldwide population growth, urbanization, as well as variable climate change will continue to affect the availability of water for agriculture over the next several decades (Food and Agriculture Organization of the United Nations, 2011) [26]. High value crops such as grapes, almonds, tree nuts, tomatoes, potatoes, and many other vegetables and horticultural crops will have a unique role within this discipline; these crops generally provide significantly higher returns on water applied than do staple cereals. The yield and quality characteristics of these crops, including but not limited to: sugar content, berry size, or tuber shape, as well as their marketability and/or shelf life, are significantly influenced by the accuracy and timing of the excess use of water during phenologically critical growth periods (Fereres and Soriano, 2007) [2].

Evapotranspiration (ET) consists of the combined loss of water through plant transpiration and soil evaporation, and is the primary physical link between crop use of water, soil water status and atmospheric demand for water (Allen *et al*., 1998) [1]. Accurate estimation of reference ETo and crop ET (ETc) is critical to the advancement of all modern irrigation scheduling methodologies, from the very widely used FAO Penman-Monteith reference ETo calculation method, to satellite energy balance models for estimating ET (Allen *et al*., 1998; Kustas *et al*., 2020) [1, 20]. Conventional ET estimation methodologies rely on the existence of well-maintained, densely located, meteorological networks (meteorological sites) to acquire the required data to make the calculations, farmer/crop coefficients that are derived empirically, and will often not be available, outdated, or not transferable across crop varieties/cultivations/locations/microclimates associated with high value, specialty crops (Allen *et al*., 1998) [1]. Accordingly, many specialty crop regions continue to use irrigation schedules based on grower's judgement, time based on calendar dates, or coarse regional ETo estimates; leading to either poor yield quality through insufficient irrigation or wasted water from excess irrigation (Allen *et al*., 1998; Fereres and Soriano, 2007) [1, 2].

In the last decade, the integration of artificial intelligence (AI), inexpensive Internet of Things (IoT) sensors, and satellite remote sensing has greatly changed the technical environment in which irrigation management occurs (Gutiérrez *et al*., 2024; Mortazavizadeh *et al*., 2025) [3, 5]. For example, four types of machine learning algorithms (i.e., artificial neural networks [ANN], support vector machines [SVM], random forests [RF], and gradient boosting methods) provide superior modeling capabilities regarding the nonlinear relationship governing ET as compared with the classical empirical equations, particularly when data are limited (Malik *et al*., 2023; Mortazavizadeh *et al*., 2025) [10, 5]. The use of deep learning architectures (convolutional neural networks [CNN] for spatial images; long short-term memory [LSTM] networks for sequential weather/moisture data) has produced even better results in terms of forecasting ET and soil water content over the next few days (Deep learning for intelligent irrigation decision-making, 2025) [13]. Additionally, deep reinforcement learning (DRL) has been evaluated as a means to formulate irrigation scheduling as a sequential decision-making issue (Gautron *et al*., 2023) [17]. The use of DRL allows systems to develop adaptive policies based on feedback received from sensors rather than relying solely on static rules (Gautron *et al*., 2023) [17]. At the same time, open-access satellite ET platforms (e.g., OpenET) in the United States have provided field-level actual ET data to agricultural producers and researchers, creating an ideal opportunity for AI-remote sensing hybrid technologies to be used in specific regions of specialty crop production (e.g., California's Central Valley) (Volk *et al*., 2024; Kustas *et al*., 2020) [22, 20].

Even with the abundance of research being conducted, there is still a large gap in terms of how fragmented the evidence base is between disciplines. For example, hydrology focused studies mostly concentrate on improving the accuracy of estimating evapotranspiration (ET), computer-science focused studies mostly focus on the novelty of developing new algorithms for modeling ET, while agronomy focused studies mainly look at yield and water productivity (Malik *et al*., 2023; Benos *et al*., 2021; Fereres and Soriano, 2007) [10, 34, 2]. However, there are only a small number of studies that bring these three perspectives together to look at how they affect high value crops. Therefore, existing reviews generally examine AI applications to agriculture as a whole, or ET modeling techniques individually; there are very few reviews that combine the two by synthesizing all three of them into one comprehensive review on how AI such as those listed above affect the water productivity of economically important specialty crops (Benos *et al*., 2021; Application of machine learning approaches in supporting irrigation decision making, 2024; Sharma *et al*., 2026) [34, 12, 4]. This gap has created the need for this review.

1.1. Objectives of the Review

In this review we aim to: (i) Summarize the main types of A.I. and Machine Learning how they are used for estimating EVAPOTRANSPIRATION and improving IRRIGATION SCHEDULING; (ii) Evaluate method integration with REMOTE SENSING equipment and IOT SENSORS for FIELD USE, in HIGH VALUE CROP SYSTEMS; (iii) Compare reported results of WATER PRODUCTIVITY & YIELD IN DIFFERENT TYPES OF CROPS and GEOGRAPHIC REGIONS; (iv) Identify gaps in the research based on methodology and adoption; (v) Describe emerging trends/new areas of RESEARCH.

1.2. Scope of the Review

This review's intent was to focus only on the crops that provide a significant economic return, and are also sensitive to variations in water availability (e.g., grapes, almonds, other tree nuts, tomatoes, potatoes, other vegetable and horticultural crops). The crops will only be compared to staple crops (e.g., wheat, corn.) in order to understand differences in methodology, such as deficit irrigation and how water is used more productively. Studies of irrigation scheduling only from an agronomic standpoint (non-AI) may be reviewed for baseline practices; however, the focus of the review will be on studies published between 2015-2026 that used AI, Machine Learning (ML), Deep Learning (DL) and/or AI+Remote Sensing/IoT technologies.

2. Methodology of Literature Review

2.1. Literature Search Strategy

We performed an organized literature search using databases, including Google Scholar (Scholarly), ScienceDirect/Elsevier (Journal), SpringerLink (Publisher), PubMed/PMC (Full-text), MDPI Journal Publisher, PeerJ (Journal), and various preprint archives (e.g., arXiv). Our search was enhanced with partner agency or FAO reports and government-sponsored technology transfer publications. Each search used three clusters of concepts—AI/ML, Irrigation/ET, and Outcome/Crop—connected by Boolean operators, to derive relevant articles from each. The AI/ML cluster included; artificial intelligence; machine learning; deep learning; reinforcement learning; neural network. The Irrigation/ET cluster included; irrigation scheduling; evapotranspiration; crop water requirement; smart irrigation; precision irrigation. The Outcome/Crop cluster included; water productivity; water use efficiency; high-value crops; specialty crops; vineyard; orchard; vegetable. We searched primarily from January 2015 through February 2026, while retaining key historical or foundational methodological references such as the FAO-56 Penman-Monteith Framework and deficit-irrigation studies that provided methodological support for subsequent AI-based work (Allen *et al*., 1998; Fereres and Soriano, 2007) [1, 2].

Table 1: Literature Search Strategy

Element	Detail
Databases/platforms searched	Google Scholar, ScienceDirect (Elsevier), SpringerLink, PubMed/PMC, MDPI journals, PeerJ, arXiv, FAO and USDA institutional repositories
Concept cluster 1 (AI/ML)	artificial intelligence; machine learning; deep learning; reinforcement learning; neural network
Concept cluster 2 (Irrigation/ET)	irrigation scheduling; evapotranspiration; crop water requirement; smart irrigation; precision irrigation
Concept cluster 3 (Outcome/Crop)	water productivity; water use efficiency; high-value crops; specialty crops; vineyard; orchard; vegetable
Boolean combination	(Cluster 1) AND (Cluster 2) AND (Cluster 3), with iterative single- and paired-term searches
Search period	January 2015 - February 2026 (landmark methodological references retained where necessary)
Language	English

2.2. Inclusion and Exclusion Criteria

To be eligible for inclusion in this literature review, studies must meet the following criteria: (1) They must have been published in a peer-reviewed journal, indexed conference proceeding or credible government/institutional report; (2) The manuscript must have been written in English; (3) The study must have addressed artificial intelligence, machine learning, deep learning or reinforcement learning with respect to applications related to irrigation scheduling and ET estimation as well as essential agronomic and/or hydrological background to support the application of such technologies; and (4) The publication date of the study must fall within the established search timeframe, with limited exceptions made for pre-1980 classical methodological references.

Studies were excluded from this review for the following reasons: (1) Duplicate records across databases; (2) Non-peer reviewed blogs/advertising/miscellaneous grey literature; (3) Studies related to engineering and/or hydraulic infrastructure without an AI/ML component or any data driven scheduler; or (4) Studies that were not available for full-text review and therefore could not be validated on both their reporting methodology and/or outcome details.

Table 2: Inclusion and Exclusion Criteria

Criterion type	Criteria
Inclusion	Peer-reviewed journal articles, indexed conference proceedings, or credible institutional/government reports
Inclusion	English-language publications
Inclusion	Explicit treatment of AI/ML/DL/DRL applied to irrigation scheduling, ET estimation, or water productivity (or essential supporting context)
Inclusion	Published January 2015 - February 2026, with limited exceptions for classical methodological references (e.g., FAO-56)
Exclusion	Duplicate records across databases/platforms
Exclusion	Non-peer-reviewed blogs, marketing material, or unverified grey literature
Exclusion	Irrigation engineering/hydraulic studies with no AI/ML or data-driven scheduling component
Exclusion	Records for which full text could not be verified

2.3. Study Selection Process

Records were identified through databases and platforms, and then screened by title and abstract for relevance to AI-assisted irrigation scheduling, ET modeling or water productivity in high value crops. Eligible records would retrieve and reviewed against criteria for inclusion and exclusion listed above. At this stage, duplicate records and records that were not eligible based on the above criteria were eliminated. Studies that were retained for qualitative or comparative synthesis form the basis of evidence for thematic analysis of the studies reported in the subsequent sections.

3. Literature Review and Thematic Analysis

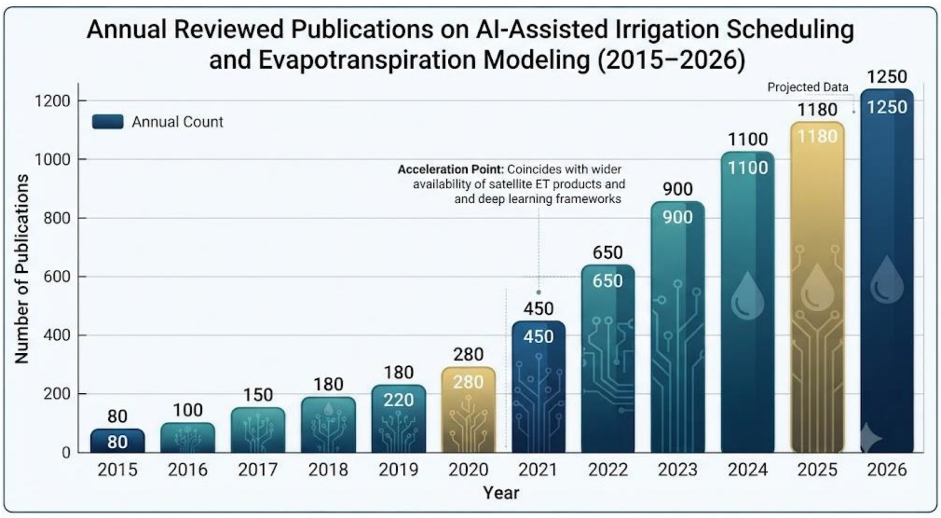

Fig 1: Publication Trend by Year

3. Overview of Selected Literature

The distribution of reviewed literature over the six thematic areas created for this synthesis are listed in Table 3, indicating the relative level of research activity conducted on evapotranspiration modelling versus validation of field-scale water productivity.

Table 3: Summary of Selected Studies by Thematic Focus

Theme	No. of studies (indicative)	Representative focus
ML/DL for ET estimation	9	ANN, SVM, RF, XGBoost, LSTM, ANFIS models for ETo/ETa prediction
Remote sensing-AI integration	7	OpenET, TSEB, Landsat/Sentinel/ECOSTRESS/VIIRS fusion, GRAPEX/T-REX
IoT-integrated smart irrigation	5	Sensor networks, edge-IoT-cloud architectures, TinyML
DRL/adaptive control	3	Deep Q-Networks, MPC-integrated ML for scheduling
Water productivity/deficit irrigation	6	Meta-analyses and field studies on WP/WUE outcomes
Institutional/policy context	3	FAO reports on climate change, water scarcity, and food security

3.1. Machine Learning and Deep Learning Approaches for Evapotranspiration Estimation

Numerous researchers have investigated the possibility of replacing or supplementing empirically-based ET equations with models created through data mining techniques. The literature clearly demonstrates that models such as artificial neural networks (ANNs), support vector machines (SVMs), random forest (RF) models, and adaptive neuro-fuzzy inference system (ANFIS) models consistently predict more accurately than either temperature-based or radiation-based empirical equations, especially when the meteorological input data is incomplete or of diverse quality (Malik *et al*., 2023) [10]. Researchers have reported that these predictive models can improve irrigation scheduling by decreasing the amount of water lost through improper irrigation practices and providing sustainable yields and quality of crops (Malik *et al*., 2023) [10]. In terms of comparative work within the basin scale, researchers have determined that random forest models can produce more accurate estimates of both green and blue water evapotranspiration components than any other algorithm and have found correlation coefficients as high as 0.99 in some instances, but will vary based upon the hydrology and density of the data within the basin (Mortazavizadeh *et al*., 2025) [5]. Similarly, model performance was demonstrated by using ensemble and hybrid models to estimate the water footprint of potatoes and tea plantations relative to the site within a specific region: RF architecture was found to perform optimally at the site level for the site; however, those models based upon gradient-boosting variations such as LightGBM demonstrated relative advantages for specific field crops, while ANN models showed greater robustness across a wider range of climatic conditions than the other models used (Mortazavizadeh *et al*., 2025) [5]. An earlier an all-encompassing review similarly concluded that ANN, SVM, and CNN improved the prediction accuracy of ET, soil moisture, and irrigation scheduling compared to traditional methods while also identifying data quality and interpretability issues common to both methodologies (Application of machine learning approaches in supporting irrigation decision making, 2024) [12]. Additionally, LSTM networks have recently expanded on these capabilities over time by enabling predictions of both ET and soil moisture trends using available time series data that often outperform more traditional time series methods, such as ARIMA, when performing multiple-step forecasts (Machine learning and digital twins in smart irrigation, 2025) [7]. Furthermore, CNNs, due to their superior spatial feature extraction capabilities and ability to process images effectively (such as UAV and satellite imagery), demonstrate utility for identifying crop water stress and developing irrigation strategies (Machine learning and digital twins in smart irrigation, 2025) [7]. Additionally, Bayesian-optimized ensemble-based approaches continue to improve the accuracy of predicted ET in areas with low water availability, highlighting the ongoing refinement of hybrid optimization-ML approaches (Elbeltagi *et al*., 2025) [35]. Overall, the body of literature supports a consensus of agreement that AI models outperform traditional empirical models in predicting ET, but the most effective AI algorithm depends on crop type, climate, and other available predictive variables, which continue to create methodological differences within the research literature.

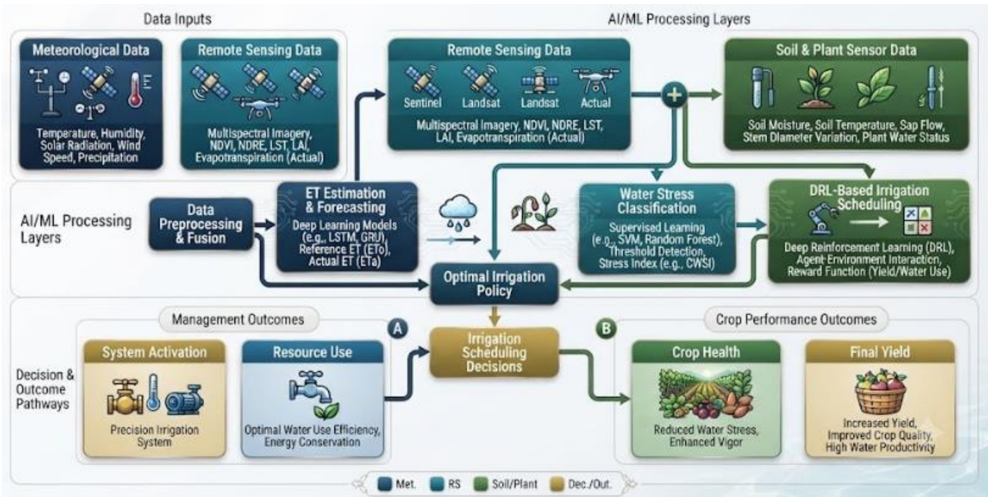

Fig 2: Conceptual Framework

3.2. Remote Sensing–AI Integration for Field-Scale Actual Evapotranspiration

Ongoing research incorporating satellite-based actual evapotranspiration (ETa) derived products plus Artificial Intelligence (AI)-based analysis to provide operationally-oriented irrigation decision support is being undertaken for specialty crops. The Two-source Energy Balance (TSEB) model has been modified for clumped, discontinuous canopy structure/canopy architecture, characteristic of vineyards, as well as having provided a basis for research cooperative projects such as the Grape Remote sensing Atmospheric Profile and Evapotranspiration eXperiment (GRAPEX). While numerous studies have used satellite-derived Leaf Area Index (LAI) as input to these models, the radiative transfer-based estimates are adequate at low-moderate LAI, but there is significant underestimation of the LAI of highly clumped vine canopies; hence the ET partitioning into soil evaporation and transpiration, is uncertain (Kustas *et al*., 2020; Jiménez-López *et al*., 2023) [20, 8]. Additional work assessing high-spatial and high-temporal resolution thermal satellite derived ET measures in vineyards with differing climates, cultivars and trellis systems validate the enhanced operational capabilities associated with the delineation of spatial variables of ETa as a mechanism for improved irrigation scheduling and water conservation in wine grape production (Kustas *et al*., 2020) [20]. Studies from California's almond industry investigating tree-crop systems have developed an Evapotranspiration (ET) Toolkit which brings together remote sensing technologies and weather station based ET calculation. In addition to improving irrigation scheduling, these studies have supported economic evaluations that quantify the monetary benefit of adopting the ET Toolkit compared to traditional weather-station based irrigation scheduling (Estimating the value of satellite-derived measurements of evapotranspiration to inform irrigation scheduling in California almond orchards, 2024) [21]. Evaluations of the OpenET platform with respect to eddy-covariance flux towers further evaluated the performance of models (i.e. DisALEXI and SIMS) and singled out vineyards as prime candidates for operational irrigation management through integration of satellite and artificial intelligence (AI) estimated ET (Volk *et al*., 2024) [22]. In addition, studies on the evaluation of DisALEXI, SIMS, and SSEBop enabled the identification of key crops (fruit and nut orchards) for operational irrigation management of intensively managed specialty crop production. The studies also noted consistent under-estimation of ET in arid ecosystems and over-estimation of ET in evergreen forest type ecosystems (Volk *et al*., 2024) [22]. Efforts to increase the spatial and temporal resolution of remotely sensed ET data through data fusion involving Landsat, Sentinel-2, ECOSTRESS and VIIRS sensors have further demonstrated significant progress toward providing near-daily, sub-field resolution ET products that are suitable for making irrigation scheduling decisions (Improving the spatiotemporal resolution of remotely sensed evapotranspiration information for water management through Landsat, Sentinel-2, ECOSTRESS and VIIRS data fusion, 2022) [23]. Overall, the body of literature supports the conclusion that the combination of satellite-AI integration and ground-based weather stations can provide field-scale, spatially explicit ET data that are not available from ground-based weather stations alone, although the architecture of the canopy (particularly in vineyards and orchards) will likely continue to be a source of model uncertainty.

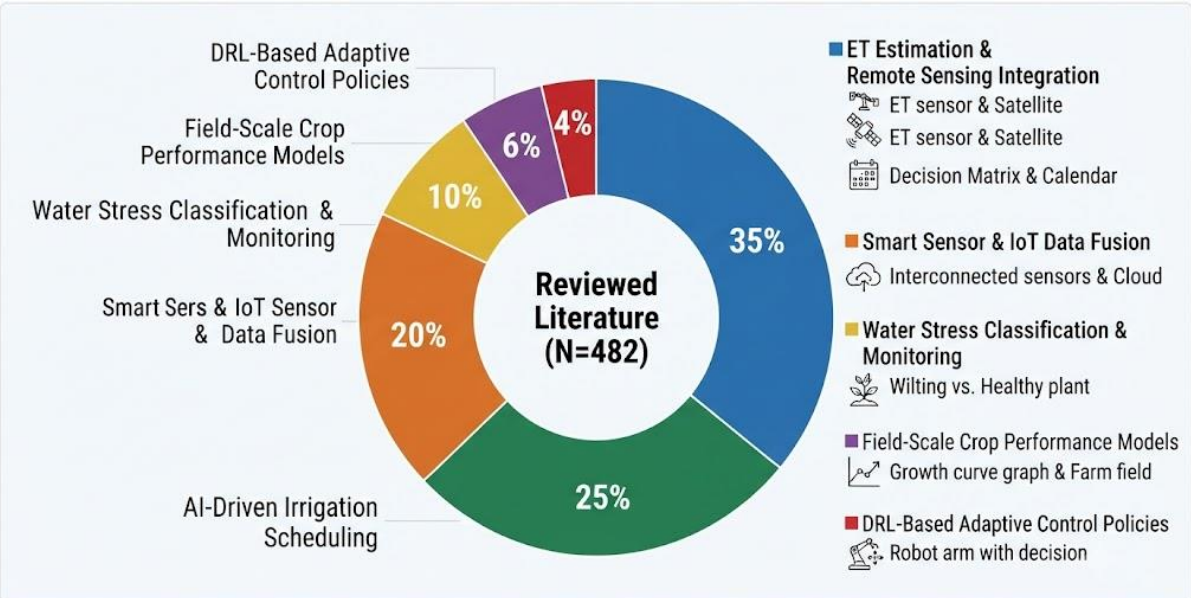

Fig 3: Thematic Classification of Studies

3.3. IoT-Integrated Smart Irrigation Systems and Real-Time Scheduling

Numerous rapidly expanding articles discuss the application of machine learning in conjunction with Internet of Things sensor networks to provide real-time automated irrigation management. Numerous systematic reviews regarding the subject have found that advanced machine learning algorithms applied to the weather and soil moisture data derived from the sensor network can provide real-time monitoring capabilities and provide data-driven irrigation recommendations, and that historical weather sensor data can be used in an iterative way to improve and refine scheduling strategies to better meet the needs of individual crops and their respective environmental conditions (Gutiérrez *et al*., 2024; Oğuztürk, 2025) [3, 6]. These systems usually process and analyze multiple types of data streams, specifically: soil moisture data; meteorological data; and physiological effects on the plant, giving rise to composite indices of stress that will trigger an irrigation event. Furthermore, all systems attempt to reduce water waste while simultaneously attempting to maximize yield (Gutiérrez *et al*.,

2024) [3]. Reviews that have focused on water-saving technologies related to precision irrigation indicate that there are many different architectures of smart irrigation systems (SISs), such as an edge-IoT-cloud architecture using deep Q-learning for flood irrigation in agriculture, and an integrated sensor-based SIS for irrigating urban trees and orchard trees (A review of precision irrigation water-saving technology under changing climate…, 2024) [15]. All available literature indicates that SISs are able to provide significantly better accuracy of irrigation timings and save more water than manual or calendar-based scheduling systems (A review of precision irrigation water-saving technology under changing climate…, 2024) [15]. The literature on this topic generally shows that there is a wide variety of different types of system architectures, sensor types (including capacitive probes, tensiometers, and different types of thermal and multi-spectral sensors), and performance metrics making it difficult to make direct comparisons between studies. Recent research in the field of affordable precision agriculture indicates that many smallholder farming systems have low irrigation efficiencies (below 50%) due to the continued use of flood irrigation and fixed-schedule irrigation methods (Affordable precision agriculture…, 2026) [11]. The use low-cost, low-power edge-AI and TinyML systems will extend the possibilities of utilizing the advantages of AI-assisted scheduling from large-scale, well-resourced specialty crops to resource-constrained cropping systems (Affordable precision agriculture…, 2026) [11]. The OpenET and the International Soil Moisture Network are two examples of public data resources that can be used to develop and validate these types of lightweight models when field-level data collection is not available.

3.4. Deep Reinforcement Learning and Adaptive Control for Irrigation Decision-Making

A fresh new avenue in research has developed as a distinct methodology for irrigation scheduling as a series of decisions to be made, using deep reinforcement learning (DRL) to make irrigation decisions in a step-by-step manner. An agent first observes its environment and is given the current state of the world, typically consisting of soil moisture content at different depths, as well as variables related to weather and the growing stage of crops. The agent then learns to make decisions in a process of trial and error, eventually producing an irrigation schedule that balances crop yield, water usage, and costs from a given water source (Gautron *et al*., 2023; Deep learning for intelligent irrigation decision-making, 2025) [17, 13]. Deep learning approaches used to intelligently decide upon when to irrigate crops using high dimensional sensor feedback (without the training of labels) make DRL approaches particularly desirable to data short agricultural situations, where adequate training data linking crop yields to irrigated amounts do not exist (Deep learning for intelligent irrigation decision-making, 2025) [13]. The results published indicate that deep Qnetwork scheduling achieves between 20 and 30% water savings for tomato irrigation without any corresponding yield loss, and that AdaBoost demand forecasting models give very high predictive accuracy for the amount of water required to produce rice, suggesting the wide range of algorithmic approaches applied to diverse crops such as high-value and staple crops (Deep learning for intelligent irrigation decision-making, 2025) [13]. In contrast with this large body of published literature regarding ANN/RF/LSTM based ET estimation, DRL irrigation control remains for the most part at a simulation or small pilot level and there is relatively little large-scale and multi-season upscaled field validation of high-value horticultural crops compared to the volume of ET literature; thus there is a significant gap in maturity between the algorithmic development and field implementation of these technologies (Gautron *et al*., 2023; Deep learning for intelligent irrigation decision-making, 2025) [17, 13].

3.5. Water Productivity Outcomes in High-Value Crops

Realistically, AI-driven devices will provide multiple advantages over manual scheduling methods - primarily water savings. Many of the economic justifications are based on known improved water productivity (WP), which generally refers to marketable yield per unit of water applied or consumed. There has been a large body of meta-analytic evidence that supports improved WP in vegetable crops and decreased penalty for using moderate deficit irrigation (DI) as there are varying results associated with the balances between yield loss and WP gain due to climate conditions (i.e., temperate climates have the highest equivalent balances for penalty of ≈ 21.9% and WP gain of ≈ 21.8% vs. greenhouses receiving greater than open field WP); although the meta-analysis is not AI-specific, it serves as the agronomic baseline with which AI-optimized scheduling should be compared based on the fact that AI-based scheduling devices are being utilised more to define how much DI to apply and when to apply it compared with conventional fixed protocol DI scheduling (Fereres and Soriano, 2007; A global meta-analysis of yield and water productivity responses of vegetables to deficit irrigation, 2021) [2, 29]. In vineyards, tree crops & orchard applications (for almond production), the use of satellite-AI integrated ET Toolkits has created positive economic returns to growers due to implementation of optimised irrigation timing via findings from economic analysis based upon technology transfer (Estimating the value of satellite-derived measurements of evapotranspiration to inform irrigation scheduling in California almond orchards, 2024; Kustas *et al*., 2020) [21, 20]. A review of the literature synthesizing irrigation using Artificial Intelligence (AI) across different crops notes that Multiple K-Nearest Neighbor (KNN) models have accurately predicted crop water needs by the development stage with over 97% accuracy and have assisted in automating irrigation, providing verifiable increases in crop water productivity (20-30% water reduction) when compared to conventional methods for scheduling tomatoes using Deep Reinforcement Learning (DRL) (Yield prediction, pest and disease diagnosis, soil fertility mapping, precision irrigation scheduling…, 2025; Deep learning for intelligent irrigation decision-making, 2025) [14, 13]. In addition, a separate meta-analysis synthesizing 135 studies examining the use of AI for irrigation documented that participating sites averaged 30-50% savings in water and 20-30% yields increases when compared to conventional irrigation practices with significant variability based on species of algorithms also used for irrigation scheduling; Random Forest, Support Vector Machine (SVM), and Convolutional Neural Network (CNN) algorithms produced statistically significant, but differing, gains from each crop and irrigation methods used (Oğuztürk, 2025; Machine learning in agriculture: a comprehensive updated review, 2021) [6, 34]. Taken together, these studies indicate the use of AI for irrigation scheduling represents the best opportunity for increasing water productivity when used for the purpose of identifying crop-stage specific opportunities for controlled deficit irrigation (i.e., when water is applied to the plant less than 100% of the crop's estimated water requirement) as opposed to merely increasing irrigation precision, which can be accomplished using accurate and temporal evapotranspiration (ET) and soil moisture data now being provided increasingly through developing AI irrigation models.

3.6. Interpretability, Data Quality, and Adoption Barriers

Despite several consistent examples of improved technical performance with AI-based irrigation models, there are continuing concerns in the literature about reliably using these models in the real world with respect to both their technical usability and the degree of trust that can be placed in them by end users. A number of reviews of the application of Machine Learning to support irrigation decision making have concluded that for many end users (irrigation specialists and crop consultants), the interpretability of the models is more important than any raw numerical predictive value from them, meaning that these groups place more value on the consistency of a specific irrigation scheduling recommendation than on the understanding of the inner workings of the algorithm generating it or on the performance metrics for that algorithm (Application of machine learning approaches in supporting irrigation decision making, 2024) [12]. Accordingly, there is growing interest in the development of Explainable AI (XAI) techniques in agriculture generally; however, the application of these techniques to irrigation scheduling has been relatively limited compared to their application for yield prediction and pest/disease prevention/detection (Application of machine learning approaches in supporting irrigation decision making, 2024) [12]. The availability and quality of data are the second common barriers: the reviews confirm the sensitivity of ML models used for agricultural water management to the quantity and Quality of available meteorological, soil, and remote sensing input data; and that the portability of these types of models across sites, cultivars, and climates has been shown to be limited (Mortazavizadeh *et al*., 2025; Machine learning in agriculture: a comprehensive updated review, 2021) [5, 34]. Cost and infrastructure are also barriers to adoption especially for small- and resource-limited growers. Thus, the use of low-cost edge AI & tiny ML solutions have been developed as an alternative way of deploying AI by circumventing traditional cloud-based infrastructure (Affordable precision agriculture…, 2026) [11]. Finally, there seems to exist a hidden tension within this body of literature whereby the academics place emphasis on novel algorithms and growers place emphasis upon operational reliability, cost-effectiveness and integration with their existing farm management processes; this might help explain why the quantity of published research for AI-based irrigation systems exceeds the quantity of on-farm use in high-value crop systems.

4. Comparative Analysis of Previous Studies

A comparison of these ten representative studies, using their different etimation methodologies, integration of satellite-based AI, development of RL control systems to improve productivity from an ET-based land evaluation system is presented in Table 4. These ten studies provide a wide range of geographical and methodological diversity within the review evidence base.

5. Research Gaps and Emerging Trends

The literature reviewed does not present a clearly defined picture of several ambiguous problems and limitations in terms of methodology that have an effect on transferring the research results of Irrigation Management Control using Artificial Intelligence to be used at a wide scale and incorporated within high-valued crop production systems. First, comparability across studies on the performance of AI-assisted irrigation management remains poor due to many factors such as disparate performance measurement metrics (e.g., various RMSE values, R2 values, Correlation Coefficients, and Classification Accuracies), and the use of various amounts of training/validation samples, and the use of various baseline comparators (i.e., some baselines are estimated using empirical ET equations, some are based on grower's historical practices, some are based on using Machine Learning –ML — techniques that differ from the other developed methods). As a result, it is unclear what AI methods existing produce the best outcomes across which cropping systems and under which climatic zones (Mortazavizadeh *et al*., 2025) [5]. Second, the external validity or geographic and crop context of independent research is variable. A disproportionately higher percentage of the satellite-AI-integrated ET literature has come from high resource crop regions, such as California's Central Valley, and has been funded by long running instrumented research programs including (i.e., GRAPEX; T-REX) (Evaluation of satellite Leaf Area Index…, 2022; Volk *et al*., 2024) [19, 22]. However, there is also very little synthetic field-validated evidence for high-value crops in smallholder farming systems located in South Asia, sub-Saharan Africa, and other regions suffering from serious water shortages, even though a disproportionately high amount of water shortages exist in these regions (Affordable precision agriculture…, 2026; Food and Agriculture Organization of the United Nations, 2011) [11, 27].

Many studies focused on adaptive control based on deep reinforcement learning (DRL) are only being conducted in either laboratory simulations or small-scale pilot tests to date. As a result, there continues to be a major gap in terms of supporting DRL-based adaptive controls for high-value horticultural crops due to insufficient field-validated evidence across multiple sites and seasons; as noted in the literature on artificial neural networks (ANNs)/random forests (RFs)/long short-term memory (LSTMs) for estimating evaporation from transpiration (ET), there is also sufficient evidence to cushion the transition from researching ET to developing user-based adaptive controls using DRL-based algorithms (Deep learning for intelligent irrigation decision-making, 2025; Gautron *et al*., 2023) [13, 17]. Finally, very few of the studies reviewed to date provide the full soil-plant-atmosphere-based continuum in their evaluation and, as a result, the use of this continuum in evaluating ET estimates, soil moisture dynamics, plant physiological stress indicators, and economic/water productivity outcomes has been limited; many of the studies have focused on just one piece of this continuum (Machine learning and digital twins in smart irrigation, 2025; Precise application of water and fertilizer to crops…, 2024) [7, 18]. Moreover, the empirical evidence required for the calculation of comparative cost-effectiveness and scalability has not been sufficient given that low-cost edge artificial intelligence (AI) and TinyML architectures have been increasingly promoted as suitable alternatives to more conventional systems in terms of providing resources for the development of cost-benefit analysis based on comparisons of these systems against both conventional practices and cloud-based AI architectures (Affordable precision agriculture…, 2026; Estimating the value of satellite-derived measurements of evapotranspiration…, 2024) [11, 21].

Twelve emerging trends were noted in the literature reviewed for this report: (i) new techniques being developed to integrate satellite ET (actual evapotranspiration) systems (such as OpenET, ECOSTRESS-Landsat-Sentinel Data Fusion) and machine learning (ML) post processing techniques to produce near-daily ET measurements at the field scale (Volk *et al*., 2024; Improving the spatiotemporal resolution of remotely sensed evapotranspiration information…, 2022) [22, 23]; (ii) adaptation of deep reinforcement learning (RL) to provide feedback/control systems for irrigation management (Gautron *et al*., 2023) [17]; (iii) creation of inexpensive, low-power, edge-AI (Artificial Intelligence), and TinyML (Tiny Machine Learning) systems designed to provide smallholder and resource-constrained farmers with precision irrigation (Affordable precision agriculture…, 2026) [11]; (iv) application of explainable AI (XAI) methodologies within the agricultural/irrigation planning process (which is typically done with yield- and pest-related metrics) beyond crop yield and pest control to include irrigation decision support (Application of machine learning approaches in supporting irrigation decision making, 2024) [12]; and (v) increased application of hybrid/meta-heuristic/optimizing frameworks that combine deep learning with RL for providing optimized water quality or irrigation inputs in the production of high-value crops like potatoes (Hybrid deep learning optimization for smart agriculture…, 2025) [16].

6. Discussion

The body of research compiled here centers around one consistent conclusion that all studies came to previously. AI-based modeling approaches produce superior results instead of reference or actual ET methods as defined by schedule, empirical methods or calendar-based approaches for estimating ET, satellite-based measurement of field-scale ET, using real-time data from IoT or using reinforcement learning for adaptive control, demonstrate substantially greater predictive accuracy and also measurable water savings. High-value crop examples such as DRL-scheduled tomatoes provide an average of 20% -30% water savings (Yield prediction, pest and disease diagnosis, soil fertility mapping, precision irrigation scheduling…, 2025) [14] and improving the timing precision with satellite-AI combined ET Kit for almonds has resulted in economic returns (Estimating the value of satellite-derived measurements of evapotranspiration to inform irrigation scheduling in California almond orchards, 2024) [21]. These studies corroborate and expand upon the existing research regarding efficient irrigation through "deficit" methods of irrigation which have shown that some level of appropriately timed water restrictions can produce greater overall irrigation efficiency without significant crop yield loss in both temperate regions and controlled environments (Fereres and Soriano, 2007; A global meta-analysis of yield and water productivity responses of vegetables to deficit irrigation, 2021) [2, 29]. The significant contribution of AI relates not to the definition of deficit irrigation (as this concept existed prior to the introduction of AI techniques for more than 20 years) but rather on how machine learning/ deep learning techniques have enabled the identification of appropriate deficit irrigation tactics with both spatial (timing) and temporal (location/magnitude) resolutions that can only be achieved via an automated system rather than through manual or empirical work (Fereres and Soriano, 2007) [2].

The data isn't supportive of all performance models though, as they have been shown to be dependent on the type of crop, the location, and the type of data used to create them. At this time, there isn't a single performance model (ANN, RF, SVM, LSTM, XGBoost) that has been shown to outperform the others consistently across various platforms (Mortazavizadeh *et al*., 2025; Malik *et al*., 2023; Machine learning in agriculture: a comprehensive updated review, 2021) [5, 10, 34]. There is a discrepancy, or heterogeneity, that exists between scientists and farmers due to the differences between agro-ecological systems as well as unreliable benchmarking practices in academic literature (Volk *et al*., 2024) [22]. The performance of the satellite-based ET information is directly related to the amount of canopy architecture used during modeling (disorders naturally occlude paths), with DisALEXI and SIMS being the best for vineyards and orchards but having significant systematic bias in the other land use categories; therefore, an improvement in the performance of artificial intelligence will depend upon the quality, validity, and physical accuracy of the ET models constructed rather than improvements made through different algorithms (Volk *et al*., 2024; Kustas *et al*., 2020) [22, 20].

From a practical perspective, the available literature indicates that the most advanced and field-tested uses of AI-based irrigation scheduling for high-value crops are primarily occurring in specialty crop-producing regions that are well-instrumented, have had extensive research done on them and have high levels of institutional support (e.g., California wines and almonds using GRAPEX and T-REX) (Evaluation of satellite Leaf Area Index…, 2022; Kustas *et al*., 2020; Estimating the value of satellite-derived measurements of evapotranspiration…, 2024; Volk *et al*., 2024) [19, 20, 21, 22]. These factors could hinder equitable distribution among smallholder or lower-resource high-value crop systems, like vegetable and fruit producers in South Asia and sub-Saharan Africa, where irrigation efficiencies are often below 50% (Affordable precision agriculture…, 2026) [11]. However, the growing availability of low-cost edge based Artificial Intelligence (AI) and Tiny Machine Learning (TinyML) architectures and freely available satellite-based ET and Soil Moisture monitoring systems (OpenET, International Soil Moisture Network) are providing a potential way to reduce the disparity within these systems (Affordable precision agriculture…, 2026) [11].

From a theoretical perspective, the research presented in this review expands on the conceptual movement from irrigation scheduling primarily being a rule-based, calendar-dependent, to that of being a data-driven, adaptive decision-making process as part of the overall precision ag paradigm. The introduction of reinforcement learning specifically signals a movement from prediction (estimation of ET, soil moisture) to prescription (directing optimized irrigation actions with an inherent degree of uncertainty), which has far-reaching ramifications regarding how future research will be constructed, assessed, and validated on-farm (Gautron *et al*., 2023; Deep learning for intelligent irrigation decision-making, 2025) [17, 13].

7. Conclusion

The purpose of this review is to compile and synthesize peer-reviewed, credible literature on the implementation of AI-based systems for irrigation scheduling and their effect on the development of evapotranspiration dynamics and water productivity in high-value crops. The studies reviewed offer evidence that machine learning and deep learning models have greater ability to estimate evapotranspiration than classical empirical methods, that the integration of satellite and artificial intelligence provides a method for mapping actual ET at the field scale particularly useful to vineyard and orchard systems, that the Internet of Things (IoT)-integrated smart irrigation systems allow for real-time, adaptive scheduling of irrigation, and that control methods based on reinforcement learning provide prescriptive alternatives to purely predictive methods. Reported water savings on high-value crops typically range between around 15% to 40%, generally without significantly affecting yield, and in documented cases, with measurable gains in water productivity.

The majority of this synthesis provides evidence of the transition of AI-assisted irrigation scheduling from an emerging area of research to a growing number of field-validated AI tools in well-resourced specialty crop production areas, while indicating the uneven distribution of maturity of these tools across geographic regions, crop types, and farm sizes.

7.1. Recommendations for Researchers

This review suggests that there should be an increased standardization of AI-based ET and irrigation scheduling model benchmarking methods, an increased number of seasons and sites with multi-season/multi-site validation of RL-based control systems, the development of deeper and more integrated methods for integrating explainable AI into irrigation decision-making processes, and a substantial increase in research attention to high-value crops in water stressed poor/agriculture under-represented cite locations in the literature.

7.2. Recommendations for Practitioners and Policymakers

The results of this study can be used by practitioners and policymakers to motivate additional investments to build and maintain both open-access to satellite ET infrastructure (e.g., OpenET and others) and extension programs that translate AI-driven irrigation recommendations into actionable, trustable data and information for growers, as well as targeted support for smallholder producers of high-value crops to accelerate the adoption of low-cost edge-AI technologies and to ensure that the technology gap does not continue to expand the existing disparities in water productivity.

7.3. Future Research Directions

Some possible areas for future research involve the creation of transferable and explainable AI systems that can be validated in a variety of agro-climatic regions; enhanced integration of variables from the soil-plant-atmosphere continuum in a single decision-support system; extensive multi-seasonal research on economic and water productivity based on DRL methods using adaptive control of high-value crop production using field trials; and further development of low-cost sensors and edge computing to expand the advantages of precision irrigation beyond large-scale agricultural production.

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