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A Review on Optimizing Water Management in Agriculture through Smart Irrigation Systems and Machine Learning

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Abstract. Optimizing irrigation water usage is crucial for sustainable agriculture, especially in the context of increasing water scarcity and climate variability. Accurate estimation of evapotranspiration (ET), a key component in determining water requirements for crops, is essential for effective irrigation management. Traditional methods of measuring and estimating ET, such as eddy-covariance systems and lysimeters, provide valuable data but often face limitations in scalability, cost, and complexity. Recent advancements in machine learning (ML) offer promising alternatives to enhance the precision and efficiency of ET estimation and smart irrigation systems. This review explores the integration of machine learning techniques in optimizing irrigation water usage, with a particular focus on ET prediction and smart irrigation technologies. We examine various ML models, that have been employed to predict ET using diverse datasets comprising meteorological, soil, and remote sensing data. In addition to ET estimation, the review highlights smart irrigation systems that optimize irrigation schedules based on real-time data inputs. Through this review, we aim to provide a comprehensive overview of the state-of-the-art in ML-based ET estimation and smart irrigation technologies, contributing to the development of more resilient and efficient agricultural water management strategies.

1 Introduction

Water plays a vital role in irrigation and agriculture worldwide. The Food and Agriculture Organization of the United Nations (FAO) reported in 2017 that 70% of freshwater withdrawn globally is used in agriculture to sustain the growing human population [1]. Future projections indicate that water demand for irrigated food production will double by 2050, increasing pressure on already limited freshwater supplies. Although the FAO anticipates only a 10% increase in agricultural water withdrawal by 2050 due to improved management

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and irrigation practices, efficient water use within the irrigation and agricultural sectors remains crucial to alleviate the strain on global water resources [2].

The application of Artificial Intelligence (AI), particularly Machine Learning (ML), is revolutionizing various sectors, including agriculture. AI technologies are being leveraged to address the pressing challenges of modern agriculture, such as resource optimization, yield improvement, and sustainability. According to [3], AI in agriculture can be broadly divided into four categories: water management, soil management, livestock management, and crop management (Fig. 1).

Soil management focuses on maintaining soil health and fertility. AI techniques are used to analyze soil properties, monitor nutrient levels, and provide precise recommendations for soil amendments, leading to improved crop yields and soil conservation.

Livestock management includes monitoring the health and productivity of animals using AI-driven tools. Sensors and machine learning algorithms track animal behavior, detect diseases early, and optimize feeding strategies, contributing to better livestock welfare and productivity.

Crop management encompasses a range of activities from sowing to harvesting, aimed at maximizing crop yields and quality. AI applications in crop management include disease detection, yield prediction, and precision farming techniques that optimize planting and harvesting times.

Water management involves optimizing irrigation practices to ensure efficient use of water resources, a critical aspect given the increasing scarcity of freshwater. Machine learning models can predict evapotranspiration (ET) and automate irrigation schedules, significantly enhancing water use efficiency. This review will focus on this last category, providing a comprehensive synthesis of the existing literature on ML applications in water management, particularly in optimizing ET prediction and irrigation practices.

Recent technological advancements have spurred innovations such as mobile solutions for real-time monitoring of irrigation requirements [4] and Internet of Things (IoT)-based systems for precise water management in controlled environments [5].

Despite these advancements, accurately estimating water requirements remains a challenge in open-field agriculture due to the intricate interplay of environmental variables. Effective irrigation management necessitates a comprehensive understanding of climatic, physical, chemical, biological, and hydrological field characteristics to optimize water use efficiency [6].

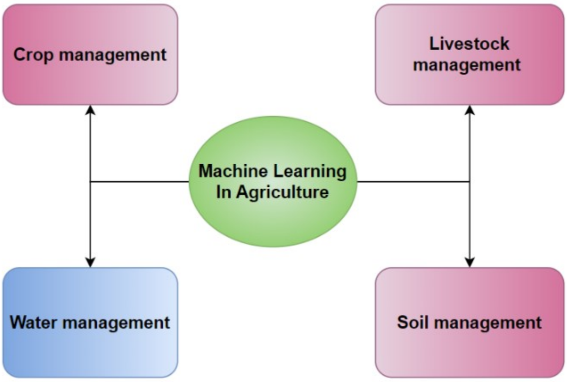

Fig. 1. Categories of AI Applications in Agriculture

In recent years, numerous survey articles have been published focusing on improving water use efficiency in irrigated agriculture [2, 7-12]. Other reviews have concentrated on the use of advanced technologies like smart sensors, Internet of Things (IoT), and Wireless Sensor Networks (WSN) in agriculture [13-20]. One of the most valuable survey papers in the realm of smart irrigation was conducted by [21], highlighting the application of monitoring and control strategies in precision irrigation. The authors provide a valuable starting point for researchers interested in smart irrigation. However, there appears to be a scarcity of systematic literature reviews that delve into how monitoring and control strategies specifically enhance water use efficiency in precision agriculture. This gap has been addressed by [22], who aim to build upon existing literature by integrating smart strategies for monitoring crop water use with ML-based irrigation control techniques, offering a comprehensive overview of smart irrigation systems.

While previous reviews have discussed various advancements in the application of machine learning (ML) in agriculture, there remains a need to systematically explore its specific role in optimizing evapotranspiration (ET) prediction and irrigation water management. The primary goal of this review is to provide a comprehensive synthesis of the existing literature on ML applications in these areas. This review aims to identify gaps in the current research landscape and highlight areas requiring further investigation. Additionally, this review critically assesses the effectiveness of various ML models and techniques used for predicting ET and managing irrigation water usage. Furthermore, this review addresses the challenges and limitations associated with implementing ML-based irrigation systems.

2 Review methodology

To comprehensively synthesize the literature on the application of machine learning (ML) in optimizing evapotranspiration (ET) prediction and irrigation water management, a systematic review methodology was employed. The sources of information included a variety of academic and professional publications, such as articles, books, and online databases. Key databases utilized for this review included Science Direct, IEEE Xplore, Springer, Wiley, Web of Science, MDPI, Google Scholar, and other Scopus-indexed journals.

The selection of sources was guided by several criteria to ensure the relevance and quality of the included literature. The focus was primarily on publications from the period 2017 to 2024 to capture the most recent advancements and trends in the field. Only articles that specifically addressed the application of ML, ET prediction or irrigation water management were considered, with peer-reviewed journals and conference papers prioritized to ensure the reliability and validity of the findings. A broad range of studies, including empirical research, review articles, and theoretical papers, were included to provide a holistic view of the topic.

A structured search strategy was implemented using specific keywords related to the research topic. The primary keywords and phrases used in the search included: Machine Learning in Agriculture, Evapotranspiration Prediction, Irrigation Water Management, Smart Irrigation Systems, AI in Agriculture, and Precision Agriculture. These keywords were used individually and in combination to retrieve a wide array of relevant articles. Additionally, references within the retrieved articles were also reviewed to identify further pertinent studies.

A total of approximately 82 articles were initially identified through the database searches. These articles were then screened based on their titles and abstracts to assess their relevance to the review's objectives. Following this initial screening, about 51 articles were selected for full-text review. Each of these articles was thoroughly examined, and key information was extracted and synthesized. The review process ensured that the most relevant and high-quality studies were included, providing a comprehensive overview of the state-of-the-art in ML applications for ET prediction and irrigation water management. This methodology facilitated the identification of current trends, research gaps, and potential future directions in the field.

3 Smart irrigation systems

Smart irrigation systems represent a significant advancement in agricultural water management, integrating advanced technologies to optimize water usage, improve crop yields, and enhance sustainability. These systems utilize real-time data collection, analysis, and automation to ensure that crops receive the precise amount of water they need at the right time. By leveraging technologies such as sensors, Internet of Things (IoT) devices, and machine learning algorithms, smart irrigation systems can dynamically adjust irrigation schedules based on various environmental and crop-specific factors. This results in more efficient water use, reduced wastage, and better crop health.

3.1 Monitoring strategies for smart irrigation systems

Effective monitoring is a crucial component of smart irrigation systems, enabling the continuous collection and analysis of data. This monitoring is divided into three essential categories [21]: soil-based, weather-based, and plant-based. Fig. 2 illustrates these monitoring strategies within smart irrigation systems.

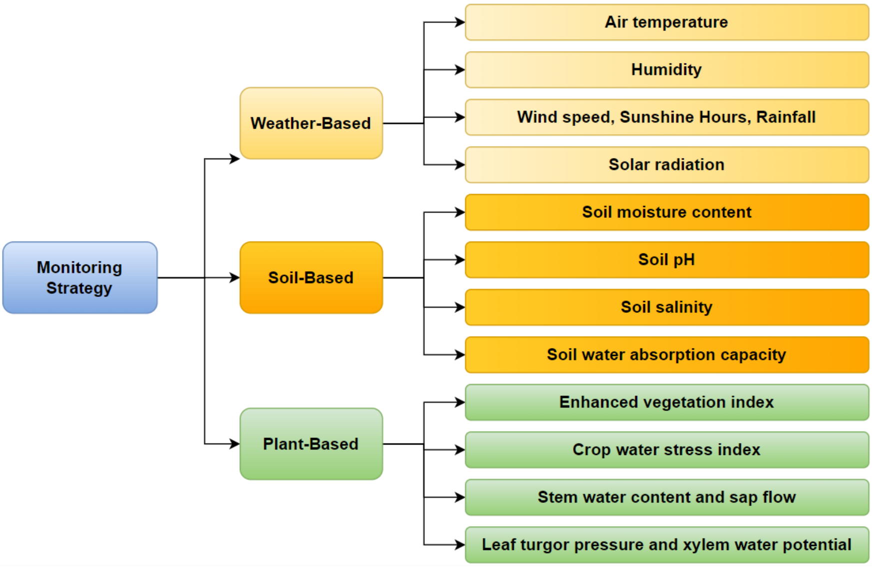

Fig. 2. Monitoring methods in smart irrigation. Adopted from [22]

3.1.1 Soil moisture monitoring

Soil moisture monitoring involves measuring either soil water potential or soil water content, crucial for effective irrigation scheduling [23]. Monitoring soil moisture in the plant root zone is essential for understanding moisture dynamics and its relationship with irrigation water volume and plant water uptake. Various methods exist for determining soil moisture levels, including direct methods like gravimetric sampling and indirect methods such as electromagnetic properties, heat conductivity, neutron count, water potential, and electrical resistance [22]. Advances in microcomputer and communication technology have facilitated the development of diverse soil sensors, including ground, aerial, and satellite-based moisture sensors, which are gaining prominence in irrigation management [24].

Soil moisture sensors deployed at multiple depths can capture soil moisture dynamics accurately. Sensors measuring physical, chemical, and mechanical properties of soil, using optical, radiometric, mechanical, acoustic, electrical, electromagnetic, pneumatic, or electrochemical methods, offer comprehensive data for irrigation decisions [25]. Recent advancements include combining remote sensing with ground sensors to address soil heterogeneity issues [26].

Soil-based monitoring for irrigation scheduling, while effective, comes with several inherent limitations that must be carefully considered in agricultural applications. One of the primary challenges is spatial variability, where soil moisture levels can vary significantly across fields due to differences in soil type, topography, and vegetation cover [27]. This variability necessitates the deployment of multiple sensors at various locations to capture representative data, which can escalate costs and complicate logistics [28].

Another critical consideration is depth variability in soil moisture measurement. Sensors typically measure moisture content at fixed depths, which may not always correspond with the active root zone of crops or account for variable root distributions [29]. This limitation can lead to inaccuracies in determining actual water requirements, potentially resulting in under or over-irrigation practices [30].

Sensor accuracy and calibration are essential but challenging aspects of soil moisture monitoring. Factors such as soil compaction, sensor placement, and calibration drift over time can affect the reliability and consistency of sensor readings [31]. Ensuring sensors are properly calibrated and maintained is crucial to obtaining accurate data on soil moisture dynamics.

The temporal dynamics of soil moisture also pose challenges. Soil moisture levels fluctuate diurnally and seasonally, influenced by factors such as weather patterns, evapotranspiration rates, and irrigation practices [32]. Continuous monitoring and real-time data analysis are essential to adapt irrigation schedules dynamically, but these processes require robust infrastructure and reliable communication networks [33].

Addressing these limitations requires ongoing advancements in sensor technology, data analytics, and decision support systems tailored to agricultural settings. Innovations that enhance sensor accuracy, improve data integration, and reduce operational costs will be crucial for realizing the full potential of soil-based monitoring in sustainable agriculture [16]. Table 1 shows some of the parameters that are monitored and used in smart irrigation systems.

3.1.2 Plant-Based monitoring

Plant-based monitoring using optical sensors has become a pivotal method for assessing plant water stress and overall crop health, including responses to threats like drought, nutrient deficiencies, and pest infestations [34]. This approach utilizes sensors that can be fixed near the plant or mounted on various moving platforms such as drones, UAVs, and satellites [35]. Optical sensors are categorized as contact or non-contact, with non-contact sensors being proximal or remote. Proximal sensors are handheld or vehicle-mounted, while remote sensors operate from aerial or satellite platforms [36].

Recent advancements have integrated optical sensor data with decision support systems (DSS) to enhance irrigation management precision. For instance, UAVs equipped with high-

Table 1. Summary of basic monitoring and control parameters for precision irrigation system [21]

Parameters	Common value/unit	Measuring device
Soil monitoring parameters		
Soil moisture content	Gravimetric /Volumetric water content: 0% to 100%/0 m3 /m3 to 5 m3 /m3	Soil moisture sensor (VH400, ECH2O EC Sensor, DS200, TDR Probe, tension and neutron sensors, etc.)
Salinity	Low: (0–0.15), Medium: (0.51–1.25) Very high: (1.76–2.00 mmhos/cm)	EC measuring device
Soil water absorption capacity	Wilting point, field capacity	Mini drain system
pH	Acidic: 0–6.9, Neutral: 7, Alkaline: 8–14	pH meter
Weather monitoring parameters		
Greenhouse canopy light	0% to 100%	Light dependent resistor (LDR)
Crop canopy/air temperature/humidity	0ºC to 40ºC/0% to 100%	SHT 11, DHT 22 sensor, handheld infrared thermometer, etc.
Environmental weather variables (Rainfall, wind, solar radiation, etc.)	mm, %, W/m^2 etc.	Weather station (Davis Vantage), etc.
Reference Evapotranspiration (ETo)	0–1 (mm/s)	Lysimeter, IoT- based weather station, etc.
Plant monitoring parameters		
Normalized difference vegetative Index (NDVI)	Pixels (Images of plant/crops) Low: 0.2–0.4, Mid: 0.4–0.6, High: 0.6 above.	Raspberry pi camera, UAV, drones, Satellites imaging, AVHRR Instrument, Decagon' spectral reflectance sensor, etc.
Leaf Area Index (LAI)	0 (bare ground) to 10 (dense vegetation) (m2 /m2)	AccuPAR LP-80 Ceptometer, CI-110, 202, 203 Plant canopy imager. MODIS and. Moderate-resolution Imaging Spectroradiometer
Enhanced Vegetation Index (EVI)	−1 to 1	Satellite, UAV Camera, NIR Spectroscopy, AVHRR Instrument
Crop water stress index (CWSI))	0(no water stress) to 1(Maximum water stress)	Derived from the measurement of the TDR method
Stem water content	cm3 cm−3	Derived from the measurement of the TDR method
Sap flow	m3 m−2 s −1	Sap flow Sensor
Leaf turgor pressor	kPa	Pressure LPCP probe
Xylem water potential	Mpa	Scholander-type chambers or with microtensiometers
Stomatal conductance	mol m−2 s −1	Porometer
Stem Diameter Variation (SDV)	µm	Linear variable differential transformers (LVDT) Sensor.

resolution cameras have been employed to capture multispectral images, such as the normalized difference vegetation index (NDVI), which correlates with crop health and water requirements [37, 38]. These technologies allow for precise irrigation scheduling by providing real-time data on plant conditions, optimizing water use efficiency [39].

Despite these benefits, plant-based monitoring has limitations. Unlike soil-based methods, plant-based sensors do not directly measure the quantity of irrigation water needed, requiring supplementary data from soil moisture measurements and water balance models [40]. Additionally, the effectiveness of plant-based indices can vary depending on crop type, growth stage, and environmental conditions, affecting the reliability of irrigation scheduling based solely on plant water status [41].

3.1.3 Weather based monitoring

Weather-based monitoring is a crucial aspect of smart irrigation systems, involving the real-time estimation of reference evapotranspiration (ET) using measured weather parameters. This method provides an indication of water loss from both plants and the soil environment, which is influenced by factors such as humidity, wind speed, solar radiation, and air temperature [21, 36]. The temporal dynamics of evapotranspiration, observed on hourly or daily timescales, are particularly suitable for determining crop water use in smart irrigation systems. In situations where soil or plant measurements are not feasible, weather parameters offer an approximate irrigation schedule [40].

The FAO Penman-Monteith equation, discussed in [42], is widely used for calculating hourly or daily evapotranspiration values using standard climatological measurements. The equation takes into account air temperature, solar radiation, humidity, and wind speed to estimate crop water use, which is crucial for developing effective irrigation schedules. Most real-time weather-based monitoring systems include automatic weather stations equipped with sensors for various parameters, and data loggers that automatically acquire data and transmit it via communication systems to online portals. These systems often integrate with site-specific variables, such as soil type, to adjust irrigation schedules accurately [22].

Implementations of weather-based monitoring systems frequently utilize IoT platforms and wireless sensor networks (WSN). For example, [43] developed a smart water management system using affordable components and LoRa LPWAN technology for efficient data transmission. [44, 45] demonstrated similar approaches, using weather-based sensors to monitor and transmit real-time data for precise irrigation management.

However, while weather-based monitoring systems are widely used, they have some limitations. One significant challenge is that meteorological stations measure parameters for the entire plantation, leading to a single ET value and thus a single irrigation recommendation for all plots. To address this challenge, ML techniques are being applied to sensor-based moisture data in combination with meteorological data, leading to more accurate and plot-specific irrigation recommendations [46].

We will discuss the details of evapotranspiration (ET) estimation and its role in irrigation scheduling in more detail later in this article.

3.2 Control Techniques for Smart Irrigation Systems

Control strategies for smart irrigation systems are essential for ensuring the precise application of irrigation water, optimizing water use efficiency, energy savings, and enhancing crop yields. These strategies are primarily divided into open-loop and closed-loop systems (Fig. 3).

3.2.1 Open-loop irrigation control

In open-loop systems, irrigation decisions are pre-determined and set by the operator, based on fixed schedules or volumes. These systems are simple and cost-effective as they do not require sensors for monitoring soil moisture or environmental conditions. However, they are less responsive to changing conditions and often result in lower water use efficiency. Examples of open-loop systems include basic irrigation timers and volume-based controls, which operate on fixed schedules without feedback from the environment [21].

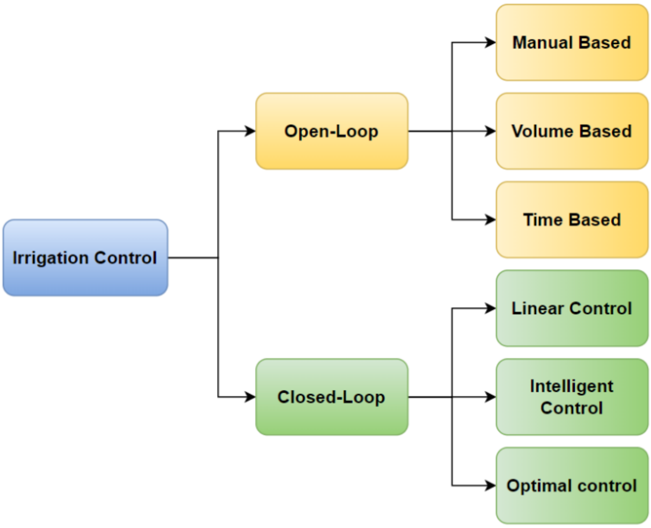

Fig. 3. irrigation control strategies. Adapted from [21] ; [22]

3.2.2 Closed-loop irrigation control

Closed-loop systems, on the other hand, utilize feedback from various sensors to make real-time irrigation decisions. These systems continuously monitor environmental and soil conditions such as soil moisture, air temperature, solar radiation, and humidity. Based on this data, the system dynamically adjusts irrigation schedules and amounts to meet the specific needs of the crops. This approach enhances water use efficiency and responds effectively to varying conditions [47].

Closed-loop control strategies are further categorized into different types, including linear control, intelligent control, and optimal control. Intelligent control systems, which are of particular interest, employ AI technologies like Artificial Neural Networks (ANN), fuzzy logic, and expert systems. These AI-based systems mimic human decision-making processes and adapt to the complex, non-linear, and time-varying dynamics of agricultural environments.

AI technologies have significantly advanced the field of irrigation control. AI algorithms can analyze large datasets and make precise irrigation recommendations based on historical data and real-time sensor inputs. Studies have demonstrated the effectiveness of AI in optimizing irrigation schedules. For example, [46] developed a model that captures the decision-making process of agronomists by applying machine learning to integrated datasets of sensor-based moisture data, meteorological data, and historical irrigation plans. This model improved plot-specific irrigation recommendations, enhancing overall irrigation efficiency.

In this review, we will focus on intelligent control strategies, particularly the application of AI in closed-loop systems, to explore how these advanced techniques can further optimize irrigation management and contribute to sustainable agriculture.

4 Evapotranspiration

Evapotranspiration (ET) is a crucial component of the water cycle, encompassing both soil evaporation and plant transpiration. It represents the total water loss from the land surface to the atmosphere and plays a vital role in determining crop irrigation needs [48]. Accurate ET estimation is essential for providing crops with the optimal amount of water, thereby maximizing yield and conserving water resources by replenishing the water lost since the last irrigation.

Focusing on ET for irrigation scheduling offers several advantages. It provides a comprehensive measure of water loss, accounting for both soil moisture and plant water uptake. By using ET-based irrigation schedules, farmers can achieve more precise water application, reducing wastage and ensuring crops receive the necessary water at the right time [49]. However, accurately measuring ET can be challenging due to variations in climate, soil, and crop conditions. This is where advanced methods, particularly machine learning (ML), come into play.

In recent decades, various methods for estimating evapotranspiration (ET) have been developed, which can be broadly categorized into direct, indirect, and regional approaches (Fig. 4).

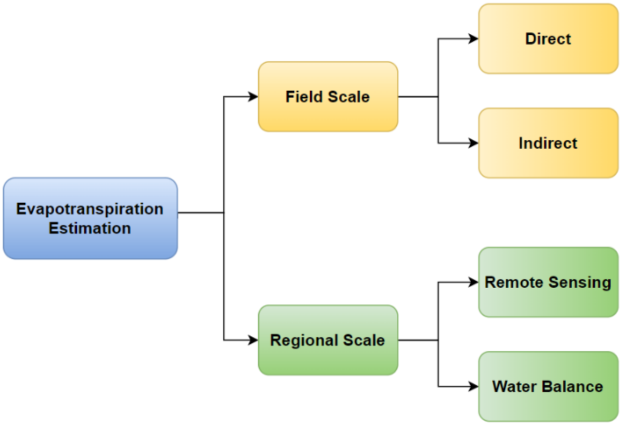

Fig. 4. Evapotranspiration estimation approaches. Adapted from [50]

Direct methods, such as lysimeters, eddy covariance systems, Bowen ratio, and sap flow techniques, provide accurate measurements but are often expensive, labor-intensive, and can disturb the natural environment [50]. Lysimeters offer precise ET measurements by directly quantifying water loss from a controlled soil volume, while eddy covariance systems measure the exchange of water vapor between the land surface and the atmosphere, providing continuous high-frequency data [51]. The Bowen ratio method calculates ET by measuring the sensible and latent heat fluxes based on temperature and humidity gradients, which can be effective in relatively uniform environments but may struggle with spatial variability and atmospheric stability issues [52]. Sap flow techniques measure the movement of water through the stems of plants, offering insights into transpiration rates directly from individual plants. However, they require extensive calibration and are typically limited to small-scale studies due to their complexity and cost [53]. Despite their accuracy, these direct methods are limited by their cost, complexity, and spatial coverage, necessitating the development and use of indirect methods for broader applications [52, 53].

The most common and practical Indirect approach is the FAO-56 method, as described by [42]. This method is preferred for operational monitoring of soil-plant water balance due to its practicality and reliability compared to more complex soil-vegetation-atmosphere-transfer models.

4.1 FAO-56 approach

In the FAO-56 approach, crop evapotranspiration (ETc) is estimated through the combination of a reference evapotranspiration (ET0) and crop coefficients (Kc). There are two different FAO-56 approaches: single and dual crop coefficients.

4.1.1 Single crop coefficient approach:

Combines plant transpiration and soil evaporation into a single crop coefficient (Kc).
ETc is calculated as:

$$ETc = Kc \times ET0 \qquad (1)$$

4.1.2 Dual crop coefficient approach:

Separates the contributions of plant transpiration (Kcb) and soil evaporation (Ke).
ETc is calculated as:

$$ETc = (Kcb + Ke) \times ET0 \qquad (2)$$

4.1.3 Reference evapotranspiration (ET0)

The reference surface for ET0 is a well-watered green grass of uniform height and infinite extent, which is actively growing and completely shading the ground. ET0 can be calculated by various methods, with the FAO Penman-Monteith equation being the most widely used:

$$ET0 = \frac{0.408\Delta(Rn\text{-}G)+\gamma\left(\frac{900}{T+273}\right)u2(es\text{-}ea)}{\Delta+\gamma(1+0.34u2)} \qquad (3)$$

where:

- ET0 is the reference evapotranspiration (mm/day),
- Rn is the net radiation at the crop surface (MJ/m²/day),
- G is the soil heat flux density (MJ/m²/day),
- T is the daily average air temperature (°C),
- u2 is the wind speed at 2 m height (m/s),
- es is the saturation vapor pressure (kPa),
- ea is the actual vapor pressure (kPa),
- Δ is the slope of the vapor pressure curve (kPa/°C),
- γ is the psychrometric constant (kPa/°C).

This method relies on meteorological data such as air temperature, solar radiation, relative humidity, and wind speed. These parameters influence the various components of the equation:

- Air Temperature (T): Affects the saturation vapor pressure and the overall energy balance.
- Solar Radiation (Rn): Provides the energy necessary for evaporation and transpiration.
- Relative Humidity (es - ea): Influences the vapor pressure deficit, driving the evapotranspiration process.
- Wind Speed (u2): Affects the transport of water vapor away from the crop surface, influencing the vapor pressure deficit.

4.1.4 Crop coefficients (Kc)

Crop coefficients (Kc) are essential for adjusting reference evapotranspiration (ET0) to specific crop conditions. These coefficients are influenced by the dynamics of crop canopies, including factors such as cover fraction, leaf area index (LAI), and greenness. By utilizing satellite data, it is possible to estimate key variables related to vegetation phenology, enabling the monitoring of spatial and temporal variability in Kc [54, 55].

Remotely sensed spectral reflectance offers an indirect method for estimating crop coefficients or basal crop coefficients, as these are related to LAI and fractional ground cover [56]. Remote sensing techniques using vegetation indices, such as the normalized difference vegetation index (NDVI) and the soil-adjusted vegetation index (SAVI), have been extensively tested for predicting crop coefficients at both field and regional scales [57].

These techniques provide a valuable tool for accurately estimating crop water requirements, contributing to more efficient and effective irrigation management.

4.1.5 Hargreaves method

To address the limitation of data availability, the Hargreaves method [58] can be used as an alternative. This physics-based method requires fewer data inputs and can estimate ET0 using only temperature data:

$$ET0 = a \times R \times (T + 17.8) \qquad (4)$$

Where:

- a is a calibration coefficient
- R is extraterrestrial radiation
- T is the mean air temperature

The Hargreaves method is less accurate compared to the Penman-Monteith equation but provides a practical solution in data-scarce regions.

4.2 Regional estimation using remote sensing data

Since the emergence of Earth observation technology in 1957, particularly with the launch of the TIROS meteorological satellites in 1960 and the Landsat series in 1972, various methods have been developed for estimating evapotranspiration (ET) over time and space on regional and global scales [59, 60]. However, remote sensing (RS) data do not directly measure surface ET; instead, they estimate surface parameters linked to ET. Table 2 shows various remote sensing sources and their parameters

Table 2. Summary of remote sensing sources and their parameters

Remote Sensing Source	Spatial Resolution	Spectral Bands	Key Parameters Provided
MODIS (Moderate Resolution Imaging Spectroradiometer)	250m to 1000m	36 bands	- Surface temperature- Vegetation indices (e.g., NDVI)- Land surface albedo- Soil moisture- Cloud cover
Sentinel-2	10m to 60m	13 bands	- Vegetation indices (e.g., NDVI)- Surface temperature (with additional data)- Soil moisture (with additional data)- Land cover classification- Water quality parameters (e.g., chlorophyll concentration)
Landsat 8	15m to 30m	11 bands	- Surface temperature- Vegetation indices (e.g., NDVI)- Land cover classification- Soil moisture (with additional data)- Water quality parameters- Cloud cover
Landsat 9	15m to 30m	11 bands	- Surface temperature- Vegetation indices (e.g., NDVI)- Land cover classification- Soil moisture (with additional data)- Water quality parameters- Cloud cover
Sentinel-1	10m to 40m	N/A (SAR)	- Soil moisture- Surface water extent- Surface roughness- Vegetation structure (through backscatter)
Sentinel-3	300m to 1000m	21 bands	- Sea surface temperature- Land surface temperature- Vegetation indices (e.g., NDVI)- Sea surface salinity- Chlorophyll concentration in water- Surface roughness
TerraSAR-X	1m to 40m	N/A (SAR)	- Soil moisture- Surface roughness- Vegetation structure- Land cover classification
RADARSAT-2	3m to 100m	N/A (SAR)	- Soil moisture- Surface roughness- Vegetation structure- Land cover classification- Flood monitoring
ALOS-2 (Advanced Land Observing Satellite-2)	10m to 100m	N/A (SAR)	- Soil moisture- Surface roughness- Vegetation structure- Disaster monitoring- Land cover classification
WorldView-3	31cm to 1.24m	29 bands	- High-resolution imagery- Land cover classification- Vegetation indices- Urban mapping- Water quality parameters
IKONOS	1m to 4m	4 bands	- High-resolution imagery- Land cover classification- Vegetation indices- Urban mapping- Water bodies mapping
QuickBird	60cm to 2.5m	4 bands	- High-resolution imagery- Land cover classification- Vegetation indices- Urban mapping- Water bodies mapping
GOES (Geostationary Operational Environmental Satellites)	1km to 5km (varies by instrument)	16 bands	- Cloud cover- Sea surface temperature- Atmospheric water vapor- Storm tracking- Vegetation indices (e.g., NDVI)
AVHRR (Advanced Very High-Resolution Radiometer)	1.1km to 4.4km	6 bands	- Vegetation indices (e.g., NDVI)- Surface temperature- Sea surface temperature- Land cover classification- Cloud cover
Terra (EOS AM-1) / Aqua (EOS PM-1)	250m to 1km	36 bands (MODIS)	- Surface temperature- Vegetation indices (e.g., NDVI)- Evapotranspiration- Land cover classification- Cloud cover- Soil moisture (with additional data)

Satellite-based vegetation indices (VIs), such as the Normalized Difference Vegetation Index (NDVI), Leaf Area Index (LAI), and Fraction of Photosynthetically Active Radiation

(FPAR), are used to monitor green vegetation cover. NDVI, the most widely used index, is suitable for all land cover conditions and can be obtained from various satellites, including the Landsat series, AVHRR, and MODIS [61-63]. LAI, a key indicator of plant growth, helps estimate photosynthesis and is derived from RS data available from MODIS and Landsat. FPAR measures the amount of absorbed photosynthetically active radiation, aiding in biomass production and ET estimation, and is derived from RS data from MODIS and Sentinel-2 [64].

Surface temperature variations significantly impact ET rates, with increased surface temperature indicating greater energy absorption, leading to higher heat transfer and ET rates [65]. The distribution of surface temperature reveals changes in land cover and soil moisture, which can influence ET rates. Land Surface Temperature (LST) data, extensively used in ET estimation, can be obtained from various satellites, including Terra/Aqua MODIS, GOES, and AVHRR. Albedo, the measure of surface reflectivity, also affects the energy balance and, consequently, ET rates, with data obtainable from sensors like MODIS. [50] provide detailed discussions on RS input parameters used to estimate ET.

5 Machine learning models for evapotranspiration estimation

Given the limitations of both direct and indirect methods, machine learning (ML) has emerged as a valuable tool for improving ET estimation due to their ability to process vast amounts of data, identify patterns, and make accurate predictions without needing explicit biophysical mechanisms.

The application of ML models in ET estimation has grown significantly over the years, proving to be competitive or superior to traditional physical and experimental methods [66]. Research has identified over 30 ML models employed for ET estimation, with Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) being among the most frequently used [50]. These models are utilized for various purposes within the ET estimation process, such as data preparation [67] , temporal gap-filling [68], downscaling and upscaling [69, 70], combining outputs of different methods [71-73], and handling cloudy pixels (Table 3).

- Random Forest (RF): RF is a tree-based model that constructs multiple decision trees (CART) and averages their results to improve accuracy and stability. This model is robust to overfitting and can handle large datasets with high dimensionality. It has been widely used due to its ease of use and high accuracy in ET estimation tasks [60].
- Support Vector Machines (SVM): SVM is a supervised learning model effective for both classification and regression tasks. It works by finding the optimal hyperplane that separates data points in an n-dimensional space. SVM is particularly useful in low data environments and can handle both linear and nonlinear relationships. Studies have shown that SVM can explain a significant portion of ET variations using various meteorological and vegetation indices as inputs [74-77].
- Artificial Neural Networks (ANN): ANNs are composed of interconnected processing units (neurons) that can learn from data. They are highly effective in modeling complex nonlinear relationships and can handle noisy datasets. ANNs have been shown to outperform traditional methods like the Terra/MODIS PET in ET estimation and have demonstrated higher accuracy and broader applicability compared to RF and SVM models [78, 79].
- Extreme Gradient Boosting (XGBoost): XGBoost is an efficient and scalable implementation of gradient boosting that has been applied successfully in ET estimation. It combines the outputs of multiple weak learners to form a strong predictive model. Studies have demonstrated its effectiveness in various climatic regions and temporal resolutions, making it a robust choice for ET prediction [91-98].

Table 3. Summary of Machine Learning Models Used for Evapotranspiration Estimation

ML Model	Authors	Inputs	Outputs	Results/Remarks
Random Forest (RF)	[60, 67, 71, 80-84]	Meteorological and vegetation indices	ET	Effective for ET estimation at basin level, outperformed other learning models including SVM, DNN, and CNN. Robust against overfitting with appropriate tuning.
Support Vector Machines (SVM)	[75-77, 85, 86]	Temperature, relative humidity, wind speed, solar radiation, NDVI	ET	Effective in low data environments, explains 60-85% of ET variations, good for short-term prediction, surpasses ANN in accuracy.
Artificial Neural Networks (ANN)	[78, 79, 87-90]	Temperature, humidity, solar radiation, wind speed, various meteorological data	ET	High accuracy, better performance than Terra/MODIS PET, effective in modeling complex nonlinear relationships, used for various ET estimation tasks.
Extreme Gradient Boosting (XGBoost)	[91-98]	Temperature, relative humidity, wind speed, solar radiation, precipitation	ET	Robust, scalable, effective across various climatic regions and temporal resolutions, demonstrated high accuracy in multiple studies.
Convolutional Neural Networks (CNN)	[99-101]	Temperature, humidity, wind speed, solar radiation, RS data	ET	Higher accuracy in ET prediction compared to RF and XGBoost, captures spatial and temporal dependencies effectively.
Extreme Learning Machine (ELM)	[102, 103]	Temperature, humidity, wind speed, solar radiation	ET	High accuracy with biological heuristic algorithms, effective for daily ET prediction, integrates optimization algorithms like GWO for improved performance.
Multivariate Adaptive Regression Spline (MARS)	[104]	Temperature, humidity, solar radiation, wind speed	ET	Superior to FAO-56 Penman-Monteith method in estimating monthly ET, effective for various climatic conditions.
Grey Wolf Optimiser (GWO) with ELM	[102]	Temperature, humidity, wind speed, solar radiation	ET	High accuracy ($R^2 = 0.945–0.955$), avoids local optimization, effective in nonlinear and multivariate functions, demonstrated high performance in specific regions.
General Regression Neural Network (GRNN)	[103]	Temperature, humidity, wind speed, solar radiation	ET	High accuracy in regional applications, effective in handling temporal variations, used for daily ET estimation.
Hybrid Models (ANN-ELM, ANN-GRNN)	[103]	Meteorological data	ET	Combining multiple ML models to enhance prediction accuracy, effective in different regional scenarios.

- Deep Learning Models: Deep learning techniques, including Convolutional Neural Networks (CNNs) and hybrid models, have been increasingly used for ET forecasting. These models can capture spatial and temporal dependencies more effectively than traditional ML models. Research has shown that CNNs and other deep learning algorithms can achieve higher accuracy in ET prediction tasks compared to RF and XGBoost models [99-101, 105].

In summary, ML models have become indispensable tools in ET estimation due to their ability to handle complex datasets and provide accurate predictions. They offer significant advantages over traditional methods, including flexibility, scalability, and improved performance across various environmental conditions. As the field progresses, integrating ML with other advanced techniques and data sources will likely further enhance the accuracy and applicability of ET estimation models [50, 105, 106].

6 Future directions and challenges

While the application of ML models to ET estimation is promising, several challenges and future directions need to be addressed to enhance their efficacy and applicability:

- Data Quality and Availability: High-quality and comprehensive datasets are crucial for training effective ML models. In many regions, especially in developing countries, the availability of consistent and accurate meteorological and remote sensing data remains a challenge. Future research should focus on developing models that can handle sparse and noisy data, possibly through data augmentation techniques or improved preprocessing methods.
- Model Interpretability: One of the primary challenges with advanced ML models, such as deep neural networks, is their interpretability. Stakeholders, including farmers and water resource managers, need to understand the model's decision-making process to trust and effectively utilize its predictions. Efforts should be made to develop explainable AI techniques that can elucidate how these models arrive at their predictions.
- Computational Resources: Advanced ML models often require significant computational power and resources, which may not be readily available in all research settings or for practical applications in agriculture. Future developments in hardware and more efficient algorithms will be crucial to making these models more accessible.
- Integration with Physical Models: While ML models excel at pattern recognition and prediction, they often do not incorporate the underlying physical processes of ET. Hybrid models that combine ML with physical models could provide more robust and accurate ET estimates. This approach can leverage the strengths of both methods, providing a more comprehensive understanding of ET dynamics.
- Climate Change Adaptation: As climate change alters weather patterns and hydrological cycles, ML models must adapt to these changes. Developing models that can predict ET under different climate scenarios will be essential for sustainable water management and agricultural planning.
- Scalability and Transferability: Ensuring that ML models developed for specific regions or datasets can be effectively scaled and transferred to different contexts is vital. Research should focus on creating generalized models or methods for efficiently adapting models to new regions with minimal retraining.
- Real-Time Monitoring and Prediction: Integrating ML models with IoT devices and remote sensing technology can enable real-time monitoring and prediction of ET, providing timely and actionable insights for water management. This integration can help in the dynamic allocation of water resources and improve irrigation efficiency.
- Policy and Stakeholder Engagement: For ML models to be effectively implemented, there needs to be strong collaboration between researchers, policymakers, and stakeholders. Policies that support data sharing, investment in technology, and training for end-users are essential for the successful adoption of ML-based ET estimation methods.
- In conclusion, while machine learning models offer significant advancements in evapotranspiration estimation, addressing these challenges and exploring future

directions will be critical for their widespread adoption and effectiveness. Continued interdisciplinary research and collaboration will be key to harnessing the full potential of ML in water resource management and agricultural sustainability.

7 Conclusion

In conclusion, the integration of smart irrigation systems with advanced monitoring strategies and sophisticated control techniques represents a significant advancement in agricultural water management. By leveraging technologies such as soil moisture sensors, plant-based monitoring systems, and weather-based data, these systems enable precise and efficient irrigation, which is crucial for sustainable agriculture. The use of both open-loop and closed-loop control techniques further enhances the adaptability and responsiveness of irrigation practices to dynamic environmental conditions.

The application of machine learning (ML) models for evapotranspiration (ET) estimation has proven to be a powerful tool, providing more accurate and reliable predictions compared to traditional methods. The ability of ML models to process large datasets, learn complex patterns, and incorporate diverse data sources, including remote sensing inputs, has made them indispensable in modern irrigation management.

However, despite these advancements, several challenges remain. The quality and availability of data, model interpretability, computational resource requirements, and the need for integration with physical models are areas that require ongoing research and development. Additionally, adapting ML models to changing climate conditions, ensuring scalability and transferability across different regions, and fostering collaboration among researchers, policymakers, and stakeholders are essential for maximizing the benefits of these technologies.

Future research should focus on addressing these challenges, improving model robustness, and developing more accessible and explainable AI solutions. By continuing to innovate and refine these technologies, we can achieve more sustainable and efficient water use in agriculture, ultimately contributing to food security and environmental conservation.

In summary, the advancements in smart irrigation systems and ML-based ET estimation hold great promise for the future of agriculture. With continued interdisciplinary efforts and a focus on overcoming current limitations, these technologies can play a pivotal role in transforming agricultural practices and ensuring the sustainable use of water resources.

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