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Scheduling irrigation with artificial intelligence: a systematic review on evapotranspiration based techniques

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ABSTRACT

Smart agriculture relies on efficient irrigation scheduling. Crop stress, nutrient leaching, and water loss are all caused by under or over-irrigation. Consequently, intelligent irrigation scheduling techniques will be critical to addressing the above issues shortly. Smart agriculture can be made more innovative and more efficient by using artificial intelligence (AI). The AI-centred approach carries enormous potential in estimating water requirements and the right time and place of irrigation. Motivated by the benefits of AI in irrigation scheduling, this article aims to provide a systematic review of AI-enabled irrigation scheduling techniques for intelligent agriculture. We have discussed various conventional irrigation scheduling techniques based on reference and crop evapotranspiration. Then, we present an in-depth analysis of the role of AI in designing and optimizing these irrigation scheduling techniques into AI-enabled intelligent irrigation scheduling techniques. Finally, various challenges and future research directions for designing and implementing AI-based irrigation scheduling techniques have been introduced.

Subjects Human-Computer Interaction, Artificial Intelligence, Emerging Technologies, Neural Networks, Internet of Things
Keywords AI, Irrigation scheduling, Evapotranspiration, Machine learning, Deep learning

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INTRODUCTION

A nation's economic development is heavily dependent on its agricultural sector. Increasing population, climate change, and water scarcity have made it challenging to meet ever-increasing food demands. Water scarcity has threatened sustainable development since we cannot grow food without water. Water scarcity will affect approximately 1,800 million people by 2050 (*Jahura, Islam & Mostafa, 2024*). Increasing populations, industry, and agriculture demands put heavy pressure on water resources, contributing to water scarcity. Moreover, climate change will worsen the situation in the future. The global population is expected to reach 9.7 billion by 2050, increasing the demand for healthy food and water (*United Nations, Department of Economic and Social Affairs, Population Division, 2019*). Areas, where food is grown, do not expand; therefore, agricultural cropping systems must use the limited water and land resources as efficiently as possible to feed the world's expanding population.

Agriculture uses 75–80% of available freshwater globally for irrigation purposes and is considered a victim and reason for water scarcity. Irrigation in arid regions during insufficient rainfall increases agricultural growth, maintains landscapes, and patches the damaged soils. Approximately 1.55×10^9 hectares of agricultural land cultivated globally accounts for around 11% of the Earth's entire land area and is expected to increase to 13% by 2050 (*MarketsandMarkets Research Private Ltd, 2026*). Further, 17% of these agricultural areas are subject to irrigation management. However, this relatively modest area equipped for irrigation may provide as much as 30–40% of global crop production (*Walker, 1989*). It indicates that irrigated land is more likely to be the source of most of the increase in food production. However, 90% of agricultural water is consumed for irrigation (*Haddeland et al., 2014*). Therefore, the need to use water resources efficiently in irrigated areas is growing due to factors such as climate change, declining water supplies, and increased demand for water from other sectors. In this context, efficient irrigation techniques are essential for maximizing water efficiency while maintaining crop yield and quality (*Evans & Sadler, 2008*). Multiclient electronic hydrants for use on the distribution network marked the beginning of the development of the first generation of irrigation technology (*Aayog, 2017*). Deficit irrigation was the fifth generation of irrigation technology developed to deliver less water without impacting crop yield depending on the crop growth stage (*Krishnashetty et al., 2021*; *Kang et al., 2017*). Intelligent irrigation systems based on AI are the current trend in providing cost-effective and efficient models for water management in agriculture.

The amount of water supplied and its delivery time is critical in irrigation for crop growth. Irrigation scheduling determines the best time and amount of water to use on an agricultural field. Developing efficient irrigation scheduling needs better knowledge of the biophysical processes of soil root-water absorption and crop canopies' transpiration process. The principal objective of efficient irrigation scheduling is to minimize yield reduction, irrigation cost, excess groundwater withdrawal that prevents aquifer exploitation, water logging problems, and water wastage (*Gu et al., 2020*). The precise estimation of water demand is critical for irrigation scheduling. The current research examines a variety of irrigation scheduling (IS) techniques that may be used to determine the appropriate time of irrigation and depth for crop development. Numerous techniques for planning and determining the necessary depth for various irrigation treatments have been introduced during the last few decades. These developed and suggested irrigation scheduling techniques can be categorized into three categories according to factors upon which scheduling depends: evapotranspiration (ET) process, soil moisture status, and plant water status.

Smart irrigation is an excellent water-saving technique that uses sensors to determine plant, weather, and soil status to calculate the required water for irrigation and apply it at the right time and desired locations. However, integrating IoT sensors for data acquisition and artificial intelligence (AI) for estimating water demand using sensor data is essential to implementing an efficient irrigation schedule. AI-based equipment has taken the

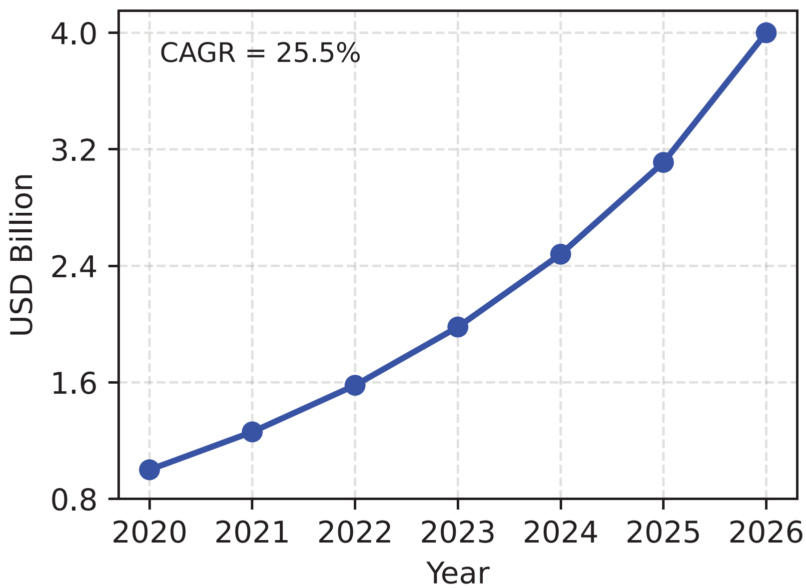

Figure 1 **Market size of AI in agriculture.** Full-size DOI: 10.7717/peerj-cs.3677/fig-1

agriculture sector to the next level. It has been estimated that the market size of AI in agriculture is expected to reach about 4 billion USD by 2026, with a CAGR of 25.5% (win (a)) as shown in Fig. 1. Deep learning (DL) and machine learning (ML) are regarded as the two main areas of AI. While AI deals with providing human intelligence to machines, ML employs statistical learning models to build a system that can learn and improve from experiences without human intervention, and DL uses a network of neurons to simulate how the brain functions (*Mao et al., 2021*). These two domains of AI significantly contribute to estimating evapotranspiration, soil moisture, and plant status on which irrigation scheduling relies. This article encompasses all the approaches used to implement efficient irrigation scheduling and the role of AI in these technologies.

Target audience

This article has been prepared for a mixed audience that includes researchers in agricultural engineering, hydrology, and environmental science, as well as practitioners responsible for day-to-day irrigation management. It is equally relevant to policymakers concerned with water allocation, postgraduate students working on sustainable farming technologies, and extension workers who translate research findings into field-level practices. Readers from allied domains such as climatology, crop science, and water economics may also find value in the review presented here.

Existing surveys

This survey article closes a knowledge gap in the field of irrigation scheduling. Although various survey articles exist that have focused on smart technology in irrigation, no prior research provides a thorough and organized study on AI's role in estimating water requirements for irrigation scheduling. Several survey articles have been published that have focused on the smart irrigation control and monitoring strategies using different IoT sensors (*Abioye et al., 2020*; *Bwambale, Abagale & Anornu, 2022*). *Gu et al. (2020)* reviewed different irrigation techniques along with their advantages and disadvantages. *Hamami & Nassereddine (2020)* have aimed to review the use of wireless sensor network (WSN) technology to manage irrigation systems. *Li et al. (2020)* have discussed using remote and IoT sensors to make intelligent irrigation monitoring systems. *Fernandez Garcia et al. (2020)* have reviewed irrigation strategies by conducting two scenarios on woody and field cultivars in the semi-arid region of Spain. In addition, they have presented detailed discussion on the variables that influence the best time to schedule irrigation.

Koech & Langat (2018) reviewed the recent developments in irrigation strategies and different challenges associated with it for improving water use efficiency within the structure of Australia. *Nandan et al. (2021)* explored different irrigation scheduling strategies that might help mitigate the impact of climate change on corn crops. Finally, the closest study to the realm of irrigation scheduling is the review of *Jimenez et al. (2020)*, which emphasizes on the use of artificially intelligent agents in irrigation scheduling and concludes that AI can help in achieving the goal of water-saving and increasing crop yield. From our perspective, the authors provide an excellent beginning for other scholars interested in learning about the potential of AI in irrigation scheduling. However, the author fails to provide the detailed contribution of AI in water estimation for irrigation, which is an integral part of irrigation scheduling.

Therefore, a more detailed systematic literature study is required to focus on the contribution of AI approaches to estimating crop water requirements using different irrigation scheduling techniques. This survey article outlines the research contributions in estimating the water requirement for irrigation scheduling using artificial intelligence techniques. Challenges and future research trends are discussed at the end of the study.

SURVEY METHODOLOGY

In order to present a balanced review, the literature search was carried out systematically across multiple databases. The process was not automated; each search and screening step was conducted manually to ensure careful judgment in including or excluding studies.

Databases consulted

The primary sources were Scopus, Web of Science, IEEE Xplore, and ScienceDirect. Google Scholar was used sparingly to locate hard-to-find references and confirm bibliographic details.

Search terms

The search queries were built around three main themes: evapotranspiration (ET), irrigation scheduling, and computational modelling. Typical keyword strings included: “evapotranspiration” AND “irrigation scheduling” “ET estimation” AND “water management” “evapotranspiration” AND “decision support system” Boolean operators (AND, OR) and quotation marks were applied where necessary to narrow or broaden the results.

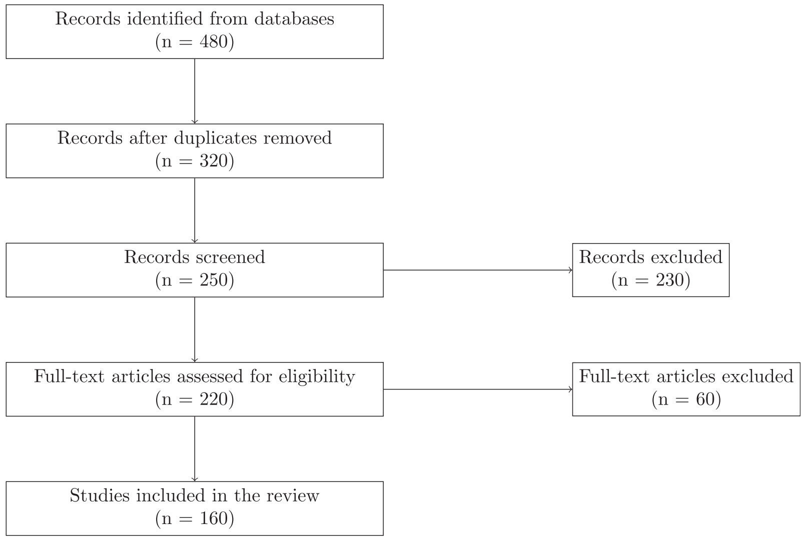

Figure 2 **PRISMA-style flow diagram of literature screening and selection process.**
Full-size DOI: 10.7717/peerj-cs.3677/fig-2

Time period covered

Only studies published from January 2010 to March 2025 were considered. This window captures the surge in technology-assisted scheduling methods while excluding earlier decades dominated by purely empirical approaches.

Inclusion criteria

Peer-reviewed journal articles, scholarly book chapters, and selected conference articles. Research explicitly linking ET-based methods to irrigation scheduling.

Exclusion criteria

Studies without a clear connection to irrigation scheduling, non-English works, short abstracts without accessible full texts, duplicate entries from different databases are kept as the exclusion criteria for conducting this survey. The overall literature screening and selection process is summarized in a PRISMA-style flow diagram (Fig. 2), showing the number of records identified, screened, excluded, and finally included.

EVAPOTRANSPIRATION BASED IRRIGATION SCHEDULING

Evapotranspiration (ET), specified as the total amount of water lost by evaporation and transpiration *via* soil and plant canopy, is the primary route by which plants lose water and interchange energy with their environment. Plants lose around 99% of the water they absorb through transpiration, with only 1% utilized for metabolic activity (*Rosenberg, Blad & Verma, 1983*). Thus accurate estimation of *ET* is one of the first and most significant steps in determining crop water needs in fields of agriculture and thus acts as an essential and necessary parameter in irrigation scheduling. It also gives decision-makers the information they need to figure out how to reduce water usage and ensure sustainable water management.

The direct measurements of ET in the field is performed by isolating a portion of the crop from its surroundings using various instruments such as lysimeters, eddy covariance, sap flow gauge, and Bowen ratio. However, direct measurement of ET is costly, extensive, and difficult. The other method is to make an estimate of ET indirectly using empirical models that use local readily available meteorological variables. However, ET is influenced by a multitude of factors, including environmental factors such as air temperature, radiation from the sun, speed of the wind, and moisture; crop parameters such as crop type, growth stage; environmental aspects including soil conditions, fertility, salinity and crop disease (*Allen et al., 1998*). Therefore, the dependency of the majority of these characteristics, as well as their geographical and temporal fluctuation, make it virtually hard to build an algorithm that can be used to calculate real ET. As a result, the concept of standardizing ET equations using reference evapotranspiration (ET_0) was established (*Doorenbos, 1975*). ET_0 is defined as a rate of ET from an extensive region of green grass with consistent height—8 to 15 cm—that is growing rapidly, completely shielding the ground, and is not water-stressed (*Doorenbos & Pruitt, 1977*; *Jensen, Burman & Allen, 1990*). Crop factors, also termed as crop coefficients K_c, are used to compute crop evapotranspiration (ET_c) for a particular crop (*Jensen, Burman & Allen, 1990*; *Allen et al., 1998*) as shown in given equation.

$$ET_c = K_c \times ET_0. \tag{1}$$

Previously, grass and alfalfa have been employed as reference surfaces for calculating ET_c under different environmental situations. Ideally, quantifying ET_c using grass-reference ET (ET_0) or alfalfa-reference ET (ET_r) should yield similar results. However, K_c values obtained using different reference surfaces can not be used interchangeably. Numerous empirical models were suggested in the past to calculate ET_0 and ET_r based on Penman-Monteith equation that fall into temperature, radiation, evaporation, and combination of climate variables. The majority of researcher recommended to standardized Penman-Monteith equation for calculation of ET_0 as this equation roughly approximate the observations made by lysimeter for ET calculations (*Allen et al., 1998*; *Jensen, Burman & Allen, 1990*; *Smith et al., 1991*).

Penman-monteith equation components and interactions

The FAO-56 Penman-Monteith equation balances energy availability with aerodynamic transport to estimate reference evapotranspiration (ET_0) [mm day^{-1}]:

$$ET_o = \frac{0.408\Delta(R_n - G) + \gamma \frac{900}{T+273} u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}. \tag{2}$$

The Penman-Monteith equation estimates reference evapotranspiration (ET_o) by combining energy balance and aerodynamic factors. It integrates net radiation (R_n) as the main energy source, soil heat flux (G), air temperature (T), wind speed at 2 m height (u_2), and vapor pressure deficit ($e_s - e_a$). The equation balances the energy available for evaporation with the atmospheric demand for moisture, weighted by the slope of the saturation vapor pressure curve (Δ) and the psychrometric constant (γ). These

Table 1 Overview of ETo estimation models and AI adaptations.

Model type	Key inputs	Equation/Form	AI replacement
Temperature	Tmin, Tmax	Hargreaves: $ET_0 = 0.0023R_a(T_m + 17.8)K_c$	ANN/ELM (2-input)
Radiation	Rs, T	Turc: $ET_0 = \frac{TR_s}{T+50}\left(1 + 0.2\frac{R_s}{R_a}\right)$	RF/CatBoost
Combination	T, Rs, u2, RH	PM (Eq. (2))	Hybrid GWO-ANN
ET_C	ET_0 x Kc	$ET_c = K_c ET_0$	CNN-LSTM

components interact multiplicatively—for example, wind speed enhances the vapor pressure deficit effect, increasing evapotranspiration. In AI-based models, these variables serve as crucial inputs, with some components sometimes approximated or substituted depending on data availability, affecting the accuracy and interpretation of the ET calculation. Table 1 shows the overview of ET_0 estimation models and their AI adaptations.

AI enabled ET_0 prediction models

This section examines artificial intelligence applications for ET_0 modeling, replacing complex Penman-Monteith calculations (Eq. (2)) with data-driven approaches that capture non-linear interactions between radiation, wind-enhanced vapor deficit, and temperature (Table 1). AI techniques outperform traditional empirical models by 10-30% across climates using limited inputs like $T_{min/max}$, R_s, and RH, enabling real-time irrigation scheduling from IoT sensors.

Evolutionary and neuro-fuzzy models for ET_0 predictions

Evolutionary Computation (EC) methodologies are inspired by nature and address optimization problems in a randomized manner. They can provide a dependable and effective solution to addressing complex issues in real-world applications (*Jiao et al., 2023*). Neuro-fuzzy systems are fuzzy systems created using a learning method based on neural network theory. Table 2 summarizes the state-of-art evolutionary and neuro-fuzzy models for ET_0 prediction. This section provides an overview of the recent literature regarding the applications of neuro-fuzzy and evolutionary computing approaches in modeling the evapotranspiration process. Adaptive neuro fuzzy inference system (ANFIS) model has shown reliable and superior performance in modeling complex non-linear ET_0 processes; hence, it is claimed to be an alternative approach.

Pour-Ali Baba et al. (2013) evaluated both the Artificial Neural Network (ANN) and ANFIS model for ET_0 prediction. The findings of their study revealed that both models could provide reliable accuracy using available climate data, and the performance of both the models decreased by using estimated R_s than using recorded sunshine hours (SSH). *Kisi & Zounemat-Kermani (2014)* examined the potential of subtractive clustering-based fuzzy inference system (S-ANFIS) and grid partition-based fuzzy inference system (G-ANFIS) for modeling of daily ET_0 in the Mediterranean climate region of Turkey. They found that both ANFIS models achieved reliable results compared to empirical models using three to four input parameter combinations. However, empirical models with two climate parameters performed better than two input ANFIS models. In another study conducted by *Petković et al. (2015)*, ANFIS model was used to identify the most influential

Table 2 **Summary of evolutionary and neuro-fuzzy models for ET_0 prediction.**

Author	Climate region	Time stamp	Input parameters	Soft computing models	Optimal input combination
Pour-Ali Baba et al. (2013)	Temperate	Daily	T, RH, SSH, WSP, R_s	ANFIS, ANN	T, RH, SSH, WSP; T, SSH
Kisi & Zounemat-Kermani (2014)	Mediterranean	Daily	T, R_s, WSP, RH	ANFIS-GP, ANFIS-SC	T, R_s; T, R_s, RH
Petković et al. (2015)	Moderate-continental	Monthly	T_{min}, T_{max}, SSH, VP, RH_{max}, RH_{min}, WSP	ANFIS	SSH, VP, T_{min}; T_{max}, RH
Keshtegar et al. (2018)	Cold semi-arid	Daily	T_{min}, T_{max}, RH, WSP, R_s	ANN, M5Tree, subset ANFIS	T_{min}, T_{max}, RH, WSP, R_s
Zakhrouf, Bouchelkia & Stamboul (2019)	Semi-arid	Daily	T, RH, SSH, WSP	S_ANFIS, F_ANFIS, MLR	T, RH, SSH, WSP
Traore, Luo & Fipps (2017)	Humid subtropical	Daily	T_{min}, T_{max}, SSH, RH, WSP	GEP	T_{min}, T_{max}
Shiri (2017)	Hyper-arid regions	Daily	T_{min}, T_{max}, R_s, RH,WSP	GEP	T_{min}, T_{max}, WSP
Mattar (2018)	Subtroical zone	Monthly	T_{min}, T_{max}, RH, WSP, R_s	GEP	T_{min}, T_{max}, RH, WSP
Mattar & Alazba (2019)		Monthly	T_{min}, T_{max}, R_s, WSP, RH	GEP, MLR	T_{min}, T_{max}, RH, WSP
Valipour et al. (2019)	Arid, Mediterranean, semi arid, very humid	Monthly	R_s, RH, T_{min}, T_{max}, WSP, R_a	GA, GEP	arid-T_{meann}, WSP; Mediterranean, semi arid-T_{min}, T_{max}; humid-T_{meann}
Kazemi et al. (2020)	Arid	Monthly	T_{min}, T_{max}, RH, R_s, WSP, P	GEP	T_{min}, T_{max}, R_s

weather parameters for estimation of ET_0. They identified SSH, vapor pressure (VP), and T_{min} as the most important parameters and further found that T_{max} and RH are the optimal combination for two parameters input combination. Further, *Keshtegar et al. (2018)* evaluated the ANFIS model by dividing data points to k-subset using uniform selection for daily ET_0 prediction and comparison to ANN, and M5Tree models revealed the superiority of subset-ANFIS model. *Zakhrouf, Bouchelkia & Stamboul (2019)* also investigated two types of neuro-fuzzy models subtractive clustering model (S_ANFIS) and fuzzy C-means clustering model (F_ANFIS) to estimate daily ET_0 under semi-arid climate situation. The statistical measure shows that S_ANFIS outperformed F_ANFIS. Genetic expression programming (GEP) uses computational learning to create data-driven mathematical models, and it is an inherent progression of genetic programming and genetic algorithms. GEP generates nonlinear entities (computer programs) that are represented in relatively basic linear string structures. The contribution of GEP in developing an expression for ET_0 estimation is widely explored.

Traore, Luo & Fipps (2017) used public weather forecast data instead of observed meteorological data to forecast one week ahead ET_0 values using the GEP model. They suggested that using public weather data (temperature data), reliable estimation of ET_0 values is possible to plan irrigation scheduling. Another study using GEP was also conducted by *Shiri (2017)*. The performance of the GEP model was compared to empirical models (Hargreaves, Turc, Priestley-Taylor, and Kimberly-Penman) for the same input combination of temperature, radiation, and humidity. The obtained results demonstrated the superiority of the GEP model over other empirical models. A similar study was also conducted to examine the suitability of GEP models for predicting ET_0 using limited input data by *Mattar (2018)*. The author further compared the performance of GEP to empirical models, and it was observed that GEP yielded better results. *Mattar & Alazba (2019)* extended this study by comparing GEP with multiple linear regression (MLR) models and other empirical models. GEP turned out to be a powerful tool as compared to all other models in case of an incomplete dataset. *Valipour et al. (2019)* examined the potential of GA and GEP on four different climate regions (arid, semi-arid, very humid, and Mediterranean) for estimating ET_0. They concluded that GEP provides reliable accuracy using a minimal dataset for all climate regions. The right selection of training/testing data sets is a crucial challenge in applying AI models. *Kazemi et al. (2020)* compared various hold-out and k-fold validation temporal data partitioning strategies to estimate daily ET_0 in arid regions using GEP approach. They found that K-fold validation provides the lowest over and underestimates of ET_0 values.

Machine learning models for ET_0 predictions

ET_0 can be thought of as a complicated multivariate nonlinear regression process that is dependent on a vast number of meteorological parameters. A significant number of environmental factors interact with ET_0 in a complex way, implying that multidimensional feature space is required in order to characterize the nonlinear variations in ET_0 in response to changes in various environmental conditions. Therefore, it is difficult to create comprehensive empirical models that accurately describe all of the complicated processes. Machine learning (ML) techniques, which can represent complex and non-linear interactions between inputs and output, can overcome this problem. As a result, researchers have proposed machine learning approaches to estimate ET_0 as they offer simple solutions for dynamic and multi-variable functions and do not need an understanding of internal variables (*Bayram & Çıtakoğlu, 2023*). This subsection provides insights into the contribution of ML techniques for ET_0 modeling process in literature. Four types of ML models have been widely used in past studies: non-linear regression models (*Rajput et al., 2023*), tree-based regression models (*TR, Reddy & Acharya, 2023*), kernel-based regression models (*Mikaeili & Samadianfard, 2023*), and machine learning-based ensemble models (*Tausif et al., 2023*). The contribution of neural networks has not been covered in this subsection and will be discussed separately in the next subsection. Table 3 summarizes the contribution of ML models for ET_0 prediction. Non-linear regression models are preferable to other AI approaches such as ANFIS, ANN, and Support Vector Machine (SVM) since they have less complexity. Furthermore, these models provide us with formulas or relationships to work with an acceptable level of accuracy.

Khoshravesh, Sefidkouhi & Valipour (2017) attempted to use multivariate fractional polynomial (MFP), robust regression and Bayesian regression to predict ET_0 in three semi-arid climate regions of Iran. The findings of this study stated that the accuracy of the MFP model was higher than the other two regression approaches, and using only T_{mean}

Table 3 **Summary of machine learning models for ET_0 prediction.**

Author	Climate region	Time stamp	Input parameters	ML models	Optimal input combination
Khoshravesh, Sefidkouhi & Valipour (2017)	Arid	Monthly	T_{mean}, R_s, RH, WSP, Pr	MFP, Robust regression and Bayesian regression	T_{mean}, R_s
Reis et al. (2019)	Semi-arid	Daily	T_{min}, T_{max}, RH, SSH, WSP	ELM, ANN, MLR	T_{min}, T_{max}
Kisi (2016)	Mediterranean	Monthly	T_{mean}, R_s, RH, WSP	LSSVR, MARS, M5 Tree	T_{mean}, R_s, RH, WSP
Feng et al. (2017a)	Humid	Daily	T_{min}, T_{max}, R_s, RH, WSP	RF, GRNN	T_{min}, T_{max}, R_a
Rashid Niaghi, Hassanijalilian & Shiri (2021)	Continental climate	Daily	T_{min}, T_{max}, R_s, WSP	GEP, SVM, LR, RF	T_{min}, T_{max}, R_s
Ponraj & Vigneswaran (2020)	Arid sub-tropical	Daily	T_{min}, T_{max}, R_s, RH, WSP	MLR, RF, GBR	T_{min}, T_{max}, R_s, RH, WSP
Fan et al. (2018)	Temperate continental; temperate monsoon; mountain plateau; subtropical monsoon; and tropical monsoon	Daily	R_s, RH, T_{min}, T_{max}, WSP, R_a	RF, M5Tree, GBDT, XGBoost	T_{min}, T_{max}, R_s (tropical/ subtropical); T_{min}, T_{max}, R_a, WSP, RH (temperate/ mountain)
Fan et al. (2019)	Humid subtropical	Daily	T_{min}, T_{max}, SSH, R_a, RH, WSP, R_s	LightGBM, RF, M5Tree	T_{min}, T_{max}, R_s
Huang et al. (2019)	Humid	Daily	R_s, T_{min}, T_{max}, WSP, RH	CatBoost, RF, SVM	T_{min}, T_{max}, R_s; T_{min}, T_{max}, WSP, RH
Granata (2019)	Humid subtropical	Daily	R_s, sensible heat flux (H), SMC, WSP, RH, T_{mean}	M5P Regression Tree, Bagging, RF, SVR	T, RH, R_n
Kisi et al. (2021)	Mediterranean	Daily	T, RH, R_s, WSP	RM5Tree, M5Tree, RSM, MLPNN, RBFNN	T, RH, R_s, WSP

and R_s, acceptable accuracy could be achieved. In another study, *Reis et al. (2019)* recommended multiple linear regression models over ANN and Extreme Learning Machine (ELM) models. The authors attempted to model ET_0 using AI models (ANN, MLR, and ELM) by considering only temperature data as input in five semi-arid regions of Brazil. Further, the performance of these models was evaluated using local data of each station and pooled data of all five stations. They found out that all models provided more accurate results than Hargreaves models in both scenarios, but MLR was recommended as it was easier to use than the other two models. The tree-based regression models have also gained popularity due to their highly high computational speed and satisfactory performance. These models are also explored in ET_0 prediction. *Kisi (2016)* introduced the M5 Model Tree (M5tree), multivariate adaptive regression splines (MARS), and least square support vector regression (LSSVR) for modeling monthly ET_0. They further evaluated the proposed models to provide reliable results using cross-station data. It was reported that M5tree could act as the best alternative approach for ET_0 modeling over other proposed models and empirical models (Valiantzas and HS model) in the absence of local input and output data. Another tree-based regression model used in the literature was the random forest (RF) tree. *Feng et al. (2017a)* evaluated the applicability of RF and generalized regression neural network (GRNN) model for predicting ET_0 values using two input scenarios: using temperature data and complete data. It was observed that using temperature data, both RF and GRNN could provide reliable accuracy. However, RF was slightly better than GRNN. The RF model also performed better in a study conducted by *Rashid Niaghi, Hassanijalilian & Shiri (2021)*. Authors applied GEP, SVM, Linear Regression (LR) and RF using three combinations of input data: T_{max}, T_{min}; T_{max}, T_{min}, WSP; and R_s, T_{max}, T_{min}. Results showed the superiority of the RF model using input combinations of R_s, T_{max}, T_{min} parameters.

Ponraj & Vigneswaran (2020) further analyzed three ML models RF, gradient boost regression (GBR) and MLR for ET_0 modeling with or without using preprocessing techniques. They found out that the preprocessed GBR model provided better results than the other two models. Moreover, they reported that the influence of soil temperature data was negligible for the estimation of ET_0. *Fan et al. (2018)* evaluated four regression tree (RF, M5Tree, gradient boosting decision tree (GBDT) and XGBoost) against SVM and ELM models for modeling daily ET_0 values using different combinations of meteorological data in different climate zones of China. Their findings indicated that R_s was the most important parameter than WSP and RH, and reliable accuracy could be achieved using tree-based models: GBDT and XGBoost in different climate zones of China. This study was further extended by *Fan et al. (2019)*. They introduced Light Gradient Boosting Machine (LightGBM) for predicting daily ET_0 in the humid subtropical region. They compared the results to empirical and traditional tree-based ML models such as M5Tree and RF. The LightGBM is an improved gradient framework for learning that employs decision trees and the idea of "weak" learners. Further, the potential of LightGBM for ET_0 prediction using cross-station meteorological data was also assessed. LightGBM was observed to be effective and generalizable using both local and cross-station data. *Huang et al. (2019)* compared a newly introduced gradient boosting model called CatBoost to well-known ML models (SVM and RF) for estimating ET_0 in sub tropical humid climate regions of China. Statistical measures proved the superiority of CatBoost over SVM and RF models. *Granata (2019)* performed a comparative study of four ML models, such as the M5P Regression Tree, Bagging, RF, and Support Vector Regression (SVR) to evaluate their capability for modeling ET_0 in humid subtropical climate zones. Four different combinations of input climate data were used, and results indicated that except SVR, all other three models provided accurate results using R_s, sensible heat flux, soil moisture content (SMC), WSP, RH, and T. *Kisi et al. (2021)* proposed a novel regression model called radial basis M5 model tree (RM5Tree) and compared to traditional M5Tree and response surface method (RSM), multi-layer perceptron neural networks (MLPNN) and radial basis function neural network (RBFNN) models. They took three different input data combinations, and the results revealed the superiority of RM5Tree over other models using T_{mean}, R_s, WSP, and RH as the input parameters.

Mehdizadeh, Behmanesh & Khalili (2017) compared sixteen empirical models with four AI models (GEP, MARS, SVM-poly, SVM-RBF) for the estimation of monthly ET_0 values. They found that MARS and SVM-RBF outperform other AI and empirical models. It also concluded that R_s showed a higher impact on the accuracy of ET_0 than R_n, and combining WSP with other input combinations enhanced the performance than using WSP as a sole input parameter. Mohammadrezapour, Piri & Kisi (2019) showed the superiority of the SVM model over ANFIS and GEP for simulating monthly ET_0 values in an arid region of Iran. Moreover, they suggested using the proposed approach in case of the unavailability of sunshine hours and relative humidity. This study was further supported by Chia, Huang & Koo (2020). They recommended SVM over other existing empirical models using the same input dataset. Seifi & Riahi (2020) proposed hybrid model using gamma test and least square support vector machine (LSSVM-GT) for the estimation of ET_0. The Gamma test revealed that T_{min}, T_{max} and WSP are the main influential parameters. Comparison with other models such as ANN, ANFIS, and empirical models proved that LSSVM performed better using the gamma test in the arid region of Iran. Ensemble learning-based approaches have also gained researchers' interest in evapotranspiration since these approaches are typically more stable, perform better, and have reduced computing costs. Manikumari, Murugappan & Vinodhini (2017) proposed an ensemble learning approach to combine ANN models for daily reference estimation. They reported that ensemble models achieved better performance than individual ANN models. Salam & Islam (2020) proposed two new ensemble learning-based models: Random tree (RT), Bagging, and Random Subspace (RS) for ET_0 prediction in the subtropical humid climate region of Bangladesh and compared the performance of these models to RF and SVM model. Statistical measures indicated that RT and RF provided better performance. Further, it was observed that R_s and WSP were most influenced parameters and combination of R_s, T_{min} and T_{max} provided satisfactory results and R_a, T_{min} and T_{max} were found as least input combination for ET_0 estimation.

Nourani, Elkiran & Abdullahi (2020) employed linear ensemble approach (simple and weighted average) and non linear ensemble (neural ensemble). They reported that neural-based ensemble performed better than SVR, ANFIS, ANN, and MLR models for estimating single and multi ahead ET_0. Martín, Sáez & Corchado (2021) further proposed a stacked-based learning approach to predict evapotranspiration using meteorological data from twenty stations of Spain. They used SVM, RF, GBM, and XGBoost as first-level predictors and XGBoost as second-level predictors. Further, the performance of the newly developed ensemble model was compared to state-of-the-art other models (SVM, RF, XGBoost, GBM, ELM, MARS, and LASSO) and empirical models (temperature-based, radiation-based, and mass-energy transfer based).

This subsection's analysis of the articles found that traditional ML models had been effectively employed to predict ET_0 values. Moreover, these models proved to be less costly in terms of computational cost. Also, ensembled learning approaches were used to address the issue of variation in the performance of ML models for different types of datasets. However, a continuous effort was made to develop AI models using the limited meteorological dataset to provide better performance than empirical models.

Table 4 Summary of neural network models for ET_0 prediction.

Author	Climate region	Time stamp	Input parameters	Neural network models	Optimal input combination
Laaboudi, Mouhouche & Draoui (2012)	Subtropical desert	Daily	T_{mean}, RH, WSP, Insolation	ANN, MLR	T_{mean}, RH, WSP
Kim et al. (2014)	Humid subtropical	Monthly	T, R_s, WSP, RH, T_{dew}, VP, soil temperature (ST)	GRNN-GA, GRNN-BP, BGRNN-GA	T_{min}, T_{max}, R_s
Kisi & Kilic (2016)	Mediterranean	Daily	T, R_s, WSP, RH	ANN, M5Tree	T_{min}, T_{max}, R_s
Yassin, Alazba & Mattar (2016)	Arid	Daily	T_{min}, T_{max}, T_{mean}, RH_{min}, RH_{max}, WSP, SSH, R_s, h_c	ANN, GEP	T_{min}, T_{max}, T_{mean}, RH_{min}, RH_{max}, WSP, SSH, R_s, h_c
Traore, Luo & Fipps (2016)	Humid subtropical	Daily	T_{min}, T_{max}, R_a, R_s	GFF, LR, MLP, PNN	T_{min}, T_{max}, R_s
Nema, Khare & Chandniha (2017)	Sub-humid	Monthly	T_{min}, T_{max}, RH, SSH, Rainfall	ANN	T_{min}, T_{max}, RH, SSH, Rainfall
Antonopoulos & Antonopoulos (2017)	Mediterranean	Daily	T_{mean}, RH, R_s, WSP	ANN	T_{min}, T_{max}, R_s
Gavili et al. (2018)	Continental climate	Monthly/Daily	T_{min}, T_{max}, RH, SSH, WSP	ANN, ANFIS, GEP	T_{min}, T_{max}, RH, SSH, WSP
Kaya et al. (2021)	Humid continental	Daily, Monthly	T_{mean}, RH, WSP, R_s	SVR, MLP, MLR	T_{mean}, R_s; T_{mean}, RH
Abdullah et al. (2015)	Mediterranean, Semi-arid	Monthly	T_{min}, T_{max}, WSP, RH, R_s	ELM	T_{min}, T_{max}, R_s

Neural network and deep learning models for ET_0 predictions

Artificial neural networks (ANNs) have been widely used in hydrological modeling over the last two decades due to their capacity to map the input and output connection without comprehending the physical process (*Sofi et al., 2023*). An artificial neural network model is a mathematical model with highly interconnected processing units structured in layers that is substantially equivalent to the learning potential of the human brain. The most fundamental technique for creating an artificial neural network-based model of system behavior is to train the network using system samples (*Wu et al., 2023*). Recently, many publications employed ANN to simulate the reference evapotranspiration process. Some of the recent articles with significant contributions in this field are discussed in this subsection. Table 4 summarizes these research studies in brief.

Laaboudi, Mouhouche & Draoui (2012) investigated the effectiveness of ANN to estimate ET_0 using an incomplete dataset and compared the results to MLR model. It was reported that the MLR model was also able to predict ET_0 at desirable accuracy. However, ANN has overcome the issue of the multi-colinearity problem present in MLR. *Kim et al. (2014)* investigated the performance of neural networks in predicting monthly ET_0 using the bootstrap resampling technique on the GRNN (GRNN-backpropagation algorithm (GRNN-BP), Bootstrap GRNN-GA (BGRNN-GA)). The analysis revealed that increasing the quantity of the training data *via* bootstrapping could not enhance the GRNN models significantly. Instead, the authors recommended training multiple models and combining the results to effectively minimize generalization error. Moreover, solar radiation was found to be the most critical parameter for monthly ET_0 estimation.

An attempt to use easily available public weather forecast data to estimate ET_0 was made by *Traore, Luo & Fipps (2016)*. They employed neural network-based four models such as Generalized Feedforward (GFF), Linear Regression network (LRN), Multilayer Perceptron (MLP), and Probabilistic Neural Network (PNN) using limited data (T_{max}, T_{min}, R_s, and R_a) retrieved from public weather forecast data. They concluded that more reliable results were obtained when R_s was used with temperature data instead of R_a. However, the authors were concerned about the reliability of the public weather data for the acceptability of the proposed approach. The best architecture of the ANN model in the sub-humid environment was identified by *Nema, Khare & Chandniha (2017)*. They compared ET_0 generated with FAO-56 PM to different ANN models, which included a variety of training functions and neuron numbers. They reported that the ANN trained using the Levenberg–Marquardt algorithm with nine neurons in a single hidden layer produced the best estimation results. Researchers were constantly exploring ANN models for ET_0 prediction from different perspectives. For instance, a study conducted by *Antonopoulos & Antonopoulos (2017)* showed that the ability of ANN to predict ET_0 was dependent on the training and testing dataset. They trained ANN using different combinations of meteorological data and compared the results with existing empirical models. Results revealed that there was a significant effect on ANN accuracy by changing the training year; therefore, it was evident that training data affected the ANN simulation.

Further, the superiority of ANN to ANFIS and GEP was also examined by *Gavili et al. (2018)* for estimating ET_0 in the continental climate region, Iran. They employed three artificial intelligence models (ANN, ANFIS, and GEP) and five empirical models, in which ANN produced the best predictions. In another study, *Kaya et al. (2021)* compared MLP to other AI models such as SVM and MLR for predicting ET_0. Findings concluded that MLP performs better using a double combination of T-R_s and T-RH. The most recent advancement in artificial intelligence models contributed to the introduction of the Extreme Learning Machine as an ANN option. Extreme Learning Machine is a quick learning technology that employs single-hidden layer feedforward neural networks to achieve excellent generalization performance. This variant of ANN was initially used to predict ET_0 in Iraq by *Abdullah et al. (2015)*, where the authors claimed that this geographical area mirrored general atmospheric and geographical circumstances. The study reported that ELM provides accurate results using complete and incomplete datasets.

The success achieved by *Abdullah et al. (2015)* gained the attention of other researchers to investigate further ELM for predicting ET_0 in other climate regions. *Feng et al. (2016)* attempted to evaluate the performance of ELM over other hybrid neural network models. They estimated ET_0 using ELM, backpropagation neural networks optimized by genetic algorithm (GANN), and wavelet neural networks (WNN) models. They found that ELM and GANN models provided equivalent performance using limited data and could be highly recommended in this scenario than other temperature based empirical models. This study was further extended by *Gocic et al. (2016)*. They compared the performance of ELM in modeling monthly ET_0 to empirical models such as adjusted Hargreaves, Priestley–Taylor and Turc methods. They concluded that ELM could be a better alternative with limited data availability. *Patil & Deka (2016)* also proved the superiority of ELM over other

AI models such as ANN and LS-SVM for predicting ET_0 values. They used different input combinations of another station's temperature data and ET_0 values. It was reported that using local temperature data and ET_0 values of another station, ELM outperformed the Hargreaves model and could be recommended for weekly ET_0 prediction. A comparable study conducted by *Kumar et al. (2016)* demonstrated the advantages of ELM in terms of accuracy and computational speed over SVM, ANN, and genetic programming (GP) for modeling the ET_0 process in the humid subtropical region of India. The introduction of the multi-linear perceptron and extreme learning machines in the field of hydrology has also encouraged exploring another variation of the ANN model. The Generalized wavelet neural networks (GWNN), Radial Basis Neural Network (RBNN) and generalized regression neural networks are examples. *Feng et al. (2017c)* introduced a new approach to generalize the ability of ELM and GRNN in modeling the ET_0 process using cross-station meteorological data (temperature data only). They trained both models in two scenarios: pooled data and local data from six stations in China. Results revealed that both the models performed better in the case of pooled data training than training these models on regional data of stations. However, ELM was slightly more efficient in the local scenario, while the GRNN model performed well in the pooled system.

Banda, Cemek & Küçüktopcu (2018) performed comparitive analysis of neuro-computing models (ANFIS, RBNN, GRNN and MLP) for predicting ET_0 values. WSP and R_s were found as dominating parameters that affect accuracy of ET_0. GRNN model was further compared to other AI models by *Sanikhani et al. (2019)*. They used different AI models (GRNN, MLP, ANFIS-GP, ANFIS-SC, and GEP) to perform temperature-based modeling of ET_0 for the Mediterranean region of Turkey. They compared these models to Hargreaves–Samani and its calibrated version and found that GRNN and GEP models provided better accuracy. *Bellido-Jiménez, Estévez & García-Marín (2021)* introduced new climate parameters called $Energy_T$ and Hourmin, based on temperature data only and also compared six AI models (MLP, GRNN, ELM, SVM, RF, and XGBoost) for modeling ET_0 using these climate parameters in five different semiarid regions of Andalusia. Results revealed that the newly introduced parameters could provide reliable accuracy in regions where data is not easily available. They also recommended the ELM model as it outperformed all other models used in the study.

Adamala et al. (2019) investigated the generalized wavelet neural networks (GWNN) for modeling ET_0 process in four different climate zones (semi-arid, arid, humid and sub-humid). Further, the generalization ability of the GWNN model was compared to GANN, GWR, and GLR models, and the results showed that GWNN and GANN models provided accurate results in all climate zones. Deep learning has received a lot of attention in the past few years and has been used in various fields, outperforming conventional machine learning models and attaining state-of-the-art results. DL models also efficiently handle multi-variate time series problems with a massive amount of data. Therefore, they have been explored to estimate ET in many recent studies. Recently, many research studies have focused on the potential of deep neural network (DNN) models to predict ET. These research studies are briefly summarised in Table 5. *Saggi & Jain (2019)* used H_2O framework to develop Gradient Boosting Machine (GBM), generalized linear model

Table 5 **Summary of deep learning models for ET_0 prediction.**

Author	Climate region	Time stamp	Input parameters	DL models	Optimal input parameters
Saggi & Jain (2019)	Semi-arid	Daily	R_s, RH, T_{min}, T_{max}, WSP, SSH	DL, GBM, GLM, and RF	R_s, RH, T_{min}, T_{max}, WSP, SSH
Yin et al. (2020)	Arid	Daily	T_{min}, T_{max}, SSH, R_a, RH, VP, weather type	BiLSTM	T_{min}, T_{max}, SSH
Ferreira & da Cunha (2020a)	Arid	Daily	T_{min}, T_{max}, RH, WSP, SSH, $ET_{0_{t-1}}$	CNN, LSTM, ANN, CNN-LSTM, RF	T_{min}, T_{max}, RH, WSP, SSH, $ET_{0_{t-1}}$
Roy (2021)	Sub-tropical	Daily	T_{min}, T_{max}, RH, WSP, SSH	BiLSTM, LSTM, SSR-LSTM, ANFIS	T_{min}, T_{max}, RH, WSP, SSH
Nagappan, Gopalakrishnan & Alagappan (2020)	Tropical	Daily	T_{min}, T_{max}, RH, WSP, SSH	DLNN, RBFNN	T_{min}, T_{max}, WSP
Granata & Di Nunno (2021)	Humid subtropical, Semi arid	Daily	R_n, T, H, RH, $ET_{a_{t-1}}$, $ET_{a_{t-2}}$,	NARX, LSTM	R_n, T, $ET_{a_{t-1}}$,$ET_{a_{t-2}}$
Sharma, Singh & Jain (2022)	Semi arid	Daily	T_{min}, T_{max}, RH, WSP, SSH, VP	CNN-LSTM, Conv-LSTM	T_{min}, T_{max}, R_s
Ferreira & da Cunha (2020b)	Tropical	Daily	T_{min}, T_{max}, R_s, RH, WSP	RF, XGBoost, ANN and CNN	T_{min}, T_{max}, RH
Chen et al. (2020b)	Warm temperate	Daily	T_{min}, T_{max}, RH, R_s, R_a,	TCN, LSTM, DNN, RF, and SVM	T_{min}, T_{max}, T_{mean}, R_a; T_{min}, T_{max}, T_{mean}, R_s,R_a
de Oliveira e Lucas et al. (2020)	Subtropical	Daily	T_{min}, T_{max}, SSH, RH, WSP	CNN, SARIMA	T_{min}, T_{max}, SSH, RH, WSP

(GLM) and RF and deep learning model for estimation of ET_0 and observed that DL model outperform all models using T_{min}, T_{max}, R_s, RH, WSP and SSH in semi-arid region of India. Chen et al. (2020b) examined DNN, Convolutional Neural Network (CNN), and Long Short Term Memory (LSTM) in predicting daily ET_0 with limited meteorological data and proposed different combinations of meteorological parameters with reasonable accuracy. Yin et al. (2020) has reported the use of Bi-LSTM for predicting daily ET_0 in an arid region of China. Ferreira & da Cunha (2020a) examined the potential of LSTM, one-dimensional CNN, and a combination of LSTM-CNN, as well as ML models (ANN and RF) for predicting daily ET_0 in the arid region of Brazil. They concluded that the proposed DL models outperformed ML models. de Oliveira e Lucas et al. (2020) employed ensemble CNN models to solve the ET_0 time series problem in the subtropical region of Brazil. They conclude that CNN models outperform seasonal autoregressive integrated moving average (SARIMA) and seasonal Naive time series models.

Hybrid models for ET_0 predictions

The introduction of optimization models to develop AI models has greatly enhanced the performance of these models. The optimization models are effective methods for reducing uncertainties related to tuning the hyper-parameters of AI models. Meta-heuristic Optimization Algorithms (MOAs) are widely employed in tackling optimization problems because they can identify several optimum solutions in a single run. Different MOAs are coupled effectively with AI models to solve non-linear ET_0 process modeling problems. Table 6 summarizes these hybrid models used in the literature for the ET_0 process.

Table 6 Summary of hybrid models for ET_0 prediction.

Author	Climate region	Time stamp	Input parameters	Hybrid models	Optimal input parameters
Gocić et al. (2015)	Humid continental	Monthly	T_{min}, T_{max}, WSP, VP, SSH	GP, SVM-FFA, ANN, SVM–Wavelet	T_{min}, T_{max}, WSP, VP, SSH
Patil & Deka (2017)	Arid	Daily	T_{min}, T_{max}, R_a, $ET_{0_{t-1}}$, RH, WSP	ANN, ANFIS, Wavelet-ANN, Wavelet-ANFIS	T_{min}, T_{max}, R_a, $ET_{0_{t-1}}$
Kisi & Alizamir (2018)	Semi-arid	Daily	T_{min}, T_{max}, RH, R_s, WSP	WELM, WANN, ANN, ELM, OS-ELM	T_{min}, T_{max}, R_s, RH
Tikhamarine et al. (2019)	Temperate, Mediterranean	Monthly	T_{min}, T_{max}, WSP, R_s, RH	ANN-GWO, ANN-MVO, ANN-PSO, ANN-WOA, ANN-ALO	T_{min}, T_{max}, R_s
Maroufpoor, Bozorg-Haddad & Maroufpoor (2020)	Sub-humid, humid, arid, semi-arid, hyper-arid	Monthly	T_{min}, T_{max}, RH, WSP, SSH	ANN-GWO, ANN, LS-SVR	T_{min}, T_{max}, WSP
Dong et al. (2021)	Various (desert, steppe, cold-temperate, *etc.*)	Monthly	T_{min}, T_{max}, RH, WSP, R_s, R_a	GWO-KNEA, KNEA, PSO-KNEA, SSA-KNEA	T_{min}, T_{max}, R_s
Tao et al. (2018)	Dry tropical	Daily	T_{min}, T_{max}, RH, R_s, WSP, VP	ANFIS, ANFIS-FA	T_{max}, T_{min}, RH_{max}, R_s, WSP
Roy et al. (2020)	Subtropical	Daily	T_{min}, T_{max}, RH, R_s, R_n, latent/sensible heat	BBO-ANFIS, FA-ANFIS, PSO-ANFIS, TLBO-ANFIS	T_{min}, T_{max}, RH, R_s, R_n, latent/sensible heat
Wu et al. (2019)	Various (temperate, plateau, monsoon)	Daily	R_s, RH, T_{min}, T_{max}, WSP	ELM, ELM-GA, ELM-ACO, ELM-CSA, ELM-FPA	R_s, RH, T_{min}, T_{max}, WSP
Mohammadi & Mehdizadeh (2020)	Arid, semi-arid, hyper-arid	Daily	T_{min}, T_{mean}, T_{max}, RH, R_s, WSP, VP, R_a	SVR, RF-SVR-WOA	T_{mean}, R_a, WSP, T_{min}

Gocić et al. (2015) explored four AI models GP, ANN, SVM-wavelet and SVM-fire-fly algorithm (SVM-FFA) to estimate monthly ET_0 in humid continental climate region of Serbia. SVM model was coupled to wavelet and optimization algorithm for hyper-parameter tuning, and it was observed that SVM coupled with wavelet transform outperformed all other models. The success of wavelet transform was also repeated in Patil & Deka (2017). Wavelet transform was coupled to ANN and ANFIS models to estimate daily ET_0 values using different input combinations of meteorological data. The authors found that ANN-wavelet with limited input data (T_{min}, T_{max}, R_a and $(ET_0)_{t-1}$) provides reliable results than compared to other models. The wavelet transform-based optimization model was further explored by Kisi & Alizamir (2018). They investigated wavelet-based ELM (WELM) and ANN for the ET_0 process using different input combinations of meteorological data. The comparison of obtained results to simple ELM, ANN, WANN, and online sequential ELM (OS-ELM) revealed the outstanding performance of WELM.

Other optimization models were also explored in past studies, *e.g.*, Tikhamarine et al. (2019) attempted to use whale optimization, Ant lion optimizer (ALO), Multi-verse Optimizer (MVO), Grey wolf optimizer (GWO), particle swarm-based hybrid model of ANN. A comparison of these models with the existing empirical model using limited data showed the remarkable performance of hybrid models. However, the ANN model coupled with the Grey wolf optimizer (ANN-GWO) outperformed all other proposed hybrid models using limited input data (T_{min}, T_{max} and R_s).

ANN-GWO model was further used by Maroufpoor, Bozorg-Haddad & Maroufpoor (2020) in their study to overcome the two constraints of the unavailability of all meteorological data and comprehensive model for all types of climate regions in Iran. The Shannon entropy test was used to analyze the importance of each meteorological parameter. Results demonstrated that ANN-GWO with limited input data (T_{min}, T_{max} and WSP) provided promising results as compared to stand-alone ANN and LS-SVR for all climate regions. Dong et al. (2021) performed the comparison of four bio-inspired algorithms (grasshopper optimization, grey wolf optimizer, particle swarm optimization and salp swarm algorithm (SSA)) to optimize kernel-based nonlinear extension of Arps decline (KNEA) for estimating monthly ET_0 for seven different climate zones of China. Results revealed that GWO-KNEA performed excellently in all climate zones of China using input combinations of T_{min}, T_{max} and R_s. ANFIS model can integrate the benefit of fuzzy features and an adaptive neural network system to process non-linear and stochastic problems and has provided comparable results to ANN in many studies. It takes advantage of the fuzzy system's ability to handle ambiguity and imprecision of the dataset. However, ANFIS showed some limitations related to parameter tuning. As a result, many researchers have attempted to couple optimization algorithms to overcome this limitation. Tao et al. (2018) explored a nature-inspired optimization model called firefly algorithm (FFA) for the first time with the ANFIS model. They reported outstanding predictive ability of hybrid ANFIS-FFA model for ET_0 estimation at the dry tropical region of Burkina Faso as compared to ANFIS. In another study, Roy et al. (2020) investigated four optimization algorithms such as FFA, Biogeography-based Optimization (BBO), Particle Swarm Optimization (PSO), and Teaching-Learning-based Optimization (TLBO) to tune ANFIS model's parameters for the estimation of ET_0 in subtropical regions of different geographical locations (Bangladesh, south Florida, and the USA). They compare the results of these hybrid models to the classical ANFIS model, whose parameters were tuned using least square back propagation gradient descent. Results supported the findings of Tao et al. (2018) and indicated that the FFA-ANFIS model outperforms other hybrid models.

AI models are recently coupled with a bio-inspired optimization algorithm to find the optimal solution to the problem and improve the computational speed.

Wu et al. (2019) coupled ELM with bio-inspired optimization models such as genetic algorithm (GA), ant colony optimization (ACO), cuckoo search algorithm (CSA) and flower pollination algorithm (FPA) for estimation of ET_0. The results indicated that the use of bio-inspired models, especially CSA and FPA, improved the performance of the ELM model in different climate zones of China. Mohammadi & Mehdizadeh (2020) coupled Whale optimization algorithm with SVM model. They also explored preprocessing approaches such as RL, RF, PCA, and COR to find optimal input parameters for different climate regions (arid, semi-arid and hyper-arid) to obtain general results for ET_0 modeling. It was observed that the SVM model coupled with WOA achieved better performance than SVM. This study is also followed by Yan et al. (2021), WOA optimizer was coupled to XGB to estimate daily ET_0 in arid and humid climate regions of China. The findings showed that in the arid region, the relevance of meteorological data for forecasting daily ET_0 was WSP > SSH > RH, while in the humid region, SSH > RH > WSP, with XGB-WOA providing outstanding performance in both the climate regions. Whale optimization was further evaluated by Gao et al. (2021) in their study. They coupled three bio-inspired optimization algorithms, such as bat algorithm, cuckoo search, and whale optimization algorithm, with the ANN model for the prediction of ET_0 in the continental monsoon region of China. Statistical comparison indicated that temperature-based ANN coupled with WOA (ANN-WOA) provided a more accurate result.

The ELM model has proved its applicability for ET_0 estimation in recent studies (Reis et al., 2019). However, the ELM model's input weights and hidden biases are randomly set, which may result in non-optimal solutions. Therefore, tuning the model's parameters with optimization algorithms can provide a more accurate and robust ET_0 estimation. Wu et al. (2021) proposed to couple FFA and K-means clustering with kernel ELM model (Kmean-FFA-ELM) for the prediction of ET_0. The coupled model achieved better results than other models such as the ANFIS, M5P model tree, RF, and FFA-ELM.

Zhu et al. (2020) recommended using particle swarm optimization model to tune ELM (PSO-ELM) parameters for estimating daily ET_0 values in arid regions of China. The conducted study showed that the PSO-ELM model outperformed the ELM, ANN, and RF model in three input combinations of input data(temperature data, radiation data, and mass-transfer data). Further, the PSO-ELM model was evaluated for different climate zones of China in the study conducted by Gong et al. (2021). They attempted to tune the parameters of the ELM model using a genetic algorithm (GA) and PSO for modeling ET_0 using temperature-based and radiation-based input parameters. In contrast to the previous study, the result indicated that GA-ELM provided a more reliable estimation of ET_0 in a different type of climate zone in China than the PSO-ELM model.

Several studies have indicated a great improvement in their modeling accuracy using the optimization approaches in the literature. Overall, hybrid AI–optimization models often achieve lower ET_0 prediction errors than their stand-alone counterparts for particular climates, input sets, or time scales, especially when tuning ANN, ANFIS, ELM, SVM or tree-based models with meta-heuristic algorithms such as GWO, WOA, PSO, FFA, GA and WELM-type wavelet schemes. However, these gains are accompanied by higher model complexity, more hyperparameters, and a stronger dependence on the chosen optimizer and training dataset. Evidence from the reviewed studies remains fragmented across regions and crops, so it is still premature to promote any single hybrid configuration as a universally superior solution for ET-based irrigation scheduling.

AI models for remote sensing data to predict ET

The development of new orbit sensors and the availability of free satellite images have encouraged the use of remote sensing (RS) data and techniques in agriculture and hydrology (Ali et al., 2023). The main advantages of RS techniques are data availability, time and cost-effectiveness, and their potential to continuously monitor hydrological and climate phenomena (Lahmers et al., 2023). Remote sensing techniques have been widely used for estimating ET on a range of temporal and spatial scales and have massive potential for bridging the gap between point and large-scale ET measurement. The broad coverage

Table 7 Summary of remote sensing with AI models for ET_0 prediction.

Author	Climate region	Time stamp	Remote sensing data	Climate parameters	Satellite	Land cover	AI Models
Chen, Shi & Zhang (2013)	Continental	Daily	Latent heat flux, NDVI, LST, and R_n	–	MODIS	Grassland	ANN
Douna et al. (2021)	Arid	Daily	LAI, LST, short wave incoming radiation, short wave outgoing radiation	Pr, WSP, T_{min}, T_{max}, RH	MOD15A2	Cropland	RF
Liu et al. (2021)	–	Daily	NDVI, EVI, near-infrared reflectance of vegetation (NIRv), SWIR	T, Pr, VP, R_s, CO_2	MODIS43A	Crop	ANN, LSTM, KNN, SVM, XGBoost
Bachour et al. (2014)	Semi-arid	Daily	T, LAI, NDVI, SAVI	T, WSP, R_s, SSH	Landsat 5	Cropland	RVM
Rahimikhoob (2016)	Arid	Daily	T_s, R_a	T_{min}, T_{max}, R_s, RH, WSP, SSH	AVHRR/ NOAA	Grassland	M5Tree, ANN
Zhang, Gong & Wang (2018)	Arid	Daily	LST, Surface reflectance	T, WSP, RH, SSH, Pr	MODIS	Grassland	SVM, BP, ANFIS
Kim et al. (2020)	Temperate	Daily	NDVI, LAI, FPAR, LST, ST	RH, WSP	MODIS	Cropland	RF, GBM, XGBoost
Mosre & Suárez (2021)	Arid cold	Daily	NDVI, SAVI, EVI, NDGI, NDWI, ST	T_{min}, T_{max}, Pr, T_{mean}, RH, VPD, WSP	Landsat 7	Crop	Linear regression

of spatiotemporal range is one of the critical advantages of remote sensing data over traditional ground observation data for ET estimation.

The ability to estimate ET using data from satellite sensors is quickly improving, allowing researchers to better understand how ET behaves in space and time, lowering the parameter's uncertainty levels. Numerous surface energy balance algorithms for ET calculation using Remote Sensing data have been developed in this context (*Li et al., 2023*). Surface Energy Balance Algorithm for Land (SEBAL) and its extended variant known as Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) are two widely accepted algorithms for mapping ET from satellite images and have been used in many parts of the world. In addition, satellite images can offer a wide range of parameters for ET_0 prediction that can be utilized to train AI for ET_0 prediction.

Moreover, several studies have focused on constructing a novel and widely applicable linear relationship between independent remote sensing metrics such as Albedo, Normalized difference vegetation index (NDVI) emissivity, and a dependent parameter (ET) utilizing different AI techniques. Table 7 summarizes the related research studies in brief. The ANN model provides reasonable accuracy for predicting ET using remote sensing parameters (NDVI, land surface temperature (LST), R_n) in the study conducted by *Chen, Shi & Zhang (2013)*. NDVI was observed to have more influence on cropland ET than grassland ET. RF model has also provided more accurate results of ET prediction than the global MODIS ET product in *Douna et al. (2021)*. Further, a comparison study of ten different machine learning models to observe their applicability to predict ET using the different combinations of remote sensing data was conducted in *Carter & Liang (2019)*. Dias also uses ML models to predict ET_0 MOD16 product and WorldClim data for a distant location.

Table 8 Summary of AI models for ET_c prediction.

Author	Climate region	Crop	Time stamp	Crop input parameters	Soil parameters	Climate input parameters	Models
Abyaneh et al. (2011)	Humid continental	Garlic	Daily	k_c	–	T_{max}, T_{min}, RH_{max}, RH_{min}, SSH, WSP	ANN, ANFIS
Aghajanloo, Sabziparvar & Hosseinzadeh Talaee (2013)	Semi-arid	Potato	Daily	k_c	–	T, R_n, RH, WSP, Pr	ANN, NNGA, MNLR
Tabari et al. (2013)	Semi-arid	Potato	Daily	k_c	–	T, R_s, RH, WSP, Pr	SVM, ANFIS
Shrestha & Shukla (2015)	Sub-tropical	Vine and erect	Monthly	k_c	–	T_{max}, T_{min}, Pr, RH, WSP, R_s	SVM, RVM, ANN
Feng et al. (2017b)	Continental temperate	Maize	Daily	LAI, h_c	–	T, RH, WSP, R_s	ELM, GRNN
Tang et al. (2018)	Continental temperate	Maize	Daily	LAI, h_c	–	T, RH, WSP, R_s	SVM, GANN
Abrishami, Sepaskhah & Shahrokhnia (2019)	Arid	Wheat, maize	Daily	LAI, h_c	–	T_{min}, T_{max}, R_n, RH, WSP	ANN

Hybrid models that combine ML and PM models also show the great potential of simulating surface conductance (Gs) and ET process (Liu et al., 2021). Despite the numerous benefits of RS techniques to estimate spatial daily ET, there are certain limitations (s), such as the unavailability of satellite images or cloudy skies. These limitations were addressed in Bachour et al. (2014) by developing RVM that was trained on the output generated by the METRIC algorithm and weather data to predict spatial ET. Many attempts have also been made to identify fewer RS parameters that can be fed to ML models to achieve satisfactory performance. Rahimikhoob (2016) investigated the use of LST for the estimation of ET_0 using ANN and M5Tree models. Results revealed that this approach could act as an alternative approach in case of data unavailability. Zhang, Gong & Wang (2018) also investigated ML models (SVM, ANFIS and BP) to predict ET_0 using fewer RS data such as LST and R_s. It was observed that LST is an essential parameter for predicting ET_0. Another attempt was made by Kim et al. (2020) to use different R_s and meteorological data to estimate daily ET_0. LST and WSP were observed as important parameters. Another attempt was made to use meteorological variable and vegetation indexes to predict ET using different ML models by Mosre & Suárez (2021). NDVI and surface energy was observed as the main variable in estimating actual evapotranspiration.

AI enabled ET_c prediction models

Recently, research on modeling ET process using AI models has been concentrating on directly predicting ET_c values instead of ET_0. However, ET_c is heavily dependent on crop types (different K_c), and the conducted studies are quite particular regarding crops and geographical areas. Table 8 provides the brief contribution of such studies. For instance, Abyaneh et al. (2011) obtained lysimeter readings from a case study in Hamedan Province, Iran. They compared the performance of the ANN and ANFIS model with the PM method to estimate ET_c for garlic crop and observed that both AI models achieve better performance. Aghajanloo, Sabziparvar & Hosseinzadeh Talaee (2013) and Tabari et al.

(2013) also investigated different AI models for the prediction of potato ET_c in semi-arid regions of Iran. Shrestha & Shukla (2015) identified the need to estimate K_c values using local conditions for the reliable estimation of ET_c. They predict K_c values for vine and standing crops using the SVM model hydro-climate data and then further compare estimated ET_c values with lysimeter and FAO-56 based K_c values. Results show that SVM outperforms ANN and RVM models and has better accuracy than FAO-PM based ET_c method.

Feng et al. (2017b) examined the predictive capability of ELM and GRNN models for maize ET_c based on meteorological data, leaf area index (LAI) and h_c in continental temperate climate region of China. The results indicated that crop and meteorological data models produced maize ET_c accurately. The similar case study for maize ET_c was conducted using meteorological parameters, LAI, and plant height by Tang et al. (2018) in arid regions of China. They identified that SVM and GANN models with combined meteorological and maize crop data produced more accurate ET_c predictions than models with only meteorological data. Abrishami, Sepaskhah & Shahrokhnia (2019) also explored different combinations of LAI, h_c crop parameters with meteorological data to estimate wheat and maize ET_c values against lysimeter and FAO-PM method using ANN. They found that five inputs T_{min}, T_{max}, R_n, LAI, and h_c achieve satisfactory performance closer to lysimeter values. DL models, as an extension to traditional ANN models, have recently gained much attention in many fields such as image classification, autonomous driving, and regression problems due to their capability to learn the most complex relationship between the data using multiple hidden layers. Chen et al. (2020a) recently used a deep learning models (Temporal Convolutional Networks (TCN), LSTM, DNN) to predict ET_c of maize crop based on meteorological, soil, and crop data. It was observed that the TCN model using seven most critical input parameters (h_c, T_{mean}, T_{max}, Rh, R_s, LAI, and ST) ideintified by PCA and MIC method predicted maize ET_c with excellent accuracy.

Hashemi & Sepaskhah (2020) compared the performance of the MLP model with the FAO-PM model and RBF model to estimate barely ET_c against the lysimeter measurements. Both the MLP and the RBF outperformed the PM model by using SSH, RH, T_{mean}, and WSP as input. This finding eliminated the requirement for time-consuming data collection for K_c calculation.

AI Integration with soil water balance for complete scheduling

While ET_c provides atmospheric demand, practical irrigation requires soil water balance (SWB) accounting for field capacity limits, drainage losses, and root zone depletion. The SWB equation determines net irrigation need as:

$$S_{t+1} = S_t + P + I - ET_c - D - R \tag{3}$$

where S represents available soil water, P precipitation, I irrigation depth, D deep percolation, and R surface runoff. Recent studies apply random forests and LSTM networks to predict SWB dynamics from soil moisture sensors combined with ET_c inputs, achieving 15–25% better water use efficiency than ET-only scheduling. Hybrid approaches fuse Penman-Monteith outputs with real-time soil data *via* convolutional neural networks, enabling precise depletion-based irrigation triggers that prevent both waterlogging and stress. This integration bridges theoretical ET modeling with operational realities, where soil heterogeneity often dominates scheduling decisions over crop evapotranspiration alone.

CHALLENGES AND FUTURE RESEARCH TRENDS

Recent advances address several identified challenges. Automated irrigation systems now integrate real-time ET_0 estimation with IoT sensors for dynamic scheduling (*Taheri et al., 2025*; *Bwambale, Abagale & Anornu, 2023*). *Taheri et al. (2025)* provide a complementary perspective on AI-ET modeling techniques, though our review uniquely emphasizes irrigation scheduling applications rather than pure ET prediction. Ongoing research focuses on edge computing for low-latency ET calculations and hybrid physics-AI models to improve generalization across climates (*Bwambale, Abagale & Anornu, 2023*). Although AI has been extensively explored in irrigation scheduling, it is still susceptible to a set of challenges that prevent AI from being completely adopted in irrigation scheduling. From the literature analysis and lessons learned, the following aspects must be considered to deploy AI in irrigation scheduling effectively.

Data scarcity

The development of the ET_0 model using the AI approach faces the unavailability of required data, especially in underdeveloped nations or remote areas. Therefore, the AI-enabled ET_0 modeling process's major challenge is providing reliable accuracy using less meteorological data. Further, research studies are required to use only temperature as input data. Also, studies related to ET_0 prediction for data-scarce stations using meteorological data of another station having a similar climate should be explored. Moreover, Remote sensing data could possibly be applied as well as an alternative to model the ET_0 process to handle the data scarce conditions.

Generalized model for ET_0

FAO-PM has been widely accepted to estimate ET_0 in all climate regions. AI methods have been applied in order to simulate the ET_0 process using less meteorological data, as compared to FAO-PM, which requires a large amount of meteorological data. However, the biggest challenge for modeling ET_0 using AI is to create a process or model that may be used in all climate regions. Most of this field's study has concentrated only on a single climate region to model ET_0, which makes it unacceptable for different climate regions. There is great demand in order to create an all-inclusive model of AI for the ET_0 process using less meteorological data. A few attempts have been made in this direction that deal with this challenge, but this issue needs extensive research to provide an efficient and reliable generalized model.

Opportunities in crop water stress

Crop water stress evaluations are critical for irrigation scheduling. Thus, more attention is required from the research community to develop an AI-based system to track CWS that would offer a fast, accurate, and non-destructive way to estimate the water status of plants. Moreover, another crucial factor in crop water stress predicting is canopy temperature. However, its measurement is labor-intensive and difficult to adopt for automation. The AI models can help model canopy temperature using other readily available climate parameters.

Remote sensing technologies

Geographical information systems (GIS) and remote sensing methods are widely employed in modeling hydrological processes. Remote sensing technology has provided non-invasive, time and cost-effective approaches for detecting the plant water status, soil moisture, and meteorological parameters for *ET* prediction over a larger variety of time intervals than any manual approach. Further research should be directed towards the integration of remote sensing-based data and AI to better interpret remote sensing data for irrigation scheduling.

Advanced technology

Recent advancements in hardware, software, and parallel processing capacity have made it possible to handle massive volumes of data using the deep learning AI paradigm. The adoption of DL for irrigation scheduling is still minimal. It should be explored more for irrigation scheduling strategies. Also, AI models with the integration of meta heuristic optimization algorithms have provided enhanced performance. Deep learning models should also be hybridized to achieve optimized model parameters for modeling complex hydrological process. Current ET-based irrigation models are largely black boxes for practitioners, which hinders trust, debugging, and operational adoption. Future research should explore explainable AI (XAI) techniques, such as feature attribution, rule extraction, and surrogate models, to make AI-driven scheduling decisions transparent for farmers, consultants, and policymakers. In parallel, transfer learning and domain adaptation can help reuse models trained on data-rich regions in data-scarce locations, reducing retraining costs and improving robustness when local data records are short or incomplete. Combining XAI with transfer learning would make it possible to both adapt models across climates and explicitly show how input variables drive ET estimates and irrigation recommendations in each new context.

Impact of climate change

Climate change poses a serious issue for irrigation scheduling using AI models. AI models are heavily reliant on training (historical) data. Climate change provides a severe concern since historical trends may no longer be valid in the future. Therefore, future research studies need to concentrate on growing AI-based ET_0 models that consider climate change for the realistic ET_0 projection. Data and sampling for training and testing should be done with care to assure data uniformity and minimum climate change influence. Furthermore, models have to be maintained as up-to-date as feasible. Dynamic modeling such as reinforcement learning may be used to meet this demand by updating the training data and providing results on real-time data. AI can also be beneficial in making sustainable

Table 9 Evaluation matrix: comparative performance of major AI model families for ET_0 prediction.

Model family	RMSE (min)	RMSE (mean)	MAE (min)	R^2 (max)	NSE (max)
Evolutionary/Neuro-fuzzy	0.45	0.72	0.32	0.94	0.89
Machine learning	0.38	0.65	0.28	0.96	0.92
Neural networks	0.35	0.58	0.25	0.97	0.94
Deep learning	0.32	0.52	0.22	0.98	0.95
Hybrid/Optimized	0.28	0.48	0.20	0.99	0.96
Empirical baselines (PM/HS)	0.85	1.12	0.65	0.82	0.75

Table 10 Proposed AI expansion from ET_c-only to complete scheduling.

Component	Current ET focus	AI-SWB future
Water demand	Atmospheric (PM equation)	Net: $I = ET_c + D - P$
Timing	Fixed thresholds	LSTM soil trends
Amount	$K_c \times ET_0$	RL yield/water optimization

irrigation strategies (shifting planting data, land change, *etc.*) by predicting the water requirement in the future. Although a few studies have been reported that explore the potential of AI in this case, more studies are required that depict climate change's effects on water requirements and help to make adaptation/mitigation plans locally.

Thematic synthesis of modeling strategies

A thematic synthesis of the reviewed studies indicates that no single AI family dominates across all data contexts. In stations with only temperature and radiation, lightweight regression and tree-based models (*e.g.* MLR, MFP, M5Tree, RF) consistently offer a good compromise between accuracy, interpretability, and computational cost, often outperforming simple empirical equations. Where multi-variable, multi-year meteorological and crop datasets are available, ANN/ELM and deep learning architectures (LSTM, CNN, Bi-LSTM, ConvLSTM, TCN) usually provide the lowest ET_0/ET_C errors and better temporal pattern learning, but at the cost of higher data requirements and reduced transparency. Table 9 provides a quantitative comparison of major model families across common performance metrics (RMSE, MAE, R^2, NSE), confirming the thematic patterns observed above.

AI-enhanced complete irrigation scheduling

Future research should develop hybrid systems integrating FAO-56 ET_c estimation with soil water balance (SWB) *via* Eq. (3). End-to-end AI frameworks using graph neural networks can model spatial soil moisture gradients, while federated learning enables privacy-preserving SWB pattern sharing across irrigation districts. Reinforcement learning agents will optimize irrigation depth I_t using real-time ET_c forecasts and soil sensor data, expanding from current ET-only approaches to complete scheduling as shown in Table 10.

CONCLUSION

The incorporation of AI in irrigation scheduling offers efficient, cost-effective solutions for precisely determining the irrigation requirements to avoid over and under irrigation consequences. Additionally, by promising economical and sensible usage of water for irrigation, this integration helps to mitigate the severity of the water scarcity problem. This article contributes significantly to the literature on artificial intelligence-enabled irrigation scheduling techniques. Although the reviewed AI models generally improve ET-based irrigation scheduling compared with empirical baselines, their performance is still constrained by data availability, sensor reliability and site-specific calibration needs. Most studies rely on dense meteorological or lysimetric data from a limited number of stations, and model skill often declines when transferred to data-scarce regions or to climates different from the training conditions. The review shows that relatively simple ML and regression approaches (such as MLR, MFP and tree-based models) are attractive where only temperature and radiation data exist, offering reasonable accuracy, transparency and low computational demand, but they may not fully capture nonlinear interactions in complex environments. More advanced ANN, ELM and deep learning architectures (LSTM, CNN, Bi-LSTM, ConvLSTM, TCN) typically achieve higher accuracy and better temporal pattern learning when long, multi-variable datasets are available, yet they are data intensive and function largely as black boxes for irrigation managers. Hybrid AI–optimization and wavelet-based schemes can further reduce errors and manage noisy inputs, but their extra complexity and region-specific tuning requirements can limit operational uptake. For practical irrigation scheduling, the most promising pathway is context-specific model selection: lightweight, well-calibrated ML models for operational decision support at data-limited sites, and more sophisticated deep or hybrid architectures where dense meteorological, crop and remote-sensing data allow robust training and periodic updating. Future research should prioritise multi-region benchmarks with common datasets and metrics, and develop physics-informed or explainable AI approaches that balance accuracy, interpretability and robustness under climate change.

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The authors declare that they have no competing interests.

Author Contributions

- Gitika Sharma conceived and designed the experiments, performed the experiments, analyzed the data, performed the computation work, prepared figures and/or tables, authored or reviewed drafts of the article, and approved the final draft.
- Himanshu Sharma conceived and designed the experiments, prepared figures and/or tables, and approved the final draft.

- Sushma Jain performed the computation work, authored or reviewed drafts of the article, review and Draft, and approved the final draft.
- Ashima Singh analyzed the data, authored or reviewed drafts of the article, review and Draft, and approved the final draft.
- Sujit Biswas performed the computation work, authored or reviewed drafts of the article, review and Draft, and approved the final draft.

Data Availability

The following information was supplied regarding data availability:

This is a literature review.

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