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Revolutionizing Agriculture: A Comprehensive Review of AI-Enabled Precision Irrigation and Water Quality Forecasting

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Abstract: Climate change poses significant challenges to the agricultural sector, exacerbating water scarcity and intensifying the irrational utilization of water reserves. In response to these pressing issues, Artificial Intelligence (AI) optimizes irrigation, predicting water quantity and quality to ensure optimal crop yields. AI-driven approaches mitigate the challenges of water scarcity, enhancing precision in irrigation management. This review explores recent AI applications in irrigation, focusing on three areas: AI-powered estimation of Crop Evapotranspiration (ETo), integration of AI with Interet of Things (IoT) for Smart Irrigation Systems (Smart-IS), and AI's role in forecasting water quality for irrigation. AI algorithms optimize water usage by quantifying water needs, enabling real-time monitoring, autonomous decision-making, and mitigating risks associated with poor water quality, thus enhancing crop productivity while minimizing environmental impacts. This review emphasizes AI's role in addressing water scarcity and optimizing irrigation in agriculture by utilizing different technologies to ensure sustainable water management and food security. Future researchers will find this review valuable for understanding AI's current impact on irrigation and identifying avenues for further innovation.

Keywords: Climate Change, Artificial Intelligence, Internet of Things, Smart Irrigation System, Crop Evapotranspiration, Irrigation Water.

Introduction

In the wake of heightened awareness about the detrimental repercussions of human interventions in natural ecosystems, including deforestation, intensive use of water resources, industrial emissions, and other anthropogenic activities, humanity grapples with the profound impacts and consequences. One notable consequence of this interference is the catalyzation of climate change. Climate change denotes the notable and rapid transformations in temperature, atmospheric carbon dioxide (CO2) levels, rainfall distribution, and the prevalence of severe climatic occurrences. These events encompass heat waves, droughts, floods, and irregular precipitation (Demem, 2023; Keutgen, 2023; G. Kumar *et al*., 2020). This environmental shift extends its influence into various sectors, with agriculture standing at the forefront of its impacts. It poses expressive challenges not only to natural biodiversity but also amplifies threats to crop productivity and food security (Mehraj et al., 2023).

Water is an essential and indispensable resource which is important to support both crop production and the livelihood *(*Zhong *et al*., 2023). As the global population is predicted to attain 9.4–10.2 billion by 2050, the dynamics of water withdrawal and consumption are undergoing a profound transformation, a growing need for resources to support an evolving lifestyle and significant changes in water usage patterns are also expected as a result of this demographic shift (Musie & Gonfa, 2023). Irrigation entails supplying water to agricultural land to complement natural rainfall and ensure sufficient moisture for the development of crops. It enables farmers to grow crops in areas with insufficient natural water supplies, increasing agricultural productivity and food security. However, agriculture, being a crucial sector, requires significant water resources for irrigation (Akhare, 2023). The demand for agricultural irrigation constitutes a substantial portion, approximately 90%, of the total water usage worldwide (Siebert *et al*., 2010). It is noteworthy that, although various sectors contribute to the withdrawal of water, agriculture remains the largest user, necessitating the optimization of agricultural water resources (Musie & Gonfa, 2023).

As climate change and global population growth influence water distribution and availability worldwide, challenges in the quantity and quality of accessible water are becoming increasingly evident (Kirby & Mainuddin, 2022). Also, higher temperatures coupled with changes in precipitation distribution result in an increased rate of soil water evaporation and plant transpiration, which in turn, leads to a higher water demand for crops and natural vegetation (Bussi *et al*., 2021; Ragab, 2023).

Moreover, these climate-induced changes can markedly affect the irrigation needs of agricultural crops, which ultimately influence grain production (Amanullah *et al*., 2020; Lamichhane, 2022). This scenario underscores the profound impact of population growth and changing global living standards on water usage for agriculture (Kumar S *et al*., 2023). Against this backdrop, projections indicate a concerning 11% increase in irrigation water withdrawal by 2050, raising alarms about the sustainability of this essential resource (Sandhu, 2016). Aside from its critical function in crop irrigation, agricultural water—which comes from a variety of artificial and natural sources—will be essential in meeting the growing demand for food production. With agriculture shaping our water landscape and, consequently, our sustainable future, urgent reviews of water management strategies are imperative (Musie & Gonfa, 2023). Moreover, The inappropriate use of water for irrigation compounds challenges related to water scarcity, defined by inefficient practices leading to waste and depletion of water resources (Mekonnen & Hoekstra, 2016), thus aggravating water scarcity and posing detrimental consequences to the environment and socio-economic development.

In response to these myriad challenges exacerbated by the escalating of agricultural and environmental repercussions of conventional practices, humanity has initiated a journey to confront these issues through the adoption of innovative technologies. The imperative to enhance food production by 70% underscores the critical role of agricultural sustainability in meeting this demand (Roy et al., 2024). As traditional agricultural practices grapple with the challenges caused by the growing population and urbanization (Radić & Cogoljević, 2022), the imperative to meet this rising demand for food becomes apparent. Traditional agriculture, which has historically acted as the basis of progress for generations, now faces challenges owing to the rapid increase in population and the scarcity of water reservoirs, this underscores the necessity for a shift towards intelligent agriculture (Lakshmi *et al*., 2023; Lytov, 2023).

Intelligent agriculture, also known as Agriculture 4.0, leverages cutting-edge technologies such as AI to boost productivity, including the management of irrigation and overall quality (Ayaz, Aytekin & Akgün, 2019; Khurape & Kirve, 2019). The incorporation of AI applications in plant production can optimize food production. AI in agriculture can significantly improve efficiency, reduce waste, and enhance water safety and quality, while simultaneously reducing production costs and promoting sustainable farming practices (Abd El-Aziz & El-Abeid, 2023; Taneja *et al*., 2023). This evolution finds its culmination in what is termed “Precision agriculture”, also known as "Smart Farming," this approach aims to minimize inefficiencies in resource utilization, including water, fertilizer, and energy (Anand *et al*., 2023). The advent of AI in agriculture entails the assimilation of different technologies, robots, data analytics, IoT, cameras, affordable sensors, drones, and widespread internet connectivity (Babakhouya *et al*., 2023; Gorobets, 2022; Hossen, 2023). This combination offers farmers actionable insights and real-time data, optimizing decision-making across various aspects including irrigation systems, fertilizer application, and nutrient deficiencies, ultimately leading to an increase in productivity and empowering farmers to promptly intervene and avert potential crop losses (Subeesh & Mehta, 2021; Lu *et al.*, 2023; Taneja *et al.*, 2023). To achieve these purposes, AI comprising Machine Learning (ML) and Deep Learning (DL) algorithms, is pivotal and plays a critical role in enabling data-driven decisions and enhancing agricultural productivity (Lakshmi *et al.*, 2023; Hussein *et al.*, 2024).

In recent years, a myriad of studies has underscored the profound impact of automation and AI on optimizing crop yields and minimizing resource consumption across diverse agricultural domains. This review specifically delves into the pivotal role that AI plays in enhancing irrigation management, focusing on both quantity and quality aspects. Through a comprehensive analysis of advancements in various studies on the integration of AI in irrigation, aiming to improve quality and reduce water waste, this paper aims to elucidate the AI algorithms and technologies employed for precision irrigation and predicting irrigation water quality.

This paper is divided into the following sections:

- Section I outlines the methodology employed for data collection, laying a robust foundation for subsequent sections.
- Section II delves into AI-powered ET_O estimation, offering insights into the progress made within this field.

- Section III explores the synergy between IoT and AI, showcasing their collaborative role in fostering smart irrigation systems.
- Section IV addresses the intervention of AI in predicting irrigation water quality, offering an in-depth exploration of related studies and methodologies.
- In Section V, we summarize the findings of our literature review and present our final thoughts.

By following this structured approach, the review seeks to enhance comprehension of the diverse applications of AI in improving irrigation techniques.

Methodology

Literature search

The initial step involved an exhaustive search of academic databases, including but not limited to PubMed, IEEE Xplore, ScienceDirect, and Google Scholar, to identify studies focusing on the incorporation of AI in irrigation management and irrigation water quality prediction. Utilizing key terms such as 'AI in Irrigation Management,' 'Smart Irrigation Systems,' and 'AI for Irrigation Water Quality Prediction,' our search aimed to cover this specific domain comprehensively.

Inclusion criteria

The criteria specifically targeted studies addressing the application of AI in irrigation ensuring the inclusion of recent and pertinent contributions in the realm of AI's role in irrigation management and water quality prediction.

Organizing and presenting findings

The findings are presented coherently, with dedicated sections addressing AI-powered irrigation management and AI applications in predicting irrigation water quality. This thematic organization, complemented by chronological insights, provides a detailed narrative review of the present status of AI integration within these particular aspects of irrigation.

Documentation

Every step of the methodology process was meticulously documented to ensure transparency. The documentation includes essential details such as title, authors, publication year, study objectives, methodologies employed, major findings, and technological contributions discussed, specifically to enhancing irrigation management and water quality prediction.

Ai-powered ETo estimation

ET_O is an index that reflects the volume of water crops lost through soil evaporation and plant transpiration **Fig. (1)** (Dingman, 2015; Tausif et al., 2023). The ET_O serves a crucial function in hydrological studies, irrigation scheduling, and facilitating effective water resource management by serving as a fundamental factor in calculating the water requirements of crops (Ferreira *et al*., 2019).

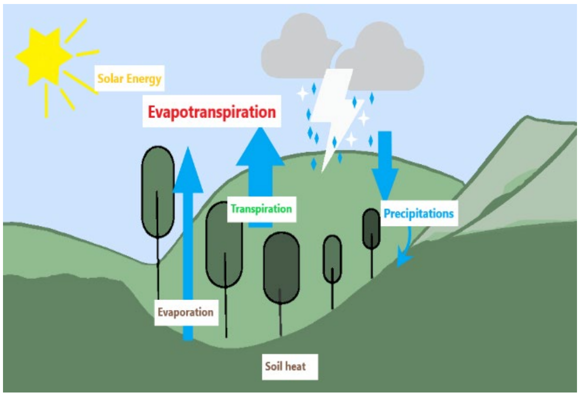

Fig. (1): Evapotranspiration ET_O

Precise ET_O assessments are crucial in many fields, such as climatological research, developing and scheduling irrigation systems, assessing environmental consequences, and simulating soil moisture dynamics. Nevertheless, there are significant expenses and difficult obstacles associated with measuring ET_O directly (Almorox, Quej & Martí, 2015). Lysimeters are frequently used to directly estimate ET_O however, due to their high maintenance and operating costs, their use for ET_O estimation is very restricted (López-Urrea *et al*., 2006). Many choose to use mathematical models as a more practical option, frequently using reference evapotranspiration or prospective evapotranspiration (PET) as key variables for ETo estimation (Almorox, Quej & Martí, 2015). The most widely accepted mathematical model for ETo is Penman-Monteith (Eq.1) (Allen *et al*., 1998).

Equation1*:Penman-Monteith-equation (FAO56-PM eq)*

$$ET_O = \frac{0.408\Delta\,(R_n - G) + \gamma \frac{900}{T+273} u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34\, u_2)}$$

where; ETo is daily referenced ET (mm day-1), Δ is the slope of the relationship between saturation vapor pressure and mean daily air temperature (kPa °C-1), Rn is the net radiation at the crop surface (MJ m-2 day-1), G is the soil heat flux density (MJ m-2 day-1), γ is the psychrometric constant which depends on the altitude of each location (kPa °C-1), T is the mean daily air temperature (°C), u2 is the wind speed at 2 m height (m s-1); e_s is the saturation vapor pressure (kPa); e_a is the actual vapor pressure (kPa).

Despite its acceptance, applying the FAO-Penman-Monteith equation (FAO56-PM eq) at the field scale is challenging, due to the method's demands for a multitude of meteorological parameters, making it impractical for individual farms (Valiantzas, 2015; Mohammadi & Mehdizadeh, 2020). The Hargreaves-Samani (HS) Method is put forward as an alternate solution, requiring a more limited set of variables (George H. Hargreaves & Zohrab A. Samani, 1985; Yin *et al*., 2020). However, studies (Valipour, 2013, 2015) have indicated that the (HS) method tends to undervalue ET_O in various scenarios (Yin *et al*., 2020). The Hargreaves-Samani (A&G) and (HS) equations demonstrated reduced accuracy in predicting daily evapotranspiration when contrasted with the FAO56-PM eq (Koç & Erkan Can, 2023).

Due to climate change, arid regions have grappled with challenges related to shifting weather patterns, notably a decrease in precipitation. After a series of droughts, these changes have led to enormous economic losses (Smith & Katz, 2013; Prein *et al.*, 2016; Djaman, Mohammed & Koudahe, 2023). This has led to a discernible rise in the demand for real evapotranspiration ET_O, both on a daily and seasonal basis. High temperatures, strong wind velocity, and comparatively little seasonal rainfall are some of the factors contributing to this increased demand (Mohammed *et al.*, 2019; Djaman, Mohammed & Koudahe, 2023). Precise ET_O data are necessary for effectively managing water resources, enhancing crop water productivity, and innovating water management techniques. They play a crucial role in guaranteeing a steady supply of water for farming in arid areas (Djaman, Mohammed & Koudahe, 2023).

Related works

(Yu *et al*., 2020) investigated ET_O estimation in China using diverse combinations of meteorological parameters. They evaluated three Machine Learning models (ML) models Artificial Neural Network (ANN), Support Vector Regression (SVR), and Extreme Learning Machine (ELM), highlighting SVR and ELM's effectiveness in handling incomplete data. Besides, the study results revealed that integrating relative humidity

(RH), maximum and minimum temperatures (Tmax), (Tmin), wind speed (U2), and solar radiation (Rs) into SVR and ELM models yielded the most accurate ET_O estimations, indicating their significant potential in practical applications. Impacting the evaporation rates of water from both soil and plants, temperature significantly influences ET_O. Elevated temperatures increase evaporation and transpiration rates, resulting in elevated ET_O levels; conversely, elevated humidity levels reduce evaporation and transpiration, resulting in lower ET_O values (Abdel-Fattah *et al*., 2023). To estimate daily sugar beet evapotranspiration, (Yamaç, 2021) explored the efficacy of four AI- algorithms k-Nearest Neighbor (k-NN), Support Vector Machine (SVM), Random Forest (RF), and Adaptive Boosting (AB)— Utilizing eight different sets of input variables derived from field experiments in Çumra, Konya in Turkey. The performance of the AI models was assessed against a model constructed following the FAO approach. Despite using fewer input variables, all the models have demonstrated satisfactory performance. However, with the input combination crop coefficient Kc, Tmax, Tmin, Rs, and U2, SVM model outperformed the other models and highlighted the suitability to estimate ET_O. Another study (Katimbo *et al*., 2023) in the United States aimed to the prediction of ET_O and crop water stress index (CWSI) which are two essential factors that affect directly the proportion of water in the plant, by evaluating different AI algorithms and their ensembles: ANN, Long Short-Term Memory (LSTM), RF, SVM, k-NN, Categorical Boosting (CatBoost), three Ensembls of ML models, Multiple Linear Regression (MLR). The study focused on the improvement of water sustainability through intelligent irrigation scheduling based on an automated Irrigation Decision Support System (IDSS). The datasets used in this study include the Normalized Difference Vegetation Index (NDVI), canopy temperature (Tc), and soil moisture data obtained from irrigated and non-irrigated maize fields. The predictions are compared against established benchmarks, including the FAO56-PM eq ET_O and Jackson's theoretical (CWSI). Utilizing the inputs: RH, Tmax, ∑SWC @ 0.9 m (soil moisture at 0.9 m depth), and Tmin, one of the ML ensembles which is Stacked Regression (Stacked-Regr) demonstrated superior performance in predicting ET_O. On the other hand, CatBoost emerged as the best model in (CWSI) prediction incorporating features such as T°, Rs, vapor pressure deficit VPD, RH, U2, and ∑SWC @ 0.9 m. The study emphasizes the potential of these models in the establishment system for IDSS incorporating the Crop Water Stress Index and soil water feedback. (Quej *et al*., 2022) demonstrated that the temperature-based AI models provide better results in estimating the daily ET_O of Mexico's warm sub-humid climate, in circumstances where solely temperature records are accessible, by comparing the performance of three models SVM, Adaptive Neuro-Fuzzy Inference System (ANFIS), and CatBoost with the conventional Hargreaves-Samani method. The outperformed is the SVM, as the analysis explores the impact of RH and rainfall upon the accuracy of the model in warm sub-humid regions studied. The ET_O value may differ based on the climatological conditions of the region, whether it is arid, semi-arid, or humid (Gao *et al*., 2017). Within China, specifically in arid and humid regions, (Yan *et al*., 2021) focused on estimating daily ET_O where long-term or complete climatic variables may be unavailable. Extreme gradient boosting (XGB), and the whale optimization algorithm (WOA), are combined to create a hybrid model. Which is trained and tested at four stations in both humid and arid regions. The study considered seven partial configurations of meteorological variables, including RH, Tmax, and Tmin, extra-terrestrial radiation (Ra), U2, relative sunshine duration (n/N), and Rs. These results put into light the fact that Local WOA-XGB models outperformed the simplified FAO56-PM eq, mainly under arid and humid climates in terms of accuracy. This study will also outline the dominant variables by highlighting U2 as the most important during arid climates and n/N during humid climates. Similarly, this study will outline the most influential variables: U2 during arid climates and n/N during humid climates. In addition, one more study Similarly, another study (Liu *et al*., 2021) in China focused on ET_O estimation in humid regions by applying XGB and RF models with an assessment of various strategies for data and period segmentation. The results showed that the RF model showed better performances than XGB and highlighted the importance of Rs for accurate predictions over southern China. The recommended approach involves using the RF model with a 30-year dataset as a promising alternative to the FAO56-PM eq for daily ET_O estimation in regions with Inadequate climatic data in areas of high humidity in the south of China. In Iran, specializing in arid and semi-arid climates (Samadianfard & Valizadeh Kamran, 2023) centered on estimating evapotranspiration with an innovative approach that combines ML techniques, including RF and Multi-Layer Perceptron (MLP), with remote sensing data from Land Remote Sensing (Landsat) and Moderate Resolution Imaging Spectroradiometer (MODIS) satellites. Input parameters include monthly averages of Land Surface Temperature (LST) and NDVI. Models are evaluated against the FAO56-PM eq incorporating various input parameters "scenarios". The research identifies the optimal model configuration (The RF-4 and MLP-4 models, scenario 4) using MODIS LSTMOD and NDVIMOD for precise monthly ET_O estimation. Lastly, comparing monthly ET_O estimation in arid and semi-arid climates, the MLP model yields the best performance with a high correlation coefficient in semi-arid climates. These findings highlight the paramount role of satellite imagery and ML in refining water management strategies, offering valuable insights applicable to environmental science across diverse climatic conditions.

Egypt, one of the countries which are characterized by arid regions, (Abdel-Fattah *et al*., 2023) found that the ANNs estimate the ET_O more precisely in comparison with the Stepwise Regression (SWR) referencing the FAO56-PM eq. The study identifies crucial variables affecting ET_O in arid regions such as Tmax, RH, Rs, and U2. In parallel line (Makwana, Tiwari & Deora, 2023) compared the accuracy of ANN with ELM, M5 Tree, and MLR to estimate ET_O against the FAO-56 PM Eq. The findings indicate that the ANN outperformed across different indicators, demonstrating their practical and reliable applicability for accurate ET_O estimation. Alternatively, in Iran, (Bidabadi *et al*., 2022) results indicate that the ANFIS model demonstrated superior performance in areas with arid and semi-arid climates compared to the ANN. Particularly with average temperature and wind speed inputs. (Heramb *et al*., 2023) used four ML algorithms RF, SVM, Light Gradient Boosting Decision (LightGBDT), and Extreme Gradient Decision Trees (XGDT), to estimate the ET_O in 11 regions with arid and semi-arid climates in India. FAO56-PM eq-derived ET_O served as the focal point for model adjusting. Conversely to other research, they concluded that models using all inputs did best, and those with only temperature data were less accurate. Additionally, the SVM model proved superior even with fewer inputs, which showed their effectiveness. In particular, U2 and Rs turned out to be the most important parameters to achieve accurate results. These studies (**Table 1)** have utilized AI for a dual objective: firstly, to identify the precise combination of parameters necessary for accurate ET_O estimation and, secondly, to calculate ET_O precisely. This aims to determine the exact irrigation water needed, enhancing accuracy and reducing wastage compared to traditional methods. However, AI models assessing ET_O based on reference methods may have limitations in accuracy and practicality. Statistical metrics like R^2: Coefficient of determination; RMSE: Root Mean Square Error; MAE: Mean Absolute Error; NSE: Nash-Sutcliffe Efficiency are used to evaluate their reliability. It is quite difficult to obtain ample meteorological data, especially in remote or mountainous areas, which may compromise the accuracy of the models (Irvem & Ozbuldu, 2023). Input variables should be optimally selected to reduce inaccuracy and represent spatial and temporal variability under varying climatic conditions. This suggests that the reliability of ETo estimation models will change with a change in the specific climatic region being studied (Makwana, Tiwari & Deora, 2023).

Calculating ET_O in real time is feasible, as demonstrated by (Hu *et al.*, 2022), and involves utilizing an Internet of Things (IoT) architecture to directly sense environmental conditions in crop fields for ET_O rate determination. The model utilizes directly sensed temperature and humidity data from the crop fields in Pakistan spanning 2015 to 2021. Four ML algorithms Gaussian Naive Bayes (GNB), SVM, k-NN, and ANN are compared to assess their accuracy in estimating ET_O rates. k-NN model demonstrates superior performance, achieving 92% accuracy and outperforming other models. The solution complies with the Penman-Monteith methodology and is tailored to developing intelligent irrigation techniques that could optimize water usage and maintain crop yields. The proposed approach, by integrating IoT technology, enables real-time observations and acquisitions of data on environmental parameters in the crop field for better accuracy of ET_O estimation.

Over and above, IoT can be a better choice instead of the ETo process, as proven by (Kumar S *et al*., 2023) in India. Their research was conducted to determine the most efficient irrigation technique by comparing the performance of IoT-based soil moisture monitoring (IoT-SM) with an evapotranspiration-based strategy. Sweet corn plants' growth parameters were the basis for a comparison between these two techniques. Two irrigation regimes were employed for the method of monitoring soil moisture based on IoT technology.

The first regime was to maintain soil moisture at 43.5% of soil field capacity, while the second regime was to maintain soil moisture at 34.8%. Meanwhile, for the ET_O-based method, irrigation was sophisticated to achieve 100% ET_O. IoT-SM device was developed and implemented in the fields throughout which the soil data were collected by different sensors (Temp-sensor, HR-sensor, as well as soil moisture sensors) in real conditions using the ESP8266 Wi-Fi Module. The program was developed using C and C++ programming languages. to manage the operation of the IoT-SM.

Table (1): AI-Powered ETo Estimation.

Author (year)	Country	Objective	Technology/model	Results	Contribution to Water Management
(Wu *et al*., 2020)	China	Estimate ETo using ML models	SVM and ELM	SVM and ELM showed significant potential in ETo estimation.	Provides insights into accurate ETo estimation, aiding efficient water management in agriculture
(Yamaç, 2021)	Turkey	Evaluate AI algorithms for sugar beet ETo	k-NN, SVM, RF, AB	SVM outperformed with a specific input combination.	Offers a method for precise sugar beet irrigation, contributing to water-use efficiency
(Katimbo *et al.,* 2023))	United States	Predict ETo and CWSI using various ML models	Stacked-Regr, CatBoost	Stacked-Regr for ETo and CatBoost for CWSI showed superior performance.	Supports smart irrigation practices, optimizing water use and maintaining crop yields
(Quej *et al*., 2022)	Mexico	Compare temperature-based AI models for daily ETo	SVM, Adaptive Neuro-Fuzzy, CatBoost	SVM outperformed in warm sub-humid climate.	Enhances understanding of temperature-based models for ETo in specific climates
(Yan *et al*., 2021)	China	Estimate daily ETo using XGB and WOA	XGB, WOA	Local WOA-XGB outperformed FAO-56 PM models.	Provides an effective model for daily ETo estimation, improving water management decisions
(Liu *et al*., 2021)	China	Estimate ETo in humid regions using ML models	Random Forest	RF with a 30-year dataset promising for daily ETo estimation.	Offers a reliable alternative to traditional methods for daily ETo estimation in humid regions
(Samadianfard & Valizadeh Kamran, 2023)	Iran	Estimate evapotranspiration using ML with remote sensing	RF, MLP	RF-4 and MLP-4 models with MODIS data for precise monthly ETo estimation.	Utilizes remote sensing for precise monthly eto estimation, aiding water management strategies
(Abdel-Fattah *et al*., 2023)	Egypt	Compare ANNs with stepwise regression for ETo estimation	ANN	ANNs more precise than stepwise regression.	Improves accuracy in ETo estimation, contributing to effective water management in agriculture
(Makwana *et al*., 2023)	India	Compare ANN, ELM, M5 Tree, MLR for ETo estimation	ANN	ANN outperformed other models across different indicators.	Demonstrates the practical applicability of ANN for accurate ETo estimation, aiding water management
(Bidabadi *et al*., 2022)	Iran	Compare ANFIS and ANN for ETo estimation	ANFIS	ANFIS superior, especially with average temperature and wind speed inputs.	Highlights the effectiveness of ANFIS in arid and semi-arid regions, guiding water management decisions
(Heramb *et al*., 2023)	India	Estimate evapotranspiration using ML models	SVM	SVM demonstrated superior performance.	Recommends SVM models for accurate evapotranspiration estimation, crucial for water management in arid regions.
(Hu et al., 2022)	Pakistan	Predict ETo rates using IoT and ML algorithms	k-NN	k-NN demonstrated superior accuracy.	Introduces IoT for real-time ETo rate prediction, enhancing water management practices at the farmer level.
(Kumar S *et al*., 2023)	India	Compare IoT-SM and ETo-based irrigation methods	IoT	IoT-SM 43.5% sensor-based drip irrigation led to water savings and yield improvement.	Validates IoT-based soil moisture monitoring as a water-saving irrigation strategy with improved crop yield.

The soil moisture content, soil temperature, relative humidity, and temperature are then stored on the ThingSpeak IoT platform every two minutes. The study results show that the IoT-SM 43.5% sensor-based drip irrigation technique led to significant benefits in terms of water saving and yield improvement, compared to the other methods (ET_O-based irrigation and the IoT-SM34.8%). This strategy led to about 11% saving of water and accomplishing 12.05% growth in crop production. So, we can conclude that IoT also acts as an effective tool for deciding accurate irrigation levels in the fields, giving more excellent real-time output, especially in water usage and crop production

IoT and AI: Smart Irrigation Systems

The concept of the IoT pertains to a system of interconnected devices and objects capable of exchanging data and executing functions via the Internet. It enables the online connection and communication of physical objects, allowing for automated data collection, interaction between objects, and engagement with humans (John, Lakshmi & Kuncharam, 2023; Salama *et al.*, 2023). The inception of the IoT arose from the idea that all digital entities would be interconnected and operating intelligently, evolving since its inception in 2000 (Chae, 2019). The primary goal of this technology is to enhance human life by connecting and optimizing all accessible resources, including humans, information, and technology (Khalid, 2023). Several studies have offered reviews or surveys about pertinent technologies and obstacles in the deployment of IoT-based services and applications (He *et al.*, 2016; Mujawar and Mujawar, 2019; Perwej *et al.*, 2019; Sathiyanathan, 2020; Bhuiyan *et al.*, 2021; Ameri *et al.*, 2022; S. Kumar *et al.*, 2023) Additionally, IoT integrates AI and ML to develop intelligent and more effective systems capable of real-time responsiveness. AI and IoT are swiftly evolving technologies that are transforming diverse industries and daily activities (Law and Policy, 2023; Thakur, Pathan & Ismat, 2023). Applications of AI and IoT extend across various sectors, such as healthcare, agriculture, industry, and more (Singh & Singh, 2020). In the agriculture field, leveraging IoT and AI technologies holds the promise of positively transforming conventional agriculture practices. This implementation holds considerable potential in addressing the pressing challenges confronted by traditional agriculture (Alreshidi, 2019). This union of technologies offers a solution to boost the efficiency and effectiveness of water utilization in agriculture (Akhare, 2023). Additionally, IoT and AI can be used to oversee irrigation practices to optimize crop yield while reducing water usage, using sensors and advanced algorithms to collect and analyze data on plant growth. Besides the Intelligent Irrigation Systems based on IoT and AI can ensure the right quantities of water for plants, improving water management in agriculture (Bhandari *et al.*, 2023; Hamdoon & Zengin, 2023). The importance of IoT for smart irrigation has been proven in numerous studies. The recent advances in IoT technologies permit precise data collection even more spatially and empower higher levels of automation (Togneri *et al.*, 2023). Due to the real-time monitoring of various parameters, the deployment of IoT systems usually generates a large amount of data and by analyzing this and taking into account variables including crop variety, soil characteristics, and weather patterns, the models can predict the optimal watering needs of specific crops at different stages of growth (Obaideen *et al*., 2022).

Related works

Vij *et al*. (2020) in Singapore, addressed the imperative need for technological advancements in the agriculture industry, especially in the context of water scarcity and efficient farm maintenance. The proposal focuses on automating irrigation systems using the IoT for a cost-effective and accurate resolution. A monitoring system is envisaged to combat issues like excessive irrigation, soil erosion, and irrigation issues specific to crops. A wireless sensor network (WSN) deployed across various areas of the agricultural land is suggested, transmitting data to a common server. ML algorithms, including Support Vector Regression (SVR) and Random Forest Regressor (RFR), enhance irrigation predictions based on crop types and weather conditions. The research concludes by highlighting the economic and sustainable nature of the proposed IoT-based automation. Another study in United Arab Emirates, Al-Ali *et al*. (2019) present An IoT-enabled solar energy system designed for smart irrigation to address global challenges of water scarcity and power shortages. Following this, another research study conducted in Jordan, Khalifeh *et al*. (2021), focused on designing and implementing an intelligent irrigation system using IoT, AI, and the LORAWAN (Long Range Wide Area Network) communication technology. In this work, a lot of emphasis has been placed on the weather prediction mechanism, which becomes very essential to the irrigation prediction system. By accurately predicting the meteorological variables like temperature, humidity, and atmospheric pressure, the system can make a proper decision regarding optimum water irrigation. For that, the research proposes to use the Wind Driven Optimization Least Square Support Vector Machine (WDO-LS-SVM) algorithm for weather prediction. The designed system is based on the following four main components by using Internet of Things (IoT) technology:

1-The sensors that measure the humidity, temperature, and pressure.

2- The LORAWAN Gateway which acts as a bridge between the LoRaWAN sensor nodes and the network server.

3-The open-source LoRaWAN network ChripStack framework.

4- Grafana cloud is used as a Database and Cloud integration.

Sensors collect the data and are sent to the LoRaWAN gateway through a LoRa communication link. After making decisions concerning the data, the results are sent back to the irrigation system through the same LoRa communication link. The major findings of this study have pointed out the importance of accurate weather forecasting in achieving effective irrigation. Integrating artificial intelligence, LoRaWAN communication technology, and the WDO-LS-SVM algorithm, the system showed promising results in optimizing water irrigation. Another Smart-IS was developed by Tace *et al*. (2022) in Morocco, utilizing ML algorithms and IoT technology. The system integrates sensors of soil moisture, temperature, and humidity, including rain sensors, which are connected to an Arduino board for real-time data collection. They used Node-Red and MongoDB for storing and pre-processing data. ML models like Neural Networks (NN), SVM, logistic Regression (LogReg), Naïve Bayes (NB), and k-NN were trained for the prediction of irrigation, and the highest accuracy achieved by k-NN is 98.3%. From the study, it is possible to achieve a web application for system visualization and data supervision. Incorporating the IoT into the Smart-IS presents a viable option for enhancing water management also in small plots, open gardens, and green spaces as indicated by Jain (2023) in India, where the study demonstrated the effectiveness of IoT-enabled drip irrigation, integrating web/android apps and sensors for soil moisture monitoring. The system, consisting of three layers (sensing, internet, and application), utilizes Arduino and NodeMCU for data communication to the cloud. An Android/web application facilitates user interaction and ensures optimal watering for gardening purposes. In Peru, Alanya-Arango *et al*. (2022) introduced a method for recommending fluid ounces tailored for embedded devices to optimize water usage in agriculture. Leveraging IoT sensors capturing atmospheric and surface data, the information is processed using ML on a cloud-based server to provide water use recommendations to farmers. The recommender system, developed internally, demonstrates resilience and flexibility. Testing on datasets from the National Institutes of Technology (NIT) Bhubaneswar confirms the effectiveness of the proposed method in optimizing water usage with minimal farmer intervention. R *et al*.(2023) in India introduced an AI and 6G-IoT-based autonomous irrigation system for smart agriculture. The system uses a prediction algorithm on a microprocessor, using IoT-acquired weather data to predict rainfall and climatic changes. The system will automatically irrigate the fields according to the environmental conditions and the exact measurement of soil moisture, hence reducing irrigation water wastage. It also disseminates weather information to farmers and converts conventional irrigation into an effortless smart agriculture model. The experimental setup entails collection of sensor data collection and a hybrid ML technique for precise soil moisture prediction. Real-time monitoring and data visualization are enabled through the 6G-IoT network. The proposed framework is effective under diverse environmental conditions, which allows it to be one of the potential frameworks in the future for smart agriculture systems. Routis & Roussaki (2023) introduced a smart IoT-based precision irrigation system in agriculture, utilizing microprocessors, a Single-Board Computer (SBC), and various sensors, including those for soil moisture, atmospheric humidity, temperature, and ultraviolet radiation. The study has shown the effectiveness of the system through experiments by making appropriate decisions on irrigation and has incorporated an RNN-LSTM for forecasting and ML for smart agriculture. Similarly, ongoing research activities were involved with scale-up of the prototype over maize agricultural fields in Northern Greece and an intelligent actuation application, which will be developed using artificial intelligence and focused on water conservation and maintaining crop health. Tawfeek, Alanazi, & Ahmed (2022) in Saudi Arabia set up an intelligent fertigation scheme by utilizing Adaptive Particle Swarm Optimization (PSO) and ANN to enhance olive cultivation. The suggested PSO-ANN system, which has two units in the output layer for irrigation and fertilization decisions, freely accommodates new datasets, without re-establishment. Using IoT tools, including sensors for temperature, soil moisture, wind, and humidity, the system autonomously makes decisions on irrigation and fertilization, contributing to increased efficiency and reduced human intervention. Similarly, Nazar & Altalb (2022) in Turkey utilizes the ANN with real-time hardware applications within the framework of IoT. The researchers use FC-28 soil and DHT11 humidity/temperature sensors to gather environmental data. The system is designed using Arduino and Node MCU ESP 8266 microcontrollers for automating the water pump control (ON/OFF) and irrigation water flow that depends upon inputs from sensors. The IoT-based agricultural irrigation is automated using ANN, through automatically adjusting parameters to efficiently manage water according to the environment. Back to Saudi Arabia, Yanes (2023) presents the design of an intelligent greenhouse based on Internet of Things technology and a one-dimensional Convolutional Neural Networks (CNN) architecture for adaptive control of agricultural processes. The core crops on which this framework is based are cucumber, pepper, tomato, and bean. IoT implementation allows real-time monitoring and control, ensuring optimal conditions for plant development through fertilization, irrigation, lighting, and temperature management. Experimental results demonstrate the effectiveness of the proposed system with 1D-CNN attaining an accuracy value of 97.56%. The long-term advantages were more highlighted in water usage reduction, enhanced crop quality, higher crop yield, and decreased labor cost. Lakshmi *et al*. (2023) in India, introduce a cost-effective and adaptable irrigation strategy for smart agriculture, utilizing ML algorithms. Using MongoDB and the Node-RED platform, a sensor array measures soil moisture, temperature, and rain to optimize plant development. Comparing models, k-NN stood out with a 98.6% identification rate. An online tool integrates model predictions with sensor data for improved environmental visualization and control. Aruna *et al*. (2023), present ML-Driven Smart-IS with Arithmetic Optimization Algorithm (AOAML-Smart-IS) technique in an IoT framework. AOAML-Smart-IS employs a MLP classification model to evaluate irrigation needs, incorporating vital parameter tuning through the (AOA). Experimental assessments on agricultural data underscore the superior efficacy of the AOAML-Smart-IS technique in irrigation classification.

These studies **(Table 2)** and others show that the use of different hardware modules, communication technologies, and storage systems in Smart-IS further enhances irrigation efficiency and effectiveness. The earlier studies were specifically conducted to explore and address various aspects related to the management and control or prediction of irrigation water, and forecast water requirements, also aimed to enhance the general effectiveness and sustainability of irrigation methods utilizing the different algorithms of the AI-power and IoT technology. Optimum irrigation and a good crop harvest require not only the consideration of precision irrigation techniques but also the quality of water as a whole. Precision irrigation is undoubtedly critical in applying water in a controlled and efficient manner, allowing for water-saving and healthier plants. However, the influence of water quality on agricultural success should not be underestimated. Irrigation water quality has a significant impact on soil quality, plant growth, and crop yield or plant produce, in general.

Table (2): *IoT and AI: Smart-IS*

Author	Country	Objective	Technology/model	Results	Contribution to water management
(Vij *et al*., 2020)	Singapore	Addressing water scarcity and efficient farm maintenance.	IoT for automating irrigation systems, WSN, ML algorithms SVR, RFR	Cost-effective IoT automation system addresses over-irrigation, soil erosion, and crop-specific irrigation in a healthy way	Improve irrigation efficiency, reduce water wastage, and ensure sustainability of agriculture
(Al-Ali *et al*., 2019)	United Arab Emirates	Introduces an IoT-powered solar irrigation system to combat global water scarcity and power shortages.	IoT, System-on-a-chip controller, WiFi, Solar cells	Solar-powered system tested with remote monitoring and control. Very user-friendly website. Understandable and accessible for farming	Consuming minimal conventional power supply, reducing the need for human intervention at regular intervals, and contributing toward efficient irrigation techniques
(Khalifeh *et al*., 2021)	Jordan	Implementing a smart irrigation system using IoT, AI, and LORAWAN with weather forecasting focus.	IoT, AI, LORAWAN, WDO-LS-SVM algorithm, Sensors, LoRaWAN Gateway, ChripStack, Grafana Cloud	Highlights importance of accurate weather forecasting for efficient irrigation. System utilizes WDO-LS-SVM algorithm	Promises water irrigation optimization with AI, LORAWAN, and WDO-LS-SVM. Reduces water wastage through accurate weather-based decisions
(Tace *et al*., 2022)	Morocco	Development and Deployment of an AI-Powered Smart-IS by (ML algorithms) and IoT technology.	IoT, ML: NN,SVM, LogReg, NB, k-NN),Sensors, Arduino, Node-Red, MongoDB	k-NN model achieved 98.3% recognition rate. Web app for environment supervision	Enhances water management in small plots, open gardens, green spaces, using IoT-based smart irrigation. k-NN model's accuracy improves irrigation efficiency
(Jain, 2023)	India	Implementation of IoT-enabled drip irrigation for small surfaces using Web/Android applications.	IoT, Sensors, Microcontroller, NodeMCU, Arduino, Cloud, Android/Web application	The system ensures optimal water delivery for gardening by monitoring soil moisture conditions	Improves water management in small-scale irrigation, providing precise control through IoT technology
(Alanya-Arango *et al*., 2022)	Peru	Introducing an Embedded Device for Efficient Water Use in Agriculture.	IoT sensors, ML, Cloud-based server	The recommender system optimizes water usage with minimal farmer intervention.	Enhances water management in agriculture by providing efficient water-use recommendations
(R *et al*., 2023)	India	Introducing an AI and 6G-IoT-based autonomous irrigation system for smart agriculture.	AI, 6G-IoT, Prediction Algorithm, IoT, ML	Reduced water wastage, effective in different conditions	Improves water management through reduced wastage and adaptability
(Routis & Roussaki, 2023)	Northern Greece	Introducing a revolutionary smart IoT-based prototype system for precision irrigation in agriculture	Microprocessors, SBC, Various Sensors, RNN-LSTM, ML	Effective informed irrigation decisions, ongoing work in scaling up	Improves water conservation and crop health with AI-enabled irrigation decisions
(Tawfeek, Alanazi & Ahmed, 2022)	Saoudi Arabia	Introducing a smart agriculture approach using Adaptive PSO and ANNs to enhance olive irrigation and fertilization	PSO-ANN system, IoT Tools	Autonomous decisions on irrigation and fertilization, increased efficiency	Contributes to water efficiency and reduces human intervention through smart irrigation and fertilization decisions
(Nazar & Altalb, 2022)	Turkey	Automate water pump control (ON/OFF) and manage irrigation water	ANN, IoT (Fc-28 soil sensor, DHT11 sensors)	Automated water pump control, and dynamic adjustment for efficient irrigation	Contributes to water efficiency through automated irrigation based on real-time environmental conditions
(Yanes, 2023)	Saudi Arabia	Development of a smart greenhouse utilizing IoT and a 1D-CNN for adaptive control of agricultural operations	IoT, 1D-CNN	Real-time monitoring, improved crop quality, reduced water usage, increased yield, lower labor costs.	Enhances water management through precise control of irrigation, optimizing conditions for crop growth.
(John, Lakshmi & Kuncharam, 2023)	India	Introduce a cost-effective and adaptable irrigation strategy for smart agriculture utilizing ML algorithms	MongoDB, Node-RED	k-NN model with a 98.6% identification rate, an online tool for improved environmental visualization and control	Enhances water management through optimized irrigation based on soil moisture, temperature, and rain data

AI in Irrigation water quality

The pollution of irrigation water is a matter of great concern in agricultural areas. In addition, many studies (Şener & Varol, 2020; Lin *et al.*, 2023; Shah *et al.*, 2023; Lin *et al.*, 2023) reported that some heavy metals, including Plomb, Cadmium, Chromium, and Manganese, were found to be higher than the acceptable limits in irrigation water. These heavy metals have the propensity to cross the permissible threshold of irrigation water prescribed by different authorities, and organizations such as the Food and Agricultural Organization (Uddin *et al.*, 2022). In addition, irrigation using polluted water could impact various properties of soils, including hydraulic conductivity, density, and porosity (Sulaeman, Arif, & Sudarmadji, 2018). Hence, there is a compelling necessity to estimate and predict water quality using the power of AI. The need for AI-powered methods to estimate and predict Irrigation Water Quality (IWQ) arises for several reasons. Firstly, traditional techniques for water quality assessment are costly and challenging, especially for farmers in emerging countries (Gad *et al.*, 2023; Nguyen *et al.*, 2023). ML and ANN algorithms have emerged as effective tools to forecast parameters related to water quality (Jayaraman, Nagarajan & Partheeban, 2022; Nguyen *et al.*, 2023).

Related works

The study presented by Ubah *et al.* (2021) aimed to predict one-year water quality in Ele Rivers, Nigeria, focusing on irrigation purposes using ANN modeling. It targeted four water quality parameters pH, Total Dissolved Solids (TDS), Electrical Conductivity (EC), and Sodium (Na) at four different locations. Monthly data were collected from these locations and analyzed using various methods. The ANN model, trained by supervised feed-forward back-propagation, predicted water quality parameters reasonably well, based on statistical metrics such as R2 and RMSE. However, TDS, EC, and Na values were always found above the Food and Agriculture Organization benchmarks for IWQ at some sampling point, although pH values fell within permissible ranges. In Egypt, precisely in the Nile River (Gad *et al.*, 2023) focused on assessing and predicting water quality for agricultural purposes. Physicochemical parameters T°, pH, EC, TDS, K^+, Na^+, Mg^{2+}, Ca^{2+}, Cl−, SO_4^{2-}, HCO_3^-, CO_3^{2-}, and NO_3^- were recorded at 51 superficial water sites. ANN and partial least square regression (PLSR) models, along with geographic information system (GIS) tools, were utilized to predict IWQI and other indicators. The findings demonstrated the effectiveness of integrating physicochemical features, water quality indices, ANN, PLSR models, and GIS tools to assess the appropriateness of superficial water for irrigation. IWQI results indicated that nearly 98% of samples fell within the unrestricted category, and about two percent falling into the low restriction area for irrigation.

Groundwater plays a crucial role in meeting various human needs and can serve as a reliable water source for irrigation, particularly in regions where surface water sources may be insufficient or unreliable. Especially, in regions marked by dry and semi-dry conditions, groundwater often serves as the sole irrigation source. Consequently, analyzing and assessing the IWQI emerge as valuable tools for effective water resources oversight (M'nassri *et al.*, 2022). Approximately 20% of the world's groundwater is utilized for irrigation, highlighting its critical role in supporting agricultural practices. Furthermore, regular monitoring and testing of groundwater quality are essential to detect any potential contamination and take necessary remedial actions (Ghosh & Bera, 2023). In the research conducted by Taşan (2022) in Turkey, groundwater suitability for irrigation was assessed using seven parameters: sodium adsorption ratio (SAR), residual sodium carbonate (RSC), Kelly index (KI), percentage of sodium (Na%), magnesium ratio (MR), potential salinity (PS), and permeability index (PI). Data from 37 locations were analyzed using advanced modeling techniques: ANN and ANFIS models. The ANN model showed superior performance in estimating SAR, RSC, Na%, and KI compared to PS, MR, and PI. It proved effective for groundwater quality assessment in the study area may be useful where data availability is limited. Still, it is recommendable to increase the number of sampling sites, taking the samples at various periods. El Bilali *et al*. (2021) employed ML models to forecast IWQ parameters, specifically addressing challenges faced by farmers. The study predicts parameters such as TDS, PS, SAR, Exchangeable Sodium Percentage (ESP), Magnesium Adsorption Ratio (MAR), and RSC) utilizing physical inputs like EC, T°, and pH. Four ML models: Adaboost, RF, ANN, and SVR were developed and assessed using data from the Berrechid aquifer in Morocco. Results indicate that Adaboost and RF outperform SVR and ANN, yet ANN and SVR exhibit higher capability to generalize and reduce sensitivity to the inputs. The study recommends ML models for real-time, low-cost groundwater quality monitoring for irrigation uses. In parallel using only physical parameters as inputs, Yu *et al*. (2022) addressed the challenge of limited data for vast regions with diverse surface conditions, employing data-based models such as SVM, RF, ANN, and ELM. The study examines models for estimating TDS, PS, and SAR in the Zhangye Basin, NW China, highlighting their strong performance with physical parameters like T°, pH, EC, and dissolved oxygen. EC and pH are identified as key factors. SVM, RF, and ELM models excel with physical parameters, suggesting their cost-effective utility for IWQI estimation. In the Nand Samand catchment, India, Dimple *et al*. (2023) concentrated on the application of ML models for IWQI forecasting, providing a cost-effective solution for farmers. Six models (REGD, REGD-Bagging, REGD-RSS, REGD-AR, REGD-M5P, and REGD-RF) were developed and tested for predicting (soluble sodium percentage (SSP), magnesium hazards (MH), Kelly's ratio (KR), and SAR), by the analyze of eleven physicochemical variables from 95 wells pH, EC, TDS, Ca^{2+}, Mg^{2+}, Na^{+}, K^{+}, Cl^{-}, CO_3^{2-}, HCO_3^{-} and SO_4^{2-}. The REGD-M5P showed the best fit for predicting irrigation indices. The study highlighted the ability of ML models to bring improvement in parameters of irrigation water quality and provided very vital insights for farmers and rapid decision-makers. Lap *et al*. (2023) investigated an ML-based approach for estimating the WQI in the An Kim Hai irrigation system, Vietnam. The conventional approaches are more time-consuming because many water quality parameters need evaluation. Different ML algorithms such as LR, MLP, SVM, DT, and RF, are implemented as well as feature selection methods. Results show that the RF model, using Coliform, Dissolved Oxygen (DO), Turbidity, and Total Suspended Solid (TSS) as the main parameters, achieves Water Quality prediction. Al-Shourbaji & Duraibi (2023) proposed (IWQP4Net), a CNN model developed for effective (IWQP). The model is compared with the LR, SVR, and k-NN models, by showing better performance in terms of different metrics. The study utilized historical data from the United States Geological Survey, focusing on predicting (pH) values for the next day in 37 water quality monitoring stations in Georgia, USA. (IWQP4Net) demonstrated superior performance, suggesting its potential for precision agriculture. Seven models were used by Mokhtar *et al*. (2022) to reach the same goal, estimating IWQ in Egypt using ML models: SVM, XGB and RF, also four Multiple Regression models: PCR, PLS and Ordinary Least Square Regression (OLS). The aforementioned models were utilized to predict the water quality index for 105 water samples, focusing on six commonly recognized standards for evaluating the IWQI: SSP, SAR, RSC, PS, PI, and KR, utilizing EC, Na^+, Ca^{2+}, and HCO_3^- as input variables. Upon analyzing the model outputs based on the statistical measures RMSE and SI, the research concluded that the SW model demonstrated superior performance in predicting the IWQI. Also, the models developed, especially SVR, had good results but SW had slightly better performance. Their results revealed that, based on model predictions and analysis, the studied area was unsuitable for irrigation until treated. The water quality parameters exceeded the acceptable limits for irrigation purposes. In compliance with this, Derdour *et al*. (2023) assessed groundwater quality within the dry region of Adrar, Algeria for irrigation purposes, using AI techniques like SVM and k-NN to predict the IWQI based on hydrochemical parameters. Input data include five parameters EC, Na, SAR, Cl^-, and HCO_3^-. Of 166 groundwater samples, over 57.23% are unsuitable for irrigation. SVM with normalized data achieves optimal prediction accuracy (94.2% for training, 100% for testing). The study highlights AI's potential for comprehensive groundwater quality assessment in arid regions, guiding effective water management strategies.

To reflect a comprehensive and rigorous approach toward the assessment of groundwater quality, Hussein *et al*. (2023) utilized a broad spectrum of parameters that included EC, pH, Nephelometric Turbidity Unit (NTU), TDS, Alkalinity (ALK), Total Hardness (TH), HCO_3^-, Cl^-, SO_4^{2-}, Ca^{2+}, Mg^{2+}, Na^{2+}, k^+, NO_3, F, Fe, and As. These parameters were the foundation on which data were collected and, hence, analyzed. These parameters were chosen with care to give a holistic assessment of Sakrand, Sindh province, Pakistan. The key objective was to check the suitability of 80 groundwater samples efficiently, accurately, and precisely for irrigation purposes. To achieve this, four classifiers, namely SVM, k-NN, ET, and Discrimination Analysis (DA), were adopted and compared. It was aimed to improve the effectiveness of IWQI prediction, shorten computation time, and reduce errors that could occur in the computations of sub-indices. The linear SVM classifier demonstrated the highest accuracy, proving its effectiveness for creating IWQI models and suggesting further research avenues. Similarly, the work of M'nassri *et al.* (2022) focused on calculating the IWQI for the Sidi El Hani aquifer in central-eastern Tunisia considering many parameters such as TDS, EC, pH, major ions Ca^{2+}, Mg^{2+}, Na^+, K^+, HCO_3^-, Cl^-, and SO_4^{2-}, and qualitative parameters SAR, Na, MAR, RSC, and PI. The proposed method was effective through the ANN and MLR models, based on 49 groundwater samples, the study indicated good water quality. Both ANN and MLR models performed well, although the best prediction accuracy was achieved by the ANN model. The presented ANN model is deemed to be consistent and sufficient and will undoubtedly provide critical insights for making irrigation water management decisions in the aquifer under study and possibly in other semi-arid regions.

In contrast to using multiple parameters, Docheshmeh Gorgij *et al*. (2023) focused solely on SAR as a critical criterion for assessing irrigation water quality. Using data from 101 sampling points over 18 years, they trained an LSTM model to predict SAR for 2020. The model accurately predicted SAR, as evidenced by low MAPE and RMSE values, indicating close agreement with observed values. Around 22% of the region showed moderate to non-acceptable water quality for irrigation, particularly near residential areas, suggesting human activities as contributors to groundwater quality decline. To address the need for continuous monitoring of groundwater quality for efficient smart irrigation, Raje *et al*. (2022) proposed a system for continuous groundwater quality monitoring and smart irrigation. Their system utilizes custom pre-processing methods, lab samples, and field sensors to create a dataset and predict IWQI in India. Achieving 95% accuracy, the system offers real-time surveillance of IWQI via a user interface, benefiting farmers in remote areas.

Conclusion

The proposed investigation delves into the systematic exploration of AI techniques within the agricultural domain, specifically focusing on the critical areas of irrigation including “Irrigation Water Management” and “Irrigation Water Quality”. The findings underscore AI's pivotal role in addressing critical challenges and revolutionizing traditional agricultural practices. The first part of the review focused on the precise estimation of Evapotranspiration ET_O through various AI techniques employed in different countries. The ability to accurately gauge ET_O, directly influencing water availability in agricultural parcels, signifies a breakthrough in sustainable water management. The integration of AI with the Internet of Things IoT in "Smart Irrigation System" is highlighted in the second part, showcasing transformative potential, and enabling real-time data utilization to revolutionize decision-making. Finally, the study underscores AI's capacity to predict irrigation water quality, thereby promoting healthy crop production. These technologies represent a pivot to more resource-effective and sustainable agricultural methodologies through reducing human errors and optimizing resource use. The use of artificial intelligence and advanced machinery for efficiency meets the needs of water reduction with the assurance of superior quality, which is quite an issue where water resources are restricted.

Further, the review is a deep source for all stakeholders in the agricultural sector, including policy, research, and practice. It explains what is afforded by AI-enabled solutions in irrigation and offers a relevant understanding of how technology has been altering water quality and management methods. The knowledge gained from this study will enable the stakeholders to employ AI-enabled solutions that will contribute to a resilient and sustainable agricultural sector.

Table (3): AI in Irrigation Water Quality.

Author(year)	Country	Objective	Technology/model	Results	Contribution to Water Management
(Gad *et al*., 2023)	Egypt	Assess and forecast Nile River water quality for agriculture in Egypt using physicochemical parameters, IWQI indices, ANN, PLSR models, and GIS	ANN, PLSR, GIS tools	Effectively predict IWQI and assess surface-water suitability for irrigation. 98% samples in no restriction category, 2% in low restriction	Comprehensive evaluation aids in identifying suitable surface-water sources for irrigation, contributing to water quality management
(Taşan, 2022)	Turkey	Evaluate groundwater suitability for irrigation with seven parameters. Develop ANN and ANFIS prediction models	ANN, ANFIS	Accurate groundwater quality predictions for irrigation. ANN outperformed ANFIS in estimating SAR, RSC, PS, and KI	Valuable tool for assessing groundwater quality, especially in areas with limited or no available data
(El Bilali *et al*., 2021)	Morocco	Forecast IWQ parameters employing ML models, addressing farmer challenges	Adaboost, RF, ANN, SVR	Adaboost and RF outperform SVR and ANN; ANN and SVR show higher generalization and lower sensitivity to input variables	ML models, especially ANN and SVR, predict irrigation water quality, guiding optimized water management by farmers
(Yu *et al*., 2022)	China	Accurate groundwater quality estimation for efficient irrigation, addressing challenges of limited data in diverse regions	SVM, RF, ANN, ELM	Robust performance of SVM, RF, and ELM models with physical parameters; EC and pH identified as crucial factors; Superiority of models with only physical parameters	Data-based models like SVM, RF, and ELM provide robust and cost-effective estimation of irrigation water quality indexes in data-limited regions, aiding efficient water management
(Dimple *et al*., 2023)	India	Employing ML models for predecting IWQI, providing a cost-effective solution for farmers	REGD, REGD-Bagging, REGD-RSS, REGD-AR, REGD-M5P, REGD-RF	REGD-M5P excels in predicting irrigation indices, showcasing ML's potential in enhancing IWQ parameters; Recommended for superior prediction accuracy	ML models, especially REGD-M5P, provide a cost-effective solution for forecasting irrigation water quality indices, aiding farmers and fast decision-makers in efficient water management
(Lap *et al*., 2023)	Vietnam	Calculate WQI in An Kim Hai irrigation system	ML algorithms :LR, MLP, SVM, DT, RF, feature selection	RF model achieves best accuracy using Coliform, DO, Turbidity, and TSS as key parameters. Cost-effective alternative for WQI calculation, reducing input parameters	ML-based method for efficient WQI calculation in irrigation systems
(Al-Shourbaji & Duraibi, 2023)	USA	Develop IWQP4Net for efficient IWQP	IWQP4Net CNN, LR, SVR, k-NN	IWQP4Net outperforms LR, SVR, and k-NN in various metrics	The potential application in precision agriculture, showing better performance in the WQ prediction
(Mokhtar *et al*., 2022))	Egypt	Estimate irrigation water quality using seven models (SVM, XGB, RF, SW, PCR, PLS, OLS) with six criteria	(ML) (SVM, XGB, RF), Regression Models (SW, PCR, PLS, OLS)	SW model excels in IWQI prediction; AI models, especially SVR, show promising results. The surveyed region's water is unsuitable for irrigation without treatment	Identifying the inadequacy of water for irrigation purposes and recommending if further interventions or treatments are necessary to make it suitable
(Derdour *et al*., 2023)	Algeria	Assess groundwater quality in Adrar, Algeria, for irrigation using AI techniques (SVM, KNN) to predict IWQI based on hydrochemical parameters	SVM, k-NN	Over 57.23% of groundwater samples are unsuitable for irrigation. SVM achieves 94.2% training, 100% testing accuracy	Demonstrating AI's potential for comprehensive groundwater quality assessment in arid regions, guiding effective water management strategies
(E. E. Hussein *et al*., 2023)	Pakistan	Assess groundwater quality for irrigation using SVM, k-NN, ET, and DA classifiers	SVM, k-NN, ET, DA	Linear SVM classifier proved most effective with high prediction accuracies for both training and testing dataset	Demonstrating the effectiveness of linear SVM for creating precise WQI models, providing insights for evaluating water suitability
(M'nassri *et al*., 2022)	Tunisia	Calculate IWQI using ANN and MLR models	ANN, MLR	Both ANN and MLR models performed effectively, with the ANN model showing the highest prediction accuracy	An efficient way of estimating IWQI, it is worth providing insights on irrigation water management in semi-arid regions
(Docheshmeh Gorgij *et al*., 2023)	Iran	Predict the (SAR) using LSTM model for assessing irrigation water quality based on 18-year historical data	LSTM	Accurate SAR predictions for 2020; around 22% of the area showed non-acceptable WQ for irrigation	Outlines the precision of LSTM models in predicting SAR, which helps identify areas where WQ is un-acceptable for better water management
(Raje *et al*., 2022)	India	develope a system for real-time monitoring of WQI	Custom preprocessing method, lab samples, files sensors, trained algorithm	System achieves 95% accuracy in predicting WQI. User interface enables real -time monitoring providing valuable information on groundwater suitability for irrigation, even in remote locations	Real-time WQI monitoring system, providing farmers with important information about the suitability of irrigation water

Contributions of authors

H.H: Conceptualized the review, conducted the research, and wrote the manuscript.

Y.H: Provided English language revision of the manuscript.

I.H: Assisted in the research for the articles reviewed.

H.A: Also assisted in the research for the articles reviewed.

N.K: Evaluated the work and suggested a title for the review article.

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Ethical approval

All ethical guidelines related to Fish and care issued by national and international organizations were implemented in this report.

Conflicts of interest

The authors confirm they have no conflicts of interest

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ثورة في الزراعة: مراجعة شاملة للري الدقيق وتوقع جودة المياه باستخدام الذكاء الاصطناعي

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المستخلص: يمثل تغير المناخ تحديات كبيرة للقطاع الزراعي، مما يؤدي إلى تفاقم ندرة المياه وزيادة الاستخدام غير الرشيد لمواردها. استجابةً لهذه التحديات الضرورية، يعمل الذكاء الاصطناعي(AI) على تحسين أنظمة الري من خلال التنبؤ بكميات المياه وجودتها لضمان تحقيق إنتاجية مثلى للمحاصيل. تعتمد هذه المراجعة على استكشاف تطبيقات حديثة للذكاء الاصطناعي في مجال الري، مع التركيز على ثلاثة محاور رئيسية: تقدير تبخر–نتح المحاصيل (ETo) باستخدام الذكاء الاصطناعي، تكامل الذكاء الاصطناعي مع إنترنت الأشياء(IoT) في أنظمة الري الذكية(Smart–IS) ، ودور الذكاء الاصطناعي في التنبؤ بجودة مياه الري. تسهم خوارزميات الذكاء الاصطناعي في ترشيد استخدام المياه من خلال تحديد الاحتياجات المائية، ومراقبة البيانات في الوقت الفعلي، واتخاذ القرارات الذاتية، مع تقليل المخاطر المرتبطة بسوء جودة المياه، مما يحسن الإنتاجية الزراعية ويقلل الآثار البيئية.
تؤكد هذه المراجعة أهمية الذكاء الاصطناعي في معالجة مشكلة ندرة المياه وتحسين أنظمة الري في الزراعة باستخدام تقنيات مبتكرة لضمان إدارة مستدامة للمياه وتحقيق الأمن الغذائي. كما تشكل مرجعًا هامًا للباحثين لفهم التأثير الحالي للذكاء الاصطناعي في مجال الري وتحديد مجالات التطوير المستقبلية.

الكلمات المفتاحية: تغير المناخ، الذكاء الاصطناعي، إنترنت الأشياء، نظام الري الذكي، تبخر-نتح المحاصيل، مياه الري.