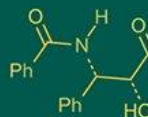


International Journal of Advanced Biochemistry Research



ISSN Print: 2617-4693
ISSN Online: 2617-4707
NAAS Rating (2026): 5.29
IJABR 2026; SP-10(4): 1135-1144
www.biochemjournal.com
Received: 09-02-2026
Accepted: 13-03-2026

Asma Fayaz
University Institute of
Agricultural Sciences,
Chandigarh University,
Mohali, Punjab, India

Sakshi Kumari
University Institute of
Agricultural Sciences,
Chandigarh University,
Mohali, Punjab, India

Smart water management: AI-driven irrigation, hydrology and water conservation

Asma Fayaz and Sakshi Kumari

DOI: <https://www.doi.org/10.33545/26174693.2026.v10.i4Sn.8270>

Abstract

Smart water management is a combination of artificial intelligence and advanced sensor technologies that allow optimization of the use of water resources in agricultural, urban, and environmental systems. AI-based irrigation systems use machine learning code to define soil moisture, weather condition, and crop water demand and apply this code to provide accurate water delivery to reduce consumption by 30 percent and retain crop yields. Predictive models are applied in hydrology to enable networks and remote sensing data to predict the state of water availability, risks of flooding, and droughts more accurately. The Real-time integrated monitoring organization with AI analytics such as assist in dynamic water supply, leak detection, and quality management in urban area. These smart systems contribute to the idea of sustainability of water conservation by detecting inefficiencies, automatic demand-apply. Specifically, we refer to the potentials of the integration of AI with remote sensing, IOT-based hydrological networks, and simulation models that are designed to provide intelligent and responsive systems of water management. With the ever-growing scarcity of water in the world, the use of AI-based smart water management seems to be a vital solution to the provision of water security, agricultural sustainability, and ecosystem maintenance.

Keywords: Artificial intelligence, IOT based hydrological, remote sensing applications, smart water management, water resource optimization

1. Introduction

1.1 Global Water Scarcity Crisis

The shortage of water has become one of the most important problems of the twenty-first century on the planet. The United Nations estimates that close to 2.2 billion individuals have no access to adequately controlled drinking water supplies and more than 4 billion individuals face intense water shortage at least one month annually ^[1]. The increase in population, urbanization, rise in industrial activities, and uncontrolled exploitation of ground water have increased the stress on fresh water supplies. This crisis is further worsened by climate change which changes the distribution of precipitation, and makes droughts and floods more common and glaciers melts faster. According to reports by the Intergovernmental Panel on Climate Change, the increasing global temperature is affecting hydrological cycles, and thereby lowering water availability in arid and semi-arid areas and increase extreme rainfall in other areas.

Food and Agriculture Organization has noted that agriculture is the highest user of freshwater in the world as it consumes about 70% of the total freshwater withdrawals ^[2]. The use of traditional irrigation methods such as flood and furrow irrigation can cause loss of water through evaporation, run off and deep percolation. Lack of real-time monitoring and inefficiencies in the distribution systems also leads to additional instances of wastage. Due to the increasing water demands in the various sectors, sustainable distribution and effective utilization of the same becomes a necessity to food security, ecosystems, as well as socio-economic development.

1.2 Need for Smart Water Management

The traditional water management systems rely on the manual monitoring, fixed schedule and reactive decision making patterns to a large extent. Such methods cannot find a way of coping with the changing environmental conditions like changing soil moisture, weather patterns and water requirements by crops ^[3].

Corresponding Author:
Asma Fayaz
University Institute of
Agricultural Sciences,
Chandigarh University,
Mohali, Punjab, India

The conventional irrigation timing can be based on predetermined calendars as opposed to the information-based ideas and result in over-irrigation or under-irrigation. On the same note, historical average based hydrological forecasting is not precise in climate variability.

Smart water management brings in a smart, technology-driven model aligned with artificial intelligence (AI), Internet of Things (IoT), remote sensing and cloud computing to manage water utilization. AI-based systems use real time data sources, including soil sensors, satellite imagery, weather stations, flow meters, etc. to formulate predictive and adaptive decisions. Water governance aimed at data improves transparency, better resource distribution, and proactive planning as opposed to crisis management. Smart systems can profoundly decrease water losses, increase crop productivity, and become more resilient to uncertainties created by the climate because of the transition of reactive to predictive management [4].

1.3 Objectives of the Study

The main aim of the research is to focus on how artificial intelligence can revolutionize water management functions in the areas of irrigation, hydrology and conservation. First of all, the study discusses the AI-based irrigation technology that can be adopted in order to allocate water so that it would meet the demands of crops, soil properties, and weather conditions through machine learning algorithms. Second, it includes studies of how AI models would be applied in hydrological forecasting including rainfall-runoff prediction, flood risk prediction, and drought prediction. Finally, the paper considers smart water conservation models, grounded on IoT network implementation, real-time analytics, and optimization algorithms, to decrease waste of water and enhance sustainability. By broadly examining the technological developments and system architecture, this study will demonstrate the transformative nature of AI-supported smart water management in solving the issue of global water scarcity.

2. Conceptual framework of smart water management

2.1 Definition and Evolution

Smart water management means the combination of modern digital technologies and old water resource systems to promote the intelligent process of monitoring, predicting, and optimization of water consumption. In the past, water management used mechanical subsystems like canals, reservoirs, and manually operated control valves and was not very automated or integrated with data [5]. Decision-making was mostly experience and reactive in nature and tended to respond to a problem after it had been realized that there was a shortage or an inefficiency.

The developmental trend to smart systems was initiated by the introduction of the automated irrigation controls and telemetry systems. The water management has expanded to a cyber-physical system with the rapid evolution of sensor technologies, wireless communication, and cloud-based analytics [6]. In contrast to the traditional systems, which “work on a fixed schedule with limited feedback, smart systems constantly gather, process and analyze data in real time. This shift is a paradigm change between resource-absorbing and stagnant management and data-based adaptive governance that takes an organization to a higher level of efficiency, sustainability, and resilience.

2.2 Components of Smart Water Systems

A smart water management system is a set of technologically related parts that can work together to achieve intelligent functionality. On the bottom level, sensors are important in the process of capturing real time environmental data. An example is soil moisture sensors that have the ability to measure volumetric water content and flow meters which determine the flow rate of water in irrigation pipes [7]. Temperature, humidity, rainfall and wind speed are recorded by weather stations which add to the proper estimation of evapotranspiration.

All these sensors are connected via IoT systems which enable a smooth flow of communication between the devices in the field and the central control stations. IoT gateways send data through the wireless networks to the cloud servers where mass datasets are stored and analyzed. Cloud computing infrastructure can be scaled and thus it can be used to compute fast and can be accessed remotely.

The central intelligence layer of the system is produced by the artificial intelligence analytics. The algorithms of machine learning utilize both historical and real-time data to identify the trends and its water demand in the future and develop effective irrigation systems. The predictive analytics models are utilized in floods and early-warners of droughts [8]. Decision support systems (DSS) convert the output of algorithm into useful information to farmers, managers and policy makers of water. All these factors are combined to create a complete ecosystem, which is efficient in distributing and conserving water.

2.3 Architecture of AI-Based Water Systems

The sensing layer, communication layer, data processing layer and application layer represent a typical architecture of an AI-based water management system. Sensing layer involves distributed sensors that are deployed in the farm fields, reservoirs and distribution networks. The machines are continuously collecting data about the environment and operation [9].

Wireless protocols based on the internet of things (IoT) such as LoRaWAN, GSM or Wi-Fi are also used by the communication layer to transmit data to centralized systems. The computational layer or data processing layer that can be individually saved in the cloud servers employs machine learning models and predictive algorithms to operate on the incoming data streams. The actions that are performed by this layer are the identification of anomalies, forecasting of demand, optimization of irrigation, and risk assessment [10].

Finally, application layer provides the user interfaces in the form of dashboards and mobile applications. The following platforms will allow the stakeholders to visualize the trend of water usage, receive notifications, and implement automatic control instructions [11, 12]. The design will be such that it will provide a close-loop control when the information given by AI systems will directly influence the water distribution systems and enable them to change in real-time and become more efficient in resource utilization.

3. AI-Driven irrigation systems

3.1 Precision Agriculture and AI

Precision agriculture is an innovative strategy of shifting a homogenous field management to a location-based and information-driven strategy of crop farming. Artificial Intelligence (AI) supports this support paradigm integrating the real-time perception of the surrounding environment, the

predictive analytics, and the automated control. Artificial intelligence based irrigation systems are dependent on different sets of data ^[13], i.e. the moisture content of the soil, the cultivated crop, the crop growth, the rate at which it evaporates/transpiration and the weather forecast ^[14, 15]. The volumetric water content data are obtained through soil moisture sensors, whereas temperature, humidity, wind speed, and rainfall data are obtained through the meteorological stations ^[14, 16]. Other crop-related parameters like rooting depth and stage of phenology also help to narrow decisions on irrigation scheduling ^[14].

With the combination of these inputs, AI systems will produce optimization irrigation programs that provide the exact amount of water based on crop demand ^[17, 18]. This reduces the water stress and avoids excessive irrigation of the land that may result in soil erosion and nutrient loss ^[18]. Precision irrigation does not only save on the use of water but also enhance quality of yield and energy efficiency ^[17]. The combination of weather prediction systems and ground-based IoT sensors makes it possible to have adaptive irrigation solutions that can react to the ever-changing environmental conditions on a real-time basis ^[17, 18].

3.2 Machine Learning Algorithms Used

The AI-based irrigation systems use numerous machine learning (ML) methods to simulate the complicated correlations between the environmental factors and the crop water demand. Regression models are widely applied in estimating evapotranspiration and forecasting the irrigation needs, in the basis of historical weather information and soil data ^[19]. The use of linear regression and the use of the poly regression models aid in quantifying the relationship between water input and crop yield, which assist in the background of decision-support information.

The ANNs provide superior productivity attributable to the fact that they realize nonlinear relationships between climatic, soil, and crop variables ^[20, 17]. Deep neural networks and multilayer perceptron's are commonly used in predicting irrigation demands in the case of uncertain weather conditions ^[17]. Their models are responsive to new inputs of data and keep on enhancing accuracy in the prediction ^[20].

Reinforcement Learning (RL) is a new model of decision-making whereby the irrigation systems adopt the best water application methods through progressive engagement with the environment ^[21]. This model involves the feedback to the system through the reward signals, which can be better yield or less water consumption and a change in the irrigation behavior of the system ^[21]. With time, RL-based controllers optimize dynamically the process of water distribution, which leads to the efficient use of the available resources in different climatic and soil conditions.

3.3 Smart Irrigation Models

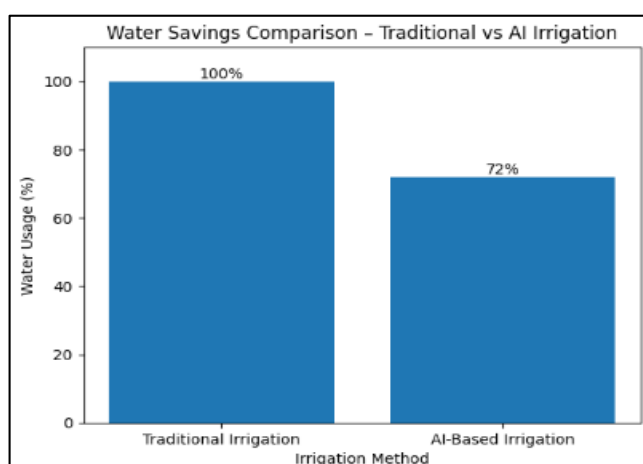
Smart irrigation models integrate AI programs with autonomous infrastructure in order to provide water management that is more accurate and efficient. Another significant irrigation innovation, which is water saving, is drip irrigation systems. AI-controlled drip systems regulate the water flow according to the sensor-measured moisture content of the soil such that the water is delivered to root zones of plants ^[22]. This method is massive in saving losses associated with evaporation compared to the usual surface irrigation ^[23].

Variable Rate Irrigation (VRI) systems as well enhance the accuracy through the subdivision of the agricultural fields under the management zones ^[24]. Artificial intelligence models are applied to analyze the dissimilarity between the characteristics and patterns of crop development to alter the intensity of irrigation in every field ^[17]. This is an accurate gauge to prevent the excess usage, and to promote positive development of plants ^[24, 17].

Decision Support Systems (DSS), are data analytics and predictive modeling with such interfaces which allow farmers and water managers to make their choices ^[25, 26]. These systems provide irrigation recommendations and drought alert and performance indication ^[25, 27]. The gap between technology innovation and practice in the agricultural industry is the availability of the translation of complex data to usable insights with the help of DSS tools ^[26, 27].

3.4 Case Studies

Israel has become a leader in AI irrigation technologies in the world. Netafim Company is among companies that have led in the production of precision drip irrigation systems enabled by artificial intelligence and technology to optimize water use in the dry parts of the world. Such technologies allow farmers to record a significant amount of water savings which is usually more than 25 30 percent without compromising or even enhancing crop yields ^[28]. The example of the implementation of AI-based fertigation in Israel shows that data-driven irrigation is capable of optimizing water use, as well as improving nutrient control. Through smart farming programs, fundamentally made institutionally through the Indian Council of Agricultural Research, AI-supported irrigation is being advanced in India in various agro-climatic zones. Pilot projects that combine IoT soil sensors and machine learning algorithms have shown resulting reductions in water consumption rates in such states as Maharashtra and Punjab. The use of AI tools by start-ups and aggrotech platforms to give real-time irrigation advice to smallholder farmers using mobile applications is another way AI is being used in agriculture.



4. AI in hydrology and water forecasting

4.1 Basics of hydrological modeling

Hydrological modeling is the modeling of the water movement, distribution, and storage in the hydrological cycle. Conventional models are based on physical-based equations of precipitation, infiltration, surface runoff and evapotranspiration and groundwater recharge. Although

there has always been a preference towards conceptual and empirical models to support water resource planning, there are usually difficulties with respect to modelling complex nonlinear interactions in varying climatic conditions ^[29].

Hydrological processes are dynamic as well as they are affected by land use spatial variability of land use, soil type and topography. The combination of AI methods increases the flexibility of the model as it allows it to be calibrated using data and predict with accuracy. In comparison to traditional deterministic methods, AI-based models can learn a vast amount of data and keep getting improved predictions.

4.2 Hydrology Software AI Uses.

The applications of AI in hydrology include rainfall-runoff, flood forecasting, and drought prediction. The rainfall-runoff model uses machine learning methods and models to determine the amount of water that stories to the surface by examining the characteristics of precipitation and watersheds. These prediction modules enhance the reservoir management and watershed planning through timely approximations of water inflow.

Flood predictive systems use AI as an analysis tool to examine the past state of hydro meteorological parameters, river flows, and satellite data. Predictive analytics can be used to find flood-prone conditions early enough and proactively prepare against disasters. Flood models based on AI decrease uncertainty and increase real-time response capability to the most dangerous areas ^[30].

To predict the situation of drought, some climatic variables are used in the drought prediction models, which include temperature variations, lack of moisture in soil, and precipitation pattern. Machine learning classifiers identify trends that show the possibility of extended periods of dry spells, which would facilitate the allocation of water and mitigation planning.

4.3 Deep Learning in Water Prediction

In the past years, deep learning methods have contributed to the fact that the accuracy of water predictions significantly improved. Recurrent neural networks (Long Short-Term Memory (LSTM) networks) are a highly specialized category of neural networks that are specifically useful in time series hydrological models ^[31]. The LSTM models compute the long-term dependence of rainfall and streamflow trends, and therefore, they are applicable in seasonable water forecasting.

CNNs are highly popular in the analysis of spatial data obtained on the basis of satellite imagery. The changes in land cover, waters, and vegetation indices can be detected using CNN-based models, which assists in enhancing hydrological evaluations. Hybrid models integrating both time-dependent (LSTM) and space-dependent (CNN) types of learning can deliver precise predictability in various complicated hydrological settings.

4.4 Remote Sensing Integration

Remote sensing technologies are very important in improving hydrological analysis that is based on AI. There are satellite systems like NASA which offer fine resolution of information about precipitation, land surface temperature and vegetation cover ^[4]. These datasets facilitate the water monitoring on large scale, and allow monitoring of the inaccessible areas.

Geographic Information Systems (GIS) combine both spatial data of watershed, floodplain analysis, and groundwater evaluation. The AI algorithms are used to analyze data obtained by satellites to determine patterns in water supply and the health of the ecosystems. The collaboration between remote sensing, GIS mapping, and machine learning leads to the development of holistic water forecasting models that have the potential to solve the problem of climate variability and extreme weather events.

5. IoT-based water monitoring systems

5.1 Smart Sensors and Data Acquisition

IoT-based water management has fundamentally altered the manner in which the water resources are monitored, measured, and controlled. Smart water monitoring systems that are based on IoT are based on interconnected smart sensors that are constantly used to acquire environmental and operational information in the fields of agriculture, reservoirs, rivers, and urban distribution networks. These sensors are the main building block of a digital hydrological infrastructure.

The smart sensors are programmed to detect high levels of parameters such as soil moisture, the level of water, flow rate, pressure, turbidity, pH, temperature, and electrical conductivity. The soil moisture sensors can give real time data on the availability of water in the root zone allowing the scheduling of irrigation schedules accurately ^[32]. Flow meters and pressure sensors in pipeline are used to identify abnormality of leakage, burst pipes, or unauthorized usage. Level sensors that are either ultrasonic or radar in nature are used to keep track of water storage and discharge in reservoirs and river basins.

IoT systems acquire data using embedded microcontrollers and wireless communication modules ^[10]. LoRaWAN, GSM, NB-IoT, Zigbee, and Wi-Fi are examples of technologies that are used to transmit the data collected by field devices into the centralized servers ^[33]. Edge computing devices can process data in real time to save latency and bandwidth by sending it to the cloud systems ^[34]. The datasets gathered are stored in cloud databases where they are organized to go through analytics and long term trends ^[35].

The real time visibility of the water systems is made available due to the continuous nature of the IoT data acquisition ^[36]. In contrast to the classical systems of manual inspection that are periodic and reactive and, therefore, do not provide continuous monitoring, IoT-based monitoring requires uninterrupted surveillance and a quick reaction to arise challenges ^[37]. This feedback mechanism is very useful in improving operational effectiveness and resource saving ^[38].

5.2 Real-Time Monitoring Platforms

The analysis and visualization layer of the IoT water systems is called real-time monitoring platforms. They incorporate the streams of sensor data in the centralized dashboards which are available to farmers, engineers and the policymakers. Complex analytics engines evaluate data in real time to identify deviations, deliver alerts and give actionable feedback.

The detection of leaks is one of the most demanding real-time monitoring applications. The water loss in the distribution networks may be a major inefficiency of the urban systems, as the non-revenue water ^[39]. The anomaly

detection learning algorithms are made by the AI processing pressure variations and flow anomalies to identify the potential leak points^[40]. By detecting the points of leakages at an early stage, the utilities will be able to reduce the water they have been wasting, limit the expenditure incurred in maintenance, and enhance the reliability of the services^[41]. Smart meters are another novel aspect of IoT based monitoring^[42]. The devices track real time water consumption within the households and industries and send data on the water consumption to the utility providers. Compared to the old fashioned mechanical meters, the smart meters allow the prospect of dynamic billing, prediction of the demands, and the studying of the consumption patterns. The consumers can also access the usage dashboards through mobile applications, and the resource will encourage the saving of water.

Urban water analytics systems refer to the systems that unify data on various sources of data such as supply networks, treatment facilities, rainfall measurements, consumer meters, and others to provide a complete picture of the water dynamics in the city^[43]. The predictive analytics can help the utilities predict the peak demand time, the pumping schedule, and the supply distribution in a better way. Through the merger with Geographic Information Systems (GIS), the utilities can map performance of the network spatially and the areas and the infrastructure vulnerability.

5.3 AI for Water Quality Monitoring

The element of the water quality monitoring is an important component of smart water management, particularly concerning the valuable state of the health of the nation as well as the sustainability of the environment. The AI is an extension of the conventional monitoring strategies because it can be used to implement the predictive modelling, detect contamination within a limited time period.

The sensors which are able to monitor the parameters such as pH, turbidity, dissolved oxygen, conductivity and chemical concentration are placed in the water bodies, and in the treatment plants. The AI models evaluate these parameters and give a verdict concerning an expression of abnormality. One such example is that predictive algorithms can also forecast pH variations based on seasonal trend, record of discharge by industries and rain hashes^[44]. The conditions of ecological damage are prevented by early identification of the abnormal pH level and the safety standards are met^[45].

Machine learning classification models that are trained with past water quality data generate contamination alerts^[46]. These models determine trends that relate either to the outbreak of microbes, chemical leakages, or heavy metals. The anomalies are identified and the automatic alert systems inform the authorities and set forth responses. The AI-based monitoring systems, therefore, shift the current water quality management regulating process to a proactive supervision^[45].

6. Water conservation strategies using AI

6.1 Demand-Supply Optimization

AI is quite central in the process of stabilizing the demand and supply of water, based on pre-emptive analytics and optimization. Demand forecasting algorithms are used to predict future levels of water demand by analysing past data on consumption, seasonal patterns, population growth rates

and climatic conditions. Supply side modelling includes the level of reservations, availability of ground water and prediction of inflows.

Through the combination of such datasets, the AI systems will come up with the best allocation plans to ensure there is minimal wastage but a fair allocation^[27]. As an example, irrigation scheduling algorithms ensure that the water application and the predicted evapotranspiration rates are in line to avoid water overuse. Dynamic pressure management in urban systems minimizes the unnecessary quantities of flow in the periods of low demand. This is a data-driven balancing method suitable to improve system resilience and resource efficiency.

6.2 Smart Reservoir Management

Reservoirs are very important in the storage of water and flood control as well as electricity production^[47]. The systems of AI-based reservoir management calculate the inflow predictions, precipitation predictions and demand downstream to conclude on the best release times. Predictive models minimize the chances of overflow in case of heavy rainfall and eliminate water inefficiency in case of drought^[48].

The machine learning routines keep on changing the set of rules of operation of the reservoirs with respect to the real-time data inputs. These systems enhance the quality of decisions made when weather forecasting and watersheds are built in. The intelligent reservoir system does not only maximize water supply but also aids in optimization of energy in hydropower plants.

6.3 Urban Water Conservation

City centres are characterized by major challenges associated with deteriorated infrastructure, water leakages and high usage rates. These issues can be addressed using smarty-monitors and analytics, which are the conservation techniques designed by AI^[49]. The consumption trends identified as irregular by the data analysis of smart meters enable carrying out particular awareness activities.

Predictive maintenance models inspect the status of the pipes and fix them before the birth of significant failures^[50]. The optimization of water recycling through the assistance of AI will ensure the efficient treatment and reused wastewater. AI controllers are used to regulate the use of non-portable water in landscape and sanitation in conjunction with greywater systems^[51]. All these measures, in order to sum up, reduce the overall water loss and improve the sustainable urban water cycle^[52].

6.4 AI-Based Policy Decision Systems

The AI based decision support systems will assist the policymakers in coming up with evidence-based water management policies. Simulation models can evaluate the effects of policy changes in the long term such as water pricing reforms, irrigation subsidies or conservation incentives.

Scenario analysis model simulates the drought conditions, population growth or the effects of climatic changes in an effort to establish the resiliency of the system^[29]. The policy makers can contrast the different strategies and make a decision that will lead to utmost sustainability and fairness. The AI-government systems are more transparent and result in informed and data-based decision-making on the regional and national levels.

7. Simulation models and mathematical framework

The analysis of smart water management systems is based on mathematical modeling. With the help of looking after physical equations and AI-based predictability models, scientists will be able to simulate the dynamics of water and optimize the allocation of resources.

7.1 Water Balance Equation

Water balance equation is the conservation of mass of a hydrological system and is defined as:

$$P = ET + R + \Delta S$$

with PPP being the precipitation, ETET being the evapotranspiration, RRR being the runoff and 8S8S8S being the change in storage in soil or reservoirs [53]. This equation forms a general framework in which water availability in agricultural and watershed systems may be evaluated. The classical model is further extended by AI which improves the estimation of each component by using data-driven calibration.

7.2 Model of Predictive Equation based on AI.

The water demand at time ttt in the case of AI-based irrigation system can be expressed as:

$$W_t = f(SM, T, RH, CropType, Rain)$$

SM is the soil moisture, T is the temperature, RH is the relative humidity, Crop Type is a crop-specific parameter and Rain represents the input of rainfall. Function f is normally obtained on the basis of machine learning techniques like neural networks or regression.

This predictive model conserves nonlinear relationships between environmental variables. The model changes its parameters as new data are presented thus improving forecasting accuracy. The dynamic characteristic of AI based modeling enables the irrigation schedules to keep adapting to the changing conditions of the field.

The Irrigation optimization model optimizes the water used in irrigation to reduce expenses and enhance efficiency.

7.3 Irrigation Optimization Model

The Irrigation optimization model is a way of optimizing the water utilized in irrigation in order to minimize the cost and maximize efficiency.

The optimization methods are used to reduce the use of water but ensure crop yield. Utilize Usage can be minimized.

within the restrictions pertaining to the crop yield, water moisture restriction and climatic variability [45]. These restrictions ensure that the agricultural production will not decline due to decrease of water. Linear programming, genetic algorithms, and the application of reinforcement learning are often used to solve such optimization problems [54].

AI-based systems can optimize power and output with the use of optimization algorithms and predictive modelling [52]. The simulation tools also contrast various circumstances of irrigation and the strategies which are most probably to be sustainable in various weather conditions are identified [55].

In general, the integration of the IoT monitoring, AI analytics, and mathematical modeling will form a

multidimensional system of intelligent water management [56]. All these technologies will contribute to the saving of water, operation efficiency and long-term sustainability in agricultural and urban ecosystems [57].

8. Challenges and limitations

Though the concept of AI-powered smart water management systems may change the state of affairs, it has several obstacles and drawbacks that do not allow it to be implemented on a massive level [18]. The initial implementation cost is one of the significant obstacles [58]. The introduction of IoT sensors, communication infrastructure, cloud services, and artificial intelligence analytics devices are expensive when it comes to financial investments [35]. This may be the case with the prices of soil moisture sensors, smart meters, automated valves and data subscription services being prohibitive in the case of the small holder farmers and the developing regions [59]. Maintenance costs are also present, software upgrading costs and highly qualified technical support that add up to the cost of operation [56]. Without government subsidies or even public-private partnership, mass adoption is only limited to economically stable or technologically advanced regions.

Data privacy and cybersecurity are also rather problematic [60]. The smart water systems generate vast data on real-time basis that are related to agriculture, consumption behaviour and functionality of infrastructure [36]. The unlawful access to such data can violate the confidential data or can destabilize the water distribution systems [36]. With the digital water governance being centralized, encrypted systems, secure cloud infrastructure and control frameworks are very important to prevent cyber threats. The data ownership policies should also be developed so as to build trust among users [61].

The other major constraint is sensor reliability [62]. IoT devices fitted in the fields and the extreme environmental conditions having temperature, humidity, dust, and mechanical loads. Sensor drift, error of calibration, and hardware failures may also cause inaccuracy in data collection and this will ultimately have similar effects to predictions made by AI models [52]. Low quality data reduces the reliability of the system and may give inaccurate irrigation times or incorrect predictions of floods. The system should also be maintained, the redundancy measures and quality assurance policies should be established to make sure the system is precise [63].

Smart water technologies are not also as useful due to the country digital divide. Many of the rural and remote places lack internet connection, power, and digital literacy. New complex dashboards or recommendations provided by AI may be hard to use by the farmers [64]. Without appropriate training and infrastructural support, their desired effect can never be realized through technological solutions. In order to bridge this digital divide, they should invest in rural broadband coverage, capacity building programs and amicable system design [65].

Finally but not the least, AI models can also be biased and over fitted [66] point out that adaptation of machine learning algorithms to other climatic or soil circumstances are prone to failure due to the small datasets which have been used to perform the training of the algorithms or region-specific datasets. Overfitting occurs when models are performing well on the training data and they perform poorly in the real

world. Such errors can render AI-based systems unreliable. It is possible to enhance reliability and fairness depending on constant verification of models and access to a range of training data in addition to a clear structure of designing algorithms. These concerns need to be touched upon to transform AI-driven water management systems into a fair, stable, and sustainable one.

9. Future trends

The future of smart water management is further digitization of the emerging digital technologies. One of the opportunities is the combination of AI and block chain to offer clear water management. Block chain technology helps to document water transactions, records of their allocation, and records of their usages safely and impossibly^{[67], [68]}. Through AI-intelligent analytics, block chain systems have the potential to facilitate the decentralization of water trade, real-time auditing, and increased accountability in the irrigation districts and urban utilities^{[69], [70]}. This kind of integration will enhance more trust among the stakeholders and increase the transparency of the policies^[67].

Edge computing is another change direction of irrigation systems that is radically different. The edge devices do not send sensor information to remote cloud servers, but rather operate their data management on-site or close. This minimizes the latency, enhances response time and decreases bandwidth. Edge-enabled controllers are also used in irrigation where the water flow is automatically adjusted, according to the soil moisture reading without consulting cloud-based analysis^[71]. This kind of decentralized processing makes the systems more resilient especially where the internet connectivity is unstable^{[72], [73]}.

Precision agriculture is another development of autonomous irrigation robots. These robotic systems are made by integrating AI vision algorithm, soil sensing and automated actuators to implement site specific irrigation and nutrient delivery^[74]. Having real-time analytics and GPS-powered navigation, autonomous units will be able to detect the areas of crop stress and water the area in the most accurate way possible. This lowers the dependency on labor and increases efficiency in operation especially in big farms^[74].

Water systems that are resistant to climate changes are gaining prominence in the global climate change. Predictive models based on AI will be a key component in changing water infrastructure in accordance with extreme weather, changes in precipitation patterns, and extended droughts. The incorporation of climate predictions and hydrological modeling in the future allows future systems to be installed to respond proactively to the changes in the operation of the reservoir, irrigation timing, and urbanized water allocation. Smart water integration with the Sustainable Development Goals (SDGs), especially SDG 6 (Clean Water and Sanitation), as an idea proposed by the United Nations framework, is a crucial aim of the world. The monitoring systems based on AI can trace the indicators of water quality, distribute resources more efficiently, and provide fair access to clean water. By harmonizing the technological advancement and the global sustainability goals, it will become easy to enhance the achievement of universal water security^[75].

10. Conclusion

The Artificial Intelligence has become a revolution in the contemporary water management as it is providing

intelligent solutions to the increasing problems of water scarcity, climatic variability, and poor use of available resources. Real-time environmental conditions improve AI-based irrigation systems, which increase precision agriculture by improving the accuracy of water application. Machine learning and deep learning models are used effectively in hydrology to predict rainfall-runoff, floods and droughts. Monitoring networks IoT can be used to monitor the functioning of the water distribution system around the clock, which allows identifying the leakage, contamination, and inefficiency of the working process.

These technologies have a huge sustainability implication. AI-based systems are directly related to environmental conservation and food security by minimizing water wastage, ensuring better allocation efficiency, and resiliency to climate change. Collectively, smart reservoir management, demand-supply optimization, and predictive analytics enhance water governance frameworks on the local and national levels.

Nevertheless, to achieve the maximum of the opportunities offered by AI-driven water management, it is necessary to manage financial, technical, and social obstacles. In future studies, it will be important to work on enhancing the model robustness, multi-source data fusion, and the low-cost sensor technology, appropriate to rural areas. The policymakers should facilitate the development of digital infrastructure, the promotion of regulations on data security and facilitate collaborative innovation by means of the public-private partnership.

To sum up, the use of AI-based smart water management is not only an act of technological innovation but also a course on a sustainable future. With data intelligence and responsible governance, the societies will be able to provide efficient, fair, and climate-resilient water systems to the generations to come.

References

1. Kataria A, Min H. AI-Based Smart Irrigation Systems for Water Conservation. *Stud Comput Intell*. 2025;1215:153-168. doi: 10.1007/978-3-031-93087-4_9.
2. Goyal MK, Kumar S, Gupta A. AI for Water Conservation. 2024;17-29. doi: 10.1007/978-3-031-72014-7_2.
3. Farooq MU, *et al*. AI-powered solutions for sustainable water conservation. *AI Ecol Chang Sustain Dev*. 2025;473-511. doi: 10.4018/979-8-3373-0680-3.ch016.
4. Krishnan SR, *et al*. Smart Water Resource Management Using Artificial Intelligence—A Review. *Sustain*. 2022;14(20). doi: 10.3390/su142013384.
5. Ahmed Z, Gui D, Murtaza G, Yunfei L, Ali S. An Overview of Smart Irrigation Management for Improving Water Productivity under Climate Change in Drylands. *Agronomy*. 2023;13(8). doi: 10.3390/agronomy13082113.
6. Plaex Technologies. The role of Artificial Intelligence in sustainable waste management. LinkedIn. 2023 [cited 2026 Apr 28]. Available from: <https://www.linkedin.com/pulse/role-artificial-intelligence-sustainable-waste-management-plaex/>
7. Et.al AK. Innovative Smart Water Management System Using Artificial Intelligence. *Turkish J Comput Math Educ*. 2021;12(3):4726-4734. doi: 10.17762/turcomat.v12i3.1895.

8. Patidar A, Chaudhary R, Mishra N, Rajpoot SK, Prasad SK, Bhushan C. Smart Water Systems: AI and IoT in Precision Irrigation. *Sustain Agric Manag Semi-Arid Clim Vol 2*. 2025;175-193. doi: 10.1007/978-3-031-94066-8_8.
9. Ali A, Hussain T, Zahid A. Smart Irrigation Technologies and Prospects for Enhancing Water Use Efficiency for Sustainable Agriculture. *AgriEngineering*. 2025;7(4). doi: 10.3390/agriengineering7040106.
10. Xu LD, He W, Li S. Internet of Things in industries. *IEEE Trans Ind Informatics*. 2020;10(4):2233-2243.
11. Adeoye S. Internet of Things (IoT): A Vision, Architectural Elements and Future Directions. *Cogniz J Multidiscip Stud*. 2025;5(1):316-338. doi: 10.47760/cognizance.2025.v05i01.027.
12. Al-Fuqaha A, Guizani M, Mohammadi M, Aledhari M, Ayyash M. Internet of Things: A Survey on Enabling Technologies, Protocols, and Applications. *IEEE Commun Surv Tutor*. 2015;17(4):2347-2376. doi: 10.1109/COMST.2015.2444095.
13. Mandal S, *et al*. Smart Water Management for SDG 6: A Review of AI and IoT-Enabled Solutions. *Water Conserv Sci Eng*. 2025;10(2). doi: 10.1007/s41101-025-00407-7.
14. Allen RG, Pereira LS, Raes D, Smith M. Crop evapotranspiration: guidelines for computing crop water requirements. FAO; 2000 [cited 2026 Apr 28]. Available from: <https://www.fao.org/4/x0490e/x0490e00.htm>
15. Irmak S, Payero JO, Martin DL, Irmak A, Howell TA. Sensitivity Analyses and Sensitivity Coefficients of Standardized Daily ASCE-Penman-Monteith Equation. *J Irrig Drain Eng*. 2006;132(6):564-578. doi: 10.1061/(asce)0733-9437(2006)132:6(564).
16. Bogaen HR, Huisman JA, Oberdörster C, Vereecken H. Evaluation of a low-cost soil water content sensor for wireless network applications. *J Hydrol*. 2007;344(1-2):32-42. doi: 10.1016/j.jhydrol.2007.06.032.
17. Ayaz M, Uddin A, Sharif Z, Mansour A. Internet-of-Things (IoT)-Based Smart Agriculture: Toward Making the Fields Talk. *ResearchGate*. 2023;1-3.
18. Kamiński C, *et al*. Smart water management platform: IoT-based precision irrigation for agriculture. *Sensors (Switzerland)*. 2019;19(2). doi: 10.3390/s19020276.
19. Nuwarapaksha TD, Udumann SS, Dissanayaka NS, Dilshan RMN, Atapattu AJ. AI-Driven Solutions for Sustainable Irrigation: Exploring Smart Technologies to Enhance Conservation and Efficiency. *Integr Agric Green Mark Strateg Artif Intell*. 2024;1-32. doi: 10.4018/979-8-3693-6468-0.ch01.
20. Haykin S. *Neural Networks and Learning Machines*. 3rd ed. New Jersey: Pearson Prentice Hall; 2008. 936 p.
21. Margaret H. Reinforcement Learning: An Introduction. *Экономика Региона*. 2020;548.
22. Ray S, Majumder S. Water management in agriculture: Innovations for efficient irrigation. In: Sil P, Chhetri P, Majumder S, Santosh DT, editors. *Modern Agronomy*. 2024. p. 169-185.
23. Shanahan J, *et al*. Subsurface drip irrigation for corn production and research. *Crop Insight*. 2012;22(11):1-4.
24. Evans RG, Sadler EJ. Methods and technologies to improve efficiency of water use. *Water Resour Res*. 2008;44(7). doi: 10.1029/2007WR006200.
25. Pereira LS, Cordery I, Iacovides I. Improved indicators of water use performance and productivity for sustainable water conservation and saving. *Agric Water Manag*. 2012;108:39-51. doi: 10.1016/j.agwat.2011.08.022.
26. Jones JW, *et al*. Toward a new generation of agricultural system data, models, and knowledge products: State of agricultural systems science. *Agric Syst*. 2017;155:269-288. doi: 10.1016/j.agsy.2016.09.021.
27. Ojadi JO, Owulade OA, Odionu CS, Onukwulu EC. AI-Driven Optimization of Water Usage and Waste Management in Smart Cities for Environmental Sustainability. *Eng Technol J*. 2025;10(03). doi: 10.47191/etj/v10i03.36.
28. Selvakumar P, Usha MS, Dhokpande SR, Raghunathreddy B, Das A. Water Conservation: AI Applications in Sustainable Water Use. *Cases AI-Driven Solut to Environ Challenges*. 2025;269-296. doi: 10.4018/979-8-3693-7483-2.ch010.
29. Abdulameer L, *et al*. Artificial Intelligence in Climate-Resilient Water Management: A Systematic Review of Applications, Challenges, and Future Directions. *Water Conserv Sci Eng*. 2025;10(1). doi: 10.1007/s41101-025-00371-2.
30. Iqbal S, Sheikh TA, Baba ZA, Yattoo AM. Artificial Intelligence in Water Conservation. *Handb Agric Technol*. 2025;1-21. doi: 10.1007/978-981-99-0862-2_46-1.
31. Egbemhenghe AU, *et al*. Revolutionizing water treatment, conservation, and management: Harnessing the power of AI-driven ChatGPT solutions. *Environ Challenges*. 2023;13. doi: 10.1016/j.envc.2023.100782.
32. P A, *et al*. Artificial Intelligence in Water Management for Sustainable Farming: A Review. *J Sci Res Reports*. 2024;30(6):511-525. doi: 10.9734/jsrr/2024/v30i62068.
33. Kumar A, Hussain J, Chun A. Low Power Wide Area Networks (LPWAN). *Connect Internet Things*. 2023;289-342. doi: 10.1007/978-1-4842-8897-9_5.
34. Shi W, Dustdar S. *The Promise of Edge Computing*. Computer (Long Beach Calif). 2016;49(5):78-81. doi: 10.1109/MC.2016.145.
35. Botta A, De Donato W, Persico V, Pescapé A. Integration of Cloud computing and Internet of Things: A survey. *Futur Gener Comput Syst*. 2016;56:684-700. doi: 10.1016/j.future.2015.09.021.
36. Lin J, Yu W, Zhang N, Yang X, Zhang H, Zhao W. A Survey on Internet of Things: Architecture, Enabling Technologies, Security and Privacy, and Applications. *IEEE Internet Things J*. 2017;4(5):1125-1142. doi: 10.1109/JIOT.2017.2683200.
37. Salam M. Smart Water Management using Internet of Things Technologies. *IIoT World*. 2017 [cited 2026 Apr 28]. Available from: <https://iiot-world.com/connected-industry/smart-water-management-using-internet-of-things-technologies/>
38. Li R, Song T, Capurso N, Yu J, Couture J, Cheng X. IoT Applications on Secure Smart Shopping System. *IEEE Internet Things J*. 2017;4(6):1945-1954. doi: 10.1109/JIOT.2017.2706698.
39. Fardan S, Al-Sartawi A. Using Artificial Intelligence for Smart Water Management Systems. *Stud Comput Intell*. 2023;1113(143):291-298.

40. Solvevila V, Puig A. Leak Detection and Localization in Water Distribution Networks: a Machine Learning. JPROCONT. 2019.
41. Romano M, Kapelan Z, Savić DA. Automated Detection of Pipe Bursts and Other Events in Water Distribution Systems. J Water Resour Plan Manag. 2014;140(4):457-467. doi: 10.1061/(asce)wr.1943-5452.0000339.
42. Al-Wakeel A, Wu J, Jenkins N. K-Means Based Load Estimation of Domestic Smart Meter Measurements. Appl Energy. 2017;194:333-342. doi: 10.1016/j.apenergy.2016.06.046.
43. Biazar SM, Golmohammadi G, Nedhunuri RR, Shaghaghi S, Mohammadi K. Artificial Intelligence in Hydrology: Advancements in Soil, Water Resource Management, and Sustainable Development. Sustain. 2025;17(5). doi: 10.3390/su17052250.
44. Amanatidis P, *et al.* Intelligent Water Management Through Edge-Enabled IoT, AI, and Big Data Technologies. IoT. 2025;7(1):5. doi: 10.3390/iot7010005.
45. Gacu JG, Monjardin CEF, Mangulabnan RGT, Pugat GCE, Solmerin JG. Artificial Intelligence (AI) in Surface Water Management: A Comprehensive Review of Methods, Applications, and Challenges. Water (Switzerland). 2025;17(11). doi: 10.3390/w17111707.
46. Geetha S, Gouthami S. Internet of things enabled real time water quality monitoring system. Smart Water. 2016;2(1). doi: 10.1186/s40713-017-0005-y.
47. Loucks DP, van Beek E. Water resource systems planning and management: An introduction to methods, models, and applications. 2017;1-624. doi: 10.1007/978-3-319-44234-1.
48. Khan Y, Coulibaly P, Dibike M. Reservoir operation optimization using machine learning and LP. Water. 2020;12(2):407-415.
49. Slany V, *et al.* Smart Water-IoT: Harnessing IoT and AI for Efficient Water Management. ACM Comput Surv. 2025;57(12). doi: 10.1145/3744338.
50. Mounce SR, Boxall JB, Machell J. Development and Verification of an Online Artificial Intelligence System for Detection of Bursts and Other Abnormal Flows. J Water Resour Plan Manag. 2010;136(3):309-318. doi: 10.1061/(asce)wr.1943-5452.0000030.
51. Makropoulos CK, Butler D. Distributed water infrastructure for sustainable communities. Water Resour Manag. 2010;24(11):2795-2816. doi: 10.1007/s11269-010-9580-5.
52. Maier HR, *et al.* Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. Environ Model Softw. 2014;62:271-299. doi: 10.1016/j.envsoft.2014.09.013.
53. Manjunathareddy GR, Raveesha HR. AI and the Future of Water Scarcity: Machine Learning for Efficient Resource Management. Handb AI Clean Water Innov Treat Monit. 2025;155-173. doi: 10.1201/9781003600718-12.
54. Deb K. Optimization for Engineering Design. 2002;381.
55. Steduto P, Hsiao TC, Fereres E, Raes D. Crop yield response to water. FAO Irrig Drain Pap No 66. 2012;505.
56. Da Xu L, He W, Li S. Internet of things in industries: A survey. IEEE Trans Ind Informatics. 2014;10(4):2233-2243. doi: 10.1109/TII.2014.2300753.
57. Kamienski C, *et al.* Smart water management platform: IoT-based precision irrigation for agriculture. Sensors (Switzerland). 2019;19(2).
58. Ayaz M, Ammad-Uddin M, Baig I, Aggoune EHM. Wireless sensor's civil applications, prototypes, and future integration possibilities: A review. IEEE Sens J. 2018;18(1):4-30. doi: 10.1109/JSEN.2017.2766364.
59. Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big Data in Smart Farming-A review. Agric Syst. 2017;153:69-80.
60. Sicari S, Rizzardi A, Grieco LA, Coen-Porisini A. Security, privacy and trust in Internet of Things: The road ahead. Comput Networks. 2015;76:146-164.
61. OECD. Enhancing Access to and Sharing of Data. OECD. 2019 [cited 2026 Apr 28]. Available from: https://www.oecd.org/en/publications/enhancing-access-to-and-sharing-of-data_276aaca8-en.html
62. Gluhak A, Krco S, Nati M, Pfisterer D, Mitton N, Razafindralambo T. A survey on facilities for experimental internet of things research. IEEE Commun Mag. 2011;49(11):58-67. doi: 10.1109/MCOM.2011.6069710.
63. ISO. Guidelines for the management of assets of water supply and wastewater systems—part 2 waterworks. Int Organ Stand. 2019 [cited 2026 Apr 28]. Available from: <https://www.iso.org/obp/ui/#iso:std:64667:en>
64. Trendov NM, Varas S, Zeng M. Digital Technologies in Agriculture and Rural Areas. Briefing Paper FAO. 2019 [cited 2026 Apr 28]. Available from: <http://www.fao.org/3/ca4887en/ca4887en.pdf>
65. Naciones Unidas. The age of digital interdependence. United Nations; 2019.
66. Dewedar OM, El-Shafie AF, Marwa MA, Abdelraouf RE. Improvement of Irrigation Water Management Using Simulation Models And Artificial Intelligence Under Dry Environment Conditions In Egypt: A Review. Egypt J Chem. 2023;66(11):93-106. doi: 10.21608/EJCHEM.2023.151289.6552.
67. Matyakubov B. International Water and Irrigation. 2003;23(3):26-27 [cited 2026 Apr 28]. Available from: <https://www.scopus.com/inward/record.uri?eid = 2-s2.0-0242525707&partnerID = 40&md5 = d41338eff4741c32948d1248d19d17d0>
68. Patil SB. The Use of Blockchain for Water Rights in Irrigation Management. Int Water Irrig. 2024;44(1):01-06. doi: 10.52783/iwi.v44i1.82.
69. Vasireddy SSDM, *et al.* Irrigation in Precision Agriculture Using Blockchain Ethereum Based on IoT. Eng Proc. 2024;66(1). doi: 10.3390/engproc2024066029.
70. Homaei M, Morales VG, Gutierrez OM, Gomez RM, Caro A. Smart Water Security with AI and Blockchain-Enhanced Digital Twins. arXiv preprint arXiv:2504.20275. 2025 [cited 2026 Apr 28]. Available from: <http://arxiv.org/abs/2504.20275>
71. Pargo TA, Shirazi MA, Fadai D. Smart and Efficient IoT-Based Irrigation System Design: Utilizing a Hybrid Agent-Based and System Dynamics Approach. arXiv preprint arXiv:2502.18298. 2025 [cited 2026 Apr 28]. Available from: <https://arxiv.org/pdf/2502.18298>
72. Yi S, Li C, Li Q. A survey of fog computing: Concepts, applications and issues. Mobidata 2015-Proc 2015

- Work Mob Big Data. 2015;2015-June:37-42. doi: 10.1145/2757384.2757397.
73. Chiang M, Zhang T. Fog and IoT: An Overview of Research Opportunities. IEEE Internet Things J. 2016;3(6):854-864. doi: 10.1109/JIOT.2016.2584538.
74. Bechar A, Vigneault C. Agricultural robots for field operations: Concepts and components. Biosyst Eng. 2016;149:94-111. doi: 10.1016/j.biosystemseng.2016.06.014.
75. United Nations. The Sustainable Development Goals Report. United Nations. 2024;26-27 [cited 2026 Apr 28]. Available from: <https://unstats.un.org/sdgs/report/2021/#>