OPEN ACCESS

Haya: The Saudi Journal of Life Sciences
Abbreviated Key Title: Haya Saudi J Life Sci
ISSN 2415-623X (Print) | ISSN 2415-6221 (Online)
Scholars Middle East Publishers, Dubai, United Arab Emirates
Journal homepage: https://saudijournals.com

Review Article

Smart Irrigation Management Using Remote Sensing and GIS for Mitigating Biotic and Abiotic Stresses in Crops

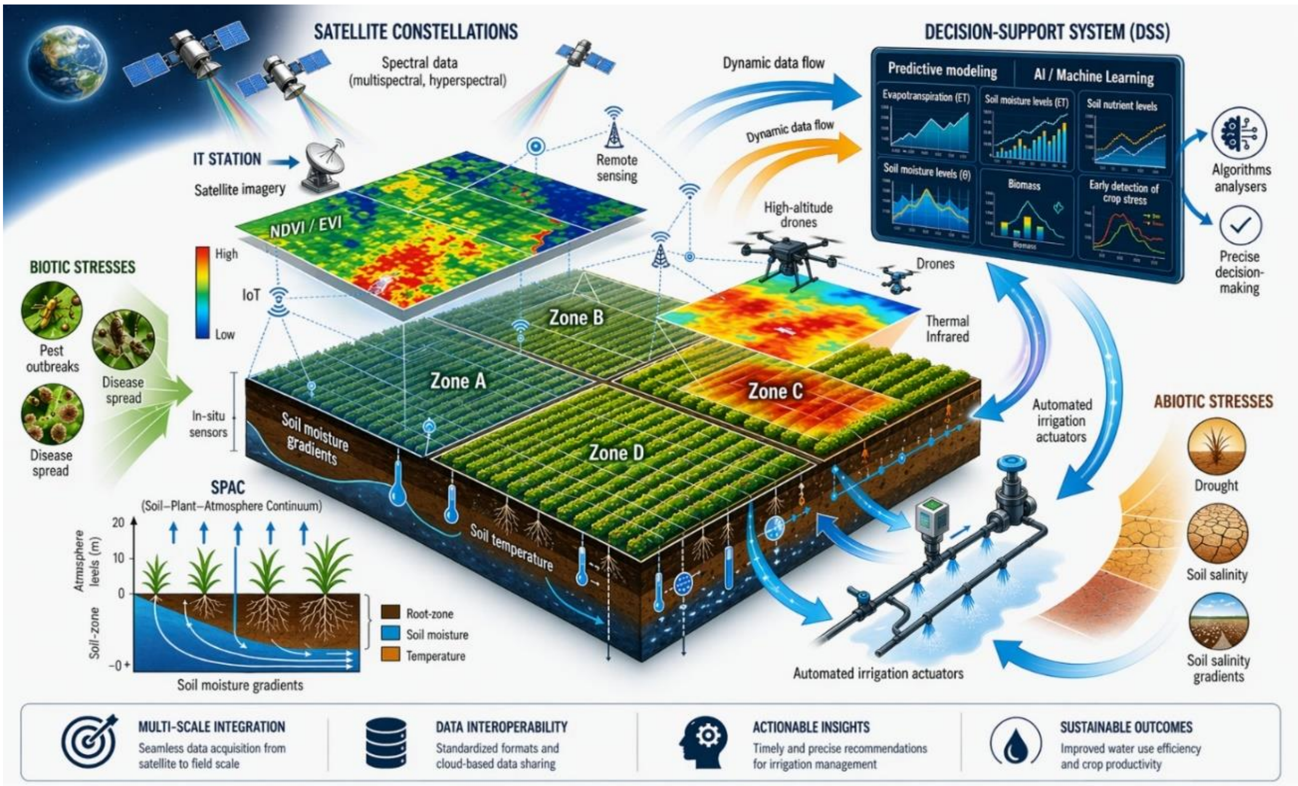
Eisha Habib[1]*, Rabia[2], Muhammad Ahmad[1], Zeshan Ali[3], Muhammad Sabir[4], Zahida Perveen[5], Hunaira Nasreen[6], Hasham Farooq Chughtai[7]

[1]Centre of Agricultural Biochemistry and Biotechnology (CABB), University of Agriculture Faisalabad, Punjab Pakistan
[2]Department of Environmental Science, Government College Women University Sialkot, Punjab Pakistan
[3]Department of Environmental Science, Government College University Faisalabad, Punjab Pakistan
[4]Department of Chemistry, University of Punjab, Pakistan
[5]Department of Botany, Government College University Faisalabad, Punjab Pakistan
[6]Department of Biochemistry, Government College University, Faisalabad. Punjab Pakistan
[7]Department of Botany, Ghaazi University Dera Ghazi Khan, Punjab Pakistan

DOI: https://doi.org/10.36348/sjls.2026.v11i04.004 | **Received:** 28.02.2026 | **Accepted:** 22.04.2026 | **Published:** 24.04.2026

***Corresponding author:** Eisha Habib
Centre of Agricultural Biochemistry and Biotechnology (CABB), University of Agriculture Faisalabad, Punjab Pakistan

Abstract



Remote sensing-based smart irrigation management based on the use of geographic information system (GIS) has become a revolution in the effort to maximize the efficiency of water use in agricultural systems and the management of complex biotic and abiotic stresses to the agricultural system. This paper integrates recent developments in satellite-based monitoring, sensor fusion, and spatial analytics to come up with adaptive irrigation systems that adapt dynamically to crop water needs. Remote sensing platforms can be used to measure vegetation indices, soil moisture, evapotranspiration, and thermal anomalies in real-time, allowing the initial identification of stress conditions resulting in drought, salinity, pests and diseases. GIS-based modeling also improves the decision-making process by incorporating multi-layered spatial data such as topography, soil characteristics and climatic variables to produce accurate irrigation timetables and risk maps. These technologies are integrated to facilitate precision agriculture through less wastage of water, low input costs, and enhanced crop resilience to the dynamic environment. Further, the predictability of stress forecasting and optimization in the process of irrigation can be improved using machine learning algorithms and geospatial data. The case studies show that smart irrigation systems can provide a great deal of stability in yield and efficiency in resource use in a wide range of agro-ecological areas. Though there are current challenges of accessing data, technical complexity and infrastructure constraints, continued technological advancements are ensuring that these systems continue to be scaled and accessible. In general, remote sensing and GIS convergence offer a sound platform of sustainable water management, which is part of food security and climate adaptation policies in contemporary agriculture. Future studies ought to be conducted on the incorporation of low-cost sensor networks, cloud computing infrastructure, and farmer-oriented decision-support systems to make them easy to use, scale, and be adopted in resource-constrained agricultural areas in the world to advance sustainable development.

Keywords: Precision agriculture, Geospatial analytics, Evapotranspiration modeling, Crop stress detection, Decision support systems, Spatial variability.

1. INTRODUCTION

The twin challenges facing agricultural systems today are how to satisfy the growing food demand in the world and how to deal with environmental limitations and climate change (Ray, West *et al.,*2019). Scarcity and unpredictable rains, land degradation have increased the necessity of effective irrigation methods that could maintain productivity without depleting natural resources. Traditional irrigation systems are typically founded on fixed-timing or generalized assumptions and do not consider the spatial and temporal variability within field. This restriction not only causes inefficient water uptake but it also increases biotic (pest and disease epidemics) and abiotic (drought, salinity and temperature extremes) stressors (Khan, Zhang *et al.,*2019; Qasim *et al.*, 2025). In that regard, the smart irrigation management has become a vital innovation, which combines innovative technologies to optimize the use of water and make crops more resilient. Remote sensing has transformed agriculture monitoring in that it allows observation of the conditions of crops over a large area in a continuous, non-destructive way. The satellite and aerial platforms are able to give precise and detailed information about the health of vegetation, the content of soil moisture, the temperature of the land surface, and the levels of evapotranspiration. These parameters are crucial parameters of stress and water demand in plants. Spectral reflectance vegetation indices, including NDVI and EVI, can be used to detect physiological processes in crops before they start showing any symptoms (Asner 2008). This early-detection feature is especially helpful in reducing the effects of stress, with timely interventions being able to save losses in the yield and decreasing the necessity of using too many inputs.

Geographic information systems supplement remote sensing by offering a spatial platform on which to integrate, analyze and visualize data. GIS allows overlaying different data sets such as soil properties, weather factors, topography, and crop coverage to create in-depth understanding of variability within the field (Rodriguez-Galiano, Ghimire *et al.,*2012). The spatial modeling allows the design of irrigation plans to be specific to certain areas in a field so that water is only applied at the correct location and time. Such a site-based practice is more efficient in water use and reduces runoff, leaching, and loss of nutrients, which leads to environmental sustainability. Precision irrigation systems are based on the integration of remote sensing and GIS. Such systems take advantage of real-time information and spatial intelligence to facilitate dynamic decision-making (Zhang and Kovacs 2012). As an example, the evapotranspiration estimates, based on a satellite, can be combined with soil moisture data to properly estimate crop water demand. This information can be used to inform irrigation events based on the real plant requirements, as opposed to a schedule, when incorporated into automated irrigation system. This flexibility is essential in responding to the uncertainty brought by climate change where conventional ways are ineffective most of the time. Biotic stresses, such as pest infestations and plant diseases are directly connected to the environmental conditions and water management practices (Bebber, Holmes *et al.,*2014; Chaudhary *et al.*, 2025). Excessive watering may provide a conducive environment in which the growth of pathogens can thrive, whereas water stress can compromise plant resistance, exposing crops to attacks. Smart irrigation systems would aid in keeping the moisture levels at the optimum, thus minimizing the chances of such interactions of stress. Moreover, in remote sensing, abnormalities in the reflectance patterns of crops that indicate presence of pests or diseases can be identified, which can be used to apply specific measures to contain the infestations (Mahlein 2016; Faazal *et al.*, 2023).

Abiotic stresses especially drought and salinity are some of the major threats to agricultural productivity. The lack of water in the arid and semi-arid areas makes it a requirement to adopt efficient irrigation technologies to maximize the output with a given amount of water (Clement, Kalpana *et al.,*2025). Remote sensing can give essential information regarding the processes of soil moisture and the distribution of salinity, and GIS can help to identify areas of vulnerability within the fields. With a combination of these tools, farmers can adopt measures like deficit irrigation, variable rate irrigation, and soil amendment applications to reduce the impact of stress. The latest changes in the data analytics and machine learning have contributed to the capabilities of smart irrigation systems. Based on historical and real-time data, predictive models may be used to predict stress conditions and optimize irrigation schedules (Del-Coco, Leo *et al.,*2024). These models enhance the accuracy of decisions and allow proactive management to be done to avoid reactive measures. Moreover, cloud-based solutions and mobile applications have been developed and have made these technologies more reachable to farmers, closing the divide between complex data analysis and field application. Even with this potential, there are many hurdles to the adoption of smart irrigation technologies. Initial cost, lack of technical know-how and proper infrastructure may be a barrier to large scale application especially in developing areas (Batini and Scannapieco 2016). Availability and quality of the data is also important issue, since proper decision-making is based on the quality of inputs. To overcome these barriers, researchers, policymakers, and technology providers need to work together to come up with cost-effective solutions and capacity building programs. In short, remote sensing and GIS integration as the area of irrigation control is one of the paradigms shifts toward the data-based agriculture. These technologies are important in reducing biotic and abiotic stress by allowing optimized, adaptive, and efficient water utilization. With the ongoing development of innovations, it is believed that smart irrigation systems will become more involved in the sustainable agriculture practice to guarantee food security and environmental sustainability amidst global challenges.

2. Multiscale Data Ecosystems and Geospatial Intelligence

The shift to smart irrigation systems is deeply rooted in the combination of multiscale data ecosystems and innovative geospatial intelligence systems. The contemporary agricultural landscape has been described as highly spatially and temporally heterogeneous, requiring the integration of heterogeneous data sets that range between sub-plant level physiological activity and regional climatic trends (Khan, Murtaza *et al.,*2026). Multiscale data ecosystems facilitate harmonious integration of data collected by remote sensing platforms, in situ sensors and predictive environmental models to form a dynamic and adaptive knowledge base to precision irrigation. Geospatial intelligence is aided by highly sophisticated Geographic Information Systems (GIS) and is used to better this capability by processing raw data into spatially explicit information that can be used to guide water allocation and ensure maximum resource use and alleviate yield losses due to the stressor. The intertwining of data-driven analytics and spatial modeling hence becomes the cornerstone of future-generation irrigation management practices (Wang, Wu *et al.,*2026).

2.1 Remote Sensing Platforms for Crop–Water Monitoring

Remote sensing technology has transformed crop-water monitoring through a non-destructive, large scale and high frequency evaluation of both plant and soil conditions. Multispectral and hyperspectral imaging systems are satellite-based systems capable of providing large spatial and long-term datasets required to understand evapotranspiration, vegetation indices (e.g., NDVI, EVI), and surface temperature changes (Srivastava and Jain 2025). The datasets play a crucial role in determining the patterns of water stress as well as informing irrigation scheduling at regional and field levels. They however have moderate spatial resolution and are vulnerable to atmospheric disturbances, which often require complementary techniques. UAVs fill this gap by providing high-resolution, flexible, and on-demand data collection. UAVs have thermal and multispectral sensors and can accurately detect canopy temperature differences, chlorophyll content, and micro-scale stress indicators. This also enables early intervention measures and location-specific irrigation control. In addition, proximal sensing (such as soil moisture probes, infrared thermometers, plant-based sensors; e.g., dendrometers, sap flow meters)) data can be used to provide real-time ground-truth data to supplement remote sensing-derived estimates. Combination of satellite, UAV and proximal sensing platforms forms a hierarchical sensing architecture, which guarantees macro-scale coverage and micro-scale accuracy (Ren, Zhou *et al.,*2025).

2.2 Soil–Plant–Atmosphere Continuum (SPAC) Data Integration

The Soil-Plant-Atmosphere Continuum (SPAC) is a comprehensive model of the processes of water flux in agroecosystems. It includes the integrative mechanisms by which water is transferred out of the soil, and into the atmosphere via transpiration through plant tissues. The use of SPAC data is essential in the precise modelling of crop water demands and the optimal use of irrigation techniques in different environments (Ullah *et al*., 2026; Amir *et al*., 2026). New sensor networks and modeling methods have now made it possible to measure soil moisture profiles and simultaneously plant physiological variables (e.g., stomatal conductance, leaf water potential) and atmospheric variables (e.g., humidity, temperature, wind speed) (Livellara, Saavedra *et al.,*2011). Through the linkage of these datasets, such researchers are able to construct mechanistic models that describe the feedback interactions in the continuum. An example is that the lack of soil moisture affects stomatal closure which in turn controls the rate of transpiration and canopy temperature which can be measured through thermal imaging. Dynamic irrigation schedules, in response to current plant water conditions and not predetermined thresholds, are made possible by incorporating SPAC-based models into decision-support systems. This paradigm shift, which involves shifting the focus of irrigation systems based on soil to those centered around plants, boosts water use efficiency and tolerance to biotic and abiotic stresses (Ali 2025).

2.3 GIS-Based Multi-Layer Spatial Modeling (Soil, Climate, Topography)

GIS represents an important platform that allows synthesizing and analyzing various spatial data through a single platform. Multi-layer spatial modeling is an overlay and interaction of different geospatial layers, such as soil properties (texture, structure, hydraulic conductivity), climatic variables (precipitation, temperature, evapotranspiration), and topographic features (elevation, slope, aspect). Through the synthesis of these layers, GIS facilitates the determination of spatial trends and limits that affect the distribution of water and performance of crops (Ines, Gupta *et al.,*2002). As an example, the soils have a coarse texture with steep slopes, which can lead to fast drainage and high irrigation requirements, whereas the low-lying land has fine-textured soils, and can be subject to waterlogging. Even more sophisticated spatial analysis methods, including weighted overlay, spatial interpolation (e.g., kriging), and classification by machine learning, can further improve the predictive power of GIS models. These combined models facilitate simulation by scenarios, thus enabling the stakeholders to analyze the effects of various irrigation plans in the changing environmental conditions (Haidri *et al*., 2026; Ullah *et al*., 2026). Therefore, multi-layer modeling that can be done using GIS is a powerful decision-making tool that can be used to optimize the allocation of water in the field and watershed levels.

2.4 Spatial Heterogeneity Analysis and Irrigation Zoning

The nature of agricultural fields is always heterogeneous, with variability in terms of soil properties, crop growth, and microclimatic conditions as shown in Figure 1. By overlooking this heterogeneity, there is a high likelihood of inefficient irrigation practices whereby there is over-irrigation in certain places and water shortage in others. The purpose of the analysis of spatial heterogeneity is to measure and map this variability and thus allows defining management zones that have different irrigation needs. Geostatistical analysis, cluster analysis, and segmentation by remote sensing are some of the commonly used techniques to determine homogenous areas in a field (Van der Meer 2012). These areas are identified according to major indicators like soil moisture variations, vegetation index, yield trends and topography. When this has been defined, it is possible to implement variable rate irrigation (VRI) systems that can be used to apply water at different rates across areas so that each area is optimally supplied with water. The zoning of irrigation does not only increase the efficiency of water use, but also crop uniformity and stability of yield. In addition, it lowers input expenses and environmental effects of excessive use of water including nutrient leaching and soil erosion (Qasim *et al*., 2026; Ullah *et al*., 2025).

2.5 Data Uncertainty, Resolution Constraints, and Preprocessing Techniques

Although there is improvement in data acquisition and integration, issues of uncertainty and resolution of data are still an important hurdle to successful adoption of geospatial irrigation systems. Uncertainties can be due to sensor inaccuracies, atmospheric interference in remote sensing data, time lag between datasets, and model assumptions. Such uncertainties may spread using analytical processes, which might result in suboptimal irrigation choices. There are also resolution constraints that make interpretation of the data most difficult. Although satellite imagery has a wide area coverage, the spatial resolution of the imagery can be low enough to detect fine-scale variations. On the other hand, UAV data with high resolution might not be scalable and have no temporal continuity (Bendig, Bolten *et al.,*2013). The trade-offs of these choices can only be balanced by having multi-resolution datasets and using data fusion methods. Preprocessing is vital in the improvement of data quality and reliability. The most frequently used methods are radiometric and atmospheric correction, noise filtering, geometric alignment, and data normalization. More sophisticated methods, including machine learning-based denoising and gap-filling algorithms, are also being introduced to deal with missing or inconsistent data. Finally, effective uncertainty quantification and preprocessing systems are needed to guarantee accuracy, reliability, and scalability of multiscale data ecosystems. Overcoming these hurdles, geospatial intelligence systems have the potential to provide more accurate and practical insights to manage sustainable irrigation.

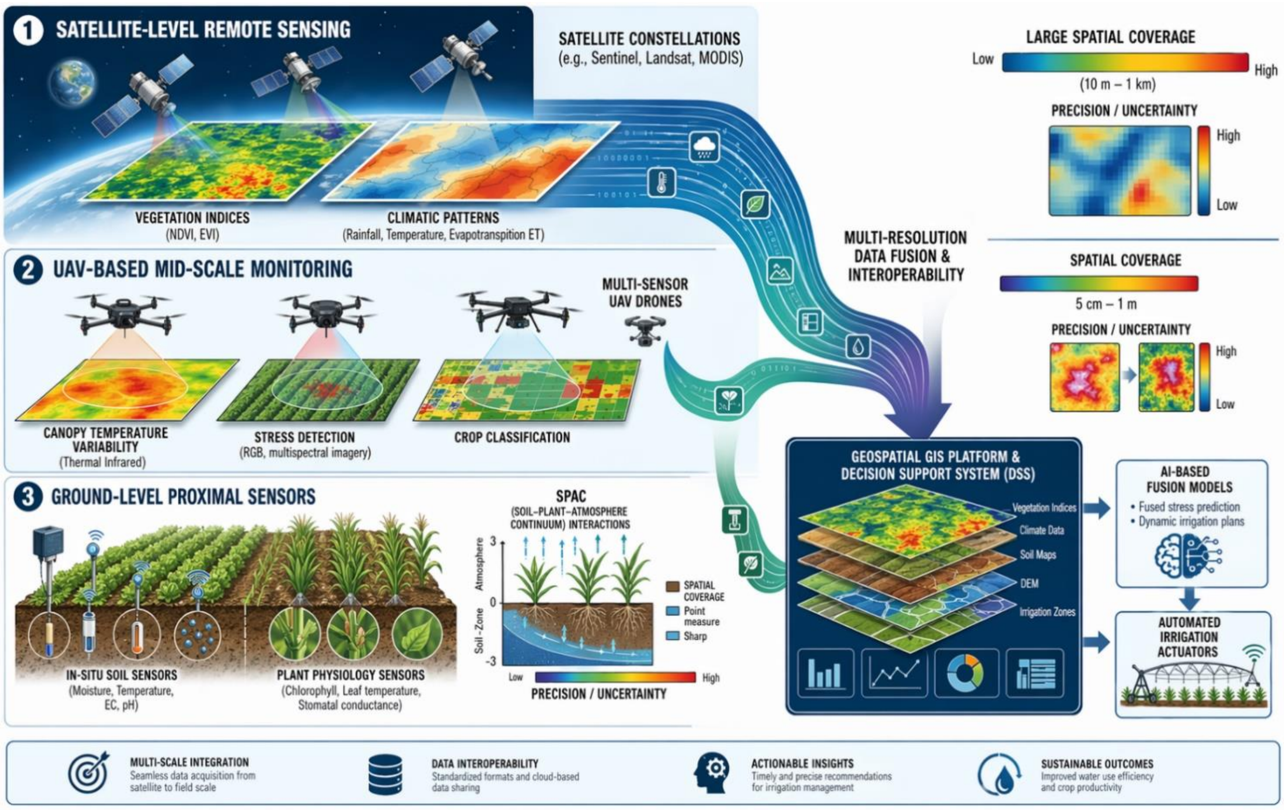


Fig 1: A multi-scale smart irrigation framework integrating satellite, UAV, and ground sensors for comprehensive crop monitoring. It employs multi-resolution data fusion and AI-driven DSS to optimize irrigation with improved precision and reduced uncertainty

3. AI-Driven Predictive Modeling for Irrigation Optimization

With the introduction of artificial intelligence (AI) into the irrigation management system, AI has transformed precision agriculture by providing predictive, adaptive, and data-driven decision-making frameworks. AI predictive modeling uses multi-source datasets, such as climatic variables, soil parameters, crop phenology, and remote sensing products, to optimize the irrigation schedule at high spatial and temporal resolution (Waseem *et al*., 2025). These models not only maximize the efficiency of water-use, but also help to ameliorate both biotic and abiotic stresses by predicting plant responses in changing environmental conditions (Hatfield and Dold 2019). Modern agriculture is shifting towards resource-efficient and resilient paradigms by moving away from the old irrigation methods towards smart systems of forecasting.

3.1 Machine Learning Models for Evapotranspiration and Soil Moisture Prediction

Machine learning (ML) models have become an effective predictor of evapotranspiration (ET) and soil moisture two essential parameters used in irrigation decisions. Although they are useful, traditional empirical and physically based models can have difficulties in modeling nonlinear interactions of the meteorological and soil variables (Yuan, Wood *et al.,*2015). Conversely, random forest (RF), support vector machines (SVM), gradient boosting machines (GBM) and artificial neural networks (ANN) are crucial in detecting complex patterns in high-dimensional data. To predict evapotranspiration, ML models combine the inputs of temperature, humidity, wind speed, solar radiation, and indices of vegetation based on satellite images. The models are more effective than a traditional method, e.g. the Penman Monteith equation, in data-sparse or heterogeneous environments by minimizing the use of rigid assumptions. Equally, the application of ML algorithms to predict soil moisture takes advantage of in-situ sensor measurements combined with remote sensing products (e.g., thermal imagery and microwave), and predict soil moisture in different depths and soil textures (Lamichhane, Mehan *et al.,*2025). In addition, the techniques of ensemble learning also improve the reliability of the predictions by pooling the results of each model, thus reducing the variance and bias. Although powered by their predictive capability, ML models require large training datasets and selective features to prevent overfitting and ensure scalability across agroecological zones.

3.2 Deep Learning for Early Detection of Biotic and Abiotic Stresses

Deep learning (DL), a branch of AI, has contributed to a remarkable level in upstream detection of crop stresses by taking advantage of high-resolution spatial and time data. CNNs and RNNs, such as Long

Short-Term Memory (LSTM) ones, are especially useful in studying satellite images, UAV data, and hyperspectral signals to identify minor physiological alterations in crops (Marri, P *et al.,*2021). In detecting biotic stress, i.e., pest infestations and disease outbreaks, CNN-based image classification models have the capability to detect early visual symptoms, which are not always visible by the human eye. These models involve the use of spectral signature and texture to distinguish between a healthy and an infected plant so that appropriate action can be taken in time to save the crop. Deep learning models are used to examine time series of vegetation indices (e.g., NDVI, EVI) and thermal anomalies in the context of abiotic stressor conditions such as drought, salinity and temperature extremes. In particular, LSTM networks are used to learn sequential dependencies, which is why they are applicable in predicting time-dependent stress progression. The combination of DL with Internet of Things (IoT) sensors will also improve real-time monitoring by enabling automated irrigation reaction to the level of crop stress. However, deep learning models are computationally expensive and need huge annotated datasets, potentially limiting their use in resource-constrained agricultural systems (Chen, Zhang *et al.,*2020).

3.3 Hybrid Modeling: Integrating Process-Based and Data-Driven Approaches

Hybrid modeling represents a synergistic approach that combines the strengths of process-based models with data-driven AI techniques. Process-based models, grounded in physical laws and crop physiology (e.g., soil-water balance equations), provide interpretability and domain knowledge, while AI models contribute adaptive learning and predictive accuracy. In irrigation optimization, hybrid frameworks integrate outputs from crop simulation models (such as DSSAT or AquaCrop) with machine learning algorithms to refine predictions of water requirements under varying climatic scenarios. For instance, process-based models can generate baseline simulations of evapotranspiration and soil moisture dynamics, which are subsequently corrected or enhanced by ML models trained on real-world observations (Aderele, Srivastava *et al.,*2025). This integration improves model robustness, particularly under conditions of climate variability and data uncertainty. Additionally, hybrid approaches facilitate scenario analysis, allowing researchers to evaluate the impact of future climate conditions on irrigation demands. Despite their advantages, hybrid models require careful calibration and validation to ensure consistency between theoretical assumptions and empirical data.

3.4 Time-Series Forecasting for Dynamic Irrigation Scheduling

Time-series forecasting plays a pivotal role in enabling dynamic irrigation scheduling by predicting future environmental conditions and crop water requirements. Advanced AI models such as LSTM, Gated Recurrent Units (GRU), and Temporal Convolutional Networks (TCN) are widely used to model sequential data patterns in climate variables, soil moisture levels, and crop growth stages. These models process historical data to forecast short-term and long-term trends, allowing irrigation systems to adjust water application proactively rather than reactively (Hsu and Lin 2024). For example, predicting rainfall events or soil moisture depletion rates enables the system to optimize irrigation timing, thereby reducing water wastage and preventing over-irrigation. Integration with real-time sensor networks enhances forecasting accuracy, as continuous data streams update model predictions dynamically. Furthermore, coupling time-series models with decision support systems (DSS) allows farmers to receive actionable recommendations, bridging the gap between data analytics and field-level implementation. However, forecasting models are sensitive to data quality and temporal inconsistencies, necessitating robust preprocessing techniques and continuous model updating.

3.5 Model Limitations, Generalizability, and Uncertainty Analysis

Despite the transformative potential of AI-driven predictive modeling, several limitations constrain its widespread adoption as discussed in Table 1. One of the primary challenges is model generalizability, as models trained on specific datasets or regions often fail to perform accurately under different agro-climatic conditions. Variability in soil types, crop varieties, and management practices introduces complexities that limit the transferability of models. Data dependency is another critical issue. High-quality, large-scale datasets are essential for training reliable AI models; however, such datasets are often unavailable in developing agricultural systems. Additionally, sensor errors, missing data, and inconsistencies in remote sensing inputs can propagate uncertainties into model predictions (Povey and Grainger 2015). Uncertainty analysis is therefore crucial to quantify prediction reliability and support risk-informed decision-making. Techniques such as Monte Carlo simulations, Bayesian inference, and ensemble modeling are employed to assess variability and confidence intervals in model outputs. Explainable AI (XAI) methods are also gaining attention for improving model transparency, enabling stakeholders to interpret predictions and build trust in AI systems. Finally, computational complexity and infrastructure requirements pose barriers, particularly for smallholder farmers. Addressing these challenges requires the development of lightweight, scalable models, improved data-sharing frameworks, and interdisciplinary collaboration to ensure that AI-driven irrigation solutions are both accessible and sustainable.

Table 1: Comparative synthesis of AI-driven modeling approaches for irrigation optimization and stress mitigation

Model/Algorithm Type	Input Data Sources	Primary Application in Irrigation	Advantages	Limitations/ Challenges	Reference
Random Forest (RF)	NDVI, soil moisture sensors, weather data	Crop stress detection, irrigation need classification	Robust to noise, handles nonlinear relationships	Requires large datasets	Rodriguez-Galiano *et al*., 2012
Support Vector Machine (SVM)	Spectral indices, temperature, humidity	Stress classification	Good generalization	Computationally intensive	Del-Coco *et al*., 2024
Gradient Boosting Machine (GBM)	Remote sensing indices, ET data	Irrigation demand prediction	High accuracy	Overfitting risk	Del-Coco *et al*., 2024
Artificial Neural Networks (ANN)	Soil moisture, ET, weather data	Irrigation scheduling	Captures nonlinear dynamics	Data intensive	Yuan *et al*., 2015
Convolutional Neural Networks (CNN)	Satellite, UAV imagery	Crop stress mapping	Strong spatial extraction	High computation	Chen *et al*., 2020
Recurrent Neural Networks (RNN)	Time-series weather, soil moisture	Temporal prediction	Captures time dependency	Vanishing gradient	Marri *et al*., 2021
Long Short-Term Memory (LSTM)	Historical ET, rainfall	Irrigation scheduling	Handles long-term patterns	Complex tuning	Hsu & Lin, 2024
Gated Recurrent Units (GRU)	Climate time-series	Forecasting irrigation	Efficient training	Slightly lower accuracy	Hsu & Lin, 2024
Temporal Convolutional Networks (TCN)	Sequential climate data	Time-series prediction	Stable gradients	Design complexity	Hsu & Lin, 2024
Hybrid ML + Process Models	Remote sensing + crop models	Irrigation optimization	Combines physics + AI	Calibration issues	Aderele *et al*., 2025
DSSAT-integrated AI	Crop simulation + weather	Water requirement prediction	Agronomic strength	Complex	Aderele *et al*., 2025
AquaCrop + ML	Soil, climate, crop data	Irrigation optimization	FAO-based reliability	Calibration intensive	Ines *et al*., 2002
Bayesian Networks	Environmental data	Probabilistic irrigation decisions	Handles uncertainty	Complex structure	Povey & Grainger, 2015
Monte Carlo Models	Climate variability data	Risk-based irrigation	Uncertainty quantification	Computational cost	Povey & Grainger, 2015
Fuzzy Logic Systems	Soil moisture, temperature	Irrigation control	Handles imprecision	Rule dependency	Sipp & Schmid, 2016
Reinforcement Learning (RL)	Real-time sensor data	Autonomous irrigation	Adaptive learning	Training intensive	Del-Coco *et al*., 2024
Deep Q-Networks (DQN)	Sensor + system states	Smart irrigation control	Handles complex decisions	High computation	Del-Coco *et al*., 2024
Transformer Models	Long-term climate data	Irrigation forecasting	Long-range dependency	Data intensive	Chang *et al*., 2025
Digital Twin Models	Sensor + simulation data	System optimization	Predictive simulation	High complexity	Kussul *et al*., 2025
Ensemble Learning	Multi-model outputs	Improved prediction	Robust results	Computational cost	Lamichhane *et al*., 2025
Explainable AI (XAI)	Model outputs	Transparent decisions	Interpretability	Reduced performance	Povey & Grainger, 2015
Edge AI Models	IoT sensor data	Real-time irrigation control	Low latency	Limited capacity	Maurya *et al*., 2024

4. Adaptive Irrigation Systems and Autonomous Control Architectures

The transition from conventional irrigation practices to adaptive, intelligence-driven systems represents a pivotal advancement in precision agriculture. Adaptive irrigation systems are engineered to dynamically respond to spatiotemporal variability in soil moisture, climatic conditions, and crop physiological status. Unlike static scheduling approaches, these systems leverage continuous data acquisition, real-time analytics, and autonomous control mechanisms to optimize water delivery with high temporal resolution. The integration of cyber-physical frameworks has enabled irrigation infrastructures to evolve into self-regulating ecosystems capable of minimizing water wastage while maximizing crop productivity under fluctuating environmental conditions (Olasehinde, Blessing *et al.,*2023). At the core of these architectures lies the convergence of sensing technologies, communication networks, and computational intelligence, forming a closed-loop paradigm where decision-making is no longer reactive but predictive and adaptive. Such systems are particularly critical in addressing the challenges posed by climate variability, water scarcity, and the need for sustainable intensification of agriculture.

4.1 Closed-loop Irrigation Systems and Real-time Feedback Mechanisms

Closed-loop irrigation systems constitute the backbone of adaptive water management by incorporating continuous feedback to regulate irrigation events. In these systems, real-time data from soil moisture sensors, evapotranspiration models, and plant stress indicators are continuously monitored and compared against predefined thresholds or dynamic models. The system then autonomously adjusts irrigation timing, duration, and volume, ensuring precise water application aligned with crop requirements. A defining feature of closed-loop systems is their ability to operate based on feedback control theory, where deviations from optimal conditions trigger corrective actions (Sipp and Schmid 2016). Advanced implementations employ proportional–integral–derivative (PID) controllers, fuzzy logic systems, or machine learning algorithms to refine control accuracy. These approaches enable the system to account for nonlinearities in soil-water-plant interactions, thereby improving irrigation efficiency beyond traditional rule-based methods. Moreover, real-time feedback mechanisms enhance system resilience by enabling rapid responses to abrupt environmental changes such as unexpected rainfall, heatwaves, or soil heterogeneity. The integration of remote sensing data further strengthens feedback loops by providing spatially explicit insights, allowing for site-specific irrigation management. Consequently, closed-loop systems significantly reduce over-irrigation, nutrient leaching, and energy consumption, while maintaining optimal crop hydration levels.

4.2 Integration of IoT-enabled Sensor Networks and Smart Actuators

The proliferation of Internet of Things (IoT) technologies has revolutionized the operational capabilities of adaptive irrigation systems. IoT-enabled sensor networks facilitate continuous, high-resolution monitoring of multiple agro-environmental parameters, including soil moisture, temperature, humidity, salinity, and solar radiation. These sensors are strategically deployed across agricultural fields to capture spatial variability, thereby enabling precision irrigation at micro-zone levels (Ren 2026). Data collected from these distributed sensors is transmitted via wireless communication protocols such as LoRaWAN, Zigbee, or cellular networks to centralized or decentralized processing units. The interoperability of these networks ensures seamless data flow, forming the foundation for intelligent decision-making. Importantly, the integration of heterogeneous sensors enhances system robustness by providing multi-dimensional insights into crop-water dynamics. Complementing sensor networks, smart actuators such as automated valves, pumps, and drip irrigation controllers execute irrigation commands with high precision. These actuators are capable of responding instantaneously to control signals, enabling variable-rate irrigation tailored to specific field conditions. The synergy between sensors and actuators establishes a responsive ecosystem where data-driven insights are directly translated into actionable outcomes. Furthermore, IoT architectures support scalability and remote accessibility, allowing farmers and agronomists to monitor and control irrigation systems via mobile or web-based platforms (Morchid, Jebabra *et al.,*2024). This connectivity not only enhances operational efficiency but also facilitates data-driven decision support systems, ultimately contributing to sustainable water resource management.

4.3 Edge and Cloud Computing for Real-time Decision Execution

The integration of edge and cloud computing paradigms has significantly enhanced the computational efficiency and responsiveness of adaptive irrigation systems. Edge computing involves processing data locally at or near the source such as on embedded devices or field gateways thereby reducing latency and enabling real-time decision execution as illustrated in Figure 2. This is particularly critical in irrigation management, where timely responses to rapidly changing conditions can directly impact crop health (Maurya, Kalhapure *et al.,*2024). Edge devices are equipped with lightweight algorithms capable of performing on-site analytics, including anomaly detection, threshold-based control, and preliminary data filtering. By minimizing the need for continuous data transmission to centralized servers, edge computing reduces bandwidth requirements and enhances system reliability in areas with limited connectivity. In contrast, cloud computing provides high-performance computational resources for large-scale data storage, advanced analytics, and model training. Cloud platforms enable the integration of historical datasets, weather forecasts, and predictive models to generate long-term irrigation strategies. Machine learning and artificial intelligence algorithms deployed in the cloud can identify complex patterns and optimize irrigation schedules based on predictive insights. The hybrid integration of edge and cloud computing creates a hierarchical decision-making framework, where immediate control actions are executed at the edge, while strategic optimization is handled in the cloud (Trigka and Dritsas 2025). This distributed intelligence enhances system scalability, adaptability, and efficiency. Additionally, cloud-based dashboards and visualization tools provide stakeholders with actionable insights, facilitating informed decision-making and long-term resource planning.

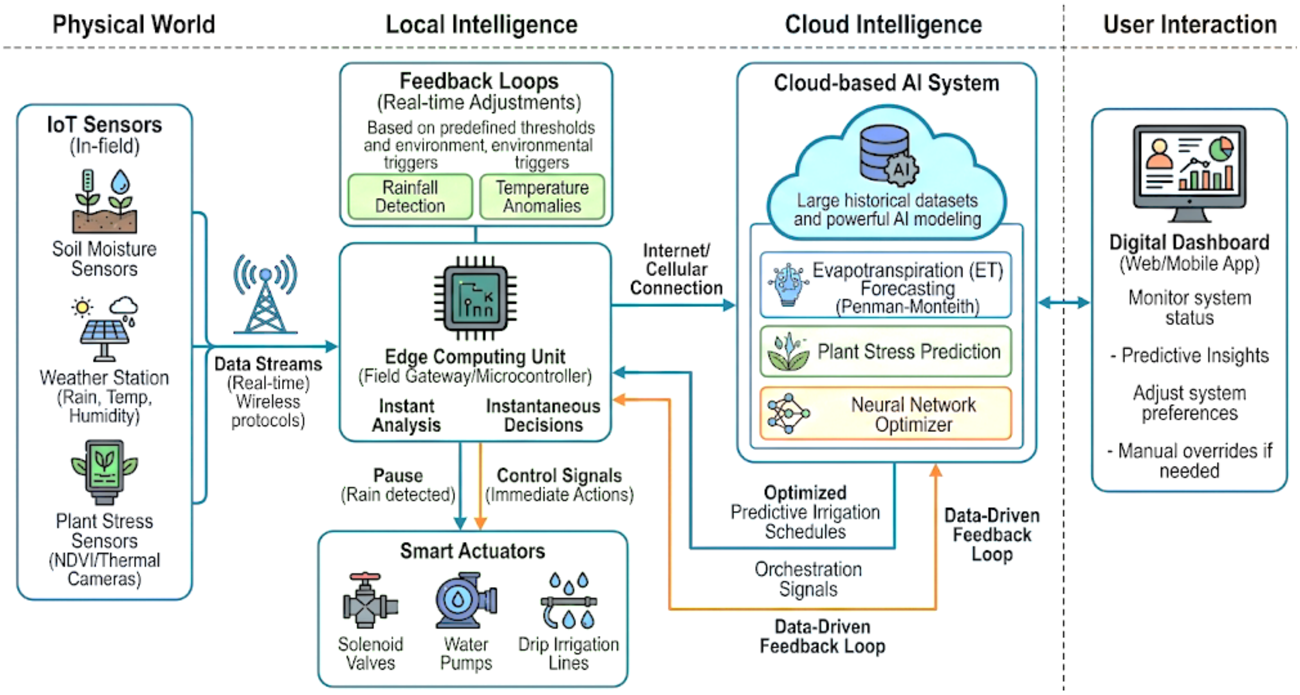


Fig. 2: A smart irrigation framework integrating IoT sensors, edge computing, and cloud-based AI for real-time monitoring and predictive decision-making. Feedback loops and user dashboards enable adaptive control and efficient water management.

5. Stress-Specific Irrigation Strategies and Sustainability Assessment

The increasing prevalence of climate-induced stressors necessitates a paradigm shift from uniform irrigation practices toward stress-responsive, precision-driven water management frameworks. Contemporary irrigation strategies are no longer confined to maximizing yield alone; instead, they are evolving into multidimensional systems that integrate plant physiology, soil chemistry, climatic variability, and biotic stress interactions. This transformation is particularly critical in regions facing concurrent water scarcity, salinity intrusion, and pest proliferation, where irrigation decisions directly influence ecosystem resilience and long-term agricultural sustainability (Mehta 2024). Stress-specific irrigation strategies therefore emphasize adaptive water allocation, real-time monitoring, and feedback-driven optimization, ensuring that water inputs are aligned with crop-specific stress thresholds while minimizing environmental degradation. Furthermore, sustainability assessment frameworks now incorporate water productivity metrics, ecological footprints, and resilience indices, enabling a holistic evaluation of irrigation practices beyond conventional efficiency measures.

5.1 Drought-Adaptive and Deficit Irrigation Frameworks

Drought stress remains one of the most limiting factors affecting global crop productivity, compelling the development of drought-adaptive irrigation paradigms that strategically balance water savings with physiological crop requirements. DI has emerged as a cornerstone approach, wherein water supply is deliberately reduced below full crop evapotranspiration levels during specific growth stages that exhibit relative tolerance to water stress (Franco-Navarro, Padilla *et al.,*2025). This controlled water limitation induces physiological acclimation mechanisms, including stomatal regulation, osmotic adjustment, and enhanced root proliferation, thereby improving water uptake efficiency and sustaining yield stability under constrained conditions. Advanced frameworks such as regulated deficit irrigation (RDI) and partial root-zone drying (PRD) further refine this approach by targeting spatial or temporal variability in water distribution. RDI focuses on applying water deficits during non-critical phenological stages, whereas PRD alternates irrigation between different root zones to trigger chemical signaling pathways, particularly abscisic acid-mediated responses, that enhance water use efficiency without significantly compromising photosynthetic activity. These strategies are increasingly supported by remote sensing technologies and soil moisture sensors, enabling precise quantification of plant water status and dynamic adjustment of irrigation schedules. Importantly, the success of drought-adaptive irrigation frameworks is contingent upon crop-specific sensitivity thresholds, soil texture, and climatic conditions, necessitating site-specific calibration (Zaidi, Das *et al.,*2026). Integrating these frameworks with predictive modeling and climate forecasts enhances their robustness, allowing proactive management of water deficits in anticipation of prolonged drought events.

5.2 Salinity-Aware Irrigation and Soil Health Management

Salinity stress, exacerbated by improper irrigation practices and poor drainage, poses a significant threat to soil fertility and crop productivity. Salinity-aware irrigation strategies prioritize the maintenance of optimal soil salinity levels through controlled water application, leaching management, and the use of high-quality irrigation water. Unlike conventional approaches that may inadvertently concentrate salts in the root zone, these strategies employ precision leaching fractions to flush excess salts beyond the effective rooting depth while minimizing water wastage. The integration of soil salinity sensors and geospatial mapping tools facilitates real-time monitoring of salt distribution patterns, enabling targeted interventions (Sahbeni, Ngabire *et al.,*2023). Additionally, the adoption of cyclic irrigation with saline and non-saline water sources has shown promise in mitigating salt accumulation while conserving freshwater resources. Soil health management practices, including the application of organic amendments, biochar, and gypsum, further enhance soil structure, improve permeability, and promote microbial activity, collectively contributing to salinity mitigation. Moreover, crop selection and breeding efforts focusing on salt-tolerant cultivars complement irrigation-based interventions, creating a synergistic approach to managing salinity stress. The integration of these strategies within a broader sustainability framework ensures that irrigation practices not only address immediate salinity challenges but also contribute to the long-term restoration of soil health and ecosystem functionality (Enahoro-Ofagbe, Ewansiha *et al.,*2025).

5.3 Irrigation-Disease-Pest Interaction Dynamics

Irrigation practices exert a profound influence on the dynamics of plant diseases and pest populations, often acting as a critical determinant of microclimatic conditions within the crop canopy. Excessive or poorly timed irrigation can create humid environments conducive to the proliferation of fungal pathogens, while water-stressed plants may become more susceptible to insect infestations due to compromised defense mechanisms. Understanding the intricate interplay between irrigation, plant health, and biotic stressors is therefore essential for developing integrated water management strategies (Pérez-Méndez, Miguel-Rojas *et al.,*2021). Precision irrigation techniques, such as drip and subsurface irrigation, have been shown to reduce leaf wetness duration and limit pathogen spread compared to traditional flood or sprinkler systems. Additionally, irrigation scheduling based on disease forecasting models and pest risk indices enables proactive mitigation of biotic stress outbreaks. For instance, avoiding irrigation during periods of high pathogen activity or synchronizing water application with pest life cycles can significantly reduce infestation risks. Emerging approaches leverage data-driven decision support systems that integrate climatic data, crop growth models, and pest surveillance information to optimize irrigation timing and volume. This holistic perspective not only enhances crop resilience but also reduces reliance on chemical control measures, thereby contributing to environmentally sustainable agricultural practices (Roberts and Mattoo 2018).

5.4 Water Use Efficiency (WUE) and Productivity Optimization

Water use efficiency (WUE) has become a central metric in evaluating the sustainability of irrigation systems, reflecting the ratio of biomass or yield produced per unit of water consumed. Optimizing WUE requires a multifaceted approach that encompasses technological innovation, agronomic practices, and system-level management (Meena, Karnam *et al.,*2024). Advances in precision agriculture, including sensor-based irrigation, automated control systems, and machine learning algorithms, have significantly improved the accuracy of water application, reducing losses due to evaporation, runoff, and deep percolation. At the crop level, strategies such as optimized planting density, mulching, and nutrient management enhance water retention and improve physiological water use. The integration of deficit irrigation techniques with high-efficiency delivery systems, such as drip irrigation, further amplifies WUE by ensuring that water is delivered directly to the root zone with minimal wastage. Productivity optimization extends beyond maximizing yield to include considerations of resource efficiency, environmental impact, and economic viability. Metrics such as water productivity, energy use efficiency, and carbon footprint are increasingly incorporated into sustainability assessments, providing a comprehensive evaluation of irrigation performance. By aligning irrigation practices with these multidimensional objectives, it is possible to achieve a balance between agricultural productivity and environmental stewardship, ensuring the long-term sustainability of water resources in agroecosystems (Boutagayout, Hamdani *et al.,*2025).

6. Challenges, Scalability, and Future Innovations

The transition toward intelligent irrigation systems represents a paradigm shift in agricultural water management; however, its large-scale adoption remains constrained by a combination of structural, technological, and socio-economic barriers. While remote sensing, GIS, IoT, and AI-driven decision support systems have demonstrated substantial potential in enhancing irrigation precision and resilience, their scalability across heterogeneous agro-ecological landscapes is far from uniform. The complexity of integrating multi-source datasets, ensuring affordability for smallholder farmers, and building technical capacity at grassroots levels continues to limit widespread implementation. Moreover, the evolving pressures of climate variability necessitate a forward-looking framework that not only addresses present limitations but also anticipates the emergence of fully autonomous, adaptive irrigation ecosystems capable of operating under uncertain environmental conditions (Granata and Di Nunno 2026). This section critically evaluates the key constraints impeding scalability and outlines future innovation pathways that can enable the transition toward resilient and self-regulating irrigation infrastructures.

6.1 Data Accessibility, Infrastructure, and Cost Barriers

A fundamental challenge in the deployment of smart irrigation systems lies in the accessibility and reliability of high-resolution, real-time data. Advanced irrigation frameworks heavily depend on multi-layered datasets, including satellite imagery, soil moisture indices, meteorological parameters, and crop-specific physiological indicators. While platforms such as NASA and European Space Agency have significantly democratized access to remote sensing data through missions like Landsat and Sentinel-2, challenges persist in terms of spatial resolution, temporal frequency, and data preprocessing requirements. In many developing regions, intermittent internet connectivity and lack of cloud-based computational infrastructure further exacerbate the difficulty of leveraging such datasets effectively (Singh, Buyya *et al.,*2024). Infrastructure limitations extend beyond digital connectivity to include the physical deployment of sensors, automated irrigation systems, and energy sources. IoT-based soil moisture sensors, weather stations, and actuators require stable power supplies, often necessitating additional investments in solar or hybrid energy systems. For smallholder farming systems, which dominate in regions such as South Asia and Sub-Saharan Africa, the initial capital expenditure associated with installing such infrastructure can be prohibitive. Even when subsidized, maintenance costs, calibration requirements, and system upgrades pose long-term financial burdens. Cost barriers are also amplified by the need for proprietary software, licensing fees, and specialized analytical tools. Although open-source platforms such as QGIS and Google Earth Engine offer viable alternatives, their effective utilization still demands technical proficiency. Consequently, the digital divide between technologically advanced agricultural systems and resource-limited farming communities continues to widen, raising concerns about equitable access to smart irrigation technologies.

6.2 Technical Complexity and Capacity-Building Requirements

The integration of diverse technological components ranging from remote sensing and GIS to machine learning and IoT introduces a significant level of technical complexity that can hinder adoption. Smart irrigation systems require seamless interoperability between hardware and software components, real-time data processing pipelines, and robust decision-support algorithms. Designing and maintaining such integrated systems necessitates expertise across multiple disciplines, including hydrology, agronomy, data science, and systems engineering. Machine learning models, for instance, are increasingly employed to predict evapotranspiration rates, soil moisture dynamics, and crop water requirements (Chang, Zhang *et al.,*2025). However, the development of accurate and generalizable models requires large, high-quality datasets and continuous validation under diverse environmental conditions. Moreover, the "black-box" nature of many AI algorithms can limit transparency and trust among end-users, particularly farmers who may be reluctant to rely on automated recommendations without clear interpretability. Capacity-building thus emerges as a critical prerequisite for successful implementation. Farmers, extension workers, and policymakers must be equipped with the knowledge and skills necessary to operate, interpret, and adapt smart irrigation systems. Training programs, digital literacy initiatives, and participatory technology development approaches are essential to bridge this gap. Institutions such as Food and Agriculture Organization have emphasized the importance of knowledge transfer and stakeholder engagement in scaling climate-smart agriculture practices. However, existing efforts remain fragmented and often fail to reach marginalized farming communities. Another layer of complexity arises from the need to customize irrigation solutions to local agro-climatic conditions. Variability in soil types, cropping patterns, and water availability necessitates context-specific calibration of models and systems. This localization requirement further complicates scalability, as solutions developed in one region may not be directly transferable to another without significant adaptation (Liu, Yang *et al.,*2010).

6.3 Pathways Toward Autonomous, Climate-Resilient Irrigation Ecosystems

Looking ahead, the evolution of smart irrigation systems is expected to converge toward fully autonomous, climate-resilient ecosystems that integrate advanced sensing, predictive analytics, and adaptive control mechanisms. Such systems will leverage real-time data streams from satellites, drones, and ground-based sensors to continuously monitor environmental conditions and dynamically adjust irrigation schedules. The integration of AI-driven decision-making frameworks will enable predictive irrigation, where water application is optimized based on anticipated weather patterns, crop growth stages, and soil moisture trends. Emerging technologies such as digital twins—virtual replicas of physical agricultural systems hold significant promise in simulating irrigation scenarios and optimizing resource allocation. By combining geospatial data with process-based models, digital twins can facilitate scenario analysis under varying climate conditions, enabling proactive decision-making (Kussul, Giuliani *et al.,*2025). Additionally, blockchain technology is being explored for transparent water resource management, ensuring equitable distribution and accountability in irrigation networks. Climate resilience will also depend on the incorporation of adaptive strategies that account for increasing variability in precipitation patterns, temperature extremes, and water scarcity. Integration with climate forecasting systems and early warning mechanisms can enhance the responsiveness of irrigation systems to extreme events such as droughts and floods. Furthermore, decentralized irrigation architectures powered by renewable energy sources can reduce dependency on centralized infrastructure and enhance system robustness. Policy frameworks and institutional support will play a decisive role in enabling these future pathways. Investments in rural digital infrastructure, subsidies for smart irrigation technologies, and the promotion of public–private partnerships can accelerate adoption. Collaborative initiatives involving organizations such as the World Bank and International Water Management Institute are already working toward scaling sustainable water management solutions globally. In conclusion, while significant challenges persist, the convergence of technological innovation, capacity-building efforts, and supportive policy environments can pave the way for next-generation irrigation systems. These systems, characterized by autonomy, adaptability, and resilience, have the potential to transform agricultural water management and ensure sustainable food production in the face of escalating climate uncertainties.

CONCLUSION

The convergence of remote sensing, geospatial intelligence, and artificial intelligence has redefined irrigation paradigms by enabling data-driven, adaptive, and stress-responsive water management systems. This review elucidates how multiscale data ecosystems, predictive modeling frameworks, and autonomous control architectures collectively enhance water-use efficiency while mitigating both biotic and abiotic stressors. Despite substantial advancements, challenges related to data accessibility, infrastructure limitations, and model generalizability continue to constrain large-scale implementation, particularly in resource-limited agroecosystems. Future trajectories lie in the development of interoperable, low-cost sensor networks, explainable AI models, and decentralized irrigation infrastructures powered by renewable energy systems. The integration of digital twins, climate forecasting, and real-time decision-support platforms will further accelerate the transition toward self-regulating irrigation ecosystems. Ultimately, achieving sustainable intensification in agriculture will depend on bridging technological innovation with policy support and capacity-building initiatives, ensuring that smart irrigation systems are not only efficient and resilient but also equitable and globally scalable.

REFERENCES

- Aderele, M. O., *et al.,*(2025). "Integrating machine learning with agroecosystem modelling: Current state and future challenges." European Journal of Agronomy 168: 127610.
- Ali, M. U. (2025). "Water Use Efficiency and Irrigation Innovations in Crop Systems." International Journal of Environment and Climate Change 15(11): 492–499.
- Amir, M. A., Ullah, Q., Haidri, I., Haider, W., Qasim, M., Promwee, A., ... & Khan, A. (2026). Oleosin-coated nanocarriers enhance mycorrhizal-mediated pollinator forage and sunflower productivity under neonicotinoid stress. *Plant Growth Regulation*, *106*(1), 41.
- Asner, G. P. (2008). Hyperspectral remote sensing of canopy chemistry, physiology, and biodiversity in tropical rainforests. Hyperspectral remote sensing of tropical and sub-tropical forests, CRC Press: 261–296.
- Batini, C. and M. Scannapieco (2016). "Data and information quality." Cham, Switzerland: Springer International Publishing 63.
- Bebber, D. P., *et al.,*(2014). "The global spread of crop pests and pathogens." Global Ecology and Biogeography 23(12): 1398–1407.
- Bendig, J., *et al.,* (2013). "UAV-based imaging for multi-temporal, very high-resolution crop surface models to monitor crop growth variability." Unmanned aerial vehicles (UAVs) for multi-temporal crop surface modelling 44.
- Boutagayout, A., *et al.,* (2025). "Advancing agroecology for sustainable water management: a comprehensive review and future directions in North African countries." Water Conservation Science and Engineering 10(1): 22.
- Chang, Y., *et al.,* (2025). "Machine learning for reference crop evapotranspiration modeling: a state-of-the-art review and future directions." Agronomy 15(9): 2038.
- Chaudhary, A., Bashir, W., Majid, A., Qasim, M., Bughio, E., Fatima, M., & Din, S. U. (2025). PFAS insights: A review of historical data, environmental applications, health effects, and pollution challenges in Pakistan. *Environmental Science & Policy*, *167*, 104056.

- Chen, C., *et al.,* (2020). "Deep learning on computational-resource-limited platforms: A survey." Mobile Information Systems 2020(1): 8454327.
- Clement, W. J. J., *et al.,*(2025). "Exploring the perilous nature of Phytophthora: Insights into its biology, host range, detection, and integrated management strategies in the fields of spices and plantation crops." The Plant Pathology Journal 41(2): 121.
- Del-Coco, M., *et al.,*(2024). "Machine learning for smart irrigation in agriculture: How far along are we?" Information 15(6): 306.
- Enahoro-Ofagbe, F. E., *et al.,* (2025). "Integrating irrigation management and soil remediation practices for sustainable agricultural production: advances, challenges, and future directions." Agroecology and Sustainable Food Systems 49(9): 1568–1594.
- Faazal, B., Qasim, M., Mumtaz, S., Iftikhar, M., Khalid, I., Muzaffar, M. J., ... & Adrees, M. (2023). Crop quality and quantity as influenced by important air pollutants in Pakistan. In *Advances in Botanical Research* (Vol. 108, pp. 109-144). Academic Press.
- Franco-Navarro, J. D., *et al.,* (2025). "Advancements in Water-Saving strategies and crop adaptation to drought: A comprehensive review." Physiologia plantarum 177(4): e70332.
- Granata, F. and F. Di Nunno (2026). "Pathways for hydrological resilience: strategies for adaptation in a changing climate." Earth Systems and Environment 10(1): 203–231.
- Haidri, I., Ullah, Q., Qasim, M., Amir, M. A., Haider, W., Nguyen, H. H., & Promwee, A. (2026). Microbiome-Mediated Cd Stabilization in Chilli Pepper: Roles of Capsaicinoids and Cultivar Genetics Under Environmental Stress. *Plants*, *15*(4), 630.
- Hatfield, J. L. and C. Dold (2019). "Water-use efficiency: advances and challenges in a changing climate." Frontiers in plant science 10: 103.
- Hsu, C.-C. and Y.-P. Lin (2024). "Incorporating long-term numerical weather forecasts to quantify dynamic vulnerability of irrigation supply system: A case study of Shihmen Reservoir in Taiwan." Agricultural Water Management 306: 109178.
- Ines, A. V., *et al.,*(2002). "Application of GIS and crop growth models in estimating water productivity." Agricultural Water Management 54(3): 205–225.
- Khan, A., *et al.,* (2026). "Genomics and precision agronomic."
- Khan, M. N., *et al.,*(2019). "Seed priming with melatonin coping drought stress in rapeseed by regulating reactive oxygen species detoxification: Antioxidant defense system, osmotic adjustment, stomatal traits and chloroplast ultrastructure perseveration." Industrial Crops and Products 140: 111597.
- Kussul, N., *et al.,* (2025). Digital Twins for Land Use Change. System Analysis and Data Mining, Springer: 371–389.
- Lamichhane, M., *et al.,* (2025). "Soil moisture prediction using remote sensing and machine learning algorithms: A review on progress, challenges, and opportunities." Remote Sensing 17(14): 2397.
- Liu, Y., *et al.,* (2010). "Location, localization, and localizability." Journal of computer science and technology 25(2): 274–297.
- Livellara, N., *et al.,* (2011). "Plant based indicators for irrigation scheduling in young cherry trees." Agricultural Water Management 98(4): 684–690.
- Mahlein, A.-K. (2016). "Plant disease detection by imaging sensors–parallels and specific demands for precision agriculture and plant phenotyping." Plant disease 100(2): 241–251.
- Marri, V. D., *et al.,*(2021). "RNN-based multispectral satellite image processing for remote sensing applications." International Journal of Pervasive Computing and Communications 17(5): 583–595.
- Maurya, S. K., *et al.,*(2024). "Irrigation scheduling and cultivar management for increasing water productivity under dryland condition: a review." International Journal of Environment and Climate Change 14(1): 461–470.
- Meena, R. P., *et al.,*(2024). "Practical approaches to enhance water productivity at the farm level in Asia: A review." Irrigation and Drainage 73(2): 770–793.
- Mehta, P. (2024). "The impact of climate change on the environment, water resources, and agriculture: a comprehensive review." Climate, Environment and Agricultural Development: A Sustainable Approach Towards Society: 189–201.
- Morchid, A., *et al.,* (2024). "IoT-based smart irrigation management system to enhance agricultural water security using embedded systems, telemetry data, and cloud computing." Results in Engineering 23: 102829.
- Olasehinde, A. A., *et al.,*(2023). "Cyber-physical system integration for autonomous decision-making in sensor-rich indoor cultivation environments." World Journal of Advanced Research and Reviews 20(2): 1563–1584.
- Pérez-Méndez, N., *et al.,*(2021). "Plant breeding and management strategies to minimize the impact of water scarcity and biotic stress in cereal crops under Mediterranean conditions." Agronomy 12(1): 75.
- Povey, A. and R. Grainger (2015). "Known and unknown unknowns: uncertainty estimation in satellite remote sensing." Atmospheric Measurement Techniques 8(11): 4699–4718.
- Qasim, M., Manzoor, S., Nabeel, M. I., Hussain, S., Waqas, R., Joseph, C. G., & Suazo-Hernández, J. (2025). Harnessing High-Valent Metals for Catalytic Oxidation: Next-Gen Strategies in Water

Remediation and Circular Chemistry. *Catalysts*, *15*(12), 1168.

- Qasim, M., Manzoor, S., Nabeel, M. I., Ullah, Q., Sair, Y. Z., Khomphet, T., ... & Gulzar, T. (2026). Waste-Derived Nanocomposites as Dual-Function Materials for Water and Energy Sustainability. *Frontiers in Sustainability*, *7*, 1777462.
- Ray, D. K., *et al.,* (2019). "Climate change has likely already affected global food production." PloS one 14(5): e0217148.
- Ren, A., *et al.,* (2025). Integrated UAV and Satellite Remote Sensing: A Survey on Integration Strategies and Data Fusion Methods. IGARSS 2025-2025 IEEE International Geoscience and Remote Sensing Symposium, IEEE.
- Ren, C. (2026). "The scientific evolution, technological system construction, and future frontiers of precision soil nutrient management." Advances in Resources Research 6(2): 1201–1229.
- Roberts, D. P. and A. K. Mattoo (2018). "Sustainable agriculture—Enhancing environmental benefits, food nutritional quality and building crop resilience to abiotic and biotic stresses." Agriculture 8(1): 8.
- Rodriguez-Galiano, V. F., *et al.,*(2012). "An assessment of the effectiveness of a random forest classifier for land-cover classification." ISPRS journal of photogrammetry and remote sensing 67: 93–104.
- Sahbeni, G., *et al.,* (2023). "Challenges and opportunities in remote sensing for soil salinization mapping and monitoring: A review." Remote Sensing 15(10): 2540.
- Singh, N., *et al.,* (2024). "Securing cloud-based internet of things: challenges and mitigations." Sensors 25(1): 79.
- Sipp, D. and P. J. Schmid (2016). "Linear closed-loop control of fluid instabilities and noise-induced perturbations: a review of approaches and tools." Applied Mechanics Reviews 68(2): 020801.
- Srivastava, A. and S. Jain (2025). Remote Sensing for Environment Assessment: Multispectral, Hyperspectral, and Thermal Imaging Applications. Remote Sensing for Environmental Monitoring, Springer: 1–31.
- Trigka, M. and E. Dritsas (2025). "Edge and cloud computing in smart cities." Future Internet 17(3): 118.
- Ullah, Q., Haider, W., Qasim, M., Waqar, M., Khomphet, T., & Farid, M. (2026). Nano-charged resilience: harnessing chitosan-based nanomaterials for enhanced vegetable crop adaptation in sustainable agriculture. *Environmental Science: Advances*, *5*(2), 393-410.
- Ullah, Q., Sajad, M., Qasim, M., Khomphet, T., Haider, W., Defri, I., & Waqar, M. (2026). Irrigation Management Through Smart Water Solutions. In *Artificial Intelligence and Data Sciences for Precision Agriculture* (pp. 257-273). Cham: Springer Nature Switzerland.
- Ullah, Q., Waqar, M., Sajad, M., Qasim, M., & Khomphet, T. (2025). Emerging Trends in Challenges in Technological Innovation for Sustainable Water Management. *Emerging Contaminants in the Aquatic Environment: Global Overview*, 193-225.
- Van der Meer, F. (2012). "Remote-sensing image analysis and geostatistics." International Journal of Remote Sensing 33(18): 5644–5676.
- Wang, X., *et al.,* (2026). "Digital Agriculture: Past, Present, and Future." Advanced Intelligent Discovery: e202500193.
- Waseem, M., Qasim, M., Rahul, F., Zahoor, M., Rizvi, S. M. J. R., Qadir, M. S., ... & Muhammad, W 2025. Soil Microorganisms' Role in Enhancing Soil Fertility and Plant Health. *Integrated Health and Sustainability: Plants, Wildlife, and Genetic Resilience*, 190.
- Yuan, X., *et al.,* (2015). "A review on climate-model-based seasonal hydrologic forecasting: Physical understanding and system development." Wiley Interdisciplinary Reviews: Water 2(5): 523–536.
- Zaidi, P. H., *et al.,*(2026). Does Breeding for Abiotic Stress Tolerance Mitigate G× E Interactions Under a Changing Climate? Genotype x Environment Interactions and its Implications for Plant Breeding, Springer: 149–185.
- Zhang, C. and J. M. Kovacs (2012). "The application of small unmanned aerial systems for precision agriculture: a review." Precision agriculture 13(6): 693–712.