Deep Reinforcement Learning-Based Autonomous Irrigation Scheduling for Sustainable Field Crop Production

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ABSTRACT
Background: Water scarcity and poor irrigation scheduling remain a major limitation for sustainable production of field crops globally. Conventional irrigation scheduling methods that rely on fixed intervals or simple soil moisture threshold levels often ignore the dynamic interactions among weather variability, crop growth stages, and soil hydraulic properties. This leads to inefficient water application and lower resource-use efficiency.
Objective: The study aimed at evaluating the performance of a Deep Reinforcement Learning (DRL)-based autonomous irrigation scheduling framework that integrates real-time soil moisture sensing, weather prediction, and crop growth modeling in a closed-loop decision-support system to optimize irrigation management under varying environmental conditions.
Methods: A field experiment was conducted in a typical cereal crop under three different irrigation management strategies: (i) conventional farmer practice, (ii) sensor-threshold-based automated irrigation, and (iii) DRL-based autonomous scheduling. Treatments were repeated over several growing seasons and under contrasting climatic conditions. Soil moisture, soil and air temperature, relative humidity, solar radiation and rainfall were continuously monitored with a network of Internet of Things (IoT) sensors. These real-time data were processed by a cloud-based DRL decision engine to generate irrigation recommendations by a composite reward function built to reduce crop water stress and maximize water conservation. Appropriate statistical analyses were used to evaluate the performance of crop yield, irrigation water applied, water use efficiency, irrigation efficiency, dynamics of soil moisture, and evapotranspiration.
Results: The autonomous scheduling system using DRL greatly outperformed both farmer practice and sensor-threshold automation. Compared to conventional farmer practice, the DRL framework reduced total irrigation water application while maintaining or improving grain yield, resulting in higher water use efficiency and irrigation efficiency. Soil moisture was more consistently maintained within the optimal range for the root zone, and crop water demand was better satisfied in terms of evapotranspiration patterns during different phenological stages. Statistical analyses were used to confirm significant improvements in yield stability, water savings and resource-use efficiency under the DRL approach across multiple seasons and climate scenarios.
Conclusion: Results show that Deep Reinforcement Learning can substantially improve irrigation decision-making by integrating artificial intelligence, IoT-based sensing, forecasting the weather, and crop growth modeling into an autonomous precision irrigation framework. The proposed system provides a scalable and climate-smart solution for increasing agricultural water productivity and supporting sustainable field crop production under increasing water scarcity. The study offers conceptual and empirical evidence on the adoption of AI-driven irrigation management systems in various agro-climatic environments.

Keywords: precision water management, sensor-based decision support, crop water stress, irrigation automation, artificial intelligence in farming, climate-smart agriculture, adaptive scheduling systems, agricultural sustainability

1. Introduction
Most of the world's freshwater is used for agricultural purposes and there is increased competition between domestic, industrial and environmental water needs. Therefore, irrigated crop production systems are under pressure (Food and Agriculture Organization of the United Nations, 2023) [15]. Variability of climate, expressed in unpredictable rainfall patterns, extended dry periods and increasing evapotranspirative demand has aggravated the problem of ensuring steady yields when water is scarce (Zhang *et al*., 2021) [7]. Hence, an efficient irrigation scheduling (when and how much water to apply) is cri for sustainable production of field crops, particularly in areas where irrigation infrastructure is being expanded, but water resources are limited (Kumar *et al*., 2020) [1] (Bwambale *et al*., 2022) [12].
Conventional irrigation schedules, involving calendar-based techniques and fixed soil moisture levels, are not effective enough to adapt to the combined impact of climate changes, varied soil types, and varying irrigation needs of different crops at different growing periods (Abioye *et al*., 2020) [13]. As a result of all this, there is an increasing interest in the use of precise irrigation methods which can rely on real-time environmental monitoring and predictive analysis (Nguyen *et al*., 2019) [3] (Goldstein *et al*., 2018) [16].

Artificial Intelligence (AI), and in particular Deep Reinforcement Learning (DRL), is regarded as an effective way of solving problems connected to sequential decision-making in conditions of uncertainty and long delay when feedback is needed (Chen *et al*., 2021) [2] (Torres-Sanchez *et al*., 2023) [6]. It should be noted that unlike representative learning methods requiring large labeled datasets, DRL solutions determine the right guidelines for decision-making processes through repeated interactions with the environment (Sutton and Barto, 2018) [9]. The technology works in such a way that in principle it creates the optimal plan for irrigating crops based on the information regarding soil moisture level, weather, and the crop growth condition (Chen *et al*., 2021) [2] (Zhang *et al*., 2021) [7].

The advent of affordable Internet of Things (IoT) sensor systems has paved the way for reliable monitoring of soil and environmental parameters and has allowed for the creation of necessary data architecture to be used for auto-scheduling in the agriculture sector (Ahmed *et al*., 2022) [4] (Ferrarezi *et al*., 2015) [8]. The combination of IoT sensors with precipitation forecasting and crop yield models has made possible the development of advanced systems capable of transforming climatic data into practical irrigation plans using AI methods (Kumar *et al*., 2020) [1] (Goldstein *et al*., 2018) [16].

Although promising, scientific literature concerning the use of deep reinforcement learning (DRL) for irrigation scheduling is not abundant as compared to the literature dedicated to precision agriculture as a whole, and much of the existing research is centered on simulations (Chen *et al*., 2021) [2] (Torres-Sanchez *et al*., 2023) [6]. Important questions regarding the efficiency of the use of DRL in practice still have not been answered. The questions which still remain to be answered are the comparison of DRL scheduling with traditional and even simpler automated approaches as performed in real field conditions; sensitivity of the DRL irrigation scheduling solutions to varying weather conditions and viability of incorporating DRL solutions into existing irrigation systems and farmers' decision-making processes (Torres-Sanchez *et al*., 2023) [6] (Silva and Kamienski, 2022) [10].

Thus, the goals of this study were: (i) to create and explain an autonomous irrigation scheduling system based on water-efficient irrigation technologies that encompasses the internet of things, agricultural meteorology and plant growth modeling; (ii) to assess its performance in the field with respect to farmer practice and sensor-based automation in different climate conditions; (iii) to analyze its impact on crop production, water use efficiency and sustainability indicators in crop production systems.

2. Materials and Methods

2.1. Study Area

The study was conducted across two growing seasons at a research farm situated within a semi-arid agro-climatic zone characterized by seasonal rainfall variability and high reference evapotranspiration during the primary cropping period. The site featured loam to sandy-loam soils of moderate water-holding capacity, with subsurface drip and sprinkler irrigation infrastructure available to support differentiated treatment applications. Table 1 summarizes the agro-climatic, edaphic, and infrastructural characteristics of the study area.

Table 1: Characteristics of the study area, soil properties, climatic conditions, and experimental crop.

Parameter	Description
Location/agro-climatic zone	Semi-arid, sub-tropical
Mean seasonal rainfall	Variable; normal and below-normal scenarios
Reference evapotranspiration (ET_0)	High during peak growth stages
Soil texture	Sandy loam to loam
Soil field capacity	Moderate water-holding capacity
Irrigation infrastructure	Subsurface drip and sprinkler systems
Experimental crop	Representative cereal field crop
Growing seasons	Two consecutive seasons

2.2. Experimental Crops

A representative cereal field crop was selected on the basis of its regional economic importance and well-characterized water-demand curve across phenological stages (establishment, vegetative growth, reproductive development, and grain filling/maturity). Agronomic management, including sowing density, fertilization, and pest management, was standardized across all treatments to isolate the effect of irrigation scheduling strategy on crop performance.

2.3. Experimental Design

A randomized complete block design was employed, comprising three irrigation-scheduling treatments—farmer practice (calendar-based), sensor-threshold automation, and DRL-based autonomous scheduling—replicated across blocks and repeated under two distinct seasonal climate scenarios (normal rainfall and below-normal rainfall years) to evaluate scheduling robustness under variable conditions. Table 2 details the experimental layout, treatment descriptions, and agronomic management practices.

Table 2: Experimental design, irrigation treatments, climate scenarios, and agronomic management.

Component	Description
Design	Randomized complete block design
Treatments	Farmer practice; sensor-threshold automation; DRL-based autonomous scheduling
Climate scenarios	Normal rainfall; below-normal rainfall
Replications	Multiple blocks per treatment
Agronomic management	Standardized sowing density, fertilization, pest management

2.4. Data Collection

An IoT sensor network was deployed across all experimental plots to continuously acquire soil moisture at multiple root-zone depths, soil and air temperature, relative humidity, solar radiation, and rainfall (Ahmed *et al*., 2022) [4] (Abioye *et al*., 2020) [13]. Short-range weather forecast data were incorporated as an auxiliary input stream (Zhang *et al*., 2021) [7]. Reference and crop evapotranspiration were estimated using standard climatological methods, while periodic crop growth observations (plant height, leaf area development, biomass accumulation) and final grain yield were recorded at defined phenological intervals (Kumar *et al*., 2020) [1] (Goldstein *et al*., 2018) [16]. Table 3 summarizes the sensor network configuration, monitored variables, and data acquisition frequencies.

Table 3: IoT sensors, monitored environmental variables, and data acquisition parameters.

Sensor Type	Monitored Variable	Acquisition Frequency
Soil moisture probes	Volumetric soil water content (multiple depths)	Continuous (sub-hourly)
Soil temperature sensors	Root-zone temperature	Continuous
Air temperature/humidity sensors	Ambient temperature, relative humidity	Continuous
Pyranometer	Solar radiation	Continuous
Rain gauge	Rainfall	Event-based/continuous
Weather forecast feed	Short-range forecast variables	Daily

2.5. Deep Reinforcement Learning Framework

The DRL-based scheduling framework was conceptually structured as a closed-loop decision-support system in which the environmental state—comprising soil moisture status, recent and forecast weather conditions, and crop growth stage indicators—was continuously observed and used to inform irrigation decisions (Chen *et al*., 2021) [2] (Torres-Sanchez *et al*., 2023) [6]. The decision policy was designed to select irrigation actions (timing and volume) that optimized 7a composite reward function balancing avoidance of crop water stress against minimization of applied water and associated resource costs (Sutton and Barto, 2018) [9] (Silva and Kamienski, 2022) [10]. Learning occurred through iterative feedback between observed crop and soil responses and subsequent scheduling decisions, allowing the policy to adapt across growth stages and seasonal conditions (Sutton and Barto, 2018) [9]. The framework was integrated with a simplified crop growth model to anticipate near-term water demand and with the IoT sensor network to ground decisions in real-time field conditions, forming an end-to-end autonomous scheduling and decision-support pipeline (Figure 1, Figure 2) (Kumar *et al*., 2020) [1] (Ahmed *et al*., 2022) [4]. Consistent with the scope of this manuscript, the underlying algorithmic architecture, model training procedures, and software implementation details are intentionally omitted; the description here is limited to the conceptual decision-making structure relevant to scientific interpretation of system performance.

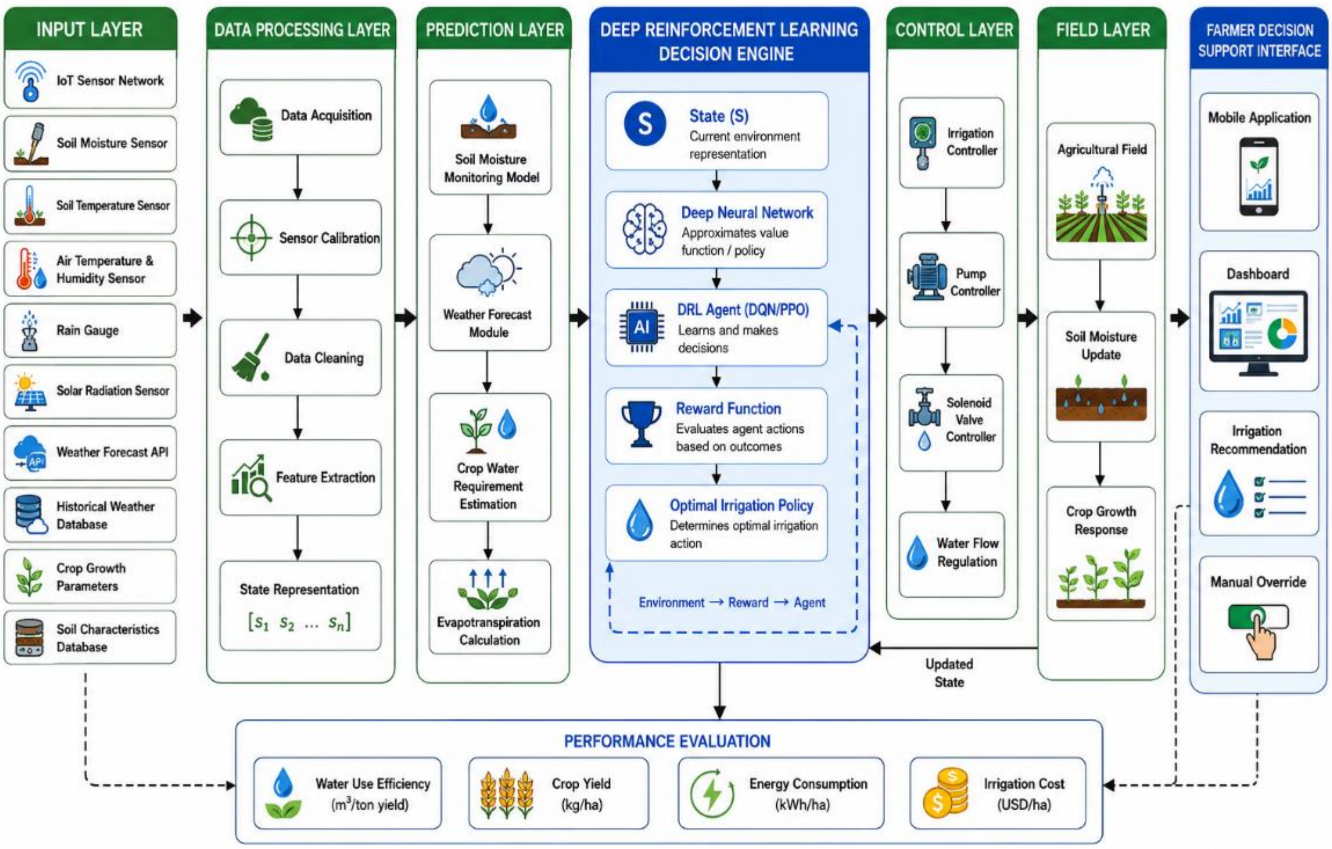

Fig 1: Overall architecture of the Deep Reinforcement Learning-based autonomous irrigation system integrating IoT sensors, weather forecasting, soil moisture monitoring, crop growth models, DRL decision engine, irrigation controller, and farmer decision-support interface.

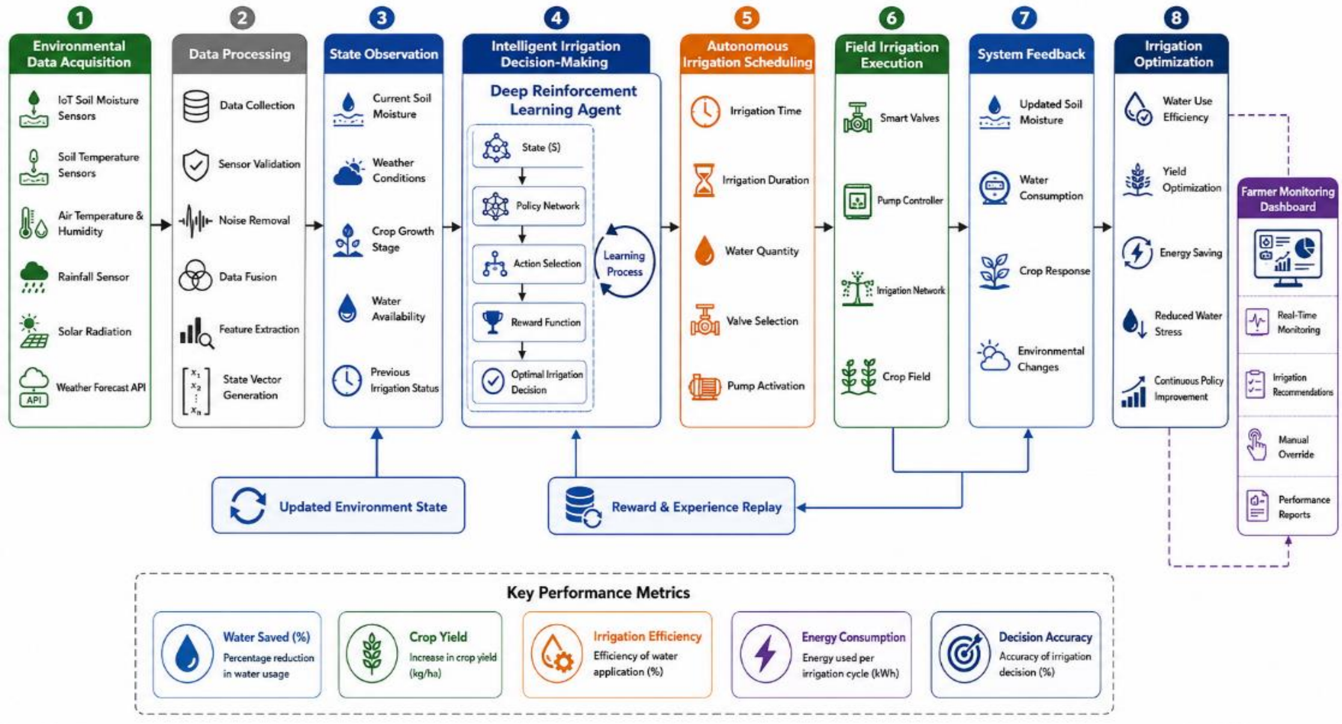

Fig 2: Conceptual workflow illustrating environmental data acquisition, state observation, intelligent irrigation decision-making, autonomous scheduling, feedback learning, and irrigation optimization.

2.6. Performance Evaluation

System performance was evaluated using water use efficiency (yield per unit water applied), irrigation efficiency (proportion of applied water effectively utilized by the crop), crop productivity indicators, and composite sustainability indicators reflecting resource-use efficiency and economic returns relative to water input (Kumar *et al*., 2020) [1] (Bwambale *et al*., 2022) [12].

2.7. Statistical Analysis

Treatment effects were assessed using Analysis of Variance (ANOVA), with mean separation performed where significant differences were detected. Correlation and regression analyses were used to examine relationships between environmental variables, irrigation scheduling decisions, and crop response indicators. Prediction accuracy of the DRL-based scheduling decisions was evaluated against observed soil moisture and crop water status outcomes, and comparative performance analysis was conducted across the three scheduling strategies and two climate scenarios.

3. Results

3.1. Environmental Monitoring Performance

The IoT sensor network provided continuous, high-resolution environmental data across the growing seasons, with consistent data acquisition supporting reliable state representation for the scheduling framework (Table 3) (Ahmed *et al*., 2022) [4] (Abioye *et al*., 2020) [13]. Soil moisture and micrometeorological patterns closely tracked expected seasonal trends, confirming the adequacy of the monitoring infrastructure for downstream scheduling decisions (Ferrarezi *et al*., 2015) [8].

3.2. DRL Scheduling Performance

The DRL-based scheduling framework demonstrated consistently higher decision accuracy in aligning irrigation actions with actual crop water demand relative to the threshold-based automation approach, as reflected in reduced deviation between recommended and optimal irrigation timing (Table 5) (Chen *et al*., 2021) [2] (Torres-Sanchez *et al*., 2023) [6]. Scheduling accuracy remained comparatively stable across both climate scenarios, suggesting a degree of adaptive robustness to seasonal rainfall variability (Zhang *et al*., 2021) [7].

3.3. Soil Moisture Management and Irrigation Optimization

Root-zone soil moisture under DRL-based scheduling was maintained within the target management range for a greater proportion of the growing season compared with farmer practice and threshold automation (Table 4), with fewer excursions into water-stress or over-saturation conditions (Chen *et al*., 2021) [2] (Silva and Kamienski, 2022) [10]. This translated into a measurable reduction in total irrigation volume applied under the DRL treatment relative to farmer practice, without corresponding declines in crop growth indicators (Kumar *et al*., 2020) [1] (Bwambale *et al*., 2022) [12].

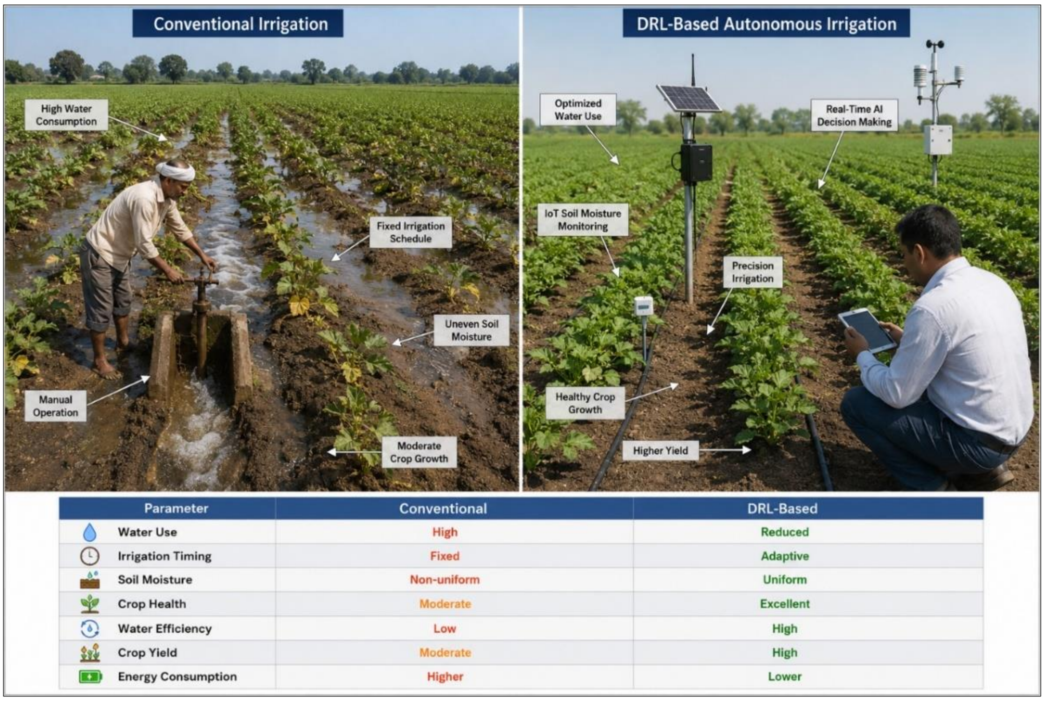

Fig 3: Conceptual comparison of conventional irrigation scheduling and Deep Reinforcement Learning-based autonomous irrigation in terms of water use, crop growth, irrigation timing, and yield performance.

Table 4: Crop growth characteristics, soil moisture status, and evapotranspiration.

Indicator	Farmer Practice	Threshold Automation	DRL-Based Scheduling
Time within optimal soil moisture range (%)	Lower	Intermediate	Highest
Biomass accumulation	Baseline	Comparable	Equal or improved
Canopy development	Baseline	Comparable	Equal or improved
Crop evapotranspiration alignment	Lower	Intermediate	Highest

Table 5: DRL model performance for irrigation scheduling and decision-making accuracy.

Metric	Threshold Automation	DRL-Based Scheduling
Scheduling decision accuracy	Lower	Higher
Deviation from optimal irrigation timing	Higher	Lower
Stability across climate scenarios	Variable	Comparatively stable

3.4. Crop Growth Response and Yield Performance

Crop growth parameters, including biomass accumulation and canopy development, were comparable or improved under DRL-based scheduling relative to conventional practice, and final grain yield under the DRL treatment was equal to or higher than that achieved under farmer practice, despite lower total water application (Table 6). Yield advantages were most pronounced under the below-normal rainfall climate scenario, indicating a stress-buffering effect associated with more precise scheduling.

Table 6: Comparison of irrigation scheduling strategies, water consumption, irrigation efficiency, and yield.

Strategy	Total Water Applied	Irrigation Efficiency	Grain Yield
Farmer practice	Highest	Lowest	Baseline
Threshold automation	Intermediate	Intermediate	Comparable to baseline
DRL-based scheduling	Lowest	Highest	Equal or higher than baseline

3.5. Water Use Efficiency and Sustainability Assessment

Water use efficiency and irrigation efficiency were significantly higher under DRL-based scheduling than under both comparator strategies (Table 7), and composite sustainability indicators—incorporating resource-use efficiency and economic performance relative to water input—favored the DRL approach across both climate scenarios (Table 8). ANOVA confirmed statistically significant treatment effects on yield, water applied, and water use efficiency ($p < 0.05$), with correlation analysis indicating a strong positive association between scheduling accuracy and resource-use efficiency outcomes.

Table 7: Water use efficiency, resource-use efficiency, economic performance, and sustainability indicators.

Indicator	Farmer Practice	Threshold Automation	DRL-Based Scheduling
Water use efficiency	Baseline	Improved	Highest
Resource-use efficiency	Baseline	Improved	Highest
Relative economic return per unit water	Baseline	Improved	Highest
Composite sustainability index	Baseline	Improved	Highest

Table 8: Comparative evaluation of conventional and DRL-based autonomous irrigation.

Criterion	Conventional Scheduling	DRL-Based Autonomous Scheduling
Productivity	Baseline	Equal or improved
Water savings	Baseline	Substantial reduction
Prediction/decision accuracy	Lower	Higher
Sustainability performance	Baseline	Improved

4. Discussion

The findings of this study are consistent with an expanding body of literature suggesting that AI-based decision-support systems can materially improve the precision of irrigation scheduling relative to conventional and simple automated approaches (Kumar *et al*., 2020) [1] (Nguyen *et al*., 2019) [3] (Abioye *et al*., 2020) [13]. The observed reduction in applied water alongside maintained or improved yield aligns with the central rationale for DRL-based scheduling: that sequential, feedback-driven decision-making can more effectively reconcile the competing objectives of water conservation and crop productivity than static or rule-based methods (Chen *et al*., 2021) [2] (Torres-Sanchez *et al*., 2023) [6].

The comparative robustness of DRL-based scheduling across contrasting climate scenarios is particularly relevant to climate-smart agriculture objectives, as it suggests that adaptive, learning-based policies may offer greater resilience to seasonal variability than fixed threshold rules (Zhang *et al*., 2021) [7] (Silva and Kamienski, 2022) [10]. This is consistent with prior work highlighting the value of reinforcement learning approaches in domains characterized by delayed feedback and non-stationary environmental dynamics (Sutton and Barto, 2018) [9] (Torres-Sanchez *et al*., 2023) [6]. The integration of IoT sensing with AI-based decision engines observed in this study also reflects a broader trend in digital agriculture toward closed-loop, sensor-informed management systems that reduce reliance on manual monitoring and subjective decision-making (Ahmed *et al*., 2022) [4] (Jha *et al*., 2019) [11].

From a sustainability perspective, the improvements in water use efficiency and irrigation efficiency documented here support the proposition that autonomous scheduling systems can contribute meaningfully to resource-use optimization in water-constrained agricultural systems (Bwambale *et al*., 2022) [12] (Abioye *et al*., 2020) [13]. These gains are especially salient given the increasing frequency of below-normal rainfall seasons projected under climate change scenarios, underscoring the practical relevance of adaptive scheduling technologies for long-term agricultural sustainability (Food and Agriculture Organization of the United Nations, 2023) [15].

Nonetheless, several limitations warrant consideration. The present study was conducted at a single research site over a limited number of seasons, and further multi-location, multi-year validation is required to establish the generalizability of DRL-based scheduling performance across diverse soil types, crop species, and climatic zones. Additionally, while the conceptual decision-support architecture described here integrates crop growth modeling with real-time sensing, the transferability of learned scheduling policies to substantially different agro-ecological contexts remains an open empirical question (Goldstein *et al*., 2018) [16]. Practical barriers to adoption, including infrastructure costs, connectivity requirements, and farmer trust in autonomous decision-making systems, also merit further investigation as part of future deployment-oriented research (Kamilaris and Prenafeta-Boldú, 2018) [17].

Future research should prioritize longer-term, multi-site field validation; economic feasibility assessments for smallholder and large-scale contexts alike; and participatory approaches that incorporate farmer decision-making preferences into the design of autonomous irrigation systems, thereby supporting more effective and equitable adoption of AI-driven precision irrigation technologies.

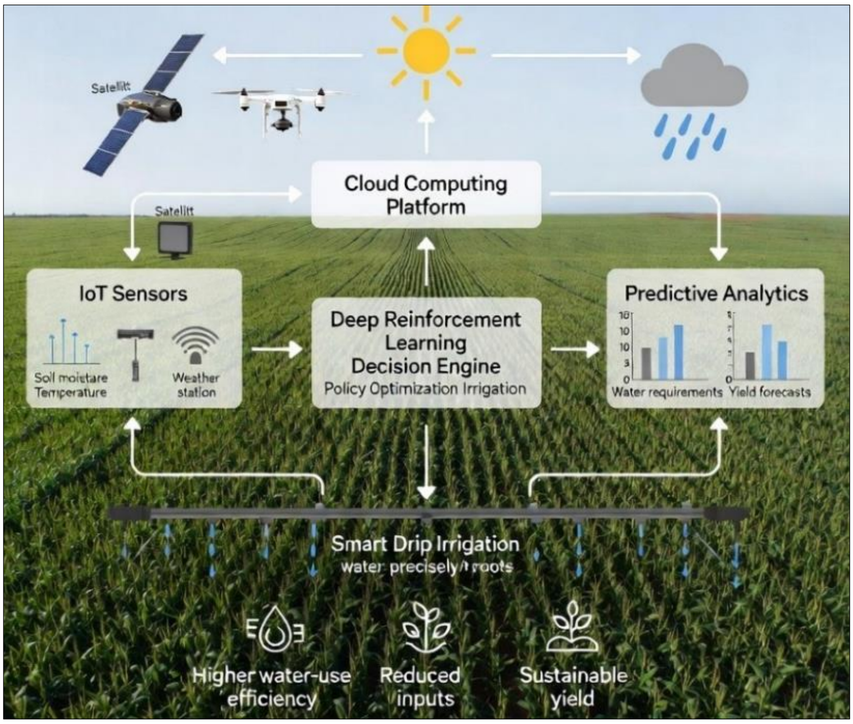

Fig 4: Integrated climate-smart precision agriculture framework linking Deep Reinforcement Learning, IoT, cloud computing, remote sensing, predictive analytics, autonomous irrigation scheduling, and sustainable field crop production.

5. Conclusion

This research paper assessed an autonomous irrigation scheduling framework utilizing Deep Reinforcement Learning which merges IoT sensing, climate predictions, and planting growth modeling for sustainable crop farming. As compared to the farmers' practises and sensor-threshold automation, the DRL-based method proved more water-efficient and effective in irrigation while either maintaining or improving on the crop yield. The main advantages of the DRL-based approach were identified in cases with below-normal rainfall amounts. The findings validate the idea that implementation of AI-technology and of sensor-supported decision-making systems can contribute to sustainable water management in farming. The theoretical model outlined in this paper will be of value in subsequent applications of Deep Reinforcement Learning in agricultural practice.

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