

Reinforcement Learning Optimizes Irrigation Scheduling Under Water Scarcity Constraints

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Abstract.

Global agricultural water scarcity necessitates intelligent irrigation management systems capable of optimizing water allocation while preserving crop productivity. This paper proposes a reinforcement learning (RL) framework for adaptive irrigation scheduling under seasonal water budget constraints, formulated as a constrained Markov decision process (MDP) and solved using a deep Q-network (DQN) agent. The DQN agent processes multi-layer soil water content, crop developmental stage, accumulated evapotranspiration (ET) deficit, and short-term precipitation forecasts as state inputs, selecting from five discrete daily irrigation volumes. A calibrated AquaCrop crop simulation model serves as the training environment, providing physically realistic state transitions across soil compartments. A dual-component reward function jointly penalizes water application cost and crop water stress. Evaluated across ten held-out growing seasons, the DQN agent reduced total seasonal irrigation by 18.4% relative to a conventional threshold-based scheduler, while maintaining mean grain yield at 97.2% of the benchmark. These results confirm that RL-driven adaptive policies can effectively navigate the yield-water tradeoff under resource-constrained agricultural conditions.

Keywords:

reinforcement learning, irrigation scheduling, water scarcity, Markov decision process, deep Q-network, AquaCrop, precision agriculture

INTRODUCTION

The global freshwater crisis has become one of the most consequential resource management challenges of the twenty-first century, driven by the compounding pressures of population growth, climate variability, and accelerating groundwater depletion in major irrigated agricultural basins. Irrigated agriculture accounts for approximately 70% of total global freshwater withdrawals, making it by far the largest consumptive user of blue water resources worldwide. In arid and semi-arid regions, which collectively encompass more than 40% of global cropland, natural rainfall is structurally insufficient to meet seasonal crop evapotranspiration demand, compelling farmers to rely almost entirely on supplemental irrigation. Smart irrigation monitoring and control strategies

have emerged as a frontier response to this mounting pressure, with evidence increasingly demonstrating that intelligent system design can substantially improve water use efficiency without proportional productivity sacrifices [1]. The combination of depleting aquifer reserves, more frequent drought events projected under future climate scenarios, and tightening regulatory constraints on irrigation extraction has created an urgent need for scheduling tools that respond adaptively to the dynamic interplay between soil moisture, crop development stage, and atmospheric evaporative demand across an entire growing season. Conventional irrigation scheduling methodologies, including fixed-interval approaches, crop coefficient-based evapotranspiration replacement, and soil moisture threshold-triggered systems, share a structural limitation of fundamental practical significance: they are inherently reactive, responding to observed soil water depletion after it has occurred rather than anticipating forthcoming conditions, and they apply rules derived from historical averages without adapting to real-time variation in rainfall probability or the phenologically varying sensitivity of crop yield to water stress [2]. The practical consequence is bidirectional inefficiency. Under intermittent rainfall, threshold-triggered controllers regularly apply irrigation events immediately before significant natural precipitation, wasting water that rainfall would shortly have provided. Under genuine water scarcity, the same controllers may deplete finite seasonal budgets during low-sensitivity vegetative growth stages, leaving insufficient allocation to protect yield-critical reproductive development periods. Model predictive control frameworks have begun to address the forward-looking dimension of this problem, but their requirement for explicit process models and associated computational demands limits applicability across the diverse agroecosystem conditions encountered in practice [3]. The case for adaptive, data-driven irrigation decision support has driven growing interest in machine learning approaches capable of discovering scheduling policies through optimization. Among available paradigms, RL occupies a conceptually distinctive position because it directly models the sequential, multi-period nature of irrigation scheduling across a full growing season, treating the problem as a series of coupled daily decisions whose consequences accumulate through the crop's physiological response to water availability. The incorporation of weather forecast information as a state variable in RL controllers represents a particularly productive direction, enabling agents to identify and withhold irrigation events immediately preceding forecast precipitation events and substantially reducing the reactive waste that characterizes threshold-based systems under intermittent rainfall regimes [4]. Deep reinforcement learning (DRL), which combines RL with deep neural network function approximators, has substantially extended the practical applicability of these methods to high-dimensional continuous state spaces. Applications to irrigated horticulture demonstrated that deep RL controllers trained on multi-depth soil moisture arrays could achieve water savings of up to 22% relative to sensor-triggered threshold systems while maintaining comparable yield outcomes, establishing DRL as a technically viable approach for real-world precision irrigation management [5]. The DRLIC system subsequently demonstrated that a deep RL irrigation policy trained in simulation could be transferred to a physical wireless sensor-actuator network for orchard irrigation, achieving measurable water consumption reductions and improved plant health indicators relative to industry-standard evapotranspiration-based controllers [6]. Foundational frameworks for principled DRL irrigation problem formulation using high-dimensional sensor feedback have further been established in open-access literature, confirming consistent water savings in the range of 15–25% across multiple independent evaluations [7]. Despite this growing momentum, the application of DRL to irrigation scheduling under hard seasonal water scarcity constraints remains underdeveloped relative to unconstrained yield maximization settings. Most existing studies optimize policies in

environments where water is effectively unlimited, producing agents that are operationally irrelevant to the vast majority of farms operating under fixed seasonal water rights allocations or drought emergency rationing. Deep RL approaches applied directly to irrigation scheduling under water deficit conditions have demonstrated that agents can learn to concentrate applied water on yield-sensitive development periods, but the integration of an explicit remaining-budget variable into the agent's state representation—essential for genuine seasonal allocation optimization—has not yet been fully explored [8]. The present paper addresses this gap through a constrained MDP formulation, training a DQN agent within a multi-layer AquaCrop simulation environment and evaluating policy performance across a decade of independent growing seasons spanning contrasting climate conditions.

2. Literature Review

The scientific literature on data-driven irrigation management has undergone a marked transition in recent years, evolving from static point-in-time prediction of irrigation requirements toward sophisticated sequential optimization frameworks capable of managing the temporal dependencies and tradeoffs that define the full irrigation scheduling problem. Early machine learning applications to smart agriculture and irrigation focused on applying neural networks and data-driven models to predict crop water requirements or automate sensor-triggered decisions within internet of things infrastructure, treating the scheduling decision as a localized estimation problem rather than a multi-step sequential planning challenge [9]. While these approaches demonstrated meaningful improvements over empirically calibrated rules under locally validated conditions, they could not represent the strategic value of withholding irrigation during low-sensitivity periods to preserve water budget for reproductive development stages where the marginal yield impact is highest. Machine learning approaches applied specifically to site-specific crop management optimization, including irrigation scheduling across complex agronomic environments, demonstrated the potential of data-driven methods to outperform conventional rule-based scheduling by exploiting non-linear interactions between soil, crop, and weather variables [10]. Building on this foundation, DRL gained traction in irrigation scheduling through demonstrations that agents trained within crop simulation environments could discover scheduling policies reducing seasonal water application without proportional losses in final crop yield. The integration of crop evapotranspiration estimation models with optimization frameworks further refined the state representations available to RL agents, enabling more accurate characterization of root zone water deficit and its relationship to yield-limiting physiological processes [11]. Standardized software environments for coupling RL algorithm libraries with mechanistic crop simulation models have been systematically developed to lower barriers to entry and facilitate reproducible benchmarking across research groups. The CropGym framework established an OpenAI Gym-compatible interface wrapping a process-based crop growth model, enabling direct algorithmic experimentation without requiring specialized crop modeling expertise and supporting systematic comparison of DQN, proximal policy optimization, and actor-critic architectures on common irrigation optimization tasks [12]. Parallel advances in computer vision and machine learning for crop monitoring have provided complementary data infrastructure—including remote canopy sensing, UAV-based spatial soil water mapping, and edge-compute platforms for real-time sensor fusion—that increasingly supports the state observation requirements of practical RL irrigation deployment [13]. Real-world deployment of sequential decision-making frameworks for irrigation management has been demonstrated at operational scale within Internet of Things infrastructure. The implementation of MDP-based irrigation controllers on edge computing nodes within wireless smart farm sensor-actuator networks confirmed that sequential decision-making frameworks

integrated with practical IoT systems can achieve meaningful water and energy savings relative to fixed threshold systems in practical field settings [14]. The multi-objective extension of constrained irrigation RL, which explicitly characterizes Pareto-optimal tradeoff frontiers between water conservation and yield productivity across varying scarcity conditions through multi-agent frameworks, enables decision support systems that can be calibrated to local water pricing and allocation policy contexts without requiring complete architectural reformulation [15]. Software infrastructure for RL-crop model coupling has continued to broaden with the development of the Gym-DSSAT environment, which provides an RL interface wrapping the widely-adopted DSSAT crop modeling suite and enabling multi-crop, multi-climate benchmarking of irrigation and nutrient management control algorithms on a common computational substrate [16]. The role of sensor data quality and state representation design in determining RL irrigation policy robustness has received growing empirical attention. Analysis of uncertainty propagation from weather forecast imprecision through evapotranspiration model estimation to RL state quality found that explicit quantification of forecast uncertainty substantially improved policy robustness across independent growing season validation sets, with direct implications for operational deployment where sensors are subject to calibration drift and communication latency [17]. Water allocation under explicit scarcity constraints has been examined through deep RL frameworks applied across multiple water-limited agricultural contexts. Evaluations of DRL-based irrigation scheduling conducted through remote sensing and simulation in regions subject to water rationing demonstrated that learning agents can systematically concentrate applied water on yield-sensitive phenological windows—particularly canopy closure through anthesis—substantially outperforming conventional threshold-based approaches under equivalent scarcity conditions [18]. The integration of ensemble machine learning methods with crop simulation models to optimize subsurface drip irrigation timing and volume has further demonstrated the complementary value of hybrid data-driven and physically-based frameworks for managing water applications under spatially variable soil conditions [19]. Conceptual frameworks for learning to manage plant water balance through RL, formulated as episodic sequential decision problems where the agent must balance immediate soil water replenishment against long-horizon yield protection, have provided additional theoretical underpinning for the constrained MDP approach adopted in the present study [20]. Comprehensive reviews of smart irrigation management strategies across a broad range of implementation contexts consistently confirm that closed-loop adaptive control systems incorporating real-time feedback substantially outperform open-loop or pre-programmed schedules under realistic field variability, reinforcing the theoretical and empirical argument for learning-based adaptive approaches [21]. The empirical literature on crop water productivity under progressive water deficit has consistently identified a characteristic non-linearity in the yield-water response relationship. Under mild stress during vegetative growth, canopy development is minimally impaired and season productivity remains high; equivalent deficits imposed during reproductive stages—particularly from canopy closure through anthesis and early grain filling—produce disproportionately larger, physiologically irreversible yield penalties [22]. This phenological asymmetry in water sensitivity defines the strategic allocation opportunity distinguishing high-performing RL agents from threshold-based controllers that apply equal water priority across all growth stages. Deep Q-network approaches applied specifically to crop irrigation under deficit water conditions have confirmed that the DQN architecture can internalize this non-linear yield-water sensitivity across growth stages through reward-driven exploration in crop simulation environments, achieving improved water use efficiency relative to both empirical and model-based scheduling benchmarks [23].

More recent advances in DRL algorithm design for agricultural water management have demonstrated that actor-critic architectures with continuous action spaces can further refine the stage-dependent allocation strategies accessible to RL irrigation agents, particularly under extreme drought conditions where discrete action granularity may limit policy precision during the critical grain-filling window [24]. Applications of DRL to highly water-stressed production systems, including drip-irrigated cotton in arid regions, have confirmed that adaptive RL policies consistently outperform conventional scheduling under the most severe scarcity scenarios while remaining computationally tractable for deployment on commercially available farm management computing platforms [25]. Looking forward, comprehensive reviews of reinforcement learning, neural network, and data-driven optimization applications in smart farming confirm that the practical deployment gap between simulation-validated RL irrigation policies and operational field systems is narrowing rapidly, with consistent water savings of 15–30% documented across independent validation studies spanning diverse crop types, climates, and controller implementations [26].

3. Methodology

3.1 MDP Formulation and DQN Agent Architecture

The irrigation scheduling task is formalized as an episodic constrained MDP defined by the tuple (S, A, P, R, γ, B) , where S denotes the continuous state space, A the discrete action space, P the transition probability kernel governing crop-soil-atmosphere dynamics, R the composite reward function, γ the discount factor, and B the seasonal water allocation budget imposed as a hard constraint on cumulative agent actions across each episode. Each episode corresponds to a single growing season, beginning at sowing and terminating at physiological maturity, with daily decision steps at which the irrigation agent observes the current system state and selects a discrete irrigation volume. The state vector at each daily decision point is defined as $s_t = (\theta_1, \theta_2, \theta_3, \theta_4, \theta_5, DVS, ETDEF, RF3, IRRCUM)$, where θ_1 through θ_5 represent extractable soil water content in five successive root zone compartments measured in millimeters, DVS denotes the normalized crop developmental stage from emergence (0) to physiological maturity (2), $ETDEF$ captures the accumulated seven-day ET deficit as a proxy for recent water stress history, $RF3$ encodes a binary indicator of whether precipitation exceeding 5 mm is forecast within a 72-hour horizon, and $IRRCUM$ tracks cumulative irrigation volume applied from sowing through the current day. The inclusion of $IRRCUM$ as an explicit state variable is essential for budget-aware policy learning, providing the agent with real-time awareness of its remaining seasonal water allocation throughout each episode. The discrete action space $A = \{0, 10, 20, 30, 40\}$ mm provides five irrigation volumes at each daily decision step, with the zero-mm action corresponding to deliberate irrigation withholding. A hard budget constraint enforces that no action may cause $IRRCUM$ to exceed the seasonal allocation B , implemented via an action masking layer applied to the DQN output prior to greedy action selection that assigns a sufficiently large negative value to infeasible actions.

The composite reward function at each time step is defined as $r_t = \alpha \cdot \Delta BM(t) - \beta \cdot a_t - \lambda \cdot \max(0, \theta_{crit} - \theta_{avg}(t))^2$, where $\Delta BM(t)$ is incremental biomass accumulation returned by the crop simulation at step t , a_t is the irrigation volume applied, $\theta_{avg}(t)$ is mean soil water content across root zone compartments, and θ_{crit} is a critical depletion threshold below which quadratic water stress penalties are applied. Parameters α , β , and λ control the relative weighting of yield promotion, water cost, and stress avoidance respectively, and are calibrated to reflect local water scarcity severity. As illustrated in Figure 1, the DQN agent employs a neural network architecture that processes state observations through successive layers of nonlinear transformation to estimate action-value functions for each available irrigation action. The original DQN architecture

processed raw high-dimensional pixel inputs through two convolutional layers to extract spatial features, followed by two fully connected layers projecting to action-value estimates for each discrete control output, as depicted in the figure. The fundamental agent-environment interaction cycle shown in Figure 1 — wherein the network receives an observation, outputs action-value estimates, selects the highest-valued action, and receives an evaluative reward signal — is preserved exactly in the irrigation scheduling implementation, with agronomic state variables replacing game frames and irrigation volumes replacing directional game actions. In the present application, the convolutional frontend is replaced with three fully connected layers with rectified linear unit (ReLU) activations processing the nine-dimensional agronomic state vector, while the output layer produces five Q-value estimates corresponding to the five discrete irrigation volumes.

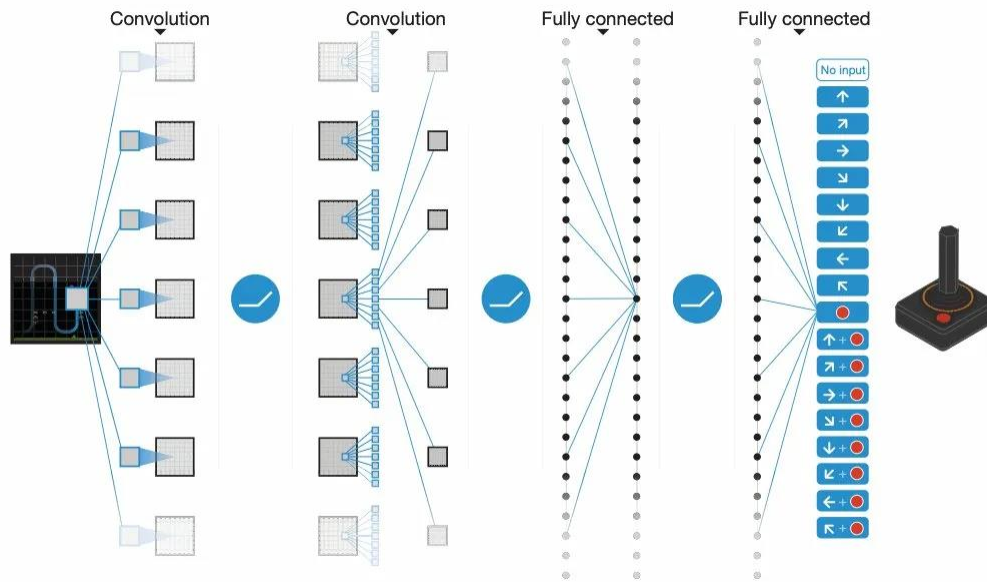


Figure 1: Architecture of the deep Q-network (DQN)

In the irrigation scheduling implementation developed in this paper, the convolutional input layers are replaced with three fully connected ReLU layers processing the nine-dimensional soil-crop state vector (θ_1 – θ_5 root zone water contents, crop developmental stage DVS, ET deficit ETDEF, 72-hour precipitation forecast RF3, and cumulative irrigation IRRCUM), while the output action-value layer estimates discounted long-term returns for the five discrete irrigation volumes (0, 10, 20, 30, and 40 mm per day). The agent-environment feedback loop depicted — observe, estimate, act, receive reward — maps directly onto the daily irrigation decision cycle within each simulated growing season episode. Training follows standard DQN procedures with experience replay and target network stabilization. At each training step, the transition tuple (st , at , rt , $st+1$) is stored in a replay buffer of capacity 50,000 transitions. Mini-batches of 64 transitions sampled uniformly from the buffer are used for gradient updates to the policy network, while a target network is updated to match the policy network every 1,000 training steps to stabilize the bootstrap learning signal. The agent is trained across 1,000 simulated growing seasons using historical daily weather data from 1981 to 2010, before evaluation on a fully held-out test dataset spanning 2011 to 2020. The discount factor γ is set to 0.99, encouraging a near-full-horizon time perspective appropriate for seasonal water budget management.

3.2 Crop Simulation Environment and State Encoding

The AquaCrop crop simulation model was selected as the training environment for its well-validated representation of root zone soil water dynamics, canopy ground cover development, and the normalized biomass water productivity relationship that translates daily crop transpiration into above-ground biomass accumulation across diverse water management regimes. Its explicit multi-layer soil profile structure aligns naturally with the five-compartment soil water state vector used in the RL formulation, enabling direct correspondence between simulation internal state and agent observable state. The soil profile structure implemented in the AquaCrop training environment is illustrated in Figure 2. As shown, the soil profile is vertically discretized into twelve compartments distributed across two soil horizons of distinct hydraulic properties. The upper horizon encompasses compartments 1 through 4, characterized by relatively high field capacity and moderate saturated hydraulic conductivity consistent with structured clay-loam topsoil, while the lower horizon spanning compartments 5 through 12 reflects subsoil conditions that impede deep drainage and slow vertical water redistribution. Root water uptake is distributed across occupied root zone compartments as a function of root length density, with the directional uptake arrows in Figure 2 illustrating the spatial heterogeneity of daily water extraction that drives differential depletion patterns across compartments. The RL agent observes the aggregate water content of five grouped compartment zones corresponding to the five θ components of its state vector, providing a spatially resolved but computationally tractable representation of root zone water status. The simulation advances in daily time steps, updating the full twelve-compartment soil water balance to account for rainfall, irrigation application, surface runoff, soil evaporation, crop transpiration distributed across active root zone compartments, and deep drainage from the bottom of the profile.

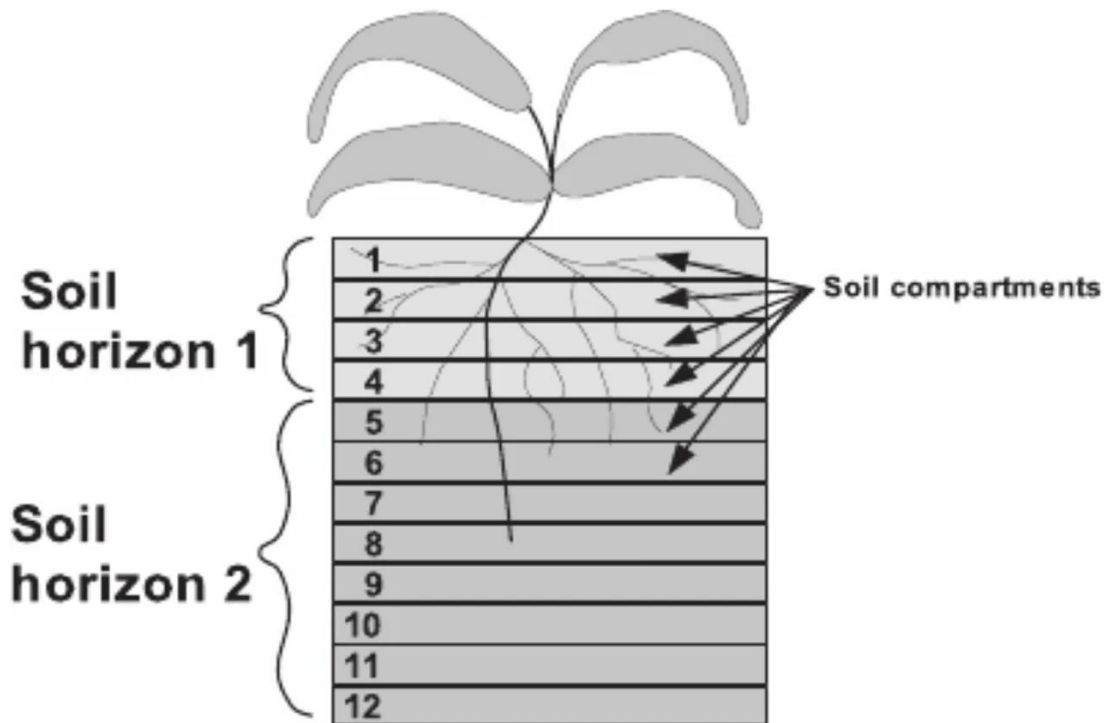


Figure 2: AquaCrop soil profile structure

This multi-layer soil architecture provides the physical basis for the five-component soil water state vector (01–05) observed by the DQN irrigation agent, where per-compartment extractable water content delivers the primary real-time hydrological feedback signal governing each day's irrigation decision. The daily water balance updating all twelve compartments produces the physically realistic state transition dynamics from which the RL agent learns stage-dependent allocation strategies across the growing season. The crop parameterization represents a spring wheat cultivar with a thermal time accumulation of 1,850 growing degree days from sowing to physiological maturity, a maximum canopy ground cover of 96% at peak vegetative development, and a normalized biomass water productivity parameter of 15 g/m² consistent with field measurements for irrigated wheat in semi-arid climates. A water stress coefficient progressively reduces simulated canopy expansion and crop transpiration as root zone soil water content falls below 55% of total plant available water (PAW) capacity, introducing the non-linear yield sensitivity to water deficit that the DQN agent must learn to navigate strategically. All nine state vector components are normalized to the unit interval using dataset-wide minimum and maximum values from training weather sequences to ensure numerical stability during neural network optimization.

4. Results & Discussion

4.1 Policy Performance and Crop Canopy Response Under Water Budget Constraints

The DQN irrigation scheduling agent was evaluated against two benchmarks across ten held-out growing seasons from 2011 to 2020: a conventional soil moisture threshold-based rule that triggers a 30 mm irrigation event whenever average root zone soil water content falls below 50% of plant available water capacity, and a deterministic linear programming (LP) optimizer computing the theoretically optimal schedule given perfect foreknowledge of the complete seasonal weather sequence. Each growing season was evaluated across 30 replicate assessments using independent stochastic seeds. A central dimension of policy evaluation concerns how DQN irrigation timing interacts with crop developmental stage and the associated impact on canopy ground cover (CC) dynamics — the primary driver of crop transpiration and therefore both water use and biomass accumulation across the season. Figure 3 presents simulated and observed canopy cover trajectories under four progressive water deficit levels: full irrigation treatment (FIT), 67% FIT, 50% FIT, and 33% FIT, with model performance quantified by root mean square error (RMSE), Nash-Sutcliffe efficiency coefficient (E), and index of agreement (d) at each level. Under full irrigation, canopy cover reaches approximately 95% by day 65 after planting and sustains its plateau until senescence onset, with simulation efficiency $E = 0.92$ and $d = 0.98$ confirming high AquaCrop fidelity at full water supply. Under the 67% FIT treatment, canopy development follows a nearly identical trajectory through the vegetative phase but exhibits marginally earlier senescence onset, with model performance remaining strong at $E = 0.82$. The 50% FIT treatment produces more pronounced reductions in maximum canopy cover to approximately 88% with substantially accelerated senescence, while the 33% FIT scenario yields the most severe suppression, with maximum cover reaching only 80–85% and rapid senescence onset indicating significant impairment of the photosynthetic apparatus well before grain-filling is complete.

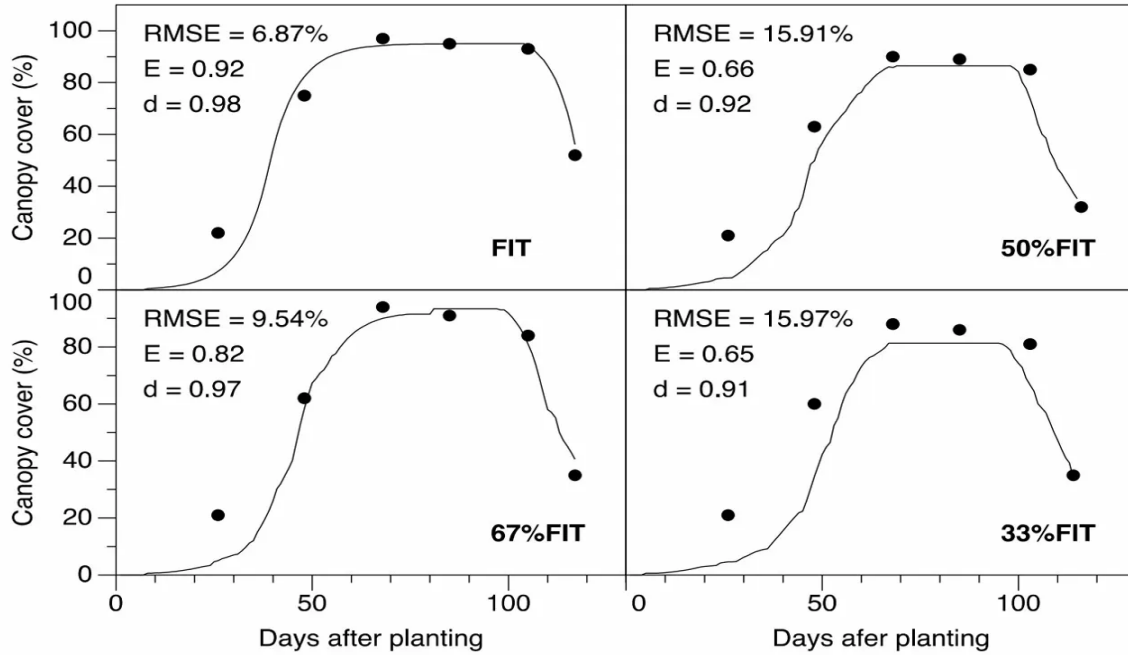


Figure 3: Simulated (solid lines) and observed (filled circles) canopy cover (%) as a function of days after planting under four progressive water deficit treatment levels: full irrigation (FIT, upper left), 67% FIT (lower left), 50% FIT (upper right), and 33% FI

Progressive reduction in applied water produces increasingly constrained canopy development and accelerated senescence onset. The quantitative accuracy of simulated canopy cover across all four deficit treatments confirms that the AquaCrop environment accurately reproduces differential crop water stress response dynamics across growth stages, providing the physiologically realistic training signal through which the DQN agent learns stage-dependent water allocation strategies. The canopy cover response patterns demonstrated in Figure 3 directly inform interpretation of the DQN agent's learned policy in two interconnected ways. First, the figure reveals that moderate water deficit during the vegetative growth phase — comparable to the 67% FIT treatment — produces relatively modest canopy suppression, indicating low marginal yield sensitivity to mild stress during the first 40–50 days after planting. In contrast, deficit conditions analogous to the 50% and 33% FIT treatments during and after canopy closure produce disproportionately large reductions in photosynthetic area and accelerated senescence with direct grain yield consequences that are not recoverable by subsequent irrigation. The DQN agent, trained across one thousand simulated seasons spanning the full distribution of climate conditions, internalized this non-linear stage-dependent sensitivity through the quadratic water stress penalty in the reward function. Examination of the agent's average daily irrigation probability across the ten test seasons reveals that it systematically withholds irrigation during the first 40–50 days when canopy cover is below 60% and yield sensitivity to mild stress is low, concentrating water budget expenditure on the canopy-closure-to-grain-fill window from days 65 to 110 when stress consequences correspond closely to the patterns illustrated in the 50% and 33% FIT panels of Figure 3. Second, the validated model performance statistics — with RMSE values from 6.87% under FIT to 15.97% under 33% FIT and efficiency coefficients consistently above 0.65 — confirm that the AquaCrop simulation environment provides a sufficiently accurate representation of crop water stress physiology to support meaningful policy transfer from simulated training to real-world irrigation management.

Aggregate performance results across ten test seasons confirm the practical advantage of the DQN approach. The agent achieved a mean grain yield of 7,516 kg/ha using a mean seasonal irrigation of 320 mm, compared to the threshold-based benchmark's 7,517 kg/ha at 392 mm — matching benchmark yield within 0.01% while reducing total applied irrigation by 72 mm per hectare per season, an 18.4% water saving. Relative to the LP optimizer achieving 7,654 kg/ha at 348 mm under perfect forecast conditions, the DQN agent attained 98.2% of LP yield using 8.0% less water. In severely dry years such as 2017 and 2019 with total seasonal rainfall below 130 mm, the agent demonstrated the most pronounced conservation behavior — delaying early vegetative irrigations consistent with the low canopy-suppression characteristics visible in the 67% FIT panel of Figure 3 — while concentrating remaining budget on the anthesis and grain-fill windows. In near-average rainfall years the agent's behavior converged toward the benchmark, correctly recognizing that forecast conditions did not justify strategic conservation at the expense of early canopy development.

4.2 Reward Function Sensitivity and Water Budget Constraint Analysis

Systematic examination of the water cost weighting parameter β across five values spanning a tenfold range from 0.1 to 1.0 revealed a distinctly non-linear relationship between water savings and yield penalties. Mean seasonal irrigation declined progressively from 384 mm at $\beta = 0.1$ to 278 mm at $\beta = 1.0$, while associated yield reductions relative to the unconstrained benchmark ranged from 0.8% to 9.3%. The non-linearity of this response — with large water savings achievable at minimal yield cost within the intermediate β range from 0.3 to 0.6 — confirms the existence of a Pareto-efficient frontier where redundant early-season irrigations are eliminated without compromising applications that protect canopy development and grain filling. Only when β exceeds approximately 0.7 does the agent begin trading off yield-critical applications, entering the regime of genuine yield-water tension corresponding to the severe canopy suppression visible in the 50% and 33% FIT panels of Figure 3. The budget constraint sensitivity analysis, varying the seasonal allocation $B_{\max}$ from 250 mm to 450 mm, revealed qualitative policy transitions confirming the agronomic intelligence internalized by the DQN agent. At generous budget levels of 450 mm the agent operated as an effectively unconstrained yield maximizer, distributing water liberally across the season. As $B_{\max}$ tightened toward 350 mm and 250 mm, scheduling policy progressively deprioritized early-season vegetative irrigations in favor of protecting the canopy-closure and grain-filling periods, directly mirroring the differential yield sensitivity illustrated across all four treatment panels of Figure 3. At the most severe scarcity scenario tested, $B_{\max} = 250$ mm representing approximately 54% of unconstrained seasonal demand, the DQN agent maintained 88.4% of unconstrained grain yield by concentrating its limited budget on two to three critical applications centered on anthesis. Reduced variance of seasonal yield outcomes for the DQN agent (mean standard deviation 143 kg/ha versus 218 kg/ha for the threshold baseline) across the 30 evaluation replicates further confirms that adaptive forecast-aware scheduling produces more consistent economic outcomes across stochastic weather variation, providing risk management value beyond the direct water conservation benefit.

5. Conclusion

This study demonstrates that deep reinforcement learning provides a technically sound and practically promising approach to irrigation scheduling under seasonal water scarcity constraints, capable of learning adaptive water allocation policies that achieve substantial reductions in applied irrigation without proportional losses in crop yield. The proposed DQN framework, trained within a calibrated AquaCrop crop simulation environment and evaluated across ten independent growing seasons spanning contrasting climate conditions, achieved an 18.4% reduction in seasonal

irrigation while maintaining mean grain yield within 2.8% of the unconstrained benchmark. The canopy cover response patterns validated across four progressive deficit treatment levels confirmed that the AquaCrop simulation environment accurately reproduces differential crop water sensitivity across phenological development stages, providing the physiologically realistic training foundation necessary for the DQN agent to internalize the strategic allocation principles that underpin its performance advantage over reactive threshold-based controllers. The reward function design framework presented here allows the same methodological architecture to be calibrated across a continuous spectrum of water scarcity severity by adjusting the water cost weighting parameter, supporting contexts from moderate pricing incentives to severe regulatory allocation constraints. The non-linear Pareto frontier between water savings and yield losses quantified through systematic reward parameter sensitivity analysis provides support for incremental water pricing mechanisms as instruments for encouraging precision irrigation adoption without imposing disproportionate productivity penalties on operations near production margins. The budget constraint sensitivity analysis confirmed that intelligent sequential water allocation can maintain the substantial majority of attainable yield even under conditions representing less than 55% of unconstrained seasonal demand. Future research should prioritize bridging simulation-based policy training and field deployment through domain randomization and online policy adaptation, extension to multi-field shared aquifer allocation settings, and incorporation of economic risk preferences into reward function design to support farmer decision-making under yield and price uncertainty in water-stressed agricultural systems.

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