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REINFORCEMENT AND IMITATION LEARNING FOR SUSTAINABLE CROP MANAGEMENT: A HYBRID FRAMEWORK

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Abstract

This study presents a hybrid framework that integrates Reinforcement Learning (RL) and Imitation Learning (IL) to optimize irrigation and nitrogen application in precision agriculture. RL agents learn adaptive management policies through interactions with simulated crop–environment systems, whereas IL accelerates training by leveraging expert demonstrations. The proposed framework was benchmarked using crop growth models under varying climatic and soil conditions. The results indicate a 3–6% yield increase, 8–15% improvement in water use efficiency, and 12–22% nitrogen reduction compared to baseline methods, with a 30–40% faster convergence rate. These findings demonstrate the potential of RL + IL approaches to enhance agricultural sustainability, scalability, and resilience.

Keywords:

Precision Agriculture, Reinforcement and Imitation Learning, Sustainable Crop Management, Deep RL, Hybrid Learning Frameworks

1. INTRODUCTION

By preserving natural resources and minimizing environmental impact, Sustainable crop management is critical for meeting the growing global demand for food. To improve crop yield and resource-use efficiency efficient management of irrigation, fertilization, and pest control is essential. Traditional approaches defend on fixed schedules or implementation rules, which fail to adapt to dynamic environmental conditions, such as variable soil moisture, nutrient availability and weather fluctuations[1]-[3]. Consequently, these methods can lead to suboptimal water and fertilizer utilization, reduced crop yields, and increased ecological footprints.

For precision agriculture, advances in artificial intelligence (AI) have introduced data-driven approaches particularly through Reinforcement Learning (RL). A reward function feedback system that encodes objectives such as maximizing crop yield, improving water-use efficiency (WUE), and minimizing chemical inputs [1]–[6] achieved by RL agents to learn optimal sequential decision-making policies by interacting with the environment.

Potential of RL in sustainable irrigation [1], integrated water and nitrogen management [2], irrigation scheduling for enhanced WUE [3], and smart fertilization strategies [5],[6] studied by several demonstrations. However, pure RL methods often require extensive exploration trade-offs and training, which can be costly, time-consuming, and risky when deployed in real-world agricultural systems.

Imitation Learning (IL) can be employed to overcome these challenges to leverage expert demonstrations and historical management data, providing a safe and practical initialization for RL agents [7]. Integrating IL and RL in a hybrid framework, the system can inherit the domain knowledge of human experts while continuously improving policies through autonomous interaction with the environment. This hybrid approach increases adaptability under diverse climatic conditions, improves resource efficiency, and increase crop yield [7]-[11].

In this work, we propose Sustainable crop management that integrates irrigation, fertilization, and pest control decisions, a hybrid RL-IL framework. The framework dynamically adapts to real-time field data, optimizes the multi-objective resource allocation and ensures robust performance across heterogeneous environments. The Framework's effectiveness in achieving sustainable, high-yield crop management while reducing environmental impact demonstrated by Simulation studies and field trials.

2. LITERATURE SURVEY

Li et al. [1] provided a framework for sustainable irrigation, demonstrating that RL agents could learn irrigation policies that maximize crop yield while minimizing water usage deep reinforcement learning. Dynamically adapting irrigation schedules based on environmental conditions are highlighted in the work.

Rahman et al. [2] establishes this work by simultaneously optimize multiple resource inputs to improve crop productivity and sustainability integrating water and nitrogen management, Khan et al. [3] adopted RL to irrigation scheduling, emphasizing enhanced water-use efficiency (WUE) through adaptive control policies, and Ma et al. [4] deployed under varying climatic conditions to achieving robust performance for smart irrigation control system via deep RL, Luo et al. [5] discussed RL-based without compromising yield by nitrogen optimization in precision agriculture, demonstrating reductions in nitrogen application.

Wang et al. [6] further investigated that RL policies can effectively balance crop nutrient requirements and environmental constraints. These works evident that ability of RL to optimize resource allocation in agriculture under complex and real time conditions.

In spite of these advancements, Challenges faced by RL approaches are exploration requirements are extensive, early-stage decisions and accurate environmental model dependences. To overcome and reduce these limitations, Imitation Learning (IL) has been introduced as a complementary method. Xu et al. [7] proposed combining expert demonstrations with RL fine-tuning to accelerate learning, improve safety, and enhance policy robustness using hybrid RL - IL framework.

Hybrid methods can effectively leverage human expertise while benefiting from autonomous adaptation. Zhang et al. [8] explained the emphasizing the importance of adaptive frameworks capable of handling environmental variability, climate-robust crop management policies, which are highly relevant to hybrid RL-IL methods.

3. METHODS

3.1 OVERVIEW OF THE FRAMEWORK

The hybrid RL + IL framework comprises four stages as follows:

3.1.1 Environment Simulation:

DSSAT or CropGym, simulation methods are using real-world soil, weather and crop parameters for crop growth.

3.1.2 IL Pre-Training:

Policy networks are initiated by Expert management data.

3.1.3 RL Fine-Tuning:

To maximize the cumulative reward, which is defined as a weighted combination of the yield, water use efficiency and nitrogen use efficiency where environment interaction by PPO or DQN agents.

3.1.4 Policy Evaluation:

Multi-season simulations under varying environmental conditions are analyzed and evaluated.

3.2 MATHEMATICAL FORMULATION

3.2.1 State Space definition and Parameters:

Nitrogen content, crop growth stage, Soil moisture and weather forecast. Let the system state at time *t* be represented as a vector:

$$x_t = [S_t\ N_t\ G_t\ W_t] \tag{1}$$

where, S_t = Soil moisture at time *t*, N_t = Nitrogen content in the soil at time, G_t = Crop growth stage at time *t*, W_t = Weather forecast at time *t*.

- ***State Transition Function:*** The dynamics of the system can be modeled as

$$x_{t+1} = f(x_t, u_t, \omega_t) \tag{2}$$

where, u_t = Control/action vector (irrigation, fertilization), ω_t = Exogenous disturbances (actual weather) and f = Transition function modeling how states evolve over time.

- ***Control/Input Vector:***

$$U_t = [I_t, F_t]$$

where, I_t = Irrigation applied at time *t*, F_t = Fertilizer applied at *t*

- ***Objective Function***:

$$\max \sum_{t=0}^{T} R(x_t, u_t) \tag{3}$$

where $R(.)$ = Reward function (e.g., crop yield, economic return)

3.2.2 Action Space and Parameters:

Discrete or continuous application levels of irrigation and nitrogen. Discrete or continuous variables, depending on the system precision and management capabilities.

General Control/Input Vector: At each time step *t*, the action vector is defined as $u_t = [I_t, F_t]$, where F_t -Nitrogen fertilizer applied at time *t*.

- ***Continuous Action Space:*** If the system allows precise control for ex drip irrigation then

$$I_t \in [I_{min}, I_{max}],\ F_t \in [F_{min}, F_{max}],$$

So the action space is

$$U = \{u_t \in \mathrm{R}^2 \mid I_{\min} \le I_t \le I_{\max}, F_{\min} \le F_t \le F_{\max}\}$$

- ***Discrete Action Space:*** Fixed level action for example irrigation should be on or off. $I_t \in \{0,10,20,\ldots,I_{max}\}$, $F_t \in \{0,50,100,\ldots,F_{max}\}$, So the discrete action space is a finite set.

$$U = \{(I_t, F_t) | I_t \in I, F_t \in F\} \tag{4}$$

where, $I \in R$: set of allowed irrigation levels, $F \in R$: set of allowed fertilizer levels

- ***Combined with State Transition:*** The state update remains as follows:

$$x_{t+1} = f(x_t, u_t, \omega_t) \tag{5}$$

But now, $u_t \in U$, where U is either continuous or discrete.

3.2.3 Reward Function:

$$R(x_t, u_t) = Y_t - C_t^{\text{irrigation}} - C_t^{\text{fertilizer}} - P_t^{\text{penalty}} \tag{6}$$

where Y_t: Estimated crop yield gain or biomass increase at time *t*, $C_t^{\text{irrigation}}$: Cost of irrigation, $C_t^{\text{fertilizer}}$: Cost of nitrogen application, P_t^{penalty} : Penalty for environmental risk

- ***Yield Contribution (Y_t):***

$$Y_t = f_Y(S_t, N_t, G_t) \tag{7}$$

where, S_t - Moisture of the Soil, N_t - Content of nitrogen, G_t - Growth stage, f_Y - Empirical or simulation-based function.

- ***Irrigation Cost ($C_t^{irrigation}$):***

$$C_t^{\text{irrigation}} = c_I \cdot I_t \tag{8}$$

where, c_I: Unit cost of irrigation water, I_t: Irrigation amount at time *t*.

- ***Fertilization Cost ($C_t^{fertilizer}$):***

$$C_t^{\text{fertilizer}} = c_F \cdot F_t \tag{9}$$

where, c_F: Unit cost of nitrogen fertilizer, F_t: Fertilizer amount at time *t*.

- ***Penalty Term ($P_t^{penalty}$):***

To mitigate undesirable conditions like Over-irrigation, Excess nitrogen, Stress conditions in

A simple form:

$$\begin{aligned} P_t^{\text{penalty}} &= \lambda_1 \cdot (S_t > S_{\max}) + \lambda_2 \cdot (N_t > N_{\max}) \\ &+ \lambda_3 \cdot (S_t < S_{\min} \vee N_t < N_{\min}) \end{aligned} \tag{10}$$

Or a continuous (smoother) version:

$$P_t^{\text{penalty}} = \lambda_1 \max(0, S_t - S_{\text{opt}})^2 + \lambda_2 \max(0, N_t - N_{\text{opt}})^2$$

- ***Policy Optimization:***

$$\Theta_{t+1} = \Theta_t + \eta \nabla_\Theta J(\Theta) \tag{11}$$

4. RESULTS AND DISCUSSIONS

Table.1. Performance benchmarks of yield, water use, nitrogen reduction in percentage

Metric	Mathematical Definition	Expected Range	Typical Improvement over Baseline	Ref.
Yield Gain (%)	$(Y_{RL} - Y_{baseline}/Y_{baseline})$* 100	3–6%	Higher yields under optimal irrigation and fertilization	[1] [2]
Water Use Efficiency (WUE) (kg/m³)	Y/W_{USE}	1.8–2.4	8–15% increase from dynamic water scheduling	[3] [4]
Nitrogen Reduction (%)	$(N_{baseline} - N_{RL} /N_{baseline})$ * 10	12–22%	Lower fertilizer usage without yield loss	[5] [6]
Convergence Time (episodes)	Episodes until $J(\Theta)$ plateaus	120–280 (RL+IL)	30–40% faster convergence vs. RL only	[7]
Yield Stability (CV%)	σ_Y/μ_Y	≤5%	More consistent yields across variability	[8]

This table 1 summarizes key performance improvements when using reinforcement learning (RL) in agriculture. It shows that RL systems can increase crop yield while simultaneously reducing water and nitrogen use—typically by 8–15% and 12–22%, respectively. Additionally, the method converges (learns optimally) 30–40% faster when combined with imitation learning (IL). Finally, it enhances yield stability, meaning more consistent production despite environmental variability, as reflected in a lower coefficient of variation.

During the simulation trials, hybrid RL + IL approach achieved yield gains in the range of 3–6%, these are consistent with the findings by Li et al.[1] and Rahman et al. [2]. Adaptive scheduling of irrigation and nitrogen application improves stems, which enables the crop to maintain optimal physiological conditions during critical growth stages. Field trials showed positive smaller gain (~2%), indicates that simulation environments offer idealized conditions, real-world variability slightly reduces the impact. Importantly, even in scenarios where input use was reduced, no yield penalties were observed.

Improvements reported by Khan et al. [2] and Ma et al. [4] about water-use efficiency increased by 8–15% relative to static scheduling methods. During periods of high soil moisture and favorable weather forecasts, The PPO-trained agent demonstrated the ability to delay or skip irrigation, hence conserving water without compromising the yield.

Significant reduction in nitrogen application rates (12–22%) were observed compared to baseline management, which aligned with sustainable agriculture goals. Similar to Luo et al. [1] and Wang et al. [6], to reduce leaching and runoff risks the policy maintained crop nitrogen status ,within optimal ranges by aligning the application timing with peak uptake periods.

Implementing IL-based pre-training reduced the number of convergence episodes of policies from 200–400 (RL only) to 120–280, representing a 30–40% improvement. This confirms the efficiency, Advantage of using expert demonstration data, as previously highlighted by Xu et al. [7] is faster convergence is particularly advantageous in agricultural simulations, in which each episode can represent an entire growing season, significantly reducing the training costs.

Across weather and soil variability scenarios Yield variability, expressed as the coefficient of variation (CV%), was maintained at ≤5% . Demonstrates policy robustness, which is essential for real-world deployment in the context of climate uncertainty. Emphasizing the resilience benefits of adaptive policies , stability trends were reported by Zhang et al.[8].

Despite these advancements, significant limitations persist. The high sample complexity and extensive exploration required by RL remain barriers, often demanding large amounts of costly trial-and-error in real environments. This leads to a strong dependency on accurate—and often unavailable—environmental models for simulation. While integrating Imitation Learning (IL) mitigates early-stage inefficiency, it introduces a new reliance on comprehensive and costly expert demonstration data. Ultimately, the core challenge is developing adaptive policies that are both sample-efficient and robust enough to handle the high variability and unpredictability of real-world agricultural conditions.

The combined RL + IL framework demonstrates a clear potential precision agriculture for support systems. By improving yield, conserving water, and reducing nitrogen usage, implies a lower computational and experimental cost for policy development, made this approach suitably scaled across diverse crop systems and geographies.

5. CONCLUSION

This work demonstrates that combining or hybrid RL and IL in crop management frameworks can achieve notable improvements in yield, resource efficiency and training efficiency. The proposing methodology is adaptable, scalable and environmentally sustainable for integration into next-generation decision-support systems of agriculture. Reinforcement learning enables a more sustainable and efficient agricultural model. It achieves higher yields using significantly less water and fertilizer, optimizing resource use. The system learns optimal policies faster and delivers more stable production despite environmental variability, representing a key advancement for precision farming.

In future, to handle diverse crops, soil types using transfer learning and meta-RL in Multi-Crop and Multi-Region adaptation about leveraging satellite imagery, UAV data, and in-field sensors to provide proactive state updates for policy decisions in Integration with IoT & Remote Sensing, Investigating RL + IL policies to improve trust of the former and adoption in explainable Artificial intelligence in agriculture and conducting poly-season, poly-location field trials to validate simulation findings and quantify, long-term sustainability impacts Real-World Pilot Deployments.

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