Smart_IrriGO: Simulation-Based Reinforcement Learning for Climate-Variable Irrigation Optimisation and Water-Use Efficiency in Corn Production

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We thank TAR UMT for essential resources and facilities.

Scan for Project Hub

https://github.com/kevin2190p/Speech_Emotion-and-Smart_IrriGO.git

1. Understanding the Bigger Picture

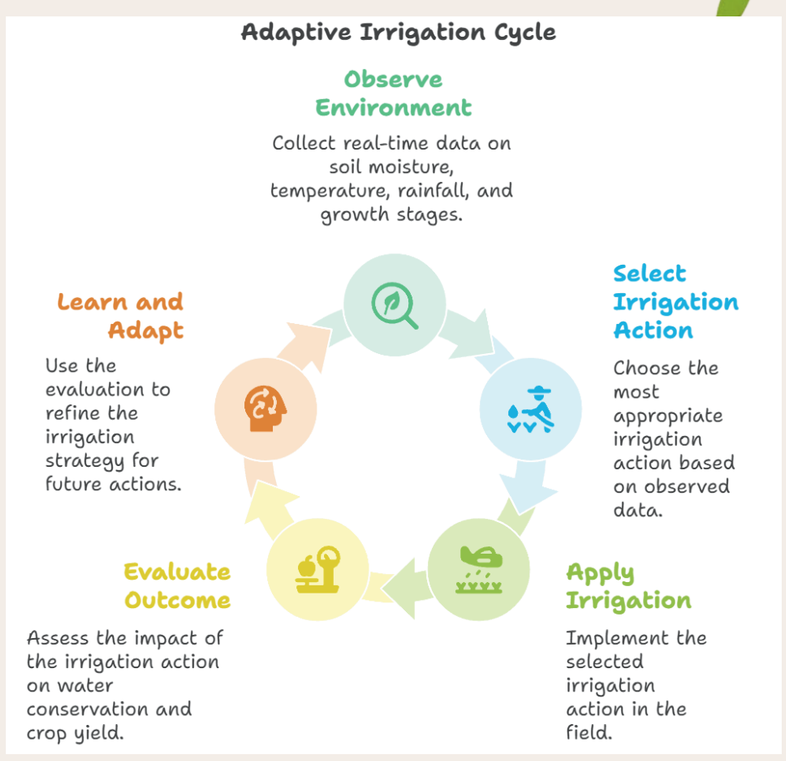
- A Reinforcement Learning (RL)-based adaptive irrigation system is proposed **to optimize water use and crop yield.**
- Four RL algorithms (**DQN, PPO, A2C, Dyna-Q**) are evaluated in a custom simulation under varied climates.
- Traditional systems follow fixed schedules, often wasting water by ignoring environmental changes.

2. What's Going Wrong?

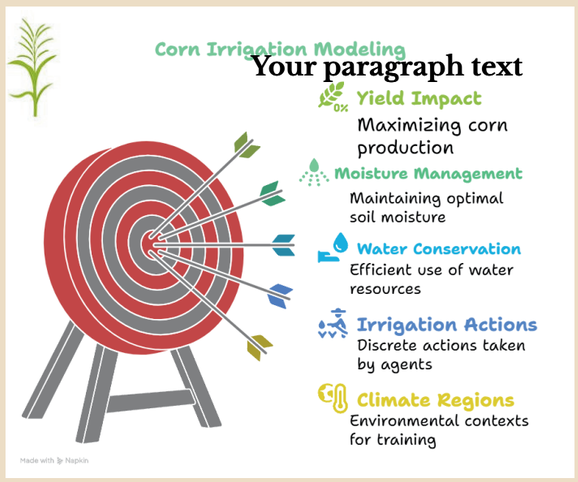
- Fixed-schedule irrigation lacks flexibility **to adapt to environmental changes**.
- Even minor shifts in conditions may require **different irrigation strategies**.

3. What Are We Aiming For?

- Develop an adaptive RL agent to **optimise irrigation in real-time,** maximising yield while **minimising water**.



4. How We Tackled It



- Corn irrigation is modelled as an MDP with 6 continuous **state** variables and **4 discrete actions**.
- Agents trained episodically over **120-day seasons** across **3 climate zones**.
- The reward function balances **moisture control** (-10 to +10), **water use** (-7 to +7), and **yield impact**.

Reward Function Table

Component	Range	Best Case	Worst Case
Moisture Management	-10 to +10	+10 (error < 5%)	-10 (error > 20%)
Water Conservation	-7 to +7	+7 (no irrigation when raining)	-7 (irrigate during rain)
Yield Impact	-0.3 to +0.015	+0.015 (healthy growth)	-0.3 (severe stress)
Base Reward	+2	+2 (always)	+2 (always)
Season Bonus	-45 to +50	+50 (yield = 2.0)	-45 (yield = 0.1)

Stage Multipliers

Seedling	Jointing	Staminate	Filling	Maturity
1.0×	1.2×	**1.5×**	1.3×	1.0×

Final Calculation

Per Step: (Moisture + Conservation) × Stage + Yield + 2

Season End: Add (final_yield - 1.0) × 50

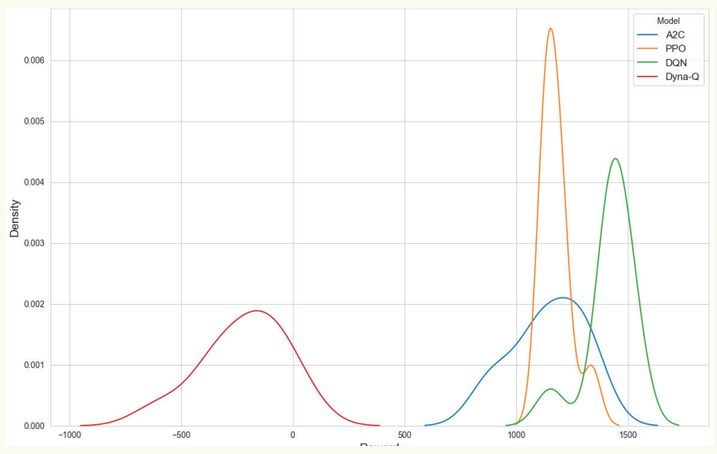
State space

Feature Name	Description	Lower Bound	Upper Bound
Current Soil Moisture	Soil moisture level (%)	0	100
Day in Season	Current day in the growing season	0	120 (Default)
Growth Stage	Current growth stage index (0-4)	0	4
Temperature	Current temperature (°C)	0	40
Recent Rainfall	Rainfall amount on the current day (mm)	0	50
Next Day Rain Probability	Probability of rain on the next day (%)	0	100

Action space

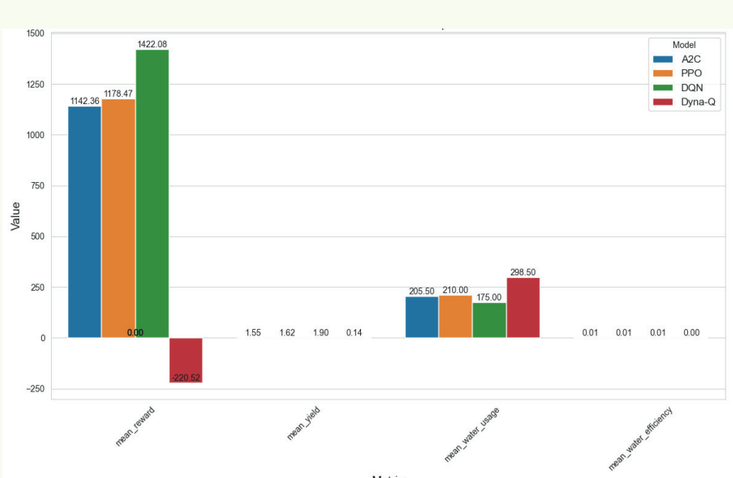
Action Index	Description	Irrigation Amount (mm) - Arid	Irrigation Amount (mm) - Temperate	Irrigation Amount (mm) - Tropical
0	No Irrigation	0	0	0
1	Light Irrigation	8	5	3
2	Medium Irrigation	16	10	6
3	Heavy Irrigation	24	15	12

5. WHAT WE FOUND



Rewards Distribution

Deep Q-Networks (DQN) achieve up to **45% water savings** while maintaining optimal yields. It rcords the **highest cumulative reward** (1,260) in complex climates, effectively balancing short-term water use and long-term yield across varying conditions.



Model Performance Comparison