IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 27 March 2025, accepted 19 May 2025, date of publication 21 May 2025, date of current version 30 May 2025.

Digital Object Identifier 10.1109/ACCESS.2025.3572288

RESEARCH ARTICLE

Comparative Analysis of Reinforcement Learning and Rule-Based System Approaches for Irrigation in Horticulture

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This work was supported in part by the Coordination for the Improvement of Higher Education Personnel (CAPES), Brazil (ROR identifier: 00x0ma614), for the Article Processing Charge; in part by CAPES under Grant 001; in part by the Financiadora de Estudos e Projetos (FINEP), project FINEP-CT-HIDRO, and the Conselho Nacional de Desenvolvimento Científico e Tecnológico–CNPq under Grant 306569/2022-1.

ABSTRACT Irrigation optimization in horticulture is highly relevant due to the high sensitivity of crops to water availability. Methods such as Reinforcement Learning (RL) and Rule-Based Systems (RBS) have been explored for automated irrigation; however, direct comparisons between these approaches for horticultural crops remain limited. This study compares RL and RBS for optimizing irrigation in lettuce cultivation using the AquaCrop-OSPy model. A Q-Learning RL agent dynamically adjusts irrigation decisions based on a customized reward function, while the RBS applies predefined water balance rules. Simulations were conducted over 30 days in each of the four seasons. Results indicate that RL achieved an average dry yield of 5.84 tonne/ha with 186.25 mm of water, while RBS produced 2.35 tonne/ha with 92.01 mm. RL consistently delivered higher productivity but at the cost of increased water use, whereas RBS demonstrated greater water efficiency under conservative irrigation strategies. The findings highlight RL's adaptability to varying conditions and RBS's reliability for water-limited scenarios. Future research can explore hybrid systems that integrate RL's flexibility with RBS's efficiency. The code and datasets are available at https://github.com/GabyQueiroz/RBS_RL_Irrigation

INDEX TERMS Aquacrop, irrigation, reinforcement learning, rule-based system, smart irrigation.

I. INTRODUCTION

Intelligent irrigation is an advanced management approach that combines sensor technologies, automation, and predictive methods to optimize water use in agriculture, integrating the crop cycle, environmental conditions, and climate forecasts to minimize waste and maximize productivity [1], [2]. With the increasing scarcity of water and the need for more sustainable agricultural practices, this technology has become an important tool for farmers in various parts of the world [2].

The advancement of technologies also directly impacts agriculture, with automation and the Internet of Things (IoT) enabling communication and operation of devices independently [3]. These systems integrate smart devices for monitoring and facilitate automated and accurate decision-making [3]. The addition of artificial intelligence (AI) enables the advanced processing of large volumes of agricultural data, transforming them into strategic information that helps make more efficient and precise decisions for crop management and development [4].

AI is transforming agricultural irrigation by offering new ways to optimize water use and improve productivity through human-machine interaction [5]. Improper water use can reduce crop growth, resulting in lower production and nutritional deficiencies [6]. Furthermore, adequate irrigation is essential not only to ensure productivity but also to address the challenges of water scarcity in regions where water is limited [7].

The associate editor coordinating the review of this manuscript and approving it for publication was Libo Huang.

Therefore, the use of artificial intelligence (AI)-based approaches, such as Reinforcement Learning (RL), and rule-based systems (RBS), has been suggested as promising ways to automate irrigation decisions in agricultural systems [8], [9], and [10]. However, for horticultural crops, which have high economic value, short growth cycles, and high sensitivity to water variations [11], [12], there are few studies focused on irrigation optimization. The high demand for precision in horticultural management and the lack of research justify the need for studies like the present one, which seeks to provide a contribution to the field.

The choice of RL and RBS models for this comparison is motivated by their distinct and complementary characteristics. RL presents the dynamic adaptation to climatic changes and the crop's needs over time, optimizing irrigation through continuous learning from rewards [8], [9], [10]. On the other hand, RBS, widely used in conventional agricultural systems, follows a deterministic and transparent approach based on predefined rules that ensure simplicity and control over decisions [8]. The comparison between these approaches is relevant to identify the advantages and disadvantages of the two methods, particularly in contexts of water scarcity and productivity.

Therefore, this study aims to compare RL and RBS approaches for irrigation optimization in horticultural cultivation, using the AquaCrop-OSPy simulation model. The proposed analysis aims to evaluate the efficiency of water use and the final crop productivity under different climatic scenarios, offering results that can support more efficient and sustainable water management decisions for horticultural crops.

II. RELATED WORKS

In recent years, the use of simulators and AI algorithms for irrigation optimization has been widely studied due to their potential in managing water resources in agriculture [13], [14], [15].

Different methodologies of Reinforcement Learning have been explored, including Markov Decision Processes (MDP), Proximal Policy Optimization (PPO), and Q-learning. These approaches have been applied to various types of crops, with solutions varying in terms of complexity, integration with simulation tools, and data analysis capabilities, enabling the modeling of irrigation decisions in different agricultural scenarios.

Markov Decision Models (MDPs) have been explored as strategies to optimize water resource use in automated irrigation systems. These models aim to maximize plant growth while minimizing water and energy consumption, based on discrete soil moisture states to guide irrigation actions [16], [17]. While this approach is effective, recent studies still do not integrate advanced simulation tools, such as AquaCrop, limiting their applicability in more complex scenarios. Additionally, approaches that combine semi-supervised methods and reinforcement learning (RL) with real sensor data are frequently used for irrigation control [18], [19]. However, these approaches lack a direct comparison with fixed-rule systems, a point that this study aims to address.

The study in [20] on rice cultivation with deep neural networks presents a relevant application of Deep Q-Learning to optimize agricultural productivity. While it is effective in using climatic and crop data to determine the best management practices, it does not directly focus on using RL for irrigation. Similarly, the authors in [21] explore yield predictions using machine learning, aiming to maximize agricultural production, but do not address irrigation control with RL.

In contrast, the work in [22] stands out by using RL for irrigation decision-making in rice plantations, considering weather forecasts to optimize water use. This study, as well as those by [23] and [24], is similar to the present one in terms of using climatic data and RL for irrigation optimization. However, our approach differs by performing a comparative analysis between RL and rule-based methods, as well as integrating AquaCrop-OSPy as a simulation tool and not being applied to horticultural.

Intelligent irrigation systems using Deep Reinforcement Learning (DRL) techniques have been proposed to optimize water use in almond orchards [9], cotton [25], and bananas [26], with an emphasis on maximizing water efficiency and promoting plant health. These models aim to respond adaptively to the specific water needs of each crop, offering a more efficient and sustainable approach [9], [26], [27]. The proposed models use real-time data from IoT sensors and climatic conditions to train irrigation policies. While similar to our work in using RL for irrigation control, they lack the flexibility and generalization provided by integration with AquaCrop, and do not compare directly with rule-based systems. Additionally, the reward function needs to be adapted for the horticulture in our case.

The authors in [28] and [29] introduce IoT-based irrigation systems and reinforcement learning modeled by MDP, aiming to maximize the efficient use of water resources. While these studies are similar to ours in terms of using RL and environmental sensing, our research advances by using AquaCrop-OSPy and comparing the effectiveness of RL with rule-based systems, enabling irrigation management in different scenarios.

The authors in [30] and [31] apply RL in controlled irrigation systems, using Double Deep Q-Learning approaches and climate forecast-based control to optimize both irrigation and chemigation. However, they do not explore integrated simulations like AquaCrop, limiting the generalization of their results to other crop contexts.

Additionally, the study by [32] explores the comparison between on-policy A2C (Advantage Actor-Critic) and off-policy DQN (Deep Q-Network) algorithms in irrigation systems in Portugal, demonstrating the superiority of A2C in water savings. However, our research stands out by comparing RL with rule-based methods using a robust simulation environment, allowing us to provide recommendations that are more applicable to different climatic conditions and crops.

Rule-based systems have been applied in various agricultural contexts due to their ability to provide automated decisions based on predefined conditions and specific environmental parameters. These systems, typically structured with *if-then* logic, enable the definition of management events, such as fertilizer application or irrigation, based on the dynamic conditions of the soil, climate, and crop. Works like [33] highlight the use of RBS in agricultural decision support systems (DSS), allowing adjustments in management events in response to temporal and spatial variations. Successful applications include crops like wheat (*Triticum aestivum L.*) and corn (*Zea mays L.*), where the accuracy of decisions was verified by aligning irrigation and management events with the conditions of the soil-crop system.

Despite the applicability and efficiency of RBS in controlled scenarios, there is a gap in the use of these approaches compared to more dynamic adaptive methods, such as Reinforcement Learning (RL). While RBS provides decisions based on static and predefined conditions, RL algorithms have the ability to learn management policies through interactions with the environment, adjusting decisions in real-time. In this context, the present study differentiates itself by performing a direct comparison between RBS and RL in irrigation management for horticultural, using the AquaCrop-OSPy simulation model as the simulation environment. This approach is unprecedented in the management of short-cycle crops, such as lettuce, offering a detailed analysis of water efficiency and crop productivity in different climatic scenarios.

Therefore, this work contributes to the field by integrating AquaCrop-OSPy with reinforcement learning, providing a detailed comparison between RL and rule-based approaches. Unlike previous works that focus on specific models or methods with little integration with simulation data, this approach offers greater flexibility and practical applicability for farmers seeking to optimize water use in different crops and environmental conditions [9], [16], [17], [18], [19], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [34].

Based on what we observe in the literature, our research has the following contributions:

1) **Automatic Irrigation for horticultural crops**: Although automatic irrigation is commonly applied in large plantations, the use of automatic systems in horticultural crops is less frequent, with most farmers still relying on water balance methods. However, the implementation of automatic irrigation can bring additional benefits in some specific scenarios, such as greater accuracy in water control and resource optimization.
2) **In-Depth Comparison of Methodologies**: The comparative analysis between reinforcement learning (RL)-based irrigation systems and rule-based systems reveals fundamental differences in adaptability, water use efficiency, and impact on productivity. A detailed comparison of these approaches is important for understanding the advantages and limitations of each in different crop contexts.
3) **Exploring RL in horticultural crops**: The use of RL for horticultural crops is still an under explored field. RL's adaptability, especially regarding the customization of the reward function, can be advantageous in addressing the specific needs of horticultural crops, which require different care compared to large-scale crops. This is an important contribution of this work.
4) **AquaCrop-OSPy with Customized Crops**: The use of AquaCrop-OSPy with customized crops and soils, along with the public availability of this data and the related codes, is a practice rarely performed. This approach promotes transparency and allows other researchers and farmers to replicate or adapt these systems to their own realities.

III. METHOD

This study was developed using an integrated approach that combines modeling and optimization methods for irrigation strategies. The AquaCrop model, widely recognized for simulating crop growth, was used in conjunction with climatic data, soil characteristics, and specific parameters for lettuce cultivation. The methodology involved data preparation, model configuration, and the application of decision-making strategies such as rule-based systems and reinforcement learning techniques, aiming to evaluate and optimize water management. The following subsections presents the main components and steps of the methodological process.

A. AQUACROP SIMULATION MODEL

AquaCrop is a simulation model developed by the FAO (Food and Agriculture Organization of the United Nations) to assess the yield of agricultural crops based on the water regime. This model is widely used to predict the productivity of various crops under different irrigation and water management conditions, being especially useful in regions with water scarcity. Based on climatic, soil, and plant variables, AquaCrop helps decide the optimal amount of water to be applied to optimize productivity without wasting resources [35].

The AquaCrop model was chosen due to its ability to simulate crop productivity based on soil, climate, irrigation management, and crop parameters. AquaCrop simulates crop growth based on the relationship between the available water in the soil and the final yield. The AquaCrop-OSPy library, an implementation of AquaCrop in Python, was used to integrate the model with reinforcement learning.

1) SOIL

The detailed data on soil type and its water retention capacity were obtained from laboratory analyses conducted

TABLE 1. Physical properties of the soil (General).

Layer (cm)	Sand (%)	Silt (%)	Clay (%)
0-10	2.40	31.16	66.44
10-20	2.01	29.38	68.61
20-30	2.03	29.64	68.33
30-40	1.55	27.51	70.93

TABLE 2. Physical properties of the soil (Details), including Total Porosity (PT), Field Capacity (CC), Permanent Wilting Point (PMP), and Saturated Hydraulic Conductivity (Ksat).

Layer (cm)	PT (m^3/m^3)	CC (m^3/m^3)	PMP (m^3/m^3)	Ksat (mm/h)
0-10	0.620	0.434	0.268	47.2
10-20	0.618	0.439	0.279	14.3
20-30	0.618	0.480	0.301	9.1
30-40	0.611	0.500	0.293	8.0

TABLE 3. Lettuce crop parameters used in the AquaCrop simulation.

Parameter	Value
Crop Name	Lettuce
Planting Date	Day 1
Harvest Date	Day 30
Crop Type	1 (leafy horticultural)
Planting Method	0 (Transplanted)
Calendar Type	1 (Calendar days)
Days to Emergence	6
Days to Maximum Root Depth	22
Days to Senescence	23
Days to Maturity	30
Start of Yield Formation (CD)	15
Flowering Duration	0 (No flowering)
Yield Formation Duration	7
Base Temperature (T_{base})	10 °C
Maximum Temperature (T_{upp})	30 °C
Minimum Rooting Depth (Z_{min})	0.1 m
Maximum Rooting Depth (Z_{max})	0.3 m
Maximum Canopy Cover (CC_x)	0.85
Crop Coefficient (K_{cb})	1.1
Normalized Water Productivity (WP)	17 g/m²
Plant Density	160,000 plants/ha
Soil Area Covered per Seedling	15 cm²
Minimum Depletion Depth (p_{lo1})	0.20
Maximum Depletion Depth (p_{up1})	0.40
Harvest Index (HI_0)	85%

at the Federal University of Paraná - UTFPR, Dois Vizinhos campus, Parana, where this study is being carried out. The soil was configured based on characteristics typical of agricultural soils, considering its water storage capacity and other physical parameters. The values used for the soil based on the analyses are presented in Tables 1 and 2:

B. CROP

The crop chosen for this study was lettuce, a short-cycle horticultural crops that is highly sensitive to irrigation and is widely cultivated in various regions of Brazil. Since lettuce is not a pre-existing crop in AquaCrop, it was necessary to parameterize its specific values. For this, the data were obtained from a literature review [36], [37], allowing the appropriate definition of the crop parameters in the model. Table 3 presents the values used for this parametrization.

1) CLIMATE

Historical data from the city of Dois Vizinhos, provided by the Institute de Devolvement Rural do Parana (IDR-Paraná), were used. This data includes information on precipitation, maximum and minimum temperatures, relative humidity, sunshine, and evaporation. The solar radiation values, necessary for calculating the Reference Evapotranspiration (ETo), were obtained through the monthly reference table and the latitude and longitude coordinates, as described by [38].

The equation used to calculate ETo was that of Hargreaves-Samani [39], as presented in Eq. 2:

$$ETc = ETo \times Kc, \tag{1}$$

where ETc is the crop evapotranspiration (mm/day). ETo is the reference evapotranspiration (mm/day). Kc is the crop coefficient, which varies according to the plant's development stages.

2) REFERENCE EVAPOTRANSPIRATION (ETo)

The reference evapotranspiration (ETo) is calculated based on the Hargreaves and Samani Eq. [39], as shown in Eq. 2:

$$ETo = 0.0023 \times Qo \times (T_{max} - T_{min})^{0.5} \times (\overline{T} + 17.8), \tag{2}$$

where T_{max} is the daily maximum temperature (°C), T_{min} is the daily minimum temperature (°C), and $\overline{T}$ is the daily mean temperature, given by $\overline{T} = \frac{T_{max}+T_{min}}{2}$. Qo is the extraterrestrial solar radiation constant obtained in [40]. Q_o is the extraterrestrial Solar Radiation. T_{max} is the Maximum Temperature. T_{min} is the Minimum Temperature. $\overline{T}$ is the Mean Temperature.

C. RULE-BASED SYSTEMS

A rule-based system is a special type of expert system, typically consisting of a set of if-then rules [41]. These rules are usually based on simple conditions, such as: *If precipitation is less than 4 mm, irrigate 10 mm.*

The rule-based system was built from a structured conditional logic, where climatic parameters and the crop cycle are evaluated through a rule engine that processes predefined conditions. This logic was implemented using the *rule_engine* library [42], which facilitates the efficient creation and execution of these rules. The implemented rules were based on the water balance and the AquaCrop model, using the methodology for calculating the relative soil water deficit (Dr) - Root Zone Depletion - in relation to critical thresholds (SMT) - Soil Moisture Targets - for each phenological stage of the crop. This method allows for automatic adjustment of SMT values, ensuring that the plant's specific water needs at each developmental stage are met. The rules implemented in the system are described below.

Rule 1 - Soil Moisture-Based Irrigation Control: Irrigation is triggered based on the relative water deficit in the soil (Dr) in relation to the critical thresholds (SMT) defined for each phenological stage of the crop. The SMT values are automatically adjusted by the system according to the plant's needs at each developmental stage [43]. The irrigation decision follows the following criteria:

Note: The term *Dr* (Root Zone Depletion) refers to the amount of available soil water in the root zone that has been depleted with respect to field capacity. More formally, it is calculated as the difference between the soil moisture at field capacity and the current soil moisture level in the plant's effective root zone. As *Dr* increases, the plant experiences greater water stress, potentially triggering irrigation if it reaches or surpasses the corresponding *SMT* threshold for that growth stage. The *SMT* values are automatically adjusted by the system according to the plant's needs at each developmental stage [43]. The irrigation decision follows the following criteria:

- **Emergence** (**$SMT = 75\%$**): Irrigation is triggered if the relative water deficit in the soil (Dr) exceeds 75% of the available moisture (UD). The amount of water applied is calculated as $IrrReq = (Dr - SMT) \times 1.5$, limited to the maximum irrigation depth.
- **Maximum Rooting** (**$SMT = 65\%$**): During this phase, irrigation occurs when the relative deficit (Dr) exceeds 65% of the UD. The irrigation volume is determined by the Eq. $IrrReq = (Dr - SMT) \times 1.5$, respecting the maximum depth of application.
- **Senescence** (**$SMT = 55\%$**): Irrigation is triggered if the relative deficit (Dr) exceeds 55% of the UD, applying the amount of water calculated as $IrrReq = (Dr - SMT) \times 1.5$, subject to the maximum irrigation depth.
- **Maturity** (**$SMT = 55\%$**): The system activates irrigation only if the relative deficit (Dr) exceeds 55% of the UD, applying water according to the Eq. $IrrReq = (Dr - SMT) \times 1.5$, respecting the maximum allowed limit.

Rule 2 - Daily Irrigation Amount Calculation: The irrigation amount is calculated daily based on the water balance of the crop, considering the crop evapotranspiration (ETc), effective precipitation (Pe), and the efficiency of the irrigation system. This calculation determines the net irrigation requirement (IRN) and adjusts the total water amount to be applied (ITN).

Rule 3 - Adjustment for Minimum Irrigation of 5 mm: If the net irrigation requirement (ITN) results in a value less than 5 mm, the system automatically adjusts the irrigation amount to 5 mm, ensuring a minimum amount of water applied. This rule does not apply when the calculated amount is zero (i.e., no irrigation is necessary).

Rule 4 - Maximum Irrigation Limit of 40 mm: When the calculated ITN exceeds 40 mm, the system limits the irrigation amount to this maximum value to avoid excessive irrigation, preventing soil saturation and water wastage.

For the calculation of the irrigation amount, several concepts based on the crop's water balance were used, considering the plant's characteristics, soil, and irrigation system efficiency. The main equations and variables used are described below.

1) CROP EVAPOTRANSPIRATION (ETc)

Crop evapotranspiration (ETc) is calculated from the reference evapotranspiration (ETo) and the crop coefficient (Kc), according to the Eq. [39].

2) EFFECTIVE PRECIPITATION (Pe)

Effective precipitation (Pe) is calculated by adjusting the total daily precipitation (P) with the adjustment factor (f) for the crop, according to Eq. 3:

$$Pe = P \times f, \tag{3}$$

in which P is the total daily precipitation (mm) and f is the precipitation adjustment factor for the crop.

3) WATER BALANCE (ETc - Pe)

The water balance is calculated by subtracting the effective precipitation (Pe) from the crop evapotranspiration (ETc), according to Eq. 4:

$$ETc{-}Pe = ETc - Pe. \tag{4}$$

4) REQUIRED IRRIGATION (IRN)

The net irrigation requirement (IRN) is calculated by accumulating the daily water deficit, which is the difference between the crop evapotranspiration (ETc) and the effective precipitation (Pe), as described by Eq. 7. However, to avoid negative values, the function $\max(0, \cdot)$ is applied, ensuring that the value of IRN is always positive or equal to zero:

$$IRN = \max(0, \sum(ETc - Pe)). \tag{5}$$

The established rule is as follows:

- If $ETc > Pe$, the crop experiences a water deficit, indicating that irrigation is required to compensate for this difference.
- If $ETc \leq Pe$, the effective precipitation is sufficient to meet the crop's water demand on that day, and therefore, $IRN = 0$, indicating that no additional irrigation is needed.

The function $\max(0, \sum(ETc - Pe))$ prevents the accumulated irrigation requirement from being negative, which would be inconsistent in irrigation management. This approach ensures that the net irrigation requirement (IRN) is applied only when there is a water deficit, and the value is limited to zero when there is no deficit, avoiding the unnecessary application of water.

5) TOTAL IRRIGATION REQUIRED (ITN)

The total irrigation depth required (ITN) is adjusted by the efficiency of the irrigation system, as:

$$ITN = \frac{IRN}{\text{Irrigation system efficiency}}, \tag{6}$$

in which ITN is the total irrigation depth required (mm). IRN is the net irrigation requirement (mm). The irrigation system efficiency varies depending on the method used (e.g., drip irrigation, and center pivot.).

6) NET IRRIGATION REQUIREMENT (IRN)

The net irrigation requirement (IRN) is calculated by accumulating the daily water deficit, which is the difference between the crop evapotranspiration (ETc) and the effective precipitation (Pe), as described by Eq. 7. To avoid negative values, the function $\max(0, \cdot)$ is applied, ensuring that the value of IRN is always positive or equal to zero:

$$IRN = \max(0, \sum(ETc - Pe)). \tag{7}$$

The established rule is:

- If $ETc > Pe$, the crop experiences a water deficit, indicating that irrigation is necessary to compensate for this difference.
- If $ETc \leq Pe$, the effective precipitation is sufficient to meet the crop's water demand on that day, resulting in $IRN = 0$, indicating that no additional irrigation is needed.

The function $\max(0, \sum(ETc - Pe))$ prevents the accumulated irrigation requirement from being negative. This ensures that the net irrigation requirement (IRN) is applied only when there is a water deficit, and the value is limited to zero when there is no deficit, avoiding the unnecessary application of water.

D. REINFORCEMENT LEARNING

Reinforcement Learning (RL) is a machine learning approach in which an agent learns to make decisions through interactions with the environment, aiming to maximize an accumulated reward over time [44], [45]. In the context of irrigation, RL allows a model to learn the best actions (such as the amount of water to be applied) under different climatic conditions, in order to optimize water use and productivity. The advantage of RL lies in its ability to adapt to complex and dynamic conditions, making it ideal for optimizing systems like irrigation.

Q-learning is a specific RL algorithm that enables the agent to learn a decision-making policy, mapping the actions that lead to the maximum return for each state of the environment. It stores in a table (Q-table) the expected reward values for each state-action pair, continuously adjusting them based on the feedback received [46], [47], [48]. This makes Q-learning effective for resource optimization problems, such as irrigation, as it allows the agent to identify the ideal amount of water to be applied under different environmental conditions, based on accumulated rewards that indicate the best outcomes.

Figure 1 shows the diagram that illustrates the flow of Reinforcement Learning applied to the irrigation model. In this scheme, the agent (represented by RL) observes the conditions of the environment, such as weather and soil, and decides the amount of irrigation required. Based on these decisions, the environment responds by providing a reward, which can be positive (+) or negative (−), depending on the effectiveness of the applied irrigation, and the process repeats.

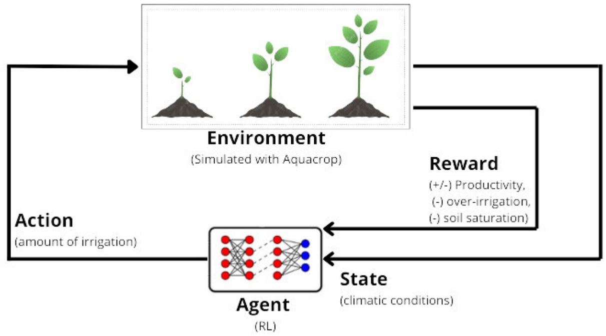

FIGURE 1. Flow of reinforcement learning in our process.

1) ENVIRONMENT DEFINITION

The environment was created using the `AquaCropEnv` class, which encapsulates the crop growth cycle and climatic data. At each step of the environment, the AquaCrop model is executed to simulate the effect of the irrigation decision on that day on the final crop yield.

States: The state observed by the agent includes the current amount of irrigation applied, the current step within the simulation cycle, the average minimum and maximum temperatures, the average precipitation, the average reference evapotranspiration (ETo), as well as the accumulated precipitation and evapotranspiration since the beginning of the simulation.

Actions: The action space was discretized into 7 irrigation levels, ranging from 0 to 15 mm per day, in increments of 2.5 mm. Each action represents the amount of irrigation that will be applied to the soil.

Rewards: The reward given to the agent is based on multiple factors related to irrigation, water balance, and crop productivity. The goal of the agent is to maximize crop productivity while avoiding over-irrigation and soil saturation. The rewards and penalties were designed based on agronomic principles and best practices in reinforcement learning, reflecting the water balance, plant development, and efficient use of water resources, as discussed in [8], [49], and [50]. To achieve this, the reward function is structured around four main components:

1) **Adequacy of Irrigation;**
2) **Penalty for Excessive Irrigation;**
3) **Penalty for Soil Saturation;**
4) **Impact on Crop Productivity.**

The first component, **adequacy of irrigation**, is based on the water balance equation [39], ensuring that irrigation meets the crop's demand without excess. The agent receives a positive reward when the applied irrigation does not exceed the difference between the Crop Evapotranspiration (ETc) and Precipitation. This mechanism prevents water stress and maintains irrigation efficiency, guiding the model to apply water only when necessary.

The second component, **penalty for excessive irrigation**, is inspired by agronomic studies [43] that highlight the negative effects of over-irrigation, such as nutrient leaching and soil aeration reduction. To mitigate these risks, an exponential penalty is applied, strongly discouraging excessive irrigation. The exponential function was chosen because small increases in excess irrigation can have significant impacts on nutrient loss and soil structure, justifying a more severe penalty as excess increases.

The third component, **penalty for soil saturation**, considers the soil's water retention capacity. If the soil moisture (θ_{soil}) exceeds the Field Capacity (FC), saturation occurs, which can restrict oxygen availability to plant roots and negatively impact growth. To address this, a penalty proportional to the deviation from the soil's field capacity is applied, aligning with soil moisture management methods used in agricultural water control [49].

Finally, the fourth component, **impact on crop productivity**, directly links irrigation decisions to crop yield. The agent is rewarded when irrigation increases productivity and penalized when productivity declines. This approach follows water-use efficiency strategies [50], where the goal is to balance water use with maximizing agricultural output. To achieve this, the agent receives a bonus proportional to the productivity gain and a penalty proportional to the productivity loss, ensuring that the model learns to optimize irrigation efficiently.

These components work together to ensure that the RL agent learns an optimal irrigation strategy, balancing water conservation with crop productivity. The mathematical formulation of each term is detailed below.

Positive Reward for Adequate Irrigation: If the amount of irrigation applied by the agent is less than or equal to the water deficit (the difference between the Reference Evapotranspiration (ETc) and the precipitation), the agent receives a positive reward $R_{\text{irrigation}}$:

$$R_{\text{irrigation}} = \begin{cases} 10, & \text{if irrigation} \leq (\text{ETc} - \text{Precipitation}), \\ 0, & \text{otherwise.} \end{cases}$$

Penalty for Over-Irrigation:

If the agent applies more water than necessary (i.e., if the irrigation amount exceeds the water deficit), an exponential penalty, P_{excess}, is applied. The excess irrigation is calculated as:

$$\text{excess} = \max\left(0, \text{Irrigation} - (\text{ETc} - \text{Precipitation})\right).$$

The exponential penalty for over-irrigation is given by:

$$P_{\text{excess}} = \begin{cases} -5 \cdot e^{\text{excess}}, & \text{if excess} > 0, \\ 0, & \text{otherwise.} \end{cases}$$

Hence, the total reward is then defined as:

$$R = 10 - |\text{excess}| + P_{\text{excess}}.$$

Penalty for Saturated Soil: If the soil moisture, θ_{soil}, exceeds the Field Capacity (FC), a penalty, P_{soil}, is applied proportionally to the difference between the soil moisture and the Field Capacity, represented by:

$$P_{\text{soil}} = \begin{cases} -10 \times (\theta_{\text{soil}} - \text{FC}), & \text{if } \theta_{\text{soil}} > \text{FC}, \\ 0, & \text{otherwise.} \end{cases}$$

Reward/Penalty for Productivity: If the agent's decisions result in an increase in productivity, the reward for the increase in productivity, $R_{\text{productivity}}$, is proportional to the gain, defined as:

$$R_{\text{productivity}} = \begin{cases} 5 \times (\text{yield increase}) \\ \quad \text{if yield increase} > 0, \\ -10 \times |\text{yield increase}| \\ \quad \text{otherwise.} \end{cases}$$

2) AGENT TRAINING

The Q-Learning agent was trained over 8000 simulation episodes, with the number of steps ranging from 50 to 100 per episode. Each episode represents a 30-day lettuce cultivation cycle, during which the agent makes daily decisions on the amount of water to be applied. At the end of each daily decision, the agent's Q-table was updated based on the reward received, adjusting the irrigation policy throughout the episodes. To minimize the risks of overfitting to the simulation environment, the reward function was structured to directly reflect the positive and negative impacts of irrigation on the water balance and crop productivity. Penalties were incorporated for excessive irrigation and soil saturation, preventing the model from learning strategies that result in water waste or negatively impact plant development. Additionally, the model was evaluated under different climatic scenarios within the simulation environment, allowing its ability to adapt to variations in meteorological conditions to be assessed and reducing dependence on a single dataset.

The main parameters of the Q-Learning algorithm were defined as follows. **Learning Rate** (α): 0.01, allowing the agent to incrementally adjust the values in the Q-table at each iteration. **Discount Factor** (γ): 0.8, the agent values both immediate and future rewards, but gives a slightly higher weight to rewards that are closer in time. **Exploration Probability** (ϵ): The agent begins by exploring the environment extensively ($\epsilon = 1.0$) and gradually reduces exploration over time (decaying to 0.1), focusing more on the best actions discovered. With each training episode, the exploration rate decreases gradually (decaying by 0.5% per episode). Over time, the agent explores less and focuses more on actions that yield higher rewards.

The Q-table update is based on the Bellman equation, using the maximum (or minimum, depending on the problem) value of the $Q(s', a')$ function to calculate the new value of $Q(s, a)$, as shown in Eq. 8:

$$Q(s, a) \leftarrow Q(s, a) + \alpha \left[R_{t+1} + \gamma \max_{a'} Q(s', a') - Q(s, a) \right], \tag{8}$$

in which, the current state (s) represents the conditions observed by the agent, including information such as the irrigation applied, the current step, as well as the averages and sums of climatic variables. The action (a) corresponds to the amount of irrigation applied on a specific day. After the state transition, the agent receives an immediate reward (R_{t+1}), which is calculated based on the dry yield of the crop, as provided by the AquaCrop model. The next state (s') is defined as the new set of observations generated after the action is taken.

E. COMPARISON BETWEEN RULE-BASED SYSTEM AND REINFORCEMENT LEARNING

To compare the *Rule-Based System* and *Reinforcement Learning*, the irrigation method 3: *predefined schedule* of the AquaCrop software was used. This choice is justified by the need for a baseline scenario that provides consistency and predictability, allowing an objective assessment of the performance of both systems in relation to a fixed irrigation schedule. The analysis was conducted in four fictional scenarios representing different seasons of the year: spring, summer, autumn, and winter, adapted to the average climatic conditions of Brazil for each of these seasons, in the region chosen for the analysis.

Initially, the Rule-Based System was applied using a dataset containing the following meteorological parameters: MinTemp: Daily minimum temperature (°C), MaxTemp: Daily maximum temperature (°C), Precipitation: Daily precipitation (mm), ReferenceET: Reference evapotranspiration (mm) over the 30-day crop cycle.

These data were configured to cover different climatic scenarios, such as dry days, days with moderate rainfall, and periods of high and low temperatures. The system's rules were applied based on these scenarios, generating the required amount of irrigation for each day.

The same meteorological data file was used as a test for the Reinforcement Learning model. During the training period, the RL learned the best irrigation strategy based on the rewards obtained, adjusting its decisions over time. After training, the model was tested using the same set of meteorological data, where the RL suggested the irrigation amounts for each day based on the knowledge acquired.

The comparison was made based on the results obtained from the simulation in AquaCrop, considering two main factors: the total irrigation applied during the season and the crop productivity resulting from the irrigations. The climatic data used throughout the crop cycle can be visualized as shown in Figure 3.

IV. RESULTS

This section will present the results obtained from the comparison between Reinforcement Learning and the Rule-Based System. The analysis is based on two main aspects: water use efficiency and final crop productivity over the 30-day cycle in different seasons of the year. Figure 3 represents the recommended irrigation values for Reinforcement Learning, and Figure 2 for the Rule-Based System. Figure 5 represents the accumulated irrigation values for each season of the year.

Table 4 and Figure 5 present the productivity results between the two models. We can observe the values of Fresh yield (tonne/ha), Yield potential (tonne/ha), and Dry yield (tonne/ha), which reflect the impact of each irrigation approach on the final crop production.

The Fresh yield (tonne/ha) refers to the total yield of the crop in its fresh form, meaning with all the water still present in the plants. This value represents the weight of the harvest immediately after it is picked, before any water loss occurs during the drying process. The Yield potential (tonne/ha), on the other hand, indicates the theoretical maximum yield that the crop could achieve under ideal conditions, with no resource limitations, such as water or nutrients, or environmental stresses.

On the other hand, the Dry yield (tonne/ha) represents the yield of the crop after the removal of water, corresponding to the dry weight of the final product. The main difference between these metrics lies in the water content: Fresh yield includes the water present in the plant, Dry yield is the dry weight after drying, and Yield potential is a theoretical estimate of yield under the best possible conditions. These data provide a quantitative view of the performance of each method throughout the 30-day cycle.

TABLE 4. Comparison of RL and RBS irrigation systems across seasons.

Seasons	Method	Fresh Yield (ton./ha)	Yield Potent. (ton./ha)	Dry Yield (ton./ha)	Seas. Irrig. (mm)
Spring	RBS	35.77	4.85	1.78	86.57
	RL	115.2	7.50	5.76	190.0
Summer	RBS	14.7	2.35	0.76	13.25
	RL	93.9	7.17	4.69	150.0
Autumn	RBS	119.8	7.87	5.99	202.0
	RL	119.5	7.87	5.95	210.0
Winter	RBS	17.34	2.36	0.86	68.25
	RL	98.5	7.69	5.97	195.0
Average	RBS	**46.90**	**5.36**	**2.35**	**92.01**
	RL	**106.28**	**7.56**	**5.84**	**186.25**

V. DISCUSSION

The results obtained highlight the differences between the two irrigation approaches. The comparison was made by observing water use efficiency and final crop productivity over a 30-day cycle across four seasons, presenting a contrast between how each approach manages the available water and maximizes crop production.

RL demonstrated a dynamic irrigation pattern adjusted to daily conditions, resulting in higher total accumulated irrigation across all seasons. RBS, in contrast, followed a predefined and conservative strategy, applying less water. This difference in the amount of water used reflects the guiding principle behind each approach. RL adapts its decisions based on the variable environmental conditions, while RBS applies water consistently, following rules that were set before the irrigation process was carried out.

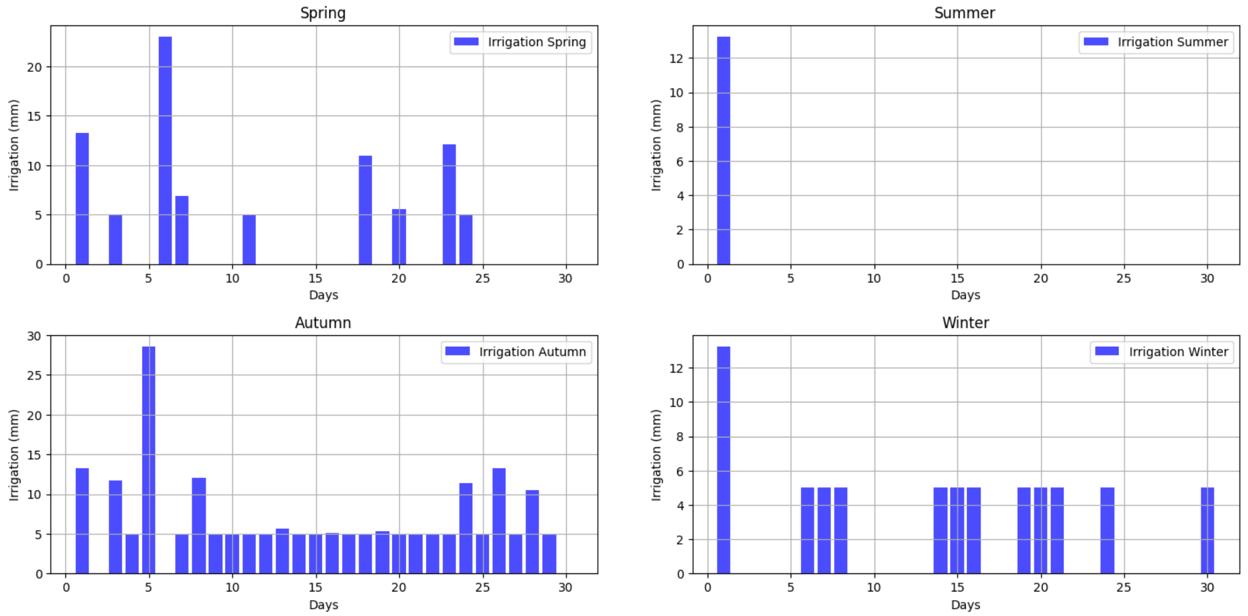

FIGURE 2. **Recommended irrigation values of the RBS model by season.**

The two irrigation approaches have distinct characteristics. RL can be considered more exploratory and adaptive, which can be both an advantage and a disadvantage. RL dynamically adjusts based on already experienced states, but when it encounters new conditions or unknown scenarios, it may make unpredictable or even random irrigation decisions. This could harm performance, as the system might apply inappropriate amounts of water while exploring new possibilities, without the guarantee that this choice will be the most efficient.

On the other hand, the Rule-Based System (RBS) follows a predefined approach, ensuring greater control and predictability. Fixed rules, such as *if Dr is above 75% SMT, irrigate 1.5 mm*, can be applied consistently throughout the crop cycle. This characteristic ensures greater precision in irrigation decisions, as the rules are clear and based on specific conditions. However, this rigidity also limits the system in scenarios with high climatic variability, where adapting to daily conditions could be important to optimize water use and maximize productivity.

In terms of productivity, the RL system showed higher productivity values across all seasons, especially in terms of *fresh yield* and *dry yield*. In spring, for example, RL achieved 115.2 tons per hectare of *fresh yield*, while RBS produced 35.77 tons per hectare, representing an increase of approximately 222% in yield. In summer and autumn, this trend continued, with RL obtaining 93.9 and 119.5 tons per hectare, respectively, while RBS produced 14.7 and 119.8 tons per hectare, resulting in increases of about 538.1% in summer and a slight reduction of 0.3% in autumn.

The *yield potential*, which reflects the maximum productive potential, was also higher in RL across all seasons. For instance, in spring and winter, RL achieved 7.50 and 7.69 tons per hectare, while RBS reached values of 4.85 and 2.36 tons per hectare, respectively. This represents increases of approximately 54.6% in spring and 225.4% in winter.

The comparison of averages between the RL and RBS approaches further reinforces the superiority of RL in terms of productivity, although with higher water consumption. The average *Fresh Yield* of RL (106.28 *ton./ha*) was 126.5% higher than that of RBS (46.90 *ton./ha*), as was the *Dry Yield*, which was 148.5% higher (5.84 *ton./ha* vs 2.35 *ton./ha*). However, RL used an average of 186.25 mm of water, approximately 102.4% more than RBS, which consumed 92.01 mm.

The lower productivity of RBS may be related to its inability to dynamically adapt to the plant's needs and the climatic conditions, resulting in irrigation decisions that, although conservative in terms of water use, are insufficient to maximize crop productivity. RL, by using historical data and patterns learned during training, adjusts irrigation amounts more efficiently over time. This allows RL to adapt better to the variable conditions of the crop, resulting in more varied and greater irrigation decisions, which may provide better conditions for plant development and, consequently, higher productivity.

The rule-based system defines irrigation values based on water balance calculations and fixed parameters, such as precipitation amount and crop coefficient (Kc). This means that for each new set of climatic data, the RBS applies a predefined amount of water, without considering variations

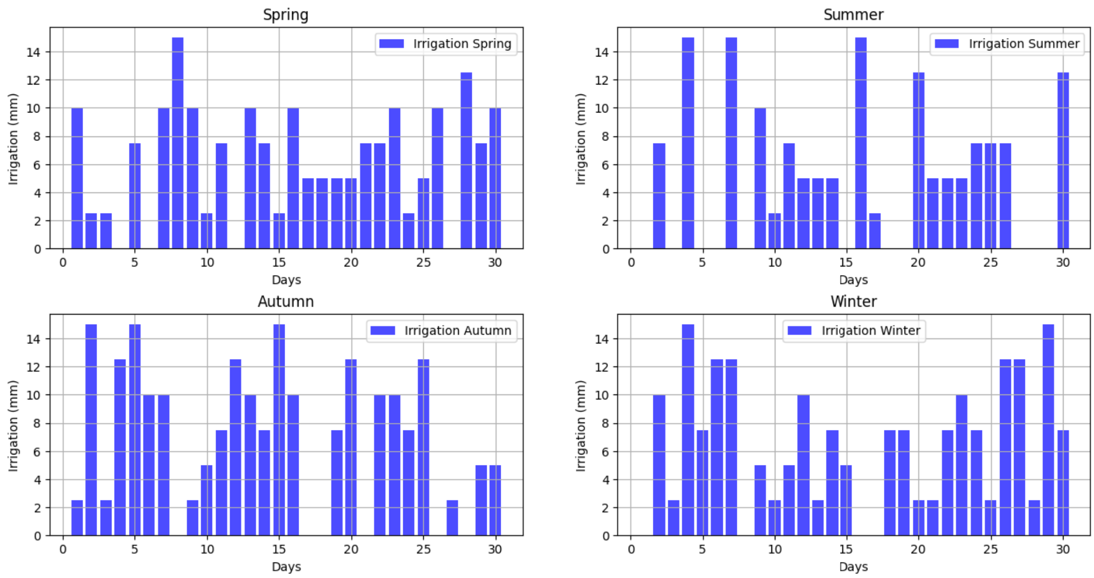

FIGURE 3. Recommended irrigation values of the RL model by season.

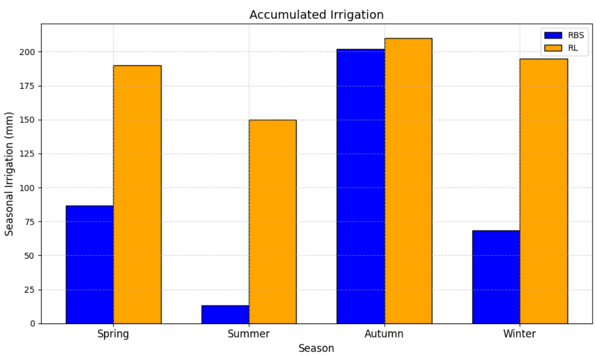

FIGURE 4. Accumulated irrigation for each season and method.

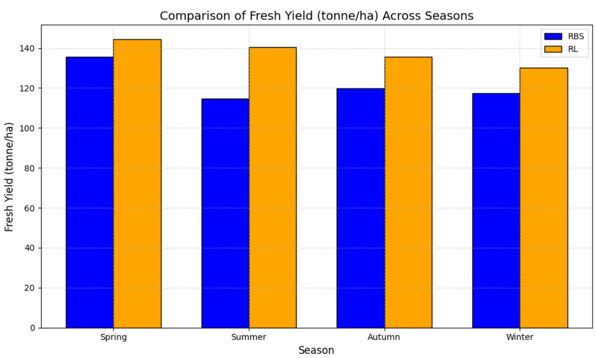

FIGURE 5. Productivity in (ton/ha) based on recommended RL and RBS irrigations per season.

that may occur throughout the crop cycle. However, RL also takes water balance into account when calculating its rewards, although it has applied irrigation on rainy days. This can be explained by the adaptive nature of the model, which, although it considers precipitation on the current day, tends to adjust its strategy by taking into account the residual water impact on subsequent days.

Upon analyzing the results, it is noted that RL applied irrigation volumes even on days with heavy rain, but reduced irrigation on subsequent days, likely in response to the previous day's precipitation and the water available in the soil. This behavior suggests that RL does not immediately react to rain but adjusts its irrigation actions as the soil loses moisture over time.

RL learns over multiple episodes of interaction with the environment, adjusting its irrigation policies based on a reward system that considers both climatic conditions and the state of the soil and crop. This allows the model to identify more complex irrigation patterns and optimize its decisions based on historical data. However, since RL depends on good initial training, there may be variations in performance when different data sets or episodes are used, which requires fine-tuning of hyperparameters to ensure consistent results.

On the other hand, the Rule-Based System does not require training. It follows a fixed set of predefined conditions, such as precipitation limits, crop coefficient, and irrigation efficiency, which makes its implementation relatively simple. Although it is easy to adjust for different crops, its static nature limits its ability to adapt to dynamic changes in climatic or soil conditions over time. Thus, while RL adapts to variable conditions, RBS depends on established parameters, which may not be ideal in scenarios with high climatic variability.

When observing the irrigation patterns over the days and seasons, it is noticeable that RL shows greater variability, with irrigation peaks on days of higher water demand. The cumulative irrigation recommended by RL at the end of the cycle was always higher, while the RBS recommended a lower cumulative irrigation. This indicates that RBS may operate with more efficient water management, while RL focuses on maximizing productivity rather than conserving water.

Summer, known for its high precipitation, shows the lowest water demand in the RBS, with only 13.25 mm of water applied. This value reflects the RBS's dependence on natural precipitation, resulting in minimal irrigation but, consequently, limited productivity (0.76 tonnes/ha of Dry Yield). In contrast, RL maintained a higher irrigation pattern even in this season (150.0 mm), ensuring higher productivity (4.69 tonnes/ha).

In autumn, where the absence of rainfall was marked, both approaches showed an increase in water consumption, but RL stood out with 210.0 mm applied, surpassing the RBS (202.0 mm). This difference highlights RL's adaptability in critical situations, resulting in similar Dry Yield (5.95 tonnes/ha versus 5.99 tonnes/ha from RBS). In winter and spring, these more moderate seasons, the average irrigation and productivity values remained consistent with the pattern observed in RL, always ensuring higher productivity. In winter, for example, RL applied 195.0 mm, compared to 68.25 mm from RBS, resulting in a higher productivity of 5.97 tonnes/ha versus only 0.86 tonnes/ha from RBS.

From a statistical point of view, RL presents a lower coefficient of variation in irrigation application across seasons (about 21%), suggesting greater uniformity in its strategy, while RBS shows high variability (51%), revealing a more direct dependence on the climatic conditions of each season. In terms of water efficiency, despite RL consuming approximately twice as much water on average (186.25 mm versus 92.01 mm), its average productivity was significantly higher in Dry Yield (5.84 tonnes/ha versus 2.35 tonnes/ha), indicating a favorable cost-benefit relationship when the priority is to maximize agricultural production.

RL demonstrated a greater ability to adapt to variable climatic conditions, which is reflected in its daily irrigation recommendations. It managed to incorporate dynamic factors such as precipitation and evapotranspiration to optimize the amount of water applied. Additionally, the system is flexible enough to adjust its decisions in real-time as new climatic data is received. However, this flexibility may also lead to over-irrigation. This variation suggests that, although RL can maximize productivity, it may, in some cases, consume more water than necessary, requiring more refined adjustments to the reward policies to prevent waste.

Excessive irrigation not only leads to increased water consumption but also significantly impacts soil health and crop sustainability. Over-irrigation can cause waterlogging, which reduces the oxygen available in the root zone, leading to hypoxia and root decay. Additionally, prolonged soil saturation can promote the proliferation of fungi and bacteria, increasing the incidence of plant diseases. Another critical issue is nutrient leaching-excessive water infiltrates deeper soil layers, carrying essential nutrients like nitrogen and potassium away from the root zone. This depletion requires higher fertilizer application rates, increasing production costs and the environmental footprint of agricultural activities [51].

From a practical standpoint, excessive irrigation also impacts operational efficiency and resource management. In large-scale farms, unnecessary water use increases energy costs for pumping, reduces overall irrigation system lifespan due to frequent operation, and contributes to water resource depletion, which is particularly critical in arid or semi-arid regions. Moreover, it may result in runoff, leading to soil erosion and contamination of nearby water bodies with agrochemicals. To mitigate these risks, we are currently evaluating a hybrid irrigation strategy that integrates RL's adaptability with RBS constraints, aiming to limit excessive water use while maintaining high crop productivity.

Moreover, RL relies on a substantial amount of historical data for training, typically including maximum temperature, minimum temperature, precipitation, and reference evapotranspiration (*ETo*). In cases where *ETo* is not available, it can be calculated. The model's performance is highly dependent on the quality and quantity of these data, and the scarcity of reliable historical records may limit its effectiveness in certain agricultural environments.

Another critical aspect is hyperparameter tuning, which significantly influences how RL balances water-use efficiency and crop productivity. Poorly adjusted parameters can lead to unstable learning, over-irrigation, or suboptimal water allocation strategies. To address this, we conducted a careful search and validation process, testing these hyperparameters across multiple analysis scenarios to ensure robust learning and effective decision-making. This challenge is further exacerbated by the fact that RL models typically require multiple training episodes to converge to an optimal decision-making policy, making real-world deployment more complex.

In practical implementations, excessive irrigation remains a risk, as RL optimizes based on past patterns but does not inherently impose water conservation constraints. Without appropriate reward adjustments, the model may prioritize short-term yield gains at the expense of long-term sustainability, leading to inefficient water use. These challenges highlight the importance of refining reward functions and integrating additional constraints to balance productivity and water conservation.

When considering the advantages and disadvantages of each approach, RL stands out for its adaptability and resource optimization. The model allows for maximizing productivity by adjusting its irrigation recommendations in real-time, but it may require constant adjustments to hyperparameters and more robust training to avoid water wastage. RBS, on the other hand, is simple and efficient in scenarios where climatic conditions are more predictable, making it ideal for situations where water conservation is a priority, even if it means a slight reduction in the final crop productivity.

The results also reflect a limitation observed in the AquaCrop model, which may influence the analyses performed. The model, although widely used and recognized for its ability to simulate crop growth under different management and climatic conditions, showed a tendency to predict higher productivity with increased irrigation, regardless of any negative effects associated with over-irrigation. This limitation may lead to an overestimation of the efficiency of RL in scenarios where excessive amounts of water are applied, not properly reflecting potential negative impacts on crop development, such as soil saturation, nutrient leaching, or increased management costs. This feature highlights the importance of validating AquaCrop's results with experimental data or field measurements to adjust the model to real conditions and minimize possible deviations in the forecasts.

Tables 6 and 5 present a summary of the main advantages and disadvantages of each model, highlighting the aspects observed in the comparison. This comparative analysis can assist in refining and choosing the most suitable model for different scenarios and needs.

TABLE 5. Summary of the advantages and disadvantages of RL for irrigation.

Criterion	Reinforcement Learning (RL)
Adaptability	High adaptability to varying climatic conditions.
Complexity	Requires initial training and fine-tuning of hyperparameters. Greater complexity, especially in different contexts.
Water Efficiency	Potential for over-irrigation, applying more water than necessary on some days due to excessive flexibility.
Productivity	Higher final productivity, focusing on maximizing output, even if it means greater water use.
Flexibility	High flexibility, adjusting recommendations based on daily water needs and data.
Applicability	Ideal for scenarios with high climatic variability and where there is enough historical data for model training.
Computational Cost	Requires more computational power due to the need for processing large volumes of data and continuous model adjustment.
Improvements	Could benefit from the introduction of fixed rules to avoid over-irrigation on rainy days, making the system more robust.

A. PRACTICAL IMPLEMENTATION AND LIMITATIONS

The implementation of an RL-based irrigation system requires significantly greater computational capacity compared to a Rule-Based System. RL training demands a large number of simulations before converging to an optimized decision policy, which can increase the time required for deployment [52]. A typical RL model may require 10,000 to 100,000 training episodes, with each simulation taking approximately 5 seconds in a crop model like AquaCrop. This results in a total training time ranging from 5 to 13 hours, depending on hardware capabilities and parallel processing. In contrast, RBS operates instantly, as it follows predefined rules without requiring iterative learning.

Additionally, RL training requires high-performance computing resources such as multi-core CPUs or GPUs, which can significantly increase power consumption - potentially

TABLE 6. Summary of the advantages and disadvantages of RBS for irrigation.

Criterion	Rule-Based System (RBS)
Adaptability	Low adaptability to climatic changes. Follows fixed, predefined rules.
Complexity	Simple to implement, does not require training or complex adjustments.
Water Efficiency	More efficient water management, with lower water consumption due to more conservative control.
Productivity	Lower productivity due to conservative irrigation control, but with a focus on water efficiency.
Flexibility	Low flexibility, with little variation in daily irrigation recommendations based on fixed rules.
Applicability	Ideal for stable and predictable climate scenarios, where fixed rules can be applied more efficiently.
Computational Cost	Low computational cost, with faster and direct execution due to following simple fixed rules.
Improvements	Could incorporate adaptive components, such as historical climate or soil conditions, to improve adaptability to climatic variations.

reaching tens to hundreds of kWh. Meanwhile, an RBS can be executed on low-power devices, such as microcontrollers (ESP32) or Raspberry Pi, making it far more computationally efficient. These factors highlight the trade-off between the adaptability of RL-based approaches and the simplicity and efficiency of rule-based systems.

Furthermore, RL relies on continuous processing to update its decisions as new environmental conditions are observed. This characteristic may limit its application in embedded devices with low computational capacity, making it more suitable for systems connected to cloud platforms. RBS, on the other hand, can be directly implemented on microcontrollers, using direct sensor measurements for real-time decision-making. This makes it a more viable option for environments with limited computational infrastructure or where cloud connectivity is not guaranteed.

Another aspect is sensor dependence. RBS requires continuous soil moisture measurements to apply its rules accurately. If sensor failures occur, decisions may be compromised. RL, in turn, bases its actions on a pre-trained model and can operate even in the absence of real-time measurements. However, this characteristic may make it less responsive to unexpected climatic variations, as the learned policy may not be updated with real conditions at the time of decision-making.

The AquaCrop model used in simulations tends to predict increasing productivity with higher irrigation levels, without explicitly incorporating the negative effects of excess water, such as nutrient leaching and soil waterlogging [53]. However, what may be occurring is not just a direct overestimation of productivity due to high irrigation but also a methodological misalignment between RL and RBS in how they regulate soil moisture.

While RBS directly monitors soil moisture and adjusts irrigation to keep it within an optimal range, our current implementation of RL relies only on the daily scenario without explicit moisture regulation. If we consider the soil moisture control threshold proposed in [54], represented by:

$$h = 10(\theta_{CC} - \theta_{CR})Z, \tag{9}$$

in which θ_{CC} is the soil moisture at field capacity, θ_{CR} is the residual soil moisture, and Z is the effective soil depth, one can observe that the irrigation suggested by RL may significantly exceed the ideal values. In real systems, excessive water use reduces water-use efficiency, impacts soil structure, and compromises nutrient absorption by plants. To mitigate this effect, a possible solution would be to incorporate additional constraints into the RL model, limiting the maximum allowable irrigation based on the soil water balance, or even combining both approaches-merging RL's adaptive flexibility with RBS's predictability and stability [55].

This hybrid approach could use RBS to ensure that irrigation values remain within appropriate limits while RL optimizes water allocation based on historical data. This way, the system would benefit from the robustness of fixed rules to prevent over-irrigation while leveraging RL's ability to learn complex patterns and adapt irrigation to specific conditions, maximizing productivity and water-use efficiency.

Although AquaCrop-OSPy is widely used for crop growth modeling and irrigation management simulations, it has some limitations that should be considered. The model assumes hydrological and physiological simplifications that may not fully capture the long-term effects of excessive irrigation, such as soil structural degradation, compaction, and impacts on soil microbiota. Additionally, its representation of soil water dynamics is based on fixed parameters, which may limit its ability to reflect spatial variations and the heterogeneity of real soils.

Another point is that AquaCrop-OSPy does not directly model the negative effects of nutrient leaching and prolonged soil saturation, which may lead to overestimation of productivity under excessive irrigation regimes. These limitations highlight the importance of validation and adjustments in modeling strategies, complementing simulations with field experiments to ensure that irrigation decisions derived from the model are applicable to real-world scenarios.

The practical implementation of automated irrigation systems, whether based on RL or RBS, presents challenges that range from infrastructure to farmer acceptance. Sensor reliability is a key aspect, as failures or improper calibrations may compromise the accuracy of irrigation decisions. Moreover, adapting these approaches to different soil types and climatic conditions requires continuous adjustments, making deployment more complex. Computational and energy costs are also relevant factors, especially for RL, which may require more robust hardware to operate efficiently.

An alternative to enable processing without overloading local devices is the use of cloud platforms such as AWS or Azure, although this may generate additional costs. Finally, the adoption of the system depends on farmer acceptance, making it essential to develop intuitive interfaces and provide adequate technical support to ensure that automated irrigation decisions are understood and effectively applied in the field [56].

VI. CONCLUSION AND FUTURE WORKS

The comparison between the RL-based and RBS-based irrigation systems revealed that RL, with greater flexibility and adaptability to climatic conditions, provides higher agricultural productivity, but often at the cost of greater water consumption. On the other hand, the RBS demonstrated better water efficiency, although with a slight loss in productivity. These results suggest that a hybrid approach could leverage the adaptability of RL and the predictability of RBS, balancing water conservation and agricultural production maximization.

To improve the models, RL could be fine-tuned by introducing fixed rules to avoid over-irrigation on days of high precipitation, while RBS could incorporate historical data and weather forecasts for more dynamic recommendations. This balance between adaptability and control could result in more efficient and sustainable irrigation systems.

A hybrid approach could be implemented by defining a decision threshold where RL operates within a predefined range of soil moisture conditions, while RBS intervenes to adjust irrigation when extreme conditions are detected. Additionally, the hybrid model could leverage RL for long-term optimization, learning from seasonal patterns, while RBS applies short-term corrections based on real-time sensor readings.

Future studies should validate these models in real-world scenarios, considering different crops and climatic conditions. This validation will allow refining irrigation policies, adapting them to the particularities of each context, and promoting efficient water resource management with high agricultural productivity.

ACKNOWLEDGMENT

The authors would like to thank Adalberto de Paula, Karla Regina Piekarski Zapella e Tiago Hachmann for the guidelines in the modeling process.

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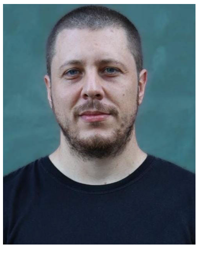

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