Irrigation Optimization in Agricultural Fields Using Deep Reinforcement Learning Approaches

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***Abstract*—In recent years, due to the world population growth, the demand for agricultural products has also increased. Global crises such as climate change, destruction of water resources, pollution and destruction of aquatic ecosystems, have limited the access to clean water to irrigate the agricultural fields in a global scale. Meanwhile, according to the reports of Food and Agriculture Organization of the United Nations (FAO), about 70% of global water consumption is allocated to agricultural activities. Therefore, it is necessary to minimize water consumption during agricultural irrigation while maximizing crop yield by the end of the season. Most IoT frameworks used in irrigation systems collect data from the soil and weather, then send it to the user, leaving the final decision on irrigation to the user. This approach may cause water wastage or even water stress for the plants as the amount of water irrigated in fields may be low. In this paper, we will use deep reinforcement learning approaches to reach this goal. We propose a novel approach to minimize water usage while keeping the yield produced at the highest level. Our approach utilizes DQN and A2C networks. The findings demonstrate that our methods reduce water wastage compared to previous approaches, making it more flexible and practical in varying weather and soil conditions.**

***Keywords*—Deep Reinforcement Learning, Water Management, Smart Agriculture, Smart Irrigation**

I. Introduction

With population growth and rising food demand, freshwater resources are under significant pressure. Climate change has led to fluctuations in rainfall patterns and air temperatures which directly affect available water resources [14], [15]. According to reports from the Food and Agriculture Organization (FAO), agriculture accounts for about 70% of global water use [18]. This highlights the urgent need for better irrigation practices and reduced water usage in food production.

Studies have also shown that in Iran [12], the agriculture is responsible for the largest share of domestic water consumption . These studies indicate that Iran uses approximately 42.43 billion cubic meters (BCM) of domestic water annually to produce 19 major agricultural products [12].

The agricultural water consumption in Iran is heavily reliant on internal water resources, significantly impacting the availability of renewable and non-renewable water sources, particularly groundwater resources [13]. Excess water usage has caused major issues such as the drying up of rivers and lakes and the declines in groundwater levels [18]. As a result, to address the water crisis in Iran, immediate attention should be given to agriculture policies to align with the constraints on water resources.

The Internet of Things (IoT), Big Data, and Artificial Intelligence (AI) have shown promising results for improving water management in agriculture [7], [20]. These technologies use sensors, wireless communication, and efficient algorithms to collect accurate data on soil, weather, and crops, helping farmers make better decisions about irrigation and water management.

A promising approach in this field is using machine learning to optimize water consumption in agricultural irrigation [4], [8]. By analyzing environmental data such as, humidity, temperature, soil moisture, and plant characteristics, machine learning algorithms can accurately predict plant water needs and soil moisture. This helps farmers determine the right timing and amount of irrigation, reducing water waste.

One limitation of certain machine learning approaches is their reliance on supervision and manual threshold configuration [2]. To address this, a reinforcement learning-based irrigation control method [5] can enable fully autonomous, optimal, or near-optimal decision making.

In this study, we implemented a deep reinforcement learning-based approach to irrigation scheduling to optimize crop yield. Compared to traditional reinforcement learning methods, this approach accommodates a larger state space and a larger number of irrigation configurations, improving its adaptability and efficiency.

In the following sections, we will first review related research in this field, then outline our methodology, and finally present and discuss our results.

II. Related Work

The integration of advanced technologies into agriculture has gained significant research attention with the aim of improving precision and efficiency in various sectors. This section reviews previous work on smart irrigation systems, highlights advances, limitations, and relevance to the proposed deep-reinforcement learning (DRL)-based approach.

A. IoT and Sensor-Based Irrigation Systems

IoT-based irrigation systems are essential for many intelligent agricultural practices. Sahu and Behera [19] introduced a cost-effective smart irrigation system in 2015 that used soil moisture sensors to automate water irrigation. This approach demonstrated simplicity but relied heavily on static thresholds, limiting adaptability to dynamic environmental conditions. Similarly, Zhao et al. [24] employed LoRa technology in 2017 to enable long-range communication for remote irrigation control, resulting in improved water efficiency but lacking integration with advanced prediction models for real-time decision-making.

Naji et al. [23] developed a WSN-based system in 2021 using Arduino and XBee for autonomous soil moisture management. While their system reduced water usage significantly, there were limitations in incorporating external factors, such as weather conditions. Bhoi et al. [3] addressed this gap by integrating weather data and machine learning models, By using an SVM model that outperformed other classifiers in optimizing water usage. However, the dependence on static machine learning models limited their adaptability in dynamic farming scenarios.

B. AI and Advanced Decision-Making Techniques

Recent research has focused on incorporating AI for smarter irrigation decision-making. Alibabaei et al. [1] employed a deep Q-Network model in 2022 for scheduling irrigation in tomato crops in Portugal, achieving an 18–30% reduction in water consumption compared to threshold-based methods. This work highlighted the potential of reinforcement learning for adaptive irrigation scheduling. However, the approach was limited to specific crop types and did not take into account broader environmental factors. Yang et al. [22] utilized DRL, specifically Deep Q-Networks (DQN), as the core methodology for their irrigation scheduling system. Their study encompassed diverse weather conditions and crop types, demonstrating the adaptability of the proposed approach. However, The evaluation relies heavily on simulated environments (using AquaCrop), which may not fully capture the complexities of real-world field conditions.

Florea et al. [6] in 2023 proposed an IoT-based system with Mamdani fuzzy logic, automatically adjusting irrigation times based on rainfall predictions and plant conditions. Despite outperforming traditional methods, their approach still relied on predefined rules and did not fully utilize the potential of dynamic learning systems.

C. Irrigation Frameworks and Their Challenges

Frameworks like the "Smart&Green" proposed by Campos et al. [10] emphasized customization, enabling outlier removal techniques for accuracy improvement. Although effective in reducing water usage by up to 90.4%, such frameworks often relied on user interventions and were challenging to implement in a small-scale or rural farms. Vallejo-Gómez et al. [21] reviewed intelligent irrigation systems in 2023 and identified IoT combined with machine learning as the recognized trend. However, they mentined that these systems often lacked scalability and applicability in urban or small-scale agricultural settings.

D. Identified Gaps and Relevance to the Proposed Method

Despite the advances, most of the studies share common limitations:

Many systems depend on static thresholds or user intervention for decision-making, reducing their effectiveness in dynamic environments. In addition, critical factors such as evapotranspiration, unexpected weather events, and soil heterogeneity are often underrepresented. Finally, existing solutions struggle to balance precision and practicality in small farms or rural settings. In our purposed method we aim to address these gaps by employing reinforcement learning for adaptive irrigation scheduling. By incorporating external factors such as weather data and soil characteristics, the method ensures higher adaptability and precision. Furthermore, DRL's ability to learn from historical data allows for reduced reliance on user intervention, making it applicable for diverse farming scales.

III. Methodology

In this section we describe our approach in data collection and model training in details.

A. Data Collection

To conduct this research, we needed to collect data on the growth characteristics of a plant and the factors influencing soil water content (e.g., temperature, humidity, wind speed, rainfall, etc.). However, since field studies and data collection for such parameters—especially for training machine learning models—often require years of effort, we opted to accelerate the process by utilizing simulated data.

For this research, we utilized the Decision Support System for Agrotechnology Transfer (DSSAT) [11] to simulate the data essential for our study. DSSAT is a powerful and widely-used suite of crop simulation models capable of analyzing and predicting the growth, yield, and resource utilization of various crops under a wide range of environmental and management conditions.

By configuring the software with specific parameters such as soil type, weather conditions, and crop varieties, we generated realistic data sets representing the growth characteristics of the selected plant and the factors influencing the soil water content. This approach allowed us to overcome the time-intensive nature of field studies and facilitate the development of machine learning models while ensuring the fidelity of the data to real-world agricultural conditions.

As mentioned above, creating a real-world dataset is complicated and requires years of effort. To address this issue, we used DSSAT to generate a dataset. We carefully configured the parameters to simulate agricultural conditions typical of Iran. For instance, we chose "Priestly-Taylor/Ritchie" for Evapotranspiration, a method suited for arid and semi-arid regions like much of Iran, where managing water loss is crucial. Similarly, the "Soleiman-Ritchie" Soil Evaporation Method accounts for significant soil evaporation in hot, dry climates with intense sunlight. The "Ceres (Godwin)" Soil Organic Matter Method reflects Iran's low-organic-matter soils common in arid areas. Parameters such as Planting Date, Depth, and Row Spacing are tailored to crops like wheat and barley, typically planted in winter or early spring to avoid extreme summer heat. In general, the selected parameters simulate conditions for semi-arid to arid climates, focusing on efficient water use and soil management for drought-resistant crops. Table I shows the complete list of parameters used to create the data set for this study.

Parameter	Value
Evapotranspiration	Priestly-Taylor/Ritchie
Infiltration	Soil Conservation Service
Init. Soil Cond.	As reported
Photosynthesis	Leaf Photosynthesis response curve (Hourly)
Hydrology	Ritchie water balance
Method of soil organic matter	Ceres (Godwin)
Soil evaporation method	Soleiman-Ritchie
Soil layer distribution	Modified soil profile
Watering Method	Sprinkler, mm
Management depth	30 cm
Threshold, % of max available	50
End point % of max available	100
End of application, growth stage	GS000
Efficiency fraction	0.75
Planting/Emergence date	03/01/2010
Planting method	Dry seed
Planting distribution	Rows
Plant population at seeding	3
Plant population at emergence	3
Row spacing	60 cm
Row direction, degrees from north	90
Planting depth	7 cm

TABLE I: Table of parameters and values used for dataset creation with DSSAT.

B. Irrigation Scheduling with Deep Reinforcement Learning

Machine learning has been widely applied across various domains to identify patterns and make predictions [17]. In agriculture, like other fields, numerous studies have employed machine learning techniques for irrigation scheduling.

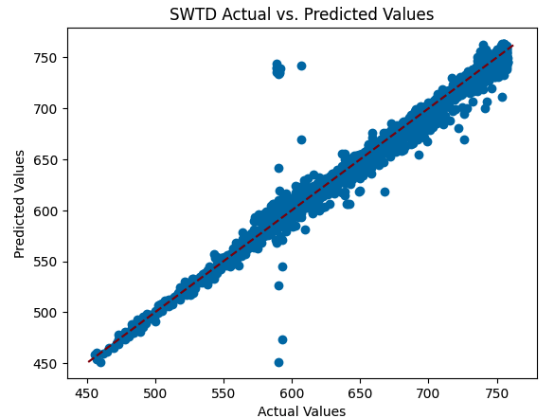

Fig. 1: Actual values vs. predicted values of The LSTM model for SWTD

Deep learning, a subset of machine learning, is faster and more efficient than traditional models, with the ability to automatically extract features from input data. Among these, deep reinforcement learning (DRL), which combines deep learning with reinforcement learning, has emerged as a powerful approach for solving complex decision-making problems. In this work, we leverage DRL techniques to optimize irrigation scheduling for improved efficiency and crop yield. More specifically two DRL models, DQN and A2C, are used which are explained in the following sections. Before delving into the specifics of these deep learning models, we first describe the learning environment for our agent and formally define the problem.

1) Environment for the DRL agent: To enable the DRL agent to determine the optimal irrigation policy, we designed an environment where the agent regulates irrigation by observing the soil water content (SWTD).

Prior to training the DRL model, two Long Short-Term Memory (LSTM) networks were utilized for pre-processing. The first LSTM model processes data from the preceding four days to predict the total soil water content (SWTD). The second LSTM model analyzes data spanning 172 days, corresponding to an agricultural season, to forecast the crop yield at the end of the season. These LSTM outputs are then fed into the DRL model to support learning.

To evaluate the performance of our LSTMs, we trained the models for up to 150 epochs. The LSTM for SWTD prediction achieved an R^2 score of 0.97 and a MAE of 0.014. Similarly, the LSTM for yield prediction, also trained for 150 epochs, achieved an R^2 score of 0.89 and a MAE of 0.08. Figures 1 and 2 show the comparison between the actual and predicted values for SWTD and yield, respectively.

In our model of irrigation, the total reward is defined as :

$$\text{Reward} = \log\left(yP_y - WP_w + n_{\text{irr}}W_{\text{max}}P_w + 0.1\right)$$

In this formula y is the total amount of yield, P_y is the

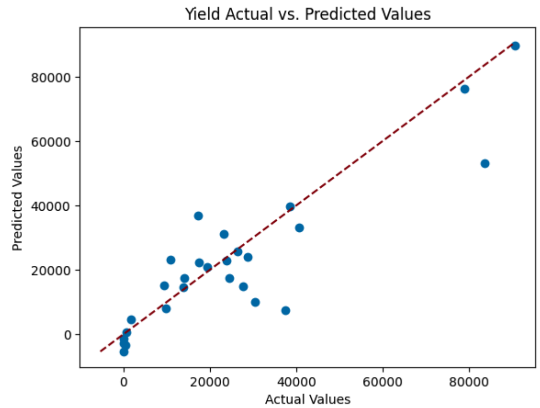

Fig. 2: Actual values vs. predicted values of The LSTM model for Yield

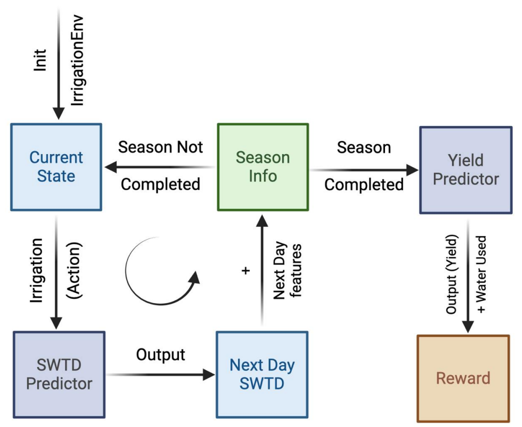

Fig. 3: The environment diagram utilized in this study.

price of 1kg of yield, W is the total quantity of used water and P_w is the price of water. Furthermore to ensure a positive reward, the formula includes a logarithmic term representing the product of the number of irrigation events to the maximum allowable water usage.

2) Problem Formulation: In this study, we employ a Markov Decision Process (MDP) [9] l. to enable the system to transition probabilistically between states. At each state $s \in S$ the agent selects an action $a \in A$ at time t that transitions the agent to state $s^{'} \in S$. Hence, the agent would receive the reward $R_a(s, s^{'})$. Moreover, the probability of transitioning from state s to $s^{'}$ using action a is defined by the state transition function $T_a(s, s^{'})$. The state represents the current situation of the environment which is observed by the agent. In this irrigation system, the soil moisture level (SWTD) is defined as the state, while the actions represent the amount of water used for irrigation. The agent transitions to a new state by adjusting the irrigation water applied. Figure 3 demonstrates the general diagram of our model.

3) Deep Q-Network: Deep Q-Network is a type of DRL model that combines Q-learning with deep learning. In Q-learning, an agent learns to make decisions by estimating the value of action-state pairs, called Q-values. A DQN uses a neural network to approximate the Q-values, enabling the agent to handle high-dimensional input spaces where traditional Q-learning would be impractical. The neural network is trained using experience replay and target networks to stabilize the learning process and enhance performance in complex decision-making tasks, such as irrigation scheduling in this research. Algorithm 1 is the pseudo code of DQN that we have used for training our irrigation optimization problem.

Algorithm 1 Deep Q-Network for Irrigation Optimization

Initialize: Replay buffer $\mathcal{D}$, Q-network $Q(s, a; \theta)$, target network $Q'(s, a; \theta^-)$, and learning rate α.
Set target network parameters $\theta^- \leftarrow \theta$.
for each episode **do**
  Reset environment; observe initial state s_0.
  for each time step t **do**
    Select action a_t using an ϵ-greedy policy:

$$a_t = \begin{cases} \text{random action with probability } \epsilon \\ \arg\max_a Q(s_t, a; \theta) \text{ otherwise.} \end{cases}$$

    Execute action a_t, observe reward r_t and next state s_{t+1}.
    Store transition (s_t, a_t, r_t, s_{t+1}) in replay buffer $\mathcal{D}$.
    Sample a random minibatch of transitions (s, a, r, s') from $\mathcal{D}$.
    Compute target value:

$$y = \begin{cases} r & \text{if episode ends at } s^{'} \\ r + \gamma \max_{a'} Q'(s', a'; \theta^-) & \text{otherwise.} \end{cases} ,$$

    Update Q-network by minimizing loss:

$$L(\theta) = \mathbb{E}_{(s,a,r,s')}\left[(y - Q(s, a; \theta))^2\right].$$

    Update network parameters: $\theta \leftarrow \theta - \alpha \nabla_\theta L(\theta)$.
    Periodically update target network: $\theta^- \leftarrow \theta$.
  end for
end for

C. Advantage Actor Critic (A2C)

A2C [16] is an on-policy algorithm that is a combination of both policy gradient and value-based methods. It is made up of two networks, the actor and the critic. In this algorithm, an agent, in the role of the Actor, learns a policy (probability distribution over actions) to choose an action, and a value function, in the role of Critic, assesses the actions performed by the Actor.

A2C introduces the concept of advantage that calculates the improvement of an action compared to the average expected action in a given state. The algorithm uses this advantage and adjusts the policy to improve performance. Furthermore, the actor maximizes the rewards and the critic minimizes the prediction errors.

in A2C , $\pi_\theta(a_t|s_t)$ represents the policy the agent uses to take actions and produces a probability distribution on the possible actions for the state s. While $V_\phi(s)$ is the value function that estimates the expected cumulative reward from a given state. s. Accordingly the advantage is calculated as $A_t = G_t - V_\phi(s_t)$ which shows how much better the action a_t worked compared to the estimation of the critic ($V_\phi(s)$) where G_t is the discounted cumulative reward.

Algorithm 2 shows the pseudo code of the A2C algorithm.

Algorithm 2 Advantage Actor-Critic (A2C) Algorithm

Initialize actor network $\pi_\theta(a|s)$ and critic network $V_\phi(s)$ with parameters θ and ϕ
Initialize environment
repeat
  Reset environment and initialize state s_0
  for each step in trajectory $t = 0, 1, \ldots, T-1$ **do**
    Sample action $a_t \sim \pi_\theta(a_t|s_t)$
    Execute action a_t in the environment
    Observe reward r_t and next state s_{t+1}
    Store (s_t, a_t, r_t, s_{t+1})
  end for
  Compute cumulative discounted rewards $G_t = \sum_{k=t}^{T-1} \gamma^{k-t} r_k$
  Compute advantage estimate: $A_t = G_t - V_\phi(s_t)$
  Update critic network by minimizing loss:

$$L_{\text{critic}} = \frac{1}{T} \sum_{t=0}^{T-1} (G_t - V_\phi(s_t))^2$$

  Update actor network using policy gradient:

$$\nabla_\theta J(\theta) = \frac{1}{T} \sum_{t=0}^{T-1} \nabla_\theta \log \pi_\theta(a_t|s_t) A_t$$

  Update ϕ and θ using gradient descent
until convergence or maximum episodes reached

IV. RESULTS

In this study, in order to train the agent, we have used two deep learning models, DQN and A2C. While previous studies [1] employed a DQN network to optimize irrigation scheduling, we implemented A2C to compare its performance against DQN in terms of total rewards. Figure 5 and 6 illustrate the average reward during the training of DQN and A2C models respectively.

Figure 4 shows the average rewards of the agent when evaluated on a DQN and an A2C network. As demonstrated in figure 4, The A2C agent indicates a higher stability in its performance compared to the DQN agent. The rewards for A2C are more consistent across episodes, while the DQN agent exhibits larger fluctuations in reward values. In addition, the total reward average for the agent using the A2C network scored as 21.06, while the average was 20.82 when DQN was utilized. A2C combines the benefits of both policy-based and value-based methods, which can lead to more stable and faster convergence. As shown in figure 6, A2C has less fluctuations in the convergence compared to DQN model shown in figure 5. Hence, the A2C model is particularly useful in complex environments where the irrigation system must adapt to varying conditions like weather, soil moisture, and crop requirements.

We selected A2C over DQN due to its greater stability and ability to address some inherent challenges in DQN. DQN is prone to overestimation bias in Q-values and involves complexities associated with experience replay. In contrast,

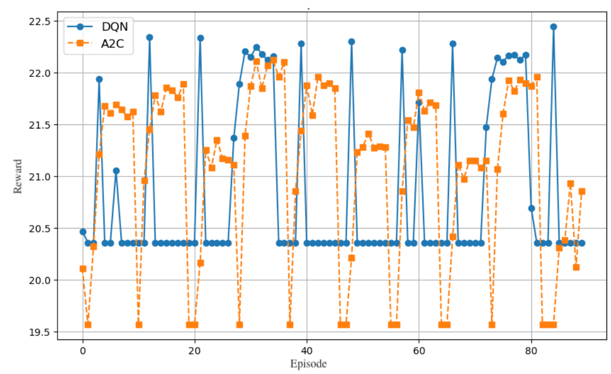

Fig. 4: Comparing DQN and A2C in rewards.

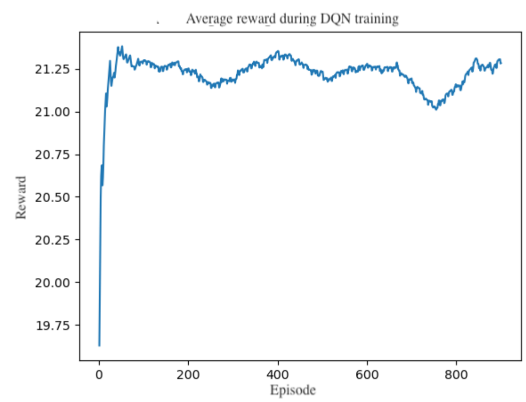

Fig. 5: The Average reward during the training of DQN.

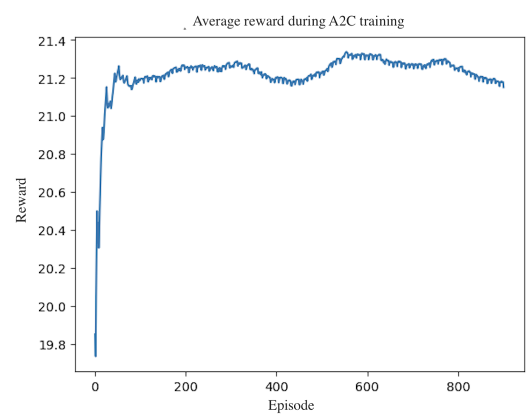

Fig. 6: The Average reward during the training of A2C.

A2C updates policies using gradient ascent, which promotes stability, and leverages the advantage function to reduce variance, making it a more robust choice.

V. Conclusion

In this study, we tackled the irrigation optimization problem using a deep learning framework, employing DQN and A2C models to improve water efficiency and crop yield. Following the simulation of our data using DSSAT, LSTM models were used for preprocessing. Eventually, the comparative results showed that A2C outperformed DQN in terms of stability and reward optimization, showcasing its robustness for complex decision-making tasks. These findings highlight the adaptability and practicality of DRL-based irrigation systems in diverse environmental conditions, providing a promising step toward sustainable agriculture. In future work, we aim to incorporate transfer learning techniques and investigate other deep learning models, such as Proximal Policy Optimization (PPO) and Asynchronous Advantage Actor-Critic (A3C). Employing Proximal Policy Optimization (PPO) could be advantageous as it could enhance the stability of policy-based methods, such as A2C, by limiting the amount of change in policy updates via a clipped objective function, preventing the agent from getting too greedy or too cautious.

References

[1] Khadijeh Alibabaei, Pedro D Gaspar, Eduardo Assunção, Saeid Alirezazadeh, and Tânia M Lima. Irrigation optimization with a deep reinforcement learning model: Case study on a site in portugal. *Agricultural Water Management*, 263:107480, 2022.

[2] Solon Barocas, Moritz Hardt, and Arvind Narayanan. *Fairness and machine learning: Limitations and opportunities*. MIT press, 2023.

[3] Ashutosh Bhoi, Rajendra Prasad Nayak, Sourav Kumar Bhoi, Srinivas Sethi, Sanjaya Kumar Panda, Kshira Sagar Sahoo, and Anand Nayyar. Iot-iirs: Internet of things based intelligent-irrigation recommendation system using machine learning approach for efficient water usage. *PeerJ Computer Science*, 7:e578, 2021.

[4] Hossein Dehghanisanij, Hojjat Emami, Somayeh Emami, and Vahid Rezaverdinejad. A hybrid machine learning approach for estimating the water-use efficiency and yield in agriculture. *Scientific Reports*, 12(1):6728, 2022.

[5] Xianzhong Ding and Wan Du. Optimizing irrigation efficiency using deep reinforcement learning in the field. *ACM Transactions on Sensor Networks*, 20(4):1–34, 2024.

[6] Adrian Florea, Daniel-Ioan Popa, Daniel Morariu, Ionela Maniu, Lasse Berntzen, and Ugo Fiore. Digital farming based on a smart and user-friendly iot irrigation system: A conifer nursery case study. *IET Cyber-Physical Systems: Theory & Applications*, 9(2):150–168, 2024.

[7] Fernando Fuentes-Peñailillo, Karen Gutter, Ricardo Vega, and Gilda Carrasco Silva. Transformative technologies in digital agriculture: Leveraging internet of things, remote sensing, and artificial intelligence for smart crop management. *Journal of Sensor and Actuator Networks*, 13(4):39, 2024.

[8] Hairong Gao, Lili Zhangzhong, Wengang Zheng, and Guangfeng Chen. How can agricultural water production be promoted? a review on machine learning for irrigation. *Journal of Cleaner Production*, 414:137687, 2023.

[9] Walter R Gilks, Sylvia Richardson, and David J Spiegelhalter. Introducing markov chain monte. *Markov chain Monte Carlo in practice*, 1, 1995.

[10] Nidia GS Campos, Atslands R Rocha, Rubens Gondim, Ticiana L Coelho da Silva, and Danielo G Gomes. Smart & green: An internet-of-things framework for smart irrigation. *Sensors*, 20(1):190, 2019.

[11] James W Jones, Gerrit Hoogenboom, Cheryl H Porter, Ken J Boote, William D Batchelor, LA Hunt, Paul W Wilkens, Upendra Singh, Arjan J Gijsman, and Joe T Ritchie. The dssat cropping system model. *European journal of agronomy*, 18(3-4):235–265, 2003.

[12] Mostafa Khorsandi, Tayebeh Omidi, and Pieter van Oel. Water-related limits to growth for agriculture in iran. *Heliyon*, 9(5), 2023.

[13] Kaveh Madani. Water management in iran: what is causing the looming crisis? *Journal of environmental studies and sciences*, 4:315–328, 2014.

[14] Rakesh Kumar Mishra. Fresh water availability and its global challenge. *British Journal of Multidisciplinary and Advanced Studies*, 4(3):1–78, 2023.

[15] Anil Kumar Misra. Climate change and challenges of water and food security. *International Journal of Sustainable Built Environment*, 3(1):153–165, 2014.

[16] Volodymyr Mnih. Asynchronous methods for deep reinforcement learning. *arXiv preprint arXiv:1602.01783*, 2016.

[17] Giang Nguyen, Stefan Dlugolinsky, Martin Bobák, Viet Tran, Álvaro López García, Ignacio Heredia, Peter Malík, and Ladislav Hluchỳ. Machine learning and deep learning frameworks and libraries for large-scale data mining: a survey. *Artificial Intelligence Review*, 52:77–124, 2019.

[18] David Pimentel, Bonnie Berger, David Filiberto, Michelle Newton, Benjamin Wolfe, Elizabeth Karabinakis, Steven Clark, Elaine Poon, Elizabeth Abbett, and Sudha Nandagopal. Water resources: agricultural and environmental issues. *BioScience*, 54(10):909–918, 2004.

[19] Chandan Kumar Sahu and Pramitee Behera. A low cost smart irrigation control system. In *2015 2nd International conference on electronics and communication systems (ICECS)*, pages 1146–1152. IEEE, 2015.

[20] A Subeesh and CR Mehta. Automation and digitization of agriculture using artificial intelligence and internet of things. *Artificial Intelligence in Agriculture*, 5:278–291, 2021.

[21] David Vallejo-Gomez, Marisol Osorio, and Carlos A Hincapie. Smart irrigation systems in agriculture: A systematic review. *Agronomy*, 13(2):342, 2023.

[22] Yanxiang Yang, Jiang Hu, Dana Porter, Thomas Marek, Kevin Heflin, and Hongxin Kong. Deep reinforcement learning-based irrigation scheduling. *Transactions of the ASABE*, 63(3):549–556, 2020.

[23] Areen ZA Naji and Adnan M. Salman. Water saving in agriculture through the use of smart irrigation system. In *2021 4th International Conference on Data Storage and Data Engineering*, pages 153–160, 2021.

[24] Wenju Zhao, Shengwei Lin, Jiwen Han, Rongtao Xu, and Lu Hou. Design and implementation of smart irrigation system based on lora. In *2017 IEEE Globecom Workshops (GC Wkshps)*, pages 1–6. IEEE, 2017.