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Reinforcement Learning Algorithm for Optimising Durian Irrigation Systems: Maximising Growth and Water Efficiency

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ABSTRACT

This study presents a Reinforcement Learning-based algorithm designed to optimise irrigation for Durio Zibethinus (i.e., durian) trees, aiming to maximise tree growth and reduce water usage. Traditional irrigation methods, as well as current machine learning models, often focus only on soil moisture and weather data, neglecting critical factors like actual tree growth. This study proposed a reinforcement learning irrigation (RL-Irr) algorithm incorporating tree growth stages, soil moisture, and weather conditions to determine precise irrigation needs. The algorithm was developed by calibrating the AQUACROP model using data from actual durian plantations where rain-fed irrigation (rain-fed) was practised. Daily irrigation volumes were calculated based on real-time soil moisture, weather forecasts, and weekly tree growth measurements. The reinforcement learning method was used to optimise irrigation schedules, with rewards based on soil moisture, tree growth, rainfall, and weather conditions. The algorithm was tested using AQUACROP simulations and compared against soil moisture balance irrigation (SMB-Irr) and rain-fed. The results showed that the RL-Irr reduced water use by up to 75 percent while maintaining tree growth. These findings suggest the algorithm could significantly improve water efficiency in durian farming, though real-world applications should consider potential model limitations.

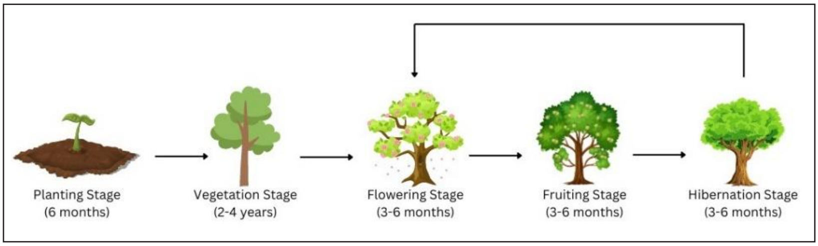
Keywords: Durian Farming, Durio Zibethinus, Machine Learning, Reinforcement Learning, Smart Irrigation.

INTRODUCTION

Durio Zibethinus, commonly known as durian and often referred to as the "king of fruits," is a well-known tropical fruit from Southeast Asia, celebrated for its intense aroma and uniquely rich flavour. This fruit is harvested bi-annually and is of significant economic value, enjoying widespread local and global demand. In Malaysia, a significant number of smallholder farmers cultivate durian, contributing to its commercial significance. In fact, durian has the largest cultivation area in Malaysia compared to all other fruits (Syafiqah et al., 2019). The maturation period of durian trees varies based on the variety, generally taking between two to six years (Chung, 2020). As illustrated in Figure 1, the cultivation of the durian tree involves five key stages: planting, vegetative growth, flowering, fruiting/harvesting and hibernation.

Figure 1

Durian Planting Stage from Seedling to Vegetation Stage



When cultivating durian trees, seedlings are first grown in polybags inside a shaded greenhouse. They are frequently provided with nutrient feedings and receive daily irrigation to ensure they stay properly hydrated. This controlled environment is essential for promoting healthy growth. Before being transferred to the open field, the trees undergo a hardening process, which includes exposing them to sunlight for at least a week to help them adapt to outdoor conditions. Once transplanted into open areas, the trees enter the vegetative stage, which is the longest and most critical phase, lasting up to four years, depending on the variety. If the trees fail to meet growth standards, farmers replace them and restart the vegetative process. Durian cultivation requires significant time, cost, resources and careful monitoring (Zakaria, 2020). Farmers watch for indicators such as leaf colour and quality, trunk diameter and overall height. Consistent irrigation and regular fertilisation are crucial during this stage. Water is more important than fertiliser for durian trees (Ketsa et al., 2020). Over-irrigation can saturate the soil, harming root growth, with excess water running off to lower areas. Under-irrigation can leave trees without enough water to survive. This emphasises the importance of precise water management in durian cultivation. Ensuring that each tree receives the right amount of water is crucial for optimal growth and hydration.

RELATED WORK

Adequate irrigation is essential for sustainable agriculture to meet the increasing food demands of the global population. Managing soil moisture is crucial for efficient water usage and boosting crop productivity. Soil moisture balance refers to the equilibrium between water added to the soil through rainfall or irrigation and water lost through evaporation and plant absorption (Ritchie, 1998). This equilibrium is vital for maintaining healthy soil and ensuring sufficient water for crops. Advancements in technology and a better understanding of the interactions of soil, water and plants have led to modern irrigation systems that utilise soil moisture data. These systems aim to align irrigation with the actual water needs of crops, conserving water and improving crop yields (Abioye et al., 2022). The use of soil moisture sensors and computerised controls demonstrates how modern technology has reformed traditional irrigation methods (Kumar et al., 2016). While soil moisture balance is vital for irrigation, challenges in its use include high costs, the need for specialised knowledge and various environmental factors affecting soil moisture (Pereira et al., 2020). This study explores the development, current technologies, benefits, challenges and valuable applications of irrigation systems based on soil moisture balance, drawing information from numerous academic and practical sources.

Integrating soil moisture balance into irrigation systems can bring about significant benefits and challenges for sustainable agriculture. One major advantage is the efficient use of water. Accurate measurement of soil moisture levels enables farmers to water crops effectively, ensuring responsible water usage, especially in areas with varying climates and soil types. Research in Nebraska shows that soil moisture and Vapour Pressure Deficit (VPD) affect plant water use, highlighting the importance of soil moisture in water management (Zhang et al., 2021). Proper irrigation reduces plant stress, promoting better growth and potentially higher crop yields. However, there are challenges involved. These include the time, labour and cost of installing and maintaining soil moisture sensors. Probes, particularly the advanced versions that collect data from multiple soil layers, are generally easier to install than point sensors but can be more expensive (Soothar et al., 2021). The precision of soil moisture sensors presents an additional challenge. Sensor accuracy can vary based on soil characteristics, such as clay content or salinity (Shakya et al., 2021). Electromagnetic sensors, for example, may be less accurate in soils with high clay or salinity. Therefore, choosing the correct sensor for the specific field conditions is crucial.

Moreover, the data from these sensors require careful analysis. Understanding all aspects of soil moisture levels is essential for accurate irrigation decisions. Some sensors provide easy-to-read graphical data, while others offer information in less intuitive formats, complicating the decision-making process for farmers (Jabro et al., 2020). Soil moisture balance-based irrigation (SBM-Irr) systems offer significant benefits, like optimised water use and potential yield increases. However, challenges include sensor accuracy, data analysis and costs. Addressing these issues is essential to fully realise the potential of these systems for sustainable farming. When cultivating durian trees, seedlings are first grown in polybags inside a shaded greenhouse. They are frequently provided with nutrient feedings and receive daily irrigation to ensure they stay properly hydrated. This controlled environment is essential for promoting healthy growth. Before being transferred to the open field, the trees undergo a hardening process, which includes exposing them to sunlight for at least a week to help them adapt to outdoor conditions. Once transplanted into open areas, the trees enter the vegetative stage, which is the longest and most critical phase, lasting up to four years depending on the variety. If the trees fail to meet growth standards, farmers replace them and restart the vegetative process. Durian cultivation requires significant time, cost, resources and careful monitoring (Zakaria, 2020). Farmers watch for indicators such as leaf colour and quality, trunk diameter and overall height. Consistent irrigation and regular fertilisation are crucial during this stage. For durian trees, water is more important than fertiliser (Ketsa et al., 2020). Over-irrigation can saturate the soil, harming root growth, with excess water running off to lower areas. Under-irrigation can leave trees without enough water to survive. This emphasises the importance of precise water management in durian cultivation. Ensuring that each tree receives the right amount of water is crucial for optimal growth and hydration.

The integration of Artificial Intelligence (AI) and machine learning (ML) into irrigation systems has transformed agriculture by optimising water usage, enhancing crop productivity, and reducing environmental impacts. These technologies have become vital in the face of global water shortages and increasing food demand due to population growth. AI-driven irrigation employs precision agriculture techniques, where irrigation schedules are tailored based on real-time data inputs, such as soil moisture levels, weather forecasts, and satellite imagery. By analysing these data streams, AI systems recommend precise irrigation schedules and automating water distribution to increase efficiency and reduce the need for manual labour.

ML algorithms, including Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Convolutional Neural Networks (CNN), are integral to this process, analysing complex data patterns to predict ideal watering schedules, as well as potential disease and pest outbreaks. These algorithms also enable adaptive irrigation strategies to respond dynamically to climate shifts. Recent advancements in IoT and cloud computing have further strengthened data collection and processing capabilities, creating highly responsive irrigation systems. Despite these advancements, challenges such as high initial setup costs, data reliability issues, and the learning curve for new technologies still pose barriers to widespread adoption. However, AI-driven irrigation remains essential for fostering sustainability and efficiency in agriculture (Talaviya et al., 2020). AI has significantly impacted agricultural irrigation systems. The MIT GEAR Lab has proposed an Automatic Scheduling-Manual Operation (AS-MO) irrigation tool to bring precision irrigation benefits to farmers in resource-limited regions. This tool integrates automatic scheduling to optimise water usage with manual operation of irrigation valves, allowing farmers to maintain control while benefiting from precision irrigation's efficiency. Designed specifically for East Africa and MENA regions, the AS-MO tool uses cloud-based algorithms to generate optimal irrigation schedules without the need for costly and complex soil moisture sensors. Instead, it uses soil water balance calculations based on affordable sensors for weather, solar power, and crop details. This design addresses the high cost and complexity of fully automated systems, which are often prohibitive for small and medium-sized farms. The AS-MO tool sends schedule updates via SMS to farmers' mobile phones, guiding them on when to manually open or close irrigation valves. This approach bridges the gap between existing expensive systems and traditional manual methods, making efficient irrigation more accessible to cost-constrained farms while minimising water and energy use (Van de Zande et al., 2023).

AI also plays a vital role in agricultural management. ML algorithms such as Random Forest (RF), SVM, ANN and CNN are used to analyse soil and crop health, helping to detect and predict crop diseases. These algorithms optimise irrigation by calculating the best watering schedules and timings (Awais et al., 2023). Combining the Internet of Things (IoT) and ML in smart agriculture is a major advancement. These systems are designed to reduce human involvement and improve water management efficiency. Unmanned Aerial Vehicles (UAVs) equipped with AI technology are increasingly used in agriculture. These UAVs help identify and monitor crops, providing vital data for improving irrigation techniques through detailed analysis of crop health and soil conditions. ML algorithms such as object-based image analysis (OBIA) were applied to process the images and identify areas of crops that required attention, such as herbicide spray for diseased crops (Yousaf et al., 2023).

Irrigation using real-time environment data is required to integrate various sensors, controllers, and communication networks to monitor and manage water delivery to crops based on real-time data such as soil moisture, weather conditions, and crop water requirements. AI techniques like ML and deep learning (DL) are used to analyse large datasets, including soil, water content, and environmental factors, enabling precise irrigation schedules. The system's ability to adapt to changing conditions helps improve water efficiency, reduce waste, and maintain crop health. Furthermore, the AI model leverages predictive tools to forecast future irrigation needs and adjusts the irrigation schedule dynamically, optimising water use while ensuring crop growth. This approach is particularly valuable for addressing challenges such as water scarcity and the unpredictable nature of climate change in agriculture (Obaideen et al., 2022). ML predicts irrigation needs, enabling proactive water management strategies that reduce consumption and increase productivity. Technologies such as ANN, fuzzy logic and expert systems enable adaptive decision-making and real-time monitoring, leading to higher yields and optimised water use. ANN-based controllers are particularly effective due to their learning and adaptability, making irrigation more efficient and sustainable (Bwambale et al., 2022). The algorithm can analyse large amounts of data to identify patterns and predict future water needs, helping farmers in planning and managing their irrigation systems more effectively. Other than that, in-situ AI sensors monitor soil moisture levels and provide alerts when irrigation is needed, reducing manual labour and improving overall efficiency (Tomar et al., 2023).

Smart irrigation systems offer numerous benefits for both urban and rural agriculture. These systems enhance agricultural productivity by minimising water waste and ensuring crops receive the precise amount of water needed for optimal growth and yield. Additionally, they contribute to reducing agriculture's environmental impact by promoting efficient water use, decreasing runoff, and supporting sustainable farming practices. These systems can be tailored to various agricultural environments, including urban areas with varying access to space, water, and electricity, although they may involve higher costs or operational limitations in some cases. Overall, AI-driven smart irrigation systems offer improved sustainability, efficiency and adaptability in various farming environments (Vallejo-Gómez et al., 2023).

However, implementing AI-based irrigation systems faces several key challenges. First, data availability is a significant issue as ML algorithms require large volumes of data to construct accurate predictions. In many regions, there is limited reliable data on soil moisture, weather patterns and crop growth, which impacts the accuracy of data predictions. Second, sensor reliability is a concern due to the high cost of installation and maintenance, as well as susceptibility to environmental factors such as temperature, humidity and electromagnetic interference, which can affect their accuracy. Third, a stable and reliable power supply is required in areas with limited electricity, especially in remote agricultural areas. The high cost of implementing intelligent irrigation systems is another significant obstacle, particularly for small-scale farmers (Ghareeb et al., 2023). Finally, farmers may lack the technical expertise to operate and maintain these systems, which hinders widespread adoption (Mohan et al., 2021). Apart from that, the concerns about privacy and security related to storing, processing and sharing sensitive data collected by the system, alongside the potential for cyber-attacks, further complicate the implementation of AI in irrigation (Tzachor et al., 2022).

Integrating AI into irrigation systems has revolutionised agriculture by optimising water use, boosting crop productivity and reducing environmental impacts. This is especially important given global water shortages and the rising demand for food due to population growth. AI in irrigation uses ML algorithms to provide precise agriculture techniques, tailoring irrigation based on data inputs like soil moisture, weather forecasts and satellite images. The ML algorithms analyse this data to recommend optimal irrigation schedules. Apart from that, the systems can also automate watering, improving efficiency and reducing the need for manual labour.

Reinforcement learning (RL) irrigation is considered a superior approach compared to conventional irrigation techniques and other AI irrigation models due to its adaptive decision-making ability (Saikai et al., 2023). While traditional methods rely on fixed schedules or basic rules, RL-based irrigation systems continuously learn and evolve by interacting with the environment. This allows them to optimise water use based on real-time conditions and weather forecasts. The flexibility of RL irrigation enables it to effectively manage water resources, minimise wastage and maintain crop productivity, even in the face of uncertain weather patterns. Moreover, RL irrigation has the potential to surpass other AI-driven methods by refining its strategies over time, balancing both immediate and future considerations for water efficiency and crop yield. Consequently, RL irrigation offers a more robust, efficient and viable solution for sustainable agricultural practices, especially in areas where water is a limiting factor. The Deep Reinforcement Learning for Irrigation Control (DRLIC) system is practical for irrigation because it seamlessly integrates with existing agricultural infrastructure, such as micro-sprinklers and soil moisture sensors and leverages real-time data to optimise water use efficiently. By employing a data-driven approach, DRLIC dynamically adapts to varying soil and weather conditions, reducing the need for manual adjustments and ensuring optimal irrigation levels to maintain crop health. The inclusion of a safety mechanism further enhances its practicality by preventing potential crop damage from unforeseen conditions, while its training methodology using a soil-water simulator accelerates deployment without lengthy field trials.

Moreover, the system has demonstrated significant water savings in real-world tests, making it a cost-effective and sustainable solution for irrigation in water-scarce regions. Overall, DRLIC's adaptability, compatibility, safety, and efficiency make it a highly practical choice for modern irrigation management (Ding & Du, 2024). The Deep Q-Learning Network Reinforcement Learning Irrigation (DQN RL-Irr) strategy leverages short-term weather forecasts to make optimal irrigation decisions, conserving water by reducing unnecessary irrigation and improving rainfall utilisation. This strategy effectively balances the risks of water waste and potential yield loss due to uncertainties in weather forecasts, making it a practical and efficient solution for managing irrigation in paddy rice cultivation (Chen et al., 2021). The proposed Semi-centralised Multi-agent Reinforcement Learning (SCMARL) framework combines both centralised and decentralised RL agents to handle spatial variability in large-scale agricultural fields, optimising water use across different management zones. The SCMARL approach achieved better water savings and improvement in Irrigation Water Use Efficiency (IWUE) compared to a learning-based multi-agent model predictive control (MPC) approach (Agyeman et al., 2024). This demonstrates RL's ability to efficiently coordinate irrigation decisions while addressing non-stationarity and scalability issues, making it a robust solution for precise irrigation management.

This work aims to propose an irrigation algorithm that minimises water usage while maintaining tree growth based on typical irrigation practices at the farm. Reinforcement Learning Irrigation (RL-Irr), an approach that relies heavily on weather conditions, current tree growth, and soil conditions, was introduced to attain this objective. RL-Irr is a non-model AI approach that adapts and learns dynamically as it uses real-time data and continuous interaction with the environment to optimise water usage efficiently and does not require any pre-built models to plan irrigation. In this study, the irrigation performance was compared with the rain-fed irrigation (rain-fed) and SMB-Irr models, and the results were evaluated based on the amount of water used and the simulated tree growth by AQUACROP. The Related Work section explains that SMB-Irr is the farmers' most used tool to identify the best daily irrigation volume. Therefore, it is crucial to recognise that the results obtained from the simulation rely on replicating real-world processes, interactivity, models, algorithms, and randomness, and thus, the findings provide insights for further empirical investigations to imitate real-world processes of durian farming and adaptive irrigations over time.

METHODOLOGY

Research Design

This work approach consists of four distinct steps, each with an intended output.

1) Soil sensor and weather station installation at the site and data collection
   Soil sensors were installed at specific locations to collect daily soil moisture readings. A weather station was positioned at the site's highest point to record daily weather data. Data from

both the soil sensors and the weather station were utilised to calculate rewards in the proposed algorithm.

2) AQUACROP parameters calibration
Rain-fed was the system practised on the farm, where irrigation was carried out based on rainfall data. The growth of selected durian trees was measured weekly, and the irrigation volume was measured daily, starting in November 2020. In this study, a custom crop was created in the AQUACROP model, as durian or biologically similar species (e.g., apple) were not available in the AQUACROP library. The model parameters were calibrated using the tree growth data collected on-site as the target output, with adjustments made to reflect the rain-fed model applied on the farm.

3) Development of Irrigation Model
Soil moisture and weather data will be incorporated into the proposed irrigation model. This model will analyse all relevant factors for initiating the irrigation system, including current and forecasted weather conditions, soil characteristics, and historical irrigation records. The model's performance will be evaluated by comparing the irrigation volume used, ensuring that water efficiency is achieved without compromising tree growth.

4) Testing and evaluation for the proposed irrigation model
The proposed model aims to reduce irrigation volume without compromising tree growth. The model was validated using independent tree growth data from the farm, which was not used during the tuning the AQUACROP parameters. The irrigation model's performance was evaluated by comparing the total irrigation volume with other existing irrigation models.

Farm Irrigation Setup

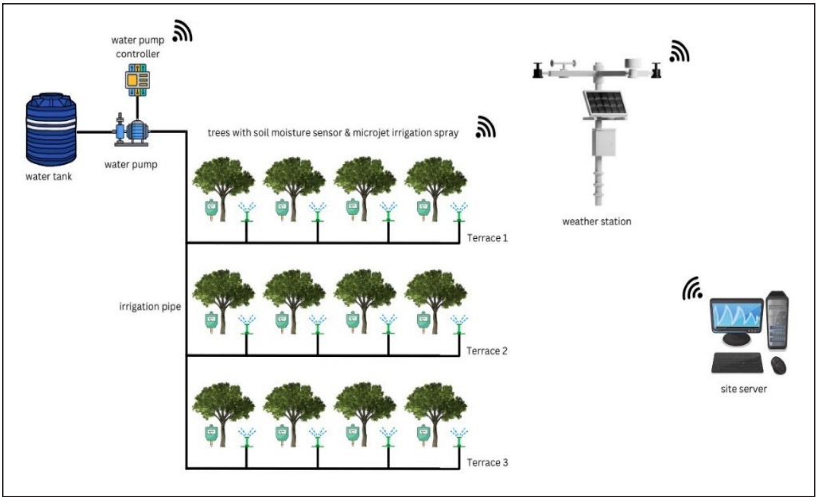
The work was conducted at MIE Agro Durian Farm in Selangor, Malaysia, located at coordinates 1°33'30.3336" N 103°37'33.4596" E. Each sub-block of the farm has a 2200-litre water reservoir with a pump for irrigation. Water was applied to each tree using a 180-microjet spray, which dispersed water at a flow rate of 0.5 litres per minute. Water was sprayed within the tree's canopy during irrigation to ensure optimal root absorption (Zakaria, 2020), as shown in Figure 2. The microjet spray flow rate was 0.5 litres per minute. Figure 3 shows the setup overview of the system implemented at the site.

Figure 2

Microjet Irrigation Spray

Figure 3

Setup Overview of the System at MIE Agro Farm



On the farm, 5,000 durian trees were planted in four blocks, each containing multiple sub-blocks. The trees in each sub-durian block are planted on terraces. The number of terraces varies between subblocks, and each terrace's slope gradient depends on the subblock's characteristics. Each sub-block is equipped with a 2200-litre water tank for irrigation purposes. In this work, sub- block D13, A1 and A3 were selected where the trees were planted between five and eight trees on each terrace. Each tree had a soil moisture sensor and a microjet irrigation sprinkler. A controller was connected to the water pump to control its operation, such as turning it on and off. A weather station was installed at the site's highest point, and a server was located in the site control room. The sensors, weather station and water pump controller were powered by batteries and solar panels and connected to the site server using wireless connectivity to facilitate future implementation scaling. The data were transmitted by the soil sensors and weather station to the server at the frequency of 5-minute intervals and were processed daily by the server using the proposed algorithm to control the irrigation system.

AQUACROP Simulation Software

AQUACROP is a simulation software that models how crop yield responds to water. It models based on user input data, considering factors like soil type, climate, crop type and management practices to predict how changes in water availability affect crop yield. It simulates water movement within the soil-plant-atmosphere system and the impact of different irrigation strategies on crop yield. This helps optimise water use in agriculture and promotes sustainable water management.

In the present work, the AQUACROP model is utilised to simulate the efficacy of the suggested irrigation strategy. AQUACROP employs above-ground biomass as an indicator of tree growth, which is determined through calculations involving the height of the trees for the forest-type trees, as shown in Equation 1.

$$Y = 10 + 6.4\, x\ tree\ height \qquad (1)$$

where Y is the above-ground tree biomass in kilogram (kg), and the tree height is in metres (m). Data about the trees were systematically gathered weekly at the farm, and information from the trees exhibiting optimal growth was aggregated and established as the growth benchmark for this research. Consequently, the recommended irrigation strategy was modified daily to align with the attainment of this growth objective.

Standard parameters were configured in a custom crop setup in AQUACROP. As shown in Table 1, some parameters are standard for the trees, which refer to the crop-dependent parameters based on the crop's biological characteristics, while others are site-dependent parameters, which are based on the site setup and conditions that significantly affect tree growth.

Table 1

AQUACROP Custom Crop Input Parameters

Parameters	Definition	Remarks
Maximum temperature (°C)	Maximum temperature at site	Site dependent
Minimum temperature (°C)	Minimum temperature at the site	Site dependent
Canopy growth coefficient, CGC	Rate canopy cover (CC) increase at the initial planting state	Crop dependent
Canopy decline coefficient, CDC	Rate canopy cover (CC) decreases due to ageing or dying	Crop dependent
Crop coefficient, K_{ct}	Ratio crop evapo-transpiration over site evapotranspiration	Crop & site dependent
Maximum canopy cover, CC_x (%)	Maximum coverage of the canopy	Crop & site dependent
Maximum rooting depth, Z_x (m)	Maximum depth of the tree root	Crop & site dependent
Initial root depth, Z_o (m)	Initial depth of the tree root after transplant	Crop & site dependent
Irrigation efficiency (%)	Percentage efficiency of the irrigation setup	Site dependent
Soil surface wetted	Percentage of wetted area during irrigation	Site dependent
Tree spacing (m^2)	Distance between trees	Site dependent
Reference harvest index (HI_o)	Standard ratio of total biomass in ideal condition	Crop dependent

Rain-fed Irrigation (Rain-fed)

This work focused on three (3) sub-blocks on the farm: D13, A1 and A3. The sub-blocks used rain-fed irrigation, an agricultural irrigation technique that relies solely on rainfall as the water source. This method is the primary way of farming, though its success depends greatly on the amount and distribution of rainfall. A weather station was set up on-site to measure daily rainfall and help decide when to irrigate. The irrigation was done manually, providing each tree with 30 litres of water for one (1) hour. The pseudo-code of the rain-fed irrigation practised on the farm is shown in Algorithm 1.

Algorithm 1: Algorithm for Irrigation Control Based on Rain-fed

Input: Rain volume: rain volume measured from 10:00 AM the previous day until 7:00 AM on the current day.
Output: Irrigation control decision.

Procedure:

1. Check rain status at 8:00 AM daily:
2. **If** rain occurred between 10:00 AM the previous day and 7:00 AM today:
3. **If** rain volume < 5 mm
4. Irrigate 30 litres.
5. **Else If** rain volume > 10 mm
6. No irrigation for the next 2 days.
7. **Else**
8. No irrigation for the current day.
9. **Else (If No Rain Occurred):**
10. Irrigate 30 litres.

End Procedure

Soil Moisture Balance Irrigation (SMB- Irr)

The SMB-Irr system determines the optimal timing and the optimal amount of crop irrigation by considering soil moisture levels. It balances water inputs such as rain and irrigation with outputs, such as evapotranspiration, drainage and runoff relative to the soil's water-holding capacity. The SMB-Irr system used in this work was based on the Field Capacity (θfc) and Wilting Point (θwp) of the soil, the variables which are specific to the soil type and were chosen according to the Malaysia Soil Standard (Ashraf, 2017) and the USDA Soil Standard (Jabro et al., 2008). The following steps outline how to calculate irrigation volume using SMB-Irr:

Step 1: Calculate the soil threshold value, θ_x, by using the formulation in Equation 2.

$$\theta_x = \theta_{fc} - (ASMD\ x\ (\theta_{fc} - \theta_{wp}) \tag{2}$$

where ASMD stands for Available Soil Moisture Deficit, which represents the allowable deficit for the trees before they experience a deficit state of a moisture shortage, assuming the ASMD durian tree is 0.2, which is 20%.

Step 2: Calculate the weighted average soil moisture, θ_a at the root zone level by using Equation 3.

$$\theta_a = (\theta_{SM} \ x \ D_s)/RZD \tag{3}$$

where θ_{SM} is the soil moisture value from the sensor, D_s is the Sensor Depth and RZD is the Root Zone Depth, where RZD is 0.1-metre for the trees between one (1) to three (3) years of age.

Step 3: Compare θ_x and θ_a values. If θ_a is lower than θ_x, calculate the irrigation volume as in Step 4. If higher, no irrigation is required.

Step 4: Calculate the irrigation volume, V_{irr} by using Equation 4.

$$V_{irr} = (\theta_{fc} - \theta_a) \times RZD \times 1000 \tag{4}$$

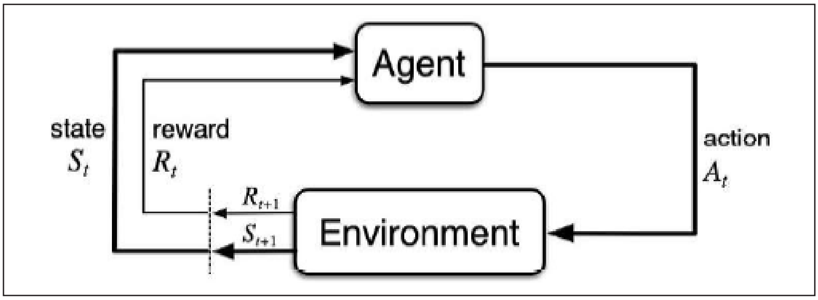
where the V_{irr} is in litre

Reinforcement Learning Irrigation (RL- Irr)

RL is a non-model type of AI that involves an agent learning to make decisions by interacting with its environment. In reinforcement learning (RL), the agent is not given explicit instructions on which actions to take. Instead, it must autonomously explore and experiment with different actions to determine which ones yield the highest rewards. This approach is inspired by behavioural psychology and is particularly effective in complex contexts where explicit programming is impractical. The agent tries different actions to see which ones produce the best rewards (Devraj et al., 2021). The process involves an agent, a set of states representing the environment and the actions taken by the agent. The agent receives feedback in the form of rewards or penalties and develops a policy, which is a systematic approach for selecting actions based on the current state of the environment. RL uses this feedback to reinforce effective strategies and diminish ineffective ones. The fundamentals of RL are shown in Figure 4.

Figure 4

Fundamental Architecture of RL (Sutton & Barto, 1999)



In RL, it is crucial to strike a balance between exploring and attempting new approaches and exploitations by using familiar knowledge (Ladosz et al., 2022). The agent interacts with the environment in discrete time steps. At each time step, t, the agent receives some representation of the state of the environment S(t) and selects an action A(t) based on that state to perform in the environment. The action then changes the state of the environment, and the agent receives a reward R(t+1) and a new state S(t+1) as feedback from the environment. If the action leads to an undesired outcome, the agent receives a penalty (a negative reward) instead of a reward. This process continues, and the agent's objective is to learn a policy by mapping from states to actions in order to maximise the cumulative reward over time. RL is utilised in various fields, including robotics, transportation, energy and computer systems (Aradi, 2022; Jayaramireddy et al., 2023; Polydoros & Nalpantidis, 2017; Yu et al., 2021).

The implementation of RL in this work is as follows:

1) Agent (*i*) is the entity that performs actions in the problem. In this work, the agent represents the system's core elements that interact with the environment, formulate decisions based on information and acquire knowledge from the consequences of those decisions.
2) Environment (ε) is the space in which the agent performs actions. In this work, the environment encompasses all the elements that influence the actions, which are soil conditions, weather conditions and tree growth.
3) Action (*A*) is the potential moves that can be performed by the agent. In this context, the action refers to the absolute irrigation

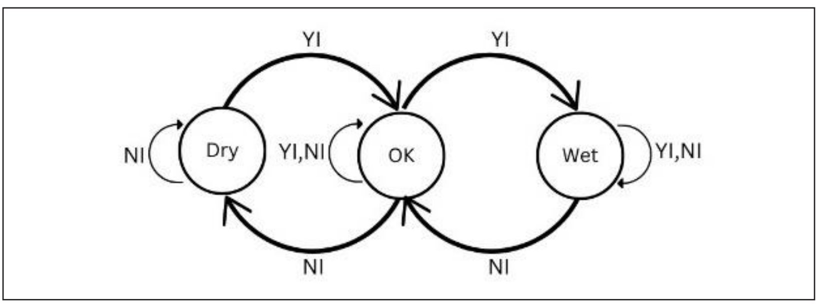
volume set in the system. These volumes ranged from 0 to 30 litres, with increments of 2 litres.

4) State (*S*) is the specific condition of the environment at a specific time. In this work, state refers to the specific condition of the soil at a given time. The soil condition is categorised as dry (soil moisture is less than 25%), good (soil moisture is between 25% to 35%) or wet (soil moisture is more than 35%).
5) Policy (π) is the guideline employed by the agent to determine the next step of action to take based on the current state. In this work, Policy refers to the sequence of irrigation actions that the agent takes to solve the problem.
6) Rewards and Penalties (*R*) are the outcomes the agent receives after taking an action. They are result-oriented and can be either positive (Reward) or negative (Penalty). The calculation of Rewards and Penalties must be in line with the environment to ensure that the agent receives them accurately. In this work, the Reward depends on soil tension, tree growth and water balance. A Penalty is incurred if the irrigation action causes the soil to become either Dry or Wet.

Figure 5 presents the RL states employed for tree irrigation in this study. YI and NI represent Yes Irrigation and No Irrigation, respectively.

Figure 5

RL State for RL-Irr



The diagram above illustrates the actions taken by the agent in response to varying soil conditions. In scenarios without irrigation, the soil retains its ‘Dry’ state. Its transition to an ‘OK’ state occurs only upon the commencement of irrigation. The soil maintains its condition without further irrigation in this ‘OK’ state. However, prolonged periods without irrigation will lead the soil back to a ‘Dry’ state. Conversely, initiating irrigation while the soil is in an ‘OK’ state causes it to become ‘Wet’. Typically, irrigation is withheld in the ‘Wet’ state to prevent soil saturation. Nonetheless, rainfall might occur when the soil is already ‘Wet’, thereby maintaining its ‘Wet’ state. The soil eventually reverts to the ‘OK’ state after a certain period without irrigation and gradually becomes drier. This dynamic reflects the agent’s adaptive responses to the evolving moisture levels in the soil, corresponding to the root water uptake from the trees.

This work has several target goals, such as enhancing water efficiency, conserving soil fertility and maximising crop vitality. An effectively designed reward function can skilfully balance these objectives by providing suitable incentives for actions that contribute to each goal. Moreover, the reward function can account for the inherent trade-offs within the application. For instance, in irrigation management, higher water consumption may initially promote crop growth but could negatively impact long-term water conservation. The reward function is crucial in reconciling these conflicting requirements. It will ensure that the RL agent’s learning path is theoretically rigorous and practically applicable, bridging the gap between mathematical modelling and the complexity of real-world implementation. Equation 5 shows the Rewards function used in this work.

$$\begin{aligned} R_{total} = (w_{soil\ tension} \times R_{soil\ tension}) \\ + \left(w_{tree\ growth} \times R_{tree\ growth}\right) \\ + (w_{rain} \times R_{rain}) + (w_{Et} \times R_{Et}) \end{aligned} \tag{5}$$

The variable w represents the weight assigned to different elements, determined by the proportion of each element relative to the overall weight distribution. These weights were set according to the specific objectives of irrigation and the prevailing conditions during that period. For example, $w_{soil\_tension}$ was assigned a higher value in instances of arid soil and a lower value in other cases. Conversely, w_{tree_growth} was high when irrigation occurred on the first day of the week, as per the standard operating procedure of the farm, which involved collecting data on tree growth exclusively on this day. This approach ensures that the weighting aligns with the immediate environmental needs and the operational procedures of the farm. Similarly, the variables w_{rain} and w_{Et} were assigned high values, respectively, if the actual value was lower than the calculated value, and a lower value if it was higher.

In Equation 6, the term 'Rewards' (R) encapsulates the rewards attributed to each critical element: soil tension, tree growth and water efficiency. These rewards are intricately linked to the prevailing conditions of the respective period, ensuring that the rewards allocated to the agent are optimised based on the actual environmental and operational circumstances. Equations 6 to 9 outline the formulas for calculating the rewards for the elements.

$$R_{soil\ tension} = -\left(soil\ tension_{target} - soil\ tension_{actual}\right) \tag{6}$$

$$R_{tree\ growth} = -\left(tree\ growth_{target} - tree\ growth_{actual}\right) \tag{7}$$

$$R_{Et} = -\left(Et_{forecast} - Et_{actual}\right) \tag{8}$$

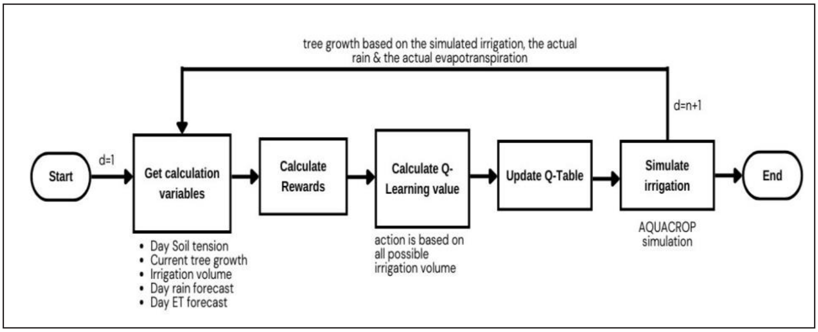
$$R_{rain} = -\left(Rain_{forecast} - Rain_{actual}\right) \tag{9}$$

The target for tree growth was calculated using a model crafted and simulated with the AQUACROP software. The study suggests that using a deseasonalised fuzzy time series model for rainfall forecasting yields higher accuracy than traditional methods, as shown by lower MSE and RMSE values (Othman & Azhari, 2016). However, the use of actual rainfall data at a specific location is preferred for real-time predictions since it reflects the real-world environmental conditions and variability. Rainfall predictions are based on forecasts from the Malaysian Meteorological Department (MET). Additionally, the forecast for evapotranspiration (Et) is computed utilising the Penman-Monteith (PM) Equation, which incorporates meteorological forecast data from the MET. This integrated approach ensures a comprehensive and accurate assessment of precipitation and evapotranspiration, which is crucial for effective irrigation planning and management.

The flowchart in Figure 6 above illustrates the proposed RL-Irr system. On the first day *(d=1)*, the system assessed the soil tension using the current soil moisture value, tree growth, previous irrigation volume, rain prediction from the MET website and calculated evapotranspiration based on forecasted weather data from the MET website. The system then calculated the Rewards using the formula from Equations 6 to 9. Q-Learning for all possible actions (irrigation volume) was calculated and updated in the Q-table. Then, the system simulated irrigation using AQUACROP and observed the simulated tree growth from the simulation output. The variance between the simulated and expected tree growth, based on actual growth data collected at the site, was calculated and input into the system for the next day's irrigation *(d=n+1)*.

Figure 6

System Flow for the Proposed RL-Irr



RESULTS AND DISCUSSION

This section compares the irrigation volume between SMB-Irr, rain-fed, and RL-Irr. In this study, the actual tree growth data were gathered on-site using the SMB technique for irrigation. The soil type was sandy clay loam, and the soil moisture threshold for the SMB was set to 35 percent based on the soil field capacity standard for sandy clay loam soil (RainMachine, 2018). If the current soil moisture fell below the threshold value, irrigation would be initiated for a few minutes until the moisture reaches the set threshold.

Tree Growth

AQUACROP evaluates irrigation efficiency using biomass values proportional to tree height, as shown in Equation (1). Weekly tree growth data were collected for trees at D13, A1 and A3. The AQUACROP model was calibrated to match tree growth using the rain-fed irrigation method practiced on-site. Since the AQUACROP model is unavailable for durian, calibration was necessary to ensure the model accurately reflected tree growth (Ismail et al., 2015). The study then simulated the suggested irrigation methods using the calibrated AQUACROP model to assess their effectiveness. Figures 6 to 9 show the tree growth pattern from November 2020 to December

2023. Weekly measurements were taken at three farm sub-blocks: D13, A3, and A1. Sub-blocks D13 and A3 consisted of five terraces of different elevations, each with 10 to 20 trees, totalling 100 trees per sub-block. Sub-block A1 consisted of one terrace with 10 trees. Since tree growth was nearly identical on each terrace, the average growth per terrace was used in this study instead of individual tree measurements.

Figure 7

Tree Height from Week 1 (November 2020) to Week 113 (March 2023)

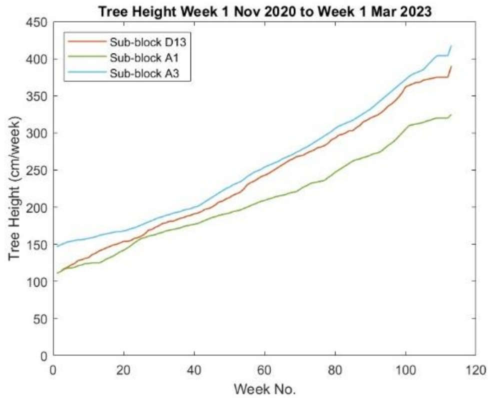


Figure 8

Tree Girth from Week 1 (November 2020) to Week 113 (March 2023)

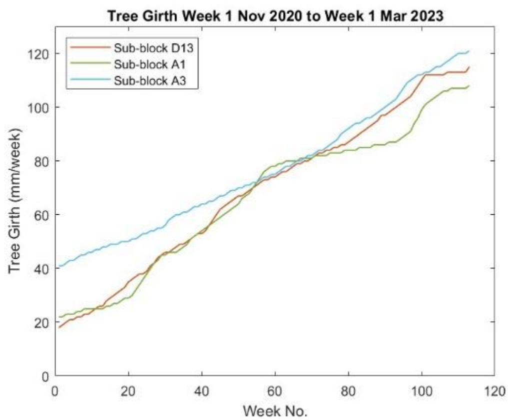


Figure 9

Tree Height Growth Rate from Week 1 (November 2020) to Week 113 (March 2023)

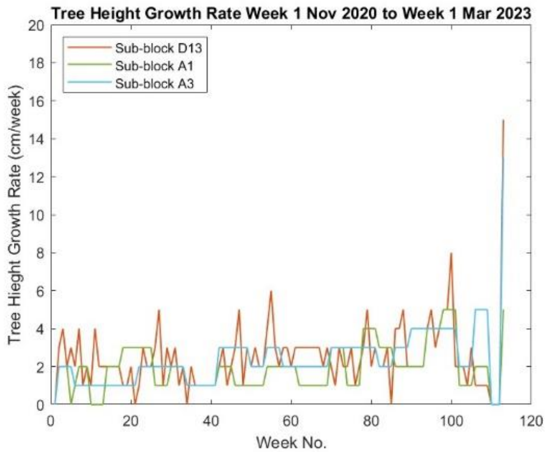
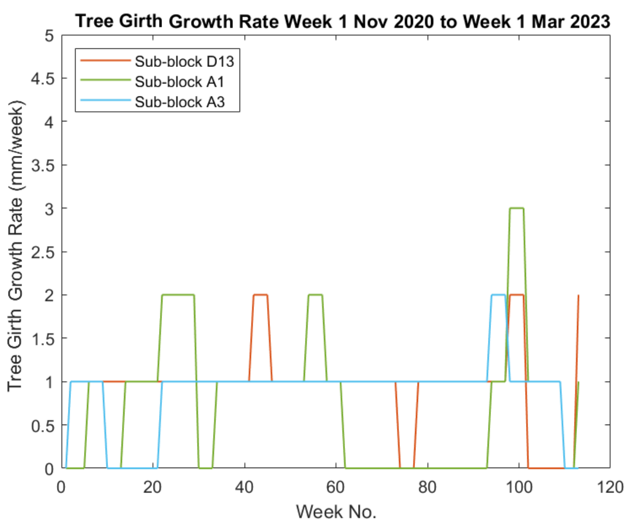


Figure 10

Tree Girth Growth Rate from Week 1 (November 2020) to Week 113 (March 2023)



The trees were transplanted at heights of 1 to 1.5 meters in Week 1. Figures 7 and 8 display the growth metrics, specifically tree height and girth, for three sub-blocks (D13, A1, and A3) from Week 1 (November 2020) to Week 113 (March 2023). Figure 7 illustrates tree height in centimetres on the y-axis and the week number on the x-axis. The trees exhibited a steady increase in height from the beginning, with the growth rate represented by the slope of the curve. The curve follows a sigmoidal pattern, typical of biological growth, with an initial slow phase, rapid growth and a slowdown as the trees matured. Sub-block D13 consistently exhibited the highest growth throughout the period, followed closely by A1, while A3 exhibited significantly lower growth. Figure 8 shows the trunk girth of the trees in millimetres (mm) on the y-axis, plotted against the week number on the x-axis. As tree height increased, the trunk girth also grew over time. All sub-blocks showed an increase in trunk size, with sub-block D13 exhibiting the most significant increase, followed by A1 and A3, similar to the height growth trend. These results suggest that soil conditions at D13 positively impacted tree growth. The consistent growth across all blocks indicates that the care provided was effective, adhering to the farm's standard operating procedures, including proper irrigation and nutrient supply (Zakaria, 2020).

Figures 9 and 10 illustrate tree height and girth growth rates for D13, A1, and A3 from Week 1 (November 2020) to Week 113 (March 2023). Figure 6 displays the weekly growth rate of tree height in centimetres. The height growth rates for all sub-blocks vary significantly each week, showing spikes and drops. This variability is likely due to environmental and biological factors, such as inconsistent weather and nutrient and water uptake variations. The growth rates for each sub-block were inconsistent throughout the monitoring period, which is typical for open-field farming, where environmental factors affect tree growth (Cocozza et al., 2021).

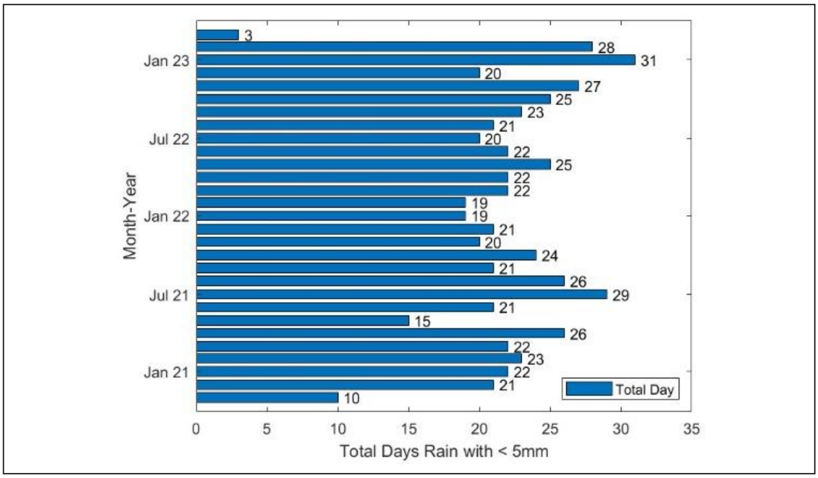
Additionally, Figure 10 indicates the weekly increase in tree girth, measured in millimetres (mm). The girth growth rates were generally lower than the height growth rates, which is typical of biological growth patterns. The girth growth rates were more consistent, with less fluctuation than height growth. Both height and girth growth were affected by weather, environmental changes, resource availability, and the trees' natural biological cycles. Trees in sub-block D13 showed higher growth peaks in both height and girth compared to those in A1 and A3. Despite using the same procedures for all trees, the trees in D13 responded better, indicating more favourable growth conditions.

Irrigation Volume

The farm utilised a rain-fed irrigation method, supplying 30 litres of water to the trees on days with no rain or less than 5 mm of rainfall. The growth of the trees based on this irrigation method is depicted in Figures 7 and 8. Additionally, Figure 11 displays the monthly total of days with less than 5 mm of rain, indicating when 30 litres of water were applied, using data from the farm's weather station.

Figure 11

Total Days of Rain with Less Than 5mm on the Farm



Based on the analysis of rainfall frequency, the farm required irrigation almost every day. In March 2023, there was the highest amount of rainfall, with only three days out of 30 receiving less than 5mm of rain. On the other hand, January 2023 experienced the least amount of rain, with all 31 days having less than 5mm of rain daily. A single weather station represented the entire farm area. When the rainfall was less than 5mm, each sub-block received 30 litres of irrigation, effectively tripling the total irrigation volume for D13, A1, and A3 combined.

Figures 12 to 14 illustrate the daily irrigation volume using SMB-Irr and RL-Irr for all terraces. Despite each sub-block having five terraces, the irrigation volume applied to the trees was consistent across all terraces within each sub-block.

Figure 12

Irrigation Volume Using SMB-Irr and RL-Irr for D13

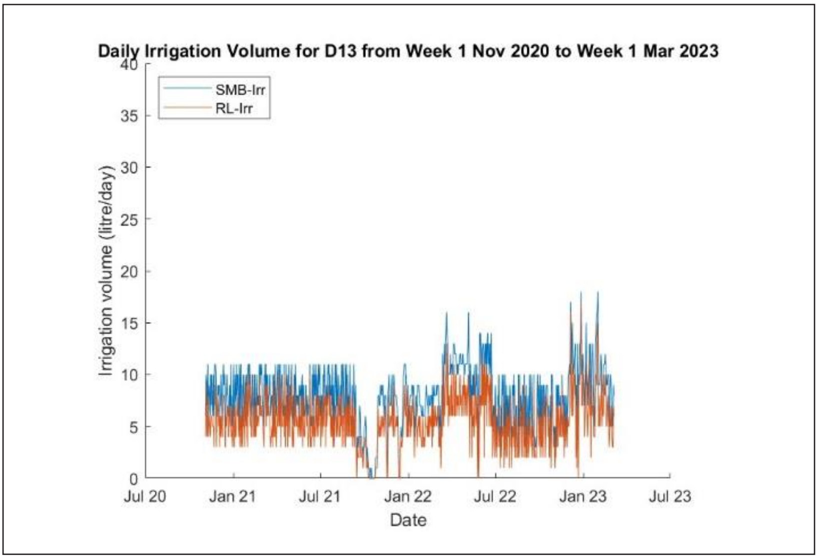


Figure 13

Irrigation Volume Using SMB-Irr and RL-Irr for A1

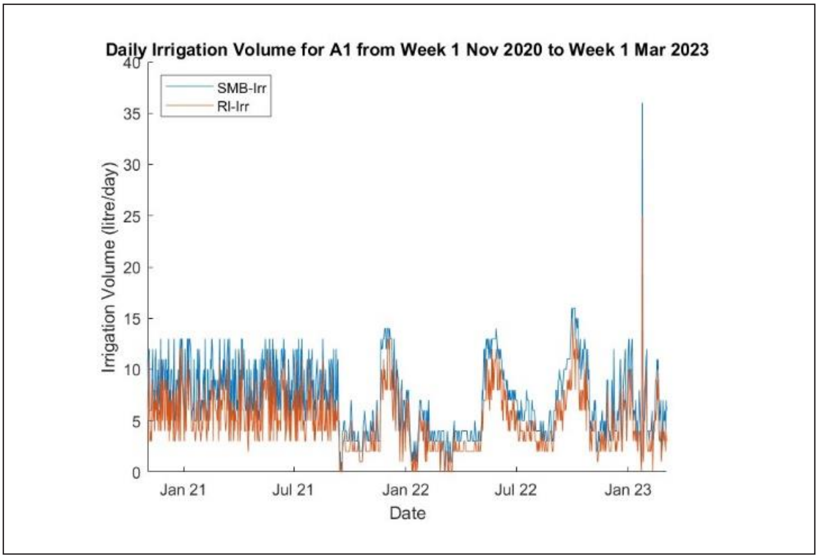
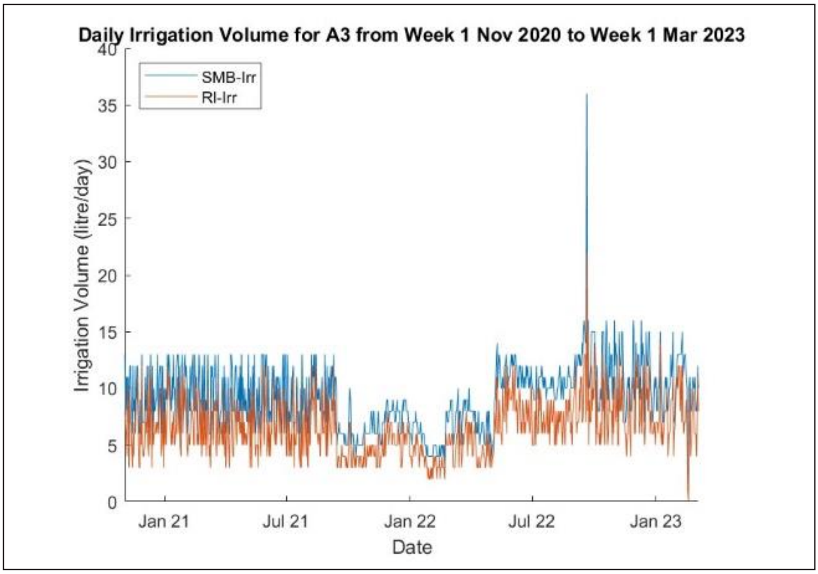


Figure 14

Irrigation Volume Using SMB-Irr and RL-Irr for A3



Figures 12 to 14 display the daily water usage for irrigation in litres for three sub-blocks (D13, A1 and A3) from November 2020 to March 2023. The data compares two irrigation methods: SMB-Irr (based on soil moisture) and RL-Irr. Both methods exhibited daily variations influenced by rainfall, temperature, evapotranspiration and the needs of the trees over the three years. Water usage fluctuated, with some days requiring significantly more water, indicating the necessity for adaptive irrigation strategies. RL-Irr used less water overall compared to SMB-Irr across all sub-blocks. RL-Irr did not perform irrigation on several days, such as November 3, 2020, September 15, 2021, and various days in October 2021, November 2021, December 2021, May 2022 and December 2022. On the other hand, SMB-Irr showed sudden increases in irrigation when soil moisture was low, but such occurrences were rare in RL-Irr. RL-Irr accounted for additional factors to determine the specific amount of water needed each day. Figures 15 to 17 illustrate the cumulative weekly irrigation volume for each terrace, and Table 2 compares the total irrigation volumes of SMB-Irr and RL-Irr with the measured rain-fed method.

Figure 15

Cumulative Irrigation Volume for Trees at D13

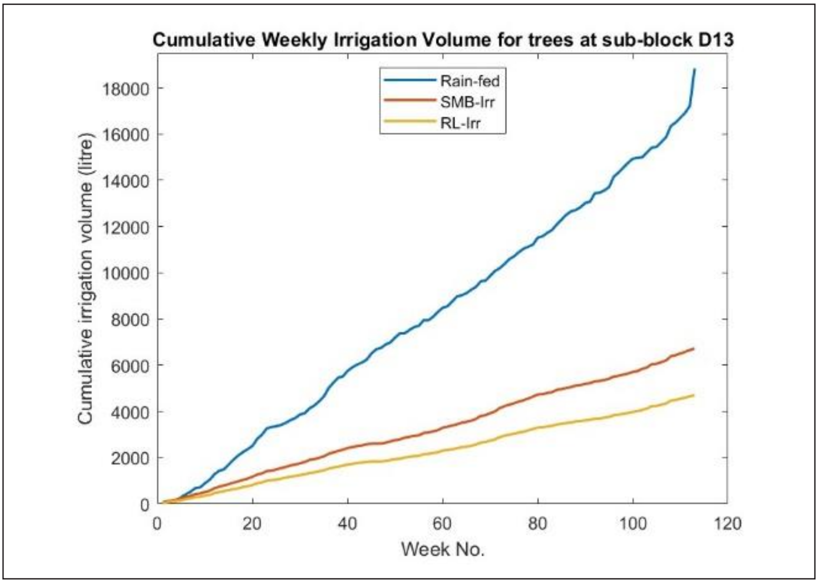


Figure 16

Cumulative Irrigation Volume for Trees at A1

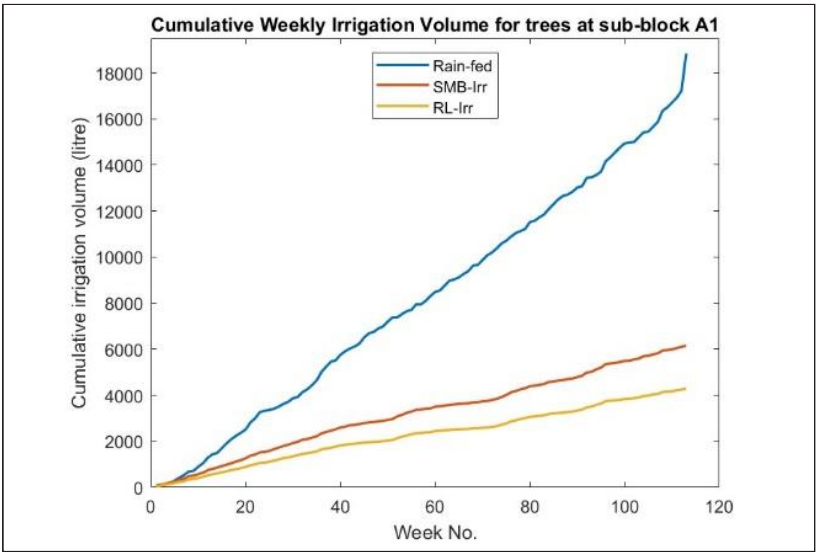


Figure 17

Cumulative Irrigation Volume for Trees at A3

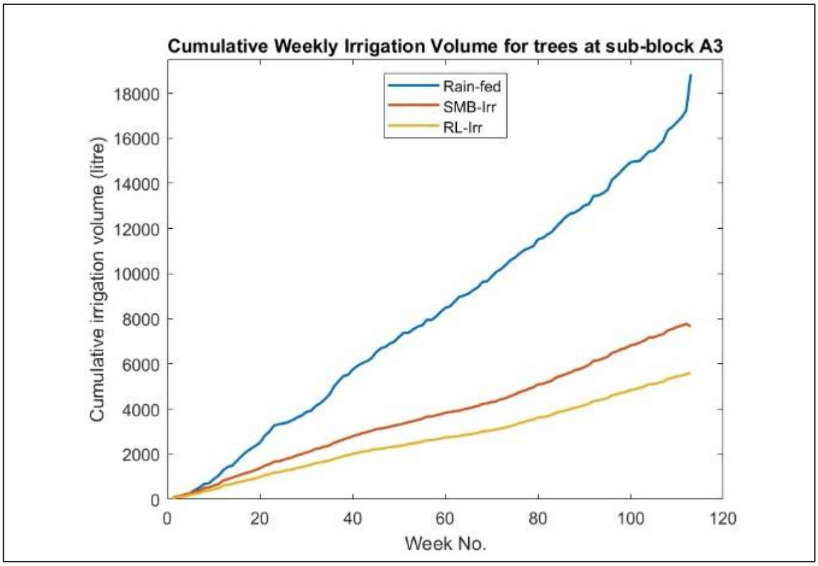


Table 2

Total Irrigation Volume for All Sub-blocks Calculated Using Different Irrigation Strategies

Irrigation Method	Irrigation Volume (litres)			
	D13	A1	A3	Total
Rain-fed	18840	18840	18840	56520
SMB-Irr	6731	6161	7862	20754
RL-Irr	4704	4290	5606	14600

The graphs illustrate the cumulative weekly irrigation volume for trees at sub-blocks D13, A1 and A3 over a period of 113 weeks. Each graph compares three irrigation methods: rain-fed, SMB-Irr and RL-Irr. The X-axis represents the number of weeks, while the Y-axis shows the cumulative volume of irrigation water in litres.

The rain-fed method indicated the highest cumulative irrigation volume across all three sub-blocks, with a consistent increase in water usage over time. The SMB-Irr method used a moderate amount of water, with its cumulative volume steadily rising but remaining below the rain-fed method throughout the period. Notably, the RL-Irr method demonstrated the lowest cumulative irrigation volume for all sub-blocks, increasing much slower than the other two methods. The RL-Irr method consistently used the least water over the 113 weeks for all sub-blocks, indicating that RL-Irr is the most water-efficient method among the three, offering substantial water savings while maintaining adequate irrigation.

Based on Table 1, the RL-Irr method uses approximately 75.03 percent, 77.23 percent and 70.24 percent less water than the rain-fed method for sub-blocks D13, A1 and A3, respectively, with a total percentage difference of about 74.16 percent. Similarly, RL-Irr uses approximately 30.13 percent, 30.39 percent and 28.72 percent less water than the SMB-Irr method for sub-blocks D13, A1 and A3, respectively, with a total percentage difference of about 29.68 percent. This indicates that RL-Irr is significantly more water-efficient than the other two methods across all sub-blocks.

The RL-Irr system is highly effective and uses less water consistently in all sub-blocks. If RL-Irr can meet the trees' water needs while maintaining their growth, it could be a more sustainable irrigation method that conserves water, especially in water-scarce regions or during droughts. Using RL-Irr instead of SMB-Irr could significantly reduce water usage, lower irrigation costs and lessen the strain on water supplies, particularly in large-scale agriculture.

Tree Height Comparison with Rain-fed, SMB- Irr and RL- Irr Strategies

Tree growth section demonstrates that measuring tree girth may be less significant due to the minimal changes observed. Consequently, comparisons are made based on the tree heights of sub-blocks D13, A1 and A3 to validate the outcomes of the irrigation strategies.

Figure 18

Simulated Tree Height for Trees Sub-block D13 Using the AQUACROP Model with Different Irrigation Strategies

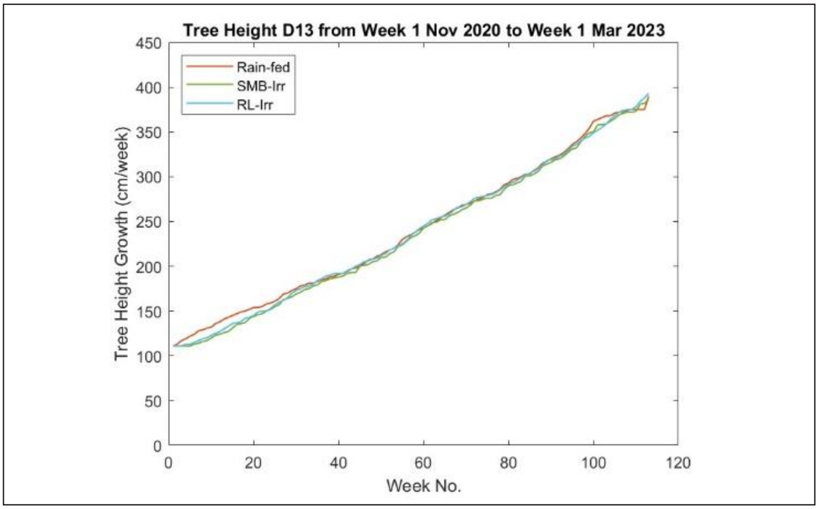


Figure 19

Simulated Tree Height for Trees Sub-block A1 Using the AQUACROP Model with Different Irrigation Strategies

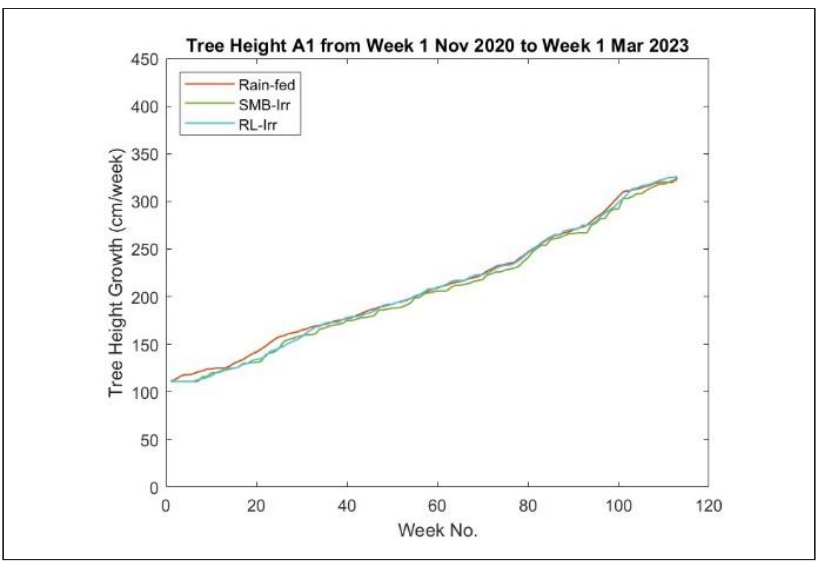
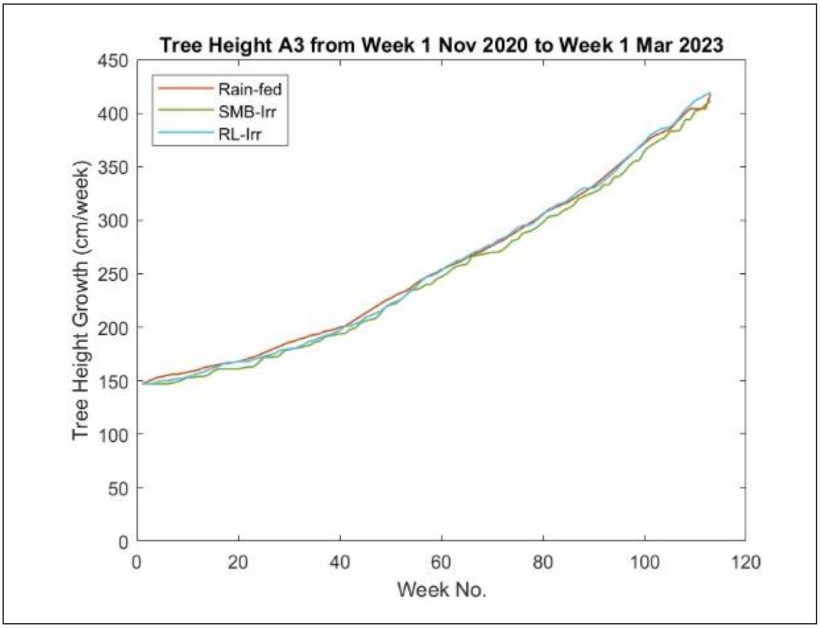


Figure 20

Simulated Tree Height for Trees Sub-block A3 Using the AQUACROP Model with Different Irrigation Strategies



Figures 18 to 20 illustrate the impact of different irrigation techniques on tree growth over a period of 113 weeks. The growth from rain-fed irrigation was used as a benchmark. The AQUACROP model was adjusted to match the growth of rain-fed trees. The data indicates that the tree growth AQUACROP simulated closely matched the rain-fed growth. The trees showed a progressive increase in height over time. The figures demonstrate that different irrigation methods and rain-fed conditions resulted in similar growth patterns, with the lines closely overlapping. The rain-fed trees exhibited steady growth that closely mirrored the growth of trees using SMB-Irr and RL-Irr methods. The proximity of the lines in each figure suggests that various irrigation methods and rain-fed conditions led to similar tree heights after the monitoring period. The growth curves illustrate that irrigation technologies and natural rainfall contributed similarly to the trees' growth. This is further illustrated in Figures 21 to 23.

Figure 21

Simulated Tree Height Growth Rate for Tree Sub-block D13 Using the AQUACROP Model with Different Irrigation Strategies

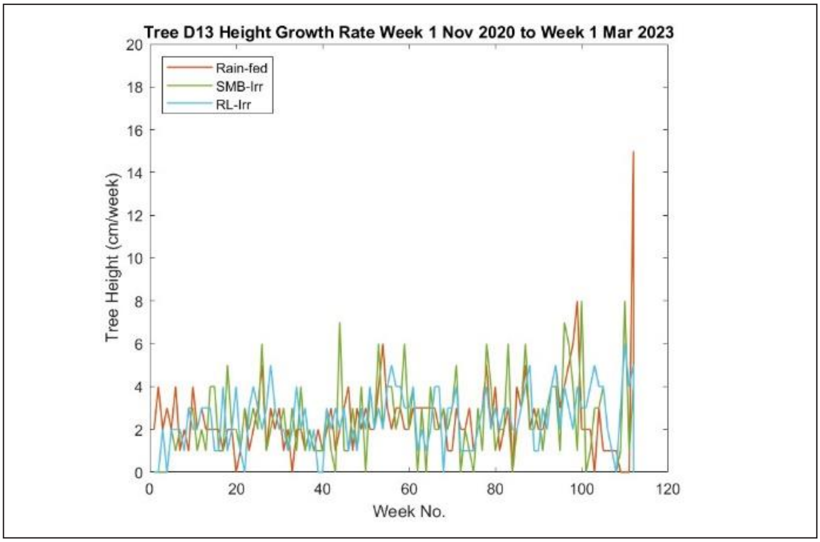


Figure 22

Simulated Tree Height Growth Rate for Tree Sub-block A1 Using the AQUACROP Model With Different Irrigation Strategies

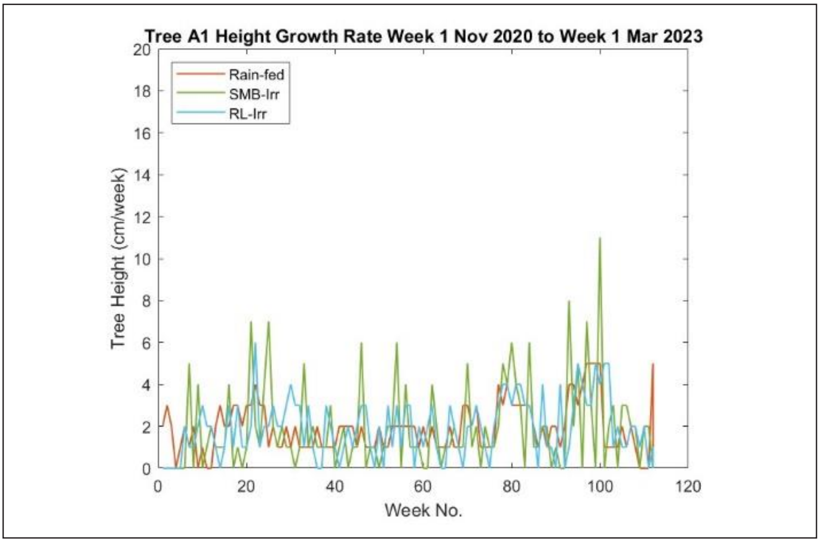
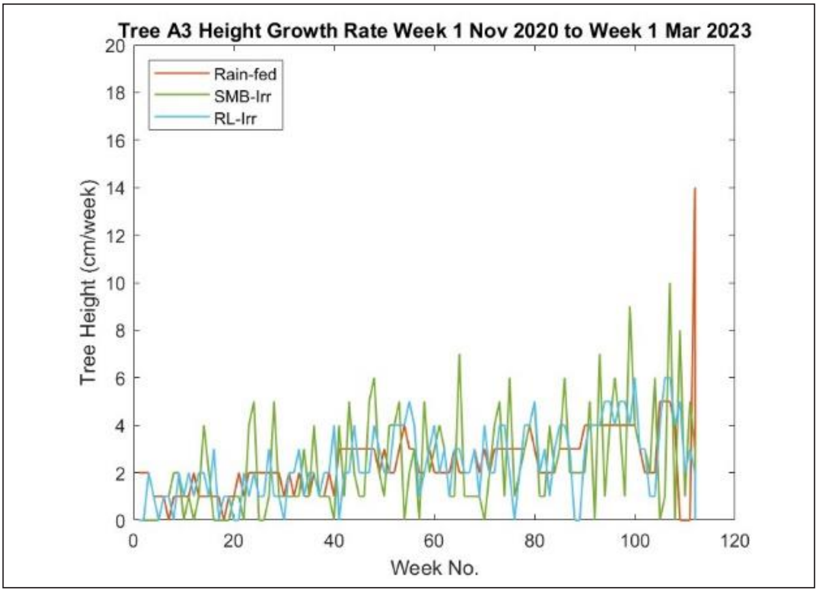


Figure 23

Simulated Tree Height Growth Rate for Tree Sub-block A3 Using the AQUACROP Model With Different Irrigation Strategies



The figures compare the growth rates of tree heights in sub-blocks D13, A1 and A3 using three different irrigation methods: rain-fed, SMB-Irr, and RL-Irr. Rain-fed serves as the baseline, SMB-Irr supplies water when soil moisture falls below 25%, and RL-Irr uses a Reinforcement Learning algorithm to optimise water usage. In sub-block D13, there is a significant increase in growth under RL-Irr towards the end of the observed period. Similarly, sub-blocks A1 and A3 also show fluctuations with peaks in growth under both SMB-Irr and RL-Irr. Overall, the RL-Irr method generally resulted in higher growth rates than rain-fed and SMB-Irr, indicating better optimisation of water usage for improved growth. However, the effectiveness of RL-Irr varied across different trees, likely due to individual tree health and conditions. In sub-block A3, RL-Irr occasionally showed the highest growth rate peaks, especially towards the end of the observed period. Across all sub-blocks, RL-Irr sometimes optimised water amounts to significantly boost growth by leveraging past and current data to predict and apply the most beneficial irrigation schedule, thus avoiding over- and under-irrigation.

Table 3

Statistical Analysis for Rain-fed, SMB-Irr and RL-Irr for Tree Growth (mm)

	Mean (m) (mm)			Standard Deviation (s) (mm)		
Sub-block	D13	A1	A3	D13	A1	A3
Rain-fed	2.47	2.46	2.51	1.84	1.87	1.35
SMB-Irr	1.89	1.88	1.92	1.20	2.10	1.41
RL-Irr	2.41	2.36	2.46	1.60	2.19	1.54

Table 3 shows a statistical comparison of tree growth under three different irrigation methods: rain-fed, SMB-Irr, and RL-Irr. The analysis revealed noticeable differences in the performance of tree growth. The rain-fed shows relatively consistent growth across all sub-blocks, with mean values of 2.47 mm, 2.46 mm and 2.51 mm, respectively, and standard deviations ranging from 1.35 mm to 1.87 mm. SMB-Irr exhibits lower mean growth values of 1.89 mm, 1.88 mm and 1.92 mm, with varying levels of consistency, with the lowest standard deviation in sub-block D13, which is 1.20 mm and higher variability in sub-block A1, which is 2.10 mm. RL-Irr demonstrates higher mean growth values closer to rain-fed, which is at 2.41 mm, 2.36 mm, and 2.46 mm, but with slightly higher standard deviations than SMB-Irr, indicating moderate consistency. Overall, RL-Irr combines near-optimal growth performance identical to rain-fed with a moderate level of variability, suggesting that it offers a balanced approach to achieving high growth and maintaining consistent results across different sub-blocks.

This study's results demonstrate the RL-Irr system's efficiency in optimising water usage for durian trees while maintaining growth performance. RL-Irr consistently reduced water consumption compared to traditional rain-fed and SMB-Irr methods. Specifically, RL-Irr achieved a water savings of up to 74.16 percent compared to rain-fed irrigation and approximately 29.68 percent compared to SMB-Irr across all sub-blocks. These findings highlight the potential of RL-Irr for water conservation and saving.

In addition, the simulation results indicate that tree growth under RL-Irr was comparable to that under rain-fed and SMB-Irr methods. Figures 18 to 23 show that tree height and girth growth patterns were similar across all sub-blocks, despite the reduced irrigation volume in the RL-Irr system. This suggests that RL-Irr can maintain optimal tree growth while using less water, providing a balanced solution for sustainable irrigation.

The implications of these results are notable for agriculture, particularly in durian cultivation, where efficient water management is critical. The RL-Irr system could be widely adopted to improve irrigation efficiency, reduce water costs, and promote sustainable farming practices. Since the RL-Irr parameters were calibrated using site-specific data, replicating the system in diverse locations with varying soil types and climates is recommended to enhance its robustness. Future studies should also consider including a larger sample of trees and different terrains to further refine the algorithm's sensitivity and overall effectiveness.

CONCLUSION

This study applied Reinforcement Learning Irrigation (RL-Irr) to irrigate durian trees grown in an open area. The amount of water given to the trees was adjusted daily based on the trees' current growth rate, soil tension, previous irrigation volume, rain forecast, and evapotranspiration forecast. This approach differs from traditional irrigation methods, as irrigation was fine-tuned daily by adjusting the RL-Irr rewards to ensure a precise water supply to the trees. The AQUACROP model was used to simulate tree growth under various irrigation volumes, and its feedback was utilised to adjust the reward system in the RL-Irr algorithm for subsequent irrigation schedules.

When comparing RL-Irr with rain-fed (practised on the farm) and SMB-Irr, RL-Irr proved to be more efficient, effectively hydrating the trees while reducing water consumption. This suggests that RL-Irr can maintain optimal tree growth while conserving water, making it an ideal solution for sustainable agriculture. Adaptive irrigation systems like RL-Irr offer a way to address water wastage, particularly in regions facing water scarcity, and help combat the challenges posed by climate change.

The study was conducted in Malaysia, where 120 trees (2.5% of the total 4,800 trees on the farm) were used. As RL-Irr parameters, such as weather data, are site-specific, replicating this system in different regions with varying weather and soil conditions is recommended to improve its robustness. Future studies should consider testing the algorithm with more trees across varying terrains to enhance sensitivity. While the results provide valuable insights into adaptive irrigation, they are based on model assumptions and should be further validated through real-world applications.

ACKNOWLEDGMENT

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