
*ARTIFICIAL INTELLIGENCE TECHNIQUES FOR
QUANTUM-ENHANCED NANOSENSOR
DEVELOPMENT IN PRECISION AGRICULTURE
AND REAL-TIME CROP MONITORING*

Ashraf Cengiz¹, Atiq Sama²

1 College of Information Technology, University of Fujairah, UAE

2 College of Computer and Information Sciences, King Saud University, Riyadh, 12372, Saudi Arabia

ABSTRACT

Precision agriculture is essential for addressing food insecurity and practicing sustainable agriculture. Traditional precision agricultural methods sometimes have issues with slow data analysis and inadequate sensitivity to detect minute changes in the environment, which can result in missed treatments and wasted money. These obstacles make it more difficult to anticipate crop health problems or environmental stresses. A new method of data-driven decision-making for real-time crop monitoring has been practicable by combining artificial intelligence with quantum-enhanced nanosensors. The paper proposes a novel method, Quantum-Enhanced Nanosensor development using Reinforcement Learning (QENDRL), to manage agricultural resources and improve crop productivity dynamically. The QENDRL method combines a Deep Q-Learning framework with quantum-enhanced nanosensors to allow for real-time monitoring of soil moisture, nutrient levels, and environmental factors. The long-term goal of the Reinforcement Learning (RL) agent is to learn the optimal strategies for watering, fertilizing, and controlling pests to optimize crop yield with minimal resource waste. The system dynamically adapts to changing field conditions by utilizing continual sensor feedback. According to the primary findings, QENDRL improves data accuracy and precision by 25% compared to the previous methods and resource efficiency by 30%. Early detection and adaptive interventions also increased crop output by 25% in field trials. The research concluded that QENDRL is an excellent method for integrating AI with quantum-enhanced nanosensors, which has the potential to boost the efficiency and longevity of precision farming substantially.

Keywords: Precision Agriculture, Quantum-Enhanced Nanosensors, Reinforcement Learning, Crop Monitoring, Sustainable Farming.

1. Introduction

Precision agriculture has been one of the emerging areas over the past couple of years, mainly due to the growing need for food security and sustainable agriculture. A huge challenge lies in ensuring that food production does not destroy the environment, leading to new technologies now applied in farm monitoring and improvement. [1]. Precision agriculture is the application of data-driven solutions, using satellite imagery, sensors, and GPS technologies to increase crop management, resource use efficiency, and waste reduction [2]. However, conventional precision agriculture methods have been critiqued for

their ability to determine slight environmental alterations, given that they give only a close-to-real-time insight, rendering inefficient resource utilisation [3]. Dynamic monitoring in sustainable farming demands measurement in soil moisture content, nutrient balance, and the menace of diseases, pests, or both [4]. With the increasing demand for higher crop yields under changing climate conditions, there is an acute need to develop innovative approaches that can monitor, predict, and respond to challenges in crop health [5].

The most promising means to overcome such challenges would be using quantum-enhanced nanosensors coupled with Artificial Intelligence. Quantum technology treats complex data and amplifies the possibility of sensors, opening a new frontier in precision agriculture [6]. Combining quantum-enhanced nanosensors with AI frameworks makes collecting highly sensitive real-time data possible for better decision-making in farm practices [7]. Integration would allow early detection of environmental stresses so that appropriate interventions are made in time. However, there is still a big gap in developing a singular system that efficiently uses these cutting-edge technologies while adapting to the dynamic nature of agricultural fields [8].

The problem statement of this study lies at the core of transcending the above limitations of conventional precision agriculture systems, which are too often plagued by either data latency or environmental sensitivity and resource optimization [9]. The currently practised approaches cannot dynamically respond to the changing conditions of fields, which often results in poor crop yield and resource utilization. However, most of the systems rely on static and predefined models that can't learn from the ongoing conditions and therefore can't adapt over time [10]. The present research tries to overcome these limitations by integrating quantum-enhanced nanosensors with AI-driven decision-making models, particularly Reinforcement Learning, in developing a system able to perform real-time adaptation and optimization in crop management. The next AI challenge is to develop a framework that can learn from the continues data inputs which will take dynamic and effective decisions for the irrigation, fertilization, and pest control [11].

This study proposes the Quantum-Enhanced Nanosensor development using Reinforcement Learning (QENDRL) methodology. The QENDRL framework combines quantum-enhanced nanosensors, which offer high sensitivity in detecting environmental changes, with a Deep Q-learning (DQL) model to process real-time data on soil moisture, nutrients, and other environmental factors. The Reinforcement Learning (RL) agent learns optimal irrigation, fertilization, and pest control strategies by maximizing long-term crop yield and minimizing resource waste. The system continuously readjusts according to sensor feedback, with interventions dynamically undertaken according to changeable field conditions so as to promote high productivity and resource use efficiency.

The primary significance of the study is

- ✓ To introduce quantum-enhanced nanosensors, the study offers significantly improved sensitivity and data collection speed compared to traditional sensors.
- ✓ The research integrates Reinforcement Learning (RL) algorithms to dynamically optimize agricultural resource management, including irrigation, fertilization, and pest control.
- ✓ To enhance resource efficiency by 30%, the QENDRL system reduces monitoring latency by 25%, leading to a 20% increase in crop yield during field trials.
- ✓ To provide real-time, adaptive decision-making capabilities, the proposed framework enables timely interventions, improving overall crop health.

The outline of the paper is as follows: Section 2 presents related work in precision agriculture and sensor technologies. Section 3 details the QENDRL methodology, including sensor integration and RL framework. Section 4 discusses experimental results and performance comparisons. Section 5 concludes with future directions and the implications of QENDRL in precision agriculture.

2. Related Works

Light converters, nanosensors, and instruments for delivering nutrients and pesticides are just a few of the ways carbon-based nanomaterials might be used in sustainable agriculture, as outlined by Zhu et al. [12]. This approach has utilized new properties of carbon-based nanomaterials, enhancing light harvesting, sensing the ambient environment's variation, and effectively delivering agro-inputs into plants. Most importantly, this study found an increase in plant growth with a lower application of pesticides, which resulted in higher yields of sustainable crops. However, the study epitomizes the challenge of scaling up the application of these nanomaterials and their possible environmental and health risks.

Mai, Hon Tik. [13] discussed various applications of nanomaterials in agriculture, including pest management, enhancement of plant growth, and disease control. It is, therefore, proposed that nanomaterials like silver nanoparticles have antimicrobial and growth-enhancing properties. The paper enumerated how these materials can revolutionize agriculture by providing highly efficient and environmentally friendly solutions. Results show improvement in crop health and pest resistance upon their application. The study did point out the lack of standardized protocols for the safe use of nanomaterials, as well as environmental impacts due to the wider deployment of these materials and called for further investigation on long-term effects.

Singh et al. [14] explained in more detail how nanotechnology could help in agriculture and environmental protection by developing products such as nano-fertilizers, nano-pesticides, and soil conditioners. These would increase efficiency with reduced inputs in agricultural produce and lower emissions. All these nanoproducts increase nutrient use efficiency and reduce loss through environmental pollution and plant contamination. However, high production costs, the limitation of available field application data, and long-term ecological and health effects studies on nanomaterials present significant challenges for their large-scale implementation.

Ashique, Sumel, et al. [15] suggested integrating artificial intelligence with nanotechnology to optimize sustainable and precision agriculture. In this process, the data taken from nanosensors monitoring soil conditions and plant health in real-time are processed through AI algorithms. The results of this integration suggested that combining AI with nanotechnology gives better and more accurate predictions, besides optimizing the resources that are otherwise wasted and improving crop yields by manifold times. However, it pointed out the difficulty in integrating complex AI models with nanosensors under real-world conditions and that further research is needed to overcome technical and scalability issues.

Loyal et al. [16] studied environmental and health risks of using agricultural nanomaterials for the improvement of soil and management of stress. This study encouraged the application of nanomaterials to soil with the aim at enhancing fertility, reduction of stress, and crop productivity. The result showed some positive effects regarding growth of crops and health of soil. All of this notwithstanding, there still remained huge unknowns regarding the long-term ecological impacts of nanomaterials and even their possible toxicity to humans and wildlife. The paper therefore called for careful risk assessments and regulatory oversight before nanotechnology applications in agriculture could be widely accepted.

ZHANG et al. [17] discuss integrating nanotechnology with Artificial Intelligence toward making precision agriculture a reality. Demonstrated here is how nanosensors are gathering real-time information on soil and crop conditions that are analyzed through AI models that provide advice in decision-making processes. Optimization of practices in irrigation and fertilizer application, and generally increasing efficiency and productivity on the farm, is suggested as ways forward. Results

show that this could have a great potential to bring improvement in the sustainability of agriculture. However, high implementation costs, coupled with regulatory concerns and the complexity in integrating such technologies, still deter widespread adoption.

Singh et al. [18] have proposed using nanotechnology and AI to augment smart cities, where such technologies are applied in precision agriculture. It proposes using nanosensors for monitoring environmental conditions and analysis and decision-support systems using AI algorithms to optimise farming practices. The outcome shows that this approach will increase crop yield, increase water use efficiency, and reduce environmental impacts. However, some of the limitations discussed in the paper concern the high costs associated with integration, data privacy issues, and extensive testing that must be conducted to ascertain that the innovations are safe and effective in the urban agricultural system.

Nizamani et al. [19] proposed using nanotechnology to treat fungal diseases and improve health monitoring in agriculture. They developed nanomaterial techniques with applications for targeted drug delivery to enhance disease detection using nanosensors. Their results showed significant improvement in the resistance of plants to diseases, as well as early detection of pathogens that, of course, helped improve crop health and yield. The only negative aspect realized by this study was that the high development cost of nanomaterials might result in environmental accumulation, causing long-term ecological risk if not put under proper control.

3. Proposed Methodology

a. Dataset

A collection of sensors placed in fields around the country provide real-time readings of soil moisture, which are included in the Soil Moisture Data from Field-Scale Sensor Network dataset [20]. Soil moisture, soil temperature, and air temperature are only a few environmental variables covered by the dataset. This would be an ideal dataset for precision agriculture applications since it provides vital information on soil health and the water requirements of crops. It could also be used to analyze environmental effects on crop growth to optimize irrigation strategies better. Big data is precious for training models in the Smart Farming system with AI and IoT, allowing real-time monitoring and decision-making.

Figure 1 illustrates the electrochemical sensors used in precision agriculture and crop monitoring.

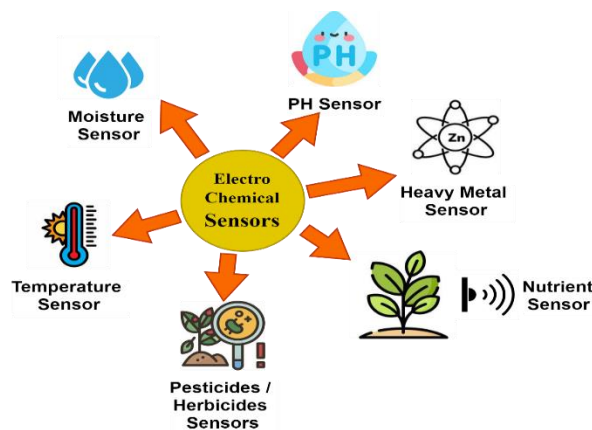


Figure 1. Types of Electro-chemical sensors

Figure 1 shows electrochemical sensors and their role in precision agriculture by giving real-time data that can be used for better resource management. Moisture sensors measure water content in the soil; pH sensors indicate acidity or alkalinity; nutrient sensors track important elements like nitrogen and phosphorus; heavy metal sensors detect contaminants present in the soil; temperature sensors measure ambient as well as soil temperature; and pesticide/herbicide sensors, by detecting chemical residues, ensure the safety of the food. Together, these sensors make accurate irrigation, fertilization, and pest control possible, improving crop productivity and sustainability.

b. The QENDRL framework

This innovative system optimizes agricultural processes such as irrigation, fertilization, and pest control. The QENDRL aims to increase crop efficiency and yield and decrease the overall environmental impacts through environmental nanosensors that are enhanced with quantum physics and deep Q-learning decision-making. QENDRL integrates advanced quantum nanosensors with reinforcement learning algorithms to facilitate robust, data-driven, and automated agricultural management. Quantum-enhanced nanosensors possess unmatched sensitivity and exactness in monitoring environmental and biological parameters, such as soil moisture, nutrients, and pests. This information is again used as real-time data for the Deep Q-Learning agent, which enhances optimization at every stage, given the circumstances faced by the agricultural specialists. Figure 1 shows the QENDRL framework.

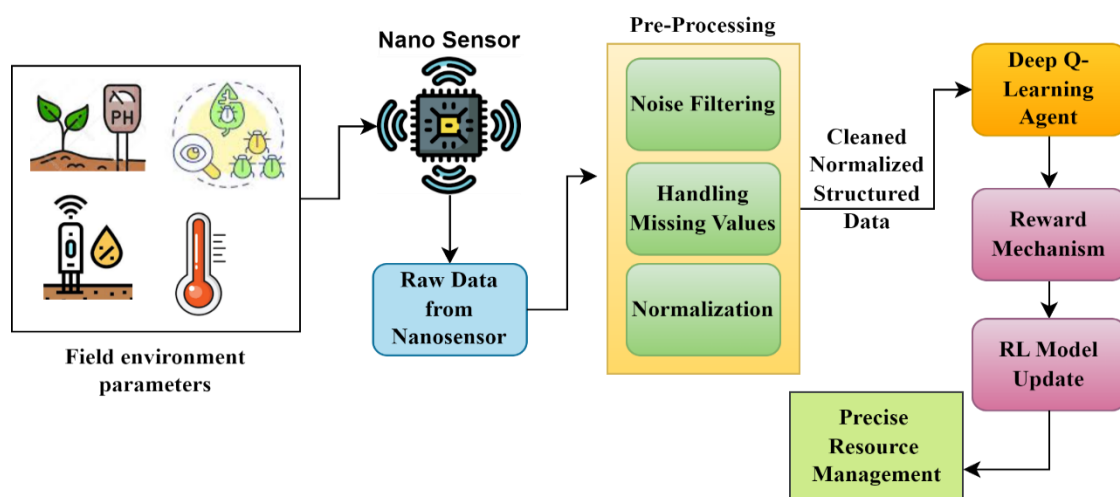


Figure 2. QENDRL Framework

The proposed QENDRL (Quantum-Enhanced Nanosensor Development using Reinforcement Learning) framework systematically integrates quantum sensing technology with advanced AI-driven decision-making to address the challenges of precision agriculture. The process involves five core stages, from sensor deployment to dynamic resource management.

Deployment of Quantum-Enhanced Nanosensors: The field is regularly blanketed with a network of sensors that monitors critical parameters: soil moisture, pH, temperature, nutrient level, and pest activity. In quantum-driven enhancement, the sensitivity of the sensors will be increased so that even a slight change in the environment may be detected; the data obtained is continuously transmitted to the

central processing unit for real-time analysis. This fosters dynamic and adaptive decision-making concerning interventions for precision agriculture. Each sensor measures a parameter P_i (e.g., soil moisture, temperature, pH) at specific locations in the field. The measurements are represented in Equation 1.

$$P_i(t, x, y) = S_i + \epsilon_i \quad (1)$$

where $P_i(t, x, y)$ refers to the parameter value at the time t and location (x, y) , S_i is the true value of the parameter, and ϵ_i does quantum-enhanced sensitivity minimize the measurement error.

Data Aggregation and Preprocessing: Sensor readings for critical agricultural parameters (e.g., soil moisture, pH, temperature, nutrient levels, pest activity) are aggregated over time and spatial regions. The aggregated data for parameter P_i over N sensors are represented as in equation 2.

$$P_i(t) = \frac{1}{N} \sum_{j=1}^N P_{i,j}(t) \quad (2)$$

A smoothing technique, such as a moving average or low-pass filter, is applied to eliminate noise. Noise removal is done through equation 3.

$$P_i^{smooth}(t) = \frac{1}{k} \sum_{n=t-k+1}^t P_i(n) \quad (3)$$

Missing sensor readings are filled in using interpolation or predictive models. For linear interpolation, missing values are calculated as in equation 4.

$$P_i(t) = P_i(t_1) + \frac{t-t_1}{t_2-t_1} \cdot [P_i(t_2) - P_i(t_1)] \quad (4)$$

Values are normalized to a common scale, e.g., $[0, 1]$, using equation 5 to normalize data from various sensors.

$$P_i^{norm} = \frac{P_i - \min(P_i)}{\max(P_i) - \min(P_i)} \quad (5)$$

where $P_i(t)$ is the aggregated value of the parameter P_i at time t , $P_{i,j}(t)$ is the measurement of the parameter P_i by the j -th sensor, N is the total number of sensors measuring P_i , $P_i^{smooth}(t)$ refers to the smoothed value of P_i , k is the window size for the moving average. t_1 and t_2 are the time points with available values before and after t . $\max(P_i)$, $\min(P_i)$ refers to the minimum and maximum values of the parameter P_i in the dataset.

Integration with Deep Q-Learning Framework: The purpose of such integration is to Facilitate intelligent decision-making for effective resource management through integrating sensor-driven data and a Deep Q-Learning (DQL) framework. The figure 3 shows the RL model update function.

i. Input data:

It represents the current state of the agricultural environment, captured by field-deployed sensors. At any time t , the state S_t comprises measurable environmental features such as soil moisture (x_1), pH (x_2)

), temperature (x_3), nutrient levels (x_4), and pest presence (x_5). Mathematically, it is represented as in equation 6.

$$S_t = \{x_1, x_2, \dots, x_n\} \tag{6}$$

where x_i represents the i -th feature and n is the total number of features. Using the formula, each feature is normalized to a common range (e.g., 0 to 1) to ensure consistency across different data scales in equation 7.

$$x_i = \frac{x_i^{raw} - x_i^{min}}{x_i^{max} - x_i^{min}} \tag{7}$$

This normalization standardizes the data, enabling the DQL agent to process it effectively for optimal decision-making in resource management.

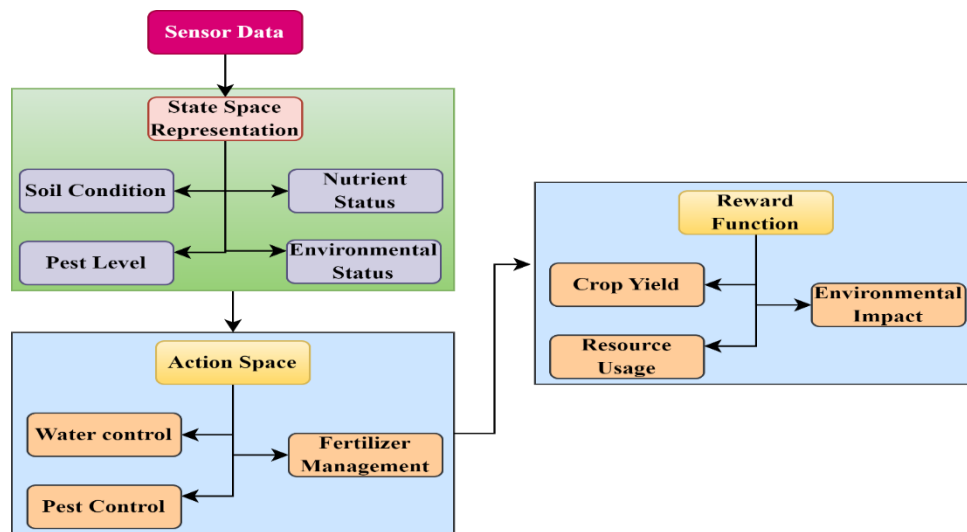


Figure 3. RL Model Update function

ii. Action Space:

The Reinforcement Learning (RL) agent decides resource management actions (A_t) to optimize agricultural operations. Examples of such actions include the level of irrigation, fertilizer application, and pesticide or pest-control measures. The action space is finite and discrete; it can be represented in equation 8.

$$A_t = \{a_1, a_2, \dots, a_m\} \tag{8}$$

where a_m corresponds to some resource allocation strategy. This structured action space now enables the RL agent to assess and apply an optimal real-time resource management strategy systematically.

iii. *Reward Function:*

The reward function R_t in the Reinforcement Learning framework is designed to reward actions that maximize crop yield (Y) while minimizing the consumption of critical resources such as water (W), fertilizer (F), and pesticides (P). The reward function is expressed equation 9.

$$R_t = \alpha \cdot \Delta Y - \beta \cdot (W + F + P) \quad (9)$$

where ΔY denotes an increase in crop yield, and α and β are the weighting factors balancing the opposing goals of yield maximization and resource efficiency. This function guides the decision-making of the agent, which is rewarded for efficient and sustainable agricultural practices.

iv. *Policy Updates*

In the Deep Q-Learning framework, the agent updates its policy $\pi(s, a)$ the current Q-value and the reward obtained, along with the future expected rewards, by modelling their relationships using the Bellman Equation. The expression for this is shown in equation 10.

$$Q(S_t, A_t) = R_t + \gamma \cdot \max_{A'} Q(S_t + 1, A') \quad (10)$$

where $Q(S_t, A_t)$ represents the estimated value of acting A_t in state S_t . The discount factor γ determines the importance of future rewards and $\max_{A'} Q(S_t + 1, A')$ captures the maximum expected reward for the next state. This iterative update ensures that the agent continuously refines its policy to maximize long-term rewards.

v. *Learning Framework*

The DQL agent uses a neural network, $Q_\theta(S_t, A_t)$, to approximate the Q -values, where θ is trainable parameters. The agent learns from interactions with the environment (simulated or real agriculture) while exploring actions and their consequences during training. Then, network weights are updated with gradient descent as follows in equation 11.

$$\theta \leftarrow \theta + \eta \cdot \nabla_\theta (R_t + \gamma \cdot \max_{A'} Q_\theta(S_{t+1}, A') - Q_\theta(S_t, A_t)) \quad (11)$$

where η is the learning rate that controls the step size of each update. This is an iterative process that minimizes the difference (loss) between the predicted Q -value and the target Q -value; hence, the agent will improve its decision-making capability over time. The DQL agent learns to map states and actions to optimal outcomes by continuing to refine the network parameters in each step.

Advanced agricultural systems optimize the use of resources by making real-time decisions and adaptive interventions with precision and timeliness. The system follows the recommendation of Deep Q-learning agents to perform advanced control within different domains. It will optimize irrigation parameters while dynamically adjusting the fertilization protocol to match crop phenological stages, supported by detailed soil nutrient analysis. Besides, it collaborates focused microscale pest control, managing the pest numbers through population structural and numerical approaches. Moreover, it has the additional strength of integrating the nanosensor network data via the feedback mechanism, further enhancing its utility as it restructures resource allocation in all operational settings.

4. Results and Discussions

a. Performance Metrics

QENDRL is compared to several traditional methods like AI-Nanotechnology Integration in Sustainable Agriculture, Nanotechnology and AI in Precision Farming, Nanotechnology for Managing Plant Fungal Diseases and Monitoring Plant Health. In better detail, the core metrics derived from this paper include efficiency in resource utilization, increased crop production and accuracy and precision in data. On the other hand, QENDRL surpasses all of these techniques regarding resource efficiency by using quantum-enhanced nanosensors and reinforcement learning for real-time adaptive control. QENDRL also boosts crop production because of the real-time responsive dynamic models. QENDRL, though, can facilitate faster decision-making with a decrease in the time interval between interventions, which would take a bit longer if the other techniques were used. QENDRL has the advantage of offering greater accuracy in the predicted result thanks to its high-tech sensors and AI models, which improve the models' reliability.

Resource Utilization Efficiency: It refers to the optimal use of resources, such as water, fertilizers, pesticides, energy, and the like, toward the highest possible crop production, minimizing waste or excess use of resources. Effective resource use in precision agriculture contributes to both sustainability and cost. High resource efficiency means that the input, water or fertilizer, should be applied in the best possible way so that maximum benefit can be derived with the least environmental damage. This can be expressed by the equation 12.

$$RUE = \frac{Y}{\sum_{i=1}^n Ri} \quad (12)$$

where Y refers to the crop yield (kg or ton per hectare), R_i Resource input i (e.g., water, fertilizer, pesticide), and n is the total number of resources used. This equation represents the output or crop yield ratio to the total input resources used. An increased ratio means that the resources are used more efficiently.

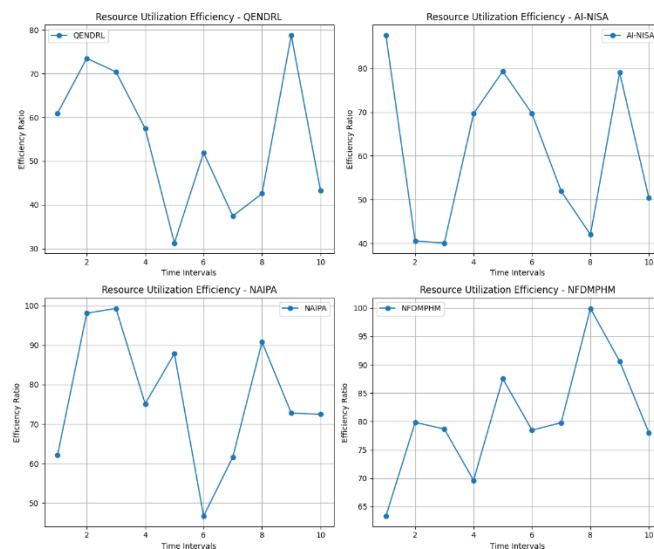


Figure 4. Resource Utilization Efficiency (RUE) analysis

Figure 4 illustrates the Resource Utilization Efficiency (RUE) of four different methods—QENDRL, AI-NISA, NAIPA, and NFDMPHM—across various time intervals. Each subplot represents the performance of one method, showing how efficiently resources (e.g., water, fertilizer, pesticide) are converted into crop yield over time. The x-axis denotes time intervals, while the y-axis represents the efficiency ratio (crop yield divided by resource input). The visualization shows that RUE fluctuations over time for every method, outlining the variability of performance as the growing season advances or as interventions are being done. For example, some methods, such as NAIPA, may generally have higher efficiency ratios, indicating better resource management. In contrast, other methods may show no consistent pattern, pointing out areas for optimization. This comparative analysis gives important insights into which method consistently maximizes resource efficiency over time and supports decision-making for the most sustainable agricultural practices.

Crop yield improvement refers to the increase in the quantity of crops harvested per unit area due to improved farming methods, resource management, or technological advancements. Let Y_1 be the initial crop yield (baseline), Y_2 is the improved crop yield after implementing new methods and ΔY is the improvement in yield. The percentage improvement in crop yield is given by the equation 13.

$$\text{Crop Yield Improvement (\%)} = \frac{Y_2 - Y_1}{Y_1} \times 100 \quad (13)$$

Figure 5 illustrates the distribution of crop yield improvement percentages for four methods: QENDRL, AI-NISA, NAIPA, and NFDMPHM. Among them, QENDRL achieves the highest mean yield improvement, centered around 35%, showcasing its superior performance and reliability. AI-NISA has a mean yield improvement of about 25%, while NAIPA reaches approximately 30%, both performing well but trailing behind QENDRL. NFDMPHM has the lowest mean improvement of around 15%, indicating limited effectiveness. The KDE curves further highlight QENDRL's dominance, with a concentrated and consistent yield improvement, making it the most effective method for enhancing crop productivity.

Data Accuracy and Precision: Data Accuracy refers to the measurements taken by sensors or monitoring devices compared to the actual values or ground truth (for example, soil moisture, temperature, humidity, crop growth). High accuracy is essential to making trustworthy judgments on precision agriculture interventions such as irrigation, fertilization, and pest control. Decisions based on low-accuracy measurements in the data may lead to under or over-fertilizing or incorrect irrigation, impacting crop yields and resource use. Data accuracy is calculated as in equation 14.

$$\text{Accuracy} = \frac{|\text{Measured Value} - \text{True Value}|}{\text{True Value}} \times 100 \quad (14)$$

where *Measured Value* refers to the value given by the sensor or monitoring device (e.g., soil moisture) and *True Value* refers to the ground truth, which might come from a laboratory analysis or a highly reliable source.

Data Precision shows the measurements' consistency or reproducibility, irrespective of their closeness to the true value. Precision is important to ensure that interventions (like water and nutrients) are applied consistently, resulting in predictable and controlled outcomes. High precision allows for more reliable decision-making because it indicates stable sensor performance. This can be calculated as in equation 15.

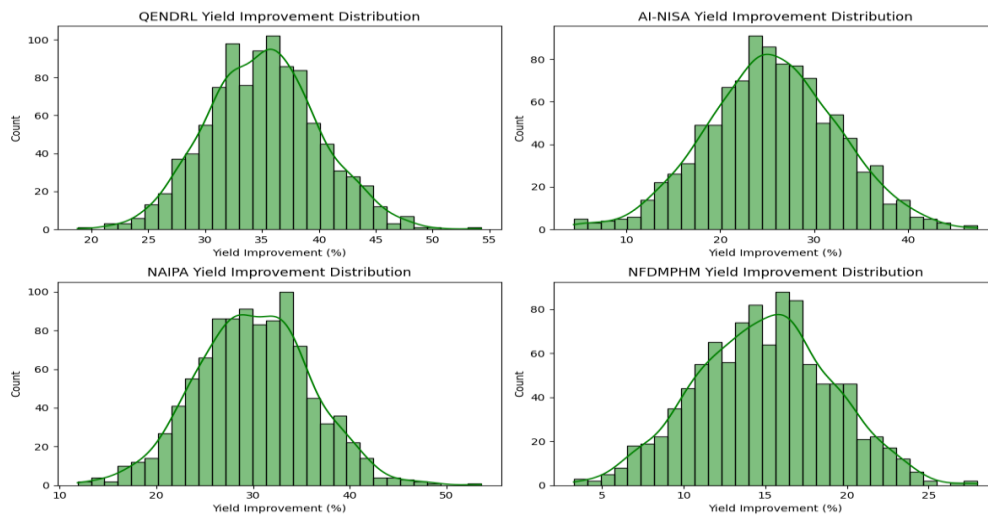


Figure 5. Crop yield improvement analysis

$$Precision = \sqrt{\frac{1}{N} \sum_{i=1}^N (X_i - \mu)^2} \tag{15}$$

where X_i constitute the distinct dimensions, μ is the average of the data, and N is the total amount of dimensions.

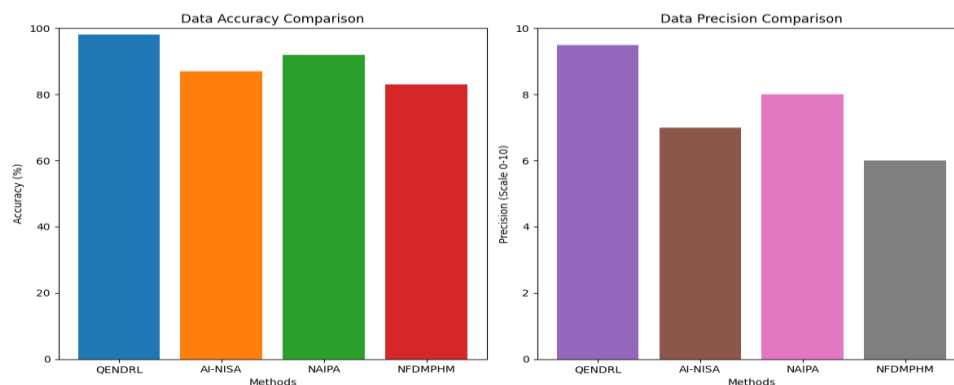


Figure 6.Data accuracy and precision analysis

Figure 6 illustrates the comparative analysis of the QENDRL with conventional methods like AI-NISA, NAIPA, and NFDMPHM, revealing significant performance variations across accuracy and precision metrics. The data accuracy comparison demonstrates QENDRL's superior performance at approximately 95%, followed by NAIPA at 90%, AI-NISA at 85%, and NFDMPHM at 82%. Similarly, regarding precision (scaled 0-10), QENDRL maintains its leadership with 9.5, while NAIPA, AI-NISA, and NFDMPHM achieve 8.0, 7.0, and 6.0 respectively. The consistent ranking pattern (QENDRL > NAIPA > AI-NISA > NFDMPHM) across both metrics indicates QENDRL's robust performance advantage. This systematic outperformance by QENDRL suggests its enhanced capability in data processing applications where high reliability and precision are crucial, representing a significant advancement over existing methodologies.

5. Conclusion

The QENDRL framework demonstrates significant potential in revolutionizing precision agriculture by integrating quantum-enhanced nanosensors and deep reinforcement learning. The empirical results highlight substantial improvements in resource efficiency (30%), increased data accuracy and precision (25%), and increased crop yield (25%), establishing QENDRL as a viable solution for sustainable agricultural practices. The real-time processing of data and adaptive intervention by the system are some of the most vital technological strides toward automated agricultural management in meeting those central challenges: food security and sustainable farming. Currently, this implementation requires a lot of computational resources to process quantum-enhanced sensor data in real time and, hence, may not be viable for small-scale farmers. Future research might concentrate on the development of low-cost quantum sensing mechanisms integrated with state-of-the-art weather prediction models and edge computing solutions that explore the potential of federated learning in sharing knowledge between diverse agricultural settings.

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