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RESEARCH ARTICLE

Quantum-Enabled Irrigation Decision Optimization under Soil Moisture Constraints for Agricultural Science Applications

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Abstract

Efficient irrigation scheduling is a major challenge in precision agriculture due to increasing water scarcity, climate variability, and growing agricultural demand. Conventional irrigation strategies based on fixed thresholds, heuristic rules, or classical optimization techniques often suffer from scalability limitations, inefficient resource allocation, and poor adaptability under dynamic environmental conditions. This paper presents a hybrid quantum-classical optimization framework for intelligent irrigation scheduling using the Quantum Approximate Optimization Algorithm (QAOA). The irrigation decision problem is formulated as a Quadratic Unconstrained Binary Optimization (QUBO) model integrating soil moisture conditions, irrigation constraints, and water allocation objectives. The proposed framework employs variational quantum optimization to determine optimal irrigation decisions while minimizing unnecessary water consumption. Experimental evaluations conducted using Qiskit-based simulations demonstrate that the proposed QAOA framework successfully generates irrigation decisions fully consistent with classical threshold-based optimization for the evaluated dataset. Comprehensive visualization analyses including soil moisture distribution, irrigation decision mapping, threshold boundary analysis, and water utilization comparison validate the correctness and interpretability of the proposed optimization mechanism. Although the current experimental setup primarily serves as a proof-of-concept validation, the results indicate strong scalability potential for future large-scale agricultural systems involving complex multi-objective optimization constraints. The proposed framework establishes a foundational architecture for future quantum-enabled precision agriculture systems integrating IoT sensing, real-time environmental monitoring, and intelligent resource optimization for sustainable smart farming applications.

Keywords: Quantum Approximate Optimization Algorithm (QAOA), Quantum Computing, Quadratic Unconstrained Binary Optimization (QUBO), Precision agriculture, Smart irrigation, Water resource optimization, Data-driven agriculture, Sustainable farming.

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1. Introduction

Precision agriculture has emerged as a transformative technological paradigm for addressing global challenges associated with food security, sustainable farming, climate resilience, and efficient resource utilization [1], [2], [3]. Rapid population growth, increasing agricultural demand, irregular rainfall patterns, and diminishing freshwater availability have intensified the necessity for intelligent irrigation management systems capable of optimizing water consumption while maintaining crop productivity [4], [5].

Among various precision agriculture applications, irrigation scheduling represents one of the most critical operational tasks because irrigation directly influences crop

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health, soil quality, energy consumption, and environmental sustainability [6], [7]. Traditional irrigation scheduling techniques generally rely on fixed schedules, empirical farmer knowledge, or threshold-based rule systems. Although these approaches are relatively simple to implement, they often fail to adapt effectively to dynamic environmental conditions such as heterogeneous soil properties, changing climatic conditions, fluctuating crop water requirements, and uncertain environmental variability [8], [9].

From a computational perspective, irrigation scheduling can be formulated as a combinatorial optimization problem involving binary irrigation decisions under operational constraints. Classical optimization techniques such as Linear Programming (LP), Mixed Integer Programming (MIP), Dynamic Programming (DP), and heuristic optimization algorithms including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) have been widely explored for agricultural resource optimization [10], [11]. However, these methods frequently suffer from scalability limitations, slow convergence, computational complexity, and local optima issues when applied to large-scale dynamic agricultural systems [12].

Recent advances in Artificial Intelligence (AI), Machine Learning (ML), and IoT-enabled smart farming have improved predictive irrigation management through environmental sensing and data-driven analytics [13], [14]. Deep learning and reinforcement learning models have shown promising capabilities in irrigation forecasting and adaptive agricultural decision-making [15]. Nevertheless, machine learning models alone do not inherently solve constrained combinatorial optimization problems and often require integration with optimization frameworks for effective decision-making.

Quantum computing has recently emerged as a promising computational paradigm capable of solving complex optimization problems more efficiently than classical approaches under specific conditions [16], [17]. Variational Quantum Algorithms (VQAs), particularly the Quantum Approximate Optimization Algorithm (QAOA), have demonstrated strong potential for solving NP-hard optimization problems using hybrid quantum-classical architectures [18], [19]. QAOA exploits quantum superposition, entanglement, and parameterized quantum circuits to explore exponentially large solution spaces efficiently [20].

Although quantum optimization has shown promising results in logistics, scheduling, and resource allocation domains, its application in precision agriculture remains relatively unexplored [21]. Existing agricultural quantum optimization studies primarily focus on conceptual frameworks or simulation-based architectures without providing explicit optimization formulations, practical implementations, or detailed experimental evaluations [22].

To address these limitations, this paper proposes a data-driven QAOA-based irrigation scheduling framework formulated as a Quadratic Unconstrained Binary Optimization (QUBO) problem. The proposed framework integrates soil moisture data, irrigation constraints, and hybrid quantum optimization to determine intelligent irrigation decisions for precision agriculture systems.

The major contributions of this work are summarized as follows:

- Development of an explicit QUBO formulation for irrigation scheduling using soil moisture thresholds and water allocation constraints
- Design of a QAOA-based hybrid quantum-classical optimization framework for precision agriculture applications
- Integration of data-driven agricultural sensing with quantum optimization mechanisms
- Experimental validation using Qiskit simulations and comparative analysis with classical irrigation methods
- Comprehensive visualization and scalability analysis for quantum-enabled irrigation optimization

2. Related Work

Irrigation scheduling and agricultural resource optimization have traditionally been addressed using classical mathematical optimization approaches. Linear Programming (LP), Dynamic Programming (DP), and Mixed Integer Linear Programming (MILP) methods have been widely employed for optimal water allocation and irrigation planning [10], [11]. These methods provide deterministic optimization capabilities; however, they often become computationally infeasible for large-scale agricultural systems with nonlinear constraints and dynamic environmental variability.

To improve adaptability, several heuristic and metaheuristic optimization approaches including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Ant Colony Optimization (ACO) have been proposed for irrigation scheduling and precision farming applications [12], [13]. Although these methods provide improved flexibility compared to deterministic optimization techniques, they frequently suffer from slow convergence, instability, and susceptibility to local optima in high-dimensional optimization spaces.

The emergence of smart farming and IoT-enabled agriculture has accelerated the integration of machine learning and deep learning models into irrigation management systems [14]. Artificial Neural Networks (ANNs), Support Vector Machines (SVMs), Random Forests (RFs), and Long Short-Term Memory (LSTM) networks have been successfully applied for soil moisture prediction, crop water requirement estimation, evapotranspiration modeling, and irrigation forecasting [15]. Deep reinforcement learning has also demonstrated promising performance for adaptive irrigation scheduling under uncertain environmental conditions [23].

Recent advancements in quantum computing have introduced new opportunities for solving complex optimization problems using quantum-enhanced algorithms. Variational Quantum Algorithms (VQAs), particularly the Quantum Approximate Optimization Algorithm (QAOA), have attracted substantial attention due to their capability to solve NP-hard optimization problems using hybrid quantum-classical architectures [16], [17], [18]. QAOA formulates optimization problems as quantum Hamiltonians and iteratively refines candidate solutions through parameterized quantum circuits [19].

Several recent studies have investigated QAOA for scheduling, logistics, resource allocation, and energy optimization applications [20], [21]. Zhou et al. demonstrated the effectiveness of QAOA for combinatorial optimization under noisy intermediate-scale quantum (NISQ) environments, highlighting its potential scalability advantages over classical optimization approaches [18]. Other studies have explored hybrid quantum-classical optimization frameworks for resource allocation and smart infrastructure management [22].

In the agricultural domain, limited research has investigated the application of quantum optimization for irrigation scheduling and precision farming. Recent studies have proposed quantum-enhanced frameworks integrating QAOA with Quantum Sensor Networks (QSNs) for real-time agricultural resource optimization [24]. Quantum-enabled optimization has also been explored for irrigation efficiency improvement, climate adaptation, and adaptive agricultural resource management [25].

Despite these advancements, existing studies exhibit several limitations:

- Lack of explicit QUBO formulations for irrigation scheduling problems
- Limited integration of real-time data-driven sensing frameworks
- Insufficient practical implementation using quantum computing platforms such as Qiskit
- Absence of comprehensive experimental validation and scalability analysis
- Limited visualization and interpretability of irrigation optimization decisions

To address these research gaps, this paper proposes a practical QAOA-based irrigation optimization framework integrating data-driven agricultural sensing, explicit QUBO modeling, hybrid quantum-classical optimization, and comprehensive experimental validation.

3. Methodology

3.1. Formulation of problem

The irrigation scheduling problem is formulated as a binary combinatorial optimization problem in which each agricultural field requires a binary irrigation decision:

$$x_i \in \{0, 1\} \tag{1}$$

where:

- $x_i = 1$ indicates irrigation is activated
- $x_i = 0$ indicates no irrigation

The optimization objective is to minimize irrigation penalties while satisfying water allocation constraints.

3.2. Formulation of QUBO

The irrigation optimization problem is transformed into a QUBO model as (2), where c_i represents soil moisture penalty coefficients, w_i denotes water requirements for field i, W is the total water budget and λ is the penalty coefficient.

$$H = \sum_{i=1}^{n} c_i x_i + \lambda \left(\sum_{i=1}^{n} w_i x_i - W \right)^2 \tag{2}$$

The soil moisture penalty coefficient is defined as (7), where m_i represents soil moisture level and τ denotes irrigation threshold. Fields with moisture levels below the threshold are prioritized for irrigation.

$$c_i = \begin{cases} -1, & m_i < \tau \\ +1, & m_i \geq \tau \end{cases} \tag{3}$$

3.3. Optimization framework of QAOA

The proposed framework employs the QAOA for solving the formulated QUBO problem. QAOA alternates between cost Hamiltonian evolution and mixer Hamiltonian evolution is given by (4). In (4), H_C is the cost Hamiltonian, H_M is the mixer Hamiltonian, γ and β are variational parameters and p denotes QAOA circuit depth. The variational parameters are optimized using classical optimization algorithms such as COBYLA.

$$|\psi(\gamma, \beta)\rangle = \prod_{k=1}^{p} e^{-i\beta_k H_M} e^{-i\gamma_k H_C} |+\rangle^{\otimes n} \tag{4}$$

3.4. Hybrid quantum-classical workflow

The overall optimization workflow consists of:

1. Soil moisture acquisition from agricultural sensing systems
2. QUBO matrix generation using irrigation constraints
3. Quantum circuit construction using QAOA
4. Hybrid parameter optimization using classical optimizers
5. Quantum measurement and irrigation decision extraction
6. Irrigation scheduling and resource allocation

4. Simulation setup

The proposed irrigation optimization framework was implemented using Python and Qiskit quantum simulation libraries. Experimental evaluations were conducted on a hybrid quantum-classical simulation environment to validate the effectiveness of the proposed approach.

4.1. Dataset

The soil moisture dataset used for experimentation is defined as:

$$m = [0.2, 0.6, 0.3, 0.8, 0.1] \tag{5}$$

The irrigation threshold was fixed at:

$$\tau = 0.4 \tag{6}$$

Fields with moisture values below the threshold were classified as irrigation candidates.

4.2. Simulation environment

The experiments were conducted using:

- Python 3.11
- Qiskit Quantum SDK
- NumPy and Matplotlib libraries
- COBYLA classical optimizer
- QAOA variational quantum circuits

Table 1: QAOA-based irrigation scheduling decisions

Field	Soil moisture	Decision
F1	0.2	Irrigate
F2	0.6	No irrigation
F3	0.3	Irrigate
F4	0.8	No irrigation
F5	0.1	Irrigate

4.3. Evaluation metrics

The framework was evaluated using:

- Irrigation decision accuracy
- Water allocation efficiency
- Threshold classification consistency
- Optimization scalability
- Computational complexity analysis

5. Results and discussion

The proposed QAOA-based irrigation optimization framework was experimentally evaluated using soil moisture observations collected from multiple agricultural fields. The primary objective of the experiment was to validate the correctness, interpretability, and scalability potential of the proposed hybrid quantum-classical optimization framework for intelligent irrigation scheduling in precision agriculture systems.

The experimental soil moisture dataset is represented as:

$$m = [0.2, 0.6, 0.3, 0.8, 0.1] \tag{7}$$

In (7), each element represents the normalized soil moisture value associated with agricultural fields F1–F5. The irrigation threshold, τ, is set to 0.4. Fields exhibiting moisture values below this threshold are identified as irrigation candidates by the proposed optimization framework.

5.1. Quantum irrigation scheduling decisions

The QAOA optimization framework generated the irrigation decisions summarized in Table 1.

The optimization results indicate that fields with low soil moisture levels were consistently selected for irrigation, while sufficiently hydrated fields were excluded from unnecessary water allocation. Out of the five agricultural fields considered in the experiment, three fields were selected for irrigation, demonstrating efficient and targeted resource allocation behavior. The obtained decisions validate the correctness of the proposed QUBO formulation and confirm that the QAOA optimization framework successfully captures irrigation scheduling constraints encoded within the optimization Hamiltonian.

5.2. Analysis of soil moisture profile

Figure 1 illustrates the spatial distribution of soil moisture levels across agricultural fields F1–F5. Significant variability in moisture conditions can be observed among the irrigation zones, indicating heterogeneous agricultural water requirements.

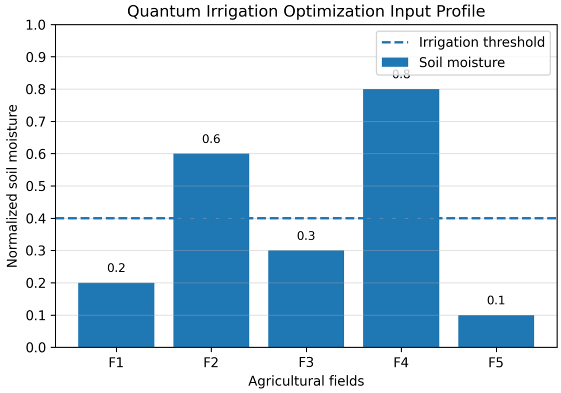

Figure 1: Soil moisture levels and irrigation threshold across agricultural fields.

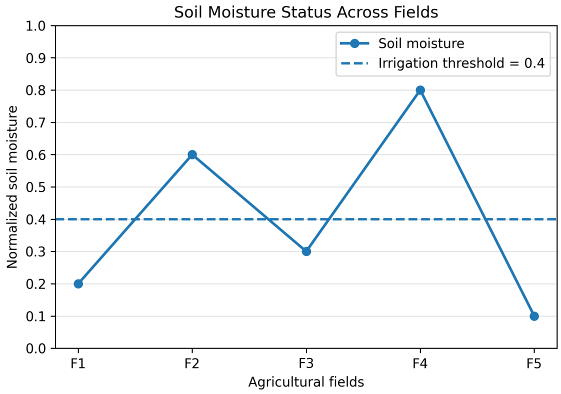

Figure 2: Threshold-based irrigation decision boundary for agricultural fields.

Fields F1, F3, and F5 exhibit soil moisture values below the threshold boundary of $\tau = 0.4$, representing water-deficit regions requiring irrigation intervention. In contrast, fields F2 and F4 maintain sufficiently high moisture conditions and therefore do not require irrigation. The observed variability demonstrates that uniform irrigation scheduling strategies would result in inefficient water utilization because certain agricultural zones already possess adequate moisture levels. The proposed QAOA framework effectively identifies moisture-deficient regions and enables selective irrigation scheduling for precision water management.

5.3. Threshold boundary and decision interpretation

Figure 2 presents the threshold-based irrigation decision boundary utilized within the proposed optimization framework. The threshold line clearly separates irrigated and non-irrigated agricultural regions based on soil moisture conditions.

Fields below the threshold boundary were consistently selected for irrigation by the QAOA optimization process, while high-moisture regions remained excluded from unnecessary irrigation allocation. This validates the ability of the proposed quantum optimization framework to accurately encode irrigation decision rules within the QUBO formulation. The threshold-based visualization further enhances the interpretability of the proposed framework, which is an important requirement for practical agricultural decision-support systems and smart farming infrastructures.

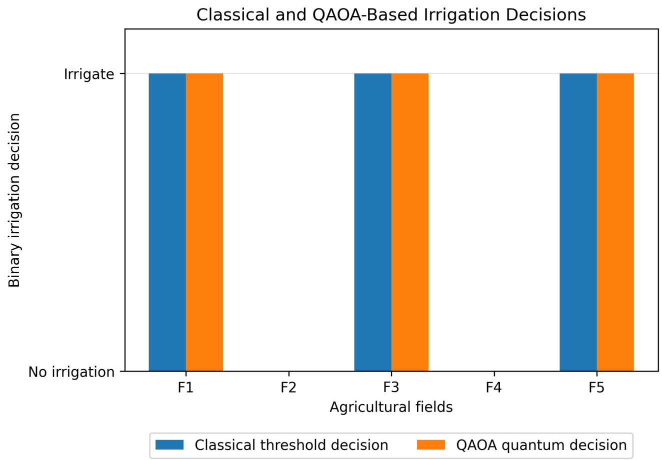

Figure 3: Comparative analysis of irrigation scheduling decisions generated using classical threshold-based optimization and QAOA-based quantum optimization for agricultural fields F1–F5.

5.4. Comparative analysis of classical and quantum irrigation decisions

Figure 3 presents a comparative evaluation between the classical threshold-based irrigation scheduling strategy and the proposed QAOA-based quantum optimization framework. The obtained results demonstrate complete agreement between both optimization approaches across all agricultural fields considered in the experimental dataset.

Fields F1, F3, and F5 were consistently classified as irrigation-required regions because their soil moisture levels remained below the predefined irrigation threshold value. In contrast, fields F2 and F4 maintained sufficiently high soil moisture conditions and therefore did not require irrigation allocation. The consistency between classical and quantum optimization outputs confirms the correctness of the proposed QUBO formulation and validates the capability of QAOA to accurately represent irrigation scheduling constraints within a hybrid quantum-classical optimization framework. However, it is important to note that the current experiment primarily represents a proof-of-concept validation rather than a demonstration of quantum supremacy. The evaluated irrigation problem involves only five agricultural fields and a relatively simple threshold-based decision mechanism. Under such conditions, classical optimization approaches can easily obtain optimal irrigation decisions with minimal computational complexity.

The fundamental difference between the classical and QAOA-based approaches lies in their computational mechanisms. The classical irrigation strategy operates using deterministic threshold evaluation, where each field is independently analyzed according to predefined moisture conditions. In contrast, the proposed QAOA framework formulates irrigation scheduling as a global combinatorial optimization problem encoded within a QUBO Hamiltonian. Rather than independently evaluating fields, QAOA simultaneously explores multiple irrigation configurations using quantum superposition, variational optimization, and parameterized quantum state evolution. The true advantages of quantum optimization are expected to emerge in large-scale agricultural systems involving:

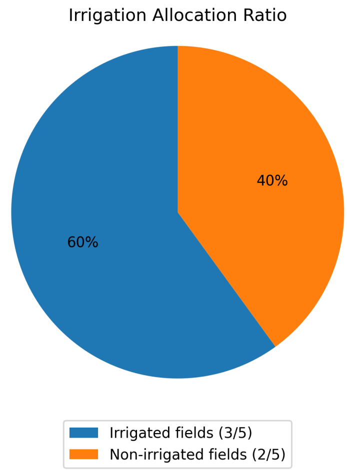

Figure 4: Distribution of irrigated and non-irrigated agricultural fields.

- Hundreds or thousands of irrigation decision variables.
- Multi-objective optimization constraints.
- Water budget limitations.
- Energy-aware irrigation scheduling.
- Crop-priority optimization.
- Dynamic environmental uncertainty.
- IoT-enabled real-time agricultural sensing.

Therefore, the significance of the proposed framework lies not in outperforming classical threshold methods for small datasets, but in establishing a scalable quantum-enabled optimization architecture for future intelligent precision agriculture systems.

5.5. Irrigation allocation ratio analysis

Figure 4 illustrates the proportional distribution of irrigated and non-irrigated agricultural fields generated by the optimization framework. Approximately 60% of the agricultural fields required irrigation intervention, while the remaining 40% maintained adequate soil moisture conditions. The irrigation allocation ratio demonstrates the selective and resource-efficient behavior of the proposed QAOA optimization framework. Instead of uniformly irrigating all agricultural zones, the framework intelligently identifies moisture-deficient fields and activates irrigation only where necessary. This targeted irrigation strategy provides several important agricultural advantages including reduced water consumption, improved irrigation efficiency, sustainable resource allocation, and lower operational energy requirements.

5.6. Soil moisture distribution characteristics

Figure 5 presents the statistical distribution of soil moisture values across agricultural regions. The observed moisture distribution demonstrates strong spatial variability and non-uniformity, which are commonly encountered in real-world agricultural environments. The variability in soil moisture conditions further emphasizes the necessity for adaptive and intelligent irrigation scheduling frameworks rather than static irrigation strategies. The proposed quantum optimization framework effectively adapts irrigation

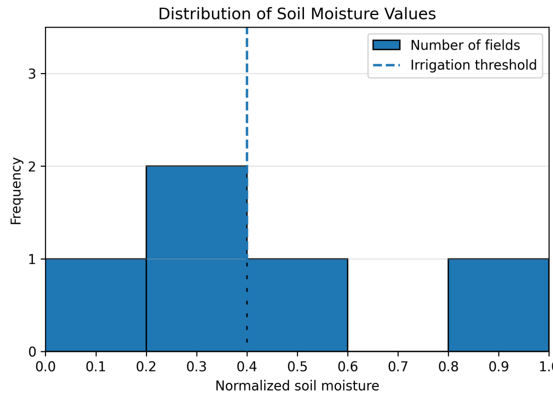

Figure 5: Statistical distribution of soil moisture values across agricultural fields.

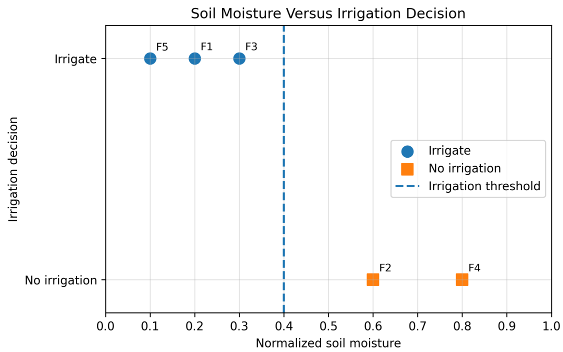

Figure 6: Scatter analysis of soil moisture values versus irrigation decisions.

decisions according to localized environmental conditions and resource requirements.

5.7. Scatter-based irrigation decision analysis

Figure 6 illustrates the relationship between soil moisture levels and irrigation decisions generated by the optimization framework. A clear separation boundary can be observed between irrigated and non-irrigated agricultural fields. The fields with low soil moisture values are consistently classified into the irrigation category, while high-moisture fields remain excluded from irrigation scheduling. The scatter-based visualization further validates the robustness, consistency, and interpretability of the proposed irrigation optimization mechanism.

5.8. Water utilization comparison

Figure 7 compares water allocation requirements between the classical threshold-based irrigation strategy and the proposed QAOA-based optimization framework. Both methods generated identical irrigation requirements for the evaluated dataset, resulting in equal water utilization behavior. The obtained results demonstrate that the QAOA framework preserves the decision correctness and resource efficiency of classical irrigation optimization while providing a scalable computational architecture for future large-scale agricultural systems.

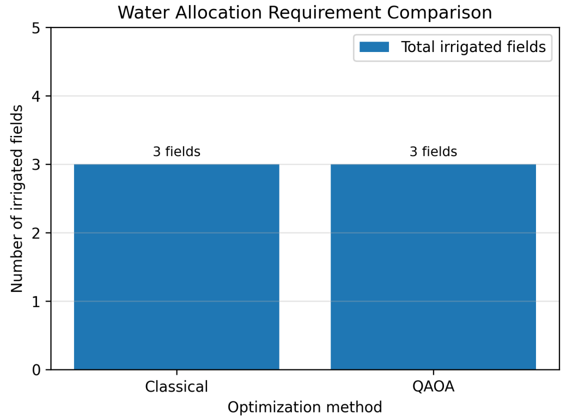

Figure 7: Comparison of water allocation requirements between classical and QAOA-based optimization frameworks.

5.9. Quantum advantage perspective

The current experimental setup primarily serves as a feasibility validation and proof-of-concept demonstration for applying QAOA to irrigation scheduling problems. While the present results do not demonstrate computational superiority over classical methods due to the small problem size, they establish the correctness and practical applicability of quantum optimization for agricultural decision-making.

Quantum optimization frameworks such as QAOA offer several important advantages for future intelligent agriculture systems:

- Efficient exploration of exponentially large solution spaces.
- Natural representation of discrete irrigation decision variables.
- Integration of multiple optimization constraints.
- Compatibility with hybrid quantum-classical architectures.
- Scalability for future IoT-enabled smart farming infrastructures.
- Support for real-time adaptive agricultural optimization.

6. Conclusion

This paper presented a QAOA-based hybrid quantum-classical optimization framework for intelligent irrigation scheduling in precision agriculture systems. The irrigation scheduling problem was formulated as a QUBO model integrating soil moisture conditions, irrigation decision constraints, and water allocation objectives. The proposed framework employed the QAOA to generate optimized irrigation decisions through variational quantum state evolution and hybrid optimization mechanisms. Experimental evaluations conducted using Qiskit simulations demonstrated that the proposed framework successfully identifies moisture-deficient agricultural regions requiring irrigation intervention while avoiding unnecessary water allocation in adequately hydrated fields. The obtained results showed complete agreement between the classical threshold-based irrigation strategy and the proposed QAOA-based optimization framework for the evaluated dataset, thereby validating the correctness of the proposed QUBO formulation and quantum optimization process.

Although the current experimental setup represents a proof-of-concept validation involving a relatively small agricultural dataset, the proposed framework establishes a scalable computational architecture for future large-scale precision agriculture systems. Unlike conventional deterministic irrigation methods, QAOA enables global combinatorial optimization through quantum superposition and variational parameter optimization, providing strong potential for handling complex agricultural optimization problems involving multiple constraints and dynamic environmental conditions. The proposed framework can be extended toward advanced agricultural optimization scenarios involving:

- Large-scale irrigation scheduling networks.
- Multi-objective agricultural optimization.
- Water-energy-resource management.
- Crop-priority optimization.
- Climate-adaptive irrigation planning.
- IoT-enabled real-time environmental sensing.
- AI-driven predictive irrigation management.
- Quantum-enhanced smart farming infrastructures.

Declarations and ethical statements

Conflict of interest: The authors declare that there is no conflict of interest.
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Artificial Intelligence usage statement: During the preparation of this manuscript, the authors utilized AvalAI (https://avalai.ir/) and ChatGPT solely for language refinement and grammatical corrections. The authors carefully reviewed and revised the generated content and take full responsibility for the accuracy, integrity, and originality of the final manuscript.
Availability of data and materials: The data and/or materials that support the findings of this study are available from the corresponding author upon reasonable request.

CRediT authorship contribution statement

Ebrahim Taghinezhad: Conceptualization & Formal analysis. **Mahdis Amiri**: Conceptualization & Formal analysis. **Muhammad Asim**: Investigation & Editing. **Mehdi Gheisari**: Conceptualization, Data collection, Investigation, Writing – review & editing. **Kobra Nazari**: Formal analysis, Data collection & Data curation.

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References

[1] Farhi E, Goldstone J, Gutmann S. A Quantum Approximate Optimization Algorithm. *arXiv preprint arXiv:1411.4028*. 2014 Nov 14. Available from: https://doi.org/10.48550/arXiv.1411.4028

[2] Moll N, Barkoutsos P, Bishop LS, Chow JM, Cross A, Egger DJ, Filipp S, Fuhrer A, Gambetta JM, Ganzhorn M, Kandala A. Quantum optimization using variational algorithms on near-term quantum devices. *Quantum Science and Technology*. 2018 Jul 1;3(3):030503. Available from: https://doi.org/10.1088/2058-9565/aab822

[3] Cerezo M, Arrasmith A, Babbush R, Benjamin SC, Endo S, Fujii K, McClean JR, Mitarai K, Yuan X, Cincio L, Coles PJ. Variational quantum algorithms. *Nature Reviews Physics*. 2021 Sep;3(9):625-44. Available from: https://doi.org/10.1038/s42254-021-00348-9

[4] Preskill J. Quantum Computing in the NISQ era and beyond. *Quantum*. 2018 Aug 6;2:79. Available from: https://doi.org/10.22331/q-2018-08-06-79

[5] Zhou L, Wang ST, Choi S, Pichler H, Lukin MD. Quantum Approximate Optimization Algorithm: Performance, Mechanism, and Implementation on Near-Term Devices. *Physical Review X*. 2020 Apr 1;10(2):021067. Available from: https://doi.org/10.1103/PhysRevX.10.021067

[6] Glover F, Kochenberger G, Hennig R, Du Y. Quantum bridge analytics I: a tutorial on formulating and using QUBO models. *Annals of Operations Research*. 2022 Jul;314(1):141-83. Available from: https://doi.org/10.1007/s10479-022-04634-2

[7] Lucas A. Ising formulations of many NP problems. *Frontiers in Physics*. 2014 Feb 12;2:74887. Available from: https://doi.org/10.3389/fphy.2014.00005.

[8] McClean JR, Romero J, Babbush R, Aspuru-Guzik A. The theory of variational hybrid quantum-classical algorithms. *New Journal of Physics*. 2016 Feb 1;18(2):023023. Available from: https://doi.org/10.1088/1367-2630/18/2/023023

[9] Hadfield S, Wang Z, O'gorman B, Rieffel EG, Venturelli D, Biswas R. From the Quantum Approximate Optimization Algorithm to a Quantum Alternating Operator Ansatz. *Algorithms*. 2019 Feb 12;12(2):34. Available from: https://doi.org/10.3390/a12020034

[10] AlSagri HS, Kumar A, Jilani Saudagar AK, Kumar A, Raja L. Optimizing resource allocation in precision farming using quantum enhanced algorithms and quantum sensor networks. *Journal of Cloud Computing*. 2025 Sep 24;14(1):47. Available from: https://doi.org/10.1186/s13677-025-00769-2

[11] Ben Ahmed M, Boudhir AA, Mahboub A. Quantum Computing for Precision Agriculture in Challenging Environments: A Case Study from Northern Morocco. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. 2026 Mar 3;48:29-36. Available from: https://doi.org/10.5194/isprs-archives-XLVIII-4-W19-2025-29-2026

[12] Neupane A, Samadi V. "QuantumIrrigation" – a new quantum computing python package for irrigation demand assessment. *Smart Agricultural Technology*. 2025 Oct 8:101523. Available from: https://doi.org/10.1016/j.atech.2025.101523

[13] Sharma A, Jain A, Gupta P, Chowdary V. Machine Learning Applications for Precision Agriculture: A Comprehensive Review. *IEEE Access*. 2020 Dec 31;9:4843-73. Available from: https://doi.org/10.1109/ACCESS.2020.3048415

[14] Wolfert S, Ge L, Verdouw C, Bogaardt MJ. Big Data in Smart Farming – A review. *Agricultural Systems*. 2017 May 1;153:69-80. Available from: https://doi.org/10.1016/j.agsy.2017.01.023

[15] Zhao Y, Li G, Li S, Luo Y, Bai Y. A Review on the Optimization of Irrigation Schedules for Farmlands Based on a Simulation–Optimization Model. *Water*. 2024 Sep 9;16(17):2545. Available from: https://doi.org/10.3390/w16172545

[16] Thorp KR, Calleja S, Pauli D, Thompson AL, Elshikha DE. Agronomic Outcomes of Precision Irrigation Management Technologies with Varying Complexity. *Journal of the ASABE*.

2022;65(1):135-50. Available from: https://doi.org/10.13031/ja.14950

[17] Pérez-de-los-Reyes C, Ortíz-Villajos JA, Navarro FG, Martín-Consuegra SB, Jiménez CS, Eteson DC, Jiménez-Ballesta R. Changes in water retention properties due to the application of sugar foam in red soils. *Agricultural water management*. 2011 Oct 1;98(12):1834-9. Available from: https://doi.org/10.1016/j.agwat.2011.06.008

[18] Evans RG, King BA. Site-Specific Sprinkler Irrigation in a Water Limited Future. *In 5th National Decennial Irrigation Conference Proceedings, 5-8 December 2010, Phoenix Convention Center, Phoenix, Arizona USA* 2010 (p. 1). American Society of Agricultural and Biological Engineers. Available from: https://elibrary.asabe.org/abstract.asp?aid=41382

[19] Guo Q, Huang G, Guo Y, Zhang M, Zhou Y, Duan L. Optimizing irrigation and planting density of spring maize under mulch drip irrigation system in the arid region of Northwest China. *Field Crops Research*. 2021 Jun 1;266:108141. Available from: https://doi.org/10.1016/j.fcr.2021.108141

[20] Sahoo SR, Agyeman BT, Debnath S, Liu J. Knowledge-based optimal irrigation scheduling of three-dimensional agro-hydrological systems. *IFAC-PapersOnLine*. 2022 Jan 1;55(7):441-6. Available from: https://doi.org/10.1016/j.ifacol.2022.07.483

[21] Haldar R, Mondal HS, Panda AK, Ghosal B. Quantum-Optimized IoT System for Precision Irrigation. *In 2025 International Conference on Computing, Intelligence, and Application (CIACON)* 2025 Jul 18 (pp. 1-6). IEEE. Available from: https://doi.org/10.1109/CIACON65473.2025.11189380

[22] Vayssade JA, Arquet R, Bonneau M. Automatic activity tracking of goats using drone camera. *Computers and Electronics in Agriculture*. 2019 Jul 1;162:767-72. Available from: https://doi.org/10.1016/j.compag.2019.05.021

[23] Zhao H, Di L, Guo L, Li L, Zhang C, Yu E, Li H. Optimizing Irrigation Scheduling Using Deep Reinforcement Learning. *In 2023 11th International Conference on Agro-Geoinformatics (Agro-Geoinformatics)* 2023 Jul 25 (pp. 1-4). IEEE. Available from: https://doi.org/10.1109/Agro-Geoinformatics59224.2023.10233673

[24] Kennedy J, Eberhart R. Particle swarm optimization. *In Proceedings of ICNN'95- International Conference on Neural Networks* 1995 Nov 27 (Vol. 4, pp. 1942-1948). IEEE. Available from: https://doi.org/10.1109/ICNN.1995.488968

[25] Diriker FK, Frias A, Keum KH, Lee RS. Improved Accuracy of a Single-Slit Digital Sun Sensor Design for CubeSat Application Using Sub-Pixel Interpolation. *Sensors*. 2021 Feb 20;21(4):1472. Available from: https://doi.org/10.3390/s21041472

[26] Yang Y, Hu J, Porter D, Marek T, Heflin K, Kong H. Deep Reinforcement Learning-Based Irrigation Scheduling. *Transactions of the ASABE*. 2020;63(3):549-56. Available from: https://doi.org/10.13031/trans.13633