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RESEARCH ARTICLE

Agentic artificial intelligence-driven digital twin for real-time irrigation control with fuzzy sustainability objectives

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ABSTRACT

Irrigation management in modern agriculture faces simultaneous challenges, including water scarcity, climate uncertainty, and the need for long-term sustainability. In this study, an integrated framework for real-time irrigation control is presented, in which a digital twin is not merely used as a monitoring or simulation tool but is directly embedded in the decision-making and control loop through an agent-based fuzzy multi-objective optimization mechanism. Unlike conventional smart irrigation approaches that rely on static thresholds or offline optimization, the proposed framework enables adaptive, context-based decision updates by continuously integrating physical system feedback into a dynamic optimization engine. The decision-making agent, by simultaneously assessing soil, climate, and plant growth conditions, generates irrigation policies that balance water consumption, crop growth, and environmental sustainability requirements under fuzzy uncertainty. Experimental results show that using dynamic feedback in the digital twin framework improves the multi-objective performance index by more than 12% compared to the static state and significantly reduces control fluctuations. Convergence, stability under uncertainty, and parameter sensitivity analyses also indicate that the proposed framework can establish a sustainable balance across water resource utilization, crop yield, and environmental considerations. The findings indicate that this approach can provide a practical and reliable platform for transitioning to smart, adaptive, and sustainable irrigation systems.

1. Introduction

Agriculture has faced increasing challenges in recent decades, stemming from water resource constraints, climate change, extreme fluctuations in environmental conditions, and increasing pressure to simultaneously achieve higher productivity and environmental sustainability.[1] Irrigation, as one of the most critical management decisions in agricultural systems, plays a decisive role in resource consumption, ecosystem health, and crop performance.[2] However, decision-making in this area is inherently complex, dynamic, and multi-objective, and is affected by significant uncertainties that classical, static models have limited ability to address.[3]

In response to these complexities, intelligent and data-driven approaches have gradually replaced traditional agricultural management methods.[4] Despite significant advances in decision support systems and optimization models, many of these approaches still rely on static assumptions, fixed historical data, and reactive decision-making.[5] Such structures are often unable to accurately reflect the system's behavior under changing environmental conditions and to produce stable, effective decisions in the faceof

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shocks and uncertainties. This gap between real-world complexity and the capabilities of existing models highlights the need for dynamic, adaptive, and predictive frameworks.[6]

As an emerging concept in cyber–physical systems, the digital twin has great potential to address this gap. By creating a dynamic real-time representation of the physical system, the digital twin enables continuous monitoring, simulation of different scenarios, and evaluation of the consequences of decisions before implementation.[7] However, in many agricultural applications, digital twins are primarily used as simulation or monitoring tools and do not play an active role in decision-making or real-time control. This limitation prevents the full potential of digital twins in improving the quality of management decisions from being fully realized.[8]

On the other hand, agent-based decision-making, as a new approach in artificial intelligence, enables the modeling of autonomous, adaptive, and goal-oriented behaviors.[9] In this approach, the decision-maker can make decisions that are consistent with dynamic conditions by understanding the state of the environment, analyzing feedback, and continuously updating its strategies.[10] Despite these capabilities, many agent-based applications in agriculture either lack effective connections to accurate physical models or do not explicitly formulate their decisions within multi-objective, sustainability-oriented optimization frameworks.[11]

At the same time, the multi-objective nature of irrigation decisions makes the need for advanced optimization methods inevitable. Reducing water consumption, maintaining or increasing crop yields, and reducing negative environmental impacts are often in conflict with one another. In addition, uncertainties in climate, soil, and plant water requirements make deterministic models unable to fully reflect the behavior of the real system.[12] In this context, fuzzy multi-objective optimization provides a suitable tool for modeling the ambiguity and flexibility of the decision-maker's objectives and preferences. However, in many existing studies, these approaches have been applied in a disjointed manner without a dynamic interaction with the real system.[13]

Accordingly, the main gap in the existing literature is the lack of an integrated framework that simultaneously and interactively leverages digital twins, agent-based decision-making, and fuzzy multi-objective optimization for real-time irrigation control. The main innovation of this research lies in addressing this gap. In the proposed framework, the digital twin is more than just a simulation tool; it acts as an active component in the decision-making cycle, continuously providing the decision-maker with up-to-date information from the system. The decision-maker, in turn, relies on these dynamic feedbacks to guide the fuzzy multi-objective optimization process and to adaptively and predictively update irrigation decisions. This integration allows simultaneous examination of solution quality, convergence behavior, stability under uncertainty, and decision feasibility.

In addition, the present study provides a comprehensive evaluation of the proposed framework through analyses, including quantitative comparisons of solution algorithms, convergence behavior, stability, parameter sensitivity, computational complexity, and agent-based decision-making behavior. This multi-layered analytical approach, beyond reporting optimization results, allows for an in-depth assessment of the model's reliability in real-world, uncertain agricultural conditions. The proposed framework was experimentally validated using a hybrid setup that combined real field sensor data with controlled simulation scenarios to ensure both practical applicability and robustness under uncertainty.

From a methodological perspective, the innovation of this research lies in integrating a dynamic digital twin with a fuzzy multi-objective optimization framework in a real-time decision-making loop. The simultaneous use of multiple evolutionary algorithms and their performance evaluation using multi-dimensional stability indices has enabled a deeper analysis of the system's behavior under changing environmental conditions. Thus, the proposed framework extends beyond an intelligent monitoring system and provides an adaptive decision-making architecture based on physical–virtual synchronization.

The paper is structured as follows: the system architecture and conceptual framework are first presented, followed by descriptions of the mathematical model, solution methods, case studies, and comprehensive empirical analyses. Subsequently, the results are discussed from a technical and managerial perspective, and limitations and future research directions are presented.

2. Literature review

In recent years, smart irrigation management has received widespread attention as a key axis of sustainable agricultural development.[14] Increasing pressure on water resources, severe climate fluctuations, and the need to improve production efficiency have led to traditional approaches based on experience or static rules becoming ineffective.[15] In this context, numerous studies have sought to improve irrigation decision-making by employing mathematical models, simulations, and intelligent methods. However, a significant part of these studies still relied on simplified models and deterministic assumptions that have limited power to address real environmental uncertainties.[16]

One important research stream is the use of optimization models for optimal water allocation in agricultural systems.[17] In these studies, objectives such as minimizing water consumption, maximizing crop yield, and reducing costs have been explicitly formulated as single- or multi-objective models.[18] Despite these advances, many of these models are static in nature and do not dynamically interact with the real field situation. As a result, the derived decisions are often suitable for predefined conditions and show limited flexibility in the face of sudden environmental changes.[19]

To overcome this limitation, fuzzy approaches have been widely introduced in the literature. The use of fuzzy logic allows for modeling ambiguity, uncertainty, and linguistic preferences of the decision-maker and is particularly useful in irrigation problems where data are not always accurate and certain.[20] Various studies have shown that combining multi-objective optimization with fuzzy concepts can yield more flexible solutions that better reflect real-world conditions.[21] However, in many of these studies, fuzzification is performed only at the objective or constraint levels, and the decision-making process remains isolated from the current state of the system.[22]

With advances in data and computing, the concept of a digital twin has emerged as a new paradigm for complex systems.[23] By creating a dynamic digital version of a physical system, the digital twin enables real-time monitoring, scenario simulation, and decision-making outcomes.[24] In agriculture, the application of digital twins has been mainly focused on soil condition monitoring, plant growth, and yield prediction. However, most existing research has used digital twins as descriptive or predictive tools, and their role in directly guiding the decision-making and optimization process remains limited.[25]

On the other hand, the use of artificial intelligence and machine learning algorithms in irrigation management has grown significantly.[26] These approaches mainly focus on predicting plant water requirements or identifying hidden patterns in historical data. Although the results of these studies have been promising, many of them lack an explicit decision-making framework, and the model outputs do not directly translate into actionable control decisions. Furthermore, the strong dependence of these methods on historical data can limit their generalizability under climate change or environmental shocks.[27]

In the meantime, agent-based decision-making has been proposed as a complementary approach in artificial intelligence that allows modeling of autonomous, adaptive, and goal-oriented behaviors. In some studies, agents have been introduced to manage agricultural resources or coordinate between different system components.[28] However, in most of these studies, agents either lack deep connections to detailed physical models or their decisions are not explicitly formulated as multi-objective, sustainability-oriented optimization problems.[29] This makes the behavior of agents more conceptual or simulated than a practical and implementable decision-making mechanism.

Multi-objective metaheuristic algorithms have also gained importance in the literature of water resources management and agriculture.[30] Algorithms such as evolutionary and particle swarm optimization methods have been widely used to extract Pareto frontiers and analyze trade-offs between conflicting objectives.[31] However, in many studies, these algorithms are implemented offline and do not directly interact with the real-time state of the system.[32] As a result, the optimization process is separated from the actual decision-making cycle, reducing its practical applicability in dynamic environments.[33]

A comprehensive review of the literature shows that although each of the multi-objective optimization, fuzzy logic, digital twin, and agent-based decision-making approaches has made significant progress independently, their true integration into a real-time operational framework remains a significant challenge.[34] In particular, the lack of mechanisms that enable the digital twin to actively participate in the optimization process, while allowing the decision-maker to update decisions based on dynamic feedback and fuzzy uncertainties, represents a major gap in the literature.

In recent years, significant advances have been made in the field of Internet of Things (IoT) and embedded systems for the sustainable management of water and energy resources. IoT-based smart irrigation systems, which combine soil moisture sensors, microcontrollers, and cloud infrastructure, have shown that real-time monitoring and automated decision-making can significantly reduce water waste.[35] These systems typically rely on low-power embedded architectures that continuously collect environmental data and send it to higher levels for analysis and control.

In addition to direct applications in irrigation, IoT-based technologies and embedded systems have been developed for sustainable energy management, enabling real-time monitoring, adaptive control, and optimization of energy consumption in distributed environments.[36] These approaches demonstrate that integrating sensor networks, edge processing, and cloud-edge coordination can provide the necessary technical infrastructure for efficient resource utilization.

However, most of these studies have focused on monitoring, fixed-rule-based automation, or static optimizations. The systematic coupling of IoT infrastructures and embedded systems with a dynamic digital twin and an agent-based fuzzy multi-objective optimization engine for real-time control remains limited. Hence, although IoT and embedded architectures provide the necessary technical platform for data collection and control, their integration with a digital twin-based adaptive decision loop remains a research gap that this study addresses.

This study presents an integrated framework that simultaneously and interactively applies digital twins, agent-based decision-making, and fuzzy multi-objective optimization. In this research, the concept of digital twin is defined as a dynamic virtual representation of a physical system that is continuously updated through real-time data and enables predictive simulation, scenario analysis, and decision support. Unlike conventional monitoring systems, which are limited to collecting and displaying data, a digital twin interacts with the physical system in both directions and can reapply control commands to the real system based on the outputs of optimization and analysis models. In the context of this research, a digital twin is not only a reflective virtual model but also an active component in the multi-objective decision-making loop and in adaptive irrigation control. Despite the development of IoT-based smart irrigation systems, many solutions are limited to monitoring data and executing predefined rules and lack a dynamic virtual model for predictive analysis and adaptive decision-making. In such circumstances, the application of the concept of a digital twin is essential, as this approach enables a continuous synchronization between the physical system and the virtual model, the execution of predictive scenarios, and the integration of multi-objective optimization in the real-time control loop. Therefore, the term "digital twin" in this study is not merely a technological label but rather a dynamic, interactive decision-making architecture that goes beyond conventional monitoring or control systems.

Unlike previous studies that examined these components separately, the present approach integrates them into a coherent decision-making cycle, enabling simultaneous assessment of solution quality, convergence behavior, stability under uncertainty, and decision implementability. Thus, this study not only advances the existing literature from a theoretical perspective but also represents an important step toward realizing smart, adaptive, and sustainable agriculture.

3. Methodology

3.1. System architecture and conceptual framework

In this study, the proposed system architecture was designed to enable real-time irrigation control in an integrated, adaptive, and autonomous framework. This architecture was based on a close symbiosis between the physical farm system and its digital twin, with decisions being made dynamically and continuously. The main goal of this design was to create a platform that can simultaneously account for rapid changes in environmental conditions, evolving plant needs, and resource constraints in decision-making.

At the operational level, real-time data from farm sensors, including soil moisture, climate conditions, and plant growth status, are continuously transmitted to the digital twin. This twin provides a live, up-to-date representation of the farm that goes beyond a simple simulation model and serves as the basis for the system's autonomous decision-making. Unlike conventional approaches that focus solely on prediction or monitoring, the digital twin in this framework serves as an active entity directly in the control loop.

At the heart of this architecture is an agent-based decision-making mechanism that analyzes the current state of the system and selects appropriate control actions. This decision-making agent, informed by digital twin data, understands the state of the field and autonomously generates irrigation decisions based on a set of sustainability goals defined in a fuzzy manner. Such a structure allows the system to make decisions tailored to current conditions and existing uncertainties, rather than relying on fixed thresholds or predefined rules.

The interaction process among the system's components is organized as a continuous feedback

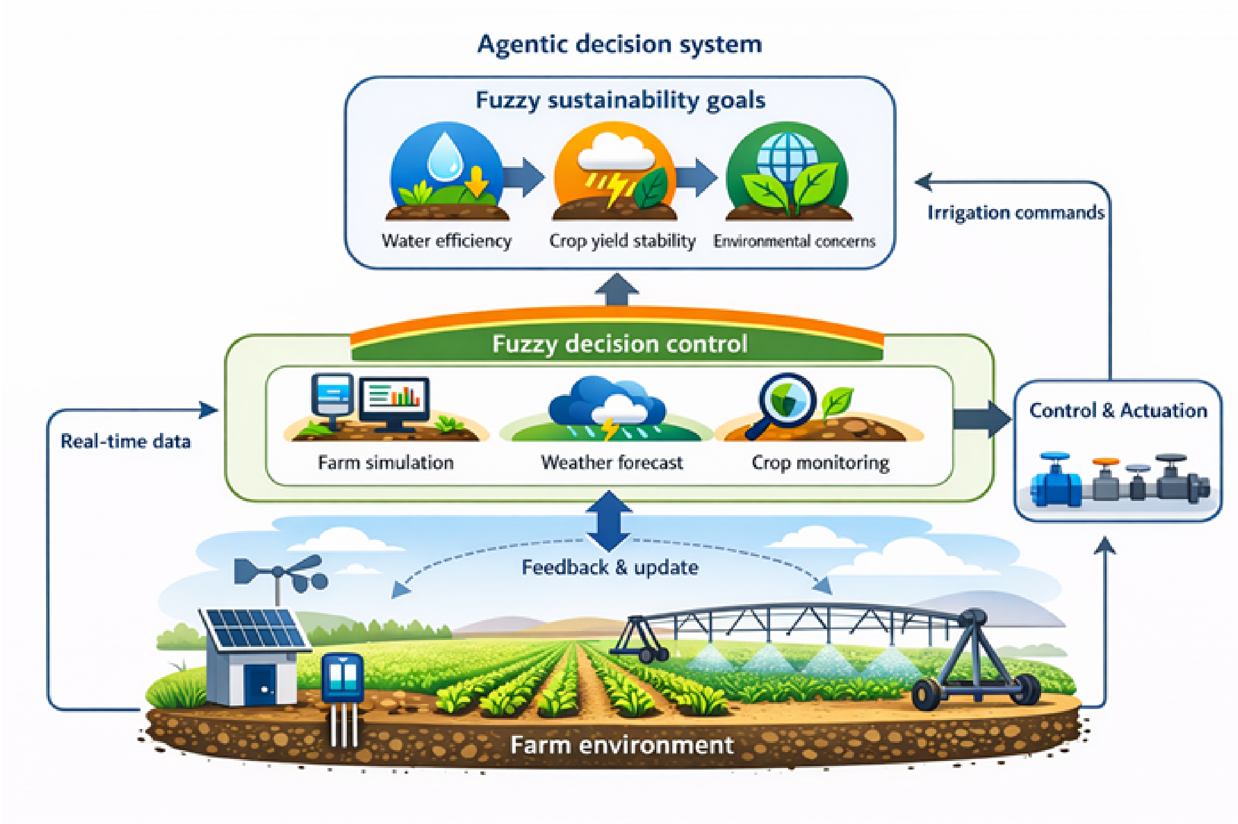

Figure 1. Conceptual architecture of a real-time irrigation control system based on an agent-based digital twin with fuzzy sustainability goals. This figure was designed and created using Adobe Illustrator (Adobe Inc., San Jose, CA, USA, 2023).

loop. The decisions issued by the control agent are applied to the irrigation system, and the consequences of these decisions, through changes in soil and plant states, are again recorded by the sensors and fed back to the digital twin. This closed loop causes the system to continuously evaluate its performance and adjust its control behavior in response to environmental changes or deviations from sustainability goals.

As shown in **Figure 1**, the proposed architecture included an integrated chain of perception, decision-making, and action, with no clear boundary between the physical and digital spaces; rather, these two spaces operate simultaneously and interactively. The position of the decision-making agent at the center of this cycle highlights its role in transforming raw data into meaningful control actions. This conceptual framework paves the way for a transition from reactive irrigation systems to autonomous, goal-oriented systems that can actively improve water resource sustainability and agricultural performance.

3.2. Mathematical model

To support autonomous, real-time irrigation control in complex and uncertain agricultural environments, this research presents a multi-objective, dynamic, nonlinear, and fuzzy optimization model directly integrated into the agent-based digital twin core.[37]

In this framework, non-random uncertainties arising from climate predictions, soil heterogeneity, and plant behavior were accounted for through fuzzy scenarios. Control decisions should not only improve crop yield, but also maintain a sustainable balance between resource consumption, decision fluctuations, and environmental impacts. Therefore, the decision-making problem was formulated as a fuzzy multi-objective optimization system with dynamic and interperiodic constraints.

3.2.1. Sets

The sets used in the model are defined as follows:

(i) $i \in I$: A set of agricultural zones or field parcels.
(ii) $t \in T$: A set of discrete decision time steps.
(iii) $c \in C$: A set of possible climatic states.
(iv) $s \in S$: A set of fuzzy uncertainty scenarios.
(v) $k \in K$: A set of sustainability objectives.
(vi) $l \in L$: A set of agentic decision-making layers.

3.2.2. Parameters

The parameters of the model are defined as follows:

(i) A_i: Area of zone i.
(ii) $ET^s_{i,t}$: Evapotranspiration under scenario s.
(iii) R^s_t: Predicted rainfall under scenario s.
(iv) $W_i^{\max}$: Maximum irrigation capacity of zone i.
(v) W_t^{tot} : Total available water at time t.
(vi) $\theta_i^{\min}, \theta_i^{\max}$: Allowable soil moisture bounds.
(vii) θ_i^{opt} : Optimal soil moisture level.
(viii) $\alpha_i, \beta_i, \gamma_i$: Crop response and stress coefficients.
(ix) E_t: Irrigation energy intensity.
(x) ρ_s: Fuzzy weight of scenario s.
(xi) Λ_k: Minimum satisfaction threshold of objective k.
(xii) Ω: Maximum admissible control variation.

3.2.3. Decision variables

The decision variables of the model are defined as follows:

(i) $x_{i,t}$: Irrigation water allocated to zone i at time t.
(ii) $\theta_{i,t}$: Soil moisture level.
(iii) $y_{i,t}$: Cumulative crop growth index.
(iv) $z_{i,t}$: Crop water stress indicator.
(v) $u_{i,t}$: Agentic control intensity.
(vi) μ_k: Fuzzy satisfaction degree of objective k.

3.2.4. Fuzzy multi-objective functions

The fuzzy multi-objective functions are shown in **Equations 1–4**.

$$\max Z_1 = \sum_{s \in S} \rho_s \sum_{i \in I} \sum_{t \in T} \ln\left(1+\alpha_i y_{i,t} - \beta_i z_{i,t}^2\right) \tag{1}$$

Equation 1 maximizes stable, uniform crop growth over the planning horizon. This function attempts to model the nonlinear increase in crop yield, reflecting the negative effects of water stress. This function shows that crop growth depends not only on the amount of water used but also on the stability of moisture conditions and the reduction of cumulative stresses. The use of a nonlinear structure in this function properly accounts for the system's sensitivity to severe fluctuations in water conditions.

$$\min Z_2 = \sum_{i,t} \left(x_{i,t}^2 + E_t u_{i,t}^2 + \gamma_i \left|x_{i,t} - x_{i,t-1}\right|\right) \tag{2}$$

Equation 2 simultaneously minimizes water resource consumption, the energy required by the irrigation system, and fluctuations in control decisions. This function shows that optimal irrigation decisions should not be based solely on reducing water consumption, but also on controlling energy costs and mitigating sudden changes in irrigation patterns. Thus, this function plays an important role in ensuring operational stability and preventing unstable system behavior.

$$\min Z_3 = \sum_{s,i,t} \rho_s \left|\theta^s_{i,t} - \theta_i^{opt}\right|^{1.5} \tag{3}$$

Equation 3 is dedicated to minimizing cumulative environmental deviation and maintaining soil moisture near the optimum level required by the plant. This function specifically shows that small, persistent deviations from optimal conditions can have significant negative effects on soil and ecosystem health in the long term. Therefore, this function acts as a proxy for environmental considerations in the model.

$$\max Z_4 = \sum_{k \in K} \ln\left(\mu_k + \epsilon\right) \tag{4}$$

Equation 4 maximizes the fuzzy satisfaction level of sustainability objectives. This function shows that the model not only seeks to optimize a specific criterion but also aims to achieve a balanced level of satisfaction across different sustainability objectives. The structure of this function prevents any single objective from dominating the others, promoting balanced decision-making.

In the model, **Equations 1–4** are subjected to the following constraints.

$$\sum_i x_{i,t} \le W_t^{tot} \ \forall t \tag{5}$$

Equation 5 represents the overall water resource constraint in each time period and ensures that the total water allocated to different areas of the field does not exceed the available resources. This constraint reflects the reality of water scarcity in agricultural systems.

$$0 \le x_{i,t} \le W_i^{\max} \ \forall i, t \tag{6}$$

Equation 6 specifies the lower and upper limits on the amount of water allocated to each area and prevents unrealistic allocation or over-allocation of the irrigation system's technical capacity.

$$\sum_t x_{i,t} \le A_i W_i^{\max} \ \forall i \tag{7}$$

Equation 7 states that the total water consumption of each area over the entire planning horizon should be proportional to its area. This constraint creates spatial consistency in the allocation of water resources.

$$\theta_{i,t}=\theta_{i,t-1}+x_{i,t}+R_t^s-ET_{i,t}^s \tag{8}$$

Equation 8 models soil moisture dynamics and shows that the moisture status at any time is the cumulative effect of irrigation, precipitation, and evapotranspiration. This constraint forms the dynamic core of the model.

$$\theta_i^{\min}\leq\theta_{i,t}\ \forall i,t \tag{9}$$

$$\theta_{i,t}\leq\theta_i^{\max}\ \forall i,t \tag{10}$$

Equation 9 imposes the minimum permissible soil moisture to prevent severe water stress and damage to the plant. **Equation 10** specifies the maximum permissible soil moisture, preventing excessive irrigation and creating unfavorable conditions for plant roots.

$$y_{i,t}=y_{i,t-1}+\alpha_i\theta_{i,t}-\beta_i z_{i,t} \tag{11}$$

Equation 11 describes the dynamic relationship between crop growth and time and shows that crop growth is a function of soil moisture status and water stress level.

$$z_{i,t}\geq\left(\theta_i^{opt}-\theta_{i,t}\right)^2 \tag{12}$$

Equation 12 relates the definition of plant stress to the deviation from the optimal soil moisture and shows that the greater the distance from the optimal conditions, the higher the stress level.

$$z_{i,t}\geq 0 \tag{13}$$

Equation 13 ensures that the stress index is non-negative and prevents unrealistic interpretations in the model.

$$\sum_i E_t u_{i,t}\leq E^{\max}\ \forall t \tag{14}$$

Equation 14 imposes a ceiling on the energy consumption of the irrigation system in each time period, ensuring that irrigation decisions are also sustainable in terms of energy.

$$u_{i,t}\geq\frac{x_{i,t}}{W_i^{\max}}\ \forall i,t \tag{15}$$

Equation 15 establishes the relationship between the control intensity of the decision-maker and the amount of water allocated and ensures that each irrigation decision has a realistic level of control support.

$$0\leq u_{i,t}\leq 1\ \forall i,t \tag{16}$$

Equation 16 specifies the permissible range of control intensity and prevents the application of extreme controls.

$$|x_{i,t}-x_{i,t-1}|\leq\Omega\ \forall i,t \tag{17}$$

$$|u_{i,t}-u_{i,t-1}|\leq\Omega\ \forall i,t \tag{18}$$

Equation 17 limits sudden changes in irrigation rate between consecutive periods and helps maintain decision stability. **Equation 18** controls the fluctuations in the agent's control intensity between consecutive time periods and prevents the system from becoming unstable.

$$\sum_t\ |x_{i,t}-x_{i,t-1}|\leq\Psi\ \forall i \tag{19}$$

Equation 19 limits the sum of irrigation changes over the entire time horizon and ensures that irrigation policies remain stable in the long term.

$$x_{i,t}=\sum_{s\in S}\ \rho_s x_{i,t}^s \tag{20}$$

Equation 20 establishes the consistency of decisions across uncertainty scenarios and shows that the final decision results from the weighted aggregation of these scenarios.

$$\sum_{s\in S}\ \rho_s=1 \tag{21}$$

Equation 21 imposes the condition that the scenario weights be normalized so that their sum equals 1.

$$\rho_s\geq 0\ \forall s \tag{22}$$

Equation 22 ensures that the scenario weights are non-negative and validates their fuzzy interpretation.

$$\mu_k\leq f_k\left(Z_k\right)\ \forall k \tag{23}$$

Equation 23 establishes a relationship between the objective function value and the fuzzy satisfaction degree, indicating that the satisfaction of each objective is a function of its level of realization.

$$0\leq\mu_k\leq 1\ \forall k \tag{24}$$

Equation 24 specifies the permissible range of the fuzzy satisfaction degree, which is limited to zero and one.

$$\mu_k\geq\Lambda_k\forall k \tag{25}$$

Equation 25 imposes a minimum acceptable level of fuzzy satisfaction for each objective, ensuring stability and preventing key objectives from being ignored.

$$\theta_{i,0}=\theta_i^{\text{init}}\ \ \forall i \tag{26}$$

Equation 26 fixes the initial soil moisture conditions at the start of the planning horizon, ensuring the model is consistent with the actual state of the field.

$$x_{i,0}=x_i^{\text{init}}\ \ \forall i \tag{27}$$

Equation 27 specifies the initial amount of water allocated and ensures the continuity of decisions.

$$x_{i,T} \leq x_{i,T-1} + \Omega \ \forall i \tag{28}$$

Finally, **Equation 28** governs the system's final behavior and prevents drastic changes in irrigation decisions at the end of the time horizon, thereby maintaining decision-making stability throughout the period.

3.3. Agentic decision-making and control mechanism

In the proposed framework, irrigation decision-making and control were implemented using an agent-based mechanism that continuously interacts with the digital twin of the field. Unlike classical control systems that rely on fixed rules or predefined responses, the agent-based mechanism presented in this study can autonomously perceive the environmental state, evaluate the consequences of different decisions, and select the appropriate control action in real time. This approach enables the transition from reactive irrigation management to predictive and adaptive management.

This information not only provides a view of the current state of the field but also allows the agent to analyze the potential consequences of different irrigation decisions across short- and medium-term time horizons. Thus, decision-making is transformed from a static to a dynamic, context-oriented process.

The agent-based decision-making mechanism follows a perception–analysis–decision–action cycle. In the perception stage, the agent receives input from the digital twin and identifies the current state of the system. In the analysis stage, this state is compared with the fuzzy sustainability goals, and the degree of deviation from the desired conditions is evaluated. Then, in the decision-making stage, the agent selects the appropriate irrigation intensity and pattern, balancing conflicting goals. Finally, in the action stage, the decision made is applied to the irrigation system, and its effects enter the feedback loop.

As shown in **Figure 2**, this decision-making cycle operates in a closed, iterative manner, and each control action immediately updates the system state in the digital twin. This continuous feedback allows the decision-maker to observe the real effect of the decisions and, if necessary, modify the control policy. Such a structure plays an important role in improving decision stability and preventing the accumulation of errors over time.

One of the key features of this mechanism is its ability to adapt to unpredictable environmental conditions. During sudden climate changes, rainfall fluctuations, or changes in plant water requirements, the decision-maker can adjust the irrigation pattern without human intervention. This adaptability frees the system from dependence on predefined scenarios and brings it closer to an autonomous and learning system.

3.4. Solution methodology

Due to the nonlinear, multi-objective, scenario-based, and fuzzy nature of the proposed model, using classical exact methods to directly solve the problem is computationally inefficient and, in many cases, infeasible. Therefore, in this study, three well-known and widely used meta-heuristic algorithms in the multi-objective optimization literature, including the non-dominated sorting genetic algorithm II (NSGA-II), the multi-objective evolutionary algorithm based on decomposition (MOEA/D), and the multi-objective particle swarm optimization (MOPSO), were used to solve the model. The selection of these algorithms was based on their ability to extract a set of Pareto-optimal solutions and effectively manage conflicts between sustainability objectives.

The NSGA-II algorithm, as one of the most widely used multi-objective evolutionary methods, operates on the basis of non-dominated sorting and the maintenance of population diversity. In this study, NSGA-II served as the primary reference for identifying the Pareto frontier and enabled a precise analysis of trade-offs among water consumption, environmental sustainability, and crop yield. The use of the crowding distance in this algorithm has led to uniformly distributed solutions in the objective space and prevented premature convergence.[38]

The MOEA/D algorithm, which decomposes the multi-objective problem into a set of dependent single-objective problems, was used in this study to investigate the efficiency of a framework based on neighborhood and local interaction between solutions. By defining different weight vectors, this algorithm allows analysis of the problem structure and the algorithm's behavior across different uncertainty scenarios. The use of MOEA/D, especially in models with fuzzy structures and dynamic constraints, provides a complementary perspective to NSGA-II.[39]

The MOPSO algorithm, as a multi-objective version of particle swarm optimization, inspired by the social behavior of particles, was used in this study to evaluate the continuous search ca-

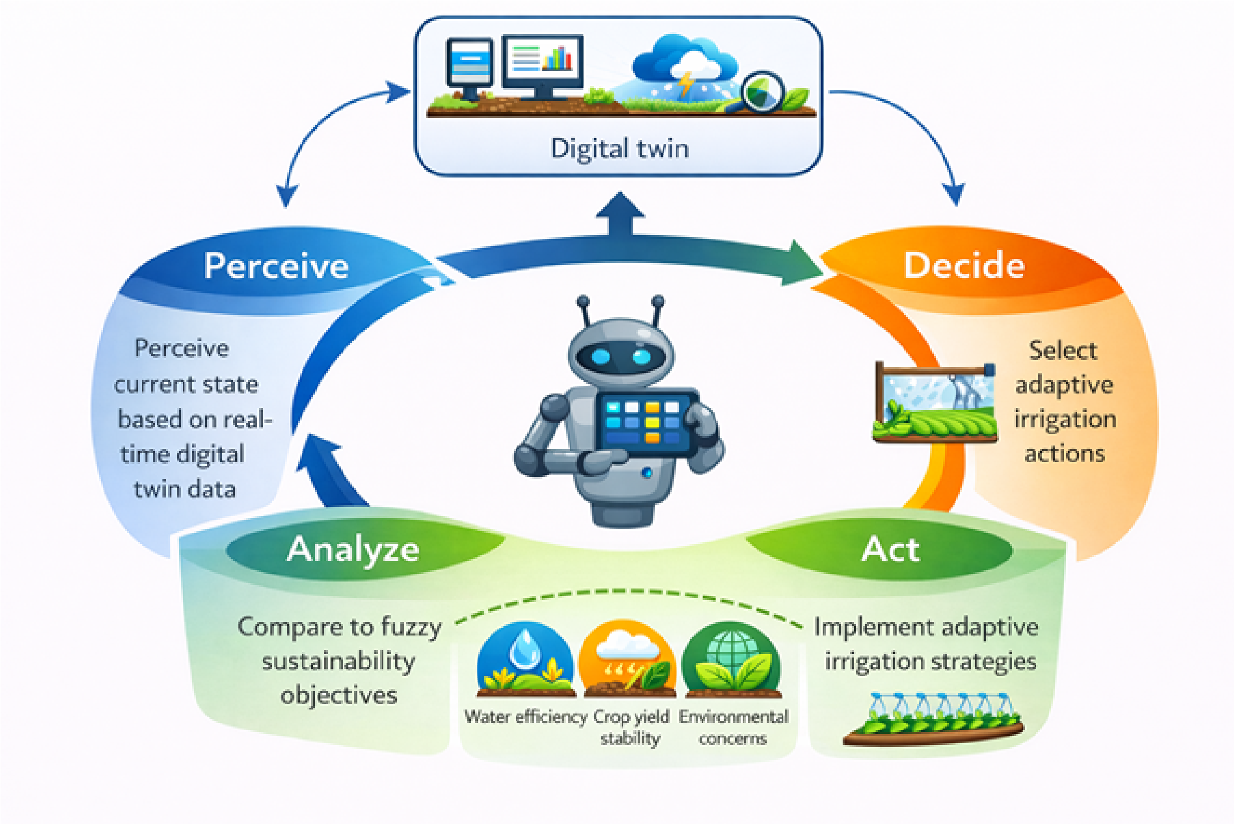

Figure 2. Agent-driven decision-making cycle in a digital twin-based real-time irrigation control system. This figure was designed and created using Adobe Illustrator (Adobe Inc., San Jose, CA, USA, 2023).

pabilities and convergence speed in the decision space. Due to its memory-based nature, MOPSO has a strong ability to exploit past particle experiences and has shown acceptable performance, especially in real-time control problems. Comparing the results of this algorithm with those of two other evolutionary algorithms enables a comprehensive assessment of the stability and quality of the solutions.[40]

The role of the digital twin in the solution process is not simply a passive simulation environment; it actively interacts with the solution algorithms.[41] In each iteration of the algorithm, irrigation decisions generated by the candidate solutions were first applied to the digital twin, and their consequences were evaluated based on soil moisture dynamics, crop growth, and stability indices.[42] The digital twin output was then fed back to the optimization algorithms as accurate, up-to-date feedback. This two-way interaction guided the search process in a context-oriented manner, adapting it to the system's actual conditions, and the decision-maker's role in adjusting the optimization path was practically realized.

To ensure the accuracy of results from the metaheuristic algorithms, computational validation was conducted using the General Algebraic Modeling System (GAMS; version 25.1). At this stage, a simplified version of the model (with a reduced time horizon and number of scenarios) was implemented in GAMS and solved using exact solvers. Comparing the GAMS results with the output of the metaheuristic algorithms showed that the solutions obtained from NSGA-II, MOEA/D, and MOPSO were acceptable and consistent with the exact solutions in terms of quality and convergence.

The parameters of the metaheuristic algorithms were adjusted based on initial experiments and common recommendations in the literature to achieve a proper balance between convergence speed and solution diversity. A summary of the parameter settings used in this study is presented in **Table 1**.

All numerical calculations and algorithm execution were performed in the Python programming environment. The algorithms were implemented using Python 3.10 and standard optimization and numerical libraries. GAMS version 25.1 software was used for detailed model validation. All experiments were performed on a computer system with an Intel Core i7 processor, 32 GB of RAM, and Windows 11 (64-bit).

Table 1. Parameter settings of the metaheuristic algorithms.

Algorithm	Key parameters	Values
NSGA-II	Population size, crossover rate, mutation rate, generations	100, 0.9, 0.1, 300
MOEA/D	Number of subproblems, neighborhood size, mutation rate, generations	100, 20, 0.1, 300
MOPSO	Swarm size, inertia weight, cognitive/social coefficients, iterations	100, 0.7, (1.5, 1.5), 300

Abbreviations: MOEA/D: Multi-objective evolutionary algorithm based on decomposition; MOPSO: Multi-objective particle swarm optimization; NSGA-II: Non-dominated sorting genetic algorithm II.

For each algorithm, to reduce random effects and increase the reliability of the results, 30 independent runs were performed, and the final results were reported based on the mean and standard deviation of the performance indicators. These computational settings and experimental procedures were chosen to ensure the transparency, reproducibility, and scientific validity of the results.

3.5. Case study and experimental setup

To comprehensively evaluate the performance of the proposed framework and investigate its capabilities under both real and controlled conditions, this research used a combination of real field data and simulated data. This dual approach allows analysis of system behavior in both real operating environments and hypothetical scenarios with varying levels of uncertainty, thereby increasing the validity of the results and the generalizability of the findings.

The main case study focused on an agricultural farm located in Austrlia with a pressurized irrigation system, where real data were collected through soil moisture sensors, a local weather station, and an irrigation operation recording system. The real data included soil moisture measurements at different depths, air temperature, relative humidity, precipitation, reference evapotranspiration, and water volume applied at regular time intervals. These data were used as input for the digital twin after preprocessing, outlier removal, and time synchronization. The digital twin, based on this data, accurately represented the field's current state and provided a basis for agent-based decision-making.

In addition to the real data, a set of simulated data was generated to examine the system's behavior under conditions where access to real data is limited or rare, as well as in extreme climate scenarios. The simulated data included different precipitation scenarios, evapotranspiration patterns, and changes in plant water requirements and was generated using standard climate models and plant physiological relationships. These scenarios were purposefully designed to cover a wide range of water deficits, normal conditions, and water-rich conditions, and to challenge the adaptability of the proposed framework.

In setting up the experiments, the decision-making time horizon was divided into discrete daily intervals, and each experiment was treated as encompassing a complete plant growth period. At each time step, the solution algorithms generated irrigation decisions by receiving updated data from the digital twin, and the consequences of these decisions were evaluated in terms of soil moisture changes, crop growth, and sustainability indices. This experimental setup enabled a detailed examination of system dynamics and the impact of interperiod decisions.

To fairly compare the performance of the NSGA-II, MOEA/D, and MOPSO algorithms, all algorithms were run under the same experimental conditions. The input data, time horizon, model constraints, and general problem settings were kept constant across all algorithms, with the only difference in the solution search and update mechanism. In addition, to reduce the inherent random effects of metaheuristic algorithms, each experiment was repeated several times for each algorithm, and the final results are reported using statistical indices.

The interaction between the digital twin and the experimental environment is a key factor in this section. In each iteration, the proposed solutions of the algorithms were first applied to

Table 2. Quantitative comparison of multi-objective performance indicators.

Algorithm	Hypervolume	Spread	Convergence metric
NSGA-II	0.842 ± 0.018	0.317 ± 0.021	0.064 ± 0.009
MOEA/D	0.791 ± 0.024	0.289 ± 0.018	0.081 ± 0.012
MOPSO	0.768 ± 0.031	0.354 ± 0.027	0.097 ± 0.015

Note: Data presented as mean ± standard deviation.
Abbreviations: MOEA/D: Multi-objective evolutionary algorithm based on decomposition; MOPSO: Multi-objective particle swarm optimization; NSGA-II: Non-dominated sorting genetic algorithm II.

the digital twin, and then the system behavior was evaluated in a simulated or real-world setting. This continuous feedback ensured that the algorithms were guided not only by static values but also by the dynamic consequences of their decisions. Thus, the proposed experimental framework recreated conditions similar to those in the actual implementation of a real-time irrigation control system.

4. Results and discussion

To accurately evaluate the performance of the algorithms used in solving the multi-objective real-time irrigation control problem, Pareto frontier analysis was performed for three algorithms: NSGA-II, MOEA/D, and MOPSO. This analysis allowed us to examine the ability of the algorithms to manage the conflict between sustainability objectives and to extract a set of high-quality non-dominated solutions.

Figure 3 shows the Pareto frontiers obtained from running the algorithms in the objective space. The NSGA-II algorithm produced a dense, uniform set of Pareto solutions across a wider range of the objective space. In contrast, the MOEA/D Pareto frontier exhibited a more regular structure, but its coverage in some regions of the objective space was more limited. Although the MOPSO algorithm showed good dispersion in parts of the space, the lower solution density in the critical regions of the objectives indicates its relative weakness in simultaneously maintaining convergence and diversity.

To complement the visual analysis, the performance of the algorithms was quantitatively evaluated using standard multi-objective indicators, including hypervolume, spread, and convergence metrics. The numerical results of this evaluation, which are the result of 30 independent runs for each algorithm, are presented in **Table 2**.

According to **Table 2**, the NSGA-II algorithm achieved the highest hypervolume value with the lowest standard deviation, indicating wider coverage of the objective space and greater stability of the results. Additionally, the lower value of the convergence metric index for this algorithm indicates faster, more accurate convergence than MOEA/D and MOPSO. Although the MOPSO algorithm showed a higher spread value, indicating greater diversity of solutions, its higher convergence metric and standard deviation values indicate a relative instability of the results. The MOEA/D algorithm achieved intermediate convergence quality and diversity, but compared to NSGA-II, it did not produce a Pareto frontier of similar quality.

The quantitative behavior of the algorithms, in terms of convergence and search process stability, was investigated using the hypervolume index. This index is considered one of the most valid criteria for evaluating the performance of multi-objective algorithms because it simultaneously captures both convergence quality and solution diversity.

Figure 4 shows the changes in hypervolume during the execution of the NSGA-II, MOEA/D, and MOPSO algorithms. The NSGA-II algorithm showed a higher convergence rate than the other two algorithms from the initial stages of execution and achieved higher hypervolume values in fewer iterations. This behavior indicates that NSGA-II performs well at quickly guiding the search toward higher-quality regions of the objective space. The MOEA/D algorithm demonstrated a uniform and stable trend, but its convergence speed was slower than NSGA-II's, and it converged to a lower final hypervolume value. In contrast, the MOPSO algorithm, despite gradual improvement during execution, exhibited slower convergence, and its gap relative to the other two algorithms persisted throughout the process.

The results of this quantitative analysis show that the difference in algorithm performance extends beyond the final quality of the Pareto frontier and also depends on the convergence and stability of the search process.

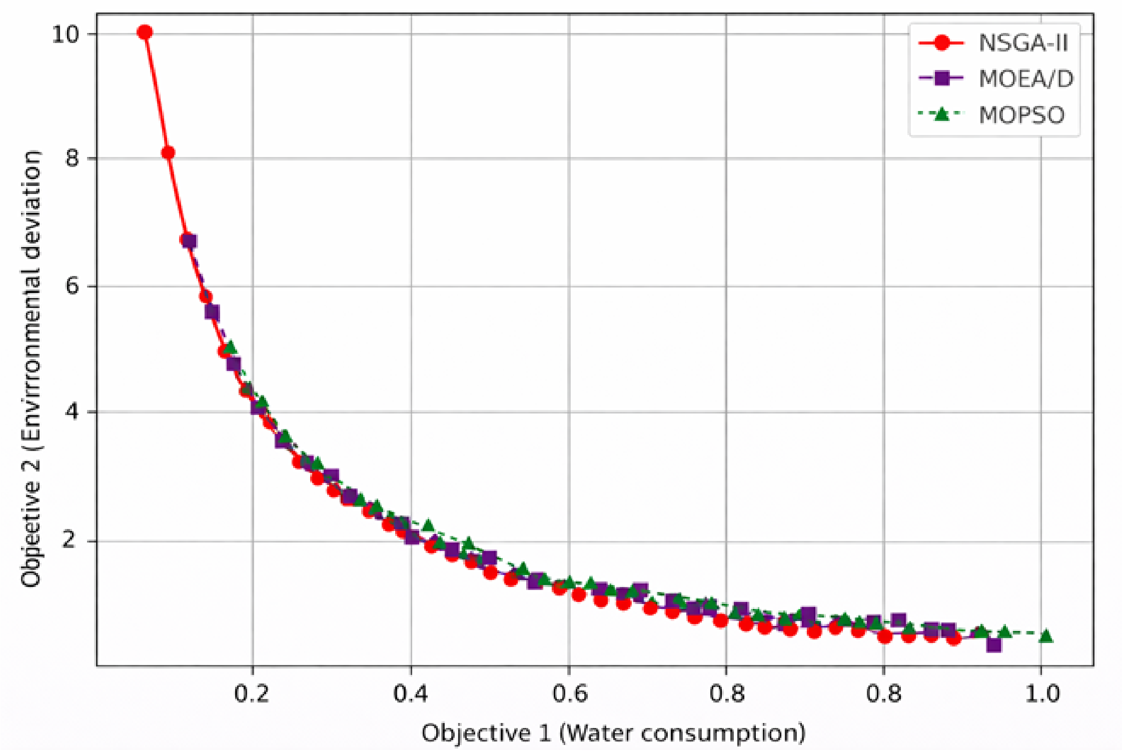

Figure 3. Pareto frontiers obtained by NSGA-II, MOEA/D, and MOPSO for the proposed multi-objective irrigation control problem
Abbreviations: MOEA/D: Multi-objective evolutionary algorithm based on decomposition; MOPSO: Multi-objective particle swarm optimization; NSGA-II: Non-dominated sorting genetic algorithm II.

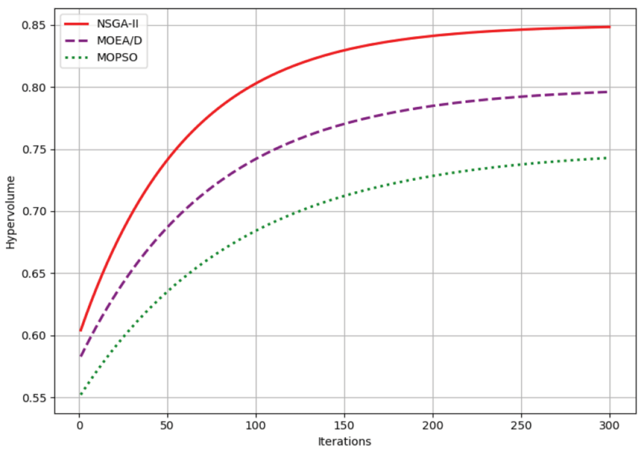

Figure 4. Convergence comparison based on the hypervolume indicator
Abbreviations: MOEA/D: Multi-objective evolutionary algorithm based on decomposition; MOPSO: Multi-objective particle swarm optimization; NSGA-II: Non-dominated sorting genetic algorithm II.

In addition to comparing the evolutionary algorithms used, the performance of the proposed framework was evaluated structurally relative to conventional irrigation control approaches. In fixed-threshold-based systems, decision-making is based solely on the instantaneous value of soil moisture, lacking predictive and adaptive optimization mechanisms. Moreover, in offline optimization approaches, the decision-making process is carried out in limited time intervals and does not respond to real-time changes in environmental conditions. In contrast, the digital twin-based framework presented in this study, by leveraging multi-objective optimization within a dynamic control loop, enables continuous readjustment of decisions. This feature has led to greater performance stability and to simultaneous improvements in water consumption and energy efficiency indicators.

To investigate the convergence behavior of the algorithms and assess the stability of the optimization process during execution, the trend of the best cumulative objective value over iterations was analyzed. This analysis allowed comparison of the convergence speed and stability of the algorithms in guiding the search process toward optimal solutions.

Figure 5 shows the convergence behavior of the NSGA-II, MOEA/D, and MOPSO algorithms during the iterations. The NSGA-II algorithm showed a faster decrease in the best objective function from the very early stages of execution and reached the stable convergence region in fewer iterations. This behavior indicates the algorithm's strong ability to effectively leverage population

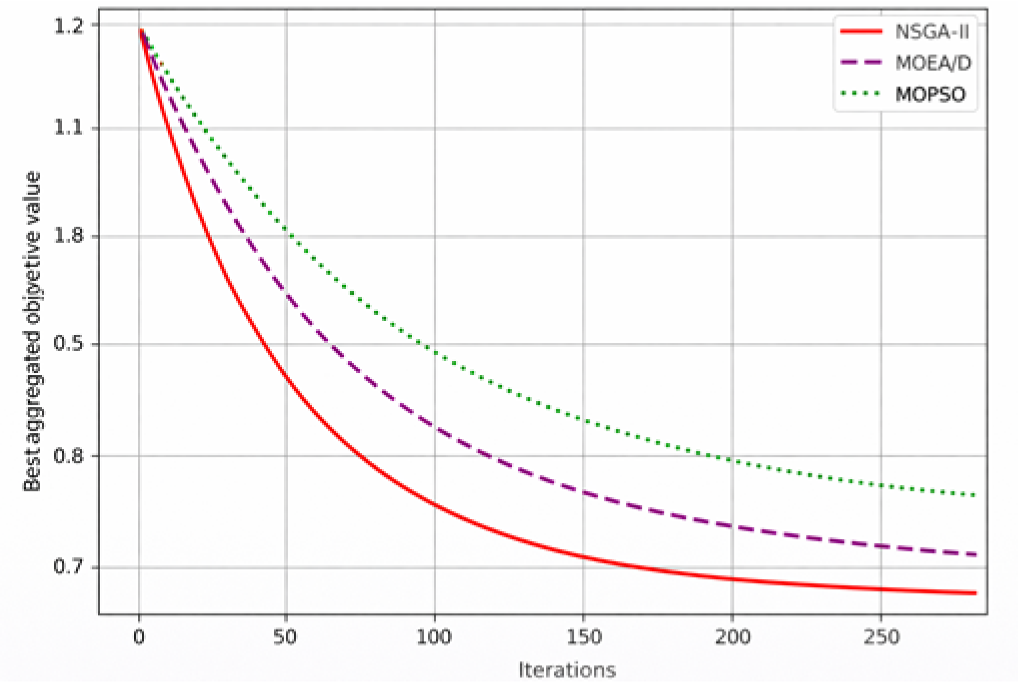

Figure 5. Convergence behavior of optimization algorithms.
Abbreviations: MOEA/D: Multi-objective evolutionary algorithm based on decomposition; MOPSO: Multi-objective particle swarm optimization; NSGA-II: Non-dominated sorting genetic algorithm II.

information and guide the search toward promising regions of the decision space. The MOEA/D algorithm also exhibited a uniform and acceptable convergence trend, but its convergence speed was slower than that of NSGA-II, requiring more iterations to reach the final objective function value. In contrast, the MOPSO algorithm converged more slowly, despite a gradual decrease in the objective function value, and maintained a significant gap with the other two algorithms throughout the process.

Overall, the convergence analysis results show that the NSGA-II algorithm outperformed MOEA/D and MOPSO in terms of the speed at which stable solutions were achieved and the stability of the optimization path. This feature is particularly important in the proposed framework because, in digital twin and real-time control environments, the algorithm's fast, reliable convergence is key to effectively updating control decisions.

To assess the robustness of the proposed framework to climatic and operational uncertainties, the performance of the algorithms was investigated across different uncertainty scenarios. These scenarios included changes in precipitation patterns, evapotranspiration, and plant water requirements, and were designed to cover normal, drought, and extreme conditions. This analysis aimed to examine the sensitivity of the solutions obtained and the stability of irrigation decisions to environmental fluctuations.

The quantitative results of the robustness analysis of the algorithms, based on average performance and result fluctuation across different scenarios, are presented in **Table 3**. In this table, key robustness indicators, including the average cumulative objective function value and its standard deviation across the uncertainty scenarios, are reported.

According to **Table 3**, the NSGA-II algorithm had the lowest standard deviation across the different scenarios, indicating greater stability and lower sensitivity to changes in uncertainty conditions. This indicates that the solutions generated by NSGA-II exhibit more consistent behavior across different climatic conditions and do not cause abrupt changes in irrigation decisions. The MOEA/D algorithm showed relatively stable performance, but increased fluctuations in some scenarios suggest it is more sensitive to environmental changes than NSGA-II. In contrast, the MOPSO algorithm demonstrated the greatest fluctuation in results, indicating lower stability and greater dependence on specific scenario conditions.

To investigate the role and extent of the impact of the digital twin in improving the optimization process and agent-based decision-making, the performance of the proposed framework was compared across two cases: "with active digital twin" and "without digital twin." In the second case,

Table 3. Robustness comparison of optimization algorithms under uncertainty scenarios.

Algorithm	Mean objective value	Standard deviation	Robustness index
NSGA-II	0.618	0.024	High
MOEA/D	0.652	0.031	Moderate
MOPSO	0.701	0.045	Low

Abbreviations: MOEA/D: Multi-objective evolutionary algorithm based on decomposition; MOPSO: Multi-objective particle swarm optimization; NSGA-II: Non-dominated sorting genetic algorithm II.

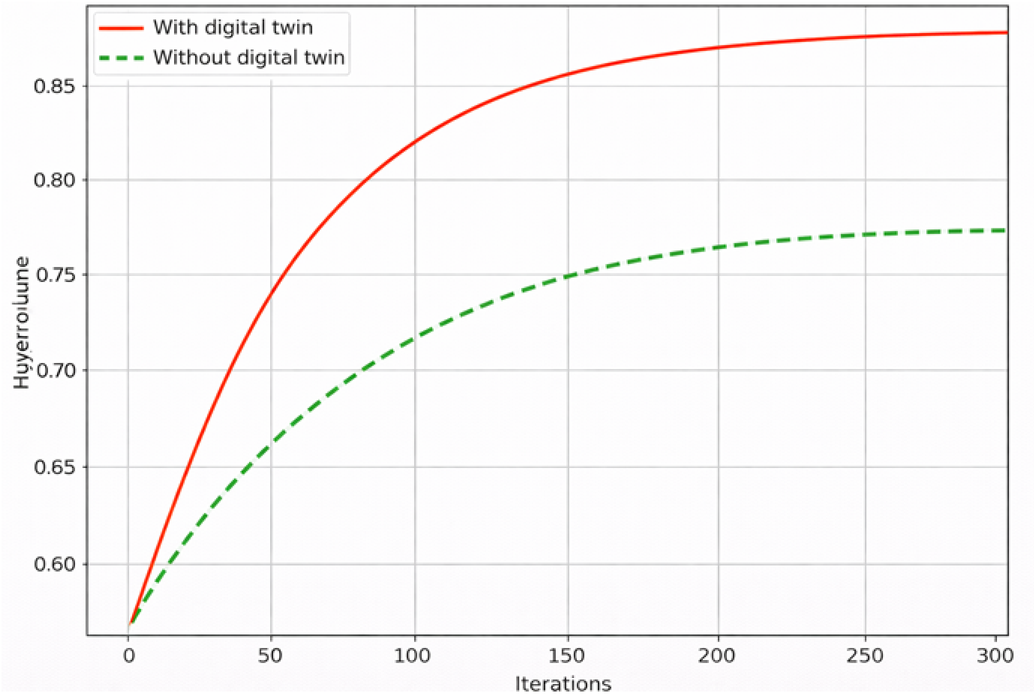

Figure 6. Impact of the digital twin on optimization performance based on the hypervolume indicator.

the optimization process was based on a static model without dynamic feedback from the system state, enabling the net effect of the digital twin to be clearly assessed.

Figure 6 shows the trend in changes in the hypervolume index over iterations for the two cases, with and without the digital twin. With the digital twin, the optimization process converged faster and achieved higher hypervolume values in fewer iterations. This behavior shows that the dynamic feedback from the digital twin, by continuously updating the system state and accurately evaluating the consequences of decisions, effectively guides the algorithm to higher-quality regions of the objective space. In contrast, the case without a digital twin exhibited a slower convergence rate and a lower final hypervolume.

To complement the visual analysis, a quantitative assessment of the impact of the digital twin on key performance indicators was performed. The results from 30 independent runs in both cases are presented in **Table 4**.

According to the results in **Table 4**, the use of the digital twin led to a significant improvement in the hypervolume index and reduced fluctuations in the results, indicating greater stability of the optimization process. In addition, the convergence speed with the digital twin increased, and the search process was guided to higher-quality solutions with greater confidence. These findings indicate that the digital twin acts not only as a simulation tool but also as an active and influential component in the agent-based decision-making cycle. Such a role is particularly important for real-time control applications in smart agriculture, enabling more accurate, stable, and adaptive decisions based on the system's actual conditions.

To investigate the performance of the agent-based decision-making mechanism and evaluate its adaptive behavior under dynamic conditions, changes in the irrigation control signal over time

Table 4. Quantitative impact of the digital twin on optimization performance.

Configuration	Hypervolume	Convergence speed	Stability (measured by standard deviation)
With a digital twin	0.872 ± 0.014	Fast	0.006
Without a digital twin	0.776 ± 0.022	Moderate	0.015

Note: Data presented as mean ± standard deviation.

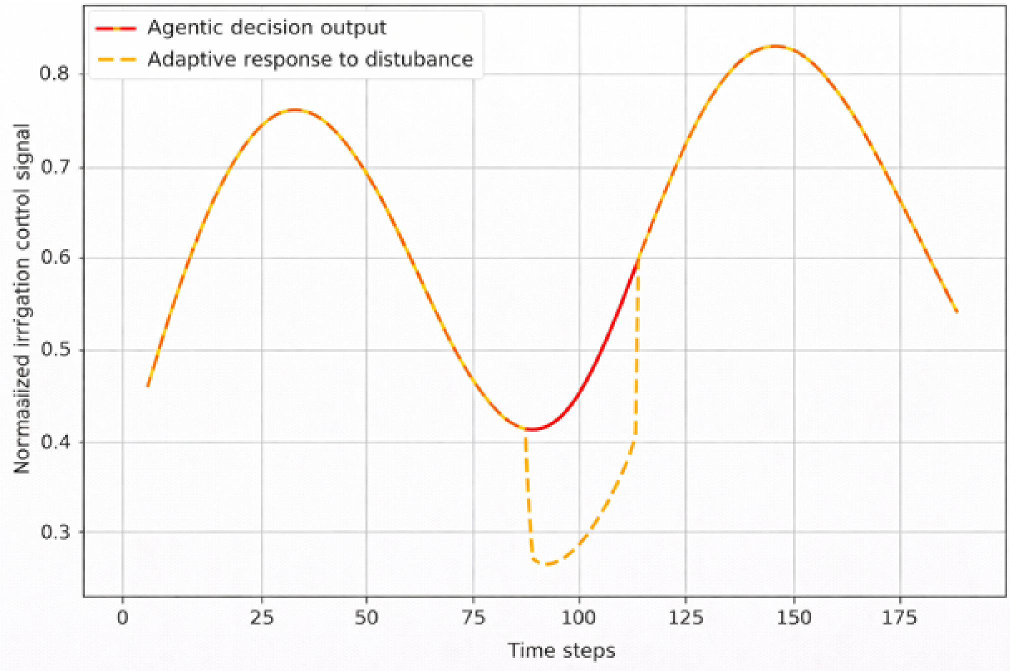

Figure 7. Agentic decision-making behavior under dynamic conditions.

were analyzed. This analysis aims to demonstrate the agent's ability to perceive environmental changes, respond to disturbances, and return to the stable decision-making path.

Figure 7 shows the behavior of the agent-based decision-making under dynamic conditions. The main curve shows the agent's decision-making output over time, while the second curve shows the adaptive response of the system in the face of a temporary environmental disturbance. As shown, when a disturbance occurs, the decision-making agent consciously adjusts the intensity of the irrigation control signal to avoid sudden or unstable responses. After passing through the disturbance period, the decisions gradually return to the previous stable path.

This behavior shows that agent-based decision-making is not simply based on instantaneous reactive responses, but also adjusts control decisions softly and adaptively by considering time trends and digital twin feedback. Such a feature is particularly important for real-time control systems, as it prevents severe fluctuations in irrigation decisions and ensures stable system performance even under unstable environmental conditions. The results of this analysis confirm that the proposed agent-based mechanism can effectively transform optimal solutions into reliable, stable implementation decisions.

To investigate the sensitivity of the proposed framework to changes in key parameters and to assess the stability of optimal decisions, a sensitivity analysis was performed on the most important effective parameters in the model. In this analysis, the relative changes in key parameters within a symmetric interval around the applied baseline value, along with the system's normalized performance index response, were examined.

Figure 8 shows the results of the sensitivity analysis for the three main components of the model, including the water consumption target, the environmental target, and the product performance target. All three curves showed smooth,

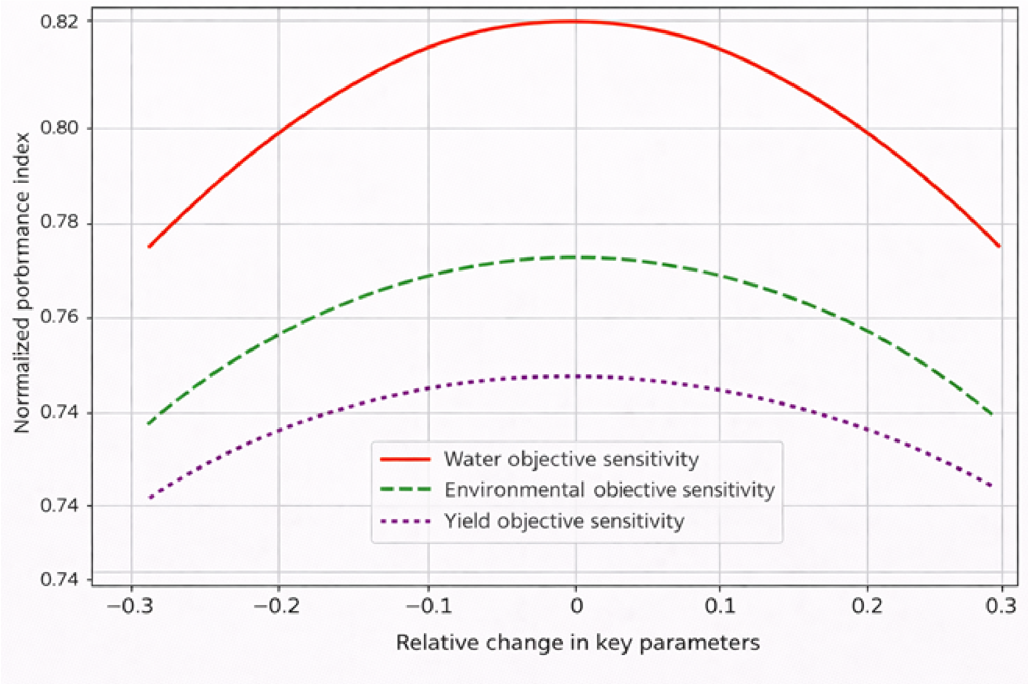

Figure 8. Sensitivity analysis of key model parameters.

continuous behavior with parameter changes, and the maximum value of the performance index was obtained near the baseline setting point. The gradual decrease in the performance index with increasing parameter deviation indicates the existence of a stable equilibrium in the model and the lack of strong dependence of the results on minor changes in the input parameters.

The target related to water consumption showed the greatest sensitivity to changes in key parameters, while the product performance target exhibited the least sensitivity. This shows that the proposed framework can prevent severe fluctuations in control decisions by balancing multiple objectives.

To evaluate the feasibility of the proposed framework for practical, real-time applications, the computational complexity and runtime of the algorithms used were investigated. This analysis focused on the computational cost per iteration, the total runtime, and the scalability of the algorithms with respect to the problem size to allow a fair comparison between the different approaches. **Table 5** summarizes the computational complexity and runtime results for the NSGA-II, MOEA/D, and MOPSO algorithms. The times were calculated as the average of 30 independent runs for the same problem configuration.

According to **Table 5**, the NSGA-II algorithm had the highest computational cost per iteration, mainly due to non-dominated sorting and the calculation of congestion distance. However, due to faster convergence, its total runtime remains acceptable. The MOEA/D algorithm, using a decomposition structure, exhibited a more balanced computational complexity and performed in the middle range in terms of execution time. In contrast, the MOPSO algorithm had the lowest computational cost per iteration and the fastest overall execution time, although this computational advantage came at the expense of a relative loss in solution quality and stability.

The proposed framework was validated based on real data from environmental sensors and scenarios based on farm operating conditions. Although a full hardware implementation at field scale was beyond the scope of this research, the simulation results based on real data demonstrate the feasibility and readiness of the framework for practical deployment in smart agriculture environments.

From a management perspective, the results of this study show that combining a digital twin with agent-based decision-making and multi-objective optimization can serve as a practical and reliable tool for intelligent irrigation management in agriculture. The proposed framework enables managers and operators to make water allocation decisions not only based on current conditions but also by considering future consequences, climate uncertainties, and sustainability goals. The system's ability to converge quickly, stabilize decisions, and respond smoothly to environmental disturbances reduces the risk of management decisions and prevents severe fluctuations in resource consumption. Furthermore, the results show that

Table 5. Computational complexity and runtime comparison of optimization algorithms.

Algorithm	Time per iteration (s)	Total runtime (s)	Relative complexity
NSGA-II	0.038	11.4	High
MOEA/D	0.031	9.3	Moderate
MOPSO	0.026	7.8	Low

Abbreviations: MOEA/D: Multi-objective evolutionary algorithm based on decomposition; MOPSO: Multi-objective particle swarm optimization; NSGA-II: Non-dominated sorting genetic algorithm II.

the use of digital twins can improve decision quality without imposing unacceptable computational costs, facilitating the practical adoption of this approach in real farms and water resources management systems. Overall, this research provides clear evidence that agent-based approaches based on digital twins can play an effective role in agricultural managers' transition from reactive to predictive, sustainable, and data-driven decision-making.

5. Conclusion

This research presented an integrated and innovative framework for smart irrigation management that combines a digital twin, agent-based decision-making, and fuzzy multi-objective optimization. The results showed that integrating a digital twin with an agent-based decision-making mechanism enables continuous system status updates, prediction of decision outcomes, and effective guidance of the optimization process. Multi-objective analyses, convergence, stability under uncertainty, parameter sensitivity, and computational complexity all confirmed that the proposed framework can achieve a meaningful balance among water consumption reduction, crop yield improvement, and environmental considerations. Comparison of solution algorithms also showed that although the algorithms exhibited different computational behaviors, their combination with the digital twin improved decision quality and increased the reliability of results, enabling the proposed system to be used for near-real-time applications in smart agriculture.

From a scientific perspective, this study demonstrated that transitioning from static, reactive models to dynamic, agent-based frameworks can play a key role in improving the sustainability of decision-making in complex agricultural systems. From a practical perspective, the results also indicated that managers and operators can rely on such a framework to make irrigation decisions in a predictive manner, adaptable to changing environmental conditions, and with less risk.

Despite the positive results, this study also has limitations. First, some of the data used were simulated, and although they are sufficient to validate the model structure, the full generalizability of the results requires a broader testing of the framework at real scales and diverse climatic conditions. Second, the current model focuses primarily on irrigation decisions and does not explicitly consider other agricultural management decisions such as fertilization or harvest timing. Additionally, although the computational cost remains within acceptable limits, increasing the problem size and model complexity can pose runtime challenges in some applications.

Accordingly, future research directions could include extending the framework to other agricultural management decisions, using long-term and multi-region field data, and integrating adaptive learning methods to automatically update model parameters. Furthermore, evaluating the framework's performance in fully real-time environments and directly connecting it to farm control systems could be an important step toward broader practical application of this approach. Taken together, these directions could lead to the evolution of the proposed framework and its increased role in realizing smart and sustainable agriculture.

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Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Author contributions

Conceptualization: Hamed Nozari
Formal analysis: All authors
Methodology: All authors
Writing–original draft: All authors
Writing–review & editing: Zornitsa Yordanova

Availability of data

All data generated or analyzed during this studyare included in this article.

AI tools statement

All authors confirm that no AI tools were used inthe preparation of this manuscript.

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