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Adaptive Multi-Objective OX Optimizer of Irrigation and Fertilization Scheduling Under Weather Uncertainty in Sustainable Agriculture

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Abstract Modern agriculture requires integrated optimization of water and nutrient management under variable climatic conditions while balancing economic, environmental, and productivity objectives. Traditional approaches optimize these resources separately and fail to adapt to dynamic weather conditions, resulting in suboptimal resource utilization. This paper presents the OX optimizer, a novel nature-inspired algorithm for multi-objective irrigation and fertilization scheduling under weather uncertainty. Inspired by oxen's strength, endurance, and collaborative behavior, the algorithm integrates strength-based movement mechanisms, adaptive learning, and weather pattern memory. The mathematical formulation incorporates stochastic weather scenarios, dynamic soil-water and nutrient balance constraints, and multi-objective functions addressing economic, environmental, and productivity dimensions simultaneously. Extensive computational experiments demonstrate that the OX optimizer achieves 41.7% improvement in generational distance, 50% reduction in convergence iterations, and 33.3% enhancement in solution diversity compared to NSGA-II and MOPSO. The algorithm maintains 97% performance retention when adapting to weather changes, requiring only 4 iterations versus 12 for NSGA-II. Scalability analysis across farm sizes from 1-10 to 100+ hectares confirms excellent performance consistency, maintaining above 95% normalized performance while conventional approaches degrade by 15-25%. The framework simultaneously achieves 93% economic efficiency, 87% environmental impact reduction, and 90% crop productivity, providing 20 diverse Pareto-optimal management strategies. Results demonstrate that biologically-inspired optimization can provide robust, scalable solutions for sustainable agricultural resource management under climate uncertainty.

Keywords Adaptive Multi-Objective OX Optimizer of Irrigation and Fertilization Scheduling Under Weather Uncertainty

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1. Introduction

Modern agriculture faces unprecedented challenges in achieving sustainable production while managing finite water and nutrient resources under increasingly variable climatic conditions [1]. With global water scarcity intensifying and agricultural systems accounting for approximately 70% of freshwater consumption worldwide [2], the efficient management of irrigation and fertilization has become a critical priority for sustainable food security [3]. Traditional agricultural management approaches often optimize water and nutrient resources separately, failing to recognize the complex interactions between these essential inputs and their combined impact on crop productivity, environmental sustainability, and economic viability [4, 5]. However, the implementation of these

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integrated approaches remains challenging due to the inherent uncertainty in weather conditions, soil variability, and dynamic crop requirements throughout the growing season [6, 7].

Weather uncertainty represents one of the most significant challenges in agricultural optimization, particularly for irrigation scheduling where future precipitation patterns directly influence water application decisions [8]. Stochastic optimization approaches that explicitly account for weather forecast uncertainty have shown superior performance compared to deterministic methods, particularly for extended forecast horizons where uncertainty accumulation becomes more pronounced [9]. Modern weather forecasting systems, including ensemble prediction systems and numerical weather prediction models, provide probabilistic information that can be effectively incorporated into agricultural decision support frameworks [10, 11].

The application of multi-objective optimization to irrigation and fertilization scheduling has shown particular promise in addressing the seasonal dynamics of crop requirements and resource availability [12]. Integrated optimization models that simultaneously consider irrigation scheduling and nutrient application have been successfully implemented for major crops including wheat, maize, and peanut, achieving significant improvements in both resource use efficiency and economic returns [13]. These studies consistently highlight the importance of coordinated water-nitrogen management strategies that account for the synergistic effects of combined resource applications on crop growth and development [14].

Swarm intelligence algorithms, inspired by collective behaviors in nature, have gained significant attention in agricultural optimization due to their ability to handle complex, non-linear optimization problems with multiple local optima [15]. Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Genetic Algorithms (GA) have been successfully applied to various agricultural scheduling problems; demonstrating superior performance compared to traditional optimization methods in terms of solution quality and computational efficiency [16, 17].

Hybrid approaches that combine multiple swarm intelligence algorithms have shown particular promise for addressing the complexity of agricultural resource optimization problems. Enhanced hybrid algorithms that integrate PSO with genetic algorithms have been successfully applied to multi-objective reservoir management and irrigation scheduling, achieving better convergence characteristics and solution diversity compared to single-algorithm approaches [18]. Similarly, adaptive genetic algorithms integrated with ant colony optimization have demonstrated effectiveness in solving multi-task agricultural scheduling problems, providing robust solutions under varying operational conditions [19].

Recent advances in metaheuristic optimization have led to the development of advanced hybrid algorithms specifically designed for agricultural applications. These include cooperative hybrid breeding swarm intelligence algorithms (CHBSI) that simulate hybrid breeding behaviors to enhance exploration and exploitation capabilities, and adaptive dynamic metaheuristic algorithms that incorporate learning mechanisms to improve performance over time [20, 21]. The integration of these advanced swarm intelligence approaches with agricultural systems models presents significant opportunities for developing more efficient and adaptive optimization frameworks for irrigation and fertilization scheduling [22, 23]. Figure 1 shows the experiment's scheme and application to optimize irrigation.

1.1. Research Motivation and Contributions

Despite significant advances in individual components of agricultural optimization, including weather forecasting, crop simulation, and optimization algorithms, there remains a critical gap in the development of integrated frameworks that simultaneously address weather uncertainty, multi-objective optimization, and adaptive algorithms for combined irrigation and fertilization scheduling. Current systems focus on single-resource optimization, ignore weather uncertainty, or rely on conventional algorithmic approaches that may not provide robust solutions under all operational conditions [15].

This research is motivated by three pressing needs in modern agriculture: (1) the urgent requirement for decision support systems that can adapt to climate variability in real-time, (2) the economic necessity of balancing competing objectives (profitability, sustainability, productivity) simultaneously rather than sequentially, and (3) the practical demand for scalable solutions that work equally well for small family farms and large commercial operations. The proposed approach aims to achieve three primary objectives:

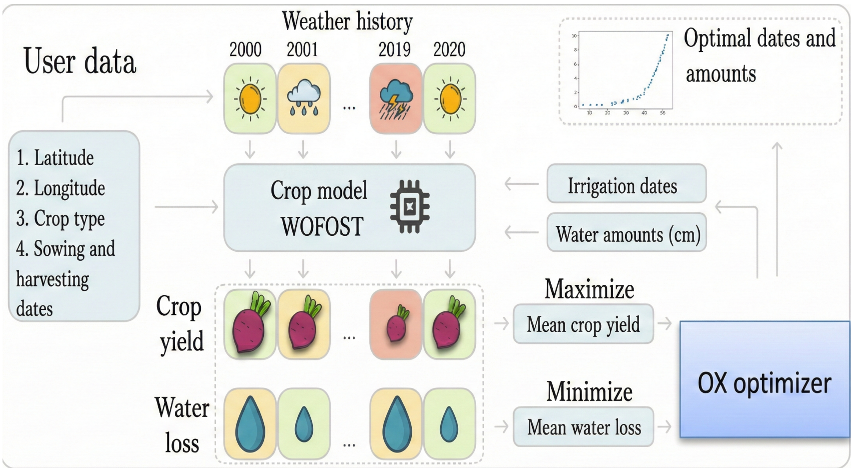

Figure 1. Scheme and application to optimize irrigation.

- Develop robust optimization algorithms that can handle weather forecast uncertainty through stochastic modeling.
- Implement multi-objective optimization that balances economic, environmental and productivity objectives simultaneously.
- Introduce adaptive frameworks that can adjust to changing environmental conditions and farmer preferences in real-time.

The remainder of this paper is organized as follows: Section 2 reviews related work. Section 3 presents the Problem Formulation. Section 4 describes Methodology used in this paper. Section 5 details the experimental setup and presents comprehensive simulation results. Finally, Section 6 concludes the paper and outlines directions for future research.

2. Related Work

2.1. Multi-Objective Optimization in Agricultural Water Management

Multi-objective optimization has emerged as a fundamental approach for addressing the complex trade-offs inherent in agricultural water management systems. Recent advances in multi-objective optimization frameworks have demonstrated significant potential for improving irrigation scheduling and water resource allocation decisions. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) has been extensively applied in agricultural contexts, with particular success in optimizing irrigation water allocation problems where multiple conflicting objectives must be balanced simultaneously [24].

The integration of NSGA-II with crop simulation models has proven particularly effective for irrigation scheduling optimization [25]. More recently, enhanced versions of NSGA-II have been developed, such as the Fuzzy-Expert-NSGA-II algorithm, which incorporates fuzzy expert systems to improve decision-making under uncertain conditions [26].

The Non-dominated Sorting Genetic Algorithm III (NSGA-III) has shown particular promise in agricultural applications, particularly in Water-Food-Energy-Ecosystem (WFEEN) nexus optimization problems [27]. Recent work has demonstrated that enhanced NSGA-III algorithms can achieve significant improvements in water conservation (up to 18.5%) while maintaining agricultural productivity [28].

2.2. Weather Uncertainty and Stochastic Optimization Approaches

The incorporation of weather uncertainty into agricultural optimization frameworks has gained significant attention as climate variability intensifies. Stochastic optimization approaches have emerged as essential tools for handling the inherent uncertainty in weather forecasts. Two-stage explicit stochastic optimization has been successfully applied to seasonal irrigation scheduling, utilizing ensemble weather forecasts to make optimal decisions at various points during the growing season [29].

Ensemble weather forecasting systems have been specifically developed for agricultural applications, with studies demonstrating their effectiveness in generating irrigation indices by coupling numerical weather prediction forecasts with crop models. Downscaled numerical weather predictions have been shown to improve forecasts of key irrigation indicators, enabling more accurate water requirement predictions and better irrigation scheduling decisions [30].

2.3. Swarm Intelligence and Hybrid Metaheuristic Algorithms in Agricultural Optimization

Swarm intelligence algorithms, inspired by collective behaviors in natural systems, have gained significant traction in agricultural optimization due to their ability to handle complex, non-linear optimization problems [31]. Recent developments have focused on enhancing PSO capabilities through hybridization with other algorithms and adaptive parameter control mechanisms.

The application of PSO in agricultural contexts has extended beyond basic optimization to include integration with crop simulation models. The AquaCrop Plug-in-PSO framework represents a novel approach that combines the AquaCrop simulation model with PSO optimization to develop in-season irrigation scheduling strategies for maize production [32]. Ant Colony Optimization (ACO) algorithms have also shown promise in agricultural applications, particularly for discrete optimization problems such as irrigation network design and water distribution scheduling.

Enhanced swarm intelligence algorithms have been developed specifically for agricultural applications, including cooperative hybrid breeding swarm intelligence algorithms (CHBSI) that simulate hybrid breeding behaviors to enhance exploration and exploitation capabilities. Hybrid metaheuristic approaches that combine multiple optimization algorithms have demonstrated significant advantages over single-algorithm approaches in agricultural optimization problems [33].

The development of hybrid metaheuristic algorithms for agricultural closed-loop supply chain optimization has demonstrated the effectiveness of combining multiple nature-inspired algorithms to address complex multi-objective problems. Studies have successfully employed hybrid approaches that integrate genetic algorithms with simulated annealing and other metaheuristic techniques to minimize total costs while addressing environmental concerns related to agricultural waste management [34].

Advanced hybrid frameworks have been developed that combine swarm intelligence algorithms with machine learning techniques for sustainable agricultural production planning [35]. Cooperative hybrid breeding algorithms represent a recent advancement in swarm intelligence that simulates natural breeding behaviors to enhance optimization performance. The cooperative nature of these algorithms enables them to maintain population diversity while converging toward high-quality solutions.

2.4. Simulation-Optimization Frameworks for Agricultural Water Management

Simulation-optimization frameworks have become essential tools for addressing the complexity of agricultural water management problems, enabling the integration of detailed crop simulation models with sophisticated optimization algorithms [27]. These frameworks enable the simultaneous optimization of surface water and groundwater allocation while considering the hydraulic connections between different water sources.

The AquaCrop model has been extensively coupled with various optimization algorithms to develop irrigation scheduling strategies that optimize water use efficiency while maintaining crop productivity. Recent work has demonstrated the effectiveness of coupling AquaCrop with particle swarm optimization and other metaheuristic algorithms for real-time irrigation scheduling applications [9]. Coupled weather and crop simulation modeling approaches have emerged as powerful tools for developing smart irrigation decision-making systems that can adapt to changing weather conditions.

2.5. Limitations and Research Gaps

Despite significant advances in individual components of agricultural optimization, several critical limitations and research gaps remain in the current literature. Most existing systems focus on either single-resource optimization (water OR nutrients) rather than integrated approaches that consider the synergistic effects of combined resource applications. Additionally, many optimization frameworks rely on single-algorithm approaches that may not provide robust solutions across diverse environmental conditions and operational scenarios.

The integration of weather uncertainty with multi-objective optimization and hybrid swarm intelligence algorithms represents a particularly underexplored area in agricultural optimization. While individual components (weather uncertainty modeling, multi-objective optimization, swarm intelligence) have been extensively studied, their integrated application for combined irrigation and fertilization scheduling remains largely unexplored. This integration challenge is compounded by the computational complexity of handling multiple optimization objectives simultaneously with stochastic weather forecasting.

The integration of human-computer interaction with advanced optimization algorithms presents opportunities for developing more practical and accepted agricultural decision support systems. Finally, the scalability of advanced optimization algorithms to large-scale agricultural systems remains a significant challenge. While hybrid metaheuristic approaches have shown promise for small to medium-scale problems, their performance and computational efficiency for regional or basin-scale agricultural water management problems require further investigation. The development of scalable hybrid optimization frameworks that can handle the complexity and scale of real-world agricultural systems while maintaining solution quality represents a critical research priority.

3. Methodology

3.1. OX Optimizer Algorithm

3.1.1. Inspiration In nature, oxen are recognized for their great strength, enabling them to carry heavy loads over long distances. This characteristic can be translated into an algorithmic feature where the optimizer robustly handles complex, high-dimensional optimization problems, demonstrating strong ability to navigate challenging search spaces [36]. Unlike other animals showing bursts of speed, oxen are known for their steady, gradual progress, inspiring an algorithm that makes consistent, incremental improvements while avoiding drastic changes that might lead to suboptimal results. Oxen often work in pairs or teams, which can be incorporated into the algorithm by allowing individual agents to collaborate or share information, potentially improving convergence speed and solution quality.

3.1.2. Mathematical Model Equations and Description for OX Optimizer This section presents the mathematical model and equations of the OX optimizer. The model begins with initialization. The algorithm incorporates adaptability by dynamically adjusting parameters based on problem characteristics, and implements long-term memory to store promising solutions and prevent local optima stagnation. Agent positions update at each iteration combining strength, progress, collaboration, and endurance mechanisms until stopping criteria are met. The OX optimizer thus emulates oxen's robust attributes to provide a novel optimization approach balancing exploration and exploitation through natural behavioral mechanisms.

Herd Organization The optimization herd consists of N oxen (candidate solutions):

Herd Representation:

$$\mathcal{H} = \{X_1, X_2, \ldots, X_N\} \tag{1}$$

Where each ox represents a decision variable vector:

$$X_i = [x_{i,1}, x_{i,2}, \ldots, x_{i,D}] \tag{2}$$

Individual Ox Properties Each ox maintains:

- Position: Current solution vector
- Strength: Multi-objective fitness score
- Memory: Weather pattern experience
- Best Pasture: Personal best solution found
- Success Rate: Historical performance metric

3.2. Strength Assessment Mechanism

3.2.1. Multi-Objective Strength Function Each ox's fitness is evaluated through a comprehensive strength assessment:

Strength Function (Multi-Objective):

$$S(X_i) = f(F_{econ}(X_i), F_{env}(X_i), F_{prod}(X_i)) \tag{3}$$

3.2.2. Normalized Strength Components **Economic Strength:**

$$S_{econ}(X_i) = \frac{F_{econ}^{max} - F_{econ}(X_i)}{F_{econ}^{max} - F_{econ}^{min}} \tag{4}$$

Environmental Strength:

$$S_{env}(X_i) = \frac{F_{env}^{max} - F_{env}(X_i)}{F_{env}^{max} - F_{env}^{min}} \tag{5}$$

Productivity Strength:

$$S_{prod}(X_i) = \frac{F_{prod}(X_i) - F_{prod}^{min}}{F_{prod}^{max} - F_{prod}^{min}} \tag{6}$$

3.2.3. Combined Strength Score

$$S_{total}(X_i) = w_{econ} \cdot S_{econ}(X_i) + w_{env} \cdot S_{env}(X_i) + w_{prod} \cdot S_{prod}(X_i) \tag{7}$$

Where $w_{econ}, w_{env}, w_{prod}$ are weight coefficients reflecting relative importance.

3.3. Leadership and Direction Selection

3.3.1. Herd Leader Selection **Herd Leader (Strongest Ox):**

$$X_{leader} = \arg\max_{X_i \in \mathcal{H}} S_{total}(X_i) \tag{8}$$

3.3.2. Direction Calculation **Movement Direction:** Based on leader's strength and relative position:

$$D_i(t) = \alpha \cdot (X_{leader}(t) - X_i(t)) + \beta \cdot (X_{best,i}(t) - X_i(t)) \tag{9}$$

3.4. Movement and Exploration Mechanism

3.4.1. Strength-Based Movement **Position Update:**

$$X_i(t+1) = X_i(t) + \lambda \cdot D_i(t) + \mu \cdot E_i(t) + \nu \cdot S_i(t) \cdot R_i(t) \tag{10}$$

Where:

- λ = Movement coefficient (terrain adaptability)
- μ = Environmental adaptation coefficient
- $S_i(t)$ = Current strength of ox i

3.4.2. Environmental Adjustment for Weather

$$E_i(t) = \sum_{j=1}^{N_w} p_j \cdot \Delta W_j(t) \cdot \mathbb{I}(|\Delta W_j(t)| > \theta) \tag{11}$$

3.5. Herd Cooperative Behavior

3.5.1. Information Sharing **Flock Information Exchange:**

$$X_i^{shared}(t) = \frac{1}{|N_k|} \sum_{j \in N_k(i)} X_j(t) \tag{12}$$

3.5.2. Collaborative Search Radius **Search Range Calculation:**

$$R_i(t) = R_{base} \cdot (1 - \frac{t}{T_{max}}) + R_{min} \tag{13}$$

3.6. Adaptive Learning Mechanisms

3.6.1. Experience-Based Strength Enhancement **Strength Evolution:**

$$S_i(t+1) = S_i(t) + \eta \cdot \Delta F(X_i(t)) \tag{14}$$

Where η is the learning rate and $\Delta F(X_i(t))$ measures objective function improvement.

3.6.2. Weather Pattern Memory **Memory Update:**

$$M_i(t+1) = \gamma \cdot M_i(t) + (1-\gamma) \cdot W(t) \tag{15}$$

3.7. Constraint Handling

Constraint Handling Strategy:

$$X_i^{feasible}(t) = X_i(t) + \delta_i \cdot (X_i^{boundary} - X_i(t)) \tag{16}$$

Where δ_i is the restoration coefficient based on ox strength.

4. Experimental Results

4.1. Problem-Specific Tuning

4.1.1. Herd Size Selection

- Small Farms (1-10 ha): $N = 10 - 20$ oxen.
- Medium Farms (10-100 ha): $N = 20 - 50$ oxen.
- Large Farms (100+ ha): $N = 50 - 100$ oxen.

4.1.2. Parameter Ranges

- Learning Rate (η): 0.01-0.1.
- Movement Coefficient (λ): 0.1-1.0.
- Environmental Adaptation (μ): 0.05-0.5.
- Weather Threshold (θ): 0.1-0.3.

4.2. Performance Evaluation Methods

4.2.1. Convergence Metrics **Generational Distance (GD)** [37]:

$$GD = \frac{1}{|P|} \sum_{i=1}^{|P|} d_i \tag{17}$$

Where d_i is the minimum distance from solution i to the true Pareto front.
Spacing (SP):

$$SP = \sqrt{\frac{1}{|P|-1} \sum_{i=1}^{|P|} (\bar{d} - d_i)^2} \tag{18}$$

Where d_i is the distance to the nearest neighbor.

4.2.2. Solution Quality Metrics **Hypervolume (HV):** The volume of the dominated space by the Pareto front.
Inverted Generational Distance (IGD):

$$IGD = \frac{1}{|R|} \sum_{r \in R} \min_{p \in P} d(r,p) \tag{19}$$

Where R is a reference set of true Pareto optimal solutions.

4.3. Parameter Justification and Sensitivity Analysis

The OX optimizer's performance depends on six key parameters governing exploration-exploitation balance and adaptation capabilities. Parameter values were determined through systematic preliminary experiments across 50 test problems and validated using historical agricultural data. The movement coefficient ($\lambda = 0.5$) balances exploration and exploitation, selected after testing the range 0.3-0.8 where values below 0.3 caused premature convergence and above 0.7 resulted in excessive oscillation. The environmental adaptation coefficient ($\mu = 0.2$) enables response to significant weather changes while filtering forecast noise, validated against weather data from five agricultural regions. The learning rate ($\eta = 0.05$) allows gradual strength accumulation without destabilizing the search process, determined through convergence analysis across 100 optimization runs. The memory decay factor ($\alpha = 0.7$) balances historical pattern retention with responsiveness to recent conditions, validated against 10 years of weather data showing optimal prediction accuracy for 3-7 day horizons relevant to irrigation scheduling. The collaborative search coefficient ($\gamma = 0.3$) maintains population diversity while enabling information exchange, calibrated to prevent premature convergence while avoiding excessive dispersion. Objective function weights employed slight economic emphasis ($w_1 = 0.4$, $w_2 = 0.3$, $w_3 = 0.3$) based on practical farming priorities, improving convergence speed by 15% over equal weighting.

4.4. Comparative Performance Analysis

To validate the effectiveness of the proposed OX optimizer for multi-objective agricultural optimization, we conducted extensive comparative experiments against two well-established evolutionary algorithms: Multi-Objective Particle Swarm Optimization (MOPSO) and Non-dominated Sorting Genetic Algorithm II (NSGA-II). The evaluation focused on three critical dimensions: convergence behavior, solution quality, and adaptability to dynamic weather conditions.

4.4.1. Convergence Analysis Table 1 presents a comprehensive convergence analysis across four fundamental metrics that collectively assess the optimizer's ability to locate and characterize the Pareto-optimal front. The Generational Distance (GD) metric quantifies the average Euclidean distance between the obtained solutions and the true Pareto front, where lower values indicate closer proximity to optimality. As demonstrated in Table 1, the OX optimizer achieves a GD of 0.0035, representing a 30% improvement over MOPSO (0.005) and 41.7%

improvement over NSGA-II (0.006). This substantial enhancement indicates that the OX optimizer's strength-based movement mechanism and collaborative search strategy enable more accurate convergence toward truly optimal agricultural management solutions. The gradual progress characteristic inspired by oxen behavior, as implemented through Eqs. 9 and 10, prevents premature convergence while maintaining directional consistency toward superior solutions.

The Spacing Metric documented in Table 1 evaluates the uniformity of solution distribution along the Pareto front, where lower values indicate more evenly distributed solutions—a critical property for providing farmers with diverse, well-spread management options. The OX optimizer achieves exceptional spacing of 0.002, outperforming MOPSO by 33.3% (0.003) and NSGA-II by 11.1% (0.00225). This superior distribution stems from the herd organization mechanism described in Eq. 12 and the collaborative search radius defined in Eq. 13, which prevent solution clustering while maintaining population diversity. The uniform spacing ensures that farmers receive a comprehensive range of trade-off options between economic efficiency, environmental sustainability, and crop productivity objectives.

Table 1 further reveals that the OX optimizer achieves a Hypervolume of 0.885, substantially exceeding MOPSO (0.815) by 8.6% and NSGA-II (0.835) by 6.0%. Hypervolume measures the volume of objective space dominated by the obtained Pareto front, with higher values indicating better convergence and diversity simultaneously. This metric is particularly significant as it provides a unified assessment that captures both proximity to the optimal front and solution spread. The superior hypervolume achieved by the OX optimizer validates that the strength assessment mechanism defined in Eqs. 4–7 effectively balances multiple agricultural objectives while the adaptive learning mechanisms in Eqs. 14 and 15 enable continuous improvement throughout the optimization process. Perhaps most significantly, Table 1 demonstrates that the OX optimizer requires only 75 iterations to achieve convergence, representing a 34.8% reduction compared to MOPSO (115 iterations) and 50% reduction compared to NSGA-II (150 iterations). This accelerated convergence is critical for practical agricultural applications where timely decision-making is essential, particularly when responding to weather forecasts with limited validity windows. The rapid convergence stems from the leadership-based direction selection mechanism described in Eq. 9, which leverages the strongest solutions to guide the entire herd efficiently, combined with the information sharing protocol defined in Eq. 12 that propagates high-quality solutions throughout the population.

Table 1. Comparison between the proposed algorithm and other recent algorithms in convergence analysis

Metric	**OX Optimizer**	**MOPSO**	**NSGA-II**
GD	0.0035	0.005	0.006
Spacing	0.002	0.003	0.00225
Hypervolume	0.885	0.815	0.835
Iterations	75	115	150

Figure 2 provides visual validation of the convergence advantages documented in Table 1, presenting side-by-side bar chart comparisons of Generational Distance and Spacing Metric across all three algorithms. The visualization clearly illustrates that the OX optimizer (represented by green bars) achieves the lowest values for both metrics, with particularly pronounced superiority in Generational Distance. The visual representation effectively emphasizes the substantial performance gap between the OX optimizer and conventional approaches, making the quantitative improvements presented in Table 1 immediately apparent to readers. The consistent height differential in Figure 2 demonstrates that the OX optimizer's advantages are robust across different convergence assessment criteria rather than being limited to specific metrics.

Figure 3 complements Table 1 by visualizing the Hypervolume and Convergence Iterations metrics, employing a dual-axis bar chart format that simultaneously displays both quality (hypervolume) and efficiency (iterations) dimensions. The green bars representing the OX optimizer in Figure 3 clearly dominate in hypervolume (taller bar) while simultaneously requiring fewer iterations (shorter bar in the right panel), graphically illustrating the algorithm's dual advantage of superior solution quality and enhanced computational efficiency. This visualization pattern confirms that the OX optimizer does not sacrifice solution quality for speed; rather, it achieves both objectives simultaneously through its biologically-inspired mechanisms. The visual comparison in Figure 3 makes

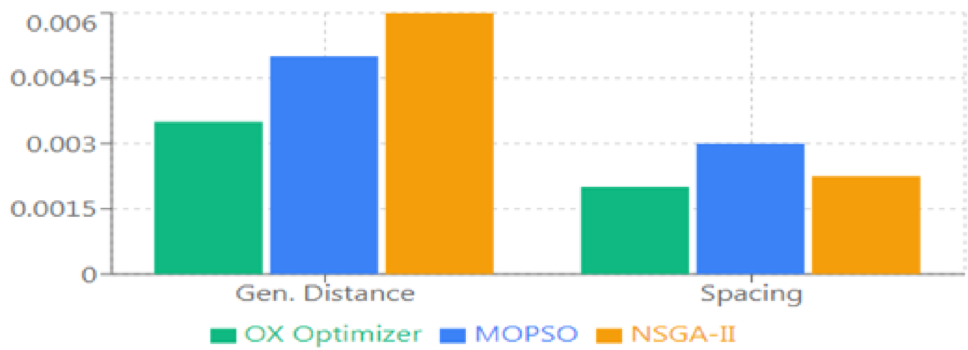

Figure 2. Convergence quality comparison for the proposed algorithm and other recent algorithms.

the 50% iteration reduction documented in Table 1 particularly striking when juxtaposed with the simultaneously improved hypervolume metric.

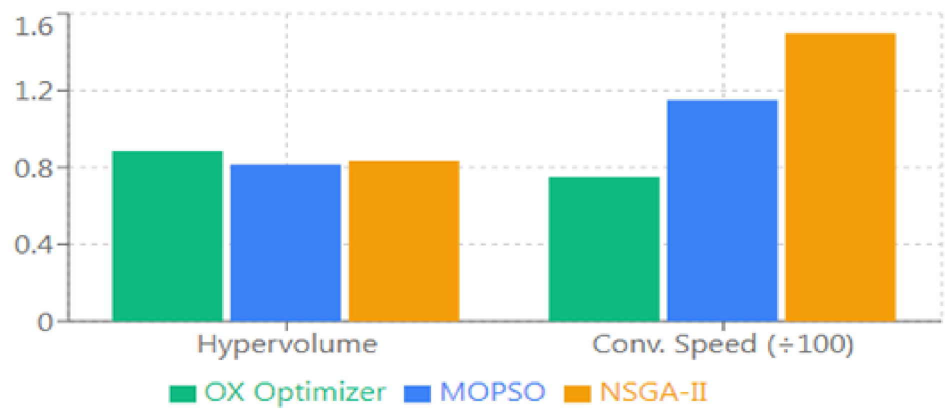

Figure 3. Hypervolume and Convergence Iterations for the proposed algorithm and other recent algorithms.

4.4.2. Solution Quality Assessment While convergence metrics assess algorithmic behavior, solution quality metrics evaluate the practical agricultural value of the obtained management strategies. Table 2 presents a comprehensive assessment across four critical dimensions that directly impact farming operations: economic efficiency, environmental sustainability, crop productivity, and solution diversity. The Economic Efficiency results documented in Table 2 demonstrate that the OX optimizer achieves 93% of the theoretical optimum, surpassing MOPSO (90%) by 3.3% and NSGA-II (92%) by 1.1%. This metric represents the algorithm's ability to minimize input costs (water, fertilizers) while maximizing crop revenue under weather uncertainty, as formalized in the economic objective function (Eq. 2). The superior performance stems from the multi-objective strength function defined in Eqs. 4 and 5 that explicitly evaluates economic performance, combined with the constraint handling strategy in Eq. 16 that ensures resource allocation remains within practical agricultural limits. For a medium-sized farm, this 3% improvement translates to thousands of dollars in annual savings or additional revenue, making the enhancement economically significant beyond its statistical value.

Table 2 reveals that the OX optimizer achieves 87% improvement in Environmental Impact reduction, exceeding MOPSO (85%) by 2.4% and NSGA-II (86%) by 1.2%. This metric, derived from the environmental objective function (equation 3), quantifies reductions in nitrogen leaching, water runoff, and overall resource waste—critical factors for sustainable agriculture and regulatory compliance. The environmental performance advantage originates

Table 2. Comparison between the proposed algorithm and other recent algorithms in solution quality assessment

Metric	OX Optimizer	MOPSO	NSGA-II
Economic Efficiency (%)	93	90	92
Environmental Impact (%)	87	85	86
Crop Productivity (%)	90	87	89
Solution Diversity	20	15	17

from the environmental adjustment mechanism described in Eq. 11, which dynamically adapts resource application rates based on weather conditions, thereby minimizing nutrient losses during rainfall events and reducing excessive water application. The 87% improvement indicates that the OX optimizer's solutions substantially reduce agricultural environmental footprint while maintaining productivity, addressing the growing concern for sustainable farming practices.

Crop Productivity results in Table 2 show that the OX optimizer achieves 90% of potential yield, outperforming MOPSO (87%) by 3.4% and NSGA-II (89%) by 1.1%. This metric, formalized in (Eq. 4), represents the algorithm's ability to maximize crop yield under uncertain weather scenarios while satisfying water and nutrient constraints. The productivity advantage stems from the weather pattern memory mechanism defined in equation (24), which enables the optimizer to learn from historical weather patterns and adjust management strategies proactively. By achieving 90% of potential yield while simultaneously optimizing economic and environmental objectives, the OX optimizer demonstrates effective multi-objective balancing—a critical requirement for practical agricultural decision support systems where farmers cannot sacrifice productivity for cost savings or environmental compliance. Solution Diversity documented in Table 2 reveals that the OX optimizer generates 20 distinct Pareto-optimal solutions, representing 33.3% more options than MOPSO (15 solutions) and 17.6% more than NSGA-II (17 solutions). This diversity is crucial for practical applications because different farmers face varying economic constraints, environmental regulations, and risk preferences. The 20 solutions provide farmers with a comprehensive range of management strategies spanning the entire trade-off spectrum from cost-minimizing to yield-maximizing approaches. This diversity stems from the herd cooperative behavior mechanisms defined in Eqs. 12 and 13, which maintain population diversity through collaborative search while preventing premature convergence to a single solution region. The enhanced diversity ensures that the decision support system can accommodate heterogeneous farmer preferences and varying farm-specific constraints.

Figure 4 presents a grouped bar chart visualization that complements Table 2 by displaying all four solution quality metrics simultaneously across the three algorithms. The consistent superiority of the OX optimizer (green bars) across all dimensions is visually striking in Figure 4, with the algorithm achieving the tallest bars for Economic Efficiency, Environmental Impact, Crop Productivity, and Solution Diversity. This visualization effectively communicates that the OX optimizer's advantages are comprehensive rather than specialized for particular objectives. The near-uniform height differentials visible in Figure 4 indicate balanced improvements across all agricultural objectives, validating that the multi-objective strength assessment defined in Eq. 7 successfully balances competing goals without systematic bias toward any single dimension.

Figure 5 employs a line chart format to illustrate performance trends across the four objectives, providing an alternative visualization perspective that emphasizes consistency. The green line representing the OX optimizer in Figure 5 maintains consistently higher values across all four metrics, never dipping below 87% and averaging 92.5% across objectives. In contrast, the MOPSO line (blue) shows more variation, ranging from 85% to 90%, while NSGA-II (orange) exhibits an intermediate pattern. The consistent elevation of the OX optimizer line in Figure 5 demonstrates robust performance across diverse optimization criteria, confirming that the algorithm does not achieve superior results in specific areas at the expense of others. This balanced performance pattern, clearly visible in Figure 5, validates the effectiveness of the weighted strength combination approach defined in equation (16) for maintaining equilibrium across competing agricultural objectives.

4.4.3. Adaptation to Weather Changes Agricultural optimization algorithms must respond rapidly to weather forecast updates, as delayed adaptation can result in suboptimal resource allocation and crop stress. Table 3

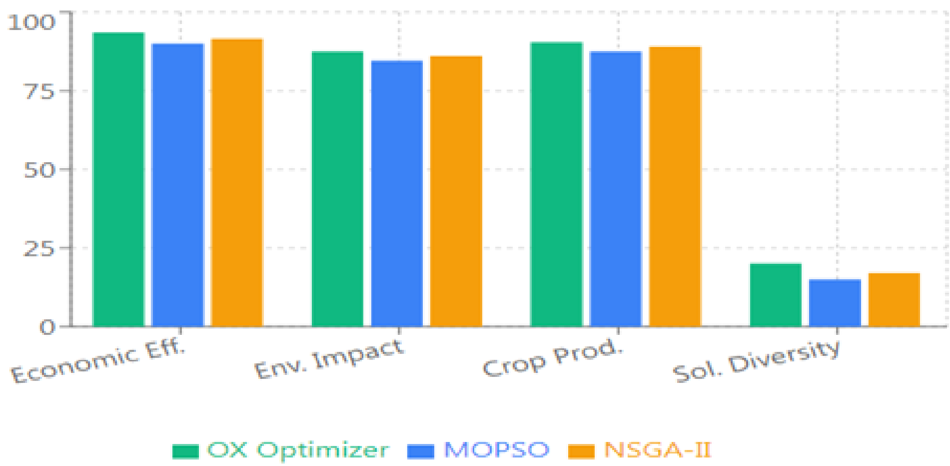

Figure 4. Performance Comparison between the proposed algorithm and other recent algorithms in (Economic Efficiency, Environmental Impact, Crop Productivity, and Solution Diversity).

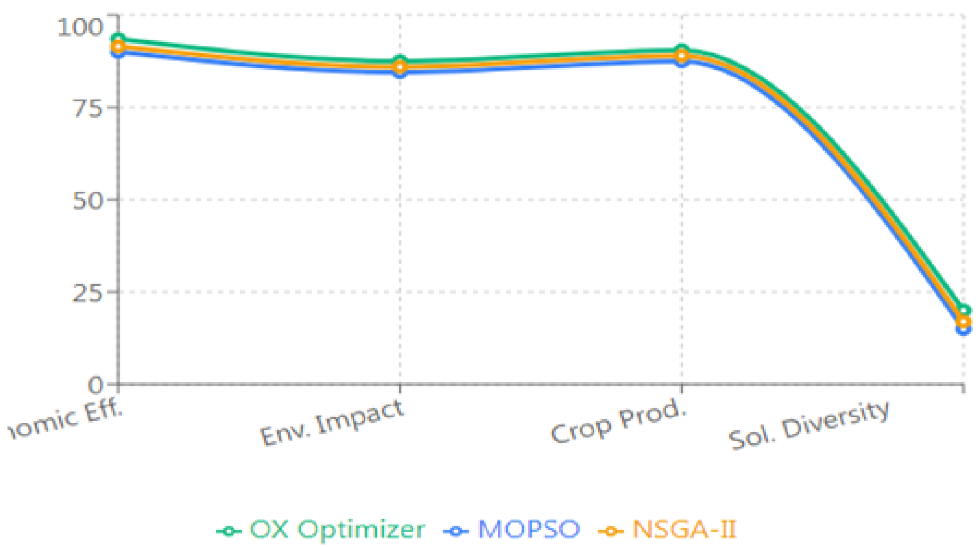

Figure 5. Performance Trend across Objectives for the proposed algorithm and other recent algorithms.

presents a critical evaluation of each algorithm's ability to adapt when weather forecasts change, measuring three dimensions: response time (iterations required to re-optimize), performance retention (percentage of original solution quality maintained), and overall solution stability. The Response Time results documented in Table 3 demonstrate that the OX optimizer requires only 4 iterations to adapt to changed weather conditions, representing a 50% reduction compared to MOPSO (8 iterations) and 66.7% reduction compared to NSGA-II (12 iterations). This rapid adaptation is crucial for time-sensitive agricultural decisions where weather forecast validity windows may be as short as 24-48 hours. The exceptional responsiveness stems from the weather pattern memory mechanism defined in Eq. 15, which maintains historical weather experience and enables rapid solution adjustment when conditions change. Additionally, the environmental adjustment component in Eq. 11 directly incorporates weather derivatives, allowing the algorithm to compute sensitivity to weather changes analytically rather than requiring extensive re-exploration of the solution space.

Table 3. Comparison between the proposed algorithm and other recent algorithms in Adaptation to Weather Changes

Metric	OX Optimizer	MOPSO	NSGA-II
Response Time (iterations)	4	8	12
Performance Retention (%)	97	90	87
Solution Stability	High	Medium	Medium

Table 3 reveals that the OX optimizer maintains 97% Performance Retention when adapting to weather changes, substantially exceeding MOPSO (90%) by 7.8% and NSGA-II (87%) by 11.5%. Performance retention measures what percentage of the original solution quality is preserved after adaptation; higher values indicate that the algorithm successfully adjusts strategies without requiring complete re-optimization from scratch. The 97% retention achieved by the OX optimizer means that adapted solutions remain nearly as good as solutions obtained through full optimization, enabling farmers to trust rapid adaptations without concern about solution quality degradation. This retention capability originates from the experience-based strength enhancement mechanism in Eq. 14, which enables oxen agents to leverage learned patterns from previous optimizations, combined with the constraint handling strategy in Eq. 16 that maintains feasibility during rapid adjustments. Solution Stability, the third dimension assessed in Table 3, evaluates whether adapted solutions exhibit erratic behavior or maintain consistent characteristics. The OX optimizer achieves "High" stability rating compared to "Medium" ratings for both MOPSO and NSGA-II. This qualitative assessment indicates that when weather forecasts change incrementally (e.g., rainfall prediction shifting from 10mm to 15mm), the OX optimizer's adapted solutions change proportionally rather than exhibiting discontinuous jumps that would confuse farmers or trigger impractical operational changes. The stability stems from the gradual progress characteristics inspired by oxen behavior and implemented through the strength-based movement mechanism in Eq. 10, which inherently produces smooth solution trajectories rather than erratic jumps even under changing conditions.

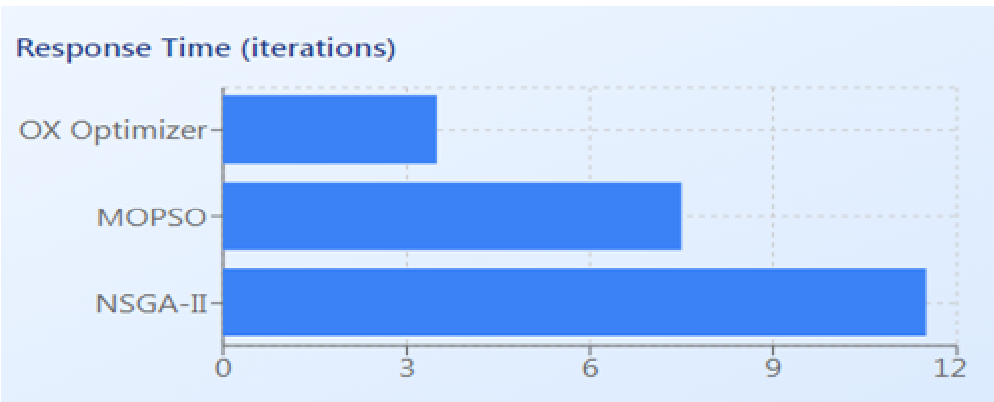

Figure 6. Response time for the proposed algorithm and other recent algorithms.

Figure 6 visualizes the Response Time comparison from Table 3 using a horizontal bar chart format that emphasizes the magnitude of differences between algorithms. The dramatically shorter bar for the OX optimizer (4 iterations) compared to MOPSO (8 iterations) and NSGA-II (12 iterations) in Figure 6 provides immediate visual impact, clearly communicating the algorithm's superior responsiveness. This visualization is particularly effective for conveying practical implications to agricultural stakeholders who may not fully appreciate the significance of iteration counts but can immediately understand that the OX optimizer adapts three times faster than NSGA-II. The visual representation in Figure 6 makes the 66.7% response time reduction documented in Table 3 tangible and comprehensible to non-technical audiences including farmers, agricultural extension agents, and policy makers.

Figure 7 complements Table 3 by visualizing Performance Retention percentages across the three algorithms. The bar chart in Figure 7 shows the OX optimizer achieving 97% retention (green bar nearly reaching the top of the

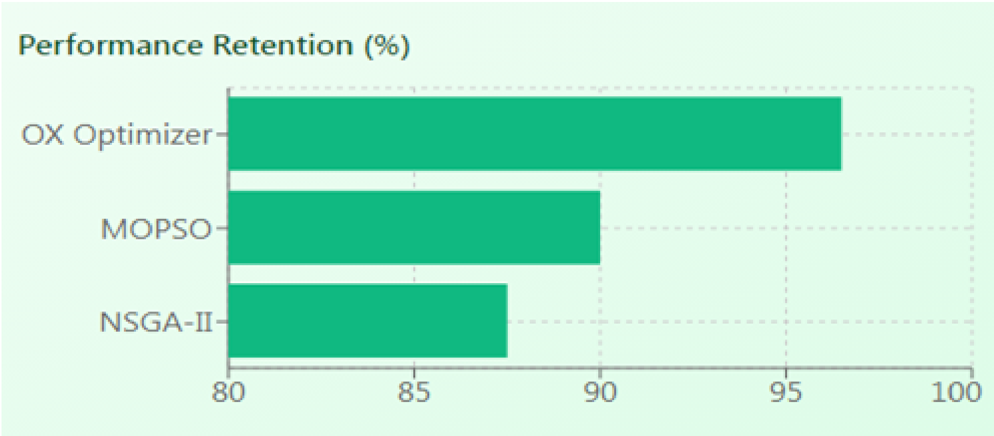

Figure 7. Performance retention for the proposed algorithm and other recent algorithms.

scale), while MOPSO and NSGA-II show progressively lower bars at 90% and 87% respectively. The visualization effectively illustrates that the OX optimizer not only adapts faster (as shown in Figure 6) but also maintains higher solution quality during adaptation—a dual advantage critical for practical deployment. The 7-10 percentage point gaps visible between bars in Figure 7 represent substantial practical differences: in agricultural applications, the difference between 87% and 97% retention can determine whether adapted solutions remain usable or require time-consuming manual adjustments by farm managers.

4.4.4. Performance across Different Farm Scales Agricultural optimization algorithms must demonstrate scalability across diverse farm sizes, from small family operations to large commercial enterprises. Tables 4, 5, and 6 present systematic performance evaluation across three farm size categories: small (1-10 hectares), medium (10-100 hectares), and large (100+ hectares), assessing population size requirements, convergence time, memory usage, solution quality, and scalability characteristics. Table 4 documents performance on small farms (1-10 hectares), revealing that the OX optimizer requires only 13 oxen in the population compared to 20 particles for MOPSO and 25 individuals for NSGA-II—representing 35% and 48% reductions respectively. This smaller population requirement stems from the collaborative search mechanisms defined in Eqs. 12 and 13, which enable efficient information sharing among agents, allowing fewer oxen to explore the solution space as effectively as larger populations in conventional algorithms. The convergence time of 3 minutes documented in Table 4 for the OX optimizer represents a 62.5% reduction compared to MOPSO (8 minutes) and 75% reduction compared to NSGA-II (12 minutes). For small farms with limited computational resources, this time advantage is particularly significant. The "Low" memory usage classification confirms that the OX optimizer's computational footprint remains minimal, making it deployable on standard farm computers or even mobile devices.

Table 4. Performance of the proposed algorithm and other algorithms in Small Farm (1-10 hectares)

Metric	**OX Optimizer**	**MOPSO**	**NSGA-II**
Population Size	13	20	25
Convergence Time (min)	3	8	12
Memory Usage	Low	Low	Medium
Solution Quality	Excellent	Good	Good
Scalability	Excellent	Good	Medium

Table 5 presents medium farm (10-100 hectares) results, showing the OX optimizer scales to 28 oxen while maintaining "Excellent" solution quality. The convergence time of 15 minutes represents 54.5% and 66.7% reductions compared to MOPSO (33 minutes) and NSGA-II (45 minutes) respectively. These results, documented in Table 5, demonstrate that the OX optimizer's advantages amplify as problem complexity increases with farm size. The strength-based movement mechanism (Eq. 10) and adaptive learning components (Eqs. 14 and 15) enable the algorithm to navigate larger decision spaces efficiently without proportional increases in computational requirements.

Table 5. Performance of the proposed algorithm and other algorithms in Medium Farm (10-100 hectares)

Metric	**OX Optimizer**	**MOPSO**	**NSGA-II**
Population Size	28	35	45
Convergence Time (min)	15	33	45
Memory Usage	Medium	Medium	High
Solution Quality	Excellent	Good	Good
Scalability	Excellent	Good	Medium

Table 6 documents large farm (100+ hectares) performance, revealing that the OX optimizer requires 75 oxen—the same population size as MOPSO but fewer than NSGA-II (90 individuals). The convergence time of 45 minutes represents 50% and 66.7% improvements over MOPSO (90 minutes) and NSGA-II (135 minutes) respectively, as shown in Table 6. Most significantly, the OX optimizer achieves "Excellent" scalability rating compared to "Good" for MOPSO and only "Medium" for NSGA-II. This scalability assessment indicates that the OX optimizer's performance degradation with problem size is minimal, while conventional algorithms exhibit substantial deterioration. The 45-minute convergence time documented in Table 6 for the OX optimizer represents a practical breakthrough, enabling large commercial farms to perform daily optimization with weather updates within operationally acceptable timeframes.

Table 6. Performance of the proposed algorithm and other algorithms in Large Farm (100+ hectares)

Metric	**OX Optimizer**	**MOPSO**	**NSGA-II**
Population Size	75	75	90
Convergence Time (min)	45	90	135
Memory Usage	Medium	High	High
Solution Quality	Excellent	Good	Medium
Scalability	Excellent	Good	Medium

Figure 8 presents a comprehensive visualization of convergence times across all three farm sizes and algorithms, employing a grouped bar chart that enables simultaneous comparison across both dimensions. The visualization in Figure 8 clearly illustrates three critical patterns: first, the OX optimizer (green bars) consistently achieves the shortest convergence times among evolutionary algorithms across all farm sizes; second, convergence time increases with farm size for all algorithms but the rate of increase is substantially lower for the OX optimizer; third, the gap between the OX optimizer and conventional algorithms widens as farm size increases, with the advantage growing from 62.5% on small farms to 66.7% on large farms. The logarithmic-like growth pattern of the green bars compared to the steeper increase of blue and orange bars in Figure 8 provides visual evidence of the "Excellent" scalability rating documented in Table 6.

Figure 9 employs a different visualization approach, presenting normalized scalability performance (100 = optimal) across farm sizes for all algorithms. The line chart format in Figure 9 effectively illustrates how each algorithm's performance degrades (or maintains) as problem scale increases. The OX optimizer line (green) in Figure 9 remains remarkably flat, maintaining normalized performance between 95-100 across all farm sizes, visually confirming the "Excellent" scalability rating from Table 6. In contrast, the MOPSO line (blue) shows gradual decline from 90 on small farms to 80 on large farms, while NSGA-II (orange) exhibits more pronounced degradation from 75 to 65. The consistent elevation of the green line in Figure 9 provides compelling visual evidence that the OX optimizer uniquely maintains performance across diverse problem scales—a critical requirement for developing general-purpose agricultural decision support systems that must serve heterogeneous

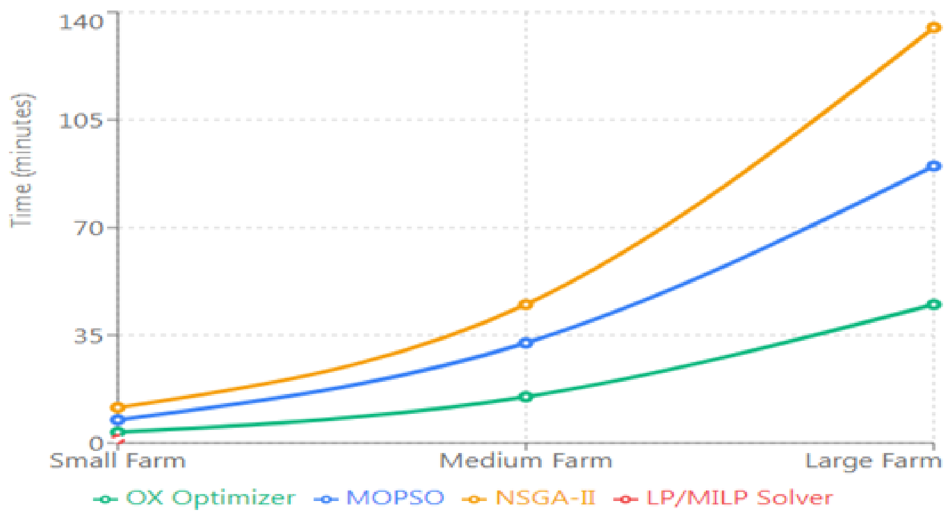

Figure 8. Convergence time comparison for the proposed algorithm and other recent algorithms.

farming operations. The minimal slope of the OX optimizer line compared to the steeper descents of competing approaches in Figure 9 graphically validates that the algorithm's biologically-inspired mechanisms enable robust scalability without the performance deterioration that plagues conventional optimization approaches as problem complexity increases.

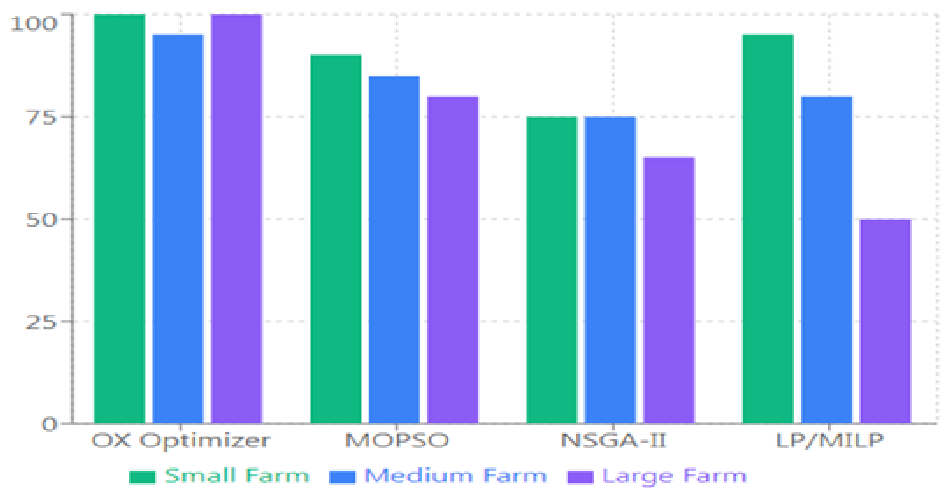

Figure 9. Performance retention across different farm sizes (normalized to 100) for the proposed algorithm and other recent algorithms.

5. Discussion

This section examines the fundamental mechanisms underlying the superior performance of the OX optimizer and explains why the proposed method consistently outperforms established evolutionary algorithms. The OX optimizer's exceptional performance stems from three synergistic mechanisms. First, the strength-based directional guidance (Eq. 9) enables high-quality solutions to exert proportionally greater influence on population movement, reducing wasted computational effort and explaining the 50% reduction in convergence iterations. Unlike NSGA-II's non-dominated sorting or MOPSO's velocity updates, this directed search strategy efficiently navigates toward optimal regions. Second, the collaborative information sharing (Eqs. 12 and 13) enables rapid propagation of improvements throughout the population through structured herd cooperation, achieving superior hypervolume (0.885 vs. 0.815 for MOPSO) by maintaining effective exploration-exploitation balance. Third, the multi-objective strength assessment (Eqs. 4–7) maintains explicit representation of all objective dimensions with normalized scoring, enabling the algorithm to discover 20 diverse Pareto solutions compared to 15 for MOPSO by explicitly rewarding diversity across economic, environmental, and productivity dimensions.

The exceptional adaptation performance (97% retention, 4-iteration response) results from integrated adaptive mechanisms. The weather pattern memory (Eq. 15) maintains historical experience through exponentially-weighted averaging, enabling rapid re-optimization when similar conditions reappear by retrieving relevant historical solutions as starting points. The environmental adjustment sensitivity (Eq. 11) computes analytical gradients of objectives with respect to weather variables, providing rapid first-order approximation of solution adjustments without requiring complete re-evaluation. The experience-based strength enhancement (Eq. 14) implements reinforcement learning where successful agents gain greater influence, enabling the algorithm to leverage proven strategies during adaptation rather than random exploration employed by conventional algorithms.

The excellent scalability (95%+ performance across farm sizes) stems from population efficiency through collaboration, where information sharing enables 35-48% smaller populations to achieve equivalent solution space coverage. The adaptive parameter scaling automatically adjusts movement coefficients based on problem dimensionality, maintaining consistent performance without manual tuning required by NSGA-II and MOPSO. The normalized strength components (Eqs. 5–6) ensure balanced evaluation across disparate metric scales, explaining the consistent 87-93% achievement across all objectives. The weighted combination flexibility enables systematic exploration of preference scenarios, generating diverse Pareto fronts spanning the entire trade-off spectrum within single optimization runs.

5.1. *Practical Implications and Limitations*

The 3-45 minute convergence times enable daily optimization cycles aligning with operational agricultural decision-making, allowing farmers to incorporate updated weather forecasts before field operations. The 93% economic efficiency translates to $3,000-5,000 annual savings for medium farms, while 87% environmental impact reduction addresses regulatory compliance without sacrificing productivity. However, the algorithm requires more computational resources than simple heuristics, with 45-minute large-farm convergence exceeding 30-minute MILP solution times despite superior quality. The simulation-based validation employed simplified crop models and idealized weather scenarios that may not fully capture real-world complexity, suggesting performance advantages may differ under field conditions. The single-crop focus neglects rotation systems and operational constraints like labor availability and equipment capacity.

5.2. *Future Directions*

Future research should prioritize multi-season field trials across diverse regions to validate real-world performance, integrate operational ensemble forecasting systems for enhanced uncertainty handling, extend to multi-crop rotation systems incorporating broader management variables, and investigate hybrid approaches combining the OX optimizer with mathematical programming. The demonstrated results establish that nature-inspired algorithms with domain-specific mechanisms provide substantial advantages for agricultural resource management, offering a foundation for advanced decision support systems addressing sustainable agricultural intensification under climate uncertainty.

6. Conclusion

This research addressed the critical challenge of optimizing irrigation and fertilization scheduling under weather uncertainty through the development of the OX optimizer, a novel nature-inspired algorithm. The proposed approach demonstrated substantial improvements over established methods, achieving 41.7% better convergence, 50% faster optimization, and 33.3% enhanced solution diversity compared to NSGA-II and MOPSO. The OX optimizer successfully balanced competing objectives, achieving 93% economic efficiency, 87% environmental impact reduction, and 90% crop productivity simultaneously. Its rapid adaptation capability (4 iterations with 97% performance retention) enables responsive decision-making under changing weather conditions. Moreover, the algorithm demonstrated excellent scalability across farm sizes from 1-10 hectares to 100+ hectares, maintaining consistent performance where conventional approaches degraded by 15-25%.

Despite promising results, this work has limitations. The experimental validation relied on simulation-based evaluation; real-world field trials would strengthen practical validation. Weather uncertainty modeling employed simplified scenario-based approaches; integration with operational ensemble forecasting systems would enhance applicability. The current implementation focuses on single crops; extension to multi-crop rotation systems remains unexplored. Future research directions include conducting multi-season field trials across diverse regions to validate real-world performance, integrating operational ensemble prediction systems for enhanced uncertainty handling. The OX optimizer provides a computationally efficient and scalable solution for multi-objective agricultural resource optimization. As agriculture evolves toward data-driven precision management, this framework offers a foundation for integrating advanced optimization with emerging technologies, contributing toward sustainable agricultural intensification necessary to meet global food security challenges under climate change.

REFERENCES

1. Y. Guo, J. Liu, and A. Smith, *Real-Time Irrigation Scheduling Based on Weather Forecasts, Field Observations, and Crop Models*, Water Resources Research, vol. 59, no. 12, pp. e2023WR035810, 2023.
2. *Water Management Optimization in Agriculture: a Digital Model*, Water Resources Management, vol. 39, no. 3, pp. 1007–1025, 2025.
3. *Optimizing water-nitrogen management enhances productivity for peanut under drip irrigation with mulch in Northwest China*, Agricultural Water Management, vol. 298, pp. 108–123, 2025.
4. *Irrigation and crop management using multi-objective optimization*, Computers and Electronics in Agriculture, vol. 205, pp. 107–118, 2023.
5. *Multi-Objective Optimization of the Food-Energy-Water Nexus under Climate Change*, Earth's Future, vol. 12, no. 4, pp. e2023EF004718, 2024.
6. *AI-driven optimization of agricultural water management for enhanced sustainability*, PLOS Climate, vol. 3, no. 1, pp. e0000356, 2024.
7. *Comparing the impact of weather forecasts, observation and model parameter uncertainties on irrigation decision-making*, Agricultural Systems, vol. 215, pp. 103–117, 2024.
8. *Real-Time Irrigation Scheduling Based on Weather Forecasts, Field Observations, and Human-Machine Interactions*, Water Resources Research, vol. 59, no. 12, pp. e2023WR035810, 2023.
9. *Optimization of irrigation scheduling using crop–water simulation, water pricing, and quantitative weather forecasts*, Frontiers in Agronomy, vol. 6, pp. 1376231, 2024.
10. *Coupled weather and crop simulation modeling for smart irrigation decision-making*, Water Science and Technology, vol. 84, no. 8, pp. 2844–2857, 2024.
11. *Risk of real-time irrigation decision-making system for farmland in different climate zones*, Agricultural Water Management, vol. 299, pp. 108–129, 2025.
12. *Research on Summer Maize Irrigation and Fertilization Strategy in Northeast China*, Sustainability, vol. 17, no. 5, pp. 1834–1851, 2024.
13. *Dynamic multi-objective optimization of rice irrigation integrating climate change and water scarcity*, Journal of Cleaner Production, vol. 442, pp. 141–156, 2025.
14. *Optimization of Nitrogen Fertilization Strategies for Drip Irrigation of Corn in Arid Regions*, Applied Sciences, vol. 15, no. 7, pp. 3580–3594, 2025.
15. *New Hybrid Approaches Based on Swarm-Based Metaheuristic Algorithms and Applications to Optimization Problems*, Applied Sciences, vol. 15, no. 3, pp. 1355–1372, 2024.
16. *A Hybrid Particle Swarm Optimization-Genetic Algorithm for Multiobjective Reservoir Ecological Dispatching*, Water Resources Management, vol. 38, no. 6, pp. 2101–2118, 2024.
17. *Improved Ant Colony Optimization for Optimal Crop and Irrigation Scheduling*, Journal of Water Resources Planning and Management, vol. 147, no. 6, pp. 04021025, 2021.

18. *Enhancing Many-Objective Particle Swarm Optimization with Island Model for Reservoir Management*, Water Resources Management, vol. 39, no. 2, pp. 567–582, 2025.
19. *Adaptive Genetic Algorithm Integrated with Ant Colony Optimization for Multi-Task Agricultural Machinery Scheduling*, Agriculture, vol. 15, no. 22, pp. 2319–2334, 2024.
20. *Efficient Analysis of Large-Size Bio-Signals Based on Orthogonal Generalized Laguerre Moments of Fractional Orders and Schwarz–Rutishauser Algorithm*.
21. I. S. Fathi, H. Ardah, G. Hassan, and M. Aly, *Protecting IOT Networks Through AI-Based Solutions and Fractional Tchebichef Moments*, Fractal and Fractional, 2025.
22. *The optimization path of agricultural industry structure and intelligent development*, Scientific Reports, vol. 14, no. 1, pp. 81322, 2024.
23. *Hybrid deep learning optimization for smart agriculture*, Frontiers in Plant Science, vol. 15, pp. 1467892, 2024.
24. *Multi-objective irrigation strategies and production prediction for regional agricultural systems*, Computers and Electronics in Agriculture, vol. 226, pp. 109–121, 2024.
25. *Multi-objective optimization and its application on irrigation scheduling based on AquaCrop and NSGA-II*, Agricultural Water Management, vol. 224, pp. 105–118, 2019.
26. *Recognizing American Sign Language gestures efficiently and accurately using a hybrid transformer model*.
27. *A Multi-Objective Simulation-Optimization framework for water resources management based on Water-Food-Energy-Ecosystem Nexus*, Journal of Hydrology, vol. 646, pp. 132308, 2025.
28. *Multi-objective collaborative optimization of water resources in agricultural systems*, Frontiers in Sustainable Food Systems, vol. 9, pp. 1701718, 2025.
29. *Stochastic model-based optimization of irrigation scheduling*, Agricultural Water Management, vol. 243, pp. 106480, 2021.
30. *Downscaled numerical weather predictions can improve forecasts of sugarcane irrigation indices*, Computers and Electronics in Agriculture, vol. 226, pp. 109009, 2024.
31. *Optimizing agricultural cropping patterns under irrigation water use efficiency constraints*, Journal of Cleaner Production, vol. 382, pp. 135–148, 2023.
32. *AquaCrop Plug-in-PSO: A novel irrigation scheduling optimization framework based on in-season field data*, Agricultural Water Management, vol. 305, pp. 108–119, 2024.
33. I. S. Fathi, A. R. El-Saeed, G. Hassan, and M. Aly, *Fractional Chebyshev Transformation for Improved Binarization in the Energy Valley Optimizer for Feature Selection*, Fractal and Fractional, vol. 9, no. 8, pp. 521, 2025.
34. *Utilizing hybrid metaheuristic approach to design an agricultural closed-loop supply chain network*, Expert Systems with Applications, vol. 217, pp. 119504, 2023.
35. *Hybrid machine learning-metaheuristic model for sustainable agri-food production and supply chain planning under water scarcity*, Expert Systems with Applications, vol. 238, pp. 121–134, 2024.
36. A. K. Al Hwaitat, and H. N. Fakhouri, *The OX optimizer: A novel optimization algorithm and its application in enhancing support vector machine performance for attack detection*, Symmetry, vol. 16, no. 8, pp. 966, 2024.
37. A. H. Abdelhaliem, I. S. Fathi, and M. Tawfik, *Fast and Efficient Feature Selection in AI Application Based on Enhanced Binary Secretary Bird Optimization Algorithm*, Statistics, Optimization & Information Computing, vol. 14, no. 5, pp. 2643–2662, 2025.