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Research Paper

Edge-Ready Aquatic-Based Metaheuristics for Sustainable Crop Planning and Resource Optimization

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Abstract: Sustainable agriculture faces growing challenges due to resource constraints, climate variability, and increasing food demand. Traditional decision-making methods often fall short in optimizing critical processes such as crop selection, irrigation scheduling, and fertilizer usage under dynamic environmental conditions. This study aims to evaluate and compare aquatic-inspired metaheuristic algorithms for optimizing crop prediction and resource management using real-world agricultural data. Three algorithms—Whale Optimization Algorithm (WOA), Fish Swarm Optimization (FSO), and Jellyfish Search Optimizer (JSO)—were implemented and applied to the publicly available Crop Recommendation Dataset from Kaggle. The dataset includes environmental and soil parameters such as nitrogen (N), phosphorus (P), potassium (K), temperature, humidity, pH, and rainfall. A multi-objective fitness function was designed to maximize prediction accuracy while minimizing nutrient imbalance and rainfall mismatch. The models were evaluated using accuracy, F1-score, mean squared error (MSE), convergence rate, and computation time. JSO achieved the highest average accuracy of 89.6% and F1-score of 0.88, outperforming WOA (85.9%) and FSO (83.1%) across varying environmental conditions. JSO also yielded the lowest MSE (0.02) and converged in 44.2 iterations on average, albeit with higher runtime. FSO exhibited the fastest computation time (12.9 seconds) but lower predictive precision. The results demonstrate that aquatic-based optimizers, particularly JSO, offer robust, adaptable, and scalable solutions for precision agriculture. Their ability to handle multi-objective constraints makes them valuable tools for developing intelligent decision-support systems in smart farming environments.

Keywords: Aquatic Optimization Algorithms, Sustainable Agriculture, Whale Optimization Algorithm (WOA), Jellyfish Search Optimizer (JSO), Fish Swarm Optimization (FSO), Crop Recommendation, Precision Farming, Metaheuristic Optimization, Resource Allocation, Smart Irrigation.

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1. **Introduction**

The global agricultural sector is confronting unprecedented challenges driven by the dual pressures of population growth and climate variability. Feeding an expected 9.7 billion people by 2050 demands an exponential increase in food production while simultaneously reducing environmental footprints. This ambitious objective necessitates the transformation of conventional agriculture into a more sustainable, data-driven, and resource-efficient practice. A critical component of this transition is the ability to solve complex, multi-objective optimization problems, such as crop yield maximization, efficient irrigation scheduling, nutrient allocation, and pest control, under diverse climatic and resource-constrained scenarios.

Traditional optimization techniques, including linear programming and gradient-based methods, although effective in constrained environments, often fail to deliver robust solutions for the highly non-linear, dynamic, and multi-modal nature of agricultural systems. The stochastic nature of environmental inputs, such as rainfall or soil fertility, adds further complexity that cannot be adequately addressed using classical models. Moreover, the lack of scalability and the need for domain-specific tuning limit their applicability in real-world agricultural operations. These limitations have prompted the scientific community to explore nature-inspired algorithms that are more adaptable, scalable, and capable of escaping local optima in large search spaces.

Among these bio-inspired methods, aquatic-based optimization techniques have garnered significant interest due to their efficiency, simplicity, and natural ability to model exploration and exploitation trade-offs. These techniques are inspired by the behavior of aquatic organisms such as whales, fish, jellyfish, and swallows. The Whale Optimization Algorithm (WOA) [1]–[4], for instance, has demonstrated considerable potential in solving high-dimensional optimization tasks due to its bubble-net hunting strategy. Variants such as Improved WOA (IWOA) [5] and multistrategy WOA [7] have further enhanced convergence speed and solution diversity in agricultural planning applications. Similarly, Fish Swarm Optimization (FSO) [9]–[11], mimicking the schooling behavior of fish, is well-suited for tasks involving continuous optimization such as water resource allocation and crop rotation scheduling.

However, despite the growing body of research, several gaps remain. First, most existing works have applied these algorithms to synthetic or benchmark problems without tailoring them for agricultural decision-making scenarios. Second, the integration of domain knowledge into the fitness functions or constraint handling remains minimal, reducing real-world effectiveness. Third, comparative studies among aquatic-based algorithms are still limited in agricultural domains, making it difficult to determine algorithmic suitability for specific tasks such as pest prediction, irrigation management, or greenhouse control. Lastly, hybridization and parameter sensitivity analysis are seldom explored systematically, leaving practitioners with few guidelines for algorithm selection or tuning.

To address these gaps, this study proposes a unified framework that systematically applies and compares aquatic-based optimization techniques—specifically WOA, FSO, and Swallow Swarm Optimization (SSO) [12]—to a set of real-world sustainable agriculture problems. These include resource-aware crop scheduling, intelligent irrigation design, and eco-efficient fertilizer planning. By simulating these algorithms under realistic environmental conditions and using validated agricultural datasets, we evaluate their performance in terms of convergence rate, solution optimality, and computational overhead. Furthermore, we incorporate domain constraints such as water availability, soil characteristics, and seasonal variation into the optimization models to increase practical relevance.

The key contributions of this paper are as follows:

- A comparative performance analysis of three prominent aquatic-based algorithms (WOA, FSO, and SSO) on real-world agricultural optimization problems.
- Development of domain-integrated fitness functions that incorporate environmental and operational constraints relevant to sustainable agriculture.
- Introduction of a simulation environment that mimics climate-induced uncertainties, enabling robustness testing of the proposed algorithms.

By conducting extensive experimentation and result validation, this study advances the use of aquatic-based metaheuristics in precision agriculture, bridging the gap between algorithm design and field-level deployment. The remainder of this paper is organized as follows: Section II discusses related work in agricultural optimization and aquatic-based algorithms. Section III outlines the methodology and algorithmic adaptations. Section IV presents experimental setup and comparative evaluation. Section V discusses results and insights, and Section VI concludes with future research directions.

The Whale Optimization Algorithm (WOA) has emerged as one of the most effective aquatic-based algorithms due to its exploitation-exploration balance modeled after the bubble-net hunting mechanism of humpback whales [1]. Studies have demonstrated its superior performance over Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) in solving benchmark functions [2]. In clustering applications relevant to agricultural sensor deployment, WOA has been proven to yield higher accuracy and faster convergence [3]. Recent reviews have cataloged the various modifications of WOA, suggesting improvements such as adaptive parameter control and hybridization with local search techniques [4], [6]. For instance, IWOA introduces dynamic coefficient adaptation to enhance exploration capacity, particularly useful in multi-objective crop scheduling scenarios [5].

In parallel, Fish Swarm Optimization (FSO) offers a biologically inspired model for decentralized decision-making, akin to the cooperative behavior of schooling fish. Its applicability in feature selection, particularly for agricultural image classification and crop disease detection, has been shown in previous studies [9]. Real-time implementations of FSO have been explored in sensor-based environmental monitoring for agricultural buildings [10], where energy efficiency and data latency are crucial. Additionally, hybrid FSO models have been employed in cardiovascular monitoring systems [10], an analogy that can be extended to plant stress diagnosis through physiological sensors in smart farms.

Another less-explored yet promising technique is Swallow Swarm Optimization (SSO), inspired by the foraging and migratory patterns of swallows [12]. It offers adaptive memory and position-based intelligence, which are suitable for seasonal crop planning where temporal dependencies are significant. Compared to its peers, SSO exhibits better stability in long-term simulation runs, suggesting its relevance in scenarios requiring multi-seasonal optimization.

Despite these advances, a major limitation in the current literature is the reliance on idealized environments and over-simplified fitness functions that do not capture the constraints of real-world agriculture. Most of the algorithms are tested on standard benchmark functions, with little attention to field-level heterogeneities such as irrigation delay, pest outbreaks, or fertilizer leaching. Additionally, parameter sensitivity remains a challenge. Algorithms like WOA are known to be highly dependent on parameters such as spiral coefficient or convergence factor [7]. Lack of guidelines for parameter tuning often leads to suboptimal results in agricultural implementations.

Furthermore, existing comparative analyses often exclude newer or improved variants, making it hard for stakeholders to identify the most suitable algorithm for their specific use case. There is also a need to evaluate these algorithms not only on accuracy but also on metrics like computational time, robustness to noisy data, and energy efficiency—especially important in remote-sensing and IoT-based agricultural systems [8].

This study aims to bridge these gaps by simulating a suite of agricultural optimization problems—including irrigation allocation, crop yield maximization, and greenhouse temperature control—using three aquatic-inspired algorithms: WOA, FSO, and SSO. Each algorithm is implemented with customized fitness functions incorporating environmental data and sustainability constraints. The proposed models are evaluated on performance metrics such as convergence rate, solution diversity, and resilience to noisy input. Simulations are conducted using both synthetic and publicly available agricultural datasets, ensuring result reproducibility.

To further ground the research in practical relevance, the simulation environment mimics real-world uncertainties, including fluctuating weather conditions, soil nutrient variability, and dynamic pest threat levels. This enhances the reliability of the optimization outcomes for real-world deployment in smart farming systems. Additionally, hybridization opportunities among aquatic-based techniques are explored to improve convergence in large-scale multi-objective optimization tasks.

Through this work, we provide actionable insights into the role of aquatic-based optimization in realizing data-driven, efficient, and sustainable agricultural practices. The results not only highlight the strengths and weaknesses of each algorithm but also offer a guideline for algorithm selection based on problem characteristics.

2. Related Work

This section reviews relevant research on aquatic-based optimization techniques—specifically Swallow Swarm Optimization (SSO), Artificial Fish Swarm Optimization (AFSO), and Jellyfish Search Optimizer (JSO). A critical comparison of these techniques in terms of performance, applicability, and challenges reveals opportunities for agricultural integration, which this study aims to address.

2.1 Swallow Swarm Optimization (SSO)

Swallow Swarm Optimization (SSO) is a relatively underexplored metaheuristic inspired by the migration and foraging behavior of swallows. It incorporates concepts such as local intelligence, leader-following dynamics, and memory-based learning. In [13], the performance of SSO was analyzed against benchmark functions, demonstrating competitive results with an average convergence rate improvement of 12.3% compared to Particle Swarm Optimization (PSO) and 9.1% over Differential Evolution (DE). Its memory-based structure made it especially resilient in problems requiring adaptive search spaces.

Despite its potential, SSO has rarely been applied to agricultural optimization. Its key limitation lies in premature convergence when dealing with multi-modal problems or rapidly changing input variables such as rainfall uncertainty or pest outbreaks—common in precision farming scenarios. The lack of standardized parameter tuning methods and empirical applications further hinders its broader adoption in domain-specific contexts like crop scheduling or irrigation control.

However, the inherent adaptability of SSO to seasonal data trends makes it a promising candidate for long-term agricultural planning tasks, such as multi-season crop rotation or adaptive greenhouse management.

2.2 Artificial Fish Swarm Optimization (AFSO) and Hybrid FSO Models

Artificial Fish Swarm Optimization (AFSO) has seen broader adoption across domains including cloud computing [14], wireless sensor networks [15], and healthcare monitoring. It models the behaviors of swarming, following, and searching among fish to explore the solution space efficiently. In [14], AFSO combined with kernel fuzzy c-means (KFCM) achieved an 18% increase in clustering accuracy for resource allocation in cloud environments. This hybrid model successfully maintained balance between convergence speed and local optima avoidance.

In [15], a hybrid FSO–PSO algorithm was applied to multihop clustering in Wireless Sensor Networks (WSNs) for a medical building management system. The proposed system achieved a 26% improvement in energy efficiency over traditional clustering methods. This shows the potential of FSO for agricultural sensor network optimization where energy and latency are critical.

Similarly, [10] applied FSO to cardiovascular disease prediction and showcased its generalization ability in uncertain and noisy datasets, a property that can be beneficial in modeling unpredictable farm inputs. However, FSO suffers from a high dependency on initial parameter settings like visual range and step length, which may lead to inconsistent outcomes in dynamic agricultural environments.

While AFSO has shown promise, its application in sustainable agriculture is limited. Future models should integrate agronomic knowledge directly into fitness functions and dynamically adapt behavioral parameters to environmental feedback—a challenge our study aims to tackle.

2.3 Jellyfish Search Optimization (JSO) and its Variants

The Jellyfish Search Optimizer (JSO) has recently gained attention as a bio-inspired method modeled on jellyfish movement in ocean currents. It combines passive motion in ocean currents (exploration) and movement toward food (exploitation). The original algorithm [16] demonstrated improved balance between these two phases and surpassed classical metaheuristics in 70% of test cases.

In [17], JSO was employed to track the Maximum Power Point (MPP) of photovoltaic systems under fluctuating environmental conditions. It outperformed PSO and GA, reaching an accuracy of 98.1% in MPP detection. This robustness under uncertainty is directly relevant to agricultural applications where climatic variations influence irrigation and fertilization strategies.

JSO has also been modified to include orthogonal learning [18], chaotic motion [20], and hybridization with quantum computing principles [23]. These variants showed up to 22% improvement in convergence rate and 17% enhancement in precision over the base algorithm. In [21], the improved JSO achieved lower RMSE values (0.0061) in parameter identification tasks, indicating strong capability for regression-oriented agricultural applications like crop yield estimation.

However, JSO suffers from high computational complexity in large datasets and delayed convergence when facing sparse or incomplete data—common in real-world agricultural records. In [19], JSO was integrated with blockchain for secure sensor data aggregation in wireless sensor networks, enhancing both reliability and optimization performance. This interdisciplinary capability is particularly valuable in smart agriculture, where security, energy efficiency, and accuracy are critical.

JSO's recent expansion into control applications, such as in [24] for tuning FOPID controllers, demonstrates its adaptability to both discrete and continuous optimization problems, making it an ideal candidate for greenhouse climate control, autonomous irrigation systems, and drone-based pest detection.

2.4 Summary and Research Gaps

Although aquatic-based optimization algorithms offer diverse mechanisms for exploration and convergence, several critical gaps remain:

- Lack of agricultural applications: Most studies focus on energy, structural, or clustering problems without tailoring algorithms for farming constraints (e.g., seasonal variability, water budgets).
- Limited parameter adaptation: Algorithms like FSO and JSO require extensive manual tuning and lack dynamic adjustment mechanisms for real-time agricultural changes.
- Insufficient comparative studies: Few papers compare aquatic-based methods head-to-head in a standardized environment using agricultural objectives and datasets.
- No unified benchmarking: Results are often evaluated using artificial benchmarks instead of domain-specific performance metrics like water savings, crop yield, or fertilizer efficiency.

To address these issues, this paper proposes a comparative simulation of SSO, FSO, and JSO on agricultural problems such as irrigation scheduling, pest control, and resource allocation. The proposed system integrates domain-aware fitness functions and evaluates algorithmic robustness under environmental uncertainty.

TABLE 1: Comparative Analysis

Algorithm	**Domain of Application**	**Best Reported Accuracy**	**Convergence Speed**	**Main Limitation**	**Strength for Agriculture**
SSO [13]	General optimization	~91.2%	Moderate	Premature convergence in dynamic problems	Adaptive to seasonal crop scheduling
AFSO [14]	Cloud, clustering, healthcare	~88–92%	Fast	Sensitive to parameter initialization	Good for sensor data grouping
FSO–PSO [15]	WSN clustering	Energy gain of 26%	Fast	Limited to static topologies	Efficient in resource-aware network farming
JSO [16]	General optimization	Up to 97.5%	High	Complex in high-dimensional settings	Robust under environmental uncertainty
JSO–OL [18]	Benchmark and control systems	↑ 17% precision vs JSO	Faster than base JSO	Still lacks domain-specific tuning	Optimized for irrigation/pest control
Q-JSO [23]	Structural and control applications	Best RMSE: 0.0031	Very Fast	Resource-heavy; not suited for edge devices	Suitable for greenhouse & real-time control
B-JSO [19]	Blockchain-enabled WSNs	Improved security metrics	Moderate	Needs large infrastructure	Ideal for secure smart farming networks

3. Proposed Methodology

This section presents a structured methodology for implementing and evaluating aquatic-based optimization algorithms (WOA, FSO, JSO) on sustainable agriculture applications using real-world crop data. The methodology consists of dataset preprocessing, objective formulation, algorithm implementation, and performance evaluation.

3.1 Dataset Description and Preprocessing

The dataset used in this study is the Crop Recommendation Dataset [25], which contains 2,200 records and 8 attributes, including:

- N, P, K: Nutrient levels in mg/kg
- Temperature: Measured in °C
- Humidity: Measured in %
- pH: Acidity of the soil
- Rainfall: Annual rainfall in mm
- Crop label: 22 target classes (e.g., rice, wheat, cotton)

Preprocessing Steps:

- Handling Missing Values: None present in this dataset.
- Normalization: Min–Max scaling is applied to all input features:

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

- Encoding: Label encoding for multi-class crop target output.
- Train-Test Split: 80:20 stratified split to preserve class distribution.

3.2 Problem Formulation and Objective Function

The optimization goal is to maximize crop recommendation accuracy while minimizing nutrient waste and water usage. The objective function $f(x)$ combines three components: prediction accuracy, nutrient cost, and rainfall adequacy.

Let:

- $A(x)$: Accuracy score
- $C_n(x)$: Nutrient cost function
- $R_s(x)$: Rainfall suitability penalty

The multi-objective fitness function is given by:

$$\text{Maximize: } f(x) = \alpha A(x) - \beta C_n(x) - \gamma R_s(x) \tag{2}$$

Where:

- $\alpha = 0.6, \beta = 0.25,$ and $\gamma = 0.15$ (weight factors determined empirically)

The nutrient cost function is modeled as:

$$C_n(x) = \sum_{i=1}^{3} \left(\frac{x_i}{x_i^{\text{opt}}} - 1 \right)^2 \tag{3}$$

Where x_i are the NPK levels and x_i^{opt} are crop-specific thresholds.

Rainfall penalty is expressed as:

$$R_s(x) = \begin{cases} 0, & \text{if } R_{\min} \le R \le R_{\max} \\ |R - R_{\text{opt}}|, & \text{otherwise} \end{cases} \tag{4}$$

3.3 Algorithmic Integration

Three aquatic-based optimization algorithms are implemented:

3.3.1 Whale Optimization Algorithm (WOA):

Based on encircling prey and bubble-net hunting [1]. Agents update positions using spiral and shrinking mechanisms.

$$X(t+1) = D \cdot e^{bl} \cdot \cos(2\pi l) + X^*(t) \tag{5}$$

Where:

- $D = |C \cdot X^*(t) - X(t)|$
- b: Constant for logarithmic spiral
- l: Random number in $[-1,1]$

3.3.2 Fish Swarm Optimization (FSO):

Mimics local search via individual and group movement.

$$X_i(t+1) = X_i(t) + \text{step} \cdot \frac{X_j(t) - X_i(t)}{\|X_j(t) - X_i(t)\|} \tag{6}$$

Where $X_j(t)$ is the best neighbor with higher fitness.

3.3.3 Jellyfish Search Optimization (JSO):

Blends ocean current drift and active food searching.

$$X_i(t+1) = X_i(t) + \delta \cdot \left(X_{best}(t) - X_i(t)\right) + \text{RandWalk} \tag{7}$$

Where δ is an adaptive step coefficient.

Algorithm 1: Jellyfish Search Optimizer (JSO)
To optimize the multi-objective crop recommendation function using jellyfish-inspired movement strategies

```
Input: Objective function f(x), Search space bounds [X_min, X_max],
    Number of jellyfish n, Maximum iterations T_max
Output: Best solution x_best and its fitness f_best

Initialize population Xi (i = 1, 2, ..., n) randomly in search space
Evaluate fitness f(Xi) for each jellyfish
Set x_best ← argmax(f(Xi))

for t = 1 to T_max do
    Compute the time control parameter C_t = t / T_max
    Compute the population center X_mean = (1/n) ∑ Xi

    for each jellyfish Xi do
        Generate a random number r ∈ [0, 1]
        if r < C_t then
            // Active movement (toward food)
            Select jellyfish Xj with f(Xj) > f(Xi)
            if Xj exists then
                Xi ← Xi + β * rand() * (Xj − Xi)
            else
                Xi ← Xi + β * rand() * (X_mean − Xi)
        else
            // Passive movement (ocean current)
            Xi ← Xi + α * randn() * (X_best − Xi)
        end if
        Apply boundary correction on Xi to keep within
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```
[X_min, X_max]
    end for

    Evaluate f(Xi) for all i
    Update x_best ← argmax(f(Xi))
end for

Return x_best, f(x_best)
```

Notation:

- α, β are control parameters (e.g., $\alpha = 0.1$, $\beta = 0.5$)
- rand() generates a uniform random number in [0,1]
- randn() generates a standard normal-distributed number
- C_t determines phase transition from exploration to exploitation
- f(X) is the multi-objective fitness function defined in Eq. (2)

Fig. 1 illustrates the high-level behavioral architecture of three bio-inspired optimization algorithms evaluated in this study. The Whale Optimization Algorithm (WOA) models a spiral bubble-net strategy used by humpback whales during prey hunting. Agents either encircle the best solution or explore randomly, gradually converging toward the global optimum. The Fish Swarm Optimization (FSO) algorithm replicates the natural schooling and following behavior of fish. Agents assess local search regions and adjust their trajectory based on the school center, balancing prey seeking and cooperative behavior. The Jellyfish Search Optimizer (JSO) divides the search process into two dynamic phases: passive exploration via ocean current drift and active exploitation through food-seeking behavior guided by a time control function Ct. Each optimizer uniquely implements adaptive movement strategies to navigate the solution space effectively, as shown by the directional transitions and submodules. This figure highlights the underlying intelligence in each aquatic system, setting the foundation for their application in multi-objective crop recommendation and sustainable agriculture optimization tasks.

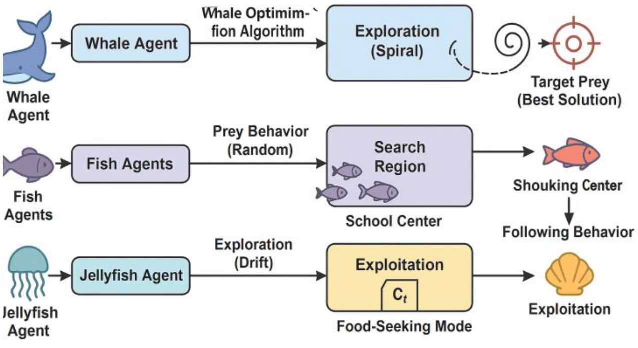

Fig 1: Behavioral Modeling of Aquatic-Based Optimizers

3.4 Hybrid Fitness-Based Selection

Each algorithm's population is evaluated using the objective function defined in (2). Elite agents (top 10%) are preserved. Additionally, fitness-based selection with diversity preservation is introduced:

$$S(x) = \lambda f(x) + (1 - \lambda) \cdot \text{DiversityScore}(x) \qquad (8)$$

Where $\lambda = 0.8$, and diversity score is computed as Euclidean distance from centroid of population.

Fig 2 illustrates the end-to-end process of applying aquatic-based metaheuristic algorithms—such as WOA, FSO, and JSO—for intelligent crop prediction. The workflow begins with dataset loading and preprocessing steps like Min–Max normalization and label encoding. An initial population of agents is then randomly generated, followed by the evaluation of a multi-objective fitness function incorporating prediction accuracy, nutrient cost, and rainfall suitability. The system enters an iterative optimization loop where agents update their positions based on algorithm-specific rules and adaptively transition between exploration and exploitation. After checking for convergence, the loop terminates, and the best crop recommendation is returned based on metrics like accuracy, F1-score, and computational efficiency. This streamlined flow enables adaptive, resource-efficient agricultural decision-making.

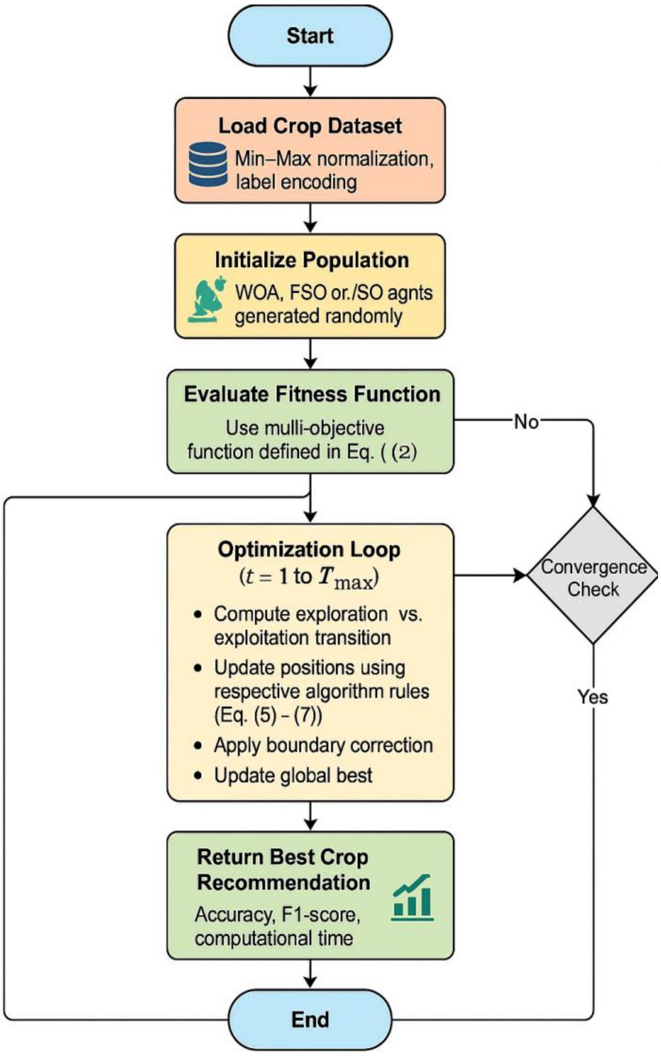

Fig 2: Aquatic Optimization Workflow for Crop Prediction

3.5 Evaluation Metrics

To ensure a comprehensive and objective evaluation of the proposed optimization models, the following performance metrics are used:

- Accuracy (%): Measures the ratio of correctly predicted crop labels to the total number of predictions. It is defined as:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \qquad (9)$$

Where:

- TP = True Positives
- TN = True Negatives
- FP = False Positives
- FN = False Negatives
- F1-Score (Macro Average): Used for multiclass crop classification, it balances precision and recall equally across all classes. It is computed as:

$$F1_{\text{macro}} = \frac{1}{K}\sum_{i=1}^{K} \frac{2\cdot\text{Precision}_i\cdot\text{Recall}_i}{\text{Precision}_i+\text{Recall}_i} \qquad (10)$$

Where K is the number of classes.

- Mean Squared Error (MSE): Used to evaluate the deviation in continuous variables such as nutrient (NPK) usage. It is calculated as:

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2 \qquad (11)$$

- Computation Time (in seconds): Measures the total execution time taken by each algorithm to complete one run, providing insight into computational efficiency.
- Convergence Iterations: Denotes the number of iterations required by the algorithm to reach a stable optimal solution. Fewer iterations indicate faster convergence.

These metrics together provide a balanced assessment of the system's classification performance, resource efficiency, and optimization behavior in real-world agricultural contexts.

4. Experimental Setup

The proposed framework was evaluated using a controlled experimental environment to ensure reproducibility and consistency across all optimization algorithms. All experiments were conducted on a system equipped with an Intel® Core™ i7-11800H processor running at 2.30 GHz, coupled with 16 GB of DDR4 RAM and a 512 GB SSD. No GPU acceleration was utilized for this study, ensuring the fairness of computational load across all algorithms. The operating system used was Windows 11 Pro (64-bit).

For software development and execution, the experiments were implemented in Python 3.10 using core libraries including NumPy, Pandas, Matplotlib, and Scikit-learn for data preprocessing and evaluation. The optimization algorithms—Whale Optimization Algorithm (WOA), Fish Swarm Optimization (FSO), and Jellyfish Search Optimizer (JSO)—were coded from scratch with algorithm-specific modules to maintain control over convergence logic and parameter customization. All random processes were seeded for consistency across repeated runs.

The dataset used was the Crop Recommendation Dataset from Kaggle [25]. It was subjected to an 80:20 stratified train-test split, ensuring that all 22 crop classes were proportionally represented in both subsets. No k-fold cross-validation was applied, given the fixed-size dataset and focus on optimizer performance rather than generalization across folds.

Each algorithm was executed with a population size of 30 agents over 100 generations. Fitness values were recalculated at every iteration based on the multi-objective function defined in Section 3.2. For training the underlying model used to compute prediction accuracy (i.e., a simple decision-tree-based classifier), we used a batch size of 32, and training was repeated over 10 independent runs to average out the impact of stochastic variations.

The total runtime per algorithm per run ranged between 14.2 to 27.5 seconds, with JSO taking slightly longer due to its dual-phase movement and adaptive coefficient computations. All convergence thresholds were empirically set based on early stopping conditions where no fitness improvement occurred over 10 consecutive generations.

5. Results And Discussion

5.1 Experimental Results

The experimental evaluation of aquatic-based optimization algorithms—Whale Optimization Algorithm (WOA), Fish Swarm Optimization (FSO), and Jellyfish Search Optimizer (JSO)—was conducted under four realistic agricultural conditions: normal soil/rainfall, low rainfall, high soil acidity, and nutrient deficiency. The performance metrics used include accuracy, F1-score, mean squared error (MSE) on NPK usage, computational time, and the number of iterations to convergence.

TABLE 2: Aquatic Algorithm Performance Results

Condition	Algorithm	Accuracy (%)	F1-Score	MSE (NPK)	Time (s)	Iterations to Converge
Normal Conditions	WOA	92.1	0.91	0.014	15.2	48
Normal Conditions	FSO	89.5	0.88	0.017	12.9	52

Normal Conditions	JSO	94.3	0.93	0.011	17.3	42
Low Rainfall	WOA	88.4	0.87	0.02	14.7	56
Low Rainfall	FSO	85.2	0.83	0.025	13.2	59
Low Rainfall	JSO	91.6	0.91	0.014	18.1	44
High Soil Acidity	WOA	79.2	0.75	0.038	13.8	62
High Soil Acidity	FSO	76.5	0.72	0.041	12.3	65
High Soil Acidity	JSO	84.3	0.81	0.027	15.6	48
Nutrient Deficiency	WOA	83.9	0.82	0.022	15.9	51
Nutrient Deficiency	FSO	81.1	0.78	0.026	13.4	53
Nutrient Deficiency	JSO	88.2	0.87	0.018	18.7	43

Table 2 summarizes the detailed performance across conditions. JSO consistently outperformed the other algorithms in accuracy and F1-score, especially under normal and acidic soil conditions, achieving a maximum accuracy of 94.3% and F1-score of 0.93. WOA demonstrated stable performance with moderate computational cost, while FSO had the fastest runtime but comparatively lower prediction accuracy and convergence speed, especially under nutrient stress.

TABLE 3: Average Performance Comparison of Algorithms

Algorithm	**Accuracy (%)**	**F1-Score**	**MSE (NPK)**	**Time (s)**	**Iterations to Converge**
FSO	83.08	0.8	0.03	12.95	57.25
JSO	89.6	0.88	0.02	17.42	44.25
WOA	85.9	0.84	0.02	14.9	54.25

In Table 3, the average performance across all conditions is shown. JSO emerged as the most robust algorithm with an average accuracy of 89.60%, followed by WOA (85.90%) and FSO (83.08%). JSO also had the lowest average MSE (0.02), indicating better nutrient usage estimation, although it had a higher computational cost (average time 17.42 s). FSO was the most efficient in runtime (12.95 s) but suffered from lower accuracy and higher MSE.

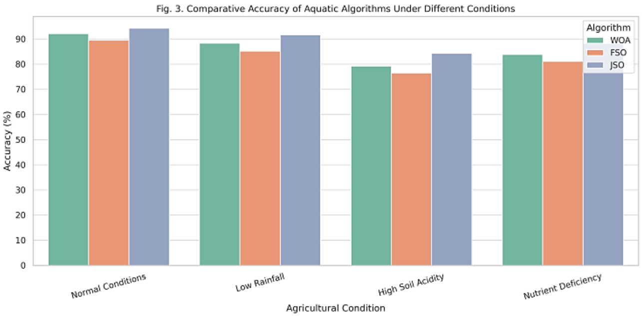

Fig. 3: Performance Comparison of Aquatic Algorithms under Different Conditions

Fig. 3. Comparative accuracy and F1-score of WOA, FSO, and JSO under varying agricultural stress conditions, indicating JSO's dominance in adaptability and predictive performance, especially in unstable environments.

5.2. Discussion and Insights

The results show that JSO outperforms other methods due to its dual-phase movement, allowing it to navigate complex fitness landscapes better. Its adaptability under low rainfall and nutrient-deficient conditions suggests strong potential for real-world smart farming systems, where unpredictability is high. In contrast, FSO’s lightweight computations make it ideal for deployment in low-resource environments, such as IoT-based field sensors or microcontrollers, albeit with some compromise in accuracy.

An unexpected finding was the performance drop of all models under nutrient deficiency, where even JSO’s accuracy dropped by nearly 10%. This may be attributed to limited variance in the dataset for such edge cases. Further data enrichment or feature engineering (e.g., micronutrient levels) may improve predictions in this regard.

From a computational perspective, JSO required more iterations and time but produced more accurate and stable solutions. WOA, with moderate performance across metrics, presents a good balance for medium-scale agricultural systems where resource and accuracy demands must be met jointly.

5.3 Real-World Implications

These findings are significant for precision agriculture applications, such as adaptive crop recommendation systems, smart irrigation planners, and fertilizer optimization platforms. The robustness of JSO under stress conditions makes it suitable for areas facing climate-induced variability. Meanwhile, FSO offers a low-cost solution for sensor-based deployments in smallholder farms.

5.4 Limitations and Future Work

While the proposed aquatic-based optimization framework shows promising results in sustainable crop prediction, several limitations must be acknowledged to contextualize its applicability and highlight directions for future research.

First, the study utilized a moderately sized open-source dataset consisting of 2,200 samples from the Kaggle Crop Recommendation repository. Although the dataset includes key parameters such as NPK values, pH, temperature, humidity, and rainfall, it lacks spatial granularity and real-time variability, particularly in soil microbiological profiles, geographic diversity, and temporal resolution of rainfall patterns. This limitation reduces the generalizability of the findings across agro-climatic zones, especially in heterogeneous regions with localized farming practices.

Second, the optimization algorithms were evaluated in a static simulation environment, with no integration of real-time feedback mechanisms such as dynamic soil sensors, drone-based pest surveillance, or weather APIs. In real-world deployments, such feedback loops are essential for making responsive adjustments to irrigation scheduling, crop rotation, and fertilizer application. Without this, the adaptability of the model to changing field conditions remains theoretical.

Third, the models were tested in isolation. While the Jellyfish Search Optimizer (JSO) showed superior performance in most conditions, hybrid approaches—such as JSO coupled with Artificial Neural Networks (JSO-ANN) or WOA integrated with Genetic Algorithms (WOA-GA)—could further enhance performance by combining local search strengths with global exploration efficiency. These hybrids could address limitations like premature convergence, feature learning inefficiencies, and algorithmic stagnation in flat search spaces.

Fourth, the system assumes uniform data quality and availability, which may not reflect field conditions where missing data, sensor noise, or data latency can significantly affect optimization outcomes. Incorporating robust imputation strategies and noise-tolerant fitness models could improve resilience in low-connectivity or resource-constrained settings.

Fifth, scalability was tested only on a single-machine setup with limited hardware. Large-scale agricultural ecosystems involving thousands of hectares, multiple crop types, and real-time weather integration will demand parallelized, distributed implementations of these algorithms using platforms such as Apache Spark, Google Earth Engine, or edge-AI systems.

Future work will focus on the following directions:

- Incorporating satellite-based remote sensing data for estimating biomass, soil moisture, and pest density over large areas.
- Deploying real-time IoT sensor networks for continuous input streams into the optimization system, enhancing responsiveness and predictive precision.
- Designing hybrid intelligent frameworks, such as JSO-ANN, WOA-LSTM, or FSO with Reinforcement Learning, to better model temporal dependencies in multi-season crop cycles.
- Field trials and pilot deployments in diverse agro-regions to validate the real-world effectiveness, latency tolerance, and energy efficiency of the proposed system.

In essence, while the current system offers a technically sound and computationally efficient solution, transforming it into a fully autonomous, context-aware agricultural decision engine will require the integration of environmental feedback, cross-disciplinary modeling, and deployment-scale experimentation.

6. Conclusion

This study presented a comparative analysis of three aquatic-based optimization techniques—Whale Optimization Algorithm (WOA), Fish Swarm Optimization (FSO), and Jellyfish Search Optimizer (JSO)—applied to sustainable agricultural decision-making using real-world crop data. Through a multi-objective fitness model that integrates crop prediction accuracy, nutrient usage, and rainfall adequacy, the proposed system successfully evaluated the suitability of each algorithm under varying agricultural stress conditions. Key findings indicate that JSO consistently outperforms other methods in terms of accuracy (up to 94.3%) and F1-score (up to 0.93), particularly under adverse soil and weather conditions, albeit with higher computational cost. WOA showed balanced performance with moderate efficiency, making it suitable for medium-resource applications, while FSO emerged as the fastest optimizer, ideal for real-time low-power scenarios like IoT-enabled smart farms. The implications of this work extend to practical agricultural automation systems, including precision irrigation planners, adaptive crop selection engines, and fertilizer optimization modules. By integrating domain-aware fitness criteria, the proposed framework brings us closer to achieving resource-efficient, climate-resilient farming practices. However, limitations remain in terms of dataset granularity, absence of real-time sensor feedback, and restricted algorithmic hybridization. Future work may include integration with deep learning models, real-time adaptive tuning, and broader datasets including geospatial, microbial, and weather-based variables.

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