

Research on Crop Planting Strategy Optimization Based on Non-Monopolize Search and Catch Fish Optimization Models

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Abstract: Crop planning under uncertainty is a critical issue in modern agriculture, especially when facing variable climate conditions, resource limitations, and unstable market demands. This study aims to develop an effective framework for optimizing multi-season, multi-crop planting strategies across heterogeneous land types, considering both deterministic and uncertain input conditions. In the deterministic setting, a profit-maximization model is formulated, incorporating realistic constraints such as land type, seasonal cycles, planting limitations, and crop rotation rules. The model is solved using the Catch Fish Optimization Algorithm, which demonstrates rapid convergence and stable performance. To account for uncertainties in crop yield, cost, and market price, we extend the model into a multi-scenario framework and apply the Non-Monopolize Search Algorithm to optimize expected profit and worst-case outcomes jointly. Two surplus-handling policies—complete disposal of excess crops and discounted post-harvest sales—are evaluated and compared. Experimental results show that the Non-Monopolize Search Algorithm significantly improves robustness, delivering high-quality solutions across diverse scenarios. The proposed dual-algorithm approach provides a practical and adaptable tool for agricultural decision-making and can be generalized to broader applications in resource allocation and policy evaluation under uncertainty.

Keywords: Crop Planning, Agricultural Optimization, Catch Fish Optimization Algorithm, Non-Monopolize Search Algorithm.

1. Introduction

In recent years, optimizing crop planting strategies has become an essential task in sustainable agriculture, especially in the context of increasing climate variability and market volatility. Traditional planting decisions often rely on fixed expectations of yield, cost, and price, ignoring the uncertainty inherent in real-world conditions. Such limitations can lead to significant economic losses and reduced resilience in farming systems. As a result, developing robust and adaptive planning models that consider both environmental and economic uncertainties is crucial for improving long-term agricultural performance.

Many scholars have explored strategies for improving agricultural planning. Xie et al. [1] demonstrated that adaptive crop switching can simultaneously increase farmer incomes and promote environmental sustainability by adjusting planting patterns to local conditions in China. Qiu et al. [2] found that cover crop practices not only improve soil health and crop yield but also reduce greenhouse gas emissions, making them a valuable tool for agroecosystem stability. Beyond agronomic techniques, recent works have introduced artificial intelligence into agricultural decision-making. Balderas et al. [3] evaluated deep reinforcement learning (DRL) algorithms for crop production management, showing that DRL can effectively optimize irrigation and fertilization decisions under dynamic environments. Tao et al. [4] further combined reinforcement and imitation learning to create intelligent crop management systems, reducing resource use while enhancing profit.

While these studies have significantly advanced crop planning methodologies, several challenges remain. Most

existing approaches focus on either agronomic adjustments or AI-based models but do not fully integrate external uncertainties, such as climate and market fluctuations, into their optimization frameworks. Additionally, many models require large datasets or complex training environments, limiting their practical application in rural and data-scarce regions. To address these issues, this paper proposes a two-stage optimization framework. First, a profit-maximization model is built and solved using the Catch Fish Optimization Algorithm (CFOA) [5]. Then, a multi-scenario optimization model is constructed to handle long-term uncertainty, solved using a Non-Monopolize Search Algorithm (NO) [6]. This integrated approach provides a flexible and practical decision-support tool for sustainable and risk-aware agricultural planning.

2. Mathematical Modeling and Metaheuristic Algorithms

2.1. Crop Planning Model Based on Catch Fish Optimization Algorithm (CFOA)

The CFOA is a metaheuristic optimization method inspired by the process by which a fisherman searches for and catches fish in water. In this algorithm, each candidate solution represents a fishing location. The objective value, such as total profit, is analogous to the quantity of fish that can be caught at that location. If no fish are caught (i.e., no improvement in solution quality), the fisherman will adjust the position within a defined search radius and try again.

Unlike swarm intelligence algorithms, CFOA operates based on an individual search strategy. It features memory retention and adaptive exploration, allowing the algorithm to

focus on promising areas in the solution space gradually. Its simplicity and efficiency make it suitable for solving nonlinear, constrained optimization problems such as

agricultural planning. The core steps of the CFOA are summarized in Algorithm 1.

Algorithm 1 The pseudocode of CFOA

Algorithm 1: The Pseudocode of CFOA

Input: $N, MaxEfs, lb, ub, d$

Output: The globally optimal solution

Initialize the population *fisher* randomly within bounds $[lb, ub]$

While $Efs \leq MaxEfs$

 Reckon the value of fit and get the globally optimal solution(Gbest)

 If $Efs/MaxEfs < 0.5$

 Reckon the value of α by Formula(2)

 Randomly shuffle the order of each fisherman

 If $\alpha > p$

 Update position using Formulas (3-5)

 Else

 Randomly group the fishermen

 Update their positions using Formulas (6-7)

 End

 Else

 Update position using Formulas (8-9)

 End

End

 Output the globally optimal solution

(1) Each fisher's position is initialized randomly within decision bounds:

$$fisher_{i,j} = lb_j + (ub_j - lb_j) \times r \quad (1)$$

where $fisher_{i,j}$ is position of fisher i in dimension j , lb_j and ub_j are lower and upper bounds for dimension j , and r is random number in $(0,1)$.

(2) In early search, fish density is high. Fishermen switch between independent and group fishing based on catch α :

$$\alpha = \left(1 - \frac{3 \times Efs}{2 \times MaxEfs}\right)^{\frac{3 \times Efs}{2 \times MaxEfs}} \quad (2)$$

where Efs is the number of current evaluations and $MaxEfs$ is the maximum number of evaluations.

Fishers are free to choose either independent search or group capture, but when the capture rate α is high, the fisher's capture strategy tends to favor the independent search method, and when the capture rate α decreases, the fisher

shifts to the group capture method, which we simulate using the random number $(0,1)$.

Independent search is chosen when $p < \alpha$ and group capture is chosen when $p \geq \alpha$, p is the probability, a random number between $(0,1)$.

Independent search:

$$Exp = \frac{fit_i - fit_p}{fit_{max} - fit_{min}} \quad (3)$$

where Exp is the empirical analysis value obtained by the fisherman using any other fisherman as the reference object, the range of values is $(-1,1)$; fit_{max} and fit_{min} are the worst and best fitness values after the T^{th} complete position update, respectively.

$$R = Dis \times \sqrt{|Exp|} \times \left(1 - \frac{Efs}{MaxEfs}\right) \quad (4)$$

where Dis is the Euclidean distance between the i^{th} individual and the referent and R is the exploration range.

$$Fisher_{i,j}^{T+1} = Fisher_{i,j}^T + (Fisher_{pos,j}^T - Fisher_{i,j}^T) \times Exp + r_s \times s \times R \quad (5)$$

where $Fisher_{i,j}^{T+1}$ and $Fisher_{i,j}^T$ are the positions of the i^{th} fisherman in the j^{th} dimension after the T^{th} and $(T+1)^{th}$ iterations, respectively, r_s is a random number in the range $(0,1)$, s is a random unit vector with dimension d .

Group capture:

$$Centre_c = \text{mean}(Fisher_c^T) \quad (6)$$

where $Centre_c$ is the mean position of group c in the current iteration, representing the center point of the group.

$$Fisher_{c,i,j}^{T+1} = Fisher_{c,i,j}^T + r_2 \times (Centre_c - Fisher_{c,j}^T) + \left(1 - \frac{2 \times Efs}{MaxEfs}\right)^2 \times r_3 \quad (7)$$

where $Fisher_{c,i,j}^{T+1}$ and $Fisher_{c,i,j}^T$ are the positions of the i^{th} fisherman in group c in the j^{th} dimension after the T^{th} and $(T+1)^{th}$ updates, r_2 is the speed at which the fisherman approaches the center, varying by individual and ranging from $(0,1)$ and r_3 is the movement offset with a value range of $(-1,1)$, which gradually decreases as the number of

evaluations Efs increases.

(3) Development phase: After the above stage, some fish escaped without being caught by the fishermen. Therefore, at this stage, the distribution of the fishermen is as follows: centered on the school of fish, the degree of aggregation from the middle to the periphery is gradually sparse, and the range of distribution outward is gradually narrowed. The fishermen in the center catch the school while the fishermen in the periphery catch the escaped fish. The fishermen fish strategically in a concerted effort to increase catch rates. We model this distribution with a Gaussian distribution.

$$\sigma = \sqrt{\left(2 \left(1 - \frac{Efs}{MaxEfs}\right) / \left(\left(1 - \frac{Efs}{MaxEfs}\right)^2 + 1\right)\right)} \quad (8)$$

$$Fisher_i^{T+1} = Gbest + GD\left(0, \frac{r_4 \times \sigma \times |\text{mean}(Fisher) - Gbest|}{3}\right) \quad (9)$$

where GD is a Gaussian distribution function, and the overall mean μ at 0, the overall variance σ increases as the

number of evaluations increases, it approaches 0 from 1, $mean(Fisher)$ is the matrix of the mean value of each dimension in the center of fishermen, $Gbest$ is the global optimal location and r_4 is a random number with a value of $\{1,2,3\}$ that distributes fishermen in three ranges.

2.2. Crop Planning Model under Uncertainty Based on Non-Monopolize Search Algorithm

The NO is a heuristic optimization method designed to avoid the premature convergence and local stagnation often encountered in traditional search techniques. Inspired by the principle of maintaining exploration diversity and preventing any single solution from dominating the population, NO guides search agents (solutions) through a balance of local refinement and global exploration.

(1) Initialization

Unlike population-based algorithms, the NO operates on a single-solution basis. Initially, a solution $X(0)$ is randomly generated within the feasible search space. This solution represents a specific area allocation for each crop.

(2) Exploration Phase

During the first half of the total number of iterations, the algorithm performs global exploration to avoid local optima. At iteration t , the j^{th} decision variable is updated as follows:

$$X_{new}(j) = rand \times X(RP) \quad (10)$$

where $rand$ is a random number in the range $[0,1]$, j is the index of the decision variable; $X(RP)$ is the value at a randomly selected index RP from the current solution; $RP \in \{1,2,\dots,D\}$, and D is the total number of decision variables. This update mechanism enables wide exploration of the solution space, increasing the likelihood of escaping local optima.

(3) Exploitation Phase

When the iteration count t exceeds half of the maximum number of iterations T , the algorithm switches to a local exploitation phase. In this phase, finer adjustments are made to the current solution using the following formula:

$$X_{new}(j) = X(j) + (X(SRP) \times rand) \times \epsilon - (X(j) - NO) \quad (11)$$

where $X(j)$ is the value of the current solution at dimension j , $X(SRP)$ is the value at a randomly selected index $SRP \in \{1,2,\dots,D\}$; $rand$ is a random number

between 0 and 1 and ϵ is a very small positive number used for fine-tuning.

(4) Termination

The algorithm terminates when the maximum number of iterations T is reached. The final solution X^* is returned as the optimal crop area allocation strategy.

3. Results

The data used in this study are derived from <https://www.mcm.edu.cn/>, based on a real-world case from Chehe Village, Lingqiu County, Datong City, Shanxi Province, China. This village, featured as a typical rural revitalization site, serves as the background for Problem C of the 2024 China Undergraduate Mathematical Contest in Modeling.

3.1. Results and Analysis Based on Catch Fish Optimization Algorithm

In this section, we evaluate the performance of the CFOA in solving the deterministic crop planning model described in Section 2.1. The primary objective is to assess the convergence behavior and solution stability of the algorithm across different agricultural scenarios. To this end, we track the value of the objective function—total profit—over iterations.

To evaluate the effectiveness of the CFOA under different market conditions, we consider two scenarios for handling surplus production:

Scenario 1: Any crop yield exceeding market demand is considered unsellable and therefore results in complete economic loss.

Scenario 2: The surplus portion is sold at a discounted price, specifically at 50% of the original market price, based on the 2023 baseline.

These two settings reflect typical real-world outcomes when supply exceeds demand, allowing us to test CFOA's adaptability and economic performance in different planning environments.

Figure 1 and Figure 2 show the convergence curves of CFOA under Scenario 1 and Scenario 2, respectively. In both cases, the algorithm aims to maximize the total profit over the 2024–2030 period by determining the optimal crop allocation strategy.

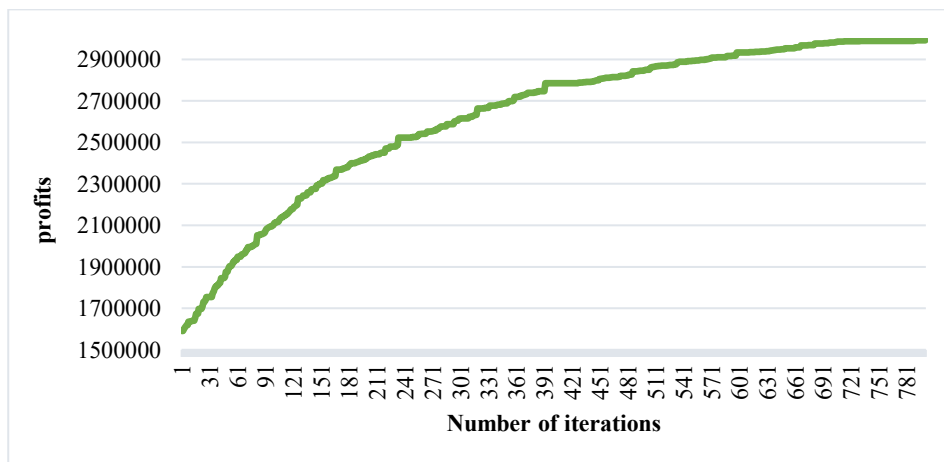


Figure 1 Convergence curve of CFOA under Scenario 1

In Figure 1, we observe that the objective function (total profit) increases rapidly in the early iterations, indicating that CFOA can quickly explore promising areas of the solution space. However, because the surplus is entirely wasted in this

case, the algorithm must be more conservative in allocating planting areas, especially for high-yield crops with limited market demand. As a result, the final profit converges to a lower value compared to Scenario 2.

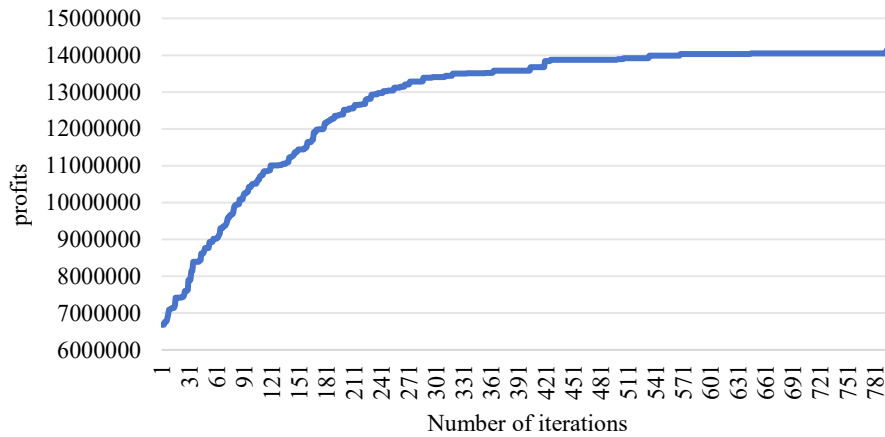


Figure 2 Convergence curve of CFOA under Scenario 2

In Figure 2, the algorithm displays a similar early-stage convergence trend, but the profit continues to grow more steadily over time. The ability to sell surplus crops at a reduced price allows the algorithm more flexibility in maximizing revenue, leading to a higher final profit. This scenario demonstrates how slight changes in market policy can significantly affect optimal decisions and outcomes.

In both scenarios, the convergence curves gradually flatten after 450 to 500 iterations, suggesting that the algorithm has stabilized and reached a near-optimal solution. The final stages show minimal fluctuation, which demonstrates the stability and robustness of CFOA in solving complex multi-constraint optimization problems. The relatively smooth convergence also indicates the algorithm does not suffer from premature stagnation or chaotic behavior.

Overall, the CFOA proves effective in adapting to different

economic assumptions, achieving high-quality solutions within a reasonable number of iterations. The comparison between the two scenarios highlights CFOA's potential to support decision-making under varying market conditions, and to guide crop planning strategies that are both profitable and risk-aware.

3.2. Results and Analysis Based on Non-Monopolize Search Algorithm

In this section, we analyze the performance of the NO in solving the uncertain crop planning problem, where crop yield, cost, and market prices vary across simulated scenarios. Unlike the deterministic setting in Section 3.1, this model considers potential planting risks and the inherent unpredictability of agricultural production.

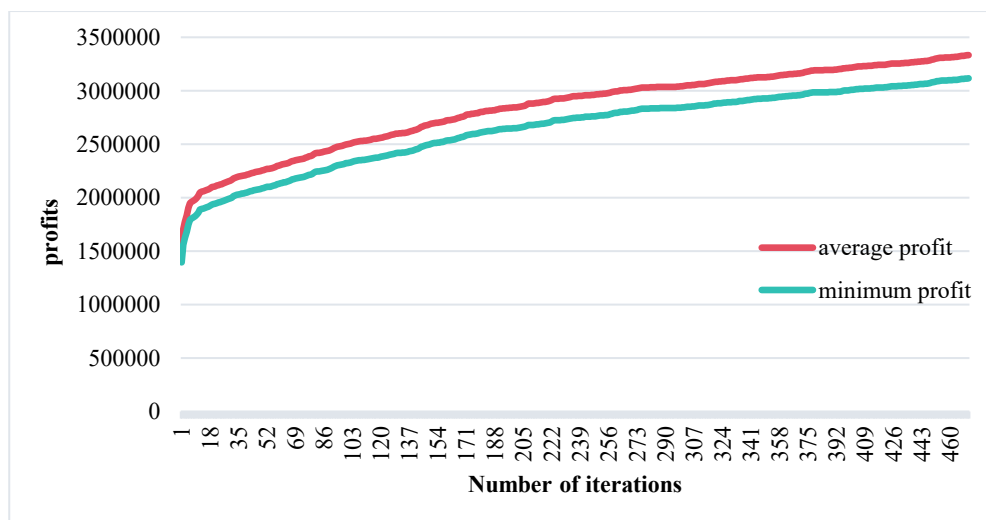


Figure 3 Convergence of expected and minimum profit under Scenario 1

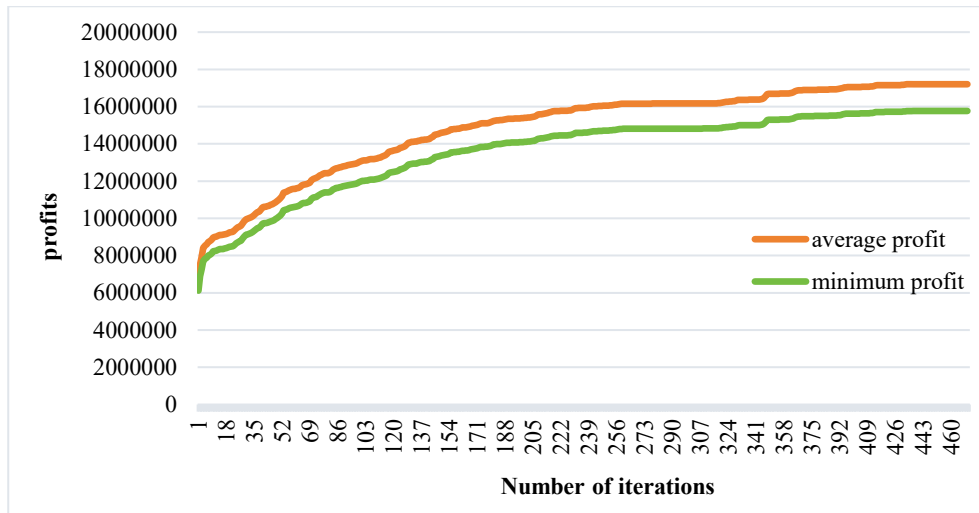


Figure 4 Convergence of expected and minimum profit under Scenario 2

The NO is designed to balance two objectives: maximizing the expected profit across all scenarios and minimizing the worst-case profit. Figure 3 and Figure 4 illustrate the evolution of both metrics over iterations under the two scenarios, respectively.

In both cases, the average and minimum profit values increase steadily as the algorithm iterates. During the early stage of the optimization process, solutions are scattered randomly across the search space, leading to large fluctuations in profit values. This is expected, as the algorithm is still in the global exploration phase.

As the algorithm proceeds, the solution population begins to concentrate around high-quality regions. The average profit shows a clear upward trend, indicating that the algorithm is successfully guiding the search toward more profitable and feasible planting strategies. At the same time, the minimum profit—representing the worst-case solution among the population—also improves steadily. This means that even the least favorable solutions are getting better, which enhances the overall robustness of the result set.

In Scenario 1, the presence of complete loss for unsold crops makes the worst-case profit lower, especially in the initial iterations. However, the algorithm gradually learns to avoid overproduction risks and improves stability by allocating land more conservatively. In contrast, Scenario 2 allows more aggressive planting decisions because surplus crops still retain partial value. As a result, both average and minimum profits converge to higher values compared to Scenario 1, as shown in Figure 4.

The results demonstrate that the NO is capable of managing trade-offs between profitability and risk, even under complex constraints and uncertain inputs. The upward trends of both metrics highlight the algorithm’s strong ability to enhance solution quality across the entire population, rather than improving only elite individuals.

4. Conclusions and outlooks

In this paper, we proposed a robust crop planning strategy that addresses both deterministic and uncertain agricultural scenarios. Specifically, we constructed a profit-maximization model under fixed input assumptions and solved it using the CFOA. To further account for the variability in crop yield, cost, and market price, we developed a multi-scenario optimization framework and applied the NO to balance

expected profit and risk exposure.

The simulation results demonstrate that CFOA effectively identifies optimal planting patterns with high economic returns and stable convergence. Meanwhile, NO proves capable of handling complex uncertainties, producing planting strategies with both strong profitability and robustness. The comparative analysis under two real-world-inspired market settings (complete surplus loss vs. discounted sales) further reveals how market policy assumptions significantly affect agricultural outcomes.

The models and algorithms developed in this study provide practical tools for rural land managers and policymakers. They can be applied not only to small-scale village-level agricultural planning, but also extended to larger regional or national agricultural systems, especially under long-term policy and climate uncertainty. The methodology is also applicable to other resource allocation problems with multi-objective trade-offs, such as water usage planning, greenhouse scheduling, and land-use optimization.

Although the proposed models achieve promising results, several limitations remain. First, the current approach relies on predefined scenario data and simple probabilistic assumptions. In future work, integrating real-time weather forecasts and market signals through machine learning or reinforcement learning techniques could further improve the adaptability and predictive accuracy of the system. Additionally, the algorithms could be further enhanced through hybridization or parallel implementation to improve computational efficiency on large-scale problems.

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