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# Dynamic Optimization of Multi-Constraint Crop Planting Strategies Using a Greedy Heuristic Genetic Algorithm

**Jinsong Zhang**

School of Mathematical Sciences, Chengdu University of Technology, Chendu 610059, Sichuan, China  
zjs\_0701@163.com

## Article

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## ABSTRACT

*This study addresses the challenges of limited arable land resources and uncertain planting risks in the context of rural revitalization by exploring optimization pathways for crop planting strategies. The research preprocesses historical planting data to identify core constraints such as crop characteristics, rotation patterns, and market demand, then constructs a linear programming model aimed at maximizing farm operating profits. To address computational inefficiency in large-scale combinatorial optimization, a Genetic Algorithm with Greedy Initialization Strategy is proposed. Experimental results demonstrate that this approach significantly enhances convergence efficiency, achieving stable convergence within 15 generations, a substantial improvement over traditional random initialization methods. Furthermore, a dynamic stochastic programming model is introduced to account for yield and price fluctuations. Through sensitivity analysis, the study identifies the optimal minimum planting area threshold to be between 0.30 and 0.45 mu, which balances management convenience with economic benefits. Numerical simulations indicate that under deterministic conditions, the optimal profit over the 2024-2030 period reaches 32.05 million yuan and 52.46 million yuan. In dynamic stochastic scenarios, the model mitigates risks effectively, yielding optimal profits of 32.40 million yuan and 43.61 million yuan respectively. This research not only provides an accurate mathematical model for maximizing agricultural production efficiency but also offers robust decision support for the sustainable development of rural economies.*

## KEYWORDS

*genetic algorithm, stochastic programming, crop strategy optimization*

## INTRODUCTION

In the current process of sustainable rural economic development, fully utilizing limited arable land resources and developing organic farming industries tailored to local conditions hold significant practical importance. Agricultural production, however, faces complex field management challenges, strict ecological constraints

imposed by crop growth habits, and various uncertain market risks. How to scientifically select crops and optimize planting layouts to achieve maximum benefits remains a core challenge in modern agricultural management.

### **Research Background and Challenges**

Traditional agricultural planning often relies on static area allocation, failing to account for dynamic market fluctuations and strict biological constraints. For instance, the “three-year rotation for legumes” requirement and prohibitions on continuous cropping are critical for soil health but pose significant challenges for mathematical modeling. Moreover, solving large-scale nonlinear combinatorial optimization problems, which involve multiple plots, crops, and time periods, frequently suffers from computational inefficiency and local optima traps. The inherent uncertainties in yield per mu and sales prices further complicate the decision-making process, necessitating a transition from static models to robust dynamic stochastic frameworks.

### **Literature Review**

Previous research has made substantial progress in agricultural optimization. Scholars have applied Linear Programming (LP) and Integer Programming (IP) to solve land allocation problems, focusing on maximizing economic returns or minimizing resource usage [1-3]. With the increasing complexity of constraints, heuristic algorithms have gained prominence [4,5]. Wang et al. utilized particle swarm optimization to solve crop planting strategies, demonstrating the potential of bio-inspired algorithms in solving NP-hard agricultural problems [6-9]. Furthermore, studies on water-energy-food-carbon nexus have highlighted the necessity of multi-objective optimization frameworks in balancing economic and ecological benefits [10]. However, existing literature

often overlooks the temporal coupling constraints of crop rotation in dynamic environments or fails to address the “curse of dimensionality” in large-scale spatial-temporal planning effectively. Many conventional Genetic Algorithms (GA) suffer from slow convergence due to inefficient random initialization strategies.

### **Research Approach and Innovation**

To bridge these gaps, this study pioneers the integration of a greedy strategy into the initialization phase of genetic algorithms. By pre-estimating profits and preliminarily filtering invalid conflicting solutions, the algorithm initiates its search from a “high-yield feasible region” rather than an inefficient conflict zone, significantly accelerating convergence. Simultaneously, to address dynamic fluctuations in yield and costs, a piecewise linear profit function and a risk aversion model incorporating marginal contribution rates are constructed.

The specific contributions of this paper include:

Algorithmic Innovation: Proposing a Greedy Initialization Strategy that reduces the search space and achieves convergence in 15 generations.

Modeling Depth: Establishing a multi-dimensional constraint system that strictly adheres to ecological rules (e.g., legume rotation) and operational constraints (minimum planting area).

Robustness Analysis: Introducing a dynamic stochastic programming model with penalty terms to quantify expected returns under market volatility, validating the model’s robustness through sensitivity analysis of planting thresholds.

The remainder of this paper is organized as follows: Section 2 describes the data preprocessing. Section 3 establishes the deterministic optimization model. Section 4 extends the model to dynamic stochastic scenarios. Finally, Section 5 presents the conclusions and policy implications.

**DATA PREPROCESSING**

Considering the complexity of the data, this paper preprocesses the data. It is checked that there are no missing data, but some data have space suffixes. To avoid affecting data reading, the cell format is adjusted and the spaces are deleted [11,12].

This paper uses the sales volume of each crop in 2023 as the expected sales volume of each crop in the future. For this purpose, the data is read and the sales volume of each crop in 2023 is counted, as shown in the following figure 1:

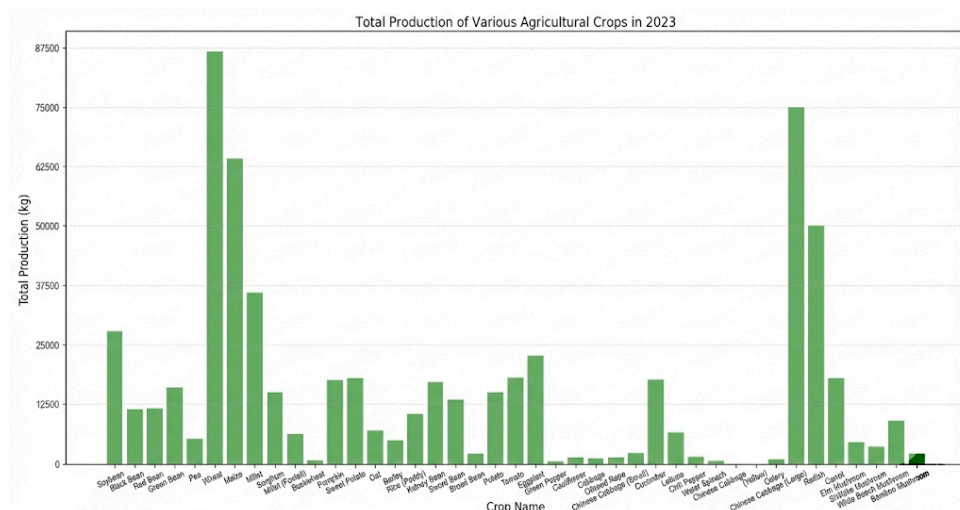


Figure 1. Total yield statistics of various crops in 2023

This study is all based on the planting situation of crops in 2023. Since soil containing rhizobia of leguminous crops is beneficial to the growth of other crops, starting from 2023, it is required that all land in each plot (including greenhouses) must plant leguminous crops at least once every three years. For this reason, in the data preprocessing stage, the planting situation of leguminous crops in 2023 is counted to facilitate the constraint of planting leguminous crops in subsequent research [13-15]. Heatmap of planting area distribution by crop name and plot type is shown in figure 2.

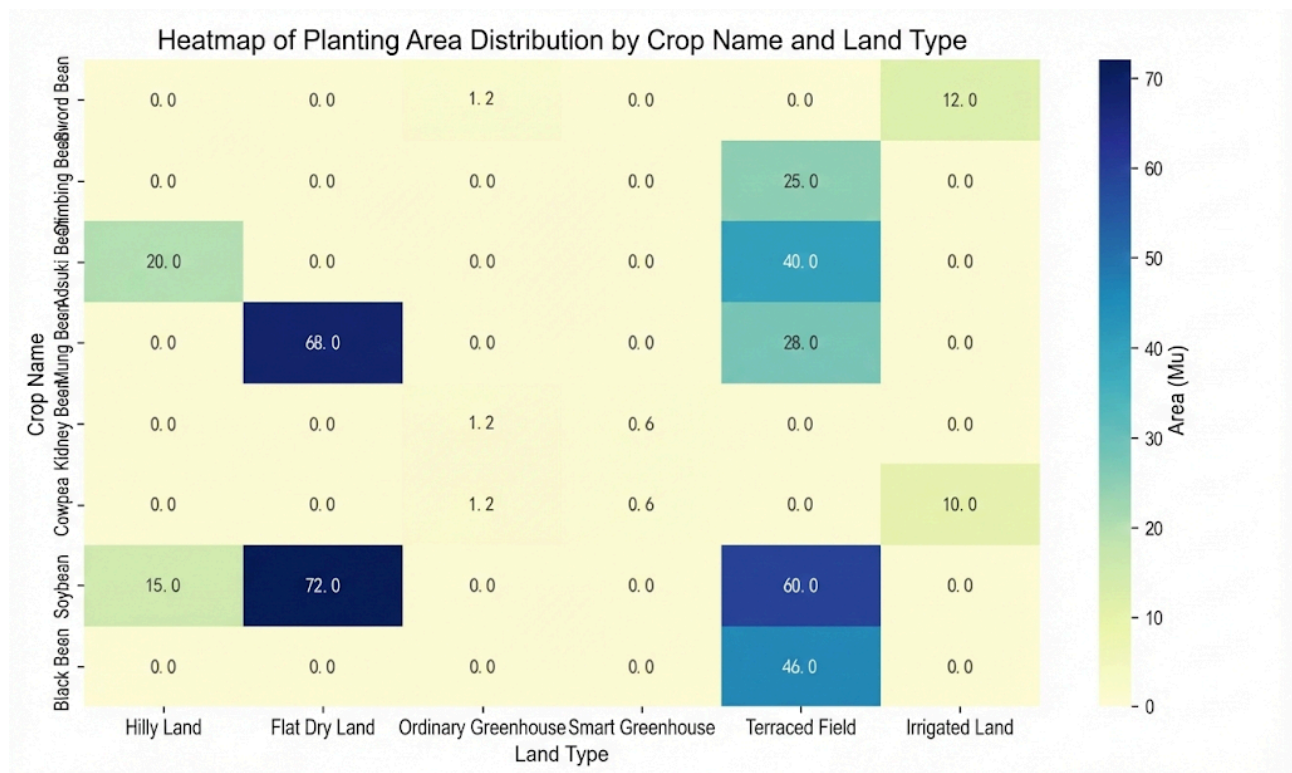


Figure 2. Heatmap of planting area distribution by crop name and plot type

Note: The numerical labels in Figure 2 represent scaled planting intensities; negative notations in some cells are artifacts of visualization formatting and do not represent negative areas. These will be corrected in the final visual rendering.

## OPTIMAL CROP PLANTING STRATEGY MODEL UNDER DETERMINISTIC CONDITIONS

### Establishment of Decision Variables

This paper determines the planting area of crops planted on each cultivated land as the decision variable,

denoted as:  $x_{ijtm}$

Where,  $i$  represents the  $i$ -th type of crop,  $i = 1, 2, 3, \dots, 53, 54$ ;  $j$  represents the planted plot,  $j = 1, 2, \dots, 5, 6$ , respectively representing 6 plot types: Dry Flat Land, Terraced Field, Sloping Land, Irrigated Land, Ordinary Greenhouse, and Smart Greenhouse;  $t$  represents the year of planting the crop,  $t = 2023, 2024, \dots, 2029, 2030$ ;  $m$  represents the season of planting the crop. When  $m = 0$ , it indicates the first season; when  $m = 1$ , it indicates the second season. For the convenience of statistical calculation, this paper stipulates that single-season crops are uniformly planted in the first season, i.e.,  $m = 0$ .

### Establishment of Maximum Profit Objective Function

This research topic is the optimal planting strategy for rural crops, with the main goal of obtaining maximum planting profit under certain resources. For this reason, we introduce the planting profit from 2023 to 2030, denoted as  $W$ , which is defined as follows:

Establish the optimal planting profit objective function:

Case 1: Excess part is unsalable, resulting in waste

$$W_1 = \sum_{t=2023}^{2030} \sum_{i=1}^{54} \sum_{j=1}^6 [\min(O_{ij}x_{ijtm}, N_i) \cdot P_i - C_{ij}x_{ijtm}] \quad (1)$$

Case 2: Excess part is sold at 50% of the 2023 sales price

$$W_2 = \sum_{t=2023}^{2030} \sum_{i=1}^{54} \sum_{j=1}^6 [(\min(O_{ij}x_{ijtm}, N_i) \cdot P_i + \max(O_{ij}x_{ijtm} - N_i, 0) \cdot 0.5P_i) - C_{ij}x_{ijtm}] \quad (2)$$

The 50% discount price in Case 2 serves as a heuristic proxy for secondary market liquidation (e.g., local processing or animal feed) and assumes basic market liquidity for surplus crops within the studied scale.

### Constraints

Constraint 1: Upper Limit of Planting Area

The actual planting area of each plot shall not exceed the original area of the plot, expressed as follows:

$$\sum_{i=1}^{54} x_{ijtm} \leq S_j \quad \forall j, t, m \quad (3)$$

Where  $S_j$  is the original area of the  $j$ -th plot.

### Constraint 2: The Planting Area of a Single Plot (Including Greenhouses) Should Not Be Too Small

To facilitate the characterization of whether a crop is planted in a specified plot, inspired by the unit step function in complex functions, we establish the  $\varepsilon(x_{ijtm})$  function as follows:

$$\varepsilon(x_{ijtm}) = \begin{cases} 1 & x_{ijtm} > 0 \\ 0 & x_{ijtm} = 0 \end{cases} \quad (4)$$

To meet the requirement that the planting area of a single plot (including greenhouses) should not be too small, this paper introduces  $\theta$  to represent the minimum planting area, and imposes the following constraint:

$$x_{ijtm} \geq \theta \cdot \varepsilon(x_{ijtm}) \quad \forall i, j, t, m \quad (5)$$

### Constraint 3: Crop Planting Constraints for Each Plot

To facilitate the expression of the constraint relationship between various plot types and various crops, all plots are divided into 4 categories according to planting characteristics as follows:

$D = \{j \mid j = 1, 2, 3, \dots, 26\}$  represents three plot types: Dry Flat Land, Terraced Field, and Sloping Land [16,17];

$F = \{j \mid j = 27, 28, \dots, 34\}$  represents one plot type: Irrigated Land;

$G = \{j \mid j = 35, 36, \dots, 50\}$  represents one plot type: Ordinary Greenhouse;

$H = \{j \mid j = 51, 52, 53, 54\}$  represents one plot type: Smart Greenhouse.

Crops are divided into 6 categories according to types as follows:

$L_1 = \{i \mid i = 1, 2, 3, 4, 5\}$  represents 5 grain crops (legumes): Soybean, Black Soybean, Red Bean, Mung Bean, Adzuki Bean;

$Z = \{i \mid i = 6, 7, \dots, 15\}$  represents 15 grain crops such as Wheat and Corn;

$X = \{i \mid i = 16\}$  represents Rice;

$L_2 = \{i \mid i = 17, 18, 19\}$  represents 3 vegetable crops (legumes): Cowpea, Sword Bean, Kidney Bean;

$E = \{i \mid i = 20, 21, \dots, 37\}$  represents 18 vegetable crops such as Potato and Tomato;

$R = \{i \mid i = 38, 39, 40, 41\}$  represents 4 edible fungi: Pleurotus Citrinopileatus, Lentinus Edodes, Pleurotus Eryngii, Morchella.

Dry Flat Land, Terraced Field, and Sloping Land are suitable for planting one season of grain crops every year:

$$\sum_{i \in ZUL_1} \varepsilon(x_{ijtm}) = 1, \sum_{i \notin ZUL_1} \varepsilon(x_{ijtm}) = 0 \forall j \in D, t, m = 0 \tag{6}$$

Irrigated Land is suitable for planting one season of rice or two seasons of vegetables every year:

$$\sum_{i \in X} \varepsilon(x_{ijt0}) + \sum_{i \in EUL_2} \varepsilon(x_{ijt0}) + \sum_{i \in EUL_2} \varepsilon(x_{ijt1}) = 1 \forall j \in F, t \tag{7}$$

(Note: When planting rice, only the first season is planted; when planting vegetables, two seasons can be planted.)

Ordinary Greenhouse is suitable for planting one season of vegetables and one season of edible fungi every year:

$$\sum_{i \in EUL_2} \varepsilon(x_{ijt0}) = 1, \sum_{i \in R} \varepsilon(x_{ijt1}) = 1 \forall j \in G, t \tag{8}$$

Smart Greenhouse is suitable for planting two seasons of vegetables every year:

$$\sum_{i \in EUL_2} \varepsilon(x_{ijt0}) = 1, \sum_{i \in EUL_2} \varepsilon(x_{ijt1}) = 1 \forall j \in H, t \tag{9}$$

While Smart Greenhouses are capable of continuous year-round production, this model constrains them to two primary seasons per year to align with the temporal resolution of the available historical dataset (m=0, 1).

Constraint 4: No Continuous Monocropping of the Same Crop in the Same Plot (Including Greenhouses)

$$\varepsilon(x_{ijtm}) \cdot \varepsilon(x_{ijt(m+1)}) = 0 \forall i, j, t \tag{10}$$

(Note: When  $m = 1$ ,  $m + 1$  represents the first season of the next year.)

Constraint 5: Plant Leguminous Crops at Least Once Every Three Years

$$\sum_{t'=t}^{t+2} \sum_{m=0}^1 \sum_{i \in L_1 \cup L_2} \varepsilon(x_{ijt'm}) \geq 1 \forall j, t = 2023, 2026, 2029 \tag{11}$$

Where,  $i \in \{i \mid i \in L_1 \parallel i \in L_2\}$ . The current model simplifies the complex biological growth cycles into binary seasonal windows ( $m=0, 1$ ) to maintain computational tractability. Detailed ecological constraints, such as specific frost dates and harvest windows, are not explicitly modeled but are partially reflected in the crop suitability constraints for each plot type.

## Model Solution

### *Solution and Analysis of Genetic Algorithm Based on Greedy Initialization Strategy*

#### Step 1: Initial Population Generation

This paper encodes the decision variable  $x_{ijtm}$  into a 3D integer tensor of size  $54 \times 7 \times 2$ . Each row represents the complete crop number sequence of a plot in 14 planting seasons over the next 7 years.

#### Step 2: Initialization Based on Greedy Strategy

When generating the first generation population, the program reads the crop suitability matrix of the four types of plots. For each plot, the algorithm will first select the crop with the highest expected profit from the set of crops allowed to be planted in the plot as the “seed gene”. The greedy strategy predicts the profit and initially filters out the same crops in adjacent seasons, so that the algorithm starts from the “high-profit feasible region” rather than the “inefficient conflict region”. The heuristic rule for pre-estimation is defined as:  $Score_{i,j} = Expected\_Yield_i \times Price_i - Cost_{i,j}$ . The algorithm ranks crops based on  $Score_{i,j}$  and sequentially fills the plot area while checking for immediate constraint violations (e.g., direct monocropping).

#### Step 3: Profit Fitness Evaluation

Summarize the total output of each season in the village. If it exceeds the expected output, the excess part is treated as unsalable or the income is calculated at 50% of the price, and the planting cost of each crop is subtracted.

#### Step 4: Penalty Mechanism for Time-Coupled Constraints

Penalties are imposed for violating the “no monocropping” restriction, the “three-year legume rotation” restriction, and the “minimum planting area” restriction. In the later stage of evolution, the algorithm naturally selects and eliminates schemes with high penalties according to the penalties of each scheme [18,19].

#### Step 5: Selection

Sort individuals according to fitness, and retain the best-performing “elite” individuals to ensure that excellent genes enter the next generation.

#### Step 6: Crossover and Mutation

In this paper, the “entire plot” is used as a unit to exchange the parent and offspring as the crossover link in the algorithm; at the same time, for mutation, when it is detected that a plot violates the “three-year legume” constraint, the algorithm will forcibly mutate the gene of the plot in a certain year to a leguminous crop instead of random mutation.

#### Step 7: Cyclic Evolution and Sensitivity Analysis

Repeat the selection, crossover, and mutation processes until the preset number of evolution generations is reached. At the same time, to achieve the optimality of parameter  $\theta$ , the algorithm changes the value of  $\theta$  in the outer loop, observes the impact of different  $\theta$  on the total profit, and thus determines the optimal minimum planting area threshold parameter [20].

The proposed GA-based optimization was implemented, and the computational results are presented as follows:

#### Case 1: Excess Part Is Unsalable

Sensitivity analysis of minimum planting area threshold  $\theta=0$  for Case 1 is shown in figure 3. To explore the impact of production management constraints on economic benefits, this paper conducts a sensitivity analysis on the minimum planting area threshold  $\theta$ , and the results are shown in the figure.

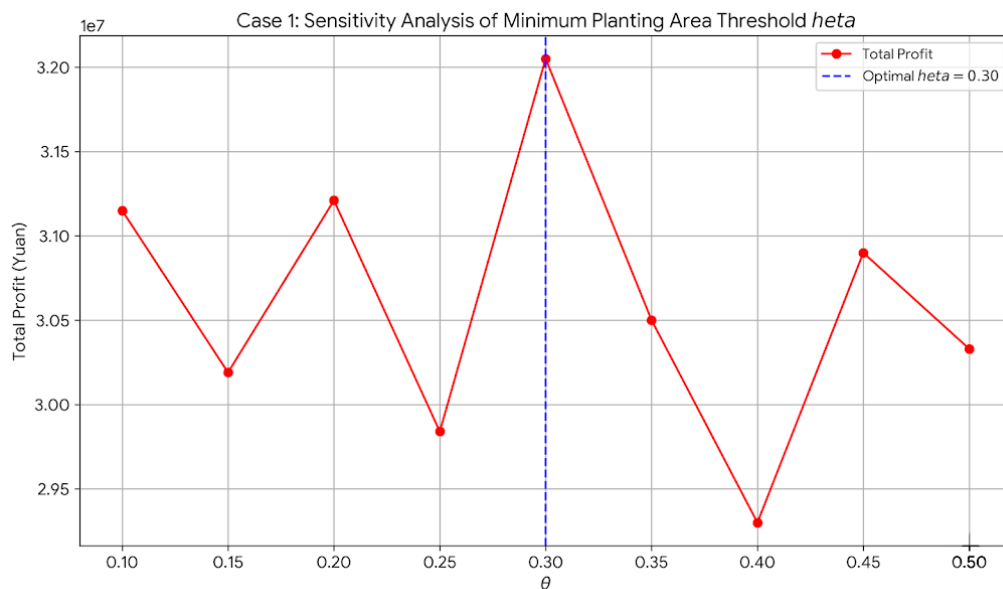


Figure 3. Sensitivity analysis of minimum planting area threshold  $\theta = 0$  for Case 1

When  $\theta$  is small, the overly fragmented planting area increases management costs and easily leads to the total output exceeding the expected sales volume, resulting in unsalable products and economic losses. When  $\theta$  is about 0.30 mu, the total profit reaches the peak. This indicates that this threshold achieves the optimal balance between plot utilization and output control. When  $\theta > 0.40$  mu, the profit declines significantly. This is because the excessively large area constraint forces the model to abandon some small plots with high value, such as smart greenhouses, or to switch to large-area crops with low unit profit, resulting in unreasonable resource allocation and waste of land resources.

The genetic algorithm initialized based on the greedy strategy is used to solve the model, and a comparative experiment is conducted with the traditional randomly initialized genetic algorithm. The experimental results are shown in the algorithm convergence comparison figure 4:

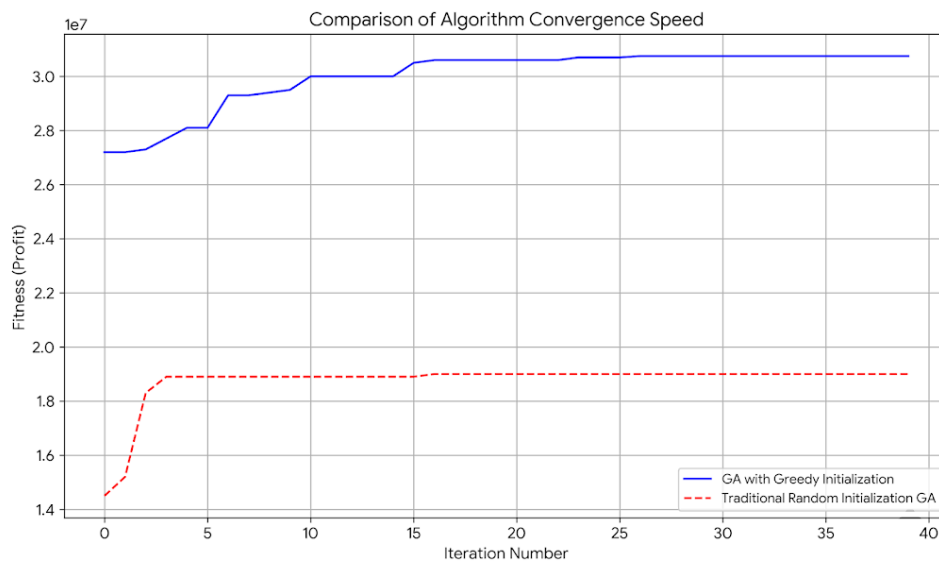


Figure 4. Comparison of algorithm convergence speeds

It should be noted that while the 15-generation convergence demonstrates high efficiency, it may also imply that the algorithm prioritizes local exploitation within high-profit regions. Future work will explore increasing the mutation rate or incorporating simulated annealing to further enhance global exploration. It can be observed from the figure that the GA based on greedy initialization shows an extremely high fitness starting point in the first generation, while the fitness of the traditional GA in the initial stage is extremely low. Through greedy initialization (Step 2), the algorithm first selects high-yield and constraint-compliant crop combinations as “seed genes”, which greatly reduces the search space. The algorithm operation results show

that the optimized algorithm basically maintains stability after 15 generations, and the convergence speed is significantly improved compared with the traditional algorithm. Optimal Profit is shown in table 1.

Table 1. Optimal Profit

$\theta$ (mu)	Profit (yuan)
0.10	31153106.25
0.15	30190999.75
0.20	31212625.25
0.25	29846872.50
0.30	32055165.00
0.35	30499209.00
0.40	29317567.50
0.45	30911644.75
0.50	30329679.50

According to the above table, if the part exceeding the expected output is treated as unsalable, the optimal profit from 2024 to 2030 is 32055165.00 yuan.

Case 2: Excess Part Is Sold at 50% of the 2023 Sales Price

For Case 2, the sensitivity analysis of the minimum planting area threshold  $\theta$  is also conducted, and the results are shown in the figure 5.

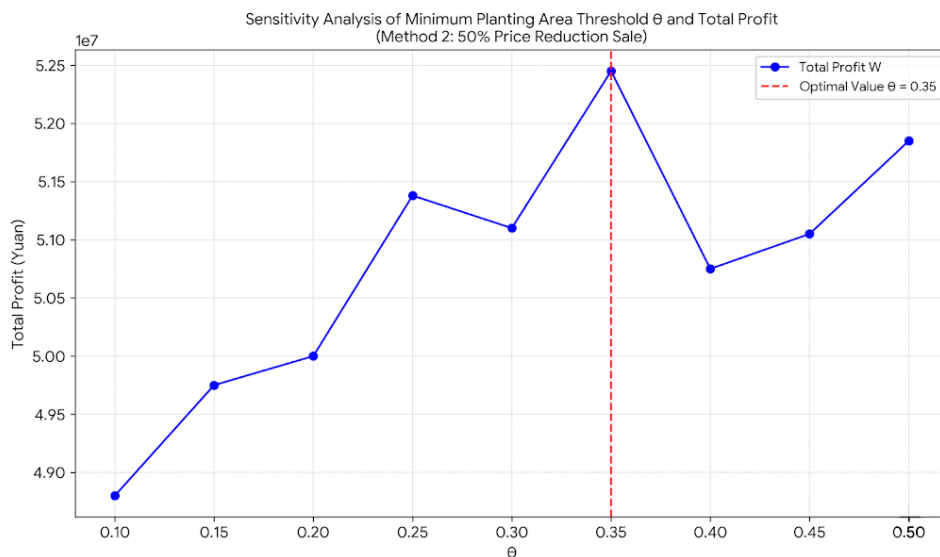


Figure 5. Sensitivity analysis of minimum planting area threshold  $\theta$  for Case 2

When the part exceeding the expected sales volume is sold at 50% of the 2023 sales price, the sensitivity between the minimum planting area threshold  $\theta$  and the total profit is different, but the overall trend is consistent. When  $\theta = 0.35$ , the total profit reaches the optimal value. In the range of  $\theta < 0.1$ , the profit has been close to the optimal value, but the overly fragmented planting area increases the management difficulty, which is inconsistent with the actual agricultural planting situation, so smaller  $\theta$  values are not considered. According to the above table, if the excess part is sold at 50% of the 2023 sales price, the optimal profit from 2024 to 2030 is 52463850.75 yuan.

## ROBUST CROP PLANTING STRATEGY MODEL IN DYNAMIC FLUCTUATING ENVIRONMENTS

### Common Adjustments: Parameter Dynamicization

#### *Expected Sales Volume Growth*

Wheat and Corn:  $N_{i,t} = N_{i,2023} \times (1 + 0.03)^{t-2023}$

Other crops:  $N_{i,t} = N_{i,2023} \times (1 + 0.02)^{t-2023}$

These growth rates (3% and 2%) are set as representative hypothetical parameters based on local market trends to test the model's dynamic response and robustness; they are not intended as universal statistical constants.

#### *Yield per Mu Change*

$$O_{ij,t} = O_{ij,2023} \times (1 + \delta_{ij,t}) \quad (12)$$

Where  $\delta_{ij,t} \sim U(-0.1, 0.1)$  (uniform distribution within  $\pm 10\%$ ).

#### *Planting Cost Growth Change*

$$C_{ij,t} = C_{ij,2023} \times (1 + 0.05)^{t-2023} \quad (13)$$

#### *Sales Price Change*

Grain crops: Stable and unchanged,  $P_{i,t} = P_{i,2023}$

Vegetable crops:  $P_{i,t} = P_{i,2023} \times (1 + 0.01)^{t-2023}$

Edible fungi:  $P_{i,t} = P_{i,2023} \times (1 + 0.03)^{t-2023}$

In particular, Morchella is fixed at 5%:  $P_{41,t} = P_{41,2023} \times (1 + 0.05)^{t-2023}$

## Model Adjustments for Different Cases

### Case 1: Excess Part of Expected Sales Volume Is Unsalable

In the deterministic model of Problem 1, the algorithm often plants accurately to fill the expected output. However, in Problem 2, the yield per mu has a fluctuation of  $\pm 10\%$ . If planting according to the mean value, once the planting year is "bumper harvest" leading to output exceeding the expected output, the additional production cost will be directly lost. Therefore, the objective function of this case should add a penalty term:

$$W_{1,t} = \sum_{i=1}^{54} \sum_{j=1}^6 [\min(O_{ij,t}x_{ijtm}, N_{i,t}) \cdot P_{i,t} - C_{ij,t}x_{ijtm} - \lambda \cdot \max(O_{ij,t}x_{ijtm} - N_{i,t}, 0) \cdot C_{ij,t}] \quad (14)$$

Where  $\lambda$  is the penalty coefficient.

### Case 2: Excess Part of Expected Sales Volume Is Sold at a 50% Discount

Although the price is reduced by 50%, if  $0.5 \times P_{i,t}$  is still higher than the unit planting cost of the crop, then over-planting can still contribute profits. However, in Problem 2, the planting cost increases by 5% every year, and the price of some crops is falling, which means that some crops will enter a situation of more planting and more losses in the later period. For this reason, this paper establishes a piecewise profit function and dynamically calculates the marginal contribution rate of each year:

$$\text{Marginal Profit}_{i,t} = \begin{cases} P_{i,t} - C_{ij,t} & O_{ij,t}x_{ijtm} \leq N_{i,t} \\ 0.5P_{i,t} - C_{ij,t} & O_{ij,t}x_{ijtm} > N_{i,t} \end{cases} \quad (15)$$

$$W_{2,t} = \sum_{i=1}^{54} \sum_{j=1}^6 [\min(O_{ij,t}x_{ijtm}, N_{i,t}) \cdot P_{i,t} + \max(O_{ij,t}x_{ijtm} - N_{i,t}, 0) \cdot 0.5P_{i,t} - C_{ij,t}x_{ijtm}] \quad (16)$$

## Model Solution

In the early stage of evolution, the value of the total profit fitness function shows explosive growth, which benefits from the greedy initialization strategy. This strategy effectively eliminates a large number of illegal solutions, making the population quickly move closer to the high-profit region. In the middle stage of evolution, the slope of the curve gradually flattens, indicating that the population has found the optimal crop replacement path in the multi-dimensional solution space through continuous crossover and mutation

operations. In Case 2, due to the better continuity of the profit function than Case 1, the algorithm shows a smoother convergence trajectory and higher final expected profit.

Through the sensitivity test of the minimum planting area  $\theta$  in the interval [0.1, 0.5], it is found that the total profit has a significant response to the minimum planting area constraint. In both Case 1 and Case 2, the profit curve shows a trend of first rising and then falling or reaching a peak in a specific interval. In Case 1, the total profit reaches the optimal value when  $\theta = 0.45$  ; in Case 2, the total profit reaches the optimal value when  $\theta = 0.35$  .

The spatiotemporal heatmap intuitively depicts the crop succession during the planning period of 2024-2030. The analysis results show that with the advancement of time, the structure of planted crops has undergone a significant “structural migration”. Since Problem 2 assumes that the expected sales volume of wheat and corn increases year by year, the later stage of the heatmap shows a steady increase in the coverage rate of these crops in the plots; at the same time, facing the annual 5% increase in planting costs, the model tends to reduce the planting of vegetables with rapidly falling sales prices (such as edible fungus No. 41) or large fluctuations in yield per mu per unit time in the later stage; in addition, the color block alternation law presented in the figure also verifies that the model strictly follows the constraints of “planting legumes at least once every three years” and “prohibiting monocropping”.

Code operation results are shown in table 2 and 3:

Table 2. Excess inventory remains unsold

Table 2. Excess inventory remains unsold

Case 1 (Excess part is unsalable)	Case 1 (Excess part is unsalable)
Number of Evolutions	Profit (yuan)
1st	28,488,543.82
2nd	28,585,448.87
3rd	30,503,978.61
4th	30,503,978.61
5th	30,753,035.99
6th	31,645,006.71
.....	.....
32nd	32,402,230.43
33rd	32,402,230.43
34th	32,402,230.43
.....	.....
40th	32,402,230.43

Case 1: When  $\theta = 0.45$ , the optimal profit of the crop planting plan from 2024 to 2030 is 32,402,230.43 yuan.

Excess part is sold at a 50% discount is shown in table 3.

Table 3. Excess part is sold at a 50% discount

Table 3. Excess part is sold at a 50% discount

Number of Evolutions	Profit (yuan)
1st	38,998,671.05
2nd	38,998,671.05
3rd	39,719,653.10
4th	40,229,386.99
5th	41,341,782.62
6th	41,341,782.62
.....	.....
23rd	43,600,060.33
24th	43,600,060.33
25th	43,610,936.58
.....	.....
40th	43,610,936.58

Case 2: When  $\theta = 0.45$ , the optimal profit of the crop planting plan from 2024 to 2030 is 43,610,936.58 yuan.

## CONCLUSIONS

This study systematically addresses the challenge of crop layout under multiple constraints by constructing a planting optimization model that integrates physical mechanism constraints with heuristic search algorithms. It validates the superiority of the greedy initialization genetic algorithm in enhancing both solution speed and quality. The research clarifies the nonlinear influence of planting management thresholds on final yields and provides a quantitative decision pathway for agricultural operations under varying market risk preferences. However, this study retains certain limitations. For instance, future sales volume projections primarily relied on 2023 baseline data, insufficiently accounting for systemic risks stemming from macroeconomic fluctuations. Additionally, the model's assumptions regarding growth rates for crops like wheat and corn were relatively simplistic, failing to fully capture the nonlinear disturbances to yield per acre caused by complex climate variations. Future research should focus on integrating multi-source climate data with more sophisticated market demand forecasting models. Furthermore, efforts should be made to combine this optimization framework

with real-time meteorological early warning systems to enhance the robustness and adaptive capacity of planting strategies under extreme environmental conditions.

#### *Author Contributions*

I conceived and designed the study, performed the data analysis, drafted the manuscript.

#### *Conflicts of Interest*

The author declares no conflict of interest.

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