# Research on Crop Planting Strategy Decision Model and Robustness Study Based on Simulated Annealing Algorithm

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**Abstract:** This paper presents a novel decision-making model for crop planting strategies based on the Simulated Annealing (SA) algorithm under static market conditions. The model incorporates two distinct sales scenarios: surplus leading to unsold produce and wastage, and selling the excess at half price. Decision variables include crop planting area, yield, unit sales price, and year sequence, integrated with a quantitative constraint assessment system consisting of a diversity coefficient, crop rotation threshold, area threshold, and a crop-terrain adaptability matrix. The SA algorithm's application yielded maximum profits of approximately 14.1 million RMB and 33.27 million RMB for the two scenarios, respectively. Furthermore, the model extends to account for market volatility and rising costs through an orthogonal experimental design to select representative test points, resulting in an optimized crop planting model inclusive of uncertainty factors. The optimized strategy predicts a profit of approximately 14.9 million RMB, with a profit growth rate of 5.67%, demonstrating significant advantages over static strategies across various market conditions. Robustness analysis under different market fluctuations confirmed the model's stability, with profit variations remaining within acceptable limits.

## 1. Introduction

Crafting efficient, flexible agricultural strategies tailored to the unique needs of rural areas is crucial for reducing farming uncertainties, fostering sustainable growth, and enhancing the economic returns vital for the advancement of rural economies.

Debnath Mridusmita and colleagues [1] introduced a model for irrigation-food-environment-opportunity-constrained (IFEC) planning. This model aims to simultaneously optimize the allocation of crop areas, irrigation water, and leftover fertilizers while considering the uncertainties in water inflow and the crop preferences of farmers. To ascertain the optimal distribution of irrigation water for favored crops, eight models for the optimization of irrigation water allocation were developed, alongside conducting sensitivity analyses on the bias in water releases downstream and the area allocated for vegetable crops.

Esteso Ana and her team [2] developed a conceptual framework for tackling the issue of scheduling crop planting and harvesting, alongside a multi-objective optimization model for organizing the planting, harvesting, and subsequent processing of medicinal plants. This model accounts for varying molecular concentrations, distribution, storage needs, and minimal intervals between harvests.

Tavares Cassiano and Munari Pedro [3] introduced a strategic planning tool for citrus farming decision-making, utilizing mathematical models and algorithms designed to meet practical requirements. Their findings demonstrate that this approach significantly bolsters decision-making support, potentially increasing citrus production substantially over a 30-year planning horizon.

López Ramos Francisco and associates [4] designed two optimization models framed within mixed integer linear programming. The first aims to minimize total production costs while meeting demand in each planning period, whereas the second seeks to maximize farmer profits by determining the demand fulfillment ratio for each period.

Ahumada Omar and his team [5] unveiled a tactical planning model for the cultivation and

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distribution of fresh produce, taking into account the impact of weather conditions on potential yields. Employing mixed integer planning, this model offers cultivation and marketing recommendations to maximize profits for individual farmers or collectives.

In the face of fluctuating market demands and the inherent risks in agricultural production, optimizing crop planting strategies becomes crucial for maximizing profitability and resource utilization. Traditional models often fall short in accommodating the dynamic nature of agricultural markets and the uncertainty of environmental factors. This paper introduces a decision-making model for crop planting strategies that leverages the Simulated Annealing (SA) algorithm to navigate static market conditions efficiently. By considering various sales scenarios, including the potential for unsold surplus and discounted excess sales, the model aims to optimize decision variables such as planting area, yield, and sales price. It integrates a comprehensive set of constraints, including diversity coefficients, crop rotation, and area thresholds, alongside a crop-terrain adaptability matrix, to establish a quantitative evaluation system. The paper further explores the model's adaptability to market volatility and cost fluctuations, employing an orthogonal experimental design to enhance research efficiency and model robustness.

## 2. A decision model for planting strategies under static market conditions

### 2.1 Modeling

#### 2.1.1 Total profit function

List the total annual profit function of the plot (including greenhouses) when the product that exceeds the expected sales will be stagnant and wasteful. The total annual production $Q_{jn}$ of vegetables of category j is:

$$Q_{jn} = \sum_{t=T}^{T+1} \sum_{i=1}^{54} A_{ijnt} M_i Y_{ijnt}, t \in \{T, T+1\} \tag{1}$$

When $Q_{jn} \leq S_i$, the jth category of vegetables is profitable in the nth year:

$$W_{jn} = Q_{jn} P_j - \sum_{t=T}^{T+1} \sum_{i=1}^{54} A_{ijnt} M_i C_{ijnt} \tag{2}$$

When $Q_{jn} > S_j$, the jth category of vegetables is profitable in the nth year:

$$W_{jn} = \cdot S_j P_j - \sum_{t=T}^{T+1} \sum_{i=1}^{54} A_{ijnt} M_i C_{ijn} \tag{3}$$

The total profit W expression is:

$$W = \sum_{j=1}^{41} \sum_{n=1}^{7} W_{jn} \tag{4}$$

Since the selling price of double-seasoned plants varies across seasons, and only smart sheds can grow crops against the seasons, the smart sheds are considered separately. When t is taken as T, it represents that the requested plot is other than the smart shed, and when t is taken as T+1, it represents that the requested plot is the smart shed.

Among them, $A_{ijn}$ is the ratio of the area of planting the jth plant in the i block of land in the nth year, $M_i$ is the area of the i block of land (acres), $S_j$ is the expected sales of the jth plant, $Y_{ijn}$ is the acre yield of planting the jth plant in the i block of land in the nth year (pounds), $P_j$ is the unit price of planting the jth plant (yuan/pound), and $C_{ijn}$ is the cost of planting the jth plant in the i block of land in the nth year (yuan/mu). Yuan/mu).

The total annual profit function of the plot (including the greenhouse) when products exceeding the expected sales volume are treated at half price is as follows. The total annual production of vegetable type j, $Q_{jn}$, is:

$$Q_{jn} = \sum_{t=T}^{T+1} \sum_{i=1}^{54} A_{ijnt} \cdot M_i \cdot Y_{ijnt}, t \in \{T, T+1\} \tag{5}$$

When $Q_{jn} \leq S_i$, the jth category of vegetables is profitable in the nth year:

$$W_{jn} = Q_{jn} \cdot P_j - \sum_{t=T}^{T+1} \sum_{i=1}^{54} A_{ijnt} M_{ijn} C_{ijnt} \tag{6}$$

When $Q_{jn} > S_j$, the jth category of vegetables is profitable in the nth year:

$$W_{jn} = S_j P_j + (Q_{jn} - S_j) \cdot \frac{R_j}{2} - \sum_{t=T}^{T+1} \sum_{i=1}^{54} A_{ijnt} M_{ijn} C_{ijnt} \quad (7)$$

The total profit W expression is:

$$W = \sum_{j=1}^{41} \sum_{n=1}^{7} W_{jn} \quad (8)$$

**2.1.2 Decision variable Aijn**

In this paper, the constraints are:

(1) No successive planting of the same crop is allowed

(2) Soybean can be planted at least once in three years

(3) The area of crops planted per acre cannot be too small

(4) The planting of the same crop cannot be too spread out

(5) Crop requirements for terrain

(6) crop requirements for the season

1) For constraints (5) (6), there is the Table 1:

Table 1 Quantitative list of crop-terrain-season adaptation constraints

| 1 means plantable 0 means not plantable | Grain Legumes (1-5) | Grain (7-16) | Grain rice (17) | Vegetables (17-34) | Vegetables (35-37) | Edible Mushrooms (38-41) |
|---|---|---|---|---|---|---|
| flat dryland | 1 | 1 | 0 | 0 | 0 | 0 |
| Terraced land | 1 | 1 | 0 | 0 | 0 | 0 |
| Hillside land | 1 | 1 | 0 | 0 | 0 | 0 |
| Watered land (single season) | 0 | 0 | 1 | 0 | 0 | 0 |
| Watered land (first season) | 0 | 0 | 0 | 1 | 0 | 1 |
| Watered land (second season) | 0 | 0 | 0 | 0 | 1 | 0 |
| Ordinary greenhouse (first season) | 0 | 0 | 0 | 1 | 0 | 1 |
| Ordinary greenhouse (second season) | 0 | 0 | 0 | 0 | 0 | 1 |
| Intelligent greenhouse (first season) | 0 | 0 | 0 | 1 | 0 | 0 |
| Intelligent greenhouse (second season) | 0 | 0 | 0 | 1 | 0 | 0 |

Where 1 means plantable and 0 means not plantable.

In order to facilitate the study, the decision variables can be regarded as n two-dimensional matrices, each of which represents a matrix of the percentage of area in which the jth plant is grown in the ith plot in a certain year. Since the two seasons of crops are mutually exclusive in all plots except the smart greenhouses, the sum of the percentages in the same plot in the same year is 2 to indicate that two seasons of crops have been planted in that plot, such as the sum of the rows of the matrices is 2, which means that two seasons of crops have been planted in that plot.

The python code was used to constrain the matrix of decision variables according to the Table 1, and the following matrix was generated to meet the requirements (the collocation is not shown in the Fig. 1 to emphasize the adaptive relationship):

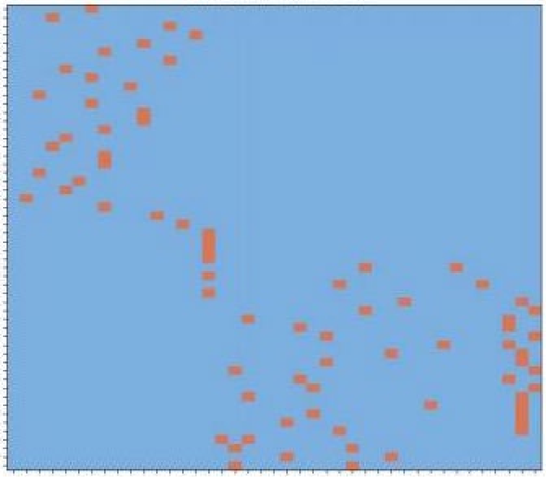

Fig. 1 Stochastic Crop-Topography-Seasonal Adaptability Constraint Matrix

Here, smart greenhouses need to be considered separately:

Since there are counter-seasonal planting situations in the smart greenhouses and the selling price of the same crop varies from season to season, we extend the 21 plants that can be planted in the smart greenhouses to 42 planting situations, which are cowpea (first season),

Cowpea (second season), Knife bean (first season), Cowpea (second season), etc., so that the decision variables of the smart greenhouse correspond to n 4×42 matrices.

2) Considering constraint (1), the problem of continuous cultivation does not exist as long as constraints (5) and (6) are met, because the seasonal requirements for double-season crops in irrigated land and ordinary greenhouses are more stringent. Here, we only need to consider the case of continuous cropping for single-season crops and smart greenhouses.

For single-season crops, there are:

$$j \in [1,16], n \in [1,7], i \in [1,34], A_{ijn}.A_{ij(n+1)} = 0 \tag{9}$$

For smart barns, there are:

$$A_{ijn}A_{i(j+21)n} = 0 \tag{10}$$

$$A_{ijn}A_{i(j+21)(n-1)} = 0 \tag{11}$$

3) consider constraint (2), there:

$$\mathrm{i} \in [1,54], n \in [1,5], \sum_{j=1}^{19} (A_{ijn} + A_{ij(n+1)} + A_{ij(n+2)}) \geq 1 \tag{12}$$

$$j \in [J_{1\sim5}, J_{17\sim19}.] \tag{13}$$

4) Considering constraint (3), we establish a threshold of 0.4 to determine whether the area planted to a single crop is too small, i.e:

$$A_{ijn} \geq \cdot\ 0.4 \tag{14}$$

5) solution of constraint (4)

The ε-constraint method comes to be a strategy specifically designed to deal with multi-objective optimization problems. In a multi-objective optimization scenario, one of the objective functions is chosen as the main optimization objective, and the rest of the objective functions are transformed into constraints. In this way, a complex multi-objective optimization problem is transformed into a relatively simple single-objective optimization problem, which contains one main optimization objective and a series of constraints transformed from other objectives. In this way, the ε-constraint method helps to find a balance between multiple conflicting objectives, so that a solution that satisfies all constraints and optimizes the main objective as much as possible can be obtained.

Here, we calculate the decentralization indicator ε1 for 2023 by using Eq:

$$\sum_{j=1}^{p}\left(\sum_{j=1}^{n} I(Aijn > 0)\right) = \varepsilon \quad (15)$$

Using this indicator as the dispersion threshold, the constraint equation for condition (4) is obtained:

$$\sum_{j=1}^{p}\left(\sum_{j=1}^{n} I(Aijn > 0)\right) \le \varepsilon_1 \quad (16)$$

### 2.1.3 Solving the model

(1) Simulated Annealing Algorithm

The simulated annealing algorithm, as a heuristic search algorithm for solving optimization problems, simulates the process of metal cooling to a crystalline state after being heated. The algorithm first sets the initial solution, the initial temperature and the cooling rate, and then generates a new solution randomly in the neighborhood of the current solution, accepts the new solution with a certain probability (the probability is related to the difference between the temperature and the objective function), and gradually reduces the temperature. This mechanism enables the algorithm to go beyond the local optimal solution to find the global optimal solution.

The steps of the algorithm are as follows.

1) Initialization.

Choose a starting solution x0 and a starting temperature T0.

Select a temperature drop rate α, usually between 0.8 and 0.99.

Determine a termination criterion, such as reaching the maximum number of iterations or the temperature dropping to a certain threshold.

2) Iteration.

Generate a new solution x' in the neighborhood of the current solution x.

Calculate the difference between the objective function values of the new solution x' and the current solution x ΔE = f(x') - f(x).

Decide whether to accept the new solution x' or not based on the probability P = exp(-ΔE/T).

Reduce the temperature T = α .T.

3)Termination.

When the termination condition is reached (e.g., the maximum number of iterations is reached or the temperature drops to a certain threshold), the current optimal solution is output.

(2) Results of the model

The simulated annealing algorithm is run through the matlab program to solve the above model, and the maximum profit iteration diagram for case 1 can be obtained:

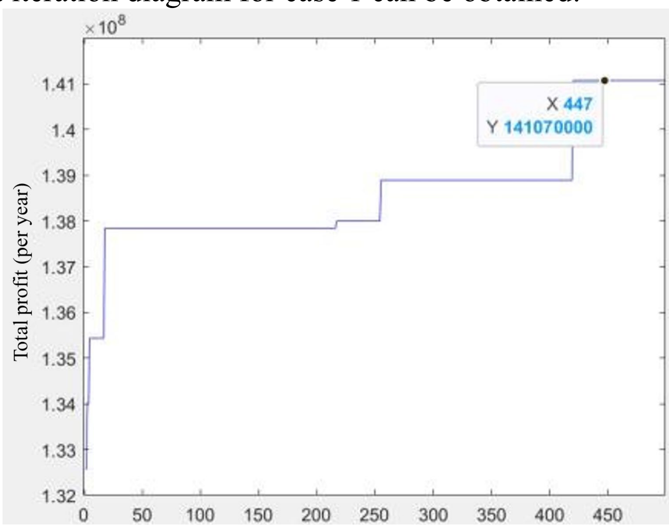


Fig. 2 Maximum Profit Iteration Chart for Case 1

As can be seen from Fig. 2, it basically converges to the neighborhood of the optimal solution at about 430 iterations, and at this time, the total profit from 2024 to 2030 is 1.4107 × 108 RMB.

The iterative diagram of maximum profit for case two is shown in Figure 3.

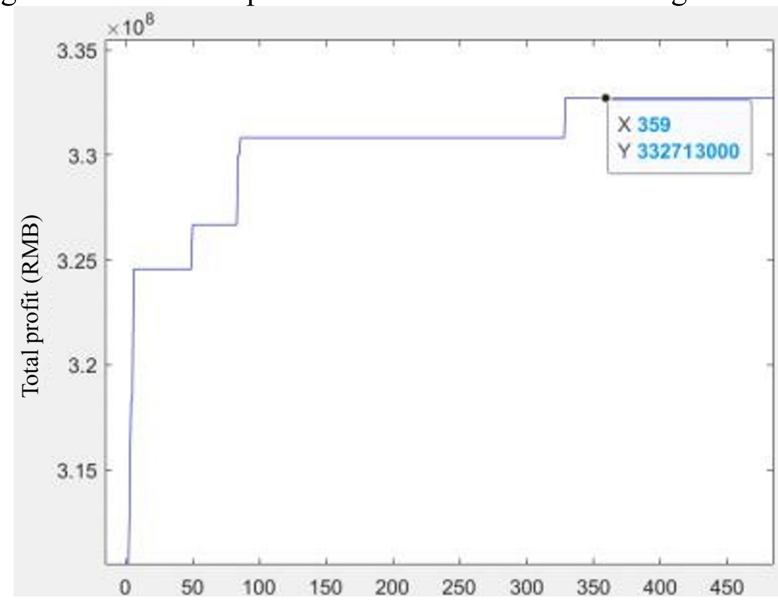


Fig. 3 Maximum Profit Iteration Plot for Case 2

As can be seen from the figure, Case 2 basically converges to the neighborhood of the optimal solution at about 330 iterations, and at this time, the total profit from 2024 to 2030 is 3.32713×108 yuan.

## 3. Planning models considering fluctuations

### 3.1 An uncertainty scheme based on orthogonal experiments

#### 3.1.1 Orthogonal experimental design

Orthogonal experimental design (OED) is a highly efficient experimental strategy that can be used to study problems involving multiple factors and levels. Its core principle is to carefully select a representative set of test points from a large comprehensive experimental space, which not only ensures the comprehensiveness of the experiment, but also ensures the comparability of results among different test points. In this way, the orthogonal experimental design can maintain the validity of the experimental results while significantly reducing the number of experiments to be conducted, thus improving the efficiency of experimental research.

The process of orthogonal experimental design is as follows:

1) Determine the objectives of the experiment:

Define the purpose of the experiment and the factors to be studied. 2. select factors and levels:

Determine the factors (independent variables) to be examined in the experiment.

Determine levels (different set values or conditions) for each factor.

2) selecting orthogonal tables:

Select an appropriate orthogonal table based on the number of factors and levels. An orthogonal table is a special kind of matrix that is used to organize an experiment to ensure that each level of each factor occurs evenly throughout the experiment.

3) Design the experimental program:

Based on the selected orthogonal table, assign the factors and levels to the rows and columns of the table. Ensure randomization of the experiment to reduce the effect of other uncontrolled factors.

4) Conducting the experiment:

Execute the experiment according to the designed protocol and record the experimental conditions and results.

### 3.1.2 Uncertainty Factors

The fluctuation of each uncertainty factor in this problem is shown in the table 2:

Table 2 Range of uncertainty fluctuations

| Item | fluctuation range |
|---|---|
| Annual growth rate of wheat and corn sales | 5%~10% |
| Fluctuations in sales of crops other than wheat and corn | -5%~5% |
| Fluctuation of acreage production | -10%~10% |
| Annual growth rate of planting costs | 5% |
| Annual growth rate of vegetable prices | 5% |
| Annual rate of price contraction for edible mushrooms other than morel mushrooms | 1%~5% |
| Annual contraction rate of price of morel mushrooms | 5% |

Here, we assume that the percentage fluctuation of uncertainties from 2024 to 2030 are all positive. The L16 ($2^7$) orthogonal real program is established as shown in the Table 3:

Table 3 Orthogonal experimental protocol

| Number of experiments | Expected annual growth rate of wheat and corn sales (rn) | Expected sales volume fluctuations for crops other than wheat and corn (σn) | Fluctuation in yield per acre (yn) | Annual rate of increase in planting costs (l) | Vegetables Annual price growth rate (m) | Annual rate of price contraction for edible mushrooms other than morel mushrooms (m) | Annual price contraction rate of edible mushrooms other than morel mushrooms (k) |
|---|---|---|---|---|---|---|---|
| 1 | 6% | 2% | 6% | 5% | 5% | 1% | 5% |
| 2 | 6% | -3% | -1% | 5% | 5% | 2% | 5% |
| 3 | 5% | -2% | 6% | 5% | 5% | 3% | 5% |
| 4 | 7% | -1% | -1% | 5% | 5% | 1% | 5% |
| 5 | 10% | 0% | -5% | 5% | 5% | 4% | 5% |
| 6 | 9% | -5% | -2% | 5% | 5% | 5% | 5% |
| 7 | 5% | 3% | 1% | 5% | 5% | 5% | 5% |
| 8 | 7% | -3% | -1% | 5% | 5% | 4% | 5% |
| 9 | 8% | 4% | 0% | 5% | 5% | 5% | 5% |
| 10 | 5% | -1% | 2% | 5% | 5% | 3% | 5% |
| 11 | 10% | 5% | -7% | 5% | 5% | 3% | 5% |
| 12 | 5% | 3% | 6% | 5% | 5% | 5% | 5% |
| 13 | 6% | 2% | 4% | 5% | 5% | 3% | 5% |
| 14 | 7% | 4% | 0% | 5% | 5% | 2% | 5% |
| 15 | 10% | -1% | -4% | 5% | 5% | 4% | 5% |
| 16 | 6% | 2% | 8% | 5% | 5% | 4% | 5% |

The orthogonal experimental scheme allows us to randomly select 7 rows for the fluctuation of crop indicators from 2024 to 2030.

### 3.2 Model solution

Here, a similar mathematical model can be developed based on the previous approach. It will not be repeated here.

The iterative plot of its maximum profit is drawn by matlab as shown in Fig. 4.

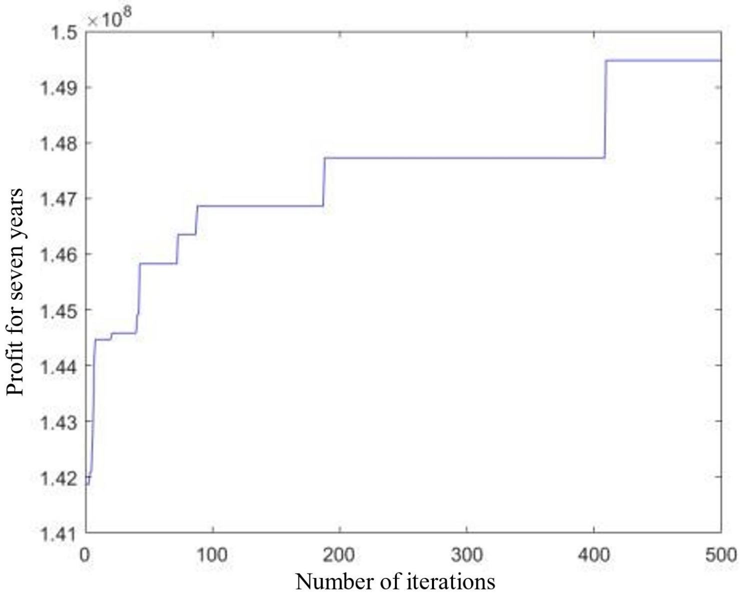


Fig. 4 Iterative chart of maximum profit in the case of volatility

As can be seen from the Figure 4, it basically converges to the neighborhood of the optimal solution at 400 iterations, at which time the total profit y in 2024~2030 is about \$1.495×108.

### 3.3 Robustness analysis

For the robustness analysis of the model, another set of fluctuation cases were selected and their iterative plots are shown in Figure 5:

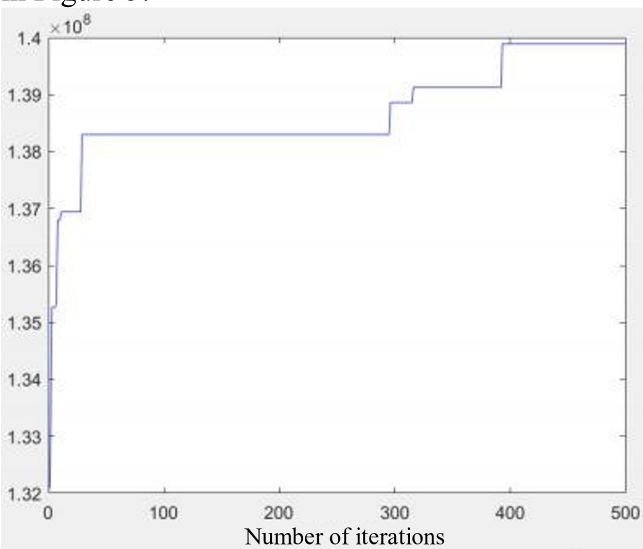


Fig. 5 Iterative plot of maximum profit for another set of volatile scenarios

This result is analyzed as reasonable, and it can be seen that the model is robust, i.e., the model has strong stability and reliability.

## 4. Summary

The research successfully demonstrates the application of the Simulated Annealing algorithm in optimizing crop planting strategies under both static and uncertain market conditions. By meticulously constructing a decision-making model that accounts for surplus scenarios, diversity in planting, and market and cost uncertainties, the study offers a robust strategy for agricultural decision-making. The findings highlight the model's capability to achieve substantial profits, with significant improvements over static strategies, indicating a potential for higher income levels across varying market scenarios. The robustness analysis further underscores the model's stability, showcasing its resilience to market fluctuations with profit variations remaining within acceptable bounds. This study not only contributes a novel approach to agricultural strategy optimization but also sets a foundation for future research in enhancing the resilience and profitability of crop planting decisions amidst market and environmental uncertainties.

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