# Genetic Algorithm-Based Crop Planning Optimization: A Modeling Study on Price Sensitivity and Crop Rotation Constraints

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**Abstract:** Agricultural cropping planning in mountainous areas faces challenges such as crop diversity, plot heterogeneity and market uncertainty. To this end, this paper constructs a plot optimization model for the years 2024-2030 for 41 types of crops in rural mountainous areas of North China, with the objective of maximizing net returns. The model is based on planting and yield data in 2023, and considers two market scenarios: overproduction of crops in Scenario 1 is stagnant and unprofitable, and overproduction is sold at a 50% discount in Scenario 2. The model introduces a price-sensitive volume discount mechanism, which maps price reduction to volume reduction through crop sensitivity coefficients to characterize the pattern of change in returns. The model combines a number of agricultural constraints, such as plot suitability, three-year crop rotation, continuous crop limitation, minimum area and concentration, etc., and is optimized year by year using genetic algorithms. The results show that Scenario 1 favors the allocation of high profit crops (e.g., morel mushrooms, elm yellow mushrooms) and realizes about 45.2 million yuan net return, which is suitable for the scenario of limited market capacity; Scenario 2 tends to be high yielding crops (e.g., soybeans, cucumbers) and realizes about 17 million yuan return, which is suitable for the environment of demand growth or discount price stability. The study provides optimization paths for mountain agriculture to adapt to different market scenarios.

## 1. Introduction

### 1.1. Background and Motivation

In the context of China's rural revitalization strategy, optimizing crop cultivation strategies has become an important path to promote agricultural modernization [1] . Agriculture in the mountainous regions of North China faces the challenges of fragmentation of arable land and ecological sensitivity, and at the same time needs to take into account food security and farmers' income. Rational planning of crop layout not only helps to avoid the yield risk caused by climate fluctuations, but also improves the sustainability of land use by optimizing the match between land resources and crop demand. Under the current background of increased fluctuations in agricultural markets, it is particularly important to develop differentiated planting plans according to local conditions.

### 1.2. Problem Statement

The target village of the study is located in the mountainous region of North China, and currently has 34 open cultivated fields with a total area of 1,201 mu, which are divided into four categories: arid land, terraced land, hillside land and watered land. In addition, there are 16 ordinary greenhouses and 4 intelligent greenhouses (each with an area of 0.6 mu) in the village. There are differences in the types and seasons of crops suitable for different plot types: most open plots are suitable for only one



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crop season per year, while watered land and greenhouses can support two seasons per year. For the convenience of table display and rule definition, this paper adopts letter code A-F to indicate six types of cultivated land, and the specific correspondence is detailed in Appendix A. The crop planting requirements as shown in Table 1.

Table 1 Crop planting requirements.

| Crop name | Crop type | Cultivated land | Cultivation period | Remarks |
|---|---|---|---|---|
| soybean, black bean, red bean<br>mung bean, climbing bean | Grain | A, B, C | Single-season planting | Beans |
| wheat, corn, millet, sorghum<br>buckwheat, pumpkin<br>sweet potato, oat, barley | | | | |
| rice | | D | Single-season planting | |
| cowpea, snap bean, kidney bean | Vegetables | D, E | First season | Beans |
| potato, tomato, eggplant, spinach<br>green pepper,cauliflower,cabbage<br>celtuce, baby bok choy, cucumber lettuce, pepper,water spinach<br>yellow-heart Chinese cabbage, celery | | F | First season<br>Second season | |
| Chinese cabbage, white radish<br>red radish | | D | Second season | |
| Hericium erinaceus<br>shiitake mushrooms, Pleurotus eryngii morel mushrooms | Edible mushrooms | E | Second season | |

In addition, cultivation is constrained by crop rotation requirements (e.g., legume crops need to be rotated once every three years) and marketability [2]. Based on planting, cost, yield and sales data for the 2023 crop, this study attempts to plan the optimal planting strategy for the seven-year period 2024-2030, considering the following two market scenarios:

1) The production in excess of the projected market sales will be stagnant and unmarketable (Scenario I);

2) The excess can be sold at a discount of 50% of the 2023 market price (Scenario II).

## 2. Data Preparation and Assumptions

### 2.1. Data Sources and Description

The data for this study mainly come from two parts: the information on cultivated land and crop adaptation rules given in Annex 1, and the actual planting records and sales data of various crops in 2023 contained in Annex 2. Among them, Annex 1 provides information on the area and classification of a total of 34 open fields and 20 greenhouses (including 16 ordinary greenhouses and 4 intelligent greenhouses), totaling 1,201 acres. Annex 2 details the cost of cultivation, acre yield, selling price range and actual sales volume of each crop under different plots and seasons.

### 2.2. Assumptions and Parameter Definitions

In order to construct a stable and solvable mathematical model, this paper proposes the following assumptions based on the analysis of the actual problem:

- It is assumed that all crops are sold immediately after harvesting in each season and there is no stock or hold-up;
- Assume that in Problem I, the acre yield, cost and selling price of each type of crop remain the same as in 2023;
- Assuming that in problem two and future extensions, the variables of interest (sales volume, price, and cost) will fluctuate normally around their historical means;
- It is assumed that the price sensitivity of the crop has a stable linear mapping relationship with the change in sales volume and is dependent on the crop type setting [3];

• Assuming that each plot is planted for a maximum of two seasons in a year and that crops are planted to meet their plot suitability requirements;

• It is assumed that all calculations are done in "acres" for area and "pounds" for yield.

In addition, in order to facilitate the subsequent modeling and matrix operation, this paper defines the coding of various parameters, such as crop number, plot number, plot type number, season number, etc., which are standardized and mapped in the preprocessing stage.

### 2.3. Handling of Missing Values and State Expansion

When organizing the sales data, it was found that the sales table in Annex 2 was missing the sales information related to the first season of the smart greenhouse. However, the planting records of cowpea, cauliflower, cabbage and other vegetables clearly exist in the corresponding planting records. In order to ensure the integrity of the model data, this paper adopts the strategy of "data interpolation under analogous facilities" to calculate the average conversion coefficients of the first season of the intelligent greenhouse relative to the first season of the ordinary greenhouse from the same crop data of the first season of the ordinary greenhouse and the second season of the intelligent greenhouse.

Specifically, the mu yield, planting cost, minimum selling price, maximum selling price of vegetable crops are scaled in the form of average ratio (e.g., the yield coefficient is about 0.90, and the selling price coefficient is about 1.20). Ultimately, the sales data of the first season of the smart greenhouse was supplemented accordingly, effectively improving the coverage and modeling accuracy of the data. Average parameter variation coefficients of intelligent greenhouses relative to ordinary greenhouses as shown in Table 2.

Table 2 Average parameter variation coefficients of intelligent greenhouses relative to ordinary greenhouses.

| Parameter | Ordinary greenhouse | Intelligent greenhouse second season | Coefficients (smart greenhouses/ ordinary greenhouses) |
|---|---|---|---|
| Average mu yield | 6,840 | 6,156 | 0.90 |
| Average planting cost | 3,480 | 3,828 | 1.10 |
| Average lower sales unit price ($) | 4.9 | 5.88 | 1.20 |
| Upper limit of average selling unit price (yuan) | 6.9 | 8.28 | 1.20 |
| Average price reduction | Consistent | Consistent | 1.00 |

This paper extends the state of some of the plot type and season combinations by $\mathcal{F}_k$ denoting the set of plot type numbers that the crop k can be planted under the planting restrictions specified in the title. It is not a mere crop attribute or plot attribute, but a coupled mapping result of both. This strategy not only improves the fineness of modeling, but also makes the model able to match and judge the cropland resources more clearly. The plot type number as shown in Table 3.

Table 3 Plot type number.

| Plot type number | Meaning | Plot type number | Meaning |
|---|---|---|---|
| 1 | Flat and dry land (open cultivated land) | 6 | Smart greenhouse (first season) |
| 2 | Terraces (open cropland) | 7 | Watered land (second season) |
| 3 | Hillside land (open cultivated land) | 8 | Ordinary greenhouses (second season) |
| 4 | Watered land (first season) | 9 | Smart Shed (second season) |
| 5 | Ordinary greenhouse (first season) | | |

Thus the number of plot type where rice is allowed to be grown is {4,7}.

### 3. Price-Sensitivity-Based Yield Adjustment Model

In the process of establishing the crop yield assessment model, in order to accurately describe the market's response mechanism to price fluctuations and marketability, it is necessary to introduce two derived variables, "price decline" and "sales volume decline", and accordingly construct the "actual sales volume" and "sales volume". The expressions of "actual sales" and "total revenue" are constructed accordingly.

a) Price Decrease

PriceDrop is defined as the ratio of the maximum drop to the ceiling price, which is calculated as follows:

$$\Delta P_{k,c,i} = \frac{U_{k,c,i} - L_{k,c,i}}{U_{k,c,i}} \tag{1}$$

Where, $U_{k,c,i}$ and $L_{k,c,i}$ are the upper/lower limit (\$/pound) of the selling price of the crop $k$ on the plot $c$ and season $i$ respectively. This ratio can be regarded as the relative degree of price volatility in the market, and also reflects the magnitude of price discount that the crop may experience in the most unfavorable scenario.

b) Price Sensitivity Coefficient

In order to characterize the responsiveness of different crops to market price fluctuations, this paper introduces the crop Price Sensitivity Coefficient (PSC), which measures the proportion of sales volume reduction caused by a decrease in unit price. The crop sensitivity coefficients by Crop Type as shown in Table 4.

Table 4 Crop Sensitivity Coefficients by Crop Type.

| Crop type code | Crop type name | Sensitivity Coefficient $\varepsilon_{T(k)}$ | Degree of sensitivity |
|---|---|---|---|
| 11 | Grain (legumes) | 0.5 | Slightly less sensitive |
| 12 | Grain (non-legumes) | 0.3 | Low sensitivity |
| 21 | Vegetables (legumes) | 0.7 | Higher sensitivity |
| 22 | Ordinary vegetables | 0.6 | Medium sensitivity |
| 30 | Edible mushrooms | 0.9 | Highly sensitive |

Grain crops (e.g., wheat, corn) are necessities, with strong rigidity of demand and low substitutability, so price changes have less impact on sales, and the sensitivity coefficient is set at 0.3. Legumes (e.g., soybeans, red beans), though belonging to grains, are more widely used (e.g., for oil extraction, soybean product processing), and are moderately elastic in terms of price, and therefore set at 0.5. Common vegetables (e.g., tomatoes, cucumbers) are seasonally strong, with high substitutability, and consumers are more flexible in their response to price changes, and the sensitivity coefficient is set at 0.6. Common vegetables (e.g. tomato, cucumber) are seasonal and highly substitutable, so consumers' response to price changes is more flexible and set at 0.6. Vegetable legumes (e.g. bean curd) are mostly taste-oriented and perishable products, with seasonal fluctuations, so their sensitivity is higher. Edible mushrooms (e.g. shiitake mushrooms, morel mushrooms) have strong non-staple food attributes, unstable supply chain, and high price elasticity, so consumers are prone to reduce purchases when prices rise, with the highest sensitivity coefficient of 0.9 set.

c) Decrease in sales volume

Further, to assess the impact of price fluctuations on marketability, the SalesDrop variable was introduced. This variable is used to measure the proportion of sales reduction triggered by price decline, reflecting the sensitivity of market demand to price changes. According to the theory of "price elasticity of demand" in economics, sales drop can usually be approximated as a linear response to price decline. We construct the following relationship accordingly:

$$\Delta Q_{k,c,i} = \varepsilon_{T(k)} \cdot \Delta P_{k,c,i} \tag{2}$$

Where $\varepsilon_{T(k)}$ denotes the harmonized price sensitivity coefficient corresponding to the crop type (e.g., grain, vegetable, edible mushroom, etc.) to which the crop k belongs. This categorical sensitivity parameter is set in terms of crop types and reflects the average strength of response of different crop types to market fluctuations.

d) Actual sales volume

Based on the relationship between sales decline and production, the **actual sales volume** $S_k$ is further defined as:

$$S_{k,c,i} = Y_{k,c,i} \cdot \left(1 - \varepsilon_{T(k)} \cdot \Delta P_{k,c,i}\right) \tag{3}$$

Where $Y_{k,c,i}$ is the unit yield of each crop on plot c and season i, the expression clearly reflects the negative impact of price volatility on marketability.

In summary, the introduction of price drop and sales drop not only makes the model have stronger market sensitivity and risk characterization ability, but also lays a mathematical foundation for the subsequent multi-objective optimization of risk management and resource allocation.

## 4. Optimization Model Formulation

### 4.1. Decision Variable and Parameter Definition

In order to accurately model the optimization process of crop arrangement of each plot in two planting seasons per year, this paper introduces four-dimensional decision variables:

$$x_{c,t,i} \in K \tag{4}$$

Where $x_{c,t,i}$ denotes the crop number planted in the plot c in the i season of the t year; $c \in \{1, 2, ..., N\}$, denotes the cropland number; $t \in \{1, 2, ..., 7\}$, denotes the planting year (the next seven years); $i \in \{0, 1, 2\}$ is the season number, where $i = 0$ denotes the single season, $i = 1$ denotes the first season, and $i = 2$ denotes the second season; K denotes the set of optional crops, and $k \in K$ denotes the crop number.

The rest of the key parameters are as follows:

- $\mu_c$ : Area (in acres) of parcel c ;
- $\mathrm{LandType}_c$ : Plot type of the parcel c ;
- $\mathcal{F}_k$ : the set of plot types allowed for the crop k (taking into account seasonal expansion);
- $\mathcal{T}(k)$ : the type of crop to which crop k belongs;

$$\mathcal{T}(k) = \begin{cases} 11, & \text{Grain legumes} \\ 12, & \text{Grain crops} \\ 21, & \text{Vegetable legumes} \\ 22, & \text{Ordinary vegetables} \\ 30, & \text{Edible mushrooms} \end{cases} \tag{5}$$

- $\theta_k$ : the upper limit of the total sales volume (in pounds) of the crop k .

### 4.2. Revenue Calculation under Market Scenarios

The objective is to maximize the net revenue, which is defined as the total sales revenue minus the total planting cost:

$$\max \text{ Total revenue} - \text{Total cost} \tag{6}$$

In this model, in order to reasonably estimate the market's acceptance of each type of crop, the price sensitivity-based sales volume prediction mechanism established above is introduced. After calculating the expected sales volume of each crop under a specific plot and season $S_{k,c,i}$ , the plot area needs to be taken into account to obtain the actual sales volume at the unit plot level, which is then summed up according to the crop number$k$ , and the important parameters used for judgment in Model 1 and Model 2 are constructed -Market cap for the crop $\theta_k$ :

$$\theta_k = \sum_{c=1}^{N} \sum_{i=0}^{2} \mu_c \cdot S_{k,c,i} \tag{7}$$

This parameter is used in the subsequent revenue function to determine whether the crop exceeds the market acceptance in a given year, and thus whether the revenue is credited or not.

### 4.2.1. Scenario 1: Unsold Surplus Treated as Loss

Only sales within the expected sales volume (market sales ceiling) can be sold, and no money can be recovered from the excess:

$$\max_{x_{c,t,i}} \sum_{t=1}^{7} \sum_{i=0}^{2} \sum_{c=1}^{N} \mu_c \cdot \left[\mathbb{I}(Q_{k,t} \le \theta_k) \cdot Y_{k,c,i} \cdot U_{k,c,i} - C_{k,c,i}\right] \tag{8}$$

$$Q_{k,t} = \sum_{c=1}^{N} \sum_{i=0}^{2} \mu_c \cdot Y_{k,c,i} \cdot \mathbb{I}(x_{c,t,i} = k) \tag{9}$$

Where $Q_{k,t}$ is the total production of crop $k$ in year $t$ . $\mathbb{I}(\cdot)$ is an indicator function, in (8), of whether the crop $k$ has not exceeded the sales cap in year $t$ ;

### 4.2.2. Scenario 2: Surplus Sold at 50% Discount

The total annual production of the crop is compared with the upper marketing limit and the surplus is calculated at half price.

$$\max_{x_{c,t,i}} \sum_{t=1}^{7} \sum_{i=0}^{2} \sum_{c=1}^{N} \mu_c \cdot \left[U_{k,c,i} \cdot Y_{k,c,i} \cdot \left(\alpha_{k,t} + 0.5 \cdot (1 - \alpha_{k,t})\right) - C_{k,c,i}\right] \tag{10}$$

$$\alpha_{k,t} = \min\left(1, \frac{\theta_k}{Q_{k,t}}\right) \tag{11}$$

Where $\alpha_{k,t}$ is the percentage that can be sold at the original price.

In Case 2, the price-sensitive sales discount model directly controls the proportion of each crop that can be sold at its original price in each year $\alpha_{k,t}$ , thus participating in a linear combination of returns (full price + discount) that materially alters the marginal return per acre.

### 4.3. Constraints Modeling

Although the two scenarios differ in their treatment of returns above the sales cap, they follow the same practical agricultural constraints of plot suitability, crop rotation, and acreage concentration to ensure the feasibility and consistency of the cropping strategies under the different revenue regimes.

a) Crop plot suitability constraints

The crop $x_{c,t,i}$ planted in each plot $c$ during the season $i$ must be available for planting on its plot type $\text{LandType}_c$ :

$$\text{LandType}_c \in \mathcal{F}_{x_{c,t,i}}, \quad \forall c,t,i \tag{12}$$

b) Continuous cropping constraints

In order to prevent soil degradation, plots within the same season in adjacent years c are restricted from growing the same crop in succession:

$$x_{c,t,i} \text{neq} x_{c,t+1,i}, \quad \forall c, t=1,...,6, i=0,1,2 \tag{13}$$

c) Three-year crop rotation constraints

To improve soil fertility, ensure that each plot is rotated at least once in any three consecutive years with a legume crop (provided that the legume type number satisfies $\mathcal{T}(k) \bmod 10 = 1$ ):

$$\sum_{t'=t}^{t+2} \sum_{i=1}^{2} \mathbb{I}\left[\mathcal{T}(x_{c,t',i}) \bmod 10 = 1\right] \geq 1, \quad \forall c, t=1,...,5 \tag{14}$$

Where $\mathbb{I}(\cdot)$ is a schematic function.

d) Minimum acreage constraints

Ensure that the total acreage of each crop type in seven years does not fall below the minimum threshold $A_{\min}$ (set to 30 acres in the experiment):

$$\sum_{t=1}^{7} \sum_{i=0}^{2} \sum_{c=1}^{N} \mu_c \cdot \mathbb{I}(x_{c,t,i} = k) \geq A_{\min}, \quad \forall k \tag{15}$$

e) Planting concentration constraint

In order to avoid too much dispersal of crops, limit the number of plots used in seven years to not exceed the proportion of the total number of plots threshold $\rho_{\max}$ (set to 30%):

$$\frac{1}{N} \cdot |\{c \mid \exists t, i \text{ such that } x_{c,t,i} = k\}| \leq \rho_{\max}, \quad \forall k \tag{16}$$

## 5. Genetic Algorithm Implementation

This problem involves the optimization of multi-plot, multi-season, and multi-crop combinations, which requires the formulation of a reasonable planting plan under complex constraints and the consideration of multiple constraints. Genetic algorithms can search for potential optimal solutions through random initialization of the initial population and subsequent crossover and mutation operations. Based on this, genetic algorithms are chosen in this paper to optimize the planting scheme for the two cases of Problem 1 [4].

The genetic algorithm first generates an initial population that satisfies the basic constraints and evaluates the individual performance by setting the fitness function; subsequently, it performs genetic operations such as selection, crossover, mutation and repair to iteratively update the population generation by generation; finally, it outputs the optimal planting scheme and visualizes it for analysis.

Through the above genetic algorithm solution steps, the planting strategy for the next seven years has been successfully constructed and optimized, and the optimal solutions for Case I and Case II have been obtained.

## 6. Results

Based on the optimization results of the genetic algorithm, the optimal planting strategies for the two market scenarios for the period 2024-2030 have been obtained in this paper. The output of the results covers the seven-year total yield, total revenue of each crop.

In terms of overall revenue, the total profit realized in Case 1 is about 45.2 million yuan, which is significantly higher than that in Case 2, which is about 17 million yuan. However, the total yield level in Case 2 is significantly higher than that in Case 1, which is characterized by "high yield and low efficiency". For example, the seven-year total production of soybeans jumped from 1,703,120 kg in Case 1 to 5,470,800 kg in Case 2, an increase of more than twofold. The result of case 1 and case 2 as shown in Figure 1, Figure 2, Figure 3 and Figure 4.

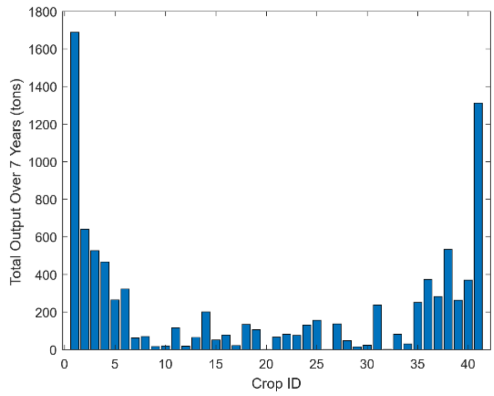


Figure 1 Seven-year total yield of each crop in Case 1.

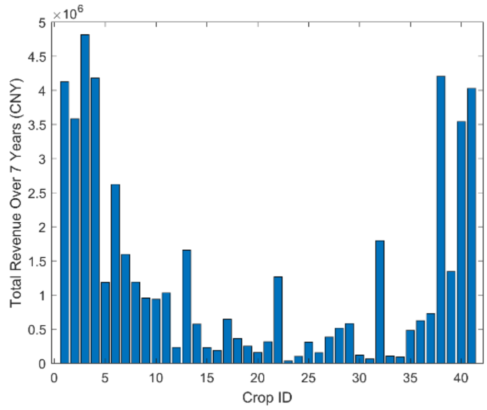


Figure 2 Seven-year total revenue for each crop in Case 1.

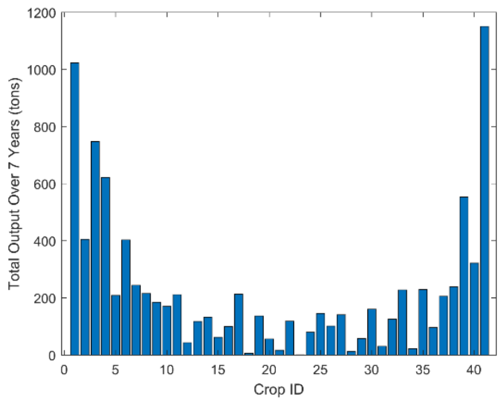


Figure 3 Seven-year total production of each crop for Case 2.

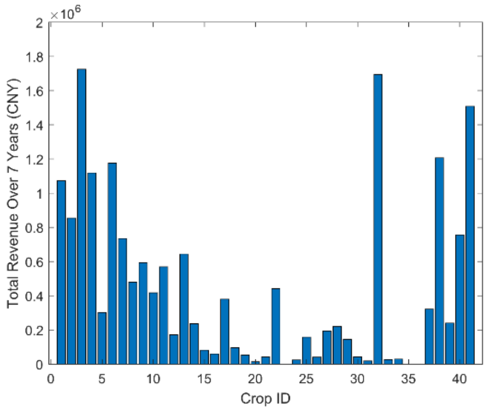


Figure 4 Seven-year total income from all crops in Case 2.

In terms of high-margin crops, Case 1 is dominated by high-end edible fungi, with morel mushrooms and elm mushrooms contributing RMB 2,952,000 and RMB 2,218,500 respectively to the cumulative net income; in contrast, Case 2 relies more on medium-yield, highly adaptable vegetables and legumes, such as cucumbers (RMB 1,835,400) and black beans (RMB 1,718,300), indicating a shift in planting strategy towards risk-tolerant varieties. This shows a trend of shifting planting strategies to risk-tolerant varieties.

Analyzed from the perspective of high-yield crops, the structure of Case 2 is more reliant on sweet potato and soybean crops, with sweet potato yielding 4,122,000 kg and soybean yielding 5,470,800 kg, making it the absolute mainstay; whereas in Case 1, soybean is the only crop that reaches the level of one million yuan, which shows that the planting structure is more focused on high-margin oriented categories. The comparison of crop data as shown in Table 5.

Table 5 Comparison of crop data between Scenario 1 and Scenario 2.

| Crop number | Crop name | Scenario I Total Production (pounds) | Situation one profit (yuan) | Situation two total production (pounds) | Situation two profit (yuan) |
|---|---|---|---|---|---|
| 1 | Soybeans | 1,703,120 | 4,408,930 | 5,470,800 | 1,348,900 |
| 2 | Black beans | 752,550 | 3,274,762.5 | 3,025,100 | 1,718,281.25 |
| 13 | Sweet Potato | 978,200 | 1,126,400 | 4,122,000 | 231,900 |
| 29 | Cucumber | 719,100 | 828,846.95 | 2,752,500 | 1,835,433.32 |
| 38 | Elodea Mushroom | 36,000 | 2,218,500 | 144,000 | 1,694,250 |
| 41 | Morel mushrooms | 24,600 | 2,952,000 | 101,400 | 1,148,400 |

The data show that at the level of strategy differences, Case I prioritizes high-margin crops (e.g., morel mushrooms, with a unit profit of $120), and Case II balances high yields (e.g., soybeans) and high-margin crops (e.g., cucumbers, $0.67); at the level of resource use, the higher yields in Case II optimize the use of resources, and in Case I, they reduce waste. In Case I, the overproduction is considered as stagnant and without any economic benefit, so the optimization model strictly controls the production to match the upper limit of market demand through genetic algorithm. This strategy is particularly applicable in regions with stable demand and limited sales channels, and can minimize the waste of resources and the risk of price collapse. In Scenario 2, overproduction can be sold at a 50% discount to the 2023 selling price, thus providing the model with a larger "incremental production incentive". This encourages the optimization algorithm to moderately exceed the demand cap and generate additional revenue from production growth, creating a "forgiving revenue buffer" mechanism. This strategy is suitable for environments with high potential for consumer demand growth, controlled market price volatility, or policy subsidies.

## 7. Conclusion

This study addresses the optimization of rural crop cultivation in the mountainous regions of North China. Based on the cultivation, sales and revenue data for 2023, an optimization model is constructed with the objective of maximizing net returns, and a scientific strategy for cultivation planning in 2024-2030 is proposed by taking price sensitivity and crop rotation constraints into account. The model accurately portrays the nonlinear impact of price reduction on sales volume by introducing a price-sensitive sales volume discounting mechanism, and realizes an efficient solution using genetic algorithms in combination with agricultural constraints such as plot suitability, three-year crop rotation, minimum planting area and concentration. The results show that in Case 1 (overproduction partly stagnant sales), the precise allocation of high-margin crops such as morel mushrooms and elm mushrooms realizes a net profit of about 45.2 million yuan, which is suitable for the areas with limited market demand; in Case 2 (overproduction partly sold at a discount of 50%), about 17 million yuan of net profit is obtained by increasing high-yield crops such as soybeans and cucumbers, which reflects the characteristic of "high-yield and low-efficiency", and is suitable for the areas with limited demand. This reflects the "high yield, low efficiency" feature, which is suitable for environments with growing demand or stable discount policies. The sensitivity analysis further verifies the robustness of the model to price fluctuations, providing theoretical support and practical guidance for planting decisions under different market scenarios.

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## Appendix

A. Comparison table of parcel type codes

| Code | Plot type name | Description |
|---|---|---|
| A | Flat and dry land | Flat, well-drained open cultivated land |
| B | Terraced | Terraced cropland built on the slopes of a hill |
| C | Hillside land | Slopes with steep topography and dependent on natural water sources |
| D | Watered land | Open cropland with an irrigation system, suitable for rice or double-cropped vegetables |
| E | Ordinary greenhouse | Plastic film structure facilities with adjustable temperature and humidity conditions |
| F | Intelligent greenhouse | Facility agricultural plots with intelligent control systems |