

# Optimization Of Crop Planting Strategies Based On 0-1 Integer Programming and Simulated Annealing Algorithm

Yaping Wu \*

School of Science, Jiangsu University of Science and Technology, Zhenjiang, China

\* Corresponding Author Email: w18158407792@163.com

**Abstract.** This paper uses 0-1 integer programming, simulated annealing algorithm, Monte Carlo simulation and multivariate statistical analysis to investigate the optimization problem of medium- and long-term crop planting strategies, aiming to achieve the synergistic goals of production efficiency improvement and risk control. Firstly, a single-objective model is constructed to maximize the total return, and the optimal solutions for different stagnant scenarios are solved. Secondly, random number generation algorithm and Monte Carlo simulation are introduced to deal with parameter fluctuations and optimize the classification strategy in response to the uncertainty of the external environment. Finally, the correlation analysis and multivariate polynomial regression model are used to compare the trend of returns in different scenarios, and it is found that the annual net return fluctuates non-monotonically. The study provides a quantitative decision-making framework for long-term agricultural planning, helps to realize the synergistic optimization of return and risk, and is of great significance to the sustainable development of rural agriculture.

**Keywords:** Crop planting strategy; integer planning; simulated annealing algorithm; scenario simulation; classification optimization.

## 1. Introduction

In the process of rural revitalization and agricultural modernization, scientific optimization of crop planting strategies is crucial for improving benefits and coping with risks, but the existing research lacks medium- and long-term systematic quantitative planning and multi-scenario adaptive analysis [1].

In this paper, we use 0-1 integer planning, simulated annealing algorithm and Monte Carlo simulation to construct a multi-dimensional optimization framework. Firstly, the optimal planting plan for different marketing scenarios is solved by single-objective planning model, and the allocation logic of dominant crops and high-value crops is clarified [2]. Secondly, the random number technique is introduced to deal with the fluctuation of climate and price parameters, which is combined with correlation analysis to optimize the adaptability of the classification strategy, and finally, the impact mechanism of external factors on yield is analyzed with the help of visualization [3]. The study breaks through the limitation of the traditional single objective, provides quantitative decision-making tools for agricultural production, and helps to realize the dynamic balance between benefits and risks in the complex environment, which is of practical significance for the sustainable development of rural agriculture [4].

## 2. Crop Planning for Yield Maximization

In this paper, a single-objective 0-1 integer planning model is established with the objective of maximizing the total return of crops, and the simulated annealing algorithm is applied to solve the problem, and the planting scheme of crops from 2024 to 2030 is given under two kinds of stagnation treatment and the results are visualized and analyzed.

### 2.1. Maximum Yield Planting Planning Modeling

A single-objective 0-1 integer planning model with the objective of maximizing the total crop yield from 2024 to 2030.

$i$  is the crop number and  $i_x$  represents grain (legume) crop, grain (non-legume non-rice) crop, rice, vegetable (legume) crop and edible fungi, respectively.

$j$  is the plot number and  $j_x$  represents arid land, terraced land, hillside land, watered land, ordinary greenhouse and smart greenhouse, respectively.

$t$  denotes the year. Where  $t \in \{2024, 2025, \dots, 2030\}$  denotes the planning time horizon.  $k$  represents the season and takes the values  $k = 1, 2$ .

The cultivation of the  $i$ -th crop in the  $j$ -th plot in the  $k$ -th season of year  $t$  is represented by the 0-1 variable  $x_{i,j,t,k}$ , i.e.,  $x_{i,j,t,k} = \begin{cases} 0, & \text{Crop } i \text{ is not planted on plot } j \text{ in season } k \text{ of year } t \\ 1, & \text{Crop } i \text{ in season } k \text{ in year } t \text{ on plot } j \end{cases}$ .

Let  $D_{i,t,k}$  be the actual sales volume of crop  $i$  in season  $k$  in year  $t$ ,  $P_{i,k}$  be the unit price at which crop  $i$  is sold in season  $k$ ,  $C_{i,j,k}$  be the cost of planting crop  $i$  in season  $k$  in plot  $j$ ,  $M_{i,j,t,k}$  be the number of acres of crop  $i$  in season  $k$  in year  $t$  in plot  $j$ ,  $Z_{i,k}$  be the sales price of the portion of crop  $i$  that is sold in excess of season  $k$ , and  $Q_{i,t,k}$  be the number of pounds of crop  $i$  that exceeds the portion of crop  $i$  that is expected to sell in season  $k$  in year  $t$ .

In summary, a single objective integer 0-1 planning model is developed. Where the decision variable is  $x_{i,j,t,k}, M_{i,j,t,k}$ , the objective function is as follows:

$$\max \sum_{t=2024}^{2030} \sum_{k=1}^2 \sum_{j=1}^{54} \sum_{i=1}^{41} (D_{i,t,k} P_{i,k} - x_{i,j,t,k} M_{i,j,t,k} C_{i,j,k} + Q_{i,t,k} Z_{i,k}) \quad (1)$$

## 2.2. Analysis of Results of Maximum Yield Cropping Planning

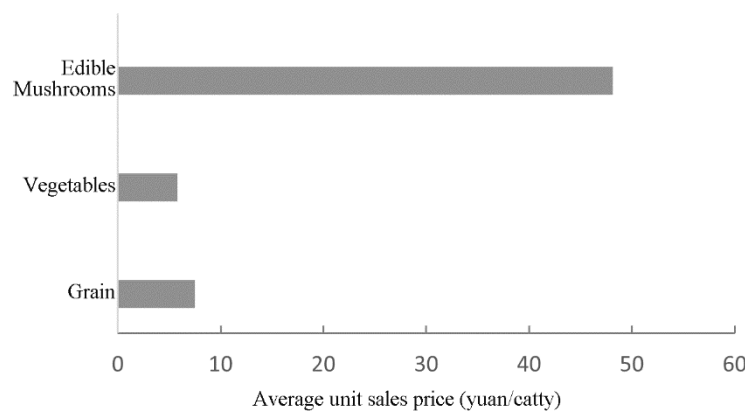
### 2.2.1 Expected future sales of each crop

Based on the number of acres of each crop planted in different plots in 2023 and the acreage yield, the total production of each crop in 2023 can be obtained and this value can be regarded as the expected future sales volume of each crop [5].

It can be calculated that the expected future sales volume of barley is the largest at 170,840 and spinach is the smallest at 900. There are 4 crops with expected annual sales volume greater than or equal to 100,000 pounds, namely wheat, cabbage, corn and white radish, and 16 crops with expected annual sales volume less than 10,000 pounds.

### 2.2.2 Sales unit price of each crop

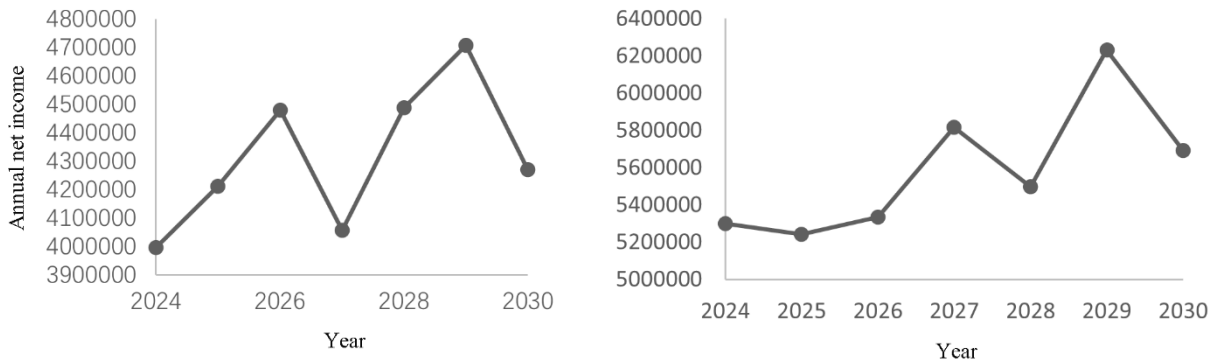
As can be seen in Fig. 1; by comparing the average sales price of the three crop types, edibles have the highest value of ¥48.125/catty and vegetables have the lowest average value of ¥5.8/catty.



**Fig. 1** Comparison of average sales prices for three crop types

Implementation of a single-objective 0-1 integer planning model with the objective of maximizing the total crop yield for the years 2024-2030. The study applies simulated annealing algorithm to the non-convex optimization problem of co-cropping crops in the same plot and given three co-cropping scenarios (same as in year 23, no co-cropping except for a small area, and co-cropping in two plots

except for watered land), the optimal planting plan for crops in the village for the period of 2024-2030 is derived by comparing the returns.



**Fig. 2** Annual net crop revenue versus year under different scenarios

Fig. 2 shows the relationship between annual net crop revenue and year for the two stunting treatments. The similarities in the trend bands for the two scenarios from 2024 to 2030 are that the annual net crop revenue fluctuates in a non-monotonous manner, with significant peaks in some years (e.g., 2029), which are influenced by external conditions (market prices, climate, etc.).

The difference is that the level of returns in Case 1 fluctuates between \$4.1-4.7 million, with less volatility, while the level of returns in Case 2 fluctuates between \$5.2-6.2 million, with more volatility. Taken together, the second scenario is significantly better than the first in terms of the level of return, but it also has a higher volatility of return, which may be accompanied by higher risk.

### 3. Scenario Simulation of Optimal Planting Program

Based on the maximum yield planting planning model, the model parameters take uncertain values due to climate, market conditions and other factors. The uncertainty variation of the parameters is handled by the nature of normal distribution and by adding white noise. The optimal planting plan is obtained by simulating several scenarios.

#### 3.1. Random Number Generation Model Based on *Box – Muller* Algorithm

The *Box – Muller* algorithm is an algorithm that constructs random variables obeying Gaussian distribution by obeying uniformly distributed random variables [6]. The algorithm can generate uniformly distributed random numbers in the hardware system and convert them to normal distribution. Suppose  $U_0, U_1$  are two random variables obeying uniform distribution on  $[0,1]$  and  $Z_0, Z_1$  satisfy:

$$Z_0 = \sin(2\pi U_1) \sqrt{-2 \ln U_0} \tag{2}$$

$$Z_1 = \cos(2\pi U_1) \sqrt{-2 \ln U_0} \tag{3}$$

Then  $Z_0, Z_1 \sim N(0,1)$ .

A linear transformation is used to obtain a normally distributed random number with any mean  $\mu$  and standard deviation  $\sigma$ . The algorithm is based on a standardized algorithm:

$$X = \mu + \sigma \cdot Z \tag{4}$$

Where  $Z$  is a standard normally distributed random number generated by the *Box – Muller* algorithm.

$N$  simulations are performed through Monte Carlo simulation, and if a certain scene  $s_n$  appears  $n_n$  times, the frequency of appearance of the scene (i.e., the probability of the scene) can be calculated by the following formula:

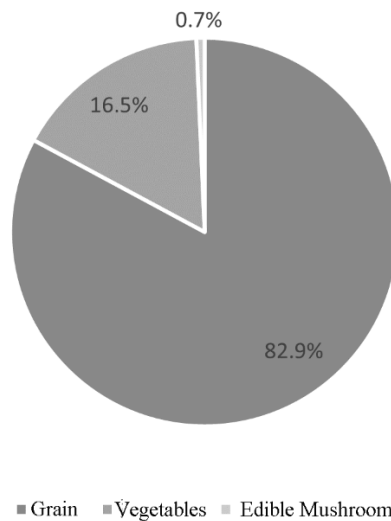
$$p_n = \frac{n_n}{N} \tag{5}$$

In summary, the following model is established. Where the decision variables are  $x_{i,j,t,k}, M_{i,j,t,k}$  and the objective function is:

$$\max \sum_{n=1}^N \left( \sum_{t=2024}^{2030} \sum_{k=1}^2 \sum_{j=1}^{54} \sum_{i=1}^{41} (D_{i,t,k} P_{i,t,k} - x_{i,j,t,k} M_{i,j,t,k} C_{i,j,t,k} + Q_{i,t,k} Z_{i,k})_{s_n} \right) p_n \tag{6}$$

### 3.2. Visualization and analysis of the optimal solution for scenario simulation

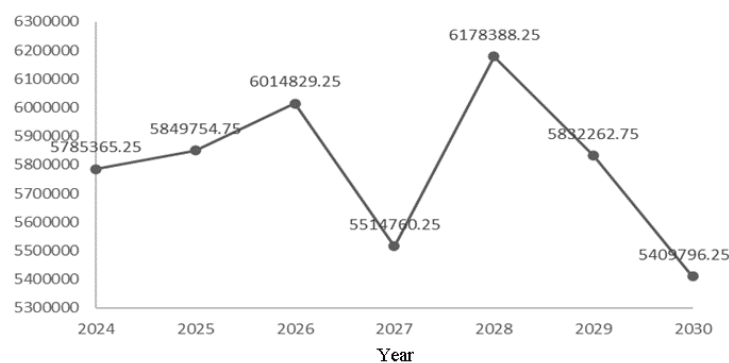
#### 3.2.1 Analysis of the average annual acreage share of three crops



**Fig. 3** Pie chart of the average annual share of area under three crops

As can be seen from Fig. 3, the area of grain crops is 82.9%, accounting for the largest proportion, and the area planted with edible fungi crops is 0.7%, accounting for the smallest proportion. This shows that food crops occupy a dominant position in agricultural production, reflecting the importance of food production for national food security and social stability. Vegetable crops account for a relatively large proportion of the area planted, indicating that vegetables play an important role in the dietary structure of the population, and are also an important manifestation of the diversification of agriculture.

#### 3.2.2 Changes in net crop returns over years



**Fig. 4** Changes in net crop returns over years

Fig. 4 demonstrates the changes in net crop returns over the years, and the analysis reveals that between 2024 and 2030, net crop returns experienced several fluctuations, and although there were two relatively large increases, the overall trend was first up and then down.

## 4. Classification and Optimization of Planting Programmers

The 54 crops were categorized into four groups: legumes, grains, vegetables and edible mushrooms, and their complementary and substitution relationships were clarified. Based on the simulation data generated in Problem 2, the Spearman correlation coefficient was calculated, and it was found that the expected sales volume was negatively correlated with the sales price and planting cost. Construct a multivariate polynomial regression model to derive the relationship between the three functions, optimize the new planting scheme in 2023, and substitute into the random number generating model to solve the optimal scheme of classified planting.

### 4.1. Modeling of Optimized Planting Scheme by Classification

#### 4.1.1 Modeling the relationship between crops

Complementarity refers to the fact that two or more crops depend on each other to some extent, usually because they can work together or bring higher benefits when used in combination.

Substitutability refers to the fact that two or more crops are in some way substitutable for each other, and a farmer can choose one of the crops to grow without significantly affecting overall yield or market demand.

#### 4.1.2 Multivariate polynomial regression modeling

1) Setting the independent variable as  $X_i$  and the dependent variable as  $y$ , there are:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 \dots + \beta_n X_n + \beta_1 X_1^2 + \beta_2 X_2^2 \dots + \beta_n X_n^2 + \varepsilon \quad (7)$$

Where  $\beta_i$  is the parameter to be estimated and  $\varepsilon$  is the error term.

2) Introduce a new variable  $x_1, x_2, \dots, x_m$ , where  $x_1 = x, x_2 = x^2, \dots, x_m = x^m$ , such that  $Y$  is the vector of observations of  $y$ ,  $X$  is the design matrix of  $x_1, x_2, \dots, x_m$ , and  $\beta$  is the parameter vector  $(\beta_0, \beta_1, \beta_2, \dots, \beta_m)^T$ , then the model is expressed as:

$$Y = X\beta + \varepsilon \quad (8)$$

3) Minimize the sum of squared deviations by least squares:

$$\sigma = \sum_{i=1}^m (y_i - \hat{y}_i)^2 = \sum_{i=1}^m (y_i - (\beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} \dots + \beta_n x_{im}))^2 \quad (9)$$

Where  $m$  is the number of observations,  $y_i$  is the  $i$ -th observation, and  $\hat{y}_i$  is the predicted value of the  $i$ -th observation.  $\sigma$  Deriving  $\beta$  such that it equals zero yields.

$$\hat{\beta} = (X^T X)^{-1} X^T Y \quad (10)$$

Where  $X^T$  is the transpose matrix of  $X$ .

#### 4.1.3 Single-objective optimization model with the objective of maximizing returns

The model was used to optimize the planting program for the year 2023. Where the decision variable is  $x_{i,j,t,k}, M_{i,j,t,k}$ , the objective function is as follows:

$$\max \sum_{k=1}^2 \sum_{j=1}^{54} \sum_{i=1}^{41} (D_{i,2023,k} P_{i,k} - x_{i,j,2023,k} M_{i,j,2023,k} C_{i,j,k} + Q_{i,2023,k} Z_{i,k}) \quad (11)$$

## 4.2. Analysis of the Results of Classification Optimization Cropping Scheme

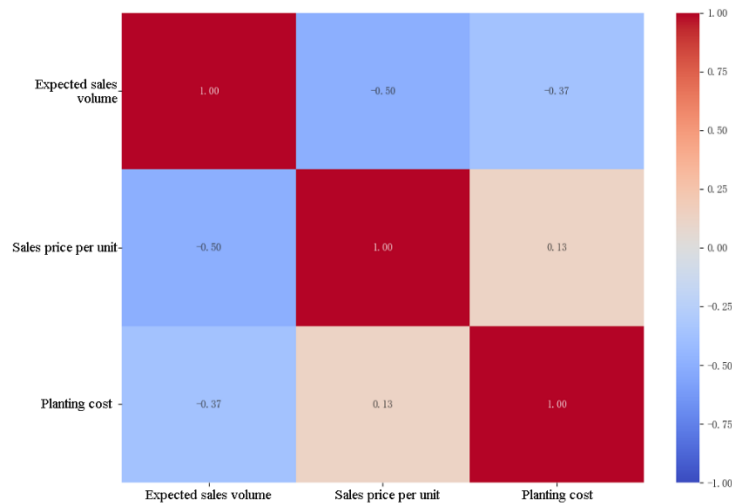
### 4.2.1 Exploration of substitutability and complementarity between crops

First, the existing crops are categorized, and the 54 crops are divided into four categories according to the requirements of the topic and the actual life: beans, grains, vegetables and edible fungi. There is some substitutability between legumes and grains, while there is complementarity between grains and vegetables.

### 4.2.2 Implementation of Spearman correlation analysis

The Shapiro-Wilk test was first used to determine whether the data conformed to a normal distribution, and it was found that the p were less than or equal to 0.05, which did not conform to a normal distribution, and then the Pearson correlation analysis could not be used.

Spearman correlation analysis was used to analyze the correlation between the two expected sales volume, sales price and planting cost to get its heat map.



**Fig. 5** Heat map of Spearman's correlation analysis

Analyzing Fig. 5 shows that expected sales volume is negatively correlated with both sales' unit price and planting cost, and planting cost is positively correlated with sales unit price.

### 4.2.3 Implementation of multivariate polynomial regression analysis

The distribution of the multivariate polynomial regression model was utilized to fit the expected sales volume  $N_{i,2023,k}$  of non-leguminous grains, non-leguminous vegetables, edible mushrooms, and leguminous crops with the sales price  $P_{i,k}$ , and the cost of cultivation  $C_{i,j,k}$  to obtain the following function:

$$\begin{aligned}
 f_1 &= -5047.132P_{i,k} - 8.989C_{i,j,k} + 101.285P_{i,k}^2 + 0.005P_{i,k}^2 + 52237.276 \\
 f_2 &= -43981.187P_{i,k} + 7.379C_{i,j,k} + 3597.608P_{i,k}^2 - 0.002P_{i,k}^2 + 133956.652 \\
 f_3 &= 0.013P_{i,k} + 0.290C_{i,j,k} + 0.728P_{i,k}^2 + 1989.592 \\
 f_4 &= -8746.272P_{i,k} - 27.652C_{i,j,k} + 373.717P_{i,k}^2 - 0.010P_{i,k}^2 + 51403.294
 \end{aligned}
 \tag{12}$$

## 5. Conclusion

This paper focuses on the optimization of medium- and long-term crop planting strategies, constructs a quantitative analysis framework integrating multiple methods, and formulates systematic research conclusions. Firstly, based on 0-1 integer programming and simulated annealing algorithm, the optimal planting scheme for different marketing scenarios is solved to clarify the dominant position of food crops and the high-value attributes of edible mushrooms. Second, to address climate and market uncertainties, Monte Carlo simulation is used to deal with parameter fluctuations, combined with multivariate analysis to reveal the negative correlation of yield-related factors, and optimize the environmental adaptability of the classification strategy. Finally, the visualization analysis reveals that the annual net returns of each scenario show non-monotonic fluctuations, and some scenarios have significant differences in return and risk, which verifies the responsiveness of the model to external factors. The study breaks through the limitation of a single objective and provides a decision-making tool that balances benefits and risks for agricultural production, which is

of practical significance for the sustainable development of rural agriculture and can be extended and applied to the dynamic planning and policy optimization of regional agriculture.

## References

- [1] Fan Minmin. Impacts of climate change on crop cultivation patterns and adaptation strategies[J]. *Agricultural Development and Equipment*,2025, (02):160-162.
- [2] Buy Buyi Haili Li. Optimization of fresh produce distribution network based on mixed integer programming[J]. *Value Engineering*,2024,43(09):51-53.
- [3] Dai Li, Zhu Qian. Analysis and Construction of Reverse Supply Chain Network of Lagging Agricultural Products Based on Uncertainty Optimization Model[J]. *Logistics Science and Technology*,2023,46(15): 112-117.DOI: 10.13714/j.cnki.1002-3100.2023.15.028.
- [4] Qian Yexia, Chen Zijing. Research on distribution path optimization based on improved simulated annealing algorithm[J]. *China Business Journal*,2023, (08): 86-89.DOI: 10.19699/j.cnki.issn2096-0298.2023.08.086.
- [5] Tao L, Hu Zhaoling. Extraction of crop cultivation information in the hilly areas of the middle and lower reaches of the Yangtze River using Sentinel-2A data[J]. *Surveying and Mapping Bulletin*,2021, (07): 39-43.DOI: 10.13474/j.cnki.11-2246.2021.0206.
- [6] Ding HJ, Tang D, Yao L, et al. Research on randomness evaluation method for pseudo-random number generation algorithm[J]. *Journal of Shanghai Institute of Electrical Engineering*,2020,23(01):44-49+62.
- [7] Liu Jinfu, Lin Fangfang, Lu Chunyan, et al. Spatial sampling scheme of regional crop cultivation area in Minhou County, Fujian Province[J]. *Journal of Fujian Agriculture and Forestry University (Natural Science Edition)*,2018,47(02): 243-249.DOI: 10.13323/j.cnki.j.fafu(nat.sci.).2018.02.018.