# Research on Crop Planting Strategy Optimization Based on Dynamic Multi-Objective Optimization and Genetic Algorithm

**Xin Guo**[1,*]

[1] Business School, Xi'an International Studies University, Xi'an, China

*Corresponding author: 3220358930@qq.com

**Keywords:** Goal Programming, Genetic Algorithm, Monte Carlo Simulation Algorithm, Correlation Analysis

**Abstract:** Under the challenges of global population growth and climate change, modern agriculture is under increasing pressure, and intelligent and sustainable management methods are urgently needed to balance the growth of food demand and environmental protection. Based on the actual planting of cultivated land and the growth law of crops in specific regions, this paper formulates the optimal planting strategy for crops in the next few years. First, data preprocessing is carried out to estimate the unit price of crop sales and analyze the relationship between planting area and total sales; secondly, single-objective optimization analysis is carried out based on historical data, an optimization model is constructed, and a genetic algorithm is used to solve it, giving the optimal planting strategy for 2024-2030 to maximize agricultural benefits when the expected sales volume is stable. Then, a single sensitivity analysis is used to find out the key variables affecting planting benefits and their expected change rates; then a multi-sensitivity analysis is used to calculate the planting data of crops in each year within a specific floating range, and a Monte Carlo simulation is used to evaluate the comprehensive impact of uncertain parameters; finally, the obtained parameter values are used to simulate the planting strategy model to obtain the optimal planting plan for 2024-2030. In addition, assuming that sales volume is linearly related to variables such as average sales price and planting cost, the sales volume of different crops is predicted based on the linear regression model. The correlation coefficient analysis shows that the sales price is negatively correlated with sales volume, and the planting area is positively correlated with sales volume. The optimal planting plan is obtained with the help of the prediction model and compared with the above plan. The results show that the total profit fluctuates greatly from 2024 to 2030, which is speculated to be related to the parameter selection.

## 1. Introduction

As a major agricultural country, China has to promote rural economic development as the key to achieving rural prosperity. Improving production methods and introducing modern technologies under the rural revitalization strategy can inject vitality into rural economic growth. Agricultural development in a village in the mountainous area of North China faces unique challenges. Due to geographical location and climate constraints, most cultivated land is only planted with one crop a year. The village has 1,201 acres of cultivated land scattered in 34 different plots, with various plot types and suitable for planting different crops. There are also 20 greenhouses (including 16 ordinary greenhouses and 4 smart greenhouses). Ordinary greenhouses can plant two crops a year, and smart greenhouses can automatically adjust the temperature to achieve winter planting and two vegetable plantings a year. However, there are restrictions on crop planting. It is necessary to avoid repeated cropping and yield reduction, and crops cannot be planted continuously in the same plot or greenhouse. It is also necessary to maintain soil fertility and plant legumes at least once in each plot within three years. In this context, it is necessary to study the optimal planting strategy for crops and formulate a land planting plan that takes into account seasonality, soil fertility, crop diversity and economic benefits to increase production, increase income and ensure the sustainable development of agriculture.

  DOI: 10.25236/iiicec.2025.006

Existing research has formed a multi-dimensional methodological system in the field of crop planting strategy optimization. [1] proposed a planting structure model based on spatial optimization, and provided a new paradigm for regional scale planting planning through the framework of geographic information system and economic-environmental benefit balance. [2] constructed a multi-objective optimization model that includes dynamic changes in molecular concentration, paying special attention to the synergistic mechanism of crop rotation cycle and quality management, but its constraint setting is still limited to the idealized agricultural system. In terms of algorithmic innovation, [3] developed an improved real genetic algorithm, which effectively enhances the efficiency of solving multiple cropping combinations. Meanwhile, [4] conducts research on sustainable crop planning in mountainous villages using linear programming, providing practical references for optimizing planting strategies under specific topographical conditions. It is worth noting that [5] used constraint programming method to deal with the planting layout problem for the first time, and its spatial constraint expression mechanism provided a more accurate solution for the heterogeneity of plots.

However, existing research still has three major limitations: first, most models use static parameter settings, which are difficult to adapt to the dynamic scenarios of climate change and technological progress; second, the goal of maximizing economic benefits is still dominant, and the integration of environmental and social benefits mostly remains at the level of indicator superposition; third, algorithm optimization focuses on improving computational efficiency, and lacks in-depth analysis of the spatiotemporal coupling characteristics of planting systems. This provides a research direction for building a new generation of planting decision models that integrate dynamic parameter update mechanisms, multi-objective trade-off strategies, and intelligent optimization algorithms.

## 2. Model building and solving

### 2.1. Data preprocessing and visualization

The volatility of sales price is a key consideration when analyzing the crop market. The lowest or highest sales price cannot effectively represent the market, so this section adopts the method of calculating the average sales price. First, the planted area and the relevant data collected in the "2023 crop planting situation" and "2023 statistics" are preprocessed, and the table containing the planted area and the table containing the sales price information are integrated. Finally, numerical calculations are performed to calculate the average sales price of various crops.

This section classifies the types of crops based on data processing, and conducts data visualization analysis on the planting area and total sales volume. The relevant analysis results are shown in Figures 1, 2, and 3.

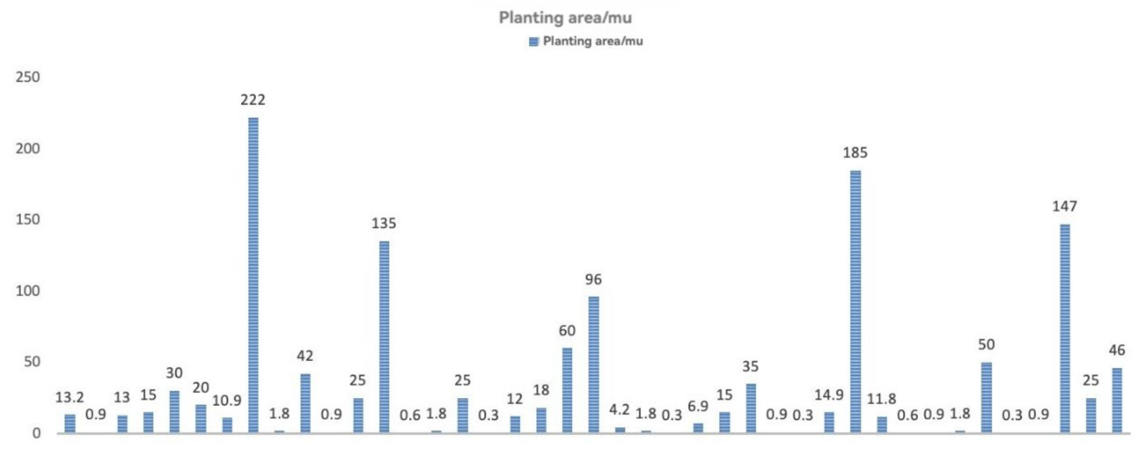


Figure 1 Area under cultivation of different crops.

As shown in Figure 1, wheat has the largest planting area, reaching 222 mu. Millet ranks second with 185 mu. The planting areas of soybeans and corn are both over 100 mu, which shows their importance in terms of scale. There is no obvious difference in the planting areas of other crops. The horizontal axis from left to right is Broad Bean , Chinese Cabbage, Pumpkin, Potato, Chinese Cabbage, Barley, Oat, Green Cabbage, Small Chinese Cabbage, Elm Mushroom, Rice, Rape, Climbing Bean, Corn, Lettuce, White Mushroom, White Radish, Hollow Heart Radish, Sweet Potato, Red Bean, Green Bean, Woolly Milk Vetch, Bean Sprout, Celery, Eggplant, Wheat Bran, Buckwheat, Cauliflower, Spinach, Tomato, Grain Amaranth, Job's Tears, Mung Bean, Pepper, Green Pepper, Mushroom, Sorghum, Celery, Yellow Heart Vegetable, Cucumber, Soy Bean, Black Bean.

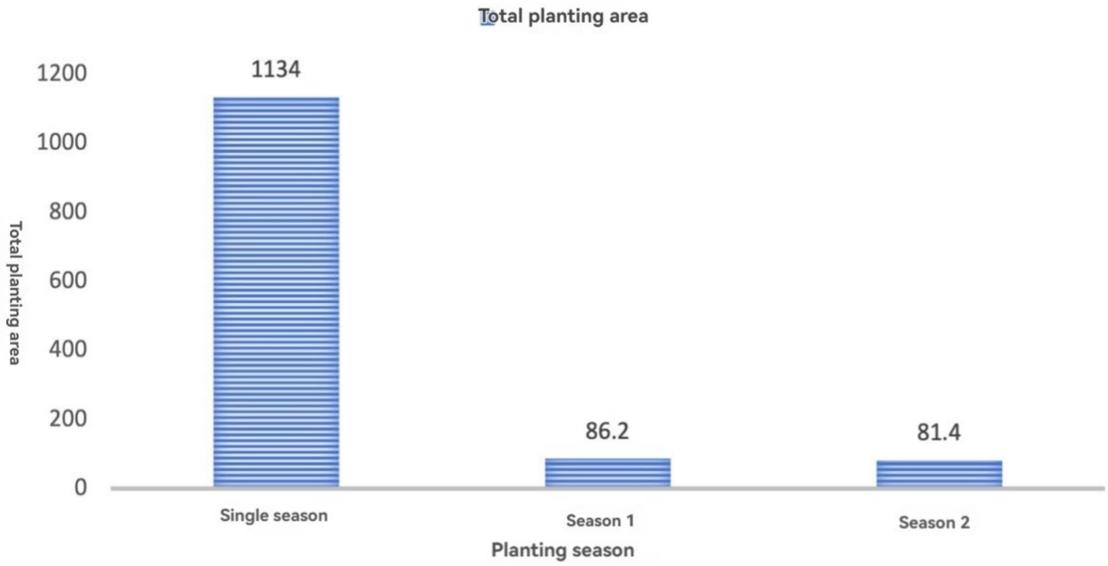


Figure 2 Planting season and total planted area.

As shown in Figure 2, the main planting mode is single-season planting, with a planting area of 1,134 mu, while the planting areas in the first and second seasons are 86.2 mu and 81.4 mu respectively, indicating that multi-season planting is not common in the area. Therefore, it is possible to consider optimizing crop varieties and planting techniques in single-season planting, while enhancing soil fertility and crop resistance through methods such as rotation and intercropping in multi-season planting.

### 2.2. Optimal eye for planting crops based on genetic algorithm

Linear programming is the optimization of a set of decision variables under a series of linear constraints to achieve the maximum or minimum value of the objective function. It usually contains three core elements: decision variables, constraints, and objective functions. Decision variables are unknowns, which are generally continuous and non-negative values; constraints are linear inequalities or equations that limit the range of decision variables, reflecting the limitations in reality; the objective function is a linear combination that defines the quantity to be maximized or minimized. Linear programming is widely used and can efficiently and stably solve practical problems such as production planning, transportation scheduling, and resource allocation, and the model is easy to understand and expand. By establishing and solving linear programming models, decision makers can find the optimal solution under the conditions that all constraints are met. The construction of a target optimization model requires the "three determination" steps: first find the known variables in the problem and determine the decision variables; then determine the objective function to be solved; and finally determine the constraints that each variable must meet.

The decision variable designed in this paper is the area (unit: mu) of the crop planted in the plot in the season. In order to solve the problem that the crop yield exceeds the market demand, resulting in the unsalable excess and waste of resources, the planting plan is optimized. The goal is to optimize the planting plan to maximize the total profit from 2024 to 2030, so the following objective function is established:

$$\max Z = \sum_i \sum_j \sum_k \left( S_{ijk} \times x_{ijk} - C_{ijk} \times x_{ijk} \right) = \sum_i \sum_j \sum_k \left( S_{ijk} - C_{ijk} \right) \times x_{ijk} \tag{1}$$

Among them, $S_{ijk}$ represents the sales price of the ith plot of land planted with the kth crop in the jth season (yuan/jin), $C_{ijk}$ represents the planting cost of the ith plot of land planted with the kth crop in the jth season (yuan/mu), and $X_{ijk}$ represents the area (mu) of the ith plot of land planted with the kth crop in the th season.

The excess will be sold at a price reduction of 50% of the 2023 sales price. The established objective function is as follows:

$$\max Z = \sum_i \sum_i \sum_k \left( S_{ijk} \times x_{ijk} - C_{ijk} \times x_{ijk} \right) + \left( S_{ijk} \times x_{ijk} - C_{ijk} \times x_{ijk} \right) \times 0.5 \times S_{ijk} - S_{ijk} \times C_{ijk} \tag{2}$$

Constraints

Plot area constraints: The planting area of each plot cannot exceed the total area of the plot.

$$\sum_j \sum_k x_{ijk} \le \mathrm{Area}_i, \quad \forall i \tag{3}$$

Among them, $Area_i$ represents the total area of the ith plot.

$$x_{ijk} \ge 0, \forall i, \mathrm{j}, \mathrm{k} \tag{4}$$

Non-negativity constraint: The planting area cannot be negative.

$$x_{ijk} \ge 0, \quad \forall i, \mathrm{j}, \mathrm{k} \tag{5}$$

Legume crop planting requirements: Each plot of land must plant legume crops at least once within three years.

$$\Sigma_k l_{ik} \ge 1, \quad \forall i \tag{6}$$

Where $l_{i,k}$ is a binary variable indicating whether the ith plot is planted with legume crops.

Minimum area constraint:

$$x_{ijk} \quad \ge 0.5 \times Area_i \quad , \forall i, j, k \tag{7}$$

Matching yields to sales: Crop yields cannot exceed expected sales

$$x_{ijk} \le \mathrm{MaxSales}_{jk}, \quad \forall i, \mathrm{j}, \mathrm{k} \tag{8}$$

Among them, $MaxSales_{jk}$ represents the expected sales volume of the crop in the season (jin).

Based on the planning model of the above objective function and constraints, a genetic algorithm is used to solve the problem. The genetic algorithm simulates the selection of biological individuals with different characteristics by nature and the phenomena of reproduction, crossover and mutation that occur in the genetic process between individuals in the biological population. It maintains a set of candidate solutions in each iteration, selects the best performing individuals from the solution group according to different optimization indicators, and uses genetic operators to select, crossover and mutate these individuals to generate a new generation of candidate solutions. The above process is repeated until the population reaches the target state.

The genetic algorithm allows the optimal planting plan to be identified from multiple feasible solutions, while taking into account the physical characteristics of the plot, the crop growth cycle, changes in market demand and the planting cost. The parallel selection method and the arithmetic crossover method are used for the selection operator and the crossover operator operation respectively. The fitness function of the algorithm evaluates the planting plan of each individual based on the total profit. Through genetic operations such as selection, crossover and mutation, the algorithm can continuously iterate the population and generate individuals that are increasingly adapted to the environment, that is, planting plans, until the termination condition is met.

In genetic algorithms, the fitness function is a mathematical representation of the degree to which an individual adapts to the environment. Individuals with high fitness will have a better chance of reproducing the next generation. Usually, individuals with fitness values higher than the average fitness value of the group are crossover, while individuals with fitness values lower than the average fitness value are mutated, thereby improving the average fitness value of the group and the performance of the best individuals from generation to generation. The goal of this article is to maximize the total profit, so the fitness function will be designed to reflect the economic benefits of each planting plan.

$$\text{Fitness(individual)} = \sum_{i=1}^{N_{\text{fields}}} \sum_{j=1}^{N_{\text{years}}} \sum_{k=1}^{N_{\text{crops}}} \left( P_{ijk} \cdot Y_{ijk} - C_{ijk} \right) \cdot x_{ijk} \text{Fitness(individual)} = \sum_{i=1}^{N_{\text{fields}}} \sum_{j=1}^{N_{\text{years}}} \sum_{k=1}^{N_{\text{crops}}} \left( P_{ijk} \cdot Y_{ijk} - C_{ijk} \right) \cdot x_{ijk} \quad (9)$$

Among them, $N_{fields}$ represents the number of plots, $N_{years}$ represents the number of years, $N_{crops}$represents the number of crop types, $P_{ijk}$ represents the unit sales price of the kth crop in the jth year, $Y_{ijk}$ represents the expected yield of the kth crop in the jth year, $C_{ijk}$ represents the unit planting cost of the kth crop in the jth year, and $x_{ijk}$ represents the area of the kth crop planted in the jth year on the ith plot.

In order to keep the individuals with the best fitness to the next generation as much as possible, the optimal individual preservation method is used to perform the survival of the fittest operation, that is, the individual with the highest fitness in the current population does not participate in the crossover operation and mutation operation, but is used to replace the individual with the lowest fitness in the current generation population after genetic operations such as mating and mutation. The optimal individual preservation method can be regarded as part of the selection operation. The implementation of this strategy can ensure that the best individuals obtained so far will not be destroyed by genetic operations such as mating and mutation. It is an important guarantee for the convergence of the genetic algorithm. After the fitness function is established, the operation from defining fitness and individual classes, defining fitness functions, genetic algorithm operations and the final results is realized. After the algorithm terminates, the individual with the highest fitness in the current population is extracted as the optimal solution and the results are visualized. In view of the different areas of various types of plots, the area of all plots is regarded as 100 mu during the calculation, and in the subsequent actual calculation, the actual area of each plot is multiplied by a certain proportional coefficient. The visualization result is shown in Figure 3, 4 below.

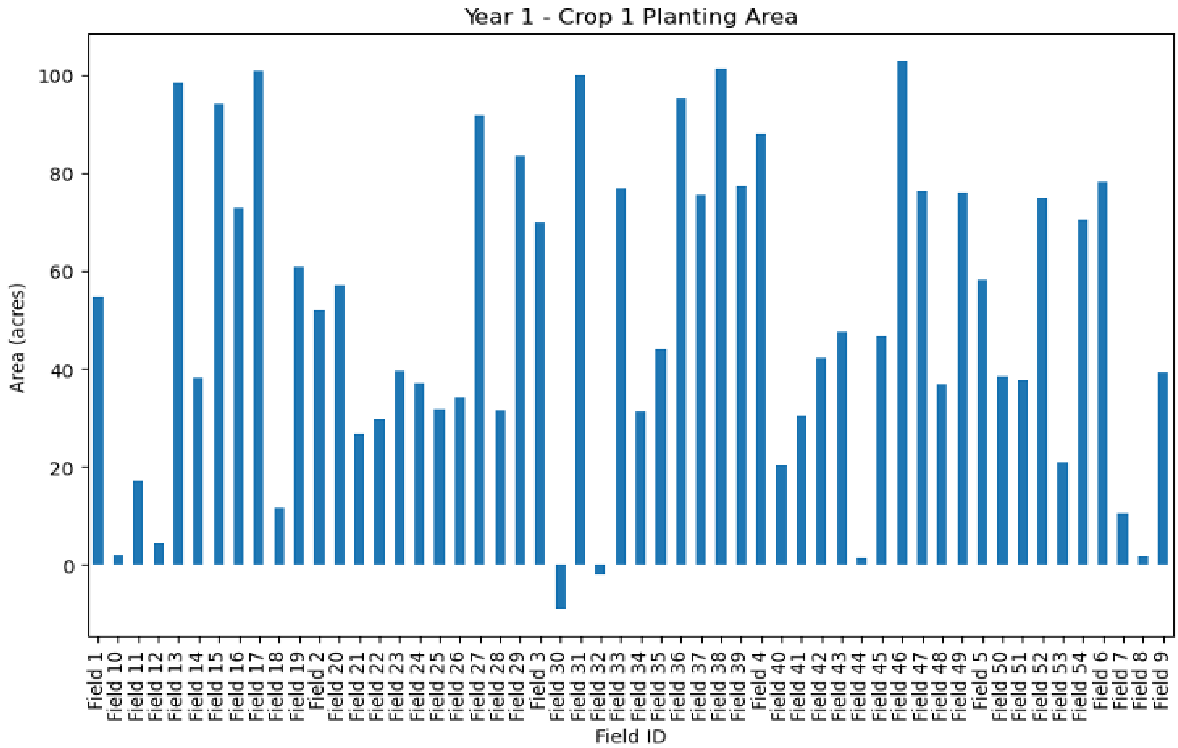


Figure 3 The first crop in the first year

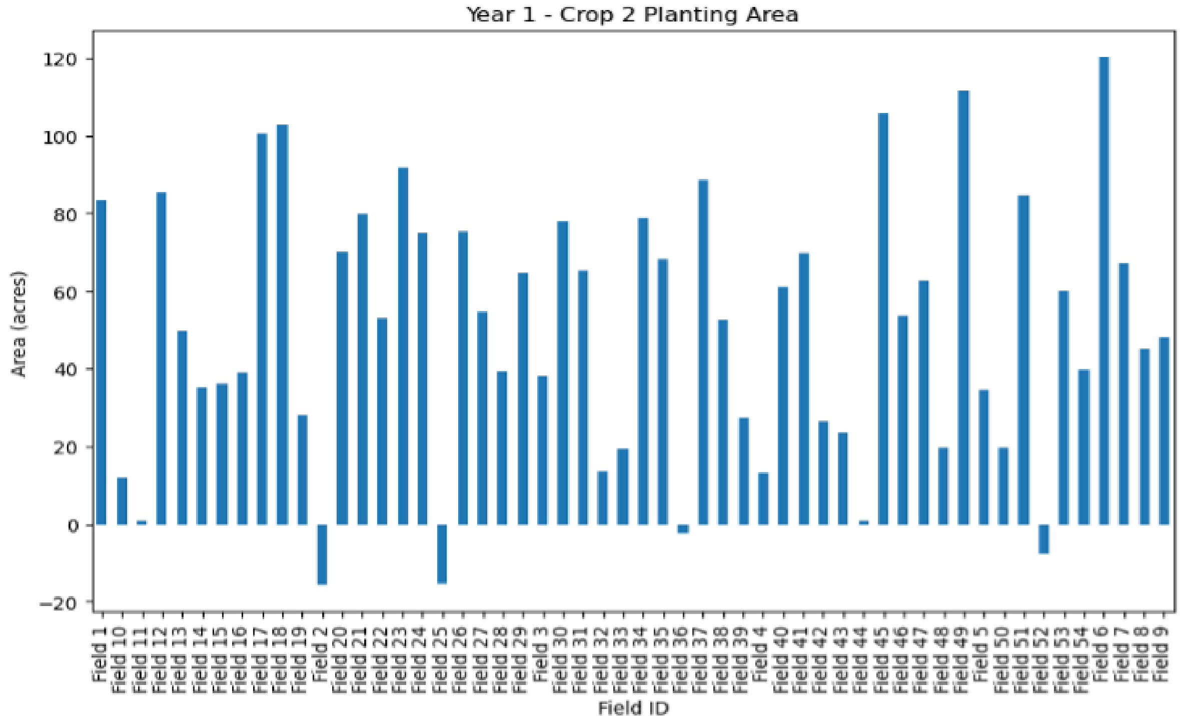


Figure 4 Second crop planting in the first year.

The results of excess unsalable crops and waste are shown in Table 1. According to calculations, the expected total profit of crops from 2024 to 2030 is 59313432.5 when excess unsalable crops and waste are caused.

Table 1 Result table for case 1

| | Plot Name | Soybean | Black Bean | Red Bean | Mung Bean |
|---|---|---|---|---|---|
| Season 1 | A1 | 0 | 68.17 | 55.16 | 7.267 |
| | A2 | 10.07 | 38.44 | 17.99 | 26.87 |
| | A3 | 26.72 | 34.65 | 23.28 | 12.64 |
| | A4 | 71.59 | 70.23 | 52.9 | 7.669 |
| | A5 | 0 | 68.17 | 55.16 | 7.267 |

The results of selling the excess at 50% of the 2023 sales price are shown in Table 2 below. It is calculated that when the excess is sold at 50% of the 2023 sales price, the expected total profit of the crops from 2024 to 2030 is 30003581.25

Table 2 Result table for case 2

| | Plot Name | Soybean | Black Bean | Red Bean | Mung Bean |
|---|---|---|---|---|---|
| Season 1 | A1 | 55.92 | 42.26 | 29.75 | 64.7 |
| | A2 | 32.28 | 46.56 | 25.54 | 56.19 |
| | A3 | 9.413 | 24.24 | 52.05 | 22.82 |
| | A4 | 4.015 | 19.84 | 0 | 39.47 |
| | A5 | 53.26 | 49.21 | 14.53 | 41.31 |

After the model was established and solved, a series of planting plans were obtained. These results were analyzed in depth to verify the effectiveness of the model. By comparing the planting area of different crops in different plots with historical data, it was found that the model results were basically consistent with the actual planting situation, but more optimized. For example, the optimization model increased the planting area of wheat and corn, which is consistent with the characteristics of high yield and high market demand of these two crops. By simulating different market conditions and climate change scenarios, it was found that the model can adapt to these changes and give corresponding adjustment suggestions. For example, in the case of increased market demand, the planting strategy can be quickly adjusted to increase the planting area of the corresponding crops.

### 2.3. Sensitivity analysis

Evaluate the key variables that affect the total revenue of crop planting strategies, including sales growth rate, per-acre yield change rate, planting cost growth rate, and sales price change rate. According to different growth rate ranges, such as the sales growth rate of wheat and corn between 5% and 10%, the sales change rate of other crops between -5% and +5%, the per-acre yield change rate between -10% and +10%, the annual planting cost growth rate is fixed at 5%, and the sales price change rate of different crops.

For each variable, calculate the sensitivity coefficient, that is, the ratio of the percentage change in revenue to the percentage change in the variable, and calculate the sensitivity of the total revenue to each parameter. The results are shown in Table 3 below:

Table 3 Sensitivity analysis

| Sensitivity analysis | Flat dry land | Terraced Fields | Hillside | irrigated land | Ordinary greenhouse | Smart greenhouse |
|---|---|---|---|---|---|---|
| Sales | 1.15 | 1.15 | 1.15 | 1.05 | 1.05 | 1.05 |
| Yield per mu | 0.21 | 0.21 | 0.21 | 0.13 | 0.68 | 0.68 |
| Planting costs | -0.005 | -0.19 | -0.19 | -0.19 | -0.07 | -0.07 |
| Sales Price | 0.17 | 0.17 | 0.03 | 0.17 | 0.34 | 0.34 |

Based on the changes in multiple parameters such as crop planting costs, per-acre yield, expected sales volume, and sales price in 2023, the crop planting data for each year from 2024 to 2030 are calculated within a certain floating range, as shown in Table 4 below.

Table 4 Forecast Change Table

| Planting cost | Soybean | Black Bean | Red Bean | Mung Bean | Climbing beans | Wheat |
|---|---|---|---|---|---|---|
| 2023 | 400 | 500 | 400 | 350 | 415 | 800 |
| 2024 | 384 | 411 | 365 | 343 | 345 | 438 |
| 2025 | 369 | 393 | 359 | 353 | 331 | 419 |
| 2026 | 382 | 401 | 364 | 370 | 321 | 417 |

The Monte Carlo method randomly draws parameter values in the simulation by defining a range of variation for each variable. For each set of parameter combinations, the planting strategy model is run to predict its impact on total revenue. This process is repeated thousands of times, and the resulting data is collected and analyzed to assess the sensitivity of each parameter to revenue.

In the simulation of the crop planting strategy, the total revenue $P$ can be expressed as sales revenue minus total costs:

$$P = \sum i = 1n(R_i \cdot X_i - Ci)P = \sum_{i=1n}(R_i \cdot X_i - C_i) \tag{10}$$

Where n is the number of crop types, $R_i$ is the unit sales price of the i-th crop, $X_i$ is the sales volume of the i-th crop, and $C_i$ is the total cost of the i-th crop.

The simulation process can be represented as a loop, where each iteration represents a different scenario or parameter combination:

$$\begin{aligned} & for\ k = 1\ to\ N\ do \\ & X_k \sim N(\mu, \sigma^2) \\ & P_k\ with\ X_k \\ & end\ for \end{aligned} \tag{11}$$

Given different growth rate intervals, the Monte Carlo simulation method is used to generate the results shown in Table 5 below

Table 5 The best planting plan for various crops in 2024

| Unit: mu | Soybean | Black Bean | Red Bean | Mung Bean | Climbing beans | Wheat |
|---|---|---|---|---|---|---|
| Plot 1 | 1.60 | 1.64 | 0.47 | 0.93 | 0.99 | 1.76 |
| Plot 2 | 0.80 | 1.07 | 0.58 | 1.31 | 2.03 | 1.64 |
| Plot 3 | 1.53 | 1.78 | 0.44 | 0.76 | 0.52 | 1.23 |
| Plot 4 | 0.52 | 0.02 | 0.68 | 0.48 | 1.15 | 1.47 |
| Plot 5 | 1.59 | 1.14 | 1.10 | 2.17 | 0.90 | 0.80 |

Through Monte Carlo simulation, a probability distribution of total revenue was obtained. The simulation results showed that sales price and per-acre yield were the two most sensitive parameters affecting total revenue, while the increase in planting costs had a relatively small impact on total revenue, verifying the consistency of the model prediction with historical data and proving the effectiveness of the model when simulating different market and climate scenarios. In addition, the sensitivity analysis revealed the risks faced by the planting strategy, prompting this paper to propose risk mitigation measures, such as crop diversification and market diversification strategies.

### 2.4. Complementary effects of different crops based on regression model

Based on the analysis of substitution and complementarity effects between different crops through regression models. For example, if the planting area of wheat increases, it may have a negative impact on the market demand for corn, or it may increase the demand for bean crops. Using the linear regression model, the total sales volume of crops is predicted.

Assuming that there is a linear relationship between the total sales volume y and x the average unit price, planting cost and sales volume, a multivariate linear regression can be established, which is expressed as

$$y = \beta_0 + \beta_1 \quad X_1 + \beta_2 X_2 + \epsilon \tag{12}$$

Among them, $y$ is the total sales of crops, $X_1$ is the average sales price, $X_2$ is the planting cost. $\beta_0$ is the intercept term, $\beta_1$ and $\beta_2$ is the coefficient to be estimated, $\epsilon$ is the error term.

Secondly, the missing values in the data were processed, and the missing data were filled with the average value of each variable. 20% of the data was reserved as the test set, and the model was trained using the training set data. In order to evaluate the performance of the model, the model's score $R^2$ was calculated. After the training was completed, the model was used to predict the total sales of the feature variables in the test set. The results are shown in Table 6 below:

Table 6 Forecast total sales

| Actual total sales/jin | Forecast total sales/jin |
|---|---|
| 813.1616971 | 18941.148 |
| 1058.868587 | 19727.94488 |
| 27873.57748 | 24338.28738 |
| 100940.0916 | 24245.05934 |
| 23448.06138 | 24291.51714 |

In order to more intuitively show the degree of fit between the prediction results and the actual data, the comparison results between the actual value and the predicted value are shown in Figure 5:

The calculation results are β_1=-196.85936917 and β_2=-2.13803559. The results show that there is a negative correlation between the average sales price, planting cost and the target variable "total sales volume", that is, an increase in the average sales price and planting cost will lead to a decrease in total sales volume. This result can also be verified based on actual experience; ϵ= 25799.45, that is, when the values of all characteristic variables are 0, the predicted value of total sales volume; the determination coefficient is R^2=0.62 , which can be considered to explain 62.38% of the variability of total sales volume.

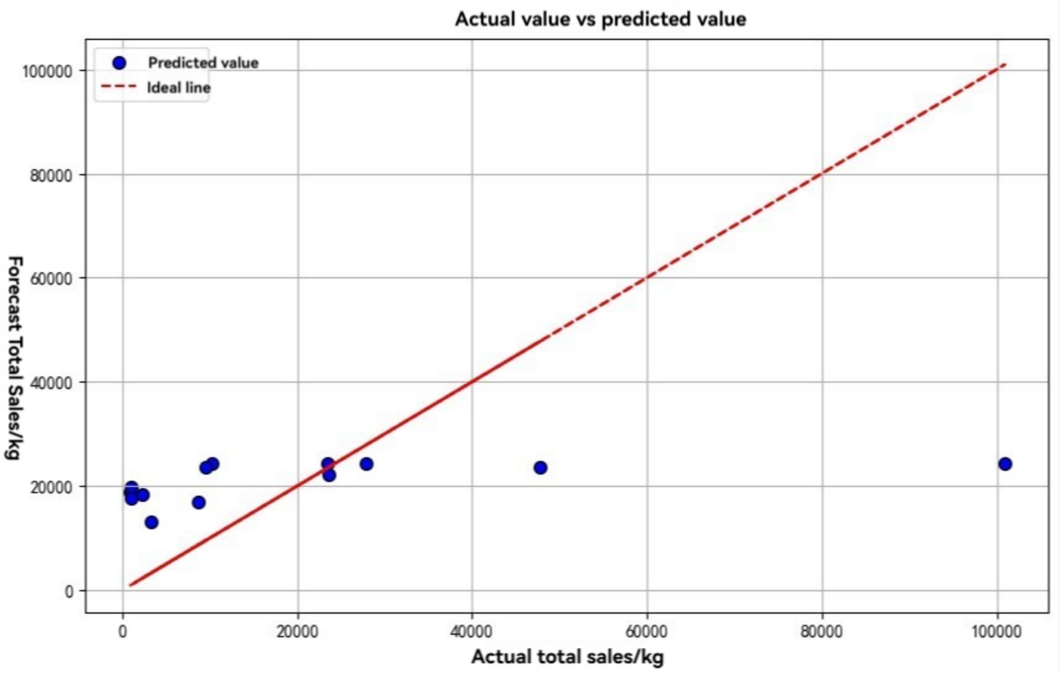

Figure 5 Comparison chart of actual value and predicted value.

After completing the construction of the multivariate linear regression model, the significance test of the model was performed. In the latest ordinary least squares (OLS) regression analysis, the coefficient of determination (R-squared) was as high as 0.941, which means that the model can explain about 94.1% of the variability of the dependent variable, and the adjusted coefficient of determination (Adj. R-squared) is also similar, which shows that the model is not overfitting and its fit is reliable; secondly, the F statistic is 776.7, which is a very high value, further confirming that at least one explanatory variable in the model has a significant effect on the dependent variable. The corresponding F statistic p-value is close to 0, providing clear evidence to reject the null hypothesis that all coefficients in the model are equal to zero.

The residual degrees of freedom (Df Residuals) of the model is 97, while the model degrees of freedom (Df Model) is 2, indicating that two explanatory variables are used to build the model. The Durbin-Watson statistic is 2.346, which is close to 2 and is generally considered to be an ideal state without autocorrelation, indicating that there is no obvious autocorrelation between the residuals and the error term of the model is appropriate.

In the initial construction stage of the model, the degree of fit of the model to the data was evaluated, proving that there is a certain relationship between the variables. However, this parameter only proves the explanatory power of the variables in the model, and does not reveal the specific relationship between the variables in detail.

This paper explores the correlation between sales volume, planting cost, per mu yield and sales price, and analyzes how these relationships affect model predictions. The Pearson correlation coefficient is used to measure the linear relationship between continuous variables. The calculation of the correlation coefficient shows that the average unit price is negatively correlated with the total sales volume ($r=-0.18$), indicating that as the price increases, the sales volume will decrease; the planting area is strongly positively correlated with the total sales volume ($r=0.58$), indicating that as the planting area increases, there is a 58% probability that the total sales volume will also increase; and the sales volume is negatively correlated with the planting cost to a certain extent ($r=-0.26$), reflecting that the price increase caused by the cost increase has suppressed the sales volume.

After establishing the linear programming model and correlation analysis, the sales volume of crops is predicted, and a function is defined to take the planting cost as input and calculate the sales volume based on the assumed proportional relationship between the sales price and the planting cost. Furthermore, another function is defined to calculate the expected profit based on the predicted sales volume and planting cost. By looping through all possible planting costs and the predicted profit under each cost, the planting cost with the highest expected profit and the corresponding profit value are finally output.

In comparison, the regression model shows greater volatility in profits between 2024 and 2030, which may be due to several key factors: First, the model may be more sensitive to market dynamics and external conditions. For example, climate affects the growth and development of crops in many ways. If the climate conditions in the area where the crops are located are favorable, it will help the growth of crops; on the contrary, it will hinder their growth. Second, the uncertainty of parameter estimation may cause the model output to be overly sensitive to small changes in input data, thereby amplifying the volatility of profits. In addition, the model takes into account more external risk factors,such as sudden changes in market demand and policy changes, which may lead to instability in the forecast results in the model.

## 3. Conclusion

In view of the resource and environmental pressure and food security needs faced by modern agriculture, this paper constructs a crop planting strategy planning model based on data-driven and intelligent optimization. The model integrates multi-dimensional data such as sales volume, cost, yield and price, and combines linear regression analysis and correlation analysis to achieve dynamic prediction and optimization of the planting plan from 2024 to 2030. The research results show that the model successfully maximizes agricultural benefits under the premise of stable expected sales volume through genetic algorithm solution and multi-scenario simulation. Its advantages are reflected in three aspects: first, the economic benefits and soil sustainability requirements are taken into account through a simple architecture design; second, the risk resistance of the scheme is verified by sensitivity analysis and Monte Carlo simulation; third, the planning accuracy is improved by fine matching of plot characteristics and crop growth cycle. However, the model still has the limitations of idealized assumptions (such as fixed growth rate setting) and static framework. In the future, the model can be further enhanced to adapt to technology iteration and market fluctuations by introducing a dynamic parameter update mechanism, developing parallel computing modules, and building a multi-objective optimization system, providing a more forward-looking support tool for smart agricultural decision-making.

## References

[1] Hu M, Tang H, Yu Q, et al. A new approach for spatial optimization of crop planting structure to balance economic and environmental benefits[J]. Sustainable Production and Consumption, 2025, 53: 109-124.

[2] Esteso A, Alemany M M E, Ortiz Á, et al. Crop planting and harvesting planning: Conceptual framework and sustainable multi-objective optimization for plants with variable molecule concentrations and minimum time between harvests[J]. Applied mathematical modelling, 2022, 112: 136-155.

[3] Wang J, Cheng Z, Ersoy O K, et al. Crop planting structure optimization based on improved real genetic algorithm[J]. International Agricultural Engineering Journal, 2018, 27(2): 169-185.

[4] Boyabatlı O, Nasiry J, Zhou Y. Crop planning in sustainable agriculture: Dynamic farmland allocation in the presence of crop rotation benefits[J]. Management Science, 2019, 65(5): 2060-2076.

[5] Adamo T, Colizzi L, Dimauro G, et al. Crop planting layout optimization in sustainable agriculture: A constraint programming approach[J]. Computers and Electronics in Agriculture, 2024, 224: 109162.