Research on the optimization of crop planting strategy under multi-dimensional uncertainty —— Based on Monte Carlo simulation, linear planning and crop correlation analysis

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Abstract. Crop cultivation in rural areas faces challenges from diversification, plot constraints, and fluctuating market demands, posing threats to farmers' economic income stability. To address this, this paper proposes a crop planting optimization model based on Genetic Algorithm (GA) for the planning period from 2024 to 2030. This model encodes planting schemes as chromosomes, simulates the natural evolution process, and maximizes economic returns through selection, crossover, and mutation operations. Additionally, nine gradient mutation rate experiments are designed to explore their impact. Meanwhile, optimal schemes are simulated and calculated for situations of crop surplus and price reductions. To address parameter uncertainty, a strategy combining Monte Carlo simulation and Linear Programming (LP) is employed to assess risk correlations and solve for optimal schemes under various scenarios. Experimental results demonstrate that this model outperforms traditional methods in enhancing returns and reducing risks, providing robust support for formulating crop planting strategies.

Keywords: Genetic Algorithm, Monte Carlo Simulation, Planting Risk, Crop Rotation.

1. Introduction

In rural areas with scarce resources or harsh environments, efficient utilization of farmland is crucial for economic revitalization. Traditional agriculture harms the ecology, and shifting to organic farming represents a sustainable development path. For mountainous regions in North China, it is necessary to scientifically plan the planting schemes for 34 plots from 2024 to 2030, considering crop growth cycles, seasonal challenges, plot functions, constraints on continuous cropping, crop rotation requirements, and market uncertainties, in order to address overproduction and unsold goods, and achieve efficient resource use and maximize economic returns.

Scholars are conducting in-depth research on models for planting optimization, agricultural risk management, and portfolio efficiency, focusing on their construction and optimal evaluation methods. In the field of agricultural planting technology, several studies have made significant progress in recent years. Wang Longgang and Li Shuai discussed mechanized planting techniques for wheat-corn rotation, aiming to enhance agricultural production efficiency [1]. Ma Linxiao built a multi-objective planting structure optimization model based on genetic algorithms, providing a scientific basis for planting decisions [2]. Tang Lei analyzed the impact of climate change on planting directions, emphasizing the importance of sustainable farmland development [3]. Jin Wanhe assessed crop seed planting risks in Jilin Province and proposed strategies to improve planting quality [4]. Li Shuo studied the optimization of crop planting structures in the Weigan River Basin under water resource constraints [5]. Liu Tao explored methods for optimizing crop planting from a strategic perspective [6]. Additionally, the rice-vegetable rotation model has proven economically beneficial (a new rural technology), and Wang Changsong et al. evaluated the comprehensive benefits of multi-year crop rotation models in red soil drylands in Jiangxi Province [7-8]. In terms of agricultural risk management, Zeng Yuzhen and Mu Yueying (2011) analyzed the classification of agricultural risks and the applicability of risk management tools [9]. Although Rong Ximin et al. focused their research on portfolio investment models, their optimization ideas also offer insights into adjusting agricultural planting structures [10]. Finally, Liu Guopeng used genetic programming algorithms to explore selection methods for key stress-resistant genes in crops, providing new ideas for crop genetic improvement [11].

In summary, based on scholarly research, this paper focuses on optimizing crop planting strategies and proposes a comprehensive solution that integrates NP programming, genetic algorithms, Monte Carlo simulations, and linear programming. This solution comprehensively examines agriculture, markets, and mathematical modeling capabilities, providing a scientific basis for the planting plan of a rural village from 2024 to 2030.

2. Theory and Methods

2.1. Research on Crop Planting Planning from 2024 to 2030 Based on Constant Expected Sales and Costs

2.1.1. Establishment of a Multi-Objective Optimization Model

Existing 54 arable land, a total of 41 different crops can be selected for planting, establishing the optimal planting planning model in two cases.

Objective function: revenue maximization

(1) Unmarketable waste

$$\max Z_1 = \sum_{j=1}^{54}\left\{\min\left[\sum_{i=1}^{41}\left(x_{ij}\cdot a_{ij}\cdot s_{ij}-l_i\right)\right]\cdot p_i-\left[\sum_{i=1}^{41} c_i\cdot x_{ij}\cdot a_{ij}\right]\right\} \tag{1}$$

(2) Excessive partial sales at a discount

$$\max Z_2 = \sum_{j=1}^{54}\left\{\left[\sum_{i=1}^{41}\left(x_{ij}\cdot a_{ij}\cdot s_{ij}-l_i\right)\right]\cdot 0.5\cdot p_i-\left[\sum_{i=1}^{41} c_i\cdot x_{ij}\cdot a_{ij}\right]\right\} \tag{2}$$

Constraint condition:

Planting area constraint: the planting area of each land shall not exceed the maximum planting area

$$\sum_{j=1}^{54}\sum_{i=1}^{41} a_{ij} \le m_j, i = 1,2\ldots,41; j = 1,2,\cdots,54 \tag{3}$$

Beume crop rotation constraints: plant beans at least once in three years

Flat dry land, terraced fields and mountain slopes:

$$\sum_{t=1}^{3}\sum_{i=1}^{5} a_{ij}^{t} > 0\,, j = 1,2,\cdots,26 \tag{4}$$

Watershed land, ordinary greenhouses, smart greenhouses:

$$\sum_{t=1}^{3}\sum_{i=17}^{19} a_{ij}^{t} > 0\,, j = 27,28,\cdots,54 \tag{5}$$

Double constraint: the same crop cannot be planted in the same plot in continuous seasons

$$a_{ij}^{1} \ne a_{ij}^{2}, j = 51,52,53,54 \tag{6}$$

Dispersed planting constraints: the planting areas of each crop should not be too dispersed per season

$$1 < SAI_{ij} < 2 \tag{7}$$

$$SAI_{ij} = \frac{a_{ij}\Big/\sum_{i=1}^{41} a_{ij}}{\sum_{j=1}^{54} a_{ij}\Big/\sum_{i=1}^{41}\sum_{j=1}^{54} a_{ij}}, j = 1,2,\cdots,54;\ i = 1,2,\cdots,41 \tag{8}$$

The comparative advantage index of regional scale of vegetable production is a yardstick to measure the professional level of regional vegetable production, reflecting its competitiveness and development potential relative to the whole country. An index greater than 1 means that the specialization level exceeds the national average. The higher the index, the deeper the scale and degree of specialization, which is conducive to the optimal allocation of agricultural resources and the coordinated development of regional economy.

Unmarketable situation selection:

$$\min \sum_{i=1}^{41}\left(x_{ij}.a_{ij}.s_{ij}-l_i\right)=\begin{cases} a_{ij}.s_{ij}-l_i, a_{ij}.s_{ij}-l_i \leq 0 \\ \min\left(a_{ij}.s_{ij}-l_i\right). a_{ij}.s_{ij}-l_i > 0 \end{cases} \tag{9}$$

Planting status of each plot:

$$x_{ij}=\begin{cases} 0, \text{To indicate the firstjNo planting on the plotsiPlanting crops} \\ 1, \text{To indicate the firstjPlot NoiPlanting crops} \end{cases} \tag{10}$$

Among them, a_{ij} represents the planting area of the i-th crop in the j-th plot; m_j represents the per - mu planting area of the j-th plot; s_{ij} represents the per - mu yield of the i-th crop in the j-th plot; p_i represents the unit selling price of the i-th crop; c_i represents the planting cost of the i-th crop; l_i represents the expected sales volume of the i-th crop; a_{ij}^1 represents the planting area of the i-th crop in the j-th plot in the first season; a_{ij}^2 represents the planting area of the i-th crop in the j-th plot in the second season.

2.1.2. Genetic algorithm optimization

This study employs a genetic algorithm to optimize the crop production plan. Binary n×m matrices are used for encoding to represent the planting schemes of plots and crops, ensuring that only one type of crop is planted in each plot and improving the search efficiency. The initial population size is set between 20 and 200, constructed by combining experience and randomness to balance the algorithm's performance and efficiency. The selection operation adopts a roulette wheel selection mechanism with the best individual retention. Whether a chromosome enters the next generation is determined according to its adaptability. The selection of genetic algorithm parameters is crucial, including the length of the coding string, population size, crossover probability, and mutation probability. This study reasonably sets these parameters and explores adaptive strategies to enhance the application effect of the algorithm.

When solving the model, a preset upper limit for the maximum number of evolutionary generations (such as 5000 or 10000 iterations) is set to ensure that the algorithm fully explores the solution space and converges to an excellent solution. This strategy shows significant advantages in practical problems such as crop production plan optimization. Finally, this paper details the planting areas of various crops on some different plots. The specific data can be found in Table 1 and Table 2. In addition, a comparative analysis of the estimated total profits of two different planting schemes from 2024 to 2030 is conducted, and the relevant data are summarized in Table 3. It is worth noting that the change in the mutation rate has a significant impact on the planting results, and the trend of this impact is shown in Figure 1.

Consider a simplified genetic algorithm model whose fitness function is used to evaluate the performance of each individual, where is a vector encoding the individual's characteristics. The goal of the algorithm is to maximize the fitness function. One iteration of the genetic algorithm can be represented by the following steps:

(1) Selection: The probability that an individual is selected for reproduction is proportional to its fitness. If we let p_i be the probability that the i-th individual is selected, then:

$$p_i=\frac{f(x_i)}{\sum_{j=1}^{N} f(x_i)} \tag{11}$$

$f(x_i)$is the fitness of the i-th individual, N is the total number of individuals in the population.

(2) Crossover: The selected individuals generate new offspring through crossover operation. If the intersection point is k,and considering two individuals x_i and x_j, the offspring x_{new} can be expressed as:

$$x_{new} = \left(x_{i1}, x_{i2}, \ldots, x_{ik}, x_{j(k+1)}, \ldots, x_{jn}\right) \tag{12}$$

(3) Mutation: Modify some genes of the newly generated individuals with a small probability μ to introduce variation and increase the diversity of the population. For gene x_{nk}, the mutation operation can be expressed as:

$$x_{nk}^{'} = x_{nk} + \delta, \text{ with probability } \mu \tag{13}$$

δ is a random amount of small variation, μ is the mutation rate.

By repeating these steps, the genetic algorithm can gradually improve the quality of the solution to the optimal solution. The fitness function usually improves for each generation, indicating the effectiveness of the algorithm in solving specific problems.

2.2. Research on Optimization and Risk Management of Crop Planting Schemes Based on Multiple Uncertainty Factors

2.2.1. Optimization by Monte Carlo Simulation

This paper will use Monte Carlo simulation method to deal with uncertainties such as expected crop sales volume, yield per mu, planting cost and selling price, in order to provide the optimal planting scheme for this rural crop from 2024 to 2030, the following Tables 5 and 6 are presented, and Table 4 below shows the optimal planting profit for the crop during the period from 2024 to 2030. The following are the detailed solution procedures and the formulas involved:

Step 1: Define the uncertainty parameter

Expected sales volume growth rate:

Wheat and corn:

an annual growth rate $r_{wheat,corn} \sim U(0.05, 0.10)(\text{uniform distribution}, 5\%\text{To } 10\%)$

Other crops:

the annual growth rate $r_{others} \sim U(-0.05, 0.10)(\pm 5\%)$

Change rate of per-mu yield:

All crops: the annual rate of change $\delta_{yield} \sim U(-0.10, 0.10)(\pm 10\%)$

Growth rate of planting cost:

All crops: an annual growth rate $\gamma_{cost} = 0.05$ (fixed 5%)

Sales price growth rate:

Food crops: remain unchanged

Vegetable crops: an annual growth rate

$r_{vegetable} \sim U(0.05, 0.05)(\text{Reduced to a fixed } 5\%, \text{Can also be set as an interval})$

Edible fungi (except morels): the annual decline rate $r_{mushroom} \sim U(-0.01, -0.05)(1\% \text{ to } 5\%)$

Morels: annual decline rate $r_{morchella} = 0.05$ (fixed 5%)

Step 2: Initialize the parameters

Read the basic data for 2023, including the sales volume of various crops, the yield per mu, planting costs, sales prices, etc.

Set the simulation times N (like 1000 times).

Step 3: Conduct a Monte-Carlo simulation

For each simulation$k = 1,2, \ldots, N$:

Update the expected sales volume:

Wheat and corn:

$$Q_{wheat,corn}^{k}(t) = Q_{wheat,corn}(t-1) \times \left(1 + r_{wheat,corn}^{k}\right) \tag{14}$$

Other crops:

$$Q_{others}^{k}(t) = Q_{others}(t-1) \times \left(1 + r_{others}^{k}\right) \tag{15}$$

Among, $r_{wheat,corn}^{k}, r_{others}^{k}$ is the value randomly drawn from the corresponding distribution, and t represents the year.

Update the per-mu yield:

$$Y_{crop}^{k}(t) = Y_{corn}(t-1) \times \left(1 + \delta_{yield}^{k}\right) \tag{16}$$

Among, δ_{yield}^{k} is a value randomly drawn from the distribution of mu yield change rates.

Update the planting cost:

$$C_{corn}^{k}(t) = C_{corn}(t-1) \times (1 + \gamma_{cost}) \tag{17}$$

Update the sales price: (Food crops remain the same)

Vegetable crops:

$$P_{vegetable}^{k}(t) = P_{vegetable}(t-1) \times \left(1 + r_{vegetable}^{k}\right) \tag{18}$$

Edible fungi (except for morels):

$$P_{mushroom}^{k}(t) = P_{mushroom}(t-1) \times \left(1 + r_{mushroom}^{k}\right) \tag{19}$$

Morel:

$$P_{morchella}^{k}(t) = P_{morchella}(t-1) \times (1 - 0.05) \tag{20}$$

Calculate the profits for each crop:

$$\mathrm{Profit}_{crop}^{k}(t) = \left(P_{crop}^{k}(t) - C_{crop}^{k}(t)\right) \times \min\left(Q_{crop}^{k}(t), Y_{crop}^{k}(t) \times \mathrm{Area}_{crop}\right) \tag{21}$$

Among Area_{crop} is the area where the crop is grown.

Optimize the planting plan:

Using linear programming, integer programming, or other optimization algorithms, based on the parameters of the current simulation.

Step 4: Summarize the simulation results

Statistics were performed for all simulated planting schemes, such as calculating the average of planting area for each crop.

Based on the statistical results, choose a suitable planting scheme (such as the scheme to maximize the average profit).

Based on the risk definition by Zeng Yuzhen and Mu Yueying, risk refers to the uncertainty of loss or the variation in outcomes. With the increase in agricultural product varieties, the role of covariance in risk assessment becomes more prominent, while the influence of variance for a single agricultural product diminishes. The Markowitz risk portfolio model proposed by Rong Ximin et al. provides a powerful tool for assessing farmers' risks. We employ a combination of variance and covariance formulas for quantitative analysis, the specific formula is as follows:

$$\mathrm{Var}(p) = \sum_{i=1}^{n} \sum_{j=1}^{n} w_i w_j \mathrm{Cov}\left(x_i x_j\right), i = 1,2,3,\ldots,41, j = 1,2,3,\ldots,41 \tag{22}$$

Among them, $\mathrm{Var}(p)$ represents the total risk value; $\mathrm{Var}(x)$ is the variance of the i-th type of agricultural product, representing its own risk; $\mathrm{Cov}\left(x_i x_j\right)$ is the covariance between the returns of the i-th and j-th types of agricultural products, representing the relative risk between them. w_i represents the planting proportion of the i-th type of crop, and the sum of the planting proportions of all crops is 1, that is $\sum_{i=1}^{n} w_i = 1$.

To facilitate the understanding and application of the above formula, we can further express it as the form of the variance-covariance matrix:

$$\begin{bmatrix} w_1w_2Var(x_1) & w_1w_2Cov(x_2x_2) & w_1w_3Cov(x_1x_3) & & w_1w_nCov(x_1x_n) \\ w_2w_1Cov(x_2x_1) & w_2w_2Var(x_2) & w_2w_3Cov(x_2x_3) & \cdots & w_2w_nCov(x_2x_n) \\ w_3w_1Cov(x_3x_1) & w_3w_2Cov(x_3x_2) & w_3w_3Var(x_3) & & w_3w_nCov(x_3x_n) \\ & \vdots & & \ddots & \vdots \\ w_nw_1Cov(x_nx_1) & w_nw_2Cov(x_nx_2) & w_nw_3Cov(x_nx_3) & \cdots & w_nw_nVar(x_n) \end{bmatrix} \tag{23}$$

Model integration is presented as follows:

$$\begin{cases} minVar(p) = \sum_{i=1}^{3}\sum_{j=1}^{3} w_iw_jCov\left(x_ix_j\right), i = 1,2,3,...,41; j = 1,2,3,...,41 \\ s.t. \sum_{i=1}^{3} R_iw_i \geq R_0 \\ \sum_{i=1}^{n} w_i = 1 \\ 0 \leq w_i \leq 1 \end{cases} \tag{24}$$

Among,w_i represents the planting proportion of the i-th type of crop, and the sum of the planting proportions of all crops is 1, that is $\sum_{i=1}^{n} w_i = 1$.R_i represents the rate of return of the i-th type of crop, and R_i^0 represents the minimum rate of return of the i-th type of crop.

3. Data preprocessing

This project conducts an analysis based on the crop planting and sales records from 2023. Although the data for the first season of the smart greenhouse is missing, the direct substitution method is used to complete the data by assuming that the first - season data of the smart greenhouse is the same as that of the ordinary greenhouse. During the data preprocessing stage, the flexibility of percentages is retained, which are directly mapped in the subsequent Monte Carlo simulation. The linear interpolation method and random number mapping are utilized to ensure that the generated percentage change values are within a reasonable range.

In the analysis process, the pandas and numpy libraries in Python are used to conduct in - depth exploration of the data, revealing the complex connections among sales volume, price, and cost. All analyses are based on the assumptions that the plot - planting decisions are independent, the future expected sales volume and planting cost remain unchanged, and the crop growth conditions, field management, and farming operation efficiency are stable during the prediction period. This provides strong data support for agricultural production planning and market strategies.

4. Research conclusions

The area distribution of different crops planted on selected plots is shown in Table 1 and Table 2. The total profits for two scenarios from 2024 to 2030 are shown in Table 3. The results caused by changes in the coefficient of variation are shown in Figure 1.

Table 1. Shows the area of different crops planted in different plots

Plot name	soya bean	black soya bean	Ormosia hosiei	urad	Climbing beans	wheat	corn	millet
A1	0	0	0	0	16	0	0	0
A2	0	0	0	0	0	0	0	0
A3	0	0	0	0	0	0	0	0
A4	11	0	0	0	0	0	1	0
A5	0	0	0	0	0	0	0	0
A6	0	0	0	0	0	0	0	0
B1	0	0	0	0	0	0	0	12
B2	0	0	0	0	0	3	0	4
B3	0	0	0	0	0	0	0	0
B4	0	0	0	0	0	0	0	0
B5	0	0	0	0	0	0	0	0
B6	0	0	2	12	6	0	0	3
B7	0	0	0	0	0	0	0	0

Table 2. Shows the area of different crops planted in different plots

Plot name	kaoliang	glutinous broom corn	buckwheat	pumpkin	sweet potato	Oat wheat	barley	paddy
A1	7	0	0	0	12	0	0	0
A2	0	0	0	0	0	0	0	0
A3	0	0	0	0	0	0	0	0
A4	0	6	0	0	0	0	0	0
A5	0	0	0	0	0	5	0	0
A6	0	5	0	0	0	0	0	0
B1	9	0	0	0	0	0	0	0
B2	0	5	0	0	0	0	0	0
B3	0	0	0	0	0	0	0	0
B4	0	0	0	0	0	0	0	0
B5	0	0	0	0	0	0	0	0
B6	0	0	12	10	0	0	0	0
B7	0	0	0	0	7	0	0	0

Table 3. Total Profits of Two Scenarios from 2024 to 2030

a particular year	1.1 Profit	1.2 Profit
2024	4770047.29	6456785.21
2025	4712725.46	6845695.73
2026	5648924.13	7425129.26
2027	5612784.89	7214954.85
2028	6000314.43	8465212.45
2029	6398591.18	8947487.56
2030	6245486.34	9145245.19
sum	39388873.73	54500510.25

The influence of the mutation rate on the optimization process was thoroughly investigated. In this study, nine mutation rate gradients including 0, 0.001, 0.01, 0.05, 0.1, 0.2, 0.3, 0.4, and 0.5 were designed for experiments. The experimental results are shown in Figure 1 below. An excessively high mutation rate will accelerate the degradation of the population, thereby reducing the optimization efficiency. Moreover, without the intervention of an elitist strategy, this degradation phenomenon will be more prominent. Conversely, an extremely low mutation rate will limit the diversity of population evolution and easily lead to the “premature convergence” problem, causing the optimization process to get trapped in a local optimum.

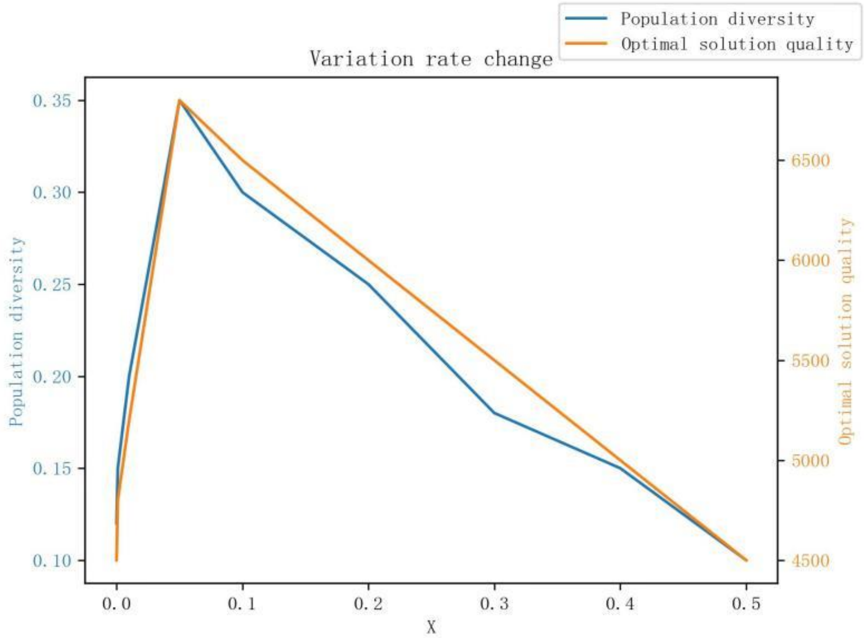

Figure 1. Results resulting from changes in variation rate

In this study, we determined the optimal crop planting scheme for the period from 2024 to 2030, and the details are listed in Table 4. To thoroughly explore the stability and reliability of this scheme under different conditions, we employed the Monte Carlo simulation method for analysis.

During the Monte Carlo simulation process, we adjusted the number of iterations (the value of k), specifically setting it to k = 10, k = 100, and k = 300, to observe the changes in the simulation results. These simulation results provide a detailed description of the area allocation for planting different crops on different plots. Notably, as the number of iterations continuously increases, the results of the Monte Carlo simulation gradually show a more stable trend. This improvement in stability helps us to more accurately reflect the actual situation, thereby obtaining a more reliable planting scheme. In particular, when the number of iterations reaches k = 300, we obtained detailed data on the planting areas of different crops on some plots, and these data have been organized and listed in Table 5 and Table 6. By comparing and analyzing these data, we can further verify and optimize our planting scheme, providing more scientific guidance for agricultural production.

Table 4. Optimal planting schemes for crops from 2024 to 2030

a particular year	profit
2024	7245278.41
2025	7459125.69
2026	7654892.33
2027	8254913.64
2028	8865492.67
2029	8912476.28
2030	9167452.92
sue for peace	57559631.94

Table 5. Shows the Monte Carlo simulation k=300 different plots of different crops:

Plot name	soya bean	black soya bean	Ormosia hosiei	urad	Climbing beans	wheat	corn
A1	0	0	0	0	0	0	0
A2	0	0	0	0	0	55	0
A3	0	0	0	0	0	35	0
A4	0	0	0	0	0	0	72
A5	0	0	0	0	0	0	0
A6	0	0	0	0	0	0	0
B1	0	0	0	0	0	0	0
B2	0	0	0	0	0	46	0
B3	0	0	0	0	0	0	0
B4	28	0	0	0	0	0	0
B5	0	0	0	0	0	0	0
B6	0	0	0	0	0	0	0
B7	55	0	0	0	0	0	0

Table 6. Shows the Monte Carlo simulation k=300 different plots of different crops:

Plot name	kaoliang	glutinous broom corn	buckwheat	pumpkin	sweet potato	Oat wheat	barley
A1	0	80	0	0	0	0	0
A2	0	0	0	0	0	0	0
A3	0	0	0	0	0	0	0
A4	0	0	0	0	0	0	0
A5	0	68	0	0	0	0	0
A6	0	55	0	0	0	0	0
B1	0	0	0	0	0	0	0
B2	0	0	0	0	0	0	0
B3	0	0	40	0	0	0	0
B4	0	0	0	0	0	0	0
B5	0	0	25	0	0	0	0
B6	0	86	0	0	0	0	0
B7	0	0	0	0	0	0	0

5. Conclusion

This thesis primarily addresses the challenges faced in crop cultivation, such as diversification, land plot constraints, and fluctuations in market demand, by proposing an optimization model for crop planting based on Genetic Algorithms (GA). It also integrates methods such as Monte Carlo simulation, linear programming, and crop correlation analysis to provide a scientific basis for formulating crop planting strategies from 2024 to 2030, with the aim of enhancing yields and mitigating risks.

This model combines NP programming, genetic algorithm, and Monte Carlo simulation, which can deal with complex optimization problems, global search to avoid local optima, comprehensively analyze uncertainty, and not strict on the data distribution, but the calculation is large and difficult to build. The model can flexibly adapt to different regions and conditions, which can be expanded to include multiple factors, and provide scientific solutions for agricultural decision-making, which is expected to improve planting benefits and promote sustainable development.

Based on the research of "Optimization of Crop Planting Strategies under Multi-dimensional Uncertainties—Based on Monte Carlo Simulation, Linear Programming, and Crop Correlation Analysis", future research directions can explore the optimization of genetic algorithms, handling of model uncertainties, integration of intelligent technologies, incorporation of crop growth models, as well as empirical research and promotion, in order to enhance the scientificity and practicability of planting strategies and promote sustainable agricultural development.

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