Analysis of Agricultural Resource Allocation and Market Response Based on Different Crop Yield Data

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Abstract. In the context of promoting rural revitalization, a crop planting strategy was developed for the diverse farmland and rich crop varieties in North China, aiming to adapt to market demand, and land characteristics, and respond to market dynamics and uncertainty. This paper developed a comprehensive planting strategy model that not only provides scientific decision support but also has flexibility and applicability, allowing for adjustments based on actual conditions. The model used the ideal point method and the maximum-minimum model to solve the dual-objective planning problem and evaluated the performance of different planting schemes in a variable environment based on an analysis of data sets. It ultimately determined the optimal planting scheme that could maintain a high yield under the influence of various uncertain factors. The establishment and application of this model can not only help farmers make the most optimal planting choices in complex and variable market and climate conditions but also significantly improve land utilization efficiency and economic benefits, providing strong scientific support for rural revitalization.

Keywords: Optimal planting strategy, dual objective programming model, ideal point method, Monte Carlo simulation

1. Introduction

Agriculture is the pillar industry of China's economy. With the continuous progress of science and technology, this paper has a new understanding and thinking on the planting methods of crops. North China is an important agricultural production base in China, with superior natural conditions[1].To improve the efficiency of agricultural production and meet the diversified needs of the market, it is necessary to adjust the crop planting structure and optimize field management scientifically. The key is to combine the optimal planting strategy with the actual production, explore the best planting mode, and maximize the benefits of agriculture.

Cui Si-meng et al. used a fast non-dominated sorting genetic algorithm based on elite strategies to adjust the crop planting structure in irrigation systems to build a multi-objective optimization model with high water resource utilization efficiency and good agricultural sustainability[2]. Ai et al. used the contemporaneous average method, Bayesian and vector autoregressive models to predict vegetable sales, and designed pricing and replenishment strategies through an optimization model to achieve optimal benefits[3]. Huang Liuting et al. mainly analyzed the impact of comparative benefits and the degree of concurrent employment on the adjustment of soybean and peanut planting structures from the perspectives of production substitution effect and selection effect by constructing a panel data model. They found that comparative benefits generally have a positive effect on the adjustment of crop planting structures [4]. Wei Zhifang mainly studies the intelligent optimization algorithm for multimodal problems and proposes a series of algorithm frameworks and strategies to balance diversity and convergence, which verifies the effectiveness of the algorithm in solving multimodal single-objective and multimodal multi-objective optimization problems [5].

However, the existing research has some problems in crop planting, such as remote sensing data limitation, high model complexity, and no consideration of regional differences. By constructing a bi-objective programming model, this paper effectively solves the problem of planting scheme optimization under abnormal sales conditions and uses Monte Carlo simulation and a single-objective programming model to ensure the robustness of the optimization scheme, and can adapt to changing environmental conditions, so as to maintain high income under the influence of uncertain factors, and improve the scientific and practical planting strategy as a whole.

2. Dual objective programming model

2.1. Structure of Dual Objective Programming Model

Dual objective programming refers to finding an approximate solution that satisfies all objectives when there are two conflicting objective functions in an optimization problem. In the maximum minimum model of dual objective programming, the goal is to find a solution that maximizes the worst value among all objective function values. This model is particularly suitable for scenarios that require balancing multiple objectives, where one objective must be maximized and another must be minimized. In the optimal planting plan scenario, it is necessary to maximize the total profit and minimize the land use area to satisfy the maximum minimum model [6].

The dual objective programming model consists of four basic elements, which are:

(1) Establish the objective function. Dual objective programming involves two objective functions that need to be optimized simultaneously. These objective functions are typically expressed as mathematical expressions that require minimization or maximization. When the objective function is positive, it indicates that the current solution performs well on that objective; On the contrary, if the objective function is negative, it indicates that the solution performs poorly on that objective.

(2) The decision variable is an unknown variable in the dual objective programming model, and its value needs to be determined through an optimization process. These variables represent the various factors that require decision-making in the problem.

(3) The constraints limit the possible range of values for the decision variable. To ensure the viability of the solution, equality or inequality constraints are imposed.

(4) Pareto optimal solution. The solution of dual objective programming is not singular, but a series of solutions called Pareto optimal solutions. The Pareto optimal solution refers to a solution that cannot be improved by changing one objective without making the other objective worse, as there are no other solutions that can improve the other objective [7].

$$W = max \sum_{t=2024}^{2030} \sum_{i=1}^{6} \sum_{j=1}^{54} \sum_{k=1}^{N_k} \left[\min\left(z_{i,j}^{k,t}, S_k\right) \times P_k - \sum_{\mathrm{j}=1}^{54} \sum_{\mathrm{i}=1}^{6} \sum_{\mathrm{t}=2024}^{2030} \sum_{\mathrm{k}=1}^{N_k} \mathrm{x}_{\mathrm{i,j}}^{\mathrm{k,t}} \times C_k \right] \tag{1}$$

where W is the maximization of total profit, S_k is the expected sales volume of the k-th crop, P_k is the sales price, C_k is the planting cost, and N_k is the crop name. $z_{(i,j)}^{(k,t)}$ is the actual yield, and $X_{(i,j)}^{(k,t)}$ is the planting area of the k-th crop on the j-th plot of land of type i in year t.

The formula for maximum profit in the case of complete saleability beyond the excess part.

$$W = max \sum_{t=2024}^{2030} \sum_{i=1}^{6} \sum_{j=1}^{34} \sum_{k=1}^{N_k} \left[S_k \times P_k + \max\left(0, z_{i,j}^{k,t} - S_k\right) \times 0.5 \times P_k - x_{i,j}^{k,t} \times C_k \right] \tag{2}$$

This is the formula for maximum profit when selling at a discounted price beyond a certain amount.

$$\min \sum_{\mathrm{j}=1}^{54} \sum_{\mathrm{i}=1}^{6} \sum_{\mathrm{t}=2024}^{2030} \sum_{\mathrm{k}=1}^{N_k} \mathrm{x}_{\mathrm{i,j}}^{\mathrm{k,t}} \tag{3}$$

This is the formula for minimizing land use area.

$$\sum_{k=1}^{N_k} X_{i,j}^{k,t} \leq A_{i,j}, \quad \forall i,j,t \tag{4}$$

This is the constraint formula for plot area. The planting area of each plot cannot exceed its total area.

$$\sum_{t}^{t+2} \sum_{k \in \text{legume crop}} X_{i,j}^{k,t} \geq A_{i,j}, \quad \forall i,j \tag{5}$$

where $A_{i,j}$ is the total area of the j-th plot in the i-th category.

This is the rotation requirement formula that requires. The formula for maximum planting leguminous crops at least once per plot within three years in order to conform to the growth pattern of crops.

$$X_{i,j}^{k,t} \times X_{i,j}^{k,t+1} = 0, \quad \forall i,j,k \tag{6}$$

This is the formula for intercropping restrictions states that the same crop cannot be planted on the same plot for two consecutive years to avoid repeated cropping.

2.2. Overview of the Monte Carlo simulation algorithm

(1) Random sampling formula [8]

To sample a random variable (for example, output fluctuations or price fluctuations), the sampling formula is:

$$X^{(k)} = X_0 \cdot \left(1 + \epsilon^{(k)}\right), \epsilon^{(k)} \sim \mathcal{N}(0, \sigma^2) \tag{7}$$

For a random sampling of output and price, they can be expressed as:

$$Y_{jt}^{(k)} = Y_{j2023} \cdot \left(1 + \epsilon_Y^{(k)}\right), P_{jt}^{(k)} = P_{j2023} \cdot \left(1 + \epsilon_P^{(k)}\right) \tag{8}$$

(2) Profit calculation formula for each scenario

In each scenario k,

$$Z^{(k)} = \sum_{i=1}^{n} \sum_{j=1}^{n} \sum_{t=2024}^{2030} \left(x_{ijt} \cdot Y_{jt}^{(k)} \cdot P_{jt}^{(k)} - x_{ijt} \cdot C_{jt}\right) \tag{9}$$

where $Z^{(k)}$ is the total revenue generated from the planting decision, $Y_{ji}^{(k)}$ is the yield, and $P_{ji}^{(k)}$ is the price, both of which are derived from randomly generated values.

This formula represents the calculation method of crop yield in each scenario, and the yield and price are derived from randomly generated values.

(3) Expected value calculation

After multiple random simulations, we can count the benefits of multiple scenarios and calculate their expected values, which is the average value of the benefits in all scenarios:

$$\mathbb{E}[Z] = \frac{1}{K} \sum_{k=1}^{K} Z^{(k)} \tag{10}$$

where K is the total number of simulations (i.e. the number of random scenarios generated), and $Z^{(k)}$ is the total benefit in each scenario.

(4) Return variance and risk assessment

To assess the risk of different decision options, we can measure the instability of returns by calculating the variance of returns:σ_Z^2

$$\sigma_Z^2 = \frac{1}{K}\sum_{k=1}^{K}\left(Z^{(k)} - \mathbb{E}[Z]\right)^2 \tag{11}$$

where $Z^{(k)}$ is the total revenue under each scenario.

Among them, the standard deviation $\sigma_Z$represents the degree of return volatility, which can help decision-makers choose a plan with lower risks. For this problem, based on the idea of the Monte Carlo algorithm:

① For wheat and corn, sales volume increased by 5% to 10% annually;

$$S_k = S_{\mathrm{k,t=2023}} \times (1 + r_1)^{t-2023}, r_1 \in [0.05, 0.10], \mathrm{k} = 6,7 \tag{12}$$

where $S_{(k,t=2023)}$ represents the sales volume of the k-th crop in the year 2023, and r_1 represents the sales fluctuation of barley and corn.

For other crops, sales may fluctuate by 5%:

$$S_k = S_{\mathrm{k,t=2023}} \times (1 + r_2)^{t-2023}, r_2 \in [0.05, 0.10], \mathrm{k} = 6,7 \tag{13}$$

where r_2 is the sales fluctuation of other crops.

② Adjustment of yield per mu:

For all crops, the yield per acre fluctuates by 10%:

$$Y_k = Y_{k,t=2023} \times (1 + r_3), r_3 \in [-0.10, 0.10] \tag{14}$$

where $Y_{\mathrm{k,t=2023}}$ is the per-acre yield of the k-th crop in 2023, and r_3 is the per-acre yield fluctuation of all crops.

③Planting cost adjustment:

The average cost of growing crops is increasing by about 5% each year.

$$C_k = C_{\mathrm{k,t=2023}} \times (1 + 0.05)^{t-2023} \tag{15}$$

where $C_{\mathrm{k,t=2023}}$ is the planting cost of the k-th crop in 2023.

④Sales price adjustment:

The sales price of vegetable crops has an upward trend, with an average annual increase of about 5%.

$$P_k = P_{\mathrm{k,t=2023}} \times (1 + 0.05)^{t-2023} \tag{16}$$

The sales price of edible fungi is stable and declining, about 1% to 5% per year.

$$P_k = P_{\mathrm{k,t=2023}} \times (1 - r_3)^{t-2023}, r_3 \in [-0.05, -0.01] \tag{17}$$

In particular, the sales price of morels has been decreasing by 5% every year.

$$P_{\mathrm{toadstool}} = P_{k,t=2023} \times (1 - 0.05)^{t-2023} \tag{18}$$

where P_k represents the sales price of the k-th crop, and $P_{(k,t=2023)}$ represents the sales price of the k-th crop in 2023.

3. Results

3.1. Solving the dual objective programming model based on the ideal point method

The ideal point method is a technique used to solve multi-objective optimization problems, to find a solution that is as close as possible to the ideal values of all objectives. The ideal point method is a multi-objective optimization method based on distance minimization, which balances the goal of maximizing total profit by minimizing the distance between the land use area and the ideal point during the optimization process.

The ideal point method consists of four basic elements, which are:

(1) Determine the ideal value for dual objectives. Determine two objective functions and record the optimal values for each objective.

(2) Due to the possible differences in dimensionality and magnitude of the objective function, normalization is required to ensure that each objective is treated fairly and has the same impact during the optimization process.

(3) The ideal point method evaluates the quality of solutions by calculating the distance between each feasible solution and the ideal solution. Use the method of weighted Euclidean distance. A solution that is closer to the ideal solution and farther away from the negative ideal solution is considered a better solution.

(4) Minimize the distance to make the two objective functions as close as possible to the ideal point.

$$Z_1^* = \max Z_1, \quad Z_2^* = \min Z_2 \tag{19}$$

where Z_1 is Maximizing total profit, Z_2 is minimizing land use area, Z_1^* is the maximum ideal profit and Z_2^* is the minimum land use area. By maximizing and minimizing respectively, the ideal maximum profit and minimum land use area are obtained.

$$\tilde{Z}_1(x) = \frac{Z_1^* - Z_1(x)}{Z_1^* - Z_1^{\min}}, \quad \tilde{Z}_2(x) = \frac{Z_2(x) - Z_2^*}{Z_2^{\max} - Z_2^*} \tag{20}$$

where $\tilde{Z}_1(x)$ and $\tilde{Z}_2(x)$ respectively represent the maximum profit and minimum land use area after normalization.

$$D(x) = \sqrt{\left(\frac{Z_1^*}{Z_1^*}\frac{Z_1(x)}{Z_1^{\min}}\right)^2 + \left(\frac{Z_2(x) - Z_2^*}{Z_2^{\max} - Z_2^*}\right)^2} \tag{21}$$

where $D(x)$ is the Euclidean distance.

Calculate the Euclidean distance between the solution and the ideal point.

They are solving the optimal crop planting plan through MATLAB software. Tables 1, Table 2, Table 3, and Table 4 are partial results.

Table 1. Partial grain production for the quarters of 2024 and 2025 in situation one

Crop	Production in the first quarter of 2024	Production in the second quarter of 2024	Production in the first quarter of 2025	Production in the second quarter of 2025
Soybean	228	216	924	0
Black soybean	43400	0	540	0
Red bean	26080	0	39380	0
Mung bean	4725	0	11250	0
Climbing beans	38425	0	9375	0
Wheat	82000	0	76400	0
Corn	111000	0	117000	0
Millet	10260	0	31460	0
Sorghum	33000	0	63150	0

Table 2. Profit from the production of grain, vegetables, and edible fungi in the quarters of 2024 and 2025 in situation one

Crop type	Profit from production in the first quarter of 2024	Profit from production in the second quarter of 2024	Profit from production in the first quarter of 2025	Profit from production in the second quarter of 2025
Grain	1092459.167	442.5453711	1141413.105	0
Vegetable	1239639.689	311385.0595	793934.0167	-309459.4956
Edible fungi	0	61909.10505	0	41687.29387

Table 3. Profit from the production of grain, vegetables, and edible fungi in the quarters of 2024 and 2025 in situation two

Crop type	Profit from production in the first quarter of 2024	Profit from production in the second quarter of 2024	Profit from production in the first quarter of 2025	Profit from production in the second quarter of 2025
Grain	1207422.888	459.0391145	1275169.495	0
Vegetable	1232182.544	250852.3477	721513.5963	-280067.771
Edible fungi	0	59734.69942	0	35975.52494

Table 4. Partial grain production for the quarters of 2024 and 2025 in situation two

Crop	Production in the first quarter of 2024	Production in the second quarter of 2024	Production in the first quarter of 2025	Production in the second quarter of 2025
Soybean	228	216	924	0
Black soybean	43400	0	540	0
Red bean	26080	0	39380	0
Mung bean	4725	0	11250	0
Climbing beans	38425	0	9375	0
Wheat	82000	0	76400	0
Corn	111000	0	117000	0
Millet	10260	0	31460	0
Sorghum	33000	0	63150	0

3.2. Solution results based on Monte Carlo algorithm

By iterating multiple times (3 years, 6 planting seasons) to calculate planting plans for different years, updating growth rate, price, yield, and cost data for each iteration, using a linear programming model to optimize crop planting plans, and finally obtaining the optimal planting combination for different years through multiple simulations [9].

The solutions for the planting area of each crop in 2024 are shown in Figure 1.

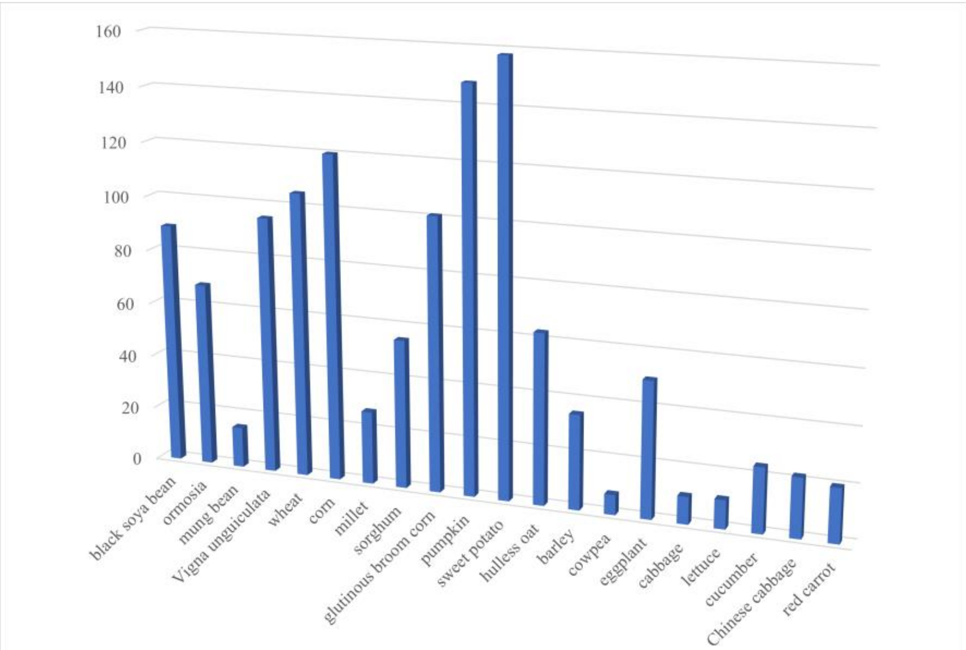

Figure 1. Calculation of Planting Area Planning for Crops in 2024

Figure 2 shows the acreage forecast for each crop in 2025, detailing the expected allocation of agricultural resources.

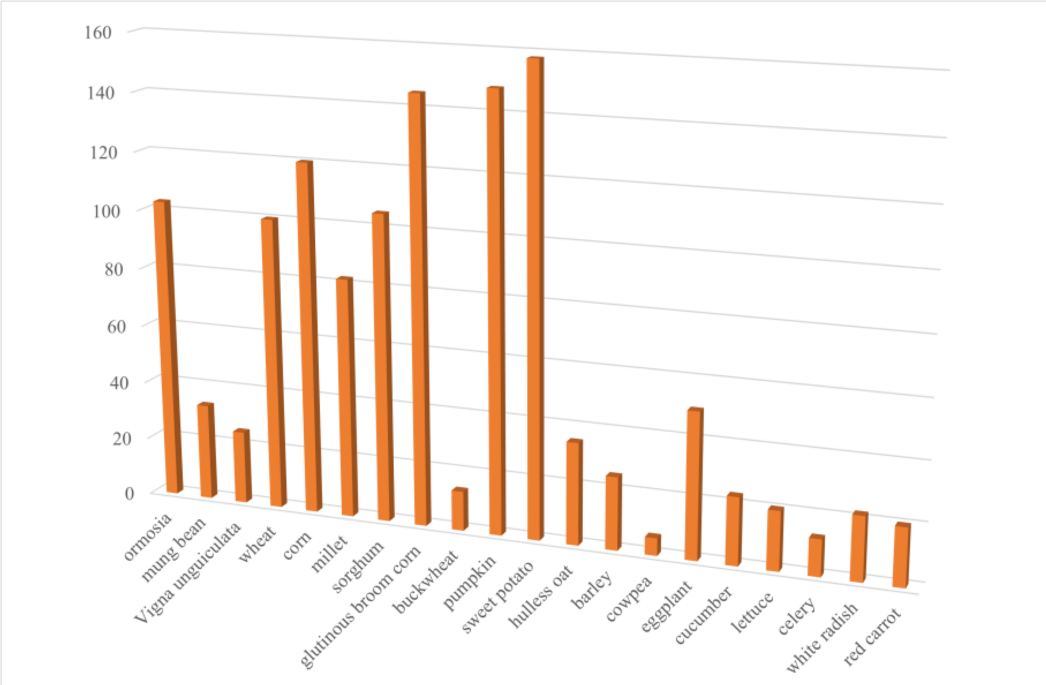

Figure 2. Calculation of Planting Area Planning for Crops in 2025

Divide crops into grains, vegetables, and edible fungi, and conduct yield statistics for each year. The specific results are shown in Figure 3.

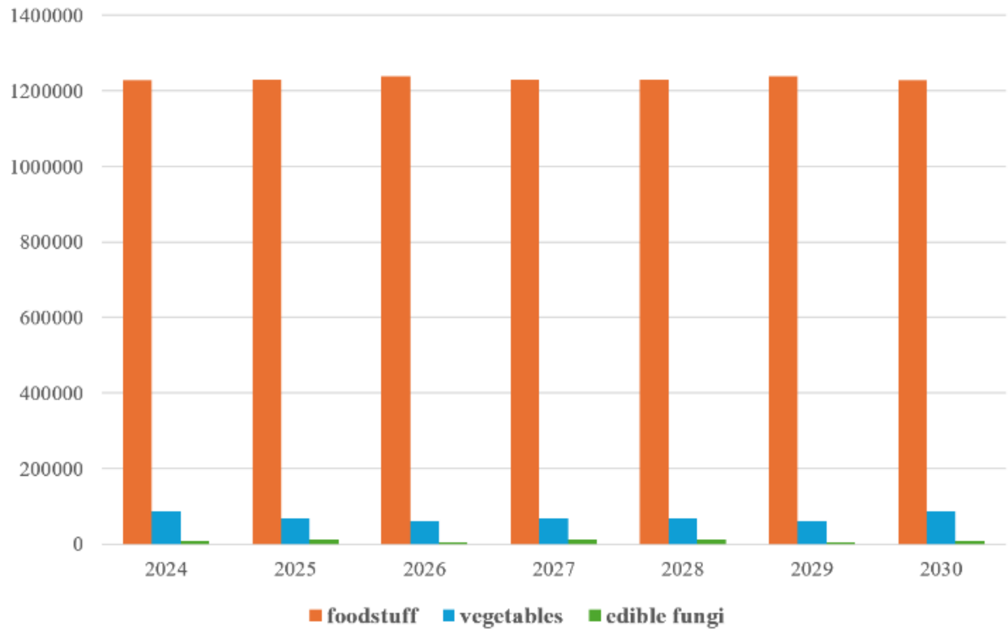

Figure 3. Total income of each crop in each year

Based on the sales volume of various categories in 2023, make predictions. Due to space limitations, only the total crop revenue forecast results for 2024 (Figure 4) and 2025 (Figure 5) will be presented here.

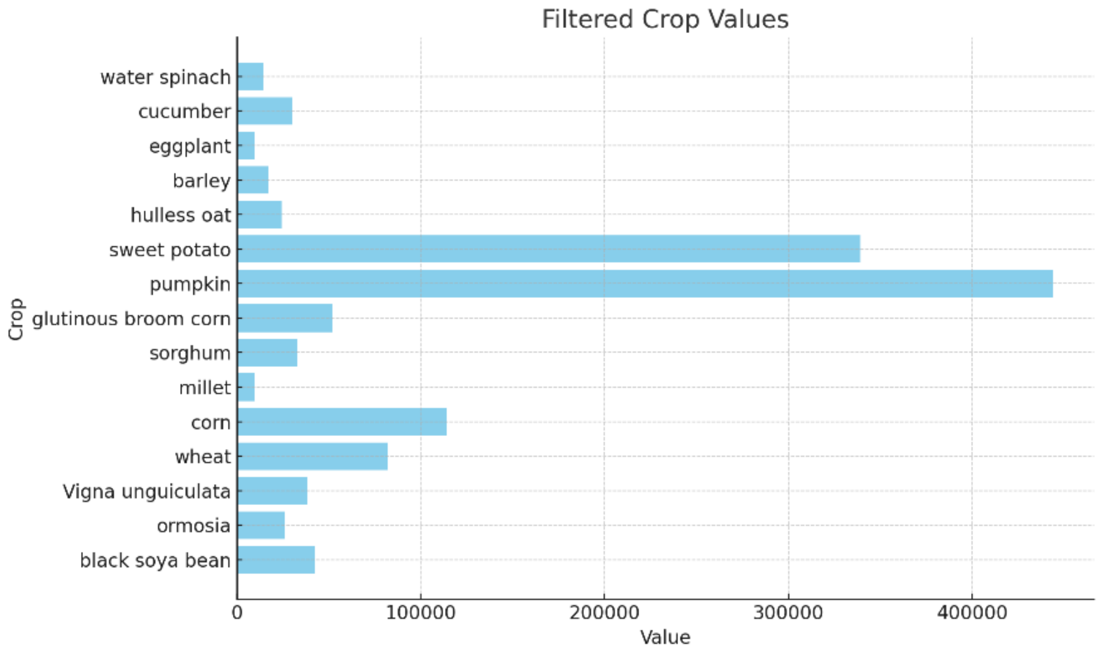

Figure 4. Forecast of Total Revenue of Various Crops in 2024

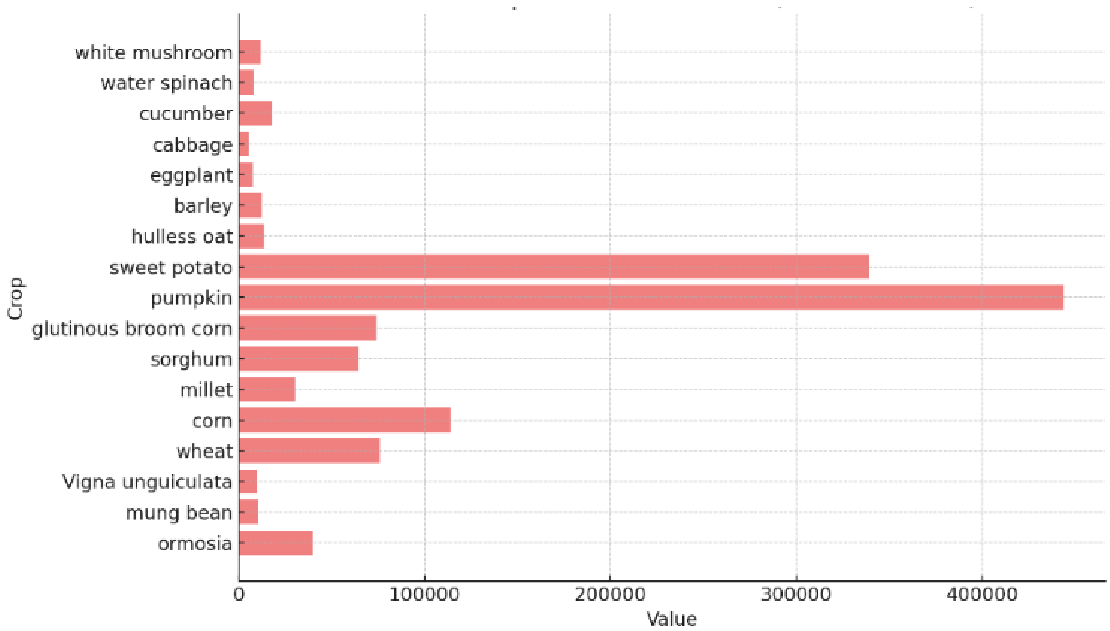

Figure 5. Forecast of Total Revenue of Various Crops in 2025

By combining the forecast graphs of total crop income for 2024 and 2025 with the simulation data, we found that the profit performance of grain shows obvious cyclical fluctuations in different years and quarters. Both lines show obvious peaks and troughs, indicating that the profit fluctuations of grain in each quarter are large [10]. This may be related to seasonal changes in agricultural cycles and market demand, such as crop sowing and harvesting times, or changes in market supply and demand. There are obvious differences in the yields of different crops: As can be seen from Figures 4 and 5, the yields of some crops (such as sweet potatoes, pumpkins, etc.) are much higher than those of other crops. This indicates that these crops may have a considerable share in terms of planting area and market demand. In addition, the figure also reflects the fluctuations in the yield of edible fungi crops, especially the sales of edible fungi such as morels are showing a downward trend, which is consistent with the expected market price decline pattern [11].

4. Conclusions

This paper establishes a decision-making framework that integrates many factors such as crop planting characteristics, market demand forecast, and land type analysis. To address the needs of farmers in changing market conditions and climate environment, to find a planting strategy that maximizes returns and ensures sustainable land use. Establish a comprehensive planting strategy model to seek the balance between the highest profit and the lowest cost under the limited land resources. With the help of Monte Carlo simulation, ensure high economic efficiency in a variable environment. This model provides farmers with a decision basis based on empirical analysis through refined data processing and application of advanced algorithms so that they can make more intelligent planting decisions in the complex and changeable external environment. Optimize land use and increase farmers' income. The design of the model has fully considered the universality and adaptability, and other regions with similar geographical environments and climate conditions can also benefit from it. In general, this paper not only provides an effective solution to the problem of planting decision-making in North China but also opens up a new path for the research and practice of agricultural sustainable development in the whole country.

Although the above-integrated planting strategy model shows significant advantages in guiding farmers to make efficient planting decisions, there are still limitations and deficiencies in practical application. The effective operation of the model depends on high-quality historical and real-time data. In practice, there may be some problems such as missing and incomplete data, which will affect the accuracy of the model. It is necessary to strengthen the construction and improvement of the data collection system and adopt advanced data mining and pre-processing technology to ensure the quality and timeliness of data.

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