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Optimization Research of Crop Planting based on Dynamic Planning Model and Optimal Planting Strategy

Haiyu Huang*, Yichen Gui[a,#], Le Sheng[b,#]

Shanghai University of Chinese Medicine, Shanghai, China

*huanghaiyu2004@outlook.com, [a]3073867420@qq.com, [b]3671534993@qq.com

[#]These authors contributed equally to this work

Abstract

This paper focuses on the problem of how to choose suitable crops and optimize planting strategies to improve production benefits and reduce planting risks. A dynamic planning model is constructed through data analysis, and based on the crop planting data in 2023, taking into account the characteristics of different types of arable land and the growth pattern of crops, two optimal planting strategies are proposed under two sales scenarios: firstly, the waste generated when the crops exceeding the sales expectation are unsaleable; and secondly, the excess portion will be sold at a reduced price of 50%. The objective function is constructed through the greedy algorithm and the dynamic programming model is solved to obtain the optimal planting area allocation scheme for the next seven years. Uncertainties in crop sales volume, mu yield, planting cost and sales price were further considered, and Monte Carlo simulation was used to generate stochastic scenarios. For different market conditions and climate changes, the simulation results demonstrate the possible crop returns and risk scenarios in the next seven years. Through a large number of simulations, this paper counts the acreage and yield expectations of various crops, and combines the data to optimize the dynamic planning model and analyze the uncertainties such as planting risks, which helps villages to develop more adaptive planting scenarios under complex external conditions. The Spearman correlation coefficient is used to conduct correlation analysis, and the complementarity matrix is constructed by combining the substitutability and complementarity of crops. Through the substitutability analysis, it is concluded that there is a competitive relationship between crops in the utilization of resources, which needs to be accurately weighed in order to optimize the allocation of resources; through the complementarity analysis, it is concluded that a reasonable combination of different crops can improve the overall efficiency. By constructing the decision model and incentive mechanism, the effects of substitutability and complementarity on planting strategies are effectively reflected. The results show that the optimization scheme not only improves the production efficiency of the villages, but also has high robustness and replicability, and can provide useful reference for crop planting planning in similar areas.

Keywords

Dynamic Programming; Spearman's Correlation Coefficient; Crop Planting Optimization.

1. Introduction

In the process of sustainable development of rural economy, it is of great significance to rationally utilize limited arable land resources and develop organic planting industry according to local conditions. For a mountainous village in northern China, due to its mountainous location, cold climate, and diverse and scattered types of arable land, the village faces the

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challenge of how to select suitable crops and optimize planting strategies under limited arable land conditions in order to improve production efficiency and reduce planting risks.

In the field of crop planting strategy optimization, many studies in recent years have explored how to improve crop production efficiency and reduce planting risks through dynamic planning and constraint planning methods. Boussios et al.[1] investigated the response of producers in the face of different agricultural management decisions through a dynamic planning model, which provided a theoretical basis for dynamic decision-making in crop management .Liu and Yang[2], on the other hand, explored how to optimize water use to improve crop yields under different climatic conditions based on a crop model combined with irrigation schedule analysis and optimization .Adamo et al. [3] investigated the optimization of crop planting layouts in sustainable agriculture by using a constraint-based planning approach, and proposed how to balance resource use efficiency and environmental sustainability in planting layouts . Diban et al. [4], on the other hand, optimized the crop rotation policy for biomass cultivation through a dynamic planning model, demonstrating an optimization path for long-term cultivation decisions .

2. Model Building and Solving

2.1. Data Preprocessing

The data were preprocessed by differentiating “Crop type”, “Legumes or not”, “Plot type”, “Crop number”, and then data were merged to integrate the statistics for 2023 and to find the cost of cultivation, total sales, and profit from sales. “Differentials were performed, and then data were merged to integrate the statistical data for 2023 and to find out the cost of cultivation, total sales volume, and profit from sales. Bar charts, point charts, and line graphs were selected to visualize the data and analyze the profitability of different crops, the relationship between acreage and mu yield, the distribution of unit prices of different crops, and the acreage of different crops in different seasons.

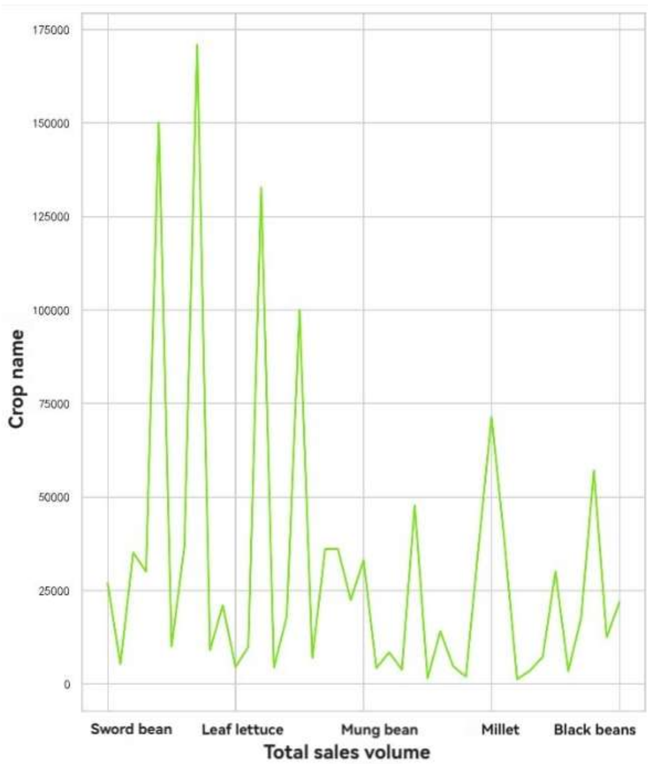

Figure 1. Sales of different crops

Figure 2. Profitability of different crops

The unit sales price data fluctuates up and down, so the average unit sales price is taken as the unit sales price of the crop for the calculation. Assuming that farmers are rational and have expectations of planting, the output is always approximately the same as the market demand. Therefore, the sales volume is equal to the output. As a result, the sales volume and profitability of different crops can be calculated, as shown in Figures 1 and 2.

By analyzing the relationship between planted area and acreage yield, divided into legume and non-legume crops for data visualization, as shown in Figure 3, it can be obtained that there is no regular relationship between planted area and acreage yield for most of the crops, and for the non-legume data, there is a part of the positive relationship, the reason may be related to the scale of scale.

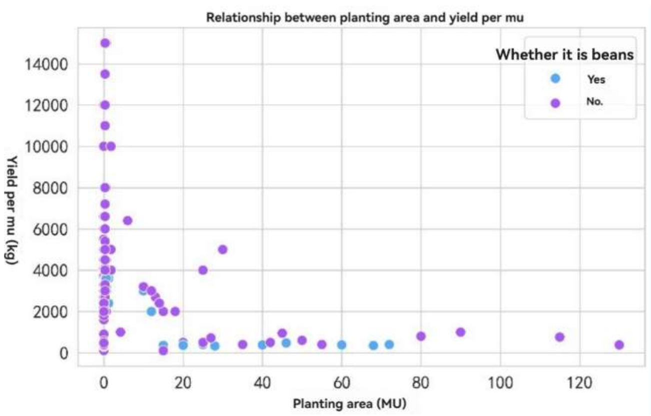

Figure 3. Sales of different crops

By integrating the cost and profit of growing each crop and visualizing the data, as shown in Figure 4. Analyzing the relationship between the two, it is clear from the figure that only highly profitable crops are produced in increased quantities, in line with standard market laws.

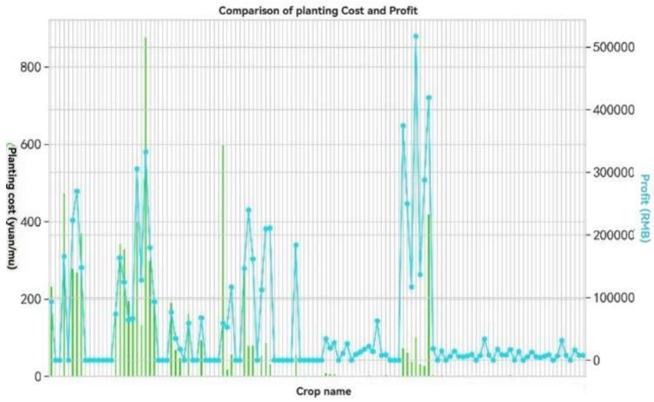

Figure 4. Sales of different crops

2.2. Dynamic Planning Model based on Optimal Planting Strategy

In solving the crop cultivation optimization problem in this countryside, a linear programming model is used to define and solve the optimal cultivation scheme. The goal of the linear programming model is to maximize the overall economic benefits of the village by reasonably allocating the arable land resources, while satisfying various constraints. By analyzing the problem, it can be obtained that there are two situations: 1. more than part of the stagnant sales, resulting in waste; 2. more than part of the price reduction by 50% of the sales price in 2023, based on the above situation for the model and solution.

To maximize the total profit as the optimization objective, the objective function is constructed, i.e., total sales minus cost. Let i denote the ith crop, j denote the jth cultivated land, the decision variable x_{ij} is the number of acres of crop i planted in cultivated land j, the unit is mu. The decision variable x_{ij} is the number of acres of crop i planted in cultivated land j in acres. The decision variable y_{ij} is whether crop i is planted on cultivated land j. Where y_{ij} is a 0-1 variable. y_{ij}=1 Crop i is planted on cropland j; y_{ij}=0 means crop i is not planted on cropland j. The decision variable y_ij is the number of acres of crop i planted on cropland j.

$$f_i = \sum_{j=1}^{M} x_{ij} y_{ij} a_{ij} \tag{1}$$

$$\text{cost} = \sum_{i}^{N}\sum_{j}^{M} x_{ij} y_{ij} b_{ij} \tag{2}$$

$$\max Z = \sum_{i}^{N} g_i - \text{cost} = \sum_{i}^{N}\left[\sum_{j=1}^{M} x_{ij} y_{ij} a_{ij}\right]\cdot c_i - \sum_{i}^{N}\sum_{j}^{M} x_{ij} y_{ij} b_{ij} \tag{3}$$

As shown in equation (1), let a_{ij} be the planted acre yield of the ith crop on the jth planted cropland. The unit is pound. b_{ij} for the i crop in the j planting of arable land on the planting cost. Unit is kg / mu, c_i for the i crop selling price, unit is yuan / kg. d_i i crop pre-sale volume, f_i for the i crop in the year the total production. Set g_i for the sales of the ith crop, $g_i = f_i c_i$, planting cost as shown in equation (2). In summary, the objective function is shown in equation (3).

Constraints: 1. the area of crop planting cannot exceed the area of cultivated land; 2. the total output of crop per season cannot exceed the expected sales volume; 3. the area of each crop planted in a single cultivated land should not be too small; 4. the planting sites of each crop per season should not be too dispersed; 5. each crop should not be planted in the same plot continuously and recrop; 6. planting legume crops at least once in three years from 2023 onwards.

$$\max Z = \sum_{i}^{N}\left[\sum_{j=1}^{M} x_{ij} y_{ij} zz_{ij}(2024) \cdot a_{ij}\right] \cdot c_i - \sum_{i}^{N}\sum_{j}^{M} x_{ij} y_{ij} zz_{ij}(2024) \cdot b_{ij} \tag{4}$$

$$\sum_{i} x_{ij} y_{ij} zz_{ij}(2024) \leqslant e_j, j = 1, 2, \cdots, 26 \tag{5}$$

$$f_i = \sum_{j=1}^{M} \chi_{ij} y_{ij} zz_{ij}(2024) \cdot a_{ij} \leqslant d_i, i = 1, 2, \cdots, 15 \tag{6}$$

$$\begin{cases} x_{ij} \leqslant 35, j = 1, 2, \cdots, 6 \\ x_{ij} \leqslant 20, j = 7, 8, \cdots, 20 \\ x_{ij} \leqslant 13, j = 21, 23, \cdots, 26 \\ \sum_{i}^{N} y_{ij} \leqslant 3, j = 1, 2, 3, \cdots, 26 \\ \{ z_{ij}(2024) = 0, z_{ij}(2023) = 1 \\ zz_{ij}(2024) = 1, z_{ij}(2023) = 0 \end{cases} \tag{7}$$

In summary, the objective function, constraints, decision variables, with time variable t , were determined and a multi-stage mathematical planning model was established. Since the planting interval of legumes is at least two years, the model for 2024 does not need to consider constraint six, while the model for 2025 and later years needs to consider constraint six.

The mathematical planning planting model for 2024 crops is as equation (4)-(7).

Mathematical planning planting models for crops in 2025 and subsequent years are as follows.

$$\max Z(t) = \sum_{i}^{N}\sum_{j=1}^{M} x_{ij} y_{ij} zz_{ij}(t) \cdot a_{ij} \cdot c_i - \sum_{i}^{N}\sum_{j}^{M} x_{ij} y_{ij} zz_{ij}(t) \cdot b_{ij} \tag{8}$$

The mathematical planning planting model for vegetable, rice and edible mushroom crops for the year 2024 is as follows.

$$\max Z = \sum_{i}^{N}\left[\sum_{k=1}^{2}\sum_{j=1}^{M} x_{ijk} y_{jkk} zz_{ij}(2024) \cdot a_{jjk}\right] \cdot c_i - \sum_{k=1}^{2}\sum_{i}^{N}\sum_{j}^{M} x_{jj/} y_{ij} zz_{ij}(2024) \cdot b_{ij} \tag{9}$$

Mathematical planning planting models for vegetable, rice, and edible mushroom crops for 2025 and subsequent years are as follows.

$$\cdot \max Z(t) = \sum_{i}^{N}\left[\sum_{k=1}^{2}\sum_{j=1}^{M} x_{ijk} y_{ijk} zz_{ij}(t) \cdot a_{ijk}\right] \cdot c_i - \sum_{k=1}^{2}\sum_{i}^{N}\sum_{j}^{M} x_{ijt} y_{ijt} zz_{ij}(t) \cdot b_{ijt} \tag{10}$$

If the excess over the expected future sales of the crop is sold at a reduced price of 50% of the sales price in 2023. Then the relationship between expected sales and actual production of the crop must be considered, $f_i(t)$ is the total production of crop i in year t. $g_i(t)$ is the sales brought in by crop i in year t. If the 50% price reduction in sales is not considered, then $g_i = f_i(t)c_i$ If the 50% price reduction in sales problem is considered, then the excess will be $f_i(t) - d_i$, and the sales will be as follows.

$$g_i = d_i c_i + \frac{1}{2}[f_i(t) - d_i]c_i \tag{11}$$

To summarize, the expression for $g_i(t)$ is given by

$$g_i(t) = f_i(t)c_i + \frac{1}{2}\max[0, f_i(t) - d_i]c_i \tag{12}$$

The mathematical planning planting model for the 2024 crop is as follows, and the constraints are just less constraints2:

$$\max Z = \sum_i^N f_i(2024)\cdot c_i + \frac{1}{2}\max[0, f_i(2024) - d_i] - \sum_i^N\sum_j^M x_{ij} y_{ij} zz_{ij}(2024)\cdot b_{ij} \tag{13}$$

$$\sum_i x_{ij} y_{ij} zz_{ij}(2024) \leqslant e_j, j = 1, 2, \cdots, 26 \tag{14}$$

$$f_i(2024) = \sum_{j=1}^M x_{ij} y_{ij} zz_{ij}(2024)\cdot a_{ij}, i = 1, 2, \cdots, 15 \tag{15}$$

$$\begin{aligned}
& x_{ij} \leqslant 35, j = 1, 2, \cdots, 6 \\
& x_{ij} \leqslant 20, j = 7, 8, \cdots, 20 \\
& x_{ij} \leqslant 13, j = 21, 23, \cdots, 26 \\
& \sum_i^N y_{ij} \leqslant 3, j = 1, 2, 3, \cdots, 26 \\
& \begin{cases} zz_{ij}(2024) = 0, z_{ij}(2023) = 1 \\ zz_{ij}(2024) = 1, z_{ij}(2023) = 0 \end{cases}
\end{aligned} \tag{16}$$

Mathematical planning planting models for crops in 2025 and subsequent years are as follows.

$$\max Z = \sum_i^N f_i(t)\cdot c_i + \frac{1}{2}\max[0, f_i(t) - d_i] - \sum_i^N\sum_j^M x_{ij} y_{ij} zz_{ij}(t)\cdot b_{ij} \tag{17}$$

Similar to the food crop planning solution problem, the objective function of the mathematical planning planting model for the 2024 crop is as follows, while the constraints are only less than before Constraint 2.

$$\max Z = \sum_i^N f_i(2024)\cdot c_i + \frac{1}{2}\max[0, f_i(2024) - d_i] - \sum_{k=1}^2\sum_i^N\sum_j^M x_{ijt} y_{ijt} zz_{ij}(2024)\cdot b_{ijt} \tag{18}$$

$$s.t.\begin{cases} \sum_{i}^{N} x_{ij} y_{ij} zz_{ij}(2024) \leqslant e_j, j = 1, 2, \cdots, 26 \\ \begin{cases} x_{ijt} \leqslant 6, j = 1, 2, \cdots, 8, k = 1, 2 \\ x_{ijt} \leqslant 0.3, j = 9, 8, \cdots, 24, k = 1, 2 \\ x_{ijt} \leqslant 0.3, j = 25, 23, \cdots, 28, k = 1, 2 \end{cases} \\ \sum_{i=1}^{N} y_{ijk} \leqslant 3, j = 1, 2, 3, \cdots, 26, k = 1, 2 \\ \begin{cases} zz_{ij}(2024) = 0, z_{ij1}(2023) + z_{ij2}(2023) \geqslant 1 \\ zz_{ij}(2024) = 1, z_{ij1}(2023) + z_{ij2}(2023) = 0 \end{cases} \\ y_{ij1} = x_{ij1} = a_{ij1} = 0, i \in I, j \in J \\ b_{ij1} = +\inf, i \in I, j \in J \\ y_{ij2} = x_{ij2} = a_{ij2} = 0, i \in I, j \in J \\ b_{ij2} = +\inf, i \in I, j \in J \end{cases} \tag{19}$$

Mathematical planning planting models for crops in 2025 and subsequent years are as follows.

$$\max Z = \sum_{i}^{N} f_i(t) \cdot c_i + \frac{1}{2} \max[0, f_i(t) - d_i] - \sum_{k=1}^{2} \sum_{i}^{N} \sum_{j}^{M} x_{ijt} y_{ijt} zz_{ij}(t) \cdot b_{ijt} \tag{20}$$

In the calculations and analysis of the results of the model, it was assumed that the sales volume of each crop would fluctuate within a range of 10% above and below its expected value. For this reason, a strategy based on extreme scenarios was used to develop a production plan to cope with potential market volatility and uncertainty.

First, the previous year's sales data was used as a baseline, assuming that demand may rise in the future, and therefore the maximum range of possible increases in sales volume was chosen as the target sales volume. After the production plan was formulated, the maximum range of possible declines in sales was used in the objective function as a scenario to simulate the actual sales. Based on the above strategy, a planning model was constructed to analyze the possible outcomes.

In this over portion stagnation and direct waste scenario, if the actual sales of a crop are lower than the planned production, the over portion of the crop will not be sold, leading directly to waste. The model's objective function thus includes losses due to stagnation, which are factored into the total return, causing the model to favor a more conservative production strategy in the optimization process to reduce potential waste.

In the sell low at fifty percent scenario, crops in excess of actual demand are not simply discarded, but are sold low at fifty percent of the original price. This model assumes that losses can be minimized by selling at a discount even when market demand is low. The objective function will reflect the discounted revenue in this scenario and weigh it against the cost of production, thus optimizing the production plan to maximize the actual profit.

Uncertainties, as well as potential planting risks, are taken into account. These uncertainties include variations in the expected sales volume of crops, acreage, growing costs, and selling prices. Specifically, there is an increasing trend in sales volume for corn and wheat, a ±5 percent fluctuation in sales volume for other crops, a ±10 percent change in acreage due to weather, an increase in planting costs of about 5 percent per year, and varying increasing or decreasing trends in sales prices for vegetables and edibles.

Monte Carlo simulations were used to randomly generate possible crop yields, sales volumes, growing costs, and selling prices for each year. Afterwards, under each simulation, a linear programming model is used to optimize the planting strategy to maximize the village's total gains or minimize losses. After simulating a large number of different possible scenarios, we can obtain the expected value and risk range of the planting options to support the village's decision making.

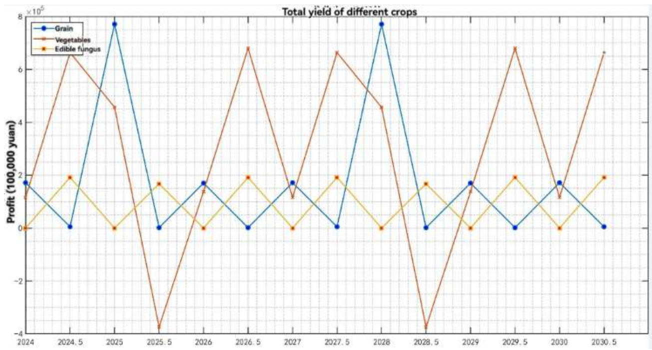

Figure 5. Total profit from different crop yields in case I

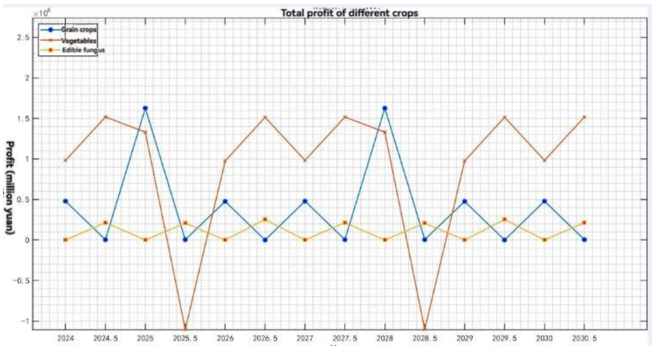

Figure 6. Total profit from different crop yields in case 2

For the next n years, a rolling optimization strategy is used, i.e., focusing on optimizing the production plan for the last three years. This is because as long as each plot of land is planted with a legume crop at least once in every three years, the fertility and nutrient status of the land will be ensured, thus ensuring sustainable cultivation in the long term. The results of each three-year optimization are used as inputs to provide decision support for the following three years. This approach allows for more flexibility in production planning and adaptation to possible future market changes. Ultimately, the goal of the entire optimization process is to measure the strength of the model by maximizing profit. Based on this, it is possible to continuously adjust the planting strategy according to the market situation each year, ensuring that economic efficiency is maximized in a complex market environment. For the next n years, it is only necessary to repeat the application of this optimization strategy, sequentially generating and implementing the planting plan for each three years, to achieve the optimal effect of the overall planning. Figure 5-6 below shows the profitability of different years after the model is solved.

2.3. Crop Complementary Mutual Exclusion Mechanism based on Spearman's Correlation Coefficient

Considering the substitutability and complementarity between crops, the correlation between expected sales volume, sales price and planting cost, a better crop planting planning model is established. The model not only focuses on the planting returns of individual crops, but also takes into account the synergistic effects and competitive relationships between multiple crops.

Pearson's correlation coefficient is a common method of correlation analysis, but Pearson's correlation coefficient requires that the data is a continuous variable, obeys a normal distribution, and has a linear relationship between the data. The Kolmogorov-Smirnov test is performed to verify that the data are normally distributed.

Spearman's correlation coefficient is calculated based on ranking. It first sorts the data by size and generates a ranking sequence for each variable separately. The correlation coefficient is then calculated by comparing the relationship between these ranked sequences. For example, in this problem, Spearman's correlation coefficient is used to study the interrelationships between six different influencing factors of crops. When the Spearman's correlation coefficient is positive, it indicates a positive correlation and the larger the Spearman's correlation coefficient, the stronger the correlation between these two influencing factors / When the Spearman's correlation coefficient is negative, it indicates a negative correlation between the two influencing factors and the larger the absolute value of the Spearman's correlation coefficient, the stronger the correlation between these two factors.

Solving for Spearman's correlation coefficient, from the results of the analysis of correlation: (1) The correlation between mu yield and planting cost is very strong (p=0.777): This shows that the crop's mu yield and planting cost show a positive correlation, in general, mu yield rises, the cost of machinery consumed, the cost of manpower have risen to varying degrees, in line with the objective law and general knowledge. (2) The correlation between the expected sales volume and the sales unit price is strong (p=-0.332): this shows that the sales unit price of crops and the expected sales volume show a negative correlation, in general, the price increase will also lead to a decline in sales volume at the same time, also in line with the objective law. (3) There is a correlation between planting cost and expected sales volume (p=-0.286):This shows that there is a negative correlation between planting cost and expected sales volume of crops, climatic factors, uncertainties, market demand will lead to irregular changes in sales volume, while increased planting costs may lead to increase in selling price of the products by the producers in order to maintain the level of profitability, and at the same time, the producers may adopt conservative strategy to reduce the scale of production when costs rise to avoid the risks associated with crop stagnation, which may also lead to a reduction in sales volume. (4) The correlation between mu yield and selling price is low (p=-0.171): this shows that there is a negative correlation between mu yield and selling price, and the corresponding market selling price of crops with high mu yield will be reduced to a certain extent. The main factor for the higher sales price is directly related to the decline in the yield of the crop (assuming stable market demand) (5) There is almost no correlation between selling unit price and planting cost (p=0.078). Sales unit price is affected by market supply and demand, sales strategy model and other influences producers may also absorb the pressure of rising costs through the cost absorption mechanism (internal management optimization, improve efficiency, etc.) rather than responding to it by raising prices. At the same time, the increase and decrease of planting costs are affected by labor and technology, and there is no obvious correlation between the two, which leads to the relationship between selling price and planting costs to become ambiguous.

Substitutability and complementarity are crucial in crop growing strategies. Substitutability implies that crops compete with each other in terms of resource utilization, and growers need to make choices based on market demand, prices and yields in order to optimize resource allocation and maximize returns. Complementarity, on the other hand, refers to the ability of certain crops to be grown in synergy to enhance resource utilization efficiency. For example, crop rotation or intercropping not only improves soil quality, but also reduces pests and diseases, thus reducing costs and increasing yields. Through the rational use of crop substitutability and complementarity, growers are able to optimize their planting strategies and improve overall returns.

Concept of crop substitutability: Crop substitutability refers to the fact that two crops are in competition for resource utilization and cannot be grown on the same land at the same time. This is usually due to the fact that they have similar needs for resources such as land, nutrients, water, etc., resulting in the necessity of choosing one of them for cultivation with limited resources. For example, maize and wheat both require the same resources such as arable land and fertilizers, hence their substitutive relationship. Increasing the area planted to one crop necessarily means decreasing the area planted to the other. Substitutability is a key factor in agricultural planning because it directly affects the choice of crop combinations and the optimization of resource allocation.

Substitutability constraint model: in agricultural optimization models, crop substitutability is usually expressed through constraints on land resources. For crops with substitution relationships, the model sets the constraint that no two crops can be grown at the same time on a given piece of land. The constraint can be expressed through a mathematical model to ensure rational allocation of resources.

For example, assuming that maize (crop number (i=6)) and wheat (crop number (i=7)) have competing resource demands, then maize and wheat cannot be grown simultaneously on the same piece of cropland (j). This constraint can be expressed as follows:

$$\begin{cases} y_{6j}(t) + y_{7j}(t) \leqslant 1, j = 1,2,\cdots,26 \\ y_{6j}(t), y_{7j}(t) = 0^{\circ}or^{\circ}1, j = 1,2,\cdots,26 \end{cases} \tag{21}$$

Among them, (y_{6j}(t)) and (y_{7j}(t)) indicate whether corn or wheat is planted on the cultivated land (j) at the time (t) time, and take the value of 0 or 1; when the value of (y_{6j}(t)) or (y_{7j}(t)) takes the value of 1, it means that the corresponding crop is planted in the cultivated land, and conversely, it takes the value of 0 to indicate that the crop is not planted. Here (j) represents 26 different types of cropland, including plains, terraces, hillsides, etc. The constraints ensure that only one of these crops can be planted on each piece of arable land, reflecting the substitutability between the two crops.

Through such a model, excessive competition for resources can be effectively avoided, ensuring the rational use of arable land and maximizing the efficiency of agricultural production. In actual agricultural production planning, crop substitutability constraints are an important means of achieving optimal resource allocation and improving land use efficiency.

Concept of crop complementarity: Crop complementarity refers to the ability of two or more crops to enhance each other's growth when grown together, thereby improving overall agricultural output. This synergistic effect stems from the ecological mutual benefit relationship between crops, for example, leguminous crops can increase the nitrogen content of the soil through nitrogen fixation, which in turn provides better growing conditions for other crops planted subsequently. Therefore, a reasonable combination of crops with complementary properties can optimize the use of resources and enhance the overall profitability and sustainability of farmland.

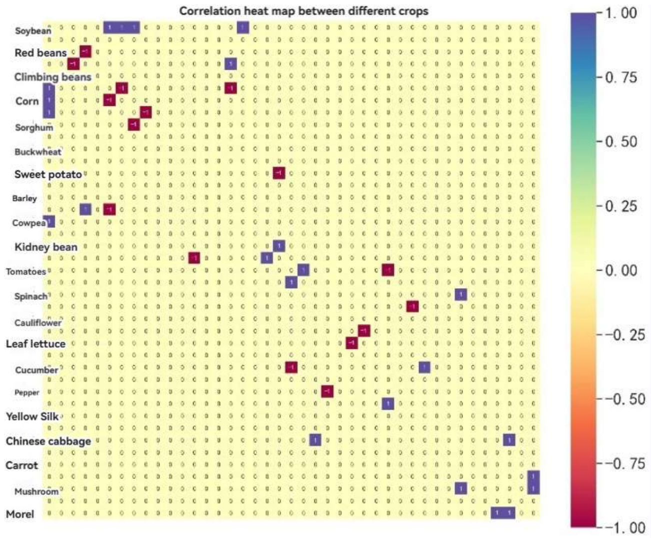

Figure 7. Correlation heat maps between different crops

Complementarity impact model: in the optimization model of agricultural production, the complementarity of crops can be reflected through the reward mechanism in the objective function. When two crops with complementary relationships are grown together, additional gains will be realized. This synergistic gain can be represented by a correlation coefficient (b_{il}) reflecting the mutually beneficial effect of crop (i) and crop (l) when grown together. Specifically, the complementarity effect can be enhanced by adding a bonus term to the objective function that enhances the returns to growing complementary crop combinations:

For example, suppose that crop (i) and crop (l) are grown on arable land (j) and their complementarity is captured by the coefficient of association (b_{il}). In this case, the combined benefits of crop (i) and crop (l) will add additional synergistic benefits based on their independent benefits.

$$Z = Z_0 + \sum_{j}^{M}\sum_{i}^{N}\sum_{l}^{N} b_{il} y_{ij} x_{ij} \tag{22}$$

In this way, the rational cultivation of complementary crops can not only maximize the output of a single crop, but also further improve the overall efficiency of the agricultural production system through synergistic effects. This optimization strategy can provide strong support for farmland management and sustainable agricultural development. Based on the substitutability and complementarity of the relevant crops, the corresponding complementary mutual exclusion matrix can be constructed as shown in Figure 7.

3. Summary

Through dynamic simulation of crop yields, sales volumes, costs and prices, it can effectively analyze the many possibilities of planting strategies in the coming years, helping to formulate more robust planting plans. The model covers crop planting decisions from 2024 to 2030, which can not only help cope with short-term market changes, but also provide a basis for long-term resource allocation and help improve the sustainability of agricultural production. The model takes into account the substitutability and complementarity of different crops, and not only focuses on maximizing the yield or return of a single crop, but also better regulates the allocation of resources among crops, thus improving the overall output value and land use efficiency. The model can be adjusted according to different crop characteristics and

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agricultural practices, and can not only deal with combinations of multiple crops, but also develop specific optimization strategies according to different plots, climatic conditions and market demands, providing multi-dimensional references for decision makers. The scalability of the model allows it to be applied not only to the current cropping environment, but also to be adjusted according to future agricultural trends. However, the model in this paper does not deeply consider more complex market mechanisms and competitive factors, such as changes in international markets and supply chain disruptions. Realistic markets are more complex and price fluctuations may not follow the model's assumptions exactly, leading to biased decision-making. In addition, the model does not take into account advances in agricultural technology (e.g., the development of new varieties, improved planting techniques, etc.), and future planting decisions may underestimate potential returns and production efficiencies.

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