

A Study of Crop Planting Schemes Based on Linear Programming and Monte Carlo Simulation

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Abstract: In this paper, based on linear programming and Monte Carlo simulation, the optimal cropping scheme for crops from 2024 to 2030 in a rural village is studied and modeled. First, considering the characteristics of different cultivated land types and the growth habit of different crops, all cultivated land is divided into six categories, and a single-objective linear programming model is established to maximize the net return. Then, considering the fluctuations brought by market, climate and other factors on the expected sales volume, mu yield, planting cost and sales price, a dynamic planning model based on Monte Carlo simulation was established, while dynamic constraints were added to analyze the optimal planting scheme of crops in this countryside. Finally, the relationship between crops is introduced, and the substitutability and complementarity between crops, the correlation between the expected sales volume and sales price, and the planting cost need to be considered, and a dynamic planning model based on Monte Carlo simulation and multi-factor variables is established to optimize the allocation of limited arable land resources in the countryside and rationally plan the planting of crops.

Keywords: Linear Programming, Monte Carlo simulation, Dynamic programming, Second-order Clustering, Relevance.

1. Introduction

In this paper, based on linear programming and Monte Carlo simulation, the optimal cropping scheme for crops from 2024 to 2030 in a rural village is studied and modeled. First, considering the characteristics of different cultivated land types and the growth habit of different crops, all cultivated land is divided into six categories, and a single-objective linear programming model is established to maximize the net return [1-2]. Then, considering the fluctuations brought by market, climate and other factors on the expected sales volume, mu yield, planting cost and sales price, a dynamic planning model based on Monte Carlo simulation was established, while dynamic constraints were added to analyze the optimal planting scheme of crops in this countryside [3-4]. Finally, the relationship between crops is introduced, and the substitutability and complementarity between crops, the correlation between the expected sales volume and sales price, and the planting cost need to be considered, and a dynamic planning model based on Monte Carlo simulation and multi-factor variables is established to optimize the allocation of limited arable land resources in the countryside and rationally plan the planting of crops [5-7].

2. Modeling Optimal Crop Planting Scheme Based on Linear Programming

The type, area, and types of crops that can be grown in the 34 plots in the village are known, as well as the planting information associated with each type of crop in 2023, including the planting plots, planting area, acreage, and planting cost. The linear programming model considers the constraints of arable land resources, minimum and maximum limits of crop planting area, and market demand constraints. In order to solve the static planting plan optimization problem of crops, this paper establishes a single-objective linear programming model to maximize the total sales profit of

crops as the goal. If the production of a certain crop in a season is greater than the expected sales volume, the exceeding part of the stagnant sales. Therefore the objective function of the linear programming model is:

$$\max \sum_{j=1}^{41} \text{profit}(R_j, C_j) = R_j - C_j \quad (1)$$

where

$$R_j = \sum_{i=1}^{54} \sum_{k=2024}^{2030} S_{ijk} q_{ij} P_j \quad (2)$$

and R_j is the firstj revenue from the sale of the crop, C_j denotes the revenue from the sale of the first cropj cost of planting the first crop, S_{ijk} denotes the cost of planting the k year, i indicates the area of land planted with the j-th area planted with the first crop in the year, q_{ij} denotes the area under cultivation of the j the acreage of the first crop planted on the first block of land in the yeari acre yield of the first crop on the plot of land, P_j denotes the price at which thej the selling price of the first crop, M_{ij} indicate the selling price of thej the cost per unit of cultivation of the first crop on the first block of land.i unit cost of cultivation of the first crop on the first plot of land.

Due to the differences in crops suitable for planting in different types of arable land, and the different growth habits of different crops, the same crop in different types of arable land per unit acre yield will also be different, we set all arable land is divided into six categories, including: flat dry land, terraces, hillside land, water-sourced land, ordinary greenhouses and smart greenhouses, numbered from 1 to 6. Crops that can be planted are soybeans, black beans, red beans, mung beans, crawling beans, Wheat, corn, grain, sorghum, millet, mangold wheat, pumpkin, sweet potato, potato, tomato, eggplant, spinach, peppers, cauliflower, cucumber, lettuce, chili pepper, Chinese cabbage, white radish, red radish, elm mushrooms, shiitake mushrooms, white lingzhi mushrooms, morel mushrooms Labeled 41 crops are numbered from 1 to

41, respectively. flat dryland, terraced fields, and hillside fields are planted with only one season of food crop, and ordinary greenhouses are planted with two seasons of crops, one season of vegetables and one season of edible fungus cross planting, smart greenhouses plant two seasons of vegetables other than Chinese cabbage, white radish and red radish, and water-consumed land plant one season of rice or two seasons of vegetables. Each type of plot uses different constraints based on its characteristics.

The specific constraints are as follows:

(1) The sum of the planned acreage of all crops on a parcel cannot exceed the area of this parcel:

$$\sum_{j=1}^{15} S_{ijk} \leq A_i \quad (3)$$

(2) Each crop cannot be planted in the same plot (including greenhouses) in consecutive heavy crops, constructing the 01 variable y_{ijk} . that, y_{ijk} equals to 0, characterizing no crops are planted, and y_{ijk} equals to 1 characterizes the planting of crops.

$$y_{ijk} + y_{ijk-1} \leq 1 \quad (4)$$

(3) Require all land in each parcel (including barns) to be planted to a legume crop at least once in three years beginning in 2023:

$$\sum_k^{k+2} y_{ijk} \geq 1, (k = 2023, 2024, \dots, 2030) \quad (5)$$

(4) The total production of crops in each quarter shall not exceed the total expected sales for that quarter:

$$\sum_{i=1}^6 S_{ijk} q_{ij} \leq D_j \quad (6)$$

(5) The area of each crop planted in a single plot (including greenhouses) should not be too small:

$$S_{ijk} \geq \alpha_t \quad (7)$$

(6) Each crop should not be spread out too thinly each season.

$$\sum_{i=1}^6 y_{ijk} \leq \beta_t \quad (8)$$

The optimal crop planting scheme based on linear programming is modeled as:

$$\begin{aligned} \max \sum_{j=1}^{15} \text{profit}(R_j, C_j) &= \sum_{j=1}^{15} (R_j - C_j) \\ R_j &= \sum_{i=1}^6 \sum_{k=2024}^{2030} S_{ijk} q_{ij} P_j \\ C_j &= \sum_{i=1}^6 \sum_{k=2024}^{2030} S_{ijk} M_{ij} \end{aligned} \quad (9)$$

where $i = 1, 2, \dots, N; j = 1, 2, \dots, 41$; $k = 2024, 2025, \dots, 2030$, A_i is the area of each parcel, N is the number of parcels in the category., α_t and β_t denote the area and dispersion judgment thresholds, respectively. $t = 1, \dots, 6$ denote flat dry land, terraced land, hillside land, watered land, ordinary greenhouses and smart greenhouses, respectively. Figures 1 and 2 below show the optimal planting scenarios for the countryside in 2024 and 2030 obtained by solving the linear programming model.

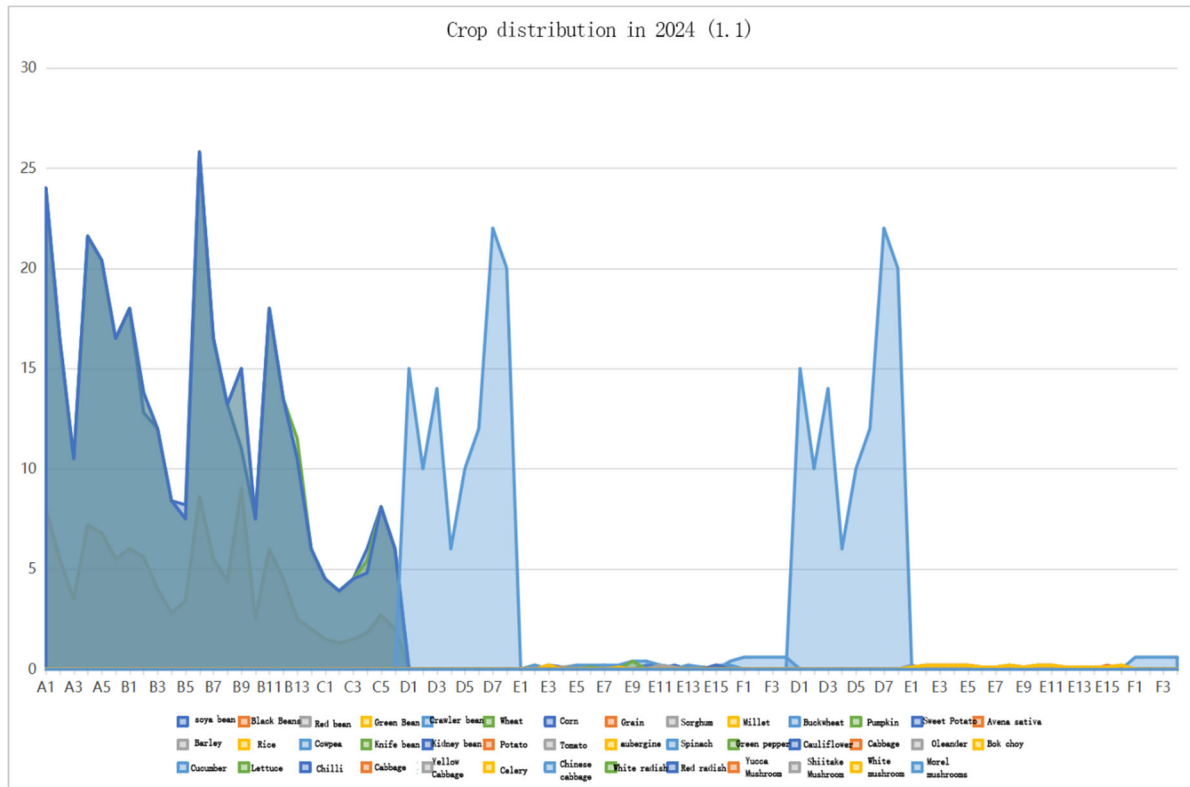


Figure 1. Linear Programming Model 2024 Optimal Planting Scenario

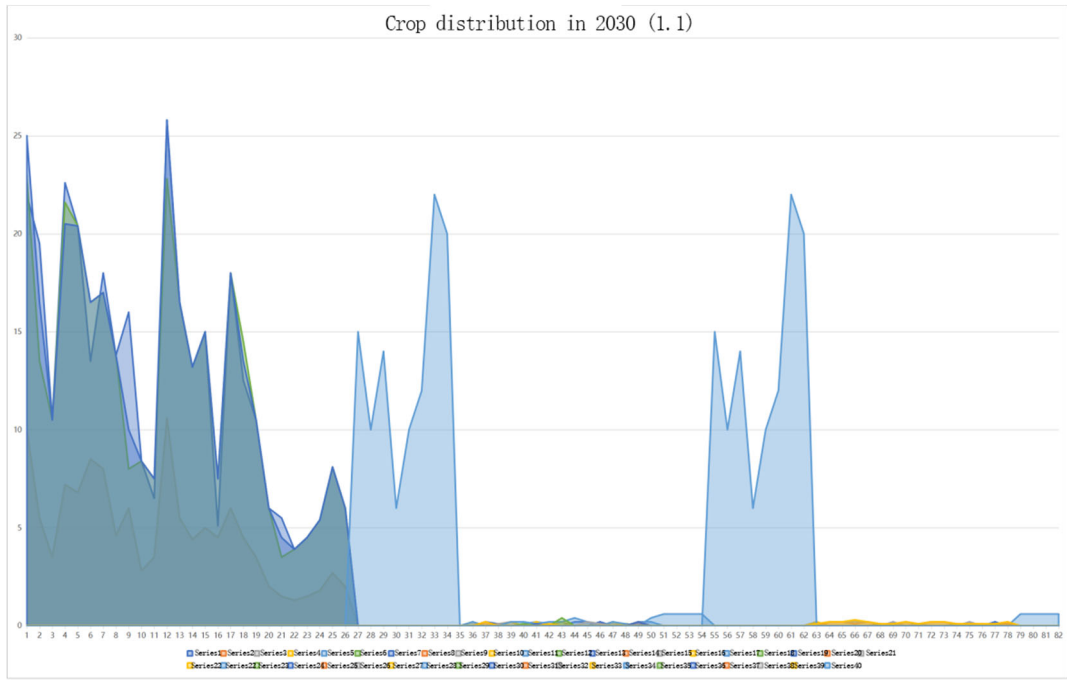


Figure 2. Linear Programming Model 2030 Optimal Planting Scenario

3. Dynamic Modeling of Optimal Crop Planting Scheme Based on Monte Carlo Simulation

3.1. The establishment of simulation model

On the basis of the previous analysis, taking into account the impact of factors such as market and climate, dynamically analyze the uncertainty of expected sales volume, yield per acre, planting cost, and sales price of various crops, as well as potential planting risks [8].

(1) Expected average annual growth in sales of wheat and corn 5%-10%:

$$D_j = D_j \times (1 + \varepsilon)^{k-2023}, \varepsilon \in [0.05, 0.1] \quad (10)$$

(2) Expected sales of other crops relative to 2023 are approximately $\pm 5\%$ change:

$$D_j = D_j \times (1 + \varepsilon'), \varepsilon' \in [-0.05, 0.05] \quad (11)$$

(3) Crop yields per acre can have annual $\pm 10\%$ change.

$$q_{ij} = q_{ij} \times (1 + \delta)^{k-2023}, \delta \in [-0.1, 0.1] \quad (12)$$

(4) The cost of growing crops averages around +5% Around.

$$C_{ij} = C_{ij} \times (1 + \eta)^{k-2023}, \eta = 0.05 \quad (13)$$

(5) Vegetable crops are sold at an average price per year +5% down around the same time:

$$P_j = P_j \times (1 + r)^{k-2023}, r = 0.05 \quad (14)$$

(6) The sales price of edible mushrooms can decline approximately annually by 1%-5%:

$$P_j = P_j \times (1 + r')^{k-2023}, r' \in [-0.05, -0.01] \quad (15)$$

(7) Sales price of morel mushrooms per year -5%:

$$P_j = P_j \times (1 + r'')^{k-2023}, r'' = -0.05 \quad (16)$$

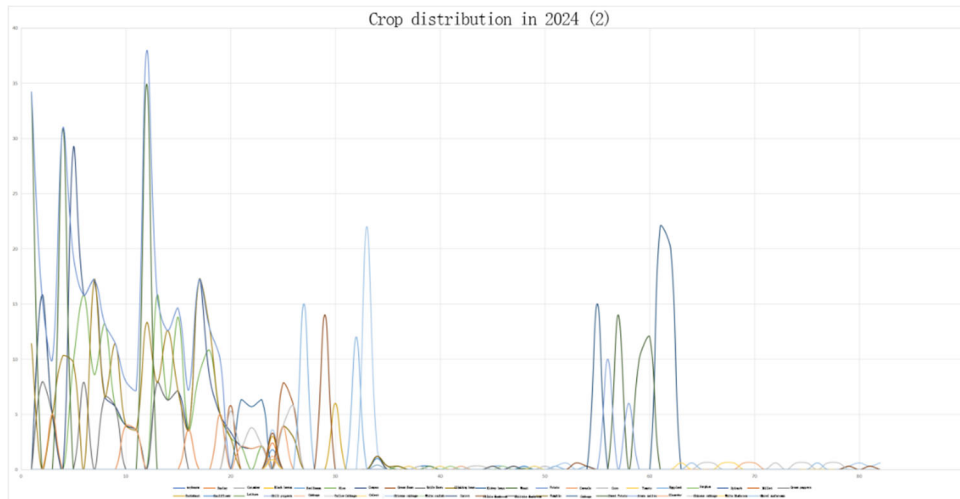
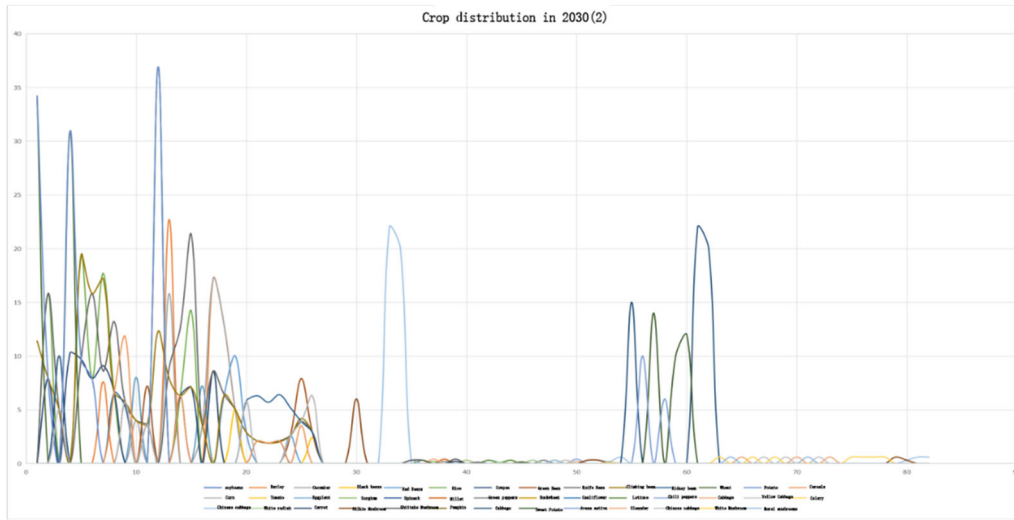


Figure 3. Dynamic model 2024 optimal planting scenario



Figures 3 and 4 above show the optimal planting scenarios for 2024 and 2030 for the village obtained by solving the dynamic model. The dynamic planning model takes into account the long-term benefits and ensures continuous optimization of planting decisions. In addition, by introducing a land restoration factor, the model takes into account changes in soil fertility in each year's decision, avoiding soil degradation due to overcultivation.

4. Integrated Planning Model Based on Monte Carlo Simulation and Multi-influence Factors

In reality, there may be some substitutability between crops. Under specific conditions, one crop can be grown in place of another without significantly affecting the efficiency of agricultural production, economic returns or ecological balance. We use similarity to measure the substitutability between crops, the higher the similarity, the stronger the substitutability.

On the basis of the previous two parts, the substitutability, complementarity and correlation between market factors among crops are further synthesized. In this paper, the second-order clustering algorithm is used to analyze the substitutability of crops, and crops with high similarity are clustered into one group in order to quantify the mutual substitutability. In addition, the complementary relationships between 41 crops were analyzed by reviewing biological and agronomic data, and the correlation between sales volume, price and planting cost was quantified based on the Spearman algorithm.

In this paper, the second-order clustering method was used to categorize the plantable crops in the first season into three classes, in which the frequency of cluster category 2 was the highest, 15, accounting for the ratio of 44.1%; the frequency of clustering category 1 is the least, which is 8, accounting for the proportion of 23.5%. The second quarter plantable crops were divided into a total of 2 categories, of which, the frequency of clustering category 2 is more, 14, accounting for the proportion of 56.0% and clustering category 1 has less frequency with 8, which is a percentage of 44.0%.

In order to further synthesize the substitutability, complementarity, and correlation between market factors among crops, we introduce multiple impact factors for describing the changes brought about by substitutability,

complementarity, and correlation.

(1) Substitutability.

In Section 4.1, based on the second-order clustering algorithm for crop substitutability analysis, we have categorized crops, and for the two agricultural products with substitutability, we establish the impact factor t_1 , which represents the impact of the price of one agricultural product on the sales volume of another agricultural product, assuming that the two agricultural products A and B are substitutable, then the sales volume of B will be affected by the price of A. The mathematical expression is as follows:

$$D_B' = D_B + t_1 P_A(t_1 > 0) \quad (17)$$

(2) Relevance.

Based on the correlation analysis between expected sales volume and sales price and planting cost of spearman algorithm, we know that the sales unit price of crops is positively correlated with planting cost, and the expected sales volume of crops is negatively correlated with planting cost and sales unit price. Establishment of influence factor t_2 、 t_3 . The expected sales volume of agricultural products can be expressed mathematically as follows

Expressed as.

$$D' = D + t_2 \Delta P + t_3 \Delta C (t_2 < 0, t_3 < 0) \quad (18)$$

(3) Complementarity.

Based on biological and agronomic knowledge of crop complementarity analysis, we know that there may be a biological mechanism of action between crops, that is, the planting of one crop may contribute to the acreage yield of another crop. Establishment of impact factors t_4 . To describe, assuming that there is a complementarity between crops C and D, and planted in the same plot one season apart, then the impact of complementarity between them can be expressed mathematically as follows.

$$q_C = t_4 S_D(t_2 > 0) \quad (19)$$

Considering the integrated planning model based on Monte Carlo simulation and multi-influence factors, the planting scheme is more decentralized and has better eco-efficiency after integrating the intrinsic relationship of crops. In the following figure, we show the dynamic model and the

integrated optimization model to solve the heat map of the

optimal planting scheme for crops in 2025, respectively.

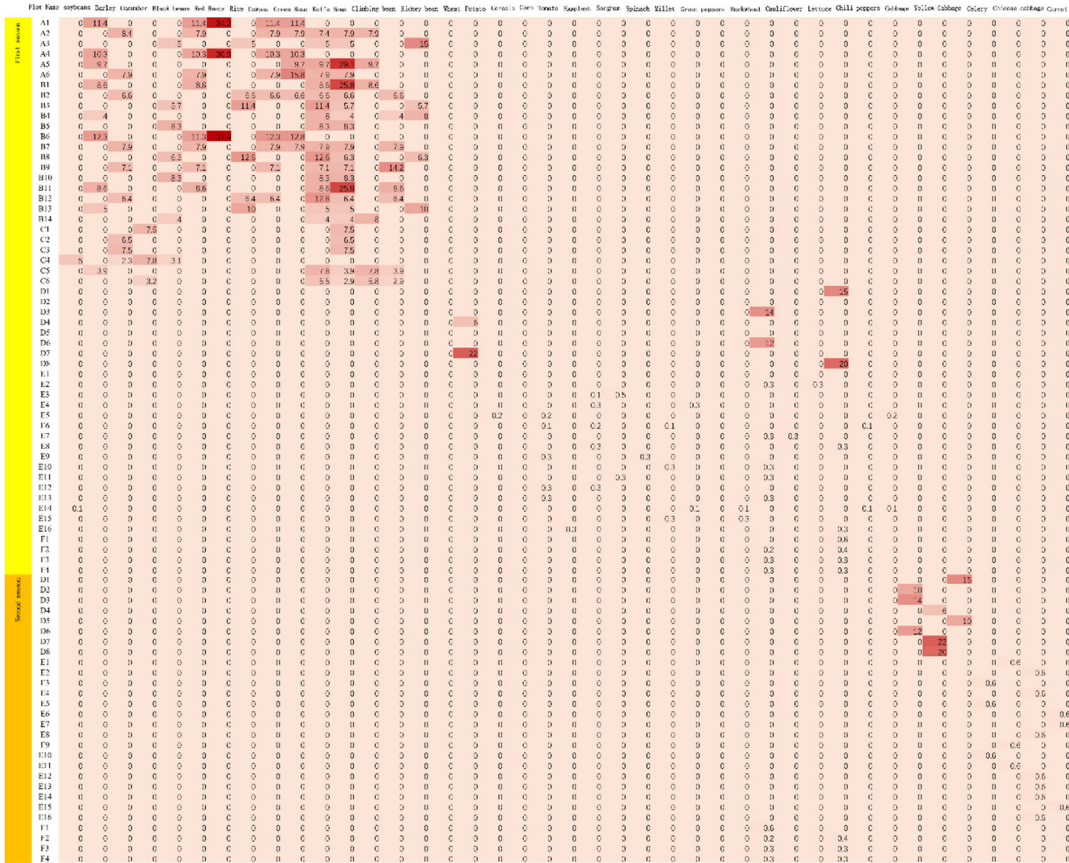


Figure 4. Dynamic model 2024 optimal planting scenario

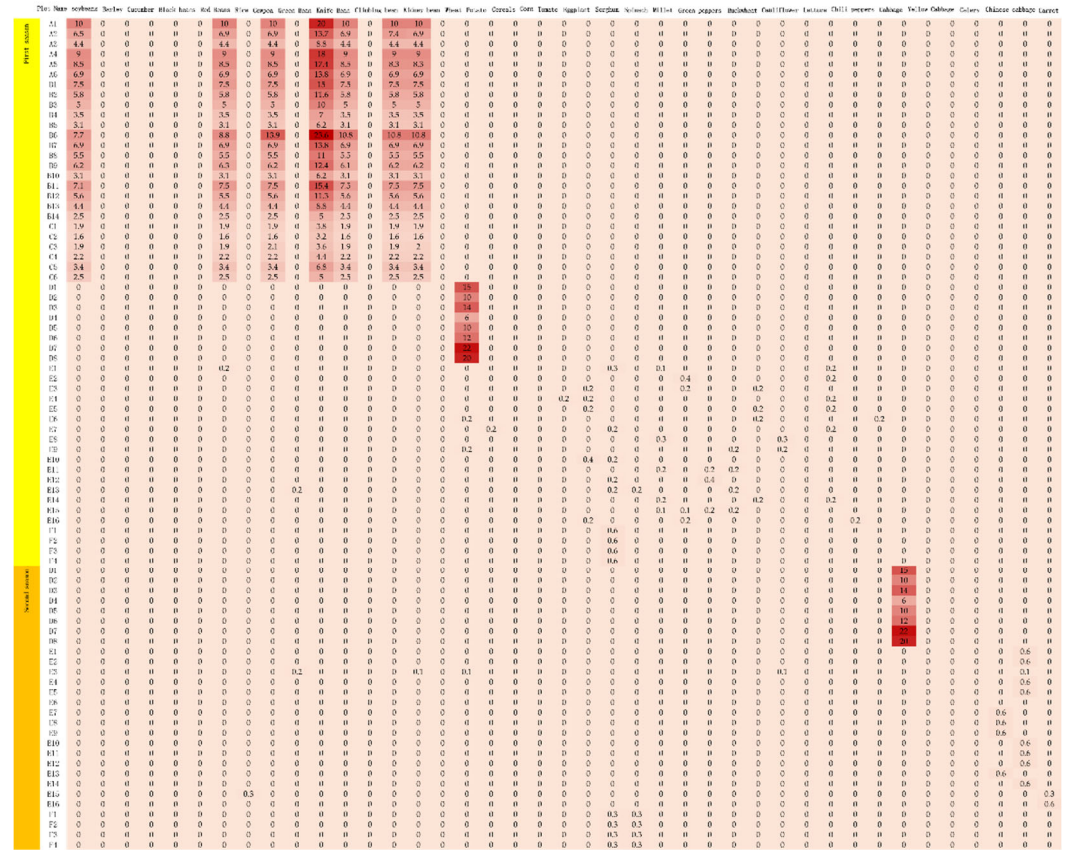


Figure 5. Dynamic model 2030 optimal planting scenario

From Figures 4 and 5, it can be clearly found that compared with the dynamic model, the strategic crop planting obtained

by the integrated planning model is relatively decentralized, and we infer that this is due to the integrated planning model

considering the substitutability and complementarity between crops.

Dynamic model of each crop as a relatively split individual, and different crops itself there are differences in profits, therefore, the dynamic model in the maximization of the profit function driven, planting strategy will be biased towards high profit crops, so there is a heat map in the darker areas more, planting area is relatively concentrated results.

On the contrary, the integrated optimization model takes into account the intrinsic relationship between crops, especially the effect of substitutability, which prevents the occurrence of a high proportion of high-margin crops from being planted, and leads to a more dispersed planting of crops, resulting in fewer dark areas in the heat map and a relatively dispersed planting area.

5. Conclusion

In this paper, the planting scheme of crops was comprehensively optimized through linear programming and Monte Carlo simulation, and the scientific and feasibility of the planting scheme was gradually improved from static to dynamic, and then considering the complex relationship between crops. The results of the study show that the model with comprehensive consideration of internal and external factors has significant advantages in enhancing returns, reducing risks and improving ecological benefits.

References

- [1] Wang, S., Z.. Research on ecological optimization of crop cultivation [J]. Agricultural Science, 2019(5): 45-50.
- [2] Wang Z. A review of intelligent optimization methods in agricultural production [J]. Modern Agricultural Science, 2020(8): 78-85.
- [3] Fan Menghan. Agricultural planting planning based on reinforcement learning and price dynamics [D]. University of Chinese Academy of Sciences, 2022.
- [4] Li H. Research on agricultural optimization model based on dynamic planning [D]. Peking University, 2021.
- [5] XU Wei-Chao. A review of correlation coefficient studies [J]. Journal of Guangdong University of Technology, 2012, (3): 12-17.
- [6] Li Lingjing, Wang Cunyou, Yu Jiayuan. Proof of the rule for automatic determination of the number of clusters in two-order clustering [J]. Statistics and Decision Making, 2010, (20): 28-29.
- [7] Zhu Yingchun. Second-order clustering model and its application [J]. Market Research, 2005, (1): 40-42.
- [8] Wang Xiuhong. Agricultural Material Inputs and the Potential Risk Assessment for Vegetable Production in China [J]. Journal of Resources and Ecology, 2016, 7(4): 269-274. DOI:10.5814/j.issn.1674-764x.2016.04.005.