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SUSTAINABLE CROP PLANNING IN A MOUNTAINOUS VILLAGE USING LINEAR PROGRAMMING

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Abstract: This study focuses on optimizing crop planning in a mountainous village in North China, where the cold climate permits only one growing season per year. The village's arable land is distributed across 34 plots of various types, including flat drylands, terraces, slopes, and irrigated fields. A linear programming model is developed to maximize planting revenue, considering crop rotation requirements, land suitability, planting costs, yields, and market prices. To simulate future conditions, crop prices in 2030 are modeled using normally distributed random numbers. The model sets two sales scenarios: (1) surplus production beyond expected sales cannot be sold, resulting in waste; and (2) surplus is sold at 50% of the 2023 market price. To address uncertainties in yield, cost, price, and demand, as well as potential planting risks, a particle swarm optimization algorithm is employed with random factors to simulate changing conditions. Results show that the village can achieve annual revenues between 8 to 9 million RMB under both deterministic and stochastic scenarios. The optimized strategies satisfy agronomic and environmental constraints and offer scientific support for sustainable agricultural development in resource-limited mountainous regions.
Keywords: Crop cultivation; Optimal planting strategy; Linear programming particle swarm algorithm; Multiple regression modeling

1 INTRODUCTION

With the in-depth promotion of the rural revitalization strategy, the sustainable development of the agricultural economy has gradually become a key issue in promoting the high-quality development of the social economy. How to realize the double enhancement of agricultural production efficiency and ecological efficiency by optimizing the crop planting structure under the conditions of limited land resources has become one of the core issues of modern agricultural development.

Du Neng first proposed the spatial pattern of crop planting structure in his agricultural location theory in 1826, and since then, scholars worldwide have explored its spatial distribution, migration and driving factors[1]. Taking the Greater Bay Area as the object, Taking the Greater Bay Area as the object, a study found that from 1990 to 2020, grain and oilseed planting declined, while vegetables and fruits increased, leading to a shift from a rice-based to a diversified vegetable-dominant planting pattern with evident spatial clustering[2]. Other scholars used GIS technology, time series trend and spatial agglomeration analysis methods to study crop structure evolution in Hunan province counties[3]. In terms of exploring the influencing factors, it has been pointed out that natural conditions and socio-economic factors jointly drive the change of cropping structure, and the influencing mechanism shows a complex development trend[4,5]. Some studies further showed that soil type, water resource status and input factors are the key constraints on cropping structure [6]. Other studies used remote sensing, fieldwork, and models to build planting databases and analyze structural evolution via indices and quantitative methods[7]. For optimization, studies generally start from the dimensions of ecological benefits, economic benefits and irrigation water consumption, and explore the sustainable models by adjusting crop sowing area[8]. Some built multi-objective models with agricultural yield, economic benefits, and water consumption as objectives, generating optimal solutions via improved weight combination methods and incorporating dialogue coordination mechanisms, thus offering a practical path to optimize planting structures in irrigation areas under water rights constraints [9].

However, the majority of existing studies focus on macro-scale regions such as provinces or counties, with limited attention to the optimization of crop planting structures at the village level under complex terrain and resource constraints. This study examines a mountainous village in North China, characterized by a cold climate, fragmented land, and a single annual growing season. A crop-plot matching optimization model based on linear programming is developed, incorporating crop rotation rules, land suitability, planting costs, yields, and market prices. To address planting risks and variability under uncertain conditions, a particle swarm optimization (PSO) algorithm is employed to solve the extended model and enhance the robustness of the planting strategy. And the aim of this research is to develop location-specific, profit-maximizing crop planning strategies that adhere to agronomic and ecological constraints, thus providing theoretical support and practical guidance for sustainable agricultural development in resource-limited mountainous regions.

2 MODELING AND SOLVING FOR OPTIMAL PLANTING SCHEMES

2.1 Data Preprocessing

Before modeling, the original planting data need to be preprocessed to ensure the accuracy of the analysis and the validity of the model inputs. This study utilizes 2023 data from a mountainous village in North China, focusing on plot information, crop adaptation and price range (Data source: https://www.mcm.edu.cn/). First of all, for the plot information and crop adaptation plot information, due to its relative simplicity and structure, the Excel tool is used to extract and organize, and the plot name, area and type are unified and summarized to ensure that each crop is accurately matched with its suitable plot. In order to more intuitively show the planting distribution and proportion of each type of 4 crop, corresponding visualization diagrams were drawn, as shown in figure 1 and figure 2, which assisted in assessing the adaptability of different plots to crops. Additionally, when dealing with the price range data of crops, a method of perturbation simulation based on the midpoint is adopted. Specifically, the midpoint value, which is the average of the maximum and minimum values, is used as the baseline. A small perturbation value that follows a normal distribution is then superimposed on this baseline to simulate the potential price fluctuations in 2023. The process is implemented in Python to ensure that the price data are both representative and reflect a certain degree of uncertainty, providing reasonable input parameters for the subsequent model.

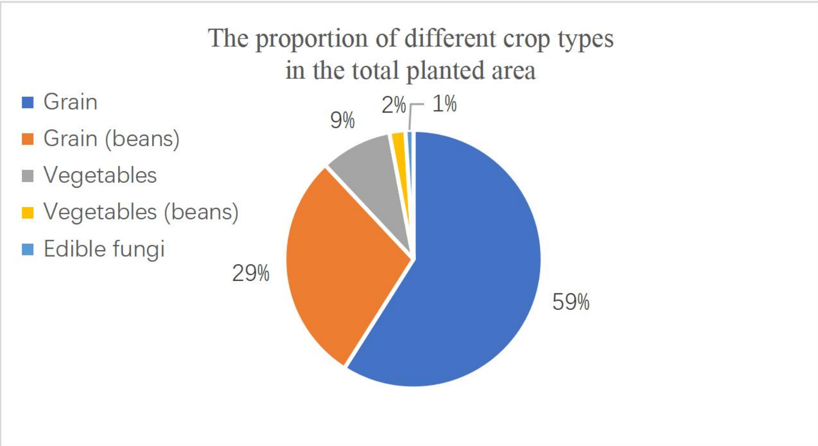

Figure 1 Proportion of Total Cultivated Area Represented by Different Crop Types

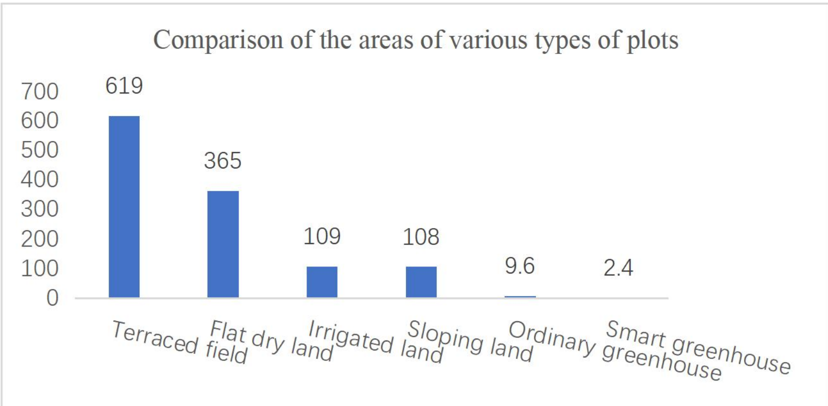

Figure 2 Ratio of Parcel Area by Type

2.2 Modeling and Solving Multi-Objective Linear Programming

2.2.1 Linear programming modeling

Linear programming is a typical mathematical optimization method for seeking optimal allocation strategies to maximize economic benefits under limited resources [10]. In crop planting decisions, linear programming can be used to determine the optimal acreage allocation scheme to maximize planting returns while satisfying various constraints.

For the crop planting problem, the model objective not only includes profit maximization, but also needs to comprehensively consider a variety of factors such as unit production, expected sales volume, planting costs, market prices and so on. In reality, when the total production of a crop exceeds its expected sales volume, there may be two ways to deal with it: one is to sell all of it, and the other is to sell the excess portion at a 50% discount. Therefore, two different yield objective functions are set in the model to reflect these two situations separately. At the same time, the model also needs to introduce planting type, plot size, seasonal arrangement, etc. as constraints, so as to construct a multi-objective linear planning model to enhance the scientific and adaptive planting decisions. The following are the multi-objective functions as well as the constraints:

$$\mathrm{MaxProfit1} = \mathrm{Max}\left(\sum_{j=2024}^{2030}\sum_{i}\sum_{k}\sum_{s}\left(\mathrm{Sales}(j,k,s)\times\mathrm{Price}(j,k)-\mathrm{Cost}(j,k)\times X(i,j,k,s)\right)\right) \tag{1}$$

$$\mathrm{MaxProfit2} = \mathrm{Max}\Big(\sum_{j=2024}^{2030}\sum_{i}\sum_{k}\sum_{s}(\mathrm{Sales}(j,k,s)\times \mathrm{Price}(j,k) - \mathrm{Cost}(j,k)\times X(i,j,k,s) + \mathrm{Excess}(i,k,s)\times \mathrm{Cost}\times 0.5\Big) \tag{2}$$

$$\text{s.t.}\begin{cases} \sum_{k=1}^{41}\sum_{s=1}^{2} X(i,j,k,s) \le A_i \\ \sum_{k=1}^{41}\sum_{s=1}^{2} Z(i,j,k,s) \ge 1, \forall i,j,k,s(\mathit{legume\ crop}) \\ \sum_{j}^{j+2}\sum_{s=2}^{2} X(i,j,k,s) \ge 0.1 \times A_i \\ Z(i,j,k,s) + Z(i,j+1,k,s) \le 1 \\ X(i,j,k,s) \le A_i \times Z(i,j,k,s) \\ X(i,j,k,s) \le A_i \times \mathrm{Suitable\_plot}_{i,k} \\ \sum_{s}^{2} X(i,j,k,s) \le A_i \times \mathrm{Suitable\_season}_{i,k} \end{cases} \tag{3}$$

2.2.2 Solving linear programming models

Python is used to solve the above multi-objective linear programming model to obtain the optimal total return of the village from 2024 to 2030 under the two scenarios: (1) surplus production beyond expected sales cannot be sold and is treated as waste; (2) surplus production is sold at 50% of the 2023 market price. The simulation results for both scenarios are shown in figure 3. It presents the simulation results for both scenarios, showing that total revenue under Scenario 2 is generally higher than in Scenario 1, despite some fluctuations in both cases. The key difference lies in the handling of surplus production. In Scenario 1, unsold surplus leads to direct losses, while in Scenario 2, even selling at a discount allows partial revenue recovery. This highlights the importance of managing overproduction through strategies such as secondary markets or discount sales, which help stabilize income and enhance agricultural resilience.

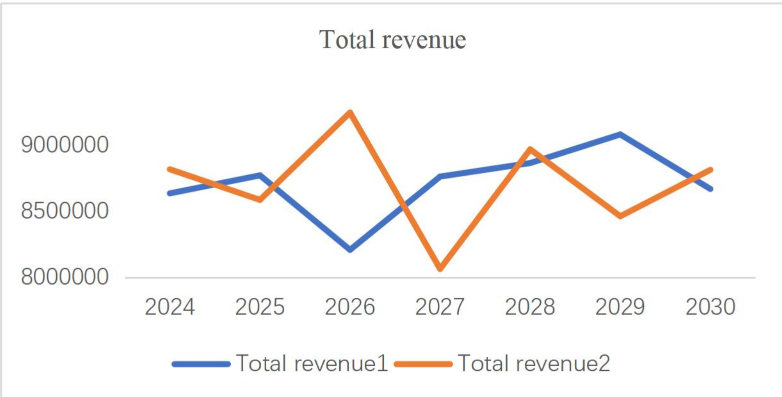

Figure 3 Total Returns from 2024 to 2030 for both Scenarios

On this basis, the optimal crop planting scheme in the corresponding time range is further obtained figure 4 and figure 5 show the distribution of planting area of different crops in each year under the two scenarios, respectively, reflecting the adjustment strategies of the model for crop types and plot configurations under different assumptions. In Scenario 1, where surplus production beyond expected sales cannot be sold and is therefore wasted, the model favors crops with stable yields and predictable market demand, such as wheat and mushrooms, to reduce financial risk. In contrast, Scenario 2 allows surplus to be sold at 50% of the 2023 market price, encouraging a more diversified planting strategy. The increase in vegetable and legume cultivation reflects an effort to extract value from potential overproduction and improve overall returns. These results demonstrate the model's ability to adapt planting strategies to different economic environments.

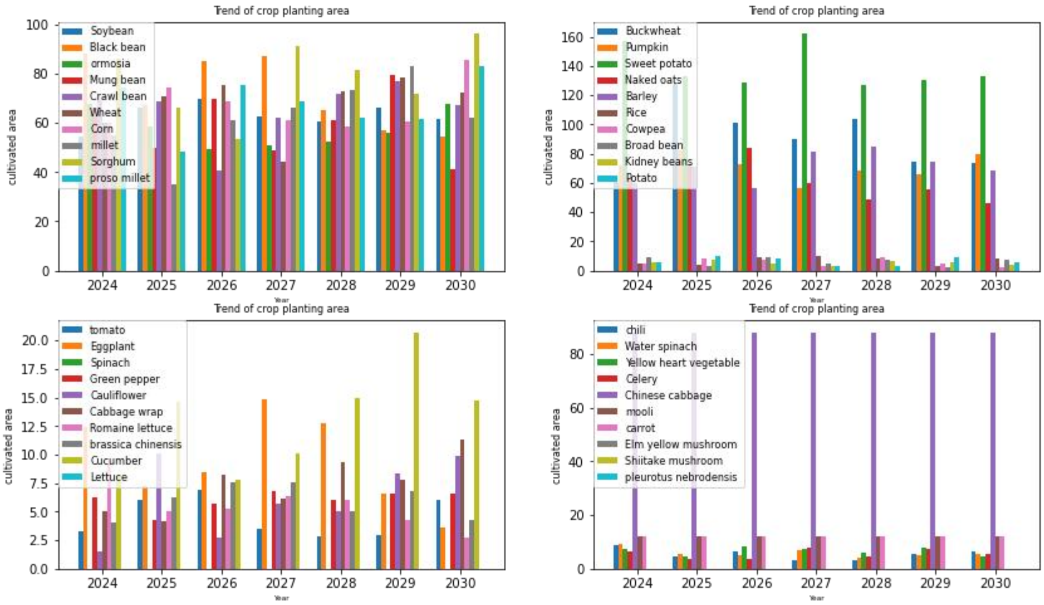

Figure 4 Scenario 1 Planting Distribution from 2024 to 2030

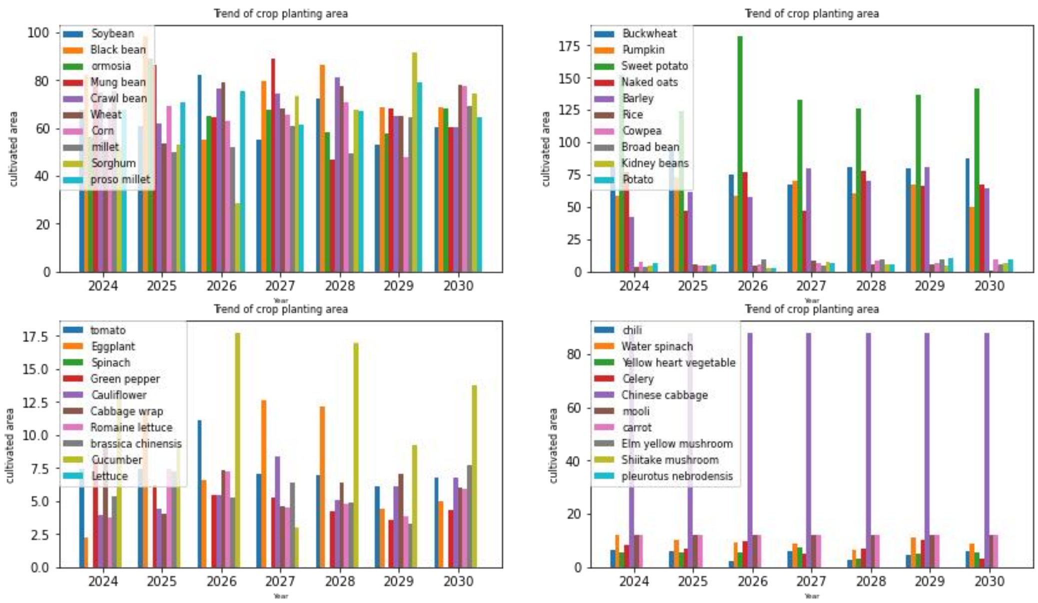

Figure 5 Scenario 2 Crop Planting Distribution from 2024 to 2030

3 MODELING AND SOLVING UNDER MULTIPLE RISK FACTORS

3.1 Optimization Modeling

While adhering to the restrictions of crop rotation and succession, the crop was modeled with different key factors using the adjust_parameters function in Python, taking into account the fluctuations in yield, cost of cultivation, sales price and expected sales volume over time, and the effects of uncertainty. The following model adjustments were made based on multi objective linear programming.

（1）Adjustments to sales volume:

For corn and wheat, sales are expected to grow at an average annual rate of 5 to 10 percent:

$$Sales_{j,k} = Sales_{0,k} \times (1+r)^{t-2023}, r \in [0.05,0.1] \tag{4}$$

For other crops, sales are expected to be 5% up or down relative to 2023:

$$Sales_{j,k} = Sales_{0,k} \times (1+r)^{t-2023}, r \in [-0.05,0.05] \tag{5}$$

（2）Adjustment of acreage: acreage fluctuates up and down by 10% per year due to climate and other factors:

$$Y_{j,k} = Y_{0,k} \times (1+r)^{t-2023}, r \in [-0.1,0.1] \tag{6}$$

（3）Adjustments to planting costs: The average annual increase in planting costs is 5% due to market factors and other factors:

$$Costs_{j,k} = Costs_{0,k} \times (1+0.05)^{t-2023} \tag{7}$$

（4）Adjustments to the sales price:
For vegetable crops, sales prices have increased by an average of 5 to 10 percent annually:

$$Price_{j,k} = Price_{0,k} \times (1 + 0.05)^{t-2023} \tag{8}$$

For morel mushrooms, the sales price declined by an average of 5% per year:

$$Price_{j,k} = Price_{0,k} \times (1 - 0.05)^{t-2023} \tag{9}$$

（5）Determine the objective function:

$$\mathrm{MaxProfit} = \mathrm{Max}(\sum_{j=2024}^{2030} \sum_{i} \sum_{k} \sum_{s} (\mathrm{Price}_{j,k} \times \mathrm{Y}_{j,k} - \mathrm{Costs}_{j,k}) \times \mathrm{X}_{i,j,ks} \tag{10}$$

The constraints of this model are the same as those of the previous model.

3.2 Particle Swarm Algorithm for Solving Optimization Models

Particle Swarm Algorithm (PSO) is a population intelligent optimization algorithm that approximates the optimal solution in an iterative manner by simulating the search behavior of particles and continuously updating the individual extremes and global extremes[11].The following are the solution steps:
（1）Initialization:
Parameters such as particle swarm size, maximum iteration number, and learning factor are set. Each particle represents a possible planting strategy, its position represents the planting area of each crop on different plots, and its speed represents the adjustment amplitude of the planting strategy. Randomly generate the position and speed of the initial particles, calculate the fitness value of each particle, and record its individual optimal position, and determine the global optimal position in the current population(gbest).
（2）Calculation and updating of adaptation values
In each iteration, the fitness values of all particles are recalculated. If the current fitness of a particle is better than its historical individual optimum, its individual extreme value (Pbest) is updated; if the fitness of a particle is better than the current global optimum, the global extreme value and the corresponding position (gbest) are updated synchronously.
（3）Particle update
In each round of iteration, the position and velocity of the particles are updated with the following formula:

$$\mathrm{V}_{i,j}(t+1) = \mathrm{V}_{i,j}j(t) + s_1 r_{1,j}(\mathrm{P}_{dbj} - \mathrm{P}_{ij}(t)) + s_2 r_{2j}(\mathrm{P}_{dbj} - \mathrm{P}_{ij}(t)) \tag{11}$$

$$\mathrm{P}_{i,j}(t+1) = \mathrm{P}_{i,j}(t) + \mathrm{V}_{i,j}(t+1) \tag{12}$$

Where $i = 1, \ldots, N$, $j = 1, \ldots, D$, t is the number of iterations, S_1 and S_2 are non-negative learning factor constants, and r_{1j} and r_{2j} are independent random numbers uniformly distributed over the interval [0,1].
（4）Examination of termination conditions
The particle swarm algorithm checks after each round of iterations whether the termination conditions are satisfied, including reaching the maximum number of iterations (set to 100) or the particle swarm converges, i.e., the value of the global optimum no longer changes significantly. If the conditions are satisfied, the iteration is stopped and the current global optimal solution is output; otherwise, the execution continues to the next round.
In order to improve the convergence speed of the particle swarm algorithm, this paper introduces a priori knowledge, sets 35% of the initial particles as human-defined parameters, and the remaining 65% of the particles are randomly generated. In addition, in order to enhance the realism of the model, a constraint function containing sales volume, mu yield, planting cost and sales price is constructed. Finally, the optimization results with corresponding total returns and crop planting distributions were obtained through 9 rounds of 100 iterations each, as shown figure 6 and figure 7.
As shown in figure 6, the total revenue shows fluctuations during the period from 2024 to 2030. A peak occurs in 2026, which may be attributed to favorable market conditions, optimized planting strategies, and other positive influencing factors. Conversely, the significant decline in 2027 might be due to adverse external factors, such as natural disasters, market price drops, or increased planting costs. And figure 7 depicts the optimal planting distribution of different crops over the years. For example, staple crops like wheat and rice maintain relatively stable planting areas, highlighting their crucial significance in ensuring food security. Meanwhile, the planting areas of cash crops such as tomatoes and eggplants exhibit certain fluctuations, which are related to market demand changes, price fluctuations, and the impact of the optimization algorithm on maximizing returns. By comprehensively analyzing these distribution changes, the planting structure can be adjusted according to market demands and resource endowments, thereby improving the overall economic efficiency of crop planting and optimizing resource utilization.

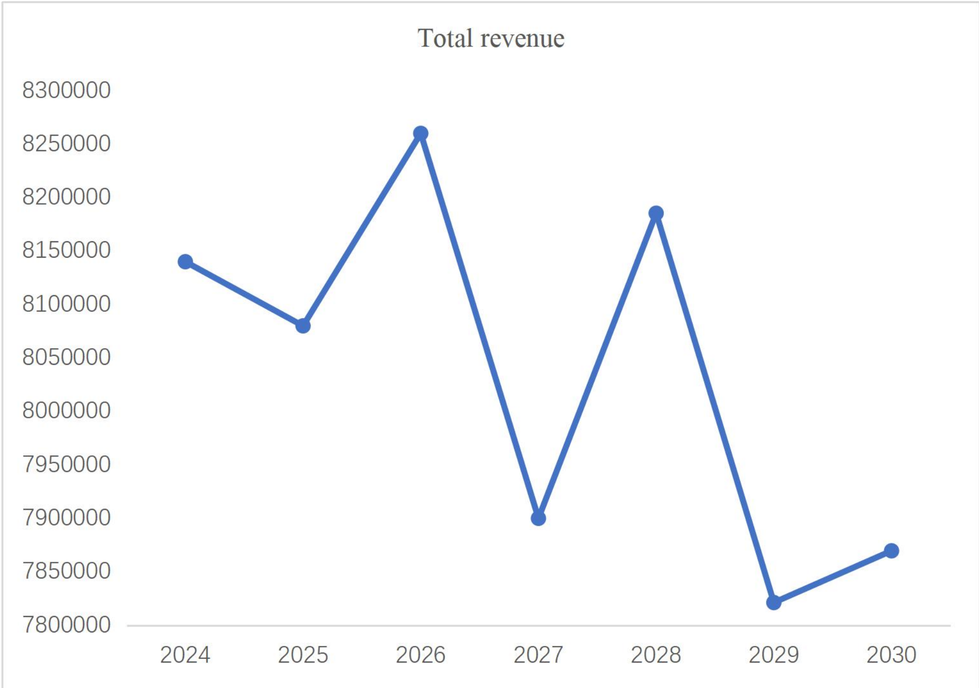

Figure 6 Total Revenue from 2024 to 2030

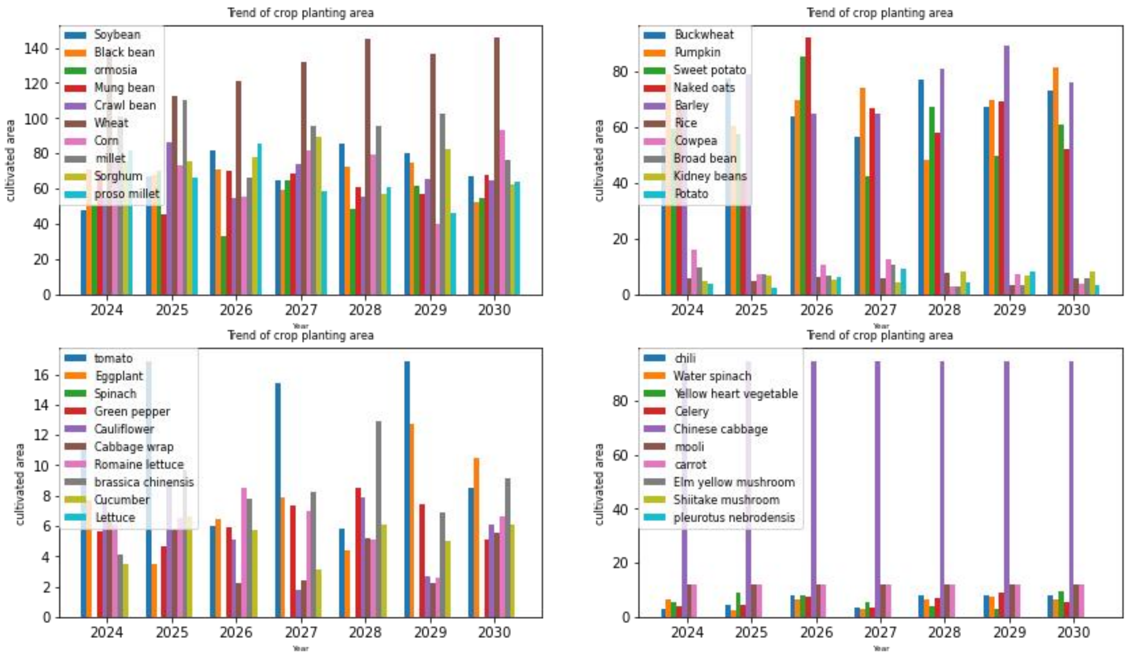

Figure 7 Optimal Planting Distribution Map of Crops

4 CONCLUSIONS

This paper focuses on the crop planting optimization problem, establishes a mathematical model based on linear programming, takes the maximization of revenue as the goal, combines the planting area, the market demand, the cost and revenue and other realistic factors, constructs a single-objective linear programming and multi-objective optimization model, and solves the optimal planting strategy under different conditions using Python.

The research results show that the linear programming model has good applicability and practical value in agricultural production decision-making, which can not only effectively improve the land use efficiency, but also provide a scientific basis for agricultural planting structure adjustment and resource allocation. However, this paper still has certain limitations. On the one hand, although a variety of influencing factors are considered in the modeling process, the actual planting environment is more complex, and there may be other factors that have not been taken into account to affect the planting efficiency. On the other hand, the particle swarm algorithm may not have optimal parameter settings in the solving process, which affects the accuracy of the final results. Future research can further expand the influencing factors of the model, optimize the parameters of the algorithm, and verify it with more actual data, so as to provide more accurate and effective decision support for the sustainable development of rural planting.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

REFERENCES

[1] LIN Dayan, ZHU Jing. Reasons for changes in the planting structure of major crops in China from the perspective of supply elasticity. Agricultural Technology and Economy, 2015(01): 33-41.
[2] HU Yunfei, LIU Xu, LIANG Junfen, et al. Spatial and temporal evolution of crop cropping structure in the Guangdong-Hong Kong-Macao Greater Bay Area from 1990 to 2020. Guangdong Agricultural Science, 2023, 50(01): 13-27.
[3] AN Yue, TAN Xuelan, TAN Jieyang, et al. Evolution of crop planting structure and influencing factors in Hunan Province. Economic Geography, 2021, 41(02): 156-166.
[4] Zhou XG. Analysis of the impact of agricultural planting factors on agricultural planting structure. Rural Practical Technology, 2023(10): 99-100.
[5] SONG Yu, LIU Weiping. Influencing factors and multivariate paths of the evolution of cultivated land planting structure - A qualitative comparative analysis of fuzzy sets based on case zones in 30 provinces. Geographic Research and Development, 2024, 43(04): 133-138.
[6] Bao Shuzong. Influence of agricultural planting factors on planting structure and optimization strategy. Agriculture and Technology, 2020, 40(13): 90-91.
[7] LUO Qiancheng,WANG Yuexiang,CHI Wenfeng,et al. Factors affecting the evolution of crop cropping structure in the black soil area of Inner Mongolia. Resource Science, 2023, 45(05): 994-1005.
[8] WU Menghan,WANG Yi. Optimized adjustment of multi-objective planting of crops in Shache Irrigation District of Xinjiang. People's Yellow River, 2024, 46(01): 120 125+131.
[9] ZHANG Hao Yang,CHEN Xing. Optimal planting structure preference method for irrigation areas under water right constraints. Modern Agricultural Science and Technology, 2024(24): 161-164.
[10] An Jinping. Application of linear programming in economic analysis. Journal of Central University of Finance and Economics, 2005(01): 44-47.
[11] Deng Chan,Li Chun,Li Mengqi, et al. Progress of particle swarm algorithm in agricultural hydrology. Anhui Agricultural Science,2021, 49(08): 16-20+29.