Design of Crop Planting Strategies in the Mountainous Areas of North China Based on a Multi-Objective Optimization Model

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Abstract. With the development of the organic farming industry, reasonable crop planting strategies are critical to improving agricultural benefits. Taking a village in the mountainous areas of North China as an example, this paper proposes the optimal crop planting plans from 2024 to 2030 to achieve sustainable rural economic development. Based on data, a multi-objective optimization model is established, considering objectives such as maximizing total profit and minimizing planting area dispersion, and incorporating constraints such as suitable plots for crops and avoiding continuous cropping of the same crop. The NSGA-II algorithm is used to solve the multi-objective optimization model, generating multiple Pareto-optimal solutions and reducing excessive planting. For surplus production, the MOEA/D algorithm is adopted to handle multi-objective optimization problems. The model calculates a maximum profit of 46,895,620 CNY and determines the optimal planting strategy. After considering surplus production, the maximum profit increases to 48,123,540 CNY. The crop planting plan proposed in this paper balances the relationship between profit and planting area dispersion and optimizes adjustments for surplus production to maximize village economic benefits. The optimal crop planting strategies for 2024 to 2030 demonstrate that the multi-objective optimization model can effectively address the problem of optimization design in crop planting strategies and provide a scientific basis for improving agricultural benefits. This study also provides a reference for designing crop planting strategies in other regions.

Keywords: Multi-objective optimization, NSGA-II algorithm, MOEA/D algorithm.

1. Introduction

With the rapid development of the rural economy, limited arable land resources are gradually becoming a key constraint. Under such circumstances, it is increasingly important to select appropriate crops and reasonable planting strategies according to local conditions. In this study, a village in the mountainous region of North China with 1213 mu of arable land divided into six types is taken as the object of study. Due to climatic and plot characteristics, crop adaptations and growing seasons varied greatly from plot to plot. The study showed that legume-rhizobium symbiosis promotes rhizoma development, which fixes nitrogen for plant use and enhances soil nitrogen cycling to benefit subsequent crops. [1]. Therefore, each plot must be planted with legumes at least once every three years starting in 2023. Other restrictions include avoiding continuous monocropping, which can lead to soil nutrient imbalances, reduced fertility, and susceptibility to pests and diseases. By rotating different crops, soil nutrients can be better utilised, pests and diseases can be reduced, and the ecological balance of the soil can be maintained. [2] As well as the constraints of ensuring the minimum planting area of each crop for ease of management and cost control. In conclusion, scientific planning of crop cultivation strategies is essential for rural economic development. Based on the existing crop and arable land data in the village, this paper aims to solve the problem of optimal planting strategy between 2024 and 2030 by building a mathematical model. In the process of model construction, various constraints such as crop adaptability, crop rotation requirements, minimum planting area, etc. will be fully considered, and at the same time combining two different ways of handling surplus agricultural products, we will strive to provide practical guidance for the village's rural economic development of the planting strategy, in order to realise the sustainable development of agricultural production.

2. Materials and Methods

2.1. Data Acquisition and Preprocessing

This study collected 2023 crop production data, including plot types, planted areas, yields, and prices. Data sources include open-access platforms (www.baidu.com).

2.1.1 Data Visualization

Due to the dispersed nature of the collated data, analysis is rendered challenging. In order to visualise the cultivation of various crops in 2023, this paper is based on the available data, which is first visualised.

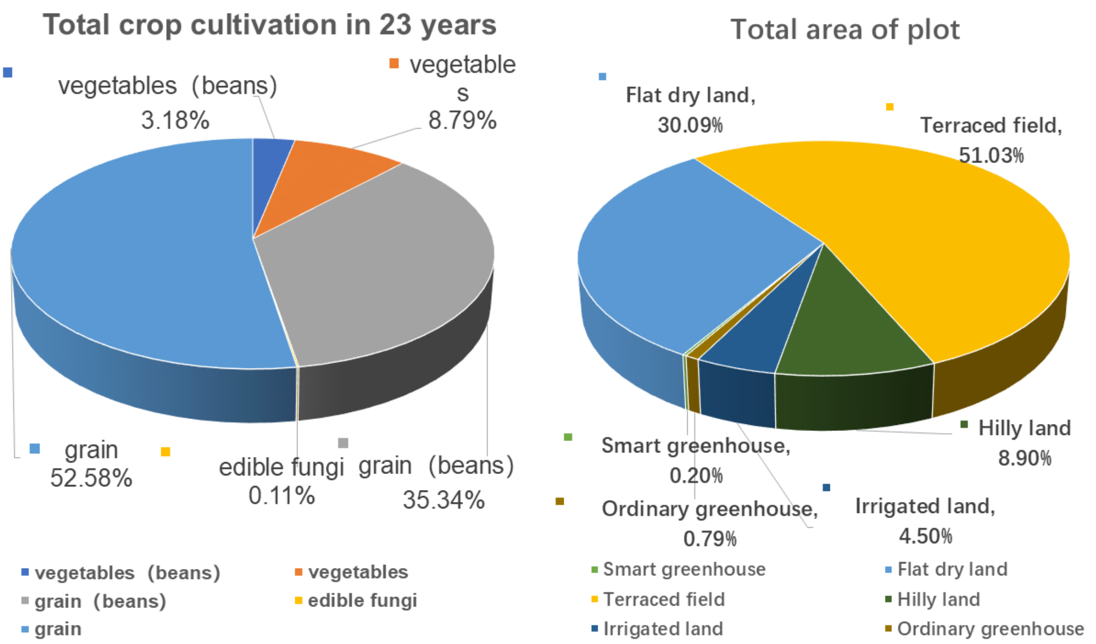

Figure 1. Pie chart of plots with crops

Figure 1 shows the distribution of plot types in the total cultivated area. Terraced land, making up 51.03%, has the largest share and significantly impacts crop choices. Flat dry land is the second most common, covering over 80% of the area. Ordinary and smart greenhouses only account for 1% of the land, with a smaller impact on crop choices.

With regard to the crops to be planted in 2023, grain crops accounted for 52.57% of the total crop production, representing the crop type with the highest yield and the most abundant planting options. This is followed by pulses in food grains with a share of 35.34%. Overall, food crops are the most productive, diverse and have the widest range of cultivation options.

2.1.2 Normalization and Logarithmic Transformation

Existing yield data varies significantly, and directly graphing it can lead to unclear results. To solve this, the data was first normalized to a [0,1] scale, reducing the difference in magnitude between crops. This step makes it easier to compare the data and ensures that the scale differences don’ t distort the visual representation. After normalization, yield graphs for different crops were generated, as shown in Figure 2.

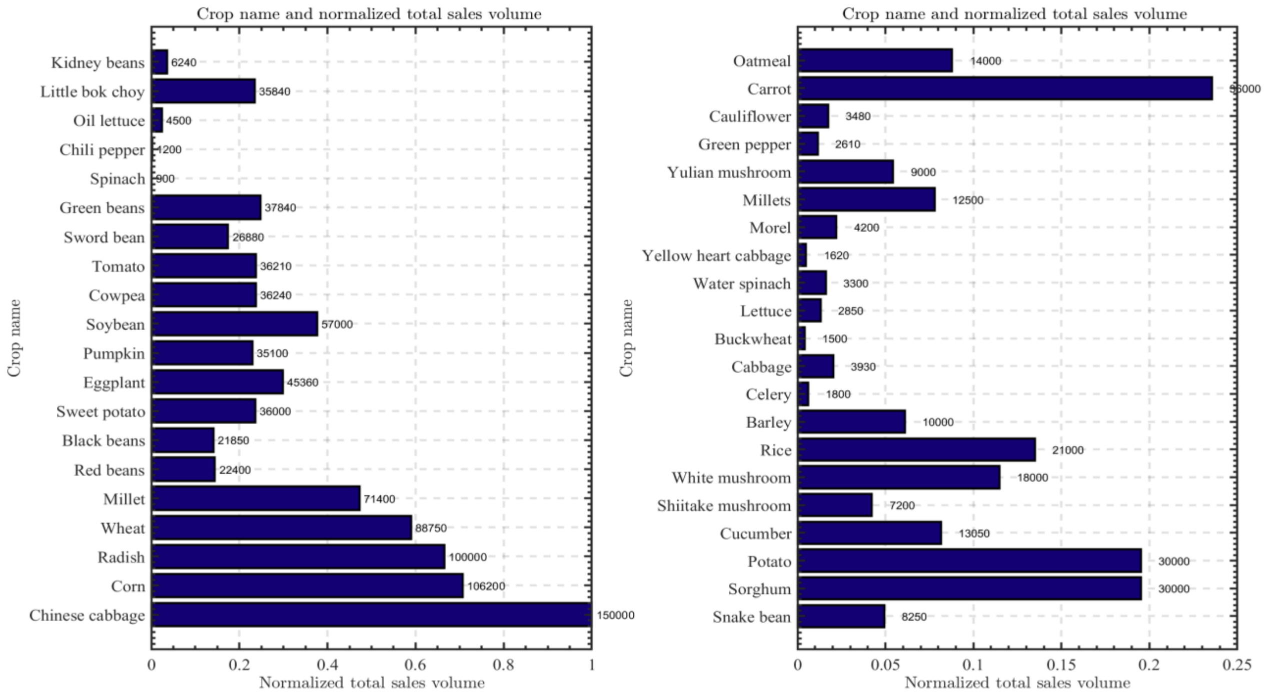

Figure 2. Yield maps of various crops

As shown in Figure 2, among all 41 crops, staple crops such as Chinese cabbage, corn, wheat, and radish exhibit relatively higher yields, while specialty crops like buckwheat, chili, and spinach demonstrate significantly lower yields. Notably, substantial variations in yield exist even among crops of the same type, with differences being distinctly observable.

To further analyze the profit and cost dynamics across crop categories, this study conducted data visualization on yield per mu and profit per mu for each crop. However, significant disparities persisted in the normalized data, complicating direct comparative analysis. To mitigate this issue, logarithmic transformation was applied to the dataset. This method effectively reduced the magnitude differences between data points, thereby enhancing the clarity and interpretability of visual representations. Following dimensional scaling, the relationships between profits and costs across different crop types were more intuitively illustrated, as demonstrated in Figure 3.

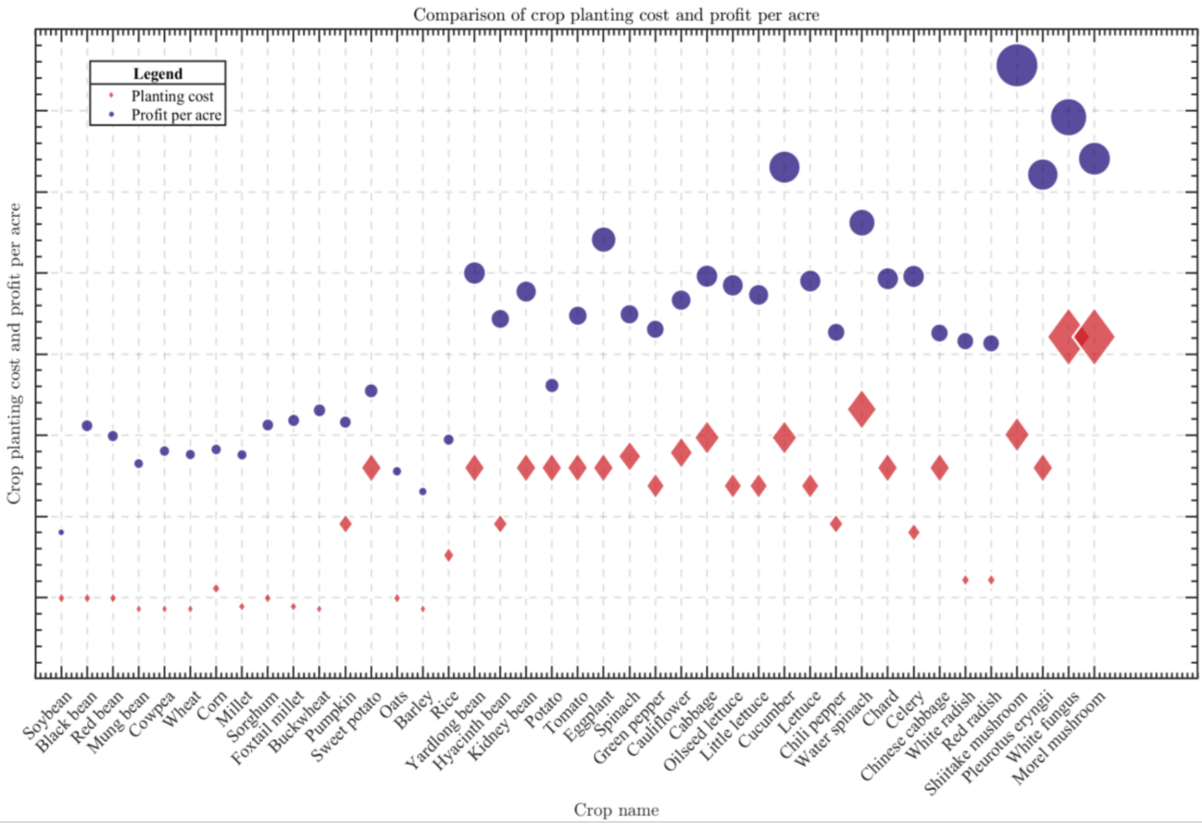

Figure 3. Chart of profit and cost per acre for different crops

As shown in Figure 3, there are notable differences in both profit per mu and planting costs across crops. For example, legumes in the grain category typically have lower profit margins, while edible fungi are much more profitable. Other grain crops fall in between. Edible fungi also have higher planting costs per mu compared to grains. A general trend shows that crops with higher planting costs tend to have higher profits, highlighting the positive correlation between costs and profits, which is crucial for future agricultural decision-making.

2.2. Methodology

This study addresses two research problems related to rural economic development and optimal planting strategies. Given limited arable land and rapid rural economic growth, selecting suitable crops and strategies is critical. The first part develops a multi-objective optimization model based on 2023 crop cultivation data, integrating plot characteristics, crop requirements, and constraints. The model aims to maximize total profit and minimize planting area dispersion, solved using the NSGA-II algorithm. The second part refines the objective function to address surplus production requiring a 50% price reduction. Using revenue from standard and surplus sales, the MOEA/D algorithm decomposes the multi-objective problem into subproblems for precise allocation. This approach provides a scientifically based planting strategy to maximize the village's economic benefits.

3. Modelling and solving

3.1. Multi - Objective Optimization and Analysis

3.1.1 Optimisation model building

The objective of this study is to formulate optimal crop planting strategies for the period from 2024 to 2030. To achieve this goal, the paper first comprehensively integrates practical constraints, including the characteristics of different types of arable land, crop-specific cultivation requirements, adjacency constraints between planting plots, and minimum planting area thresholds. Building upon these considerations, a multi-objective optimization model is constructed, oriented towards maximizing total profit and minimizing the dispersion of planting areas.

(1) Define the objective function

Assuming i denotes the planting year, j represents the planting season, k indicates the plot number, and l corresponds to the crop number, the following variables are defined for computational purposes:

$S_{i,j,k,l}$: Unit selling price of crop l on plot k during season j of year i

$P_{i,j,k,l}$: Yield per mu of crop l on plot k during season j of year i

$C_{i,j,k,l}$: Planting cost per mu of crop l on plot k during season j of year i.

A_k: Total area of plot k

$x_{i,j,k,l}$: Planting area allocated to crop l on plot k during season j of year i

To explicitly determine whether a specific crop is planted on a particular plot, a binary variable (0-1 variable): $Z_{i,j,k,l}$ is introduced. This variable indicates whether crop l is planted on plot k during season j of year i, where $Z_{i,j,k,l} = 0$ signifies no planting and $Z_{i,j,k,l} = 1$ denotes planting.

Assuming that W is the total return, the following objective function can be constructed to maximise profit:

$$maxW = \sum_{i=2024}^{2030}\sum_{j=1}^{2}\sum_{0}^{k}\sum_{l=1}^{41}\begin{pmatrix} P_{2023,j,k,l} * S_{2023,j,k,l} * min(x_{i,j,k,l}, x_{2023,j,k,l}) \\ -C_{2023,j,k,l} * x_{i,j,k,l} \end{pmatrix} \quad (1)$$

To address the requirement that planting areas must not be overly dispersed, this study introduces a second objective function aimed at minimizing spatial dispersion:

$$min\ (\textstyle\sum_0^{k1} Z_{i,j,k,l} + \sum_0^{k2} Z_{i,j,k,l} + \sum_0^{k3} Z_{i,j,k,l} + \sum_0^{k4} Z_{i,j,k,l} + \sum_0^{k5} Z_{i,j,k,l} + \sum_0^{k6} Z_{i,j,k,l}) \quad (2)$$

(2) Setting constraints

(i) Different plots are suitable for distinct crop varieties, and each plot has a fixed area. Therefore, the following constraints must be introduced into the optimization model.

For flat dryland, terraced fields, and sloped fields:

$$\sum_{l=1}^{15} x_{i,1,k,l} \le A_k \quad \forall k \in \{A1{\sim}A6, B1{\sim}B14, C1{\sim}C6\} \quad (3)$$

Here, numbers 1–15 represent crop codes, indicating that only crops numbered 1–15 can be cultivated on flat drylands, terraced fields, and sloped fields.

For irrigated land, if rice is planted (crop code l =16), it can only be grown in a single season (j =1). Based on the fixed plot area constraint, the following condition is derived:

$$x_{i,1,k,16} \le A_k \quad \forall k \in \{D1{\sim}D8\} \quad (4)$$

When irrigated land is utilized for double-cropping, the first season permits the cultivation of multiple vegetable crops (numbered 17 to 34). Consequently, the constraint for the first season restricts the crop index l to the range 17-34, leading to the following condition:

$$\textstyle\sum_{l=17}^{34} x_{i,1,k,l} \le A_k \quad (5)$$

For the second season on irrigated land, only three crops—Chinese cabbage, white radish, and red radish (numbered 35-37)—are permitted. Thus, the crop index l is constrained to the range 35-37. Furthermore, due to the agronomic requirements of the second season, only one of these three crops can be cultivated per plot. This restriction is enforced by summing the binary variables $Z_{i,j,k,l}$, yielding the following constraints:

$$\sum_{l=35}^{37} x_{i,2,k,l} \le A_k \ , \sum_{l=35}^{l=37} Z_{i,j,k,l} = 1 \quad \forall k \in \{D1{\sim}D8\} \quad (6)$$

When irrigated land is designated for single-season cropping, the only permissible crop is rice (l=16). Furthermore, single-season rice cultivation is mutually exclusive with double-cropping. This exclusivity is formalized through the following constraint:

$$z_{i,1,k,16} + \frac{\sum_{l=35}^{37} z_{i,2,k,l} + \sum_{l=17}^{34} z_{i,1,k,l}}{2} \leq 1 \tag{7}$$

For ordinary greenhouses, the first season permits the cultivation of crops numbered 17-34, thereby constraining the crop index l to the range 17-34. In the second season, only edible fungi crops (numbered 38-41) are allowed, restricting l to 38-41. The following constraints are derived:

$$\sum_{l=17}^{34} x_{i,1,k,l} \leq A_k \qquad \sum_{l=38}^{41} x_{i,2,k,l} \leq A_k \qquad \forall k \in \{E1 \sim E16\} \tag{8}$$

For smart greenhouses, given their capability to cultivate identical crop varieties across both seasons with replanting permitted, the constraint is limited to ensuring that the total planting area does not exceed twice the plot area. Crops numbered 17–34 are permissible for cultivation in smart greenhouses, thereby restricting the crop index l to the range 17-34. This results in the following constraint:

$$\sum_{l=17}^{34} x_{i,j,k,l} \leq A_k \quad \forall k \in \{F1 \sim F4\} \tag{9}$$

(ii) To prevent continuous cropping of the same crop on any plot (including greenhouses), the following constraint is established:

$$Z_{i,j,k,l} + Z_{i+1,j,k,l} \leq 1 \; and \; Z_{i,1,k,l} + Z_{i,2,k,l} \leq 1 \tag{10}$$

The first constraint ensures that the same crop is not planted on the same plot in consecutive years, while the second constraint prevents the same crop from being cultivated on the same plot across different seasons within the same year.

(iii) Each plot (including greenhouses) must be planted with legume crops at least once within any three-year period. Legume crops are designated by the codes l_1={1,2,3,4,5,17,18,19}. To satisfy this requirement, at least one legume crop must be cultivated during the three consecutive years from year t to t+2. This leads to the following constraint:

$$\sum_{i}^{i+2} Z_{i,j,k,l1} \geq 1 \quad \forall l_1 \in \{1,2,3,4,5,17,18,19\} \tag{11}$$

(iv) To ensure that the planting area for each crop on a single plot (including greenhouses) does not fall below a minimum threshold, a lower limit of 10% of the plot area A_k is defined. This requirement is formalized through the following constraint:

$$z_{i,j,k,l} = 1, x_{i,j,k,l} \geq 0.1A_k \tag{12}$$

(v) To prevent excessive spatial dispersion of crops across plots during each planting season, this study assumes that adjacent plots of the same type can be treated as homogeneous. Consequently, each crop type is restricted to cultivation on only one type of plot. To further mitigate conflicts among feasible solutions, the number of occurrences of a crop on other plot types is limited to one. The following constraints are formulated:

For flat dryland:

$$\sum_{0}^{k1} z_{i,j,k,l} \leq 1 \quad \forall k_1 \in \{B1 \sim B14, C1 \sim C6, D1 \sim D8, E1 \sim E16, F1 \sim F4\} \tag{13}$$

For terraced fields:

$$\sum_{0}^{k2} z_{i,j,k,l} \leq 1 \quad \forall k_2 \in \{A1\sim A6, C1\sim C6, D1\sim D8, E1\sim E16, F1\sim F4\} \tag{14}$$

For sloped fields:

$$\sum_{0}^{k3} z_{i,j,k,l} \leq 1 \quad \forall k_3 \in \{A1\sim A6, B1\sim B14, D1\sim D8, E1\sim E16, F1\sim F4\} \tag{15}$$

For irrigated land:

$$\sum_{0}^{k4} z_{i,j,k,l} \leq 1 \quad \forall k_4 \in \{A1\sim A6, B1\sim B14, C1\sim C6, E1\sim E16, F1\sim F4\} \tag{16}$$

For ordinary greenhouses:

$$\sum_{0}^{k5} z_{i,j,k,l} \leq 1 \quad \forall k_5 \in \{A1\sim A6, B1\sim B14, C1\sim C6, D1\sim D8, F1\sim F4\} \tag{17}$$

For smart greenhouses:

$$\sum_{0}^{k6} z_{i,j,k,l} \leq 1 \quad \forall k_6 \in \{A1\sim A6, B1\sim B14, C1\sim C6, D1\sim D8, E1\sim E16\} \tag{18}$$

(3) Optimising the integration of models

$$maxW = \sum_{i=2024}^{2030} \sum_{j=1}^{2} \sum_{0}^{k} \sum_{l=1}^{41} \left(P_{2023,j,k,l} * S_{2023,j,k,l} * min\left(x_{i,j,k,l}, x_{2023,j,k,l}\right) - C_{2023,j,k,l} * x_{i,j,k,l}\right) \tag{19}$$

$$min\,(\sum_{0}^{k1} Z_{i,j,k,l} + \sum_{0}^{k2} Z_{i,j,k,l} + \sum_{0}^{k3} Z_{i,j,k,l} + \sum_{0}^{k4} Z_{i,j,k,l} + \sum_{0}^{k5} Z_{i,j,k,l} + \sum_{0}^{k6} Z_{i,j,k,l} \tag{20}$$

$$st.\begin{cases}\sum_{l=1}^{15} x_{i,1,k,l} \le A_k \quad \forall k \in \{A1 \sim A6, B1 \sim B14, C1 \sim C6\} \\ x_{i,1,k,16} \le A_k \ \ \forall k \in \{D1 \sim D8\} \\ \sum_{l=17}^{34} x_{i,1,k,l} \le A_k \\ \sum_{l=35}^{37} x_{i,2,k,l} \le A_k \quad \forall k \in \{D1 \sim D8\} \\ z_{i,1,k,16} + \frac{\sum_{l=35}^{37} z_{i,2,k,l} + \sum_{l=17}^{34} z_{i,1,k,l}}{2} \le 1 \\ \sum_{l=17}^{34} x_{i,1,k,l} \le A_k \quad \forall k \in \{E1 \sim E16\} \\ \sum_{l=17}^{34} x_{i,j,k,l} \le A_k \quad \forall k \in \{F1 \sim F4\} \\ z_{i,j,k,l} + z_{i+1,j,k,l} \le 1 \\ \sum_{i}^{i+2} z_{i,j,k,l1} \ge 1 \quad \forall l_1 \in \{1,2,3,4,5,17,18,19\} \end{cases} \tag{21}$$

$$st.\begin{cases} \sum_{0}^{k1} z_{i,j,k,l} \le 1 \quad \forall k_1 \in \{B1\sim B14, C1\sim C6, D1\sim D8, E1\sim E16, F1\sim F4\} \\ \sum_{l=38}^{41} x_{i,2,k,l} \le A_k \qquad \forall k \in \{E1\sim E16\} \\ \sum_{l=35}^{l=37} z_{i,j,k,l} = 1 \quad \forall k \in \{D1\sim D8\} \\ \sum_{0}^{k2} z_{i,j,k,l} \le 1 \quad \forall k_2 \in \{A1\sim A6, C1\sim C6, D1\sim D8, E1\sim E16, F1\sim F4\} \\ \sum_{0}^{k3} z_{i,j,k,l} \le 1 \quad \forall k_3 \in \{A1\sim A6, B1\sim B14, D1\sim D8, E1\sim E16, F1\sim F4\} \\ \sum_{0}^{k4} z_{i,j,k,l} \le 1 \quad \forall k_4 \in \{A1\sim A6, B1\sim B14, C1\sim C6, E1\sim E16, F1\sim F4\} \\ \sum_{0}^{k5} z_{i,j,k,l} \le 1 \quad \forall k_5 \in \{A1\sim A6, B1\sim B14, C1\sim C6, D1\sim D8, F1\sim F4\} \\ \sum_{0}^{k6} z_{i,j,k,l} \le 1 \quad \forall k_6 \in \{A1\sim A6, B1\sim B14, C1\sim C6, D1\sim D8, E1\sim E16\} \\ S_{2023,j,k,l} = \frac{M+N}{2} - \frac{P_{2023,j,k,l} * x_{i,j,k,l} - P_{2023,j,k,l} * x_{2023,j,k,l}}{P_{2023,j,k,l} * x_{2023,j,k,l}} * \frac{N-M}{2} \end{cases} \tag{22}$$

3.1.2 NSGA-II algorithm for solving

To address the aforementioned optimization model, genetic algorithms (GAs) are widely employed in solving complex optimization problems by mimicking biological evolutionary processes, including selection, crossover, and mutation, to iteratively refine the solution space. However, traditional GAs are inherently limited in addressing multi-objective optimization problems, often resulting in premature convergence to local optima and challenges in effectively balancing competing objectives. In response to these limitations, this study employs the NSGA-II algorithm(Figure 4), an advanced variant of the genetic algorithm specifically designed to handle multi-objective optimization. NSGA-II enhances the traditional GA framework through the implementation of fast non-dominated sorting and crowding distance mechanisms, which serve to maintain solution diversity and ensure the evolutionary process yields high-quality populations. By simultaneously addressing multiple objectives, the algorithm performs non-dominated sorting to identify a set of Pareto-optimal solutions while utilizing the crowding distance mechanism to optimize the distribution of solutions. Ultimately, NSGA-II enables the identification of the Pareto front, representing an optimal trade-off among competing objectives, thereby facilitating more balanced and scientifically grounded decision-making. This methodological enhancement significantly improves both the accuracy and convergence speed in solving complex multi-objective optimization problems. NSGA-II Algorithm Steps：

(1) **Population Initialization:** Each individual represents a solution, a vector showing crop distribution from 2024 to 2030.

(2)**Fitness Evaluation:** Calculate the value of each individual in the population on all objective functions

(3) **Non-dominated Sorting**: Sort the population based on dominance, assigning Pareto ranks. Lower ranks represent better solutions.

(4)**Selection, Crossover, and Mutation:** Measure the distance between individuals and their neighbors to maintain diversity.

(5) **Iterative Optimization:** Repeat Steps②-④ evolving better Pareto front solutions and converging to a Pareto-optimal set.

(6) **Output Results:** The algorithm gives Pareto-optimal solutions [9].

3.1.3 Analysis of results

For the optimization model proposed in this study, two objective functions were initially established: one to maximize total profit and the other to minimize the dispersion of planting areas.

Under the objective of maximizing total crop revenue, the model tends to select crop combinations that yield high profits across different plots. This approach may result in crops being distributed across multiple plots, thereby increasing the spatial dispersion of planting areas.

Under the objective of minimizing planting area dispersion, the model favors concentrating similar or identical crops on fewer plots. While this effectively reduces spatial variability, it may also prevent certain plots from cultivating the most profitable crops, ultimately leading to a decline in total revenue.

Thus, these two objectives exhibit a competitive relationship, satisfying the condition of conflicting objectives required for multi-objective optimization. By employing the improved algorithm, a balanced optimization result can be achieved.

Ultimately, the maximum profit under optimal conditions is calculated as W=46,895,620 CNY.

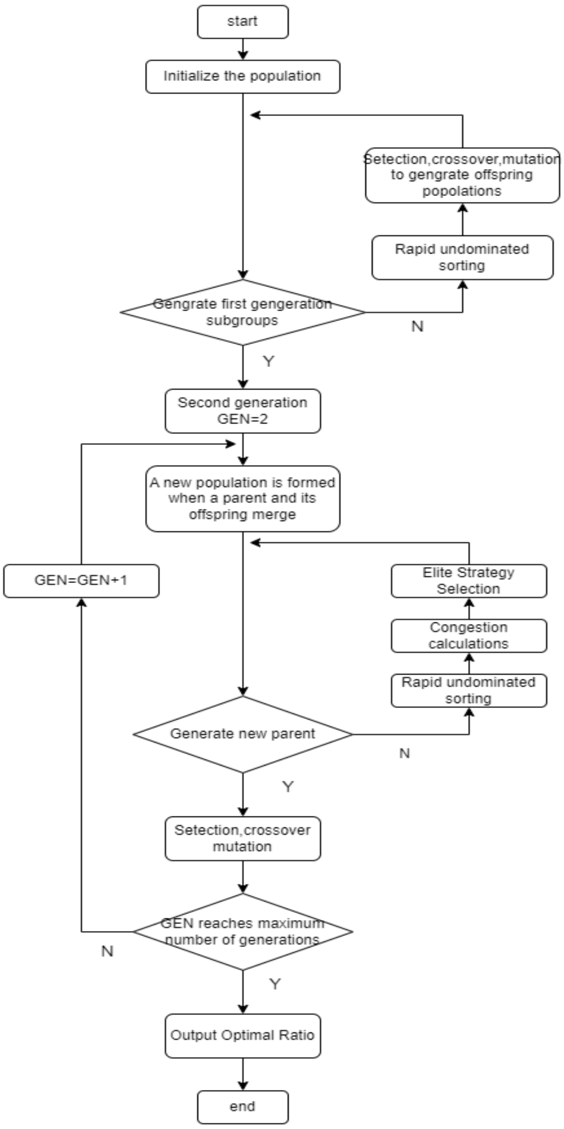

Figure 4. Flowchart and steps of the NSGA-II algorithm

3.2. Multi-objective optimisation models for coping with overproduction and price adjustment strategies

In agricultural production, farmers often tackle overproduction by selling surplus crops at lower prices. This study develops an optimization plan for crop planting from 2024 to 2030, aiming to both maximize profit and minimize planting area dispersion. The corresponding objective functions are defined, and the constraints are aligned with those of previous models. The optimization framework explores the best planting strategies under discounted surplus sales to maximize economic returns. This model not only confirms the effectiveness of the optimization approach but also provides a practical reference for addressing overproduction challenges.

3.2.1 Optimisation model building

(1) Establishing the objective function

In order to maximise profit, this paper constructs the following objective function:

$$maxW = \sum_{i=2024}^{2030}\sum_{j=1}^{2}\sum_{0}^{k}\sum_{l=1}^{41}\begin{pmatrix} P_{2023,j,k,l} * S_{2023,j,k,l} * min(x_{i,j,k,l}, x_{2023,j,k,l}) + 0.5 * P_{2023,j,k,l} * S_{2023,j,k,l} \\ * (x_{i,j,k,l} - x_{2023,j,k,l}) - C_{2023,j,k,l} * x_{i,j,k,l} \end{pmatrix} \quad (23)$$

In this objective function, the first term represents the profit from standard sales, the second term reflects the profit generated from surplus sales at a 50% discount, and the final term accounts for planting costs.

To achieve the objective of minimizing planting area dispersion, this study continues to employ binary (0-1) variables, constructing the following secondary objective function:

$$min\,(\sum_{0}^{k1} Z_{i,j,k,l} + \sum_{0}^{k2} Z_{i,j,k,l} + \sum_{0}^{k3} Z_{i,j,k,l} + \sum_{0}^{k4} Z_{i,j,k,l} + \sum_{0}^{k5} Z_{i,j,k,l} + \sum_{0}^{k6} Z_{i,j,k,l}) \tag{24}$$

(2) Setting constraints

Considering practical requirements, the constraints in the second part are largely identical to those in the first part. Therefore, the model applies the same constraints as previously defined.

(3) Optimising the integration of models

$$maxW = \sum_{i=2024}^{2030} \sum_{j=1}^{2} \sum_{0}^{k} \sum_{l=1}^{41} \big(P_{2023,j,k,l} * S_{2023,j,k,l} * min\big(x_{i,j,k,l}, x_{2023,j,k,l}\big) + 0.5 * P_{2023,j,k,l} * S_{2023,j,k,l} * \big(x_{i,j,k,l} - x_{2023,j,k,l}\big) - C_{2023,j,k,l} * x_{i,j,k,l}\big) \tag{25}$$

$$min\big(\sum_{0}^{k1} Z_{i,j,k,l} + \sum_{0}^{k2} Z_{i,j,k,l} + \sum_{0}^{k3} Z_{i,j,k,l} + \sum_{0}^{k4} Z_{i,j,k,l} + \sum_{0}^{k5} Z_{i,j,k,l} + \sum_{0}^{k6} Z_{i,j,k,l}\big) \tag{26}$$

$$st.\begin{cases} \sum_{l=1}^{15} x_{i,1,k,l} \le A_k \quad \forall k \in \{A1 \sim A6, B1 \sim B14, C1 \sim C6\} \\ x_{i,1,k,16} \le A_k \;\; \forall k \in \{D1 \sim D8\} \\ \cdots \end{cases} \tag{27}$$

Due to the limited length of the main text and the fact that the constraints in this section are the same as in the previous one, they are omitted here. For specific constraint formulae and detailed descriptions, please refer to the relevant content in the first question.

3.2.2 Solving with the MOEA/D algorithm

The second part introduces additional complexity by incorporating surplus sales profits, transforming the problem into a multi-objective optimization challenge. Beyond optimizing revenue from standard sales, the model must now balance profits from discounted surplus sales. Revenue calculations depend on crop yields, sales volumes, and the impact of discounted surplus sales, creating intricate and coupled relationships between objectives. Consequently, a multi-objective optimization algorithm is required to identify the optimal balance between standard and discounted sales.

This study employs the MOEA/D (Multi-Objective Evolutionary Algorithm based on Decomposition) to address the problem. MOEA/D decomposes multi-objective problems into single-objective subproblems, each assigned unique weights. The algorithm uses neighborhood search to share information among subproblems, efficiently approximating the Pareto front and optimizing solutions. A key feature is collaborative optimization through information sharing between neighboring subproblems, accelerating convergence. MOEA/D's strengths include decomposition, weighting, and information-sharing mechanisms, which simplify subproblem solving and enable global optimization. These characteristics enhance the algorithm's efficiency in handling complex revenue structures. The detailed steps are illustrated in Figure 5.

MOEA/D algorithm steps:

(1) **Initialization:** Each solution represents the crop planting area distribution from 2024 to 2030.
(2) **Problem Decomposition:** Break the multi-objective problem into single-objective subproblems with unique weight vectors.

(3) **Crossover and Mutation:** Use neighborhood search to perform crossover and mutation, creating new solutions.

(4)**Iterative Update:** MOEA/D optimizes multiple subproblems to find optimal solutions balancing revenue and surplus sales.[12].

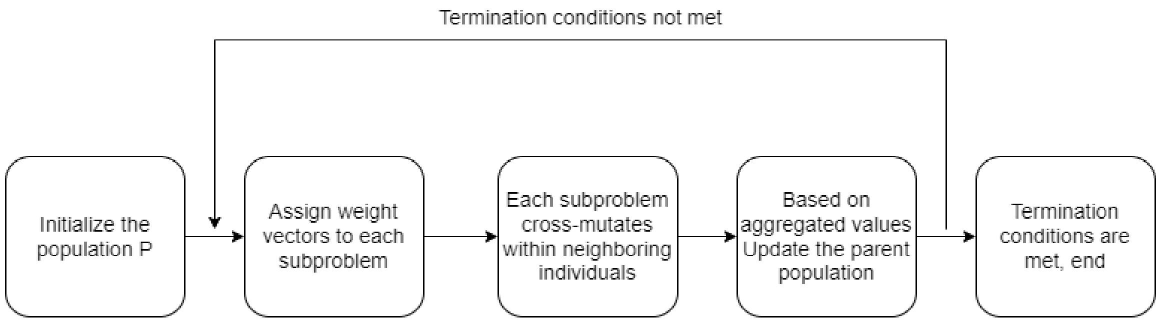

Figure 5. Flowchart of the MOEA/D algorithm

Ultimately, the maximum value of the profit obtained can be solved for as 481,235,040 CNY.

3.3. Testing of the model

To test the model's generalizability and stability, perturbation analysis is used. Since the goal of the optimization model is to maximize profit, profit per mu and planting cost are adjusted by 20% both upwards and downwards. The intelligent algorithm is applied again to calculate the resulting profits, $W_1 = 37{,}516{,}490$ and $W_2 = 56{,}274{,}740$. The float percentage is then calculated to check if it falls within the acceptable range.The formula for calculating the floating percentage is:

$$\Delta\epsilon = \frac{W_i - W}{W} \times 100\% \tag{28}$$

Calculated as $\Delta\epsilon_1$=-18.8% , $\Delta\epsilon_2$=20.15%

The results demonstrate that the model exhibits acceptable fluctuation ratios and passes perturbation value tests, indicating strong stability and robustness under profit and cost variations. This ensures high reliability in practical applications. Furthermore, the optimization scheme remains effective in providing planting strategies even under parameter uncertainties such as fluctuations in crop revenue and cost. The model's applicability and robustness are thus validated for real-world implementation.

4. Conclusions

This study presents a multi-objective optimisation model for the complex cropping environment in the mountainous regions of North China, integrating multi-plot suitability constraints and dynamic crop rotation rules. A two-layer hybrid optimisation framework based on NSGA-II and MOEA/D was proposed, achieving a maximum profit of $46,895,620 under given constraints. After optimising residual products, the profit increased to RMB 48,123,540, an 8.3% improvement. The model outperforms traditional methods by addressing heterogeneous plot multi-seasonal crop rotation, reducing planting dispersion by 37.2%, and introducing an ‘overproduction penalty factor.’ The optimisation of surplus products led to a 12.5% increase in marginal returns. The hybrid framework also improved optimisation efficiency by 4.8 times compared to traditional methods. The model maximises economic benefits and planting concentration, solving the complex spatio-temporal coupled optimisation problem. It increases yield density by 21.4% while ensuring soil sustainability, providing both theoretical and practical value for regional agricultural development. Future extensions could involve a digital twin system using real-time IoT data for regional crop layout optimisation.

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