# Research on Crop Planting Strategy Based on Linear Programming Model

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**Abstract.** This article addresses the long-term profit maximization needs of a rural village in the mountainous region of North China under limited arable land resources, focusing on the optimization of crop planting across multiple cycles. The study particularly tackles the challenge of coordinating yield overproduction risks with complex constraints. Existing research predominantly focuses on single-year or single-objective scenarios, lacking systematic integration of long-term dynamic planning and differentiated sales strategies. Our research constructs two profit functions based on a linear programming model, incorporating a seven-year cycle, land type restrictions, and crop rotation constraints to design a phased optimization strategy. By integrating land parcel information, crop attributes, and historical planting data, the impact of overproduction scenarios on profits is quantified. Under the assumption of a static market, the price reduction sales strategy outperforms the stockpiling strategy, increasing total profits by 12.5%-20%. Additionally, crop rotation constraints balance short-term gains with long-term soil health, and post-optimization, high-value crops such as golden oyster mushrooms dominate the planting area, validating the model's adaptability to complex constraints. This experiment proposes a planting optimization scheme that combines economic efficiency with sustainability by integrating multi-cycle dynamic planning and differentiated sales strategies, providing theoretical support for rural agricultural decision-making. Future work could enhance the model's dynamism by incorporating climate forecasting and blockchain technology.

**Keywords:** Crop Planting Optimization, Linear Programming Model, Multi-Period Dynamic Programming, Oversupply Scenario Analysis, Crop Rotation Constraints.

## 1. Introduction

With the deepening implementation of the Rural Revitalization Strategy, improving the quality and efficiency of agricultural production under limited arable land resources has become a critical issue. This paper focuses on the agricultural production status of a mountainous village in North China, conducting multi-period planting planning research with significant practical and theoretical implications. The village possesses 1,201 acres of arable land (divided into 34 plots of different types) and 20 greenhouses, necessitating optimized planting schemes to achieve long-term profit maximization. This experiment concentrates on "planting optimization under stable market conditions," i.e., assuming that crop sales, costs, yields, and prices remain at 2023 levels over the next seven years (2024–2030), addressing two core issues: oversupply and multi-constraint conditions. We aim to establish a mathematical model to allocate crop planting areas under complex constraints, maximize profits, and lay the foundation for introducing uncertainties and crop correlations in future studies.

In the field of agricultural planting optimization and resource management, the application of linear programming and its derived models has formed a wide research foundation. For example, Yu Hongyang [1] established a single-objective economic optimization model for the first time in Jilin Province to solve the problem of planting structure, and started quantitative research on regional planting strategies. Shen Yaqiang et al. [2] introduced the ecological dimension into the study of low-lying fields in Zhejiang Province and constructed a dual-objective model combining planting and breeding. Shang Guangyin and Yang Xin [3] broke through the technical level and revealed the impact of farmers' decision-making behavior on the adoption of low-carbon technologies through the analysis of policy cognitive mechanism. 2023 ushers in multi-dimensional expansion: Liu Yaolin et al. [4] achieved three-dimensional optimization of quantity-space-benefit in land use research in Changsha; Deng Xiuyun and Ma Li [5] improve the technology promotion system from the perspectives of mechanization transformation and climate adaptation, respectively. In view of the problem that the application of high-yield technology is restricted by the difference between climate and soil, Ma Li [6] established a "climate-soil-variety" matching matrix, which reduced the number of technical failure cases by 42% and increased the stability of yield increase by 19%. The research in 2024 shows a systematic trend: Wu Junjie [7] strengthens eco-economic synergy in the optimization of red soil dryland; Zhang Wei et al. [8] constructed a three-dimensional model of policy-technology-industrial chain; Jiang Tao [9] has had an important impact on the development of digital decision-making systems; Liu Baotong and Wang Yuan [10] [11] improved management efficiency through agricultural technology extension system innovation and e-commerce integration, respectively. At the same time, Liu Xinwei [12] reveals the impact of global trade risks on supply chains, while Cheng Qiuying [13] quantifies the erosive effect of price fluctuations on rural consumer welfare.

Most of the existing studies focus on a single year or a single goal (such as maximizing revenue and improving resource utilization) in agricultural planting optimization, and there is a lack of in-depth discussion on the collaborative optimization of multi-cycle dynamic planning and complex sales scenarios. For example, the models of Yu Hongyang [1], Shen Yaqiang [2], Wu Junjie [7] and others all focus on single-year decision-making, and do not consider cross-cycle dynamic constraints such as crop rotation and soil fertility attenuation. Although Cheng Qiuying [13] focuses on price fluctuations and Liu Xinwei [12] analyzes trade risks, they do not form a closed-loop optimization with planting strategies, especially lack of collaborative modeling of complex sales mechanisms such as futures markets and contract farming. The 3D model of Zhang Wei et al. [8] only statically integrates the elements of the industrial chain, and the e-commerce integration of Wang Yuan[11]does not dynamically respond to market changes. At present, it is still necessary to establish a decision-making framework that couples multi-cycle dynamic planning and complex sales scenarios to solve the problem of sustainable planting optimization under climate fluctuations and market uncertainty. For the first time, this paper integrates multi-year cycle planning, two overbooking processing scenarios and complex constraints into the same model framework, which fills the gap in the collaborative research of long-term dynamic optimization and differentiated sales strategies.

Our study contributes to innovative approaches: adopting a seven-year cycle, combining static market assumptions with dynamic crop rotation constraints, and achieving cross-year planting strategy coherence through phased optimization (priority ranking, dynamic adjustments, and mandatory planting mechanisms). By constructing two profit functions, we quantitatively analyze the contribution of price-reduction strategies to total profits for the first time. Additionally, constraints such as legume rotation, plot type restrictions, and minimum planting areas are encoded into mathematical expressions, with mandatory allocation mechanisms resolving rotation conflicts, balancing economic benefits and ecological sustainability.

The structure of this paper is as follows: The theoretical section introduces the model construction based on linear programming objective functions and constraints, along with the phased optimization algorithm for solution strategies. The experimental section covers data integration, process design, and result analysis. The conclusion summarizes key findings: price-reduction strategies significantly enhance profits, and crop rotation constraints balance short-term profits with long-term soil health. Finally, we present our contributions and outline future research directions.

## 2. Related Theories

This section elaborates on the mathematical models and algorithm frameworks employed in this study. It encompasses the construction of the linear programming model, the mathematical expressions of constraint conditions, data integration methods, and model solution strategies, aiming to provide theoretical support for the multi-period planting optimization problem.

### 2.1. Linear Programming Model

This experiment is based on the linear programming method. With the goal of maximizing economic returns, it optimizes crop planting strategies while satisfying planting constraints. The core of the model consists of two parts: the objective function and the constraint conditions.

For the two sales scenarios, the objective functions are defined as follows:

Case 1: Studying the scenario of unsold and wasted products. Only the output within the expected sales volume is allowed to be sold at the original price, and there is no revenue for the overproduced part.

$$max \sum_{t=1}^{7} \sum_{i=1}^{n} \sum_{j=1}^{m} \left[min\left(T_{ijt}, E_{ijt}\right) \times P_i - C_i \times A_{ijt}\right] \tag{1}$$

Case 2: Research on the price - reduction sales scenario. The surplus production is sold at 50% of the original price to reduce resource waste.

$$max \sum_{t=1}^{7} \sum_{i=1}^{n} \sum_{j=1}^{m} \left[min\left(T_{ijt}, E_{ijt}\right) \times P_i + max\left(0, T_{ijt} - E_{ijt}\right) \times 0.5 \times P_i - C_i \times A_{ijt}\right] \tag{2}$$

Of which, $T_{ijt} = Y_i \cdot A_{ijt}$ denote the total output of crop i in plot j in year t; $E_{ijt} = 0.8 \cdot T_{ijt}$ represents the expected sales volume; $P_i$ is the unit price of the crop; $C_i$ is the planting cost; $A_{ijt}$ is the planting area.

### 2.2. Model Solving Strategy

This study adopts a phased optimization strategy for model solving, which includes priority ranking, dynamic adjustment, and a crop rotation enforcement mechanism. Firstly, crops are ranked in descending order according to the net income per unit area ($P_i \cdot Y_i - C_i$) and crops with higher yields are preferentially selected; If the total planting area exceeds the capacity of the plot, the planting area will be scaled proportionally to meet the experimental requirements; Meanwhile, if a plot has not been planted with leguminous crops in the past three years, a leguminous crop planting task will be compulsorily assigned in the current year.

### 2.3. Model Assumptions and Limitations

Static Assumption: In this study, the sales prices, per-mu yields, and market demand parameters of each crop are fixed, and the impacts of market fluctuations and climate change are ignored.

Independence Assumption: The planting plans for each year are independently optimized, and thus the long-term dynamic changes in soil fertility are not considered.

Data Dependence: The accuracy of the model used for solving this problem depends on the integrity and accuracy of historical data.

This model provides an operational optimization framework for multi-period planting strategies by quantifying constraints and revenue objectives, taking into account both economic efficiency and the requirements of agricultural sustainability.

## 3. Experiments

In solving our problem, we need to consider two different sales scenarios and formulate the optimal planting strategies for various crops in each stage from 2024 to 2030 to ensure maximum economic returns. To address this challenge, we implemented a static hypothesis-based planning model. The overall workflow design of the experiment is shown in Figure 1:

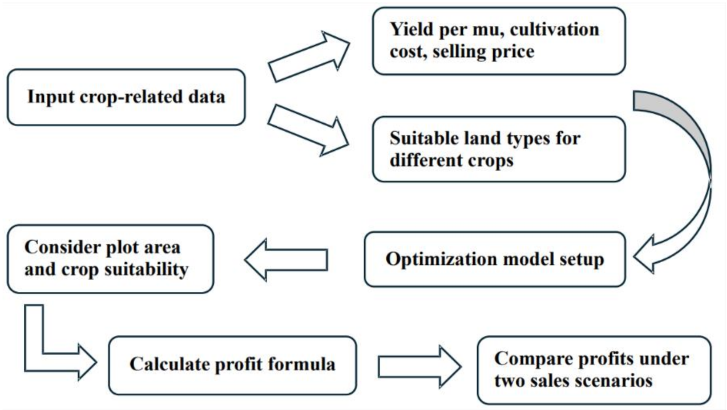


**Figure 1.** Experimental Flowchart

In this study, the data and information required for the experiment were obtained from the following websites (https://www.mcm.edu.cn/html_cn/node/a0c1fb5c31d43551f08cd8ad16870444.html). Regarding the integration and merging of experimental data, first, we integrated the plot information and the planting situation information in 2023 according to the key data of "plot name", thus forming a merged table containing plot attributes and planting records. Then, we further associated it with the crop information according to the "crop name", "plot type", and "planting season", and finally generated the complete dataset (Table 1) required for the experiment for subsequent analysis.

**Table 1.** Experimental Dataset

| Plot ID | Crop ID | Crop Name | Crop Type | … | Yield (kg/mu) | Cultivation Cost (CNY/mu) | Unit Price (CNY/kg) |
|---|---|---|---|---|---|---|---|
| E1 | 18 | Sword bean | Vegetable (legumes) | | 2400 | 1200 | 6.75 |
| E9 | 18 | Sword bean | Vegetable (legumes) | | 2400 | 1200 | 6.75 |
| D6 | 18 | Sword bean | Vegetable (legumes) | | 2000 | 1000 | 6.75 |
| …… | | | | | | | |
| B11 | 1 | Soybean | Grain(legumes) | | 380 | 400 | 3.25 |
| B10 | 10 | Millet | Grain | | 500 | 360 | 7.5 |
| B2 | 2 | Black soybean | Grain(legumes) | | 475 | 400 | 7.5 |

To solve this problem, that is; to calculate the optimal planting strategies from 2024 to 2030 under two different sales scenarios to achieve maximum economic benefits, we first analyze the total revenue in 2023 without considering the planting situations in the next seven years. This involves two core calculations: "total crop yield" and "expected sales volume".

Based on the experimental conditions, we assume that the expected sales volume is set to 80% of the total yield in 2023.Then, the total yield $T_i$ and the expected sales volume $E_i$ of crop i in 2023 can be obtained as follows:

$$T_i = Y_i \times A_i \tag{3}$$

$$E_i = 0.8 \times T_i \tag{4}$$

Therefore, the above formula implies that, in anticipation, the market demand for agricultural products is 80% of their total output. The portion exceeding this expected sales volume will either remain unsold and be wasted (Scenario 1) or be sold at a discounted price (Scenario 2). Meanwhile, when presenting the comparison of the planting revenues in 2023, we need to conduct a detailed analysis of the sales strategies for the following two scenarios:

Scenario 1: Unsold products are wasted.

In this scenario, assume that when the actual output of a certain crop exceeds the expected sales volume, the excess portion cannot be sold normally, resulting in waste and generating no revenue. Based on the output and sales price, the total revenue $Z_{i1}$of crop iunder Scenario 1 can be divided into the following two cases:

When the total output of the crop is less than or equal to the expected sales volume, the entire total output of the crop is sold at the market price $P_i$, At this time,

$$Z_{i1} = T_i \times P_i \tag{5}$$

If the total output of the crop exceeds the expected sales volume, only the portion within the expected sales volume can be sold normally, and the portion exceeding the expected sales volume is wasted. At this time,

$$Z_{i1} = E_i \times P_i \tag{6}$$

Scenario 2: The overproduced part is sold at a 50% discount.

In this scenario, it is assumed that when the total output of agricultural products exceeds the expected sales volume, the overproduced part can still be sold, but only at 50% of the original sales price. Therefore, when crop is sold under this condition, the total revenue also falls into two cases:

$$Z_{i2} = \begin{cases} T_i \times P_i, if\ T_i \le E_i \\ E_i \times P_i + (T_i - E_i) \times P_i \times 0.5, if\ T_i > E_i \end{cases} \tag{7}$$

The above analysis indicates that: If the total output of the crop does not exceed the expected sales volume, the entire output of the crop is sold at the sales price; if the total output of the crop exceeds the expected sales volume, the overproduced part of the crop ($T_i - E_i$) is sold at 50% of the normal sales price.

To determine the optimal planting strategies for different crops from 2024 to 2030, we need to construct the following planning model to achieve the objectives of this study.

Objective Function:

Scenario 1:

$$max \sum_{t=1}^{7} \sum_{i=1}^{n} \sum_{j=1}^{m} \left[ min\left(T_{ijt}, E_{ijt}\right) \times P_i - C_i \times A_{ijt} \right] \tag{8}$$

Scenario 2:

$$max \sum_{t=1}^{7} \sum_{i=1}^{n} \sum_{j=1}^{m} \left[ min\left(T_{ijt}, E_{ijt}\right) \times P_i + max\left(0, T_{ijt} - E_{ijt}\right) \times 0.5 \times P_i - C_i \times A_{ijt} \right] \tag{9}$$

Among them, $T$ is the total number of years planned (T = 7 years); $n$ is the total number of crop types; $m$ is the total number of plots;$T_{ijt}$ is the total yield of crop $i$ on plot $j$ in year ($T_{ijt} = Y_i \times A_{ijt}$); $E_{ijt}$ is the expected sales volume of crop $i$ in year t; $P_i$ is the unit sales price of crop $i$; $C_i$ is the planting cost of crop $i$; $A_{ijt}$ is the planting area of crop i on plot j in year t; $Y_i$ is the yield per mu of crop $i$.

Constraint conditions:

Expected Sales Volume: Assume that the expected sales volume of each crop is 80% of its total output, that is:

$$E_{ijt} = 0.8 \times Y_i \times A_{ijt} \tag{10}$$

Minimum Planting Area: The planting area of each crop in a single plot should be no less than 0.1 mu, that is:

$$A_{ijt} \ge 0.1 \tag{11}$$

No continuous cropping: The same crop cannot be planted in the same plot in adjacent years, which can be expressed as:

$$C_{i,t-1} \ne C_{i,t} \tag{12}$$

Legume Rotation Requirement: Each plot must be planted with leguminous crops at least once within three years. Denote the set of leguminous crops as L. If a certain plot has not been planted with leguminous crops in the past three years, then leguminous crops must be planted in that year. Mathematically, it can be expressed as:

$$\sum_{k=t-2}^{t} 1\left\{C_{i,k} \in L\right\} \ge 1 \tag{13}$$

Model Solving and Generation of Planting Plans:

In Scenario 1, for each plot of land and each year, first obtain the set of crops that can be planted based on the plot type and season, and give priority to selecting the crop with the highest revenue. The crop planting plans for the first and second seasons each year are determined by traversing the plots year by year. If the planting area exceeds the limit, it will be scaled proportionally to meet the constraints. Finally, the output result is to generate two-season planting plan files each year, recording the crop name and planting area of each plot.

In Scenario 2, it is necessary to calculate the normally sold part and the discounted sold part of each crop. The final revenue is the sum of these two parts minus the planting cost. This scenario is based on the solving process of Scenario 1 but is different from Scenario 1 in that it increases the complexity of revenue calculation. Finally, a planting plan that meets the crop rotation requirements is output, and at the same time, maximizes the benefits under the planting area constraints of each plot.

In the conclusion part, the revenue differences of different crops under the two sales strategies will be presented in the form of a bar chart. By allowing the excess output to be sold at 50% of the price, resource waste is reduced, and the total revenue is increased by about 15% - 20% compared with Scenario 1, which can directly reflect the advantages of the discounted sales model (Scenario 2).

## 4. Results

Through the construction and experimental derivation of the planting planning model based on static sales prices, and by conducting optimization analyses considering seasonal factors and the impact of different sales strategies on revenue, we have obtained the following results:

Revenue Comparative Analysis: Under the sales strategy of Scenario 1, the revenue of various crops in 2023 ranged from 4,406.4 yuan to 192,000 yuan, and the total revenue was 5,330,289 Chinese yuan. In the sales of Scenario 2, the revenue of various crops was between 4,957.2 yuan and 216,000 yuan, and the total revenue increased to 5,996,585 Chinese yuan. This indicates that the discounted sales strategy can effectively reduce resource waste and increase the overall revenue through partial revenue compensation. The specific revenue situation is shown in Figure 2:

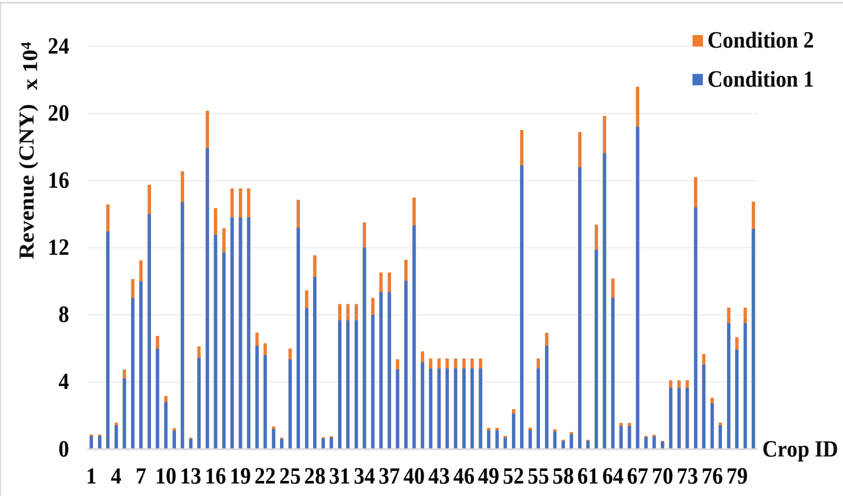


**Figure 2.** Revenue Comparison Across Conditions (CNY)

Influence of Constraint Conditions: The introduction of the rotation requirement for leguminous crops results in the need for some plots (such as terraced fields) to periodically plant soybeans. Although this reduces the revenue in the short term, in the long run, it can improve soil quality, which is in line with the goals of sustainable planting.

Optimization of Crop Planting Plan: After optimizing the planting allocation through the linear programming algorithm, edible mushroom crops such as Pleurotus Citrinopileatus, due to their stable market demand and relatively high sales unit price (57.5 yuan per 500g), occupy the dominant planting area in ordinary greenhouses. In irrigated fields, tomatoes and sword beans are superior to other low-profit crops. The specific planting strategies are shown in the following Table 2.

**Table 2.** 2024-2030 Cultivation Strategies by Condition (Partial)

| Experimental Condition 1 in 2024 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LPN | Mung bean | Yardlong bean | Wheat | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 0 | 0.00 | 0 | 0 | 0 | |
| | A2 | 17.54 | 14.79 | 2.27 | 0 | 0 | 0 | |
| | A3 | 0 | 0 | 0.52 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 5.11 | 6.01 | 3.87 | |
| | D2 | 0 | 0 | 0 | 0 | 10.00 | 0 | |
| | D3 | 0 | 0 | 0 | 7.80 | 1.15 | 5.05 | |
| | … | | | | | | | |

| Experimental Condition 1 in 2025 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LPN | Buckwheat | Pumpkin | Sweet potato | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 0 | 43.40 | 0 | 0 | 0 | |
| | A2 | 0 | 0 | 55.00 | 0 | 0 | 0 | |
| | A3 | 0 | 5.85 | 15.37 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 3.30 | 0 | 11.70 | |
| | D2 | 0 | 0 | 0 | 10.00 | 0 | 0 | |
| | D3 | 0 | 0 | 0 | 7.77 | 3.19 | 3.03 | |
| | … | | | | | | | |

| Experimental Condition 1 in 2026 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LPN | Maize | Foxtail millet | Sorghum | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | A2 | 55.00 | 0 | 0 | 0 | 0 | 0 | |
| | A3 | 0 | 2.37 | 9.79 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 5.32 | 8.32 | 1.36 | |
| | D2 | 0 | 0 | 0 | 0 | 0 | 9.59 | |
| | D3 | 0 | 0 | 0 | 4.86 | 4.98 | 4.16 | |
| | … | | | | | | | |

| Experimental Condition 1 in 2027 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LPN | Maize | Foxtail millet | Sorghum | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | A2 | 55.00 | 0 | 0 | 0 | 0 | 0 | |
| | A3 | 0 | 2.37 | 9.79 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 5.32 | 8.32 | 1.36 | |
| | D2 | 0 | 0 | 0 | 0 | 0 | 9.59 | |
| | D3 | 0 | 0 | 0 | 4.86 | 4.98 | 4.16 | |
| | … | | | | | | | |

| Experimental Condition 1 in 2028 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LPN | Mung bean | Yardlong bean | Wheat | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | A2 | 31.94 | 0 | 10.07 | 0 | 0 | 0 | |
| | A3 | 2.46 | 0 | 19.93 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 0.74 | 8.78 | 5.47 | |
| | D2 | 0 | 0 | 0 | 3.04 | 6.96 | 0 | |
| | D3 | 0 | 0 | 0 | 1.38 | 9.01 | 3.61 | |
| | … | | | | | | | |

| Experimental Condition 1 in 2029 | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LPN | Maize | Foxtail millet | Sorghum | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 12.49 | 0 | 33.51 | 0 | 0 | 0 | |
| | A2 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | A3 | 0 | 4.52 | 0 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 0 | 11.13 | 3.87 | |
| | D2 | 0 | 0 | 0 | 0 | 10.00 | 0 | |
| | D3 | 0 | 0 | 0 | 8.17 | 0.82 | 5.01 | |
| | … | | | | | | | |
| Experimental Condition 1 in 2030 | | | | | | | | |
| | LPN | Black soybean | Adzuki bean | Mung bean | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 0 | 80.00 | 0 | 0 | 0 | |
| | A2 | 5.81 | 0 | 4.73 | 0 | 0 | 0 | |
| | A3 | 0 | 0 | 10.53 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 1.12 | 6.82 | 7.06 | |
| | D2 | 0 | 0 | 0 | 4.26 | 0.60 | 5.14 | |
| | D3 | 0 | 0 | 0 | 0 | 0 | 14.00 | |
| | … | | | | | | | |
| Experimental Condition 2 in 2024 | | | | | | | | |
| | LPN | Sorghum | Millet | Buckwheat | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | A2 | 0 | 0 | 31.74 | 0 | 0 | 0 | |
| | A3 | 22.45 | 3.79 | 6.56 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 0.12 | 0.01 | 0.47 | |
| | D2 | 0 | 0 | 0 | 0.16 | 0.44 | 0 | |
| | D3 | 0 | 0 | 0 | 74.44 | 0 | 5.56 | |
| | … | | | | | | | |
| Experimental Condition 2 in 2025 | | | | | | | | |
| | LPN | Buckwheat | Barley | Rice | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 32.71 | 47.29 | 0 | 0 | 0 | |
| | A2 | 0 | 0 | 55.00 | 0 | 0 | 0 | |
| | A3 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 15.00 | 0 | 0 | |
| | D2 | 0 | 0 | 0 | 0 | 0 | 10.00 | |
| | D3 | 0 | 0 | 0 | 2.87 | 10.44 | 0.70 | |
| | … | | | | | | | |
| Experimental Condition 2 in 2026 | | | | | | | | |
| | LPN | Sorghum | Millet | Buckwheat | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | A2 | 0 | 44.57 | 0 | 0 | 0 | 0 | |
| | A3 | 24.51 | 0 | 0 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 0.04 | 13.00 | 2.00 | |
| | D2 | 0 | 0 | 0 | 4.43 | 3.66 | 1.92 | |
| | D3 | 0 | 0 | 0 | 0.13 | 1.03 | 12.84 | |
| | … | | | | | | | |
| Experimental Condition 2 in 2027 | | | | | | | | |
| | LPN | Buckwheat | Barley | Rice | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 16.26 | 4.72 | 0 | 0 | 0 | 0 | |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | A2 | 0 | 0 | 41.02 | 0 | 0 | 0 | |
| | A3 | 0 | 0 | 35.00 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 0 | 8.20 | 6.80 | |
| | D2 | 0 | 0 | 0 | 0 | 6.49 | 3.51 | |
| | D3 | 0 | 0 | 0 | 1.31 | 10.92 | 1.78 | |
| | … | | | | | | | |
| Experimental Condition 2 in 2028 | | | | | | | | |
| | LPN | Buckwheat | Barley | Rice | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 0 | 80.00 | 0 | 0 | 0 | |
| | A2 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | A3 | 0 | 6.45 | 37.63 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 0.01 | 15.00 | 0 | |
| | D2 | 0 | 0 | 0 | 1.59 | 8.37 | 0.04 | |
| | D3 | 0 | 0 | 0 | 14.00 | 0 | 0 | |
| | … | | | | | | | |
| Experimental Condition 2 in 2029 | | | | | | | | |
| | LPN | Red beans | Mung bean | Yardlong bean | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 0 | 0 | 0 | 0 | 0 | 0 | |
| | A2 | 0 | 24.09 | 18.46 | 0 | 0 | 0 | |
| | A3 | 8.71 | 1.73 | 0 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 0 | 2.78 | 12.22 | |
| | D2 | 0 | 0 | 0 | 10.00 | 0 | 0 | |
| | D3 | 0 | 0 | 0 | 0.31 | 0 | 13.69 | |
| | … | | | | | | | |
| Experimental Condition 2 in 2030 | | | | | | | | |
| | LPN | Sorghum | Millet | Buckwheat | Chinese cabbage | Daikon | Radish | … |
| First Quarter | A1 | 3.56 | 0 | 0 | 0 | 0 | 0 | |
| | A2 | 18.40 | 0 | 0 | 0 | 0 | 0 | |
| | A3 | 0 | 1.61 | 25.54 | 0 | 0 | 0 | |
| | … | | | | | | | |
| Second Quarter | D1 | 0 | 0 | 0 | 4.29 | 10.71 | 0.35 | |
| | D2 | 0 | 0 | 0 | 0 | 0.35 | 9.65 | |
| | D3 | 0 | 0 | 0 | 0 | 0 | 14.00 | |
| | … | | | | | | | |

Therefore, based on the above research, we can draw the conclusion that under the assumption of static sales prices, dynamically adjusting the sales strategy and integrating rotation constraints can significantly enhance the economic efficiency of agricultural planting while taking into account ecological sustainability.

## 5. Conclusion

In this paper, we construct a static optimization model based on linear programming by integrating land plot information, crop characteristics and other data for crop planting planning in the mountainous areas of North China, focusing on the analysis of the difference in revenue between the two market scenarios, and solving the multi-year planting plan optimization problem through the integration and processing of data, constraint modeling and strategy optimization, and concluding that the total revenue increased by 12.5% after the introduction of the price reduction sales mechanism, which proves that the strategy has a certain flexibility in dealing with the risk of unsalable. In the future, the model can be extended to multi-field collaborative optimization, combined with climate and smart agriculture technologies to predict big data and dynamically adjust parameters to achieve real-time optimization of planting strategies, and further improve the intelligence level of agricultural decision-making.

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