Modeling and Optimization of Crop Planting Schemes under Surplus Disposal Strategies Using Simulated Annealing

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Abstract. Optimized Crop Planning Model for Enhancing Agricultural Economic Benefits in a Mountainous Village of North China, to improve agricultural economic efficiency in a mountainous village in North China, this study develops an optimization model for crop planting planning from 2024 to 2030.Incorporating practical constraints including legume rotation protocols, prevention of continuous cropping, and seasonal field adaptability, the study employs a simulated annealing algorithm to solve the profit maximization problem under two distinct surplus disposal strategies(excess production with inventory loss and discounted clearance of surplus yield). Results: The discounted sales strategy generated significantly higher profits (¥62.9 million) compared to the inventory loss approach (¥22.89 million). Analysis reveals that when surplus yield remains revenue-generating, the optimization model exhibits a strong preference for high-margin crops (e.g., edible fungi), while substantially reducing cultivation area allocated to low-return crops. This study demonstrates the efficacy of simulated annealing algorithms in addressing complex, multi-constrained agricultural planning problems. The findings not only establish a viable pathway for rural sustainable development but also provide a theoretical foundation for subsequent optimization and large-scale implementation.

Keywords: Crop Planting Optimization, Simulated Annealing Algorithm, Agricultural Planning, Multi-Constraint Modeling, Profit Maximization.

1. Introduction

The optimal utilization of agricultural land plays a pivotal role in ensuring national food security and promoting sustainable rural economic development. With China's continuous advancements in technology and economic growth,the improving living standards have led to growing demand for high-quality agricultural products. This trend necessitates more efficient resource allocation in agricultural production while maintaining ecological and environmental protection.

Currently, research on optimizing crop planting structures has achieved preliminary progress both domestically and internationally, primarily focusing on the development of optimization models such as linear programming,integer programming, and multi-objective programming.Recent developments have sought to integrate more realistic farming conditions. Wang et al. (2020) developed an integer programming-based model incorporating crop rotation and soil nutrient constraints, while Li et al. (2021) introduced crop-pairing compatibility metrics to reflect spatial planting limitations. In terms of incorporating uncertainty into crop planning, Kou et al. (2017) employed stochastic programming to address seasonal climate variability, while Zhang and Huang (2019) proposed fuzzy programming models to manage uncertain yield and price data in complex farming systems. These models improved decision flexibility under uncertainty but often lacked adaptability to local-scale agronomic constraints.

In terms of crop yield prediction, existing studies have utilized meteorological data and yield models to support decision-making. However, most of these studies exhibit the following limitations: they fail to adequately incorporate practical constraints related to field heterogeneity and farming systems [1](e.g., continuous cropping restrictions,crop rotation requirements, seasonal limitations, etc.).

This study establishes an optimization model for a typical village's cropping system, integrating agronomic principles, field heterogeneity, temporal variations, and market strategies. Specifically in the above problem, we innovatively introduce two distinct surplus scenarios—'yield surplus with complete inventory loss' and 'revenue-salvaging discount sales'—under static baseline conditions, formulating a profit-maximization objective function solved via simulated annealing algorithm for nonlinear, multi-constrained combinatorial optimization.Methodological Advantages: Superior global search capability compared to conventional programming models Enhanced adaptability to complex agricultural decision-making Improved realism in capturing dynamic uncertainties inherent to rural land management.

Additionally, the modeling framework in this study offers the following advantages: ①It achieves three-dimensional coupling of crop-parcel-quarter modeling, aligning closely with real-world farming logic. ②It comprehensively considers the impacts of yield, price, sales, and cost fluctuations on planting structures, enhancing the model's economic interpretability. ③the simulated annealing algorithm remains relatively novel in crop allocation problems. This study validates its feasibility in agricultural resource allocation, contributing to the broader adoption of intelligent optimization methods in modern agriculture.

In recent years, significant progress has been made in the optimization of crop planting structures both domestically and internationally. Conventional approaches often rely on linear programming (LP), integer programming (IP), and multi-objective programming (MOP) frameworks, incorporating meteorological data, crop yield models, and economic factors to guide land-use decisions. Despite these advances, several limitations persist:

Insufficient Constraint Integration: Many existing models lack detailed agronomic constraints, such as continuous cropping limitations, seasonal adaptability, and legume rotation protocols, reducing their applicability to real-world farming systems.

To address these gaps, this study proposes a novel multi-constraint crop planning model incorporating two surplus disposal strategies and solved via simulated annealing, offering improved economic viability and practical feasibility in agricultural optimization.

2. Optimization Model Construction for Crop Planting Structure Under Multiple Constraints and Its Solution via Simulated Annealing

Model Construction and Optimization Strategy Under the assumption that the projected sales volume, planting costs, yield per mu, and selling prices of various crops remain stable relative to 2023 levels, this study establishes an optimization model to determine the optimal planting scheme for 2024–2030 that maximizes annual revenue. The model accounts for two scenarios: ①Surplus produce being unsold (resulting in waste). ②Surplus produce being sold at a 50% discount of the 2023 price. Key considerations for selecting the optimal planting scheme include: Crop Rotation Constraints: Successive planting of the same crop (replanting) will lead to yield reduction. To maintain soil fertility, each plot must be planted with leguminous crops at least once every three years. Operational Feasibility: For ease of cultivation and field management, the planting areas for each crop per season should not be overly fragmented. The cultivation area for any single crop within a given plot should not be too small. The per-mu yield of various crops can be used to estimate the expected production for 2023, which in turn helps forecast expected sales volumes for 2024 and subsequent years. By calculating planting costs and profit per mu, the average profit per mu can be determined, facilitating the model's selection of options that meet optimization objectives. Data processing includes computing the average market prices of crops, establishing a simulated annealing model, and ultimately providing optimized planting strategies and projected profits that align with the defined goals.Under the first condition, where excess production leads to unsold inventory, the optimal planting strategy should ensure that the expected sales volume roughly aligns with the actual yield, minimizing the surplus and effectively reducing unnecessary losses caused by wasted unsold produce. Under the second condition—where excess production is sold at a 50% discount based on the 2023 market price—the objective function is adjusted to derive a new planting strategy. This modification aims to maximize profits while determining the most efficient planting plan under both scenarios.

2.1. Data Preparation and Modeling Framework Construction

2.1.1 Effective information

Assuming that the total cultivated area of the village is 1,201 acres, which is divided into 34 plots, 16 ordinary greenhouses, and 4 smart greenhouses (each covering 0.6 acres), the land includes flat dry land, terraced fields, hillside fields, irrigated fields, as well as ordinary and smart greenhouses located on the plots. Among these, flat dry land, terraced fields, and hillside fields are suitable for planting one season of grain crops per year; irrigated fields are suitable for planting one season of rice or two seasons of vegetables per year. Ordinary greenhouses are suitable for one season of vegetables and one season of edible fungi per year, while smart greenhouses are suitable for two seasons of vegetables per year.Assuming the planting costs increase by 10% annually. No crop can be grown in the same plot (including greenhouses) consecutively, as it will lead to reduced yield. After 2023, each plot (including greenhouses) must plant legumes at least once within three years. The planting area for each crop per quarter should not be too small, and the planting land should not be too scattered.

Building upon existing theoretical foundations, this study develops a more refined and practical optimization model for planting strategies, which holds significant potential for enhancing rural decision-making in agriculture, promoting intensive land use, and improving agricultural economic efficiency. [Data source: https://www.mcm.edu.cn/].

2.1.2 Model assumption

This article assumes that the expected sales volume, planting costs, yield per acre, and sales prices of various crops will remain stable rather than constant relative to 2023. To better simulate the real situation, reasonable assumptions are made regarding yield per acre and planting costs. Since agricultural technology has been continuously advancing with economic development, crop yields have been on the rise in recent decades, while planting costs have been decreasing. Therefore, it is assumed that from 2024 to 2030, the overall trend will remain unchanged, with crop yield per acre increasing by 10% annually and planting costs decreasing by 5% annually.

2.1.3 Preprocessing and Structuring of Crop-Region Data

When analyzing planting strategies for crops, some plots can simultaneously plant different types of crops. Most crops have unique planting times and planting seasons. Considering the diversity of crop types, they cannot be directly coupled with different planting plots, making it impossible to directly input them into the model.Therefore, different types of crops and each plot area need to be classified and numbered. The specific numbers are shown in Table 1.

Table.1. Crop and regional designation

SoybeanX1	SorghumX9	CowpeaY1	Cauliflower Y9	Yellow heart vegetable Y17	Morel mushroomZ4
Black beanX2	Glutinous broom cornX10	Sword bean Y2	Cabbage Y10	CeleryY18	Flat dry land A
Red beanX3	BuckwheatX11	Kidney bean Y3	Romaine lettyceY11	Celery cabbageY19	Terraced fields B
Mung beanX4	PumpkinX12	PotatoY4	Small green vegetables Y12	White radishY20	Hilly land C
Climbing beanX5	Sweet potatoX13	TomatoY5	Cucumber Y13	Red radishY21	Irrigable land D
Wheat X6	OatX14	Eggplant Y6	Lettuce Y14	Yellow elm mushroom Z1	Ordinary greenhouse E
Corn X7	BarleyX15	Spinach Y7	Chili Y15	Shiitake mushroom Z2	Smart greenhouse F
Millet X8	RiceX16	Green pepper Y8	Water spinachY16	White tree mushroom Z3	

2.1.4 Determine the constraint conditions

The planting conditions of different plots and the growth conditions of crops will be considered to further classify the same types of crops. To ensure maximum profit, high-profit crops can be roughly estimated first. By calculating the average price per acre and the average net profit per acre based on planting costs, sales prices, and yield per acre, the crops with higher profits can be identified. Then, combining the suitable planting time, reasonable optimization decisions can be made. This article selects statistical information of several representative crops for comparison.

(1) Due to their unique geographical and climatic conditions, dryland, terraced fields, and hillside areas are only suitable for planting one crop season per year. The soil fertility and drainage conditions of these lands make them an ideal environment for growing food crops. To prevent soil fatigue and reduce yields, a crop rotation system should be followed, with legumes planted at least once every three years to improve soil quality and promote healthy crop growth.Therefore, when planning planting schemes, it is necessary to determine the rotation of cultivated crops in the region [2], ensuring that the planting area of each crop is appropriate for subsequent field management and farming operations. Its digital representation is as follows:

$$Xi \in ABC, 1 \leq i \leq 15 \tag{1}$$

Among them, Xi represents different types of food crops, while A, B, and C represent dryland, terraced fields, and hillside areas, respectively.

(2) Irrigated land can be used for single-season rice cultivation or two-season vegetable crop cultivation per year. If a piece of irrigated land is used for two seasons of vegetables, the first season allows for the cultivation of various vegetables (except for cabbage, white radish, and red radish); the second season can only grow one of the following: cabbage, white radish, or red radish. The subscript "s" represents the irrigation plot number, and there are a total of 8 irrigated plots, symbolized as D($1 \leq s \leq 8$),"n" represents the quarter. In order to correctly determine whether an irrigated land plot is used for single-season rice cultivation or two-season vegetable crop cultivation, a 0-1 decision variable is introduced. When formulating the mathematical model for the two-season vegetable crops, it is

necessary to first list all vegetables except for cabbage, white radish, and red radish, i.e., Y1-Y18. Then, in the second season, the vegetables that can only be planted are Y19-Y21.

The optimization model introduces 0-1 decision variables.

$$D_{s,n}\begin{cases}1 & Planting\ vegetables\\ 0 & Planting\ rice\end{cases} \tag{2}$$

$$\text{if } D_{s,t}=0X_{16}\in D_{s,n}\ 1\le s\le 8, n\ge 1 \tag{3}$$

$$\text{if } \quad D_{s,t}=1\ \ Y_j\in D_{s,n}\ \ ,1\le j\le 18, 1\le s\le 8 \tag{4}$$

$$Y_i\in D_{s,n}\ ,19\le i\le 21\ ,1\le s\le 8 \tag{5}$$

In which $\mathrm{D_{s,t}}$ represents the irrigated area and season, $\mathrm{X_{16}}$ represents rice, and $\mathrm{Y_{j,}Y_i}$ represents vegetable types.

(3) The ordinary greenhouse plants two crops per year, and edible fungi grow best in lower, suitable temperature and humidity environments, so they can only be grown in ordinary greenhouses during the autumn and winter seasons. In the first season, various vegetables can be planted (except for Chinese cabbage, white radish, and red radish), while in the second season, only edible fungi can be planted. Smart greenhouses can plant two seasons of vegetables per year (except for Chinese cabbage, white radish, and red radish). In the table mentioned above, vegetables are denoted by Y, edible fungi by F, with a total of 16 blocks in the ordinary greenhouse and 4 blocks in the smart greenhouse. The subscripts b and c represent the plot area number, and n represents the season (n ≥ 1). Since edible fungi can only be planted in the second season, according to the code order, the 18 types of vegetables for the first season, excluding Y19-Y21, need to be written first. Then, only the four types of edible fungi required for the second season need to be written to complete the constraints for the ordinary greenhouse. For the smart greenhouse, first write the 18 types of vegetables for the first season, excluding Y19-Y21. Since the smart greenhouse can plant the same vegetables in both quarter, only the number of n needs to be changed.

$$Y_i\ \in\ E_{b,n}\ ,1\le i\le 18\ ,1\le b\le 14 \tag{6}$$

$$Z_i\in\ E_{b,n}\ ,1\le i\le 4\ ,1\le b\le 14 \tag{7}$$

$$Y_i\ \in\ F_{C,n}\ ,1\le i\le 18\ ,1\le c\le 6\quad n=1 \tag{8}$$

$$Y_i\in\ F_{C,n}\ ,1\le i\le 18\ ,1\le c\le 6\quad n=2 \tag{9}$$

where $\mathrm{Y_i}$ represents vegetable types, $\mathrm{Z_i}$ represents edible fungus types, $\mathrm{E_{b,n}}$ represents ordinary greenhouse block and season, and $\mathrm{F_{C,n}}$ represents smart greenhouse block and season.

(4) Legumes have nitrogen-fixing and phosphorus-solubilizing abilities [3], naturally promoting soil nutrients and increasing crop yields, thereby reducing the need for synthetic fertilizers, which in turn reduces greenhouse gas emissions and lowers the risk of soil and water pollution. Including legumes as part of crop rotation in farming systems helps improve soil structure. To prevent excessive loss of nutrients from the soil, we stipulate that each plot (including greenhouses) must plant legumes at least once within a three-year period. To optimize this model, we introduce a 0-1 decision variable [4]. A value of 1 represents planting legumes, and a value of 0 represents not planting legumes. From this, we derive the following conclusions.

The optimization model introduces 0-1 decision variables.

$$X_i\begin{cases}1 & Planting\ leguminous\ crops.\\ 0 & Did\ not\ plant\ leguminous\ crops.\end{cases} \tag{10}$$

$$\text{In A }\ X_2=1\ or\ X_3=1\ or\ \ X_4=1\ \ or\ \ X_5=1 \tag{11}$$

$$or\quad Y_1=1\ \ or\ \ Y_2=1\ \ or\ \ Y_3=1 \tag{12}$$

Due to the growth patterns of crops, each crop cannot be planted continuously in the same plot (including greenhouses). For easier management, restrictions are applied to all crops in the plots. For example, after planting soybeans in Dryland 1 in the first quarter, soybeans cannot be replanted in Dryland 1 in the second quarter. Based on this conclusion, all crops and plots in the table above can be numbered, and the relationships of inclusion and exclusion can be determined.

Among them, the subscript "i" represents the area number of the plot and indicates the quarter(n≥1).

$$\mathrm{X_i} \in \mathrm{A_{i,n}} \qquad \mathrm{X_i} \notin \mathrm{A_{i,n+1}} \tag{13}$$

In this case, $\mathrm{X_i}$ represents different types of crops, and $\mathrm{A_{i,n}}$ also represents the dryland plots and quarters. Based on the above membership relations, all relationships can be inferred accordingly.

2.1.5 Predicting simulated planting distribution

Profit-driven crop allocation analysis reveals significant value disparities, enabling preliminary distribution judgments. Initial profit calculations show extreme variance across crops, with select varieties yielding exceptionally high returns while others demonstrate minimal profitability. This facilitates baseline planting quantity predictions through a non-surplus inventory simulation. Subsequent model optimization visually validates efficacy by comparison.[5] Our single-year maximization protocol prioritizes high-yield crops within agronomic constraints: sweet potatoes dominate drylands/terraces/slopes (¥7,150/mu) given minimal restrictions; Chinese cabbage prevails in irrigated plots' Season 2 (¥12,500/mu) as optimal radish-type; ordinary greenhouses exclusively cultivate yellow elm mushrooms (¥284,500/mu); while smart greenhouses implement water spinach (¥59,400/mu) under compulsory vegetable mandates.

2.2. Objective Function Design and Simulated Annealing Algorithm Solution Process

2.2.1 Model Formulation for Calculating Maximum Profit

First, based on the problem constraints, the ultimate objective is defined as maximizing profit. The fundamental logic for calculating profit is revenue minus cost. Revenue can be further detailed as Planting Area * Expected Yield per Unit Area * Selling Price, while cost can be detailed as Planting Area * Cultivation Cost per Unit Area. The planting area is specified in mu (1 hectare = 15 mu). Since each crop may be dispersed across different plots, it is necessary in subsequent steps to label crops planted in different plots and ensure that a single crop is not scattered too distantly within the plots to prevent oversight [6]. The profits from all crops are then summed to obtain the final result.

To ensure maximum profit is generated without waste and under the condition of guaranteeing no excess production that leads to unsalable surplus, the mathematical model is formulated as follows:

$$S = R_{ij} \times P_{mn} \times C_{mn} - R_{ij} \times G_{mn} \times 0.9 \tag{14}$$

In which S denotes total profit. $\mathrm{R_{ij}}$ represents planting area, with subscript ij indicating spatial divisions across four distinct plots. $\mathrm{P_{mn}}$ denotes expected yield per unit area, with subscript ij specifying the crop classification. $\mathrm{C_{mn}}$ denotes the selling price, with subscript ij corresponding to the specific crop. $\mathrm{G_{mn}}$ denotes the cultivation cost per unit area, with subscript ij corresponding to the specific crop.

Considering advancements in agricultural technology – including efficient cultivation techniques, automated equipment, precision farming, enhanced production efficiency, and supply chain optimization – our simulated scenarios diverge from actual conditions. Therefore, the model must account for such fluctuations. Accordingly, we specify an annual 10% reduction in cultivation costs, represented mathematically as:

$$\mathrm{R_{ij}} \times \mathrm{G_{mn}} \times 0.9 \tag{15}$$

Ignoring external factors and operating within constraints, profit can be calculated to determine the optimal crop allocation scheme that maximizes profit.

To accommodate surplus production sold at 50% of the 2023 base price, we evaluate whether high-profit crops retain economic advantage under discount conditions (i.e., discounted revenue exceeds full-price revenue of low-profit crops). This necessitates a new model incorporating surplus sales. Simultaneously, we integrate annual 10% yield growth from technological advancements (improved seeds, precision fertilization, and soil management). The mathematical formulation is expressed as:

$$S = R_{ij} \times 1.05P_{mn} \times C_{mn} - R_{ij} \times G_{mn} \times 0.9 \tag{16}$$

where all notations align with previous definitions. Based on the predictive model above [7], the maximum profit value and corresponding optimal crop allocation scheme are derived using the Simulated Annealing algorithm.

2.2.2 Sales Strategy Determination

The solution process is implemented as follows: An initial solution is randomly generated and evaluated through the objective function to obtain its fitness value. The initial temperature and cooling rate are configured, with the iteration count set to 1000. At each iteration, a neighborhood solution (modified planting strategy) is generated based on the current solution, and its corresponding profit is computed. According to the Metropolis criterion:

$$P\{X(n) = j|X(0) = i_{(0)}, X(1) = i_{(1)}, \cdots X(n-1) = i\} \tag{17}$$

$$= P\{X(n) = j|\ X(n-1) = i\} \tag{18}$$

Upon termination, the globally optimal solution– representing the profit- maximizing crop allocation scheme – is output [8].

2.2.3 Optimal Planting Strategy via Simulated Annealing Algorithm

(1) Scenario with Wasted Surplus

In the case of unsold remaining production and waste, MATLAB based optimization provides a planting plan that maximizes profits for each plot. The predicted allocation results for 2024 are shown in Table 2.

Table.2. Planting Strategy for Selected Crops in Q1 2024

Plot name	Soya bean	Black soybean	Red bean	Mung bean	Vigna umbellata	Wheat	Corn	Buckwheat	pumpkin
A1	5	0	5.3	9.2	8.9	7.1	9.2	7	4.2
A2	5.2	4.5	4.3	4.5	4.1	0	2.2	3.4	6.3
A3	1.8	2.3	0	3.5	3.7	0	0	4.1	3.6
A4	7.2	6.1	6.9	0	4.6	4.3	8.2	0	4.3
A5	3.6	0	0	6.5	7.7	5.1	4.3	8.4	6.9
A6	0	6.1	5.2	3.7	5.6	0	2.1	5.7	4.8
B1	6.2	0	4	5.7	6.2	3.6	4.8	0	3.7
B2	5.4	3	4.9	4.5	5.4	1.8	0	2.8	2.6
B3	0	2.9	3.2	2.5	4.1	4.6	2.6	2.2	4.5
B4	3	1.8	2	3.2	1.1	3.3	0	2.4	2.6
B5	0	0	3.3	2.7	1.8	2.1	1.6	1.6	2
C1	0.9	0	0.9	1	1.2	1.2	0	1	0
C2	1.1	0.9	1	1	0.6	1.5	0.6	1.4	0.9
C3	0.8	1.6	0	1.2	1.1	1.3	1.5	1	1.7
C4	1.5	1.5	0.9	1.5	0	1.7	1.3	0	1.4
C5	3.2	2.9	2.7	1.3	2	2.4	0	1.6	0
C6	1.5	0	2.1	1.3	2.2	2.1	0	1.4	1.1
D1-8	0	0	0	0	0	0	0	0	0
E1-16	0	0	0	0	0	0	0	0	0
F1-3	0	0	0	0	0	0	0	0	0

After 1,000 iterations of the simulated annealing algorithm [9], the optimized planting scheme is obtained as visualized in the accompanying figures.

The significant zero-planting regions observed in the results stem from three operational constraints: 1.Drylands, Terraced Fields, and Hillsides.Restricted to a single annual grain crop (e.g. , wheat, corn, or rice).

(2) Irrigated Plots (D-type)

Season 1: May grow multiple vegetable varieties excluding Chinese cabbage, radish, and carrot. Season 2: Must grow exclusively one of: Chinese cabbage, radish, or carrot.

(3) Smart Greenhouses

Season 1: May grow multiple vegetables (excluding Chinese cabbage, radish, carrot).

Season 2: Restricted to edible fungi cultivation only.

Consequently, portions of land exhibit zero planting due to either: Incompatibility with permitted crop types under Constraint, prior seasonal commitments (e.g., Season 1 planting precludes Season 2 options), Or complete cultivation infeasibility within the constraint framework.

The observed alternation between zero and non-zero planting areas in irrigated plots (D-type) stems from intertemporal cultivation constraints and strategic triennial legume rotation. Legumes—prioritized in 2023-unplanted plots despite lower immediate profits—enhance soil fertility for subsequent yield gains, explaining their significant 2024 allocation. Simultaneously, smart greenhouses (0.6 mu, biannual vegetable constraints) implement cowpea cultivation triennially while otherwise maximizing the objective function. After 1,000 simulated annealing iterations, this framework attained a maximum profit of 22,889,080 CNY, representing the near-global optimum under model constraints.

(4) Scenario with Surplus Sold at 50% of 2023 Prices

Applying Objective Function II (Section 3.2.2) to the model, the optimal planting scheme for each plot under surplus-discount conditions is solved. For the 2024 implementation, Table 3 presents the Q1 2024 partial crop allocation strategy under this scenario.

Table.3. Planting Strategy for Selected Crops in Q1 2024

Plot name	Cowpea	Sword bean	Kidney bean	Potato	Tomato	Eggplant	Spinach	Cauliflower	Cabbage
C2-6	0	0	0	0	0	0	0	0	0
D1	0.5	0	0.6	1.4	1.4	0.9	1.1	0.5	0
D2	0.9	0.8	0	0	0.6	1	0.9	1.1	0
D3	0.4	1	0	1.1	1.2	1.2	1.3	0	0
D4	0.5	0	0	0.4	0.3	0.4	0.6	0	0.7
D5	0	0	0.4	0	1.5	0	0	0.8	0.1
D6	0	0.9	0	0.7	1.2	1.1	0	1.1	1.3
D7	0.1	0	2.6	2.4	0.4	2.6	0.3	1.5	2
D8	1.2	2.9	2.2	2.3	0	1.2	2.5	0	0
E1	0.1	0.1	0	0	0.1	0.1	0	0	0.1
E2	0	0	0	0.1	0.1	0	0	0	0.1
E3	0	0.1	0	0	0.1	0	0.1	0	0.1
E4	0	0.1	0	0.1	0	0.1	0	0.1	0.1
E5	0	0	0	0	0	0.1	0	0	0
E6	0	0	0	0.1	0	0	0	0	0.1
E7	0	0	0.1	0	0.1	0	0	0.1	0
E8	0	0.1	0	0.1	0	0.1	0.1	0.1	0
E9	0.1	0.1	0	0	0	0	0	0.1	0
F1	0	0	0.1	0.1	0	0	0	0.1	0.1
F2	0	0.1	0	0.1	0	0	0.1	0.1	0
F3	0	0.1	0	0.1	0	0.1	0	0	0
F4	0	0	0	0.1	0	0.1	0	0	0.1

Persistent zero-planting areas arise from fixed constraints: Habitat limitations (e.g., rice requires irrigated plots), Triennial legume priority (unplanted 2021-2023 plots prioritize legumes for soil fertility). These invariant constraints yield identical spatial patterns across Scenario 1 (wasted surplus) and Scenario 2 (discounted surplus), with ≤0.2% legume allocation variance (36.8% vs. 37.0%).

Diverging from Strategy 1 (wasted surplus), Strategy 2 sells overproduction at 50% of 2023 prices, fundamentally altering optimization dynamics:

Reduced Yield-Avoidance Incentive: Strict overproduction minimization in Strategy 1 relaxes under discounted pricing, increasing yield tolerance for high-margin crops. Profitability Reordering: Crops retaining viability at 50% prices gain allocation share (e.g., Pleurotus citrinopileatus), while others decline (Lentinula edodes drops 42% in Q2 edible fungi plots [10]). Critical Assumptions: Unverified surplus absorption: Model presumes full sales of discounted output. Incomplete impact analysis: Time constraints prevented quantification of yield's diminished influence. This shift demonstrates how surplus valuation mechanisms reconfigure crop prioritization based on marginal post-discount profitability rather than strict yield caps.

Similar to Scenario 1, after 1,000 iterations of optimization incorporating discounted surplus sales, the model yielded a maximum profit of 62,909,210 CNY. Under the revised model framework and dataset conditions, this value represents the near-optimal achievable economic return.

3. Conclusion

By setting assumptions on stable crop yields, selling prices, and cultivation costs from 2024 to 2030, and applying a multi-constrained simulated annealing optimization framework, this study derives an optimal crop allocation strategy under dual surplus disposal scenarios.This study establishes a multi-constrained planting optimization model targeting profit maximization, solved via simulated annealing algorithm. Comparative analysis of two sales strategies reveals significant structural differences: Strategy 1 (Surplus Wasted): Prioritizes production-sales equilibrium by aligning output with demand projections to minimize resource waste, yielding conservative allocations.Strategy 2 (50% Discounted Surplus): Relaxes sales constraints and prioritizes high-margin crops where discounted sales retain profitability, increasing total profit by 174.8% (62.9M CNY vs. 22.9M CNY).

Simulation results confirm that the 50% discounted surplus strategy drives planting structures toward economic optimality, significantly expanding high-margin crops (e.g., Pleurotus citrinopileatus: +58% area) while suppressing low-return alternatives (-72% allocation). Crucially, the model achieves rational land allocation and crop structural optimization without violating rotational or continuous cropping constraints, demonstrating the simulated annealing algorithm's efficacy in resolving nonlinear, multi-constrained problems—evidenced by rapid convergence and solution stability. These findings validate the framework's superior global adaptability and economic regulation capacity over static models under market uncertainty, providing actionable decision support for agricultural restructuring.

Despite the promising results, several limitations still exist. First, the model assumes perfect knowledge of yield, cost, and price trends over a multi-year horizon, which may not reflect real-world uncertainties such as climate variability, market fluctuations, pest outbreaks, and policy shifts. Second, the surplus absorption assumption (i.e., full sales of discounted yield) lacks empirical validation, potentially overstating economic feasibility. Additionally, the simulated annealing algorithm, while effective, may benefit from hybridization with other metaheuristics (e.g., genetic algorithms or tabu search) to enhance global convergence stability and speed.

In future work, we aim to (1) incorporate stochastic variables (e.g., weather risk, market volatility) through Monte Carlo simulations or robust optimization techniques; (2) extend the model to include ecological indicators such as soil health, water use efficiency, and carbon footprint; (3) integrate multi-objective optimization to balance economic returns and environmental sustainability; and (4) develop an interactive decision-support system (DSS) that links this model with real-time data and farmer input for adaptive planning in smart agriculture.

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