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OPTIMAL CROP PLANTING STRATEGIES BASED ON INTEGER LINEAR PROGRAMMING AND MONTE CARLO MODELS

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Abstract: This study investigates optimal crop planting strategies for a mountainous village in North China during 2024–2030 to maximize profits. Two optimization models were developed for different market scenarios. First, assuming stable market and production parameters, an integer linear programming model is developed to maximize profits while incorporating core agricultural constraints: field type compatibility, crop rotation to avoid replanting, and legume rotation. This model solves for optimal planting schemes under two scenarios: (1) surplus production leading to unsold waste, and (2) surplus sales at a 50% discount. Second, to address uncertainties and potential risks in projected sales volume, yield per mu, planting costs, and sales prices over the coming years, a Monte Carlo model was introduced for analysis. This method simulates fluctuations in parameters (e.g., annual sales growth rate of 5%–10%, yield variation of ±10% per mu) through random sampling, calculates maximum average returns, and thereby determines the optimal planting area allocation scheme with risk resilience in uncertain environments.
Keywords: Crop planting strategy; Integer linear programming; Monte Carlo simulation; Discount

1 INTRODUCTION

With China's rapid socioeconomic development and rising living standards, agriculture—a vital component of the primary sector—must actively embrace technological innovation to pursue efficient production. Particularly in regions constrained by natural conditions, achieving efficient land utilization, organic cultivation, enhanced agricultural product value, and increased farmer income holds significant practical importance for advancing the rural revitalization strategy. However, planting crop planting schemes must account for crop growth patterns, land suitability, crop rotation requirements, and uncertainties arising from market fluctuations. Traditional experience-based decision-making models struggle to meet these complex demands. To address this challenge, this study focuses on developing a long-term planting plan for the village from 2024 to 2030. It aims to construct a scientific and systematic mathematical optimization model to overcome resource allocation difficulties in both stable and uncertain market environments. This approach will integrate integer linear programming models to determine optimal profit schemes under stable parameters, while incorporating Monte Carlo simulations to address random fluctuations and potential risks in sales volume, yield per mu, costs, and prices. Ultimately, it will provide the village with an optimal planting strategy that balances both economic and social benefits.

The core of this research lies in solving two key optimization problems in crop planting: First, determining the long-term profit-maximizing planting allocation under deterministic constraints. This involves constructing an integer linear programming model under the assumption of stable market parameters while satisfying strict agricultural constraints such as land suitability, crop rotation avoidance, and legume rotation. The goal is to identify the optimal planting area distribution over the next seven years under two risk scenarios: surplus production leading to unsold waste and discounted sales, thereby achieving long-term profit maximization. Second, developing an optimal revenue strategy under market and production uncertainties and potential risks. This involves introducing a Monte Carlo model to effectively simulate random fluctuations of core parameters—such as expected sales volume, yield per mu, and cost-sales price—within defined ranges. A mixed-integer programming model incorporating uncertainty factors is constructed, and extensive simulation experiments calculate the system's statistical characteristics and performance metrics to ultimately determine the optimal planting strategy achieving maximum average revenue.

2 LITERATURE REVIEW

Optimizing crop planting strategies represents a core issue at the intersection of agricultural systems engineering and agricultural economic management. Its objective is to achieve synergistic maximization of economic, ecological, and social benefits through scientific planning within limited arable land resources [1]. Amid intensifying global climate change, increasing market uncertainty, and growing demands for sustainable agricultural development, research in this field is shifting from traditional experiential decision-making toward model-based and data-driven precision decision-making [2]. Scholars worldwide have conducted multidimensional, multi-method explorations on planting strategy optimization, providing a robust theoretical foundation and methodological references for this study.

2.1 Macro Context and Risk Factors in Planting Strategy Optimization

The formulation of planting strategies is not an isolated economic decision but is profoundly influenced by natural environments and macro policies. Li Maoxun elevated the perspective to the water-soil-energy-food (WLEF) coupled system, highlighting that under climate change, the insecurity and misallocation of agricultural resources constitute systemic risks constraining the sustainability of cropping strategies. This underscores the necessity of identifying and regulating multi-factor coupled risks [3]. Zhang Yaoyao focuses on the impacts of multiple coupled meteorological disasters on micro-level actors. Using corn farmers in Shaanxi as a case study, the research reveals how the frequent occurrence and accumulation of extreme weather events constrain farmers' adaptation choices by affecting both yield and risk perception, highlighting the complexity of planting decisions under uncertainty [4]. Tian Pengpeng further empirically analyzed the impact of climate change and farmland water supply on grain output in the Yellow River Basin, demonstrating that infrastructure—as a key means of addressing climate risks—directly influences the stability of planting strategies and output efficiency through its effective provision [5]. Collectively, these studies indicate that a robust planting strategy optimization model must fully account for external uncertainties such as climate change, resource constraints, and disaster risks.

2.2 Evolution of Models and Methods for Crop Strategy Optimization

Mathematical models and intelligent algorithms form the technical backbone of optimization approaches in this field.
Deterministic optimization models represent traditional and core methodologies. Wang Lin and Guo Yaxin applied a linear programming model targeting yield maximization while integrating crop planting patterns and economic constraints, demonstrating its efficacy in supporting scientifically informed planting strategies [6]. Li Yujin et al. introduced dynamic programming and Markov decision models to address multi-stage decision problems, enabling optimization strategies to adapt to the dynamic patterns of crop growth [7]. While these models provide optimal solutions under the assumption of stable parameters, they struggle to handle real-world uncertainties.
To address uncertainty, researchers have adopted risk quantification and stochastic optimization techniques. Shi Jinghao et al. developed a planting strategy optimization model incorporating Conditional Value at Risk (CVaR), solved using the DEGA algorithm. This model integrates risk control objectives with profit maximization, providing a framework for robust decision-making under uncertain market conditions [8]. Following a similar approach, Monte Carlo simulations are widely employed to model random fluctuations in parameters such as sales volume, yield per acre, costs, and prices, thereby evaluating the expected returns and risks of strategies within a stochastic programming framework [1, 8].
Intelligent optimization algorithms demonstrate significant advantages in addressing high-dimensional, nonlinear-constrained crop optimization problems due to their robust global search capabilities. Wang Gangping et al. employed a genetic algorithm to solve a multi-constraint optimization model with total profit as the objective function. Results indicated that cultivating crops with high unit price and high yield per acre constitutes a dominant strategy for profit maximization [9]. Xia Wen et al. employed a particle swarm optimization algorithm to establish an optimization model for scenarios involving multiple terrains and crops. They distinguished between market scenarios characterized by yield surplus waste and discounted sales, providing concrete planting schemes for rural agriculture [1]. Tan Zhiyi and Xiao Junwen, in reviewing mathematical modeling competitions, affirmed the value of mathematical programming and heuristic algorithms in solving complex agricultural operations research problems [2].

2.3 Foundational Applications of Remote Sensing and Information Technology in Planting Strategies

Accurate and timely crop condition information is essential for optimized decision-making. Dong Tianci utilized GF-6 WFV remote sensing data combined with machine learning (random forest, support vector machine) and deep learning (CNN, CNN-LSTM) methods to achieve fine-grained classification of major summer crops in Hengshui City [10]. Such research provides technical support for rapidly acquiring large-scale spatial distribution data of crops, forming a crucial data foundation for future regional-scale precision agricultural management and dynamic adjustment of planting structures.

2.4 Relationship and Innovation of This Study Compared to Existing Literature

In summary, existing research has yielded substantial achievements in model construction, algorithmic solutions, and risk mitigation for optimizing planting strategies. However, most studies either focus on planning under deterministic conditions or concentrate on single risk factors [6-8]. Integrated research that comprehensively considers multiple uncertainties—such as market volatility, yield variations, and price fluctuations—over extended planning periods spanning several years, while systematically comparing different risk mitigation strategies (e.g., surplus product disposal or discounted sales), remains relatively scarce.
Building upon this foundation, this study aims to construct a two-stage integrated optimization framework. First, under deterministic conditions, an integer linear programming model is established to derive the optimal planting plan for the baseline scenario [2, 6]. Subsequently, Monte Carlo simulation is introduced to capture uncertainties in core parameters such as sales, yield, costs, and prices [1, 8], extending the model into a stochastic programming problem to seek robust strategies that maximize expected returns under risk. Through this approach, this study aims to combine the precision of deterministic optimization with the inclusiveness of stochastic optimization toward uncertainty. It seeks to provide a scientifically sound and practically applicable long-term decision support scheme for crop planting in mountainous rural areas of North China, thereby offering a valuable supplement to existing research.

3 MODEL ESTABLISHMENT AND SOLUTION

3.1 Establishment and Solution of the Integer Linear Programming Model

3.1.1 Establishment of the integer linear programming model

Integer linear programming is a mathematical optimization method used to maximize or minimize a linear objective function under a set of linear constraints.

Before establishing the model, it is necessary to define decision variables, parameters, objective functions, and constraints, which are detailed in the following table: $i \in \{1, \dots, N\}$: represents the i-th plot. $j \in \{1, \dots, M\}$: represents the j-th crop. $t \in \{1,2\}$: $t = 1$ for the first season and $t = 2$ for the second season. Definition of the Linear Programming Model is shown in table 1.

Table 1 Definition of the Linear Programming Model

Type	Form	Specific Meaning
Decision Variable	$y_{i,j,t}$	1: Crop j is planted on Plot i in Season t; 0: Crop j is not planted on Plot i in Season t
	p_j	Sales price of the crop
	$q_{i,j,t}$	Yield of Crop j planted on Plot i in Season t
Parameter	$D_{i,j,t}$	Expected sales volume of the j-th crop
	c_j	Cost of planting Crop j on Plot i in Season t
	A_i	Area of Plot i

Case 1: The part of the total output exceeding the corresponding expected sales volume is not included in the revenue. The mathematical expression for the total objective, i.e., the maximum profit to be obtained, is as follows:

The constraints are as follows:

Constraint 1: Flat dry land, terraced fields, and sloping land are suitable for single-crop planting of food crops (excluding rice) every year, leading to the following constraint: No replanting in the second season:

$$\sum_{j=1}^{15} y_{i,j,1} = 1, \forall i \in \{A^{1-6}, B^{1-14}, C^{1-6}\} \tag{1}$$

Constraint 2: Paddy fields can be planted with rice in a single season every year, leading to the following constraint:

$$\sum_{j=16} y_{i,j,1} = 1, \forall i \in \{D^{1-6}\} \tag{2}$$

$$\sum_{j=16} y_{i,j,2} = 0, \forall i \in \{D^{1-6}\} \tag{3}$$

Constraint 3: Paddy fields can also be planted with double-crop vegetables. A variety of vegetables (excluding white radish, carrot, and Chinese cabbage) can be planted in the first season; only one of Chinese cabbage, white radish, and carrot can be planted in the second season (for ease of management), leading to the following constraints:

$$\sum_{j=17}^{34} y_{i,j,1} = 1, \forall i \in \{D^{1-8}\} \tag{4}$$

$$\sum_{j=17}^{34} y_{i,j,2} = 1, \forall i \in \{F^{1-4}\} \tag{5}$$

$$\sum_{j=35}^{37} y_{i,j,2} \leq 1, \forall i \in \{D^{1-8}\} \tag{6}$$

Constraint 5: Ordinary greenhouses can be planted with two crops every year. A variety of vegetables (excluding Chinese cabbage, carrot, and white radish) can be planted in the first season, and only edible fungi can be planted in the second season, leading to the following constraint:

$$\sum_{j=17}^{34} y_{i,j,1} = 1, \forall i \in \{E^{1-16}\} \tag{7}$$

Constraint 6: Smart greenhouses can be planted with two crops of vegetables (excluding Chinese cabbage, white radish, and carrot) every year, leading to the following constraint:

Constraint 7: No continuous replanting of the same crop on the same plot (including greenhouses), leading to the following constraint:

Constraint 8: All land of each plot (including greenhouses) must be planted with leguminous crops at least once every three years, leading to the following constraint:

Integrating the above mathematical expressions, the problem is constructed into the following integer linear programming model:

$$\max V_1 = \sum_{i} \sum_{j} \sum_{t} \left(p_j \times \min(Q_{j,t}, D_{j,t}) \times y_{i,j,t} - c_j \times A_j \times y_{i,j,t}\right) \tag{8}$$

Case 2: Compared with Case 1, the unsold part in Case 2 is not treated as waste but sold at a 50% discount of the 2023 sales price. Therefore, it is only necessary to add this scenario to the total objective function. The specific model is established as follows:

$$\max V_2 = \sum_{i=1}^{n} \sum_{j=1}^{M} \sum_{t=1}^{2} \left\{p_j \times \min(Q_{j,t}, D_{j,t}) + 0.5p_j \times (Q_{j,t} - D_{j,t}) - c_j \times x_{i,j,0}\right\} \tag{9}$$

The constraints for this case are consistent with those in Case 1. Finally, all expressions are summarized as follows:

$$\max V_2 = \sum_{i=1}^{n} \sum_{j=1}^{M} \sum_{t=1}^{2} \left\{p_j \times \min(Q_{j,t}, D_{j,t}) \times y_{i,j,t} + 0.5p_j \times (Q_{j,t} - D_{j,t}) - c_j \times A_i \times y_{i,j,t}\right\} \tag{10}$$

3.1.2 Solution of the integer linear programming model

Step 1: Problem Understanding and Variable Definition

First, clarify the problem requirements. It can be known from the problem that the optimal crop planting plan for the village from 2024 to 2030 needs to be provided. Determine the decision variables and other relevant parameters in the problem, such as the planting area of crops in different plots in different seasons, and assign symbolic representations to each variable.

Step 2: Establish the Objective Function

According to the objective of the problem, construct the objective function. Since it is required to provide the optimal crop planting plan for the village from 2024 to 2030, the problem can be converted into finding the maximum benefit under the optimal planting plan. The objective function can be expressed as an expression of total income minus total cost, involving a linear combination of decision variables.

Step 3: Determine Constraints

Analyze various constraint factors in the problem and convert them into linear inequalities.

Step 4: Organize the Model

Integrate the objective function and constraints to form a complete integer linear programming model. Ensure all variables are non-negative and conform to the standard form of integer linear programming.

Step 5: Select the Solution Method

Use Python's PuLP library, etc., and configure corresponding parameters for software solution.

Step 6: Solve the Problem

Run the Python code to obtain the optimal solution to the integer linear programming problem. The solver will return the optimal decision variable values and the corresponding optimal objective function value.

3.1.3 Analysis of the results

The planting strategy obtained according to the planning model fully considers the constraints given in the problem. Partial Crop Planting Strategy for Q1 2024) shows that in plots such as flat dryland (A1-A6), terraced fields (B1-B14), and hillside land (C1-C5), the planting areas for soybeans, black beans, red beans, mung beans, and winged beans are all 0. Wheat, corn, sorghum, pumpkin, and sweet potato have identical planting areas across all plots (e.g., 16 mu in plot A1 and 11 mu in plot A2, with gradient variations based on plot size). The planting areas for millet, foxtail millet, and buckwheat are also zero. This indicates that during the first quarter of 2024, under the scenario of "excess production leading to unsold waste," the village prioritized uniformly planting wheat, corn, sorghum, pumpkins, and sweet potatoes across different plot types, while refraining from planting legumes, millet, sorghum, and buckwheat. The allocation of planting areas within the same plot type remained consistent, adhering to constraints such as plot type suitability (e.g., flat dryland plots only for grain crops) and crop rotation practices. The planting area of wheat has decreased in the past few years, and food crops are planted in rotation. Partial Crop Planting Strategy for Q1 2025) shows significant adjustments in crop types: Black beans became the primary crop, occupying exactly the same acreage as wheat and corn across all plots (e.g., 16 mu in Plot A1, 11 mu in Plot A2); The planting areas for wheat, corn, sorghum, pumpkin, and sweet potato become zero. The planting areas for millet and foxtail millet are the same as black beans, while soybeans, red beans, mung beans, winged beans, and buckwheat remain unplanted. This demonstrates that in the first quarter of 2025, under identical constraints and market stagnation conditions, the village adjusted its planting scheme to prioritize black beans, millet, and foxtail millet. It maintained the planting areas for each plot consistent with the core crop areas of the corresponding plots from the previous year while satisfying the legume rotation requirement (planting legumes at least once within a three-year cycle.

On flat dryland (A1-A6), terraced fields (B1-B14), and hillside land (C1-C5), the planting areas for soybeans, black beans, red beans, mung beans, winged beans, millet, foxtail millet, and buckwheat are all 0; Wheat, corn, sorghum, pumpkin, and sweet potato are planted across all plots with identical acreage, distributed in a gradient based on plot size (e.g., 16 mu in Plot A1, 11 mu in Plot A2, 3 mu in Plot C1). This indicates that under the "discounted sales for unsold surplus" revenue model, crops like wheat and corn remained the priority choices in Q1 2024. Core crop categories were not adjusted; excess production was absorbed solely through price mechanisms. The allocation of planting areas complied with plot suitability constraints (e.g., grain crops only planted on flat dryland) and crop rotation restrictions.

Black beans, millet, and sorghum occupy identical acreage across all plots (e.g., 16 mu in Plot A1, 12 mu in Plot B1, 3 mu in Plot C1). Soybeans, red beans, mung beans, cowpeas, wheat, corn, sorghum, pumpkin, sweet potatoes, and buckwheat are not cultivated. This indicates that in Q1 2025, even when adopting the “discounting unsold portions” model, the planting plan remains centered on black beans (satisfying legume rotation constraints), millet, and foxtail millet. The core crops and planting areas per plot perfectly match the “unsold waste” scenario. Profit optimization occurs solely through revenue calculation logic (including discounting), without altering crop types or area allocation strategies.

4 MODEL ESTABLISHMENT AND SOLUTION

4.1 Establishment and Solution of the Model

The Monte Carlo model is a method for simulating the behavior of complex systems through random sampling. Based on probability and statistics theory, it uses random number generators to simulate uncertain factors in the system, thereby conducting multiple simulation experiments on the system to obtain the statistical characteristics and performance indicators of the system.

4.2 Introduction of Random Disturbance Variables

The traditional integer linear programming model assumes that all parameters (such as planting costs and expected sales volumes) are deterministic and remain unchanged throughout the planning period. However, in this problem, many parameters are uncertain. For example, the future expected sales volumes of wheat and corn are expected to grow at an annual growth rate of 5% to 10%, while the sales volumes of other crops may fluctuate by approximately ±5% every year compared to 2023. The yield per mu of crops is affected by climate and other factors and may change by ±10% every year. The planting cost is expected to increase by about 5% every year. The prices of food crops are basically stable, the prices of vegetable crops are expected to increase by about 5% every year, and the prices of edible fungi may decrease by 1% to 5% every year, especially the price of morel mushrooms, which is expected to decrease by 5% every year. Therefore, instead of using the traditional integer linear programming for solving this problem, we use the Monte Carlo model to simulate various planting scenarios through generating a large number of random samples, calculate the maximum average profit, and determine the optimal planting area allocation plan to cope with uncertainty.
The following table 2 defines the decision variables, objective function, and constraints:

Table 2 Definition of the Monte Carlo Model

Type	Form	Specific Meaning
Decision Variable	$y_{i,j,t,T}$	Whether to plant on the i-th plot in the t-th quarter of the T-th year; 1 indicates planting, 0 indicates not planting
Parameter	$p_{j,T}$	Sales price of the j-th crop in the T-th year
	$q_{j,T}$	Yield of the j-th crop in the T-th year
	$D_{j,T}$	Expected sales volume of the j-th crop in the T-th year
	$c_{j,T}$	Planting cost of the j-th crop in the T-th year
	A_j	Area of Plot j

Where $T \in \{2024, \ldots, 2030\}$
The following are the mathematical expressions for various uncertain factors:
The expected sales volumes of wheat and corn will have an annual growth rate of 5%-10%:

$$r_{i,j,T} \in [0.05,0.1] \tag{11}$$

Where $T \in \{2023, \ldots, 2030\}$

$$D_{i,j,T+1} = D_{i,j,T} \times (1 + r_{i,j,T}), \forall i \in \{z_6, z_7\} \tag{12}$$

The sales volume of other crops changes by ±5%:

$$\ell_{i,j,T} \in [-0.05,0.05] \tag{13}$$

$$D_{i,j,T+1} = D_{i,j,T} \times (1 + \ell_{i,j,T}), \forall i \in \{z_{1-5}, z_{8-41}\} \tag{14}$$

The yield per mu of crops changes by ±10% every year:
The prices of food crops are basically stable:

$$p_{i,j,T+1} = p_{i,j,T}, \forall j \in \{1 \sim 16\} \tag{15}$$

The prices of vegetable crops increase by 5% every year:

$$p_{i,j,T+1} = p_{i,j,T} \times 1.05, \forall i \in \{z_{17-37}\} \tag{16}$$

The price of morel mushrooms decreases by 1%~5%:

$$\gamma_{i,j,T} \in [0.01,0.05] \tag{17}$$

The planting cost increases by an average of 5% every year:

$$c_{i,j,T} = c_{i,j,T} \times 1.05 \tag{18}$$

Potential risks (extreme drought or severe diseases and pests):

$$\eta_{j,T} \in [-0.1,0.1] \tag{19}$$

$$\mu_T \in [0.75,0.85] \tag{20}$$

Integrating the above uncertain factors and constraints, a mixed-integer programming model with uncertain factors is constructed, and the Monte Carlo method is used to simulate the optimal planting plan:

4.2.1 Solution of the Monte Carlo model

Step 1: Define Decision Variables

As in the previous model construction, determine the decision variables representing the planting plan, such as the planting area of various crops.

Step 2: Determine the Objective Function

To provide the optimal crop planting plan for the village from 2024 to 2030, convert this problem into finding the maximum benefit.

Step 3: Establish Constraints

The constraints for this problem are the same as 3.1.

Step 4: Conduct Monte Carlo Simulation

Determine the number of simulations: According to the complexity of the problem and computing resources, the number of simulations is determined to be 100 times.

Random Sampling: For each uncertain factor, perform random sampling according to its probability distribution. For example, for changes in crop yield per mu, randomly select a value from the interval [-0.1, 0.1]; for price changes, sample according to the corresponding distribution.

Calculate the Objective Function Value: For each set of uncertain factor values obtained by sampling, substitute them into the objective function and constraints to calculate the corresponding objective function value and decision variable values. This step is equivalent to simulating a possible actual situation.

Repeat Simulation: Repeat Steps 2 and 3 to conduct multiple simulations, obtain a large number of combinations of objective function values and decision variables, and finally obtain the planting plan with the maximum benefit.

4.2.2 Analysis of the results

Regarding the constraint in the problem that leguminous crops must be planted at least once every three years, we consider optimizing only the content of the most recent three years. As long as each plot is planted with leguminous crops every three years, the soil can be kept fertile, and the final objective model is measured with the goal of maximizing profit. Therefore, for the next n years, we only need to add this random disturbance and fill in the optimization results in turn.

The core crop mix shifts from “wheat + corn + sorghum + pumpkin + sweet potato” to “corn + sorghum + pumpkin + sweet potato,” with wheat acreage reduced to zero across all plots. The planting areas for corn, sorghum, pumpkin, and sweet potato in each plot increased compared to the corresponding plots in Question 1 (e.g., Plot A1 increased from 16 mu to 20 mu, Plot A2 increased from 11 mu to 13.75 mu, Plot C1 increased from 3 mu to 3.75 mu); Legumes, millet, sorghum, and buckwheat remain unplanted. This reflects the strategy of prioritizing increased planting areas for crops like corn in Q1 2024 while eliminating wheat to balance risk and reward, accounting for parameter fluctuations (e.g., uncertainty in wheat sales growth). This aligns with the Monte Carlo model's logic for addressing uncertainty. the crop mix shifts from “Black Soybeans + Millet + Sorghum” to “Black Soybeans + Wheat + Millet + Sorghum.” Wheat planting is newly introduced with an area equal to that of black soybeans, millet, and sorghum; (e.g., Plot A1: 20 mu, Plot A2: 13.75 mu, Plot C1: 3.75 mu); Soybeans, red beans, mung beans, winged beans, corn, sorghum, pumpkin, sweet potatoes, and buckwheat remain unplanted. This indicates that under uncertainty constraints, optimizing the planting structure in Q1 2025 by adding wheat and retaining black beans (to satisfy legume rotation) while maintaining core crop acreages consistent with the previous year's solution for each plot simultaneously addresses parameter fluctuations and complies with plot suitability and rotation constraints.

5 CONCLUSIONS

This study successfully constructed a two-stage optimization model for crop cultivation in the target village. Under the ideal scenario of stable parameters, the integer linear programming model provides optimal planting schemes satisfying all agricultural constraints (including crop rotation and plot limitations), explicitly indicating how to allocate resources to maximize profits when facing yield surpluses, unsold inventory, or discounted sales. For the more challenging scenario of uncertain market conditions, this study incorporates Monte Carlo simulation. By introducing random perturbations and simulations of expected sales volume, yield per mu, and price fluctuations, potential risks are effectively integrated into the decision-making process. The resulting optimal planting strategy is a robust solution measured by maximum average profit. The successful solution of this model provides scientific and reliable decision-making support for the village to fully utilize its limited arable land resources, develop organic farming tailored to local conditions, and achieve sustainable long-term economic growth.

COMPETING INTERESTS

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

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