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Optimization of Crop Planting Strategy Based on Monte Carlo Simulation

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Abstract: *Optimizing agricultural planting decisions requires addressing the multi-scale impacts of market and climatic uncertainties on production efficiency. This study proposes a decision-making framework integrating probabilistic modeling and stochastic programming. Based on farmland data from a mountainous village in North China, we construct a stochastic programming model using Monte Carlo simulation to maximize profits by quantifying uncertainties. First, a deterministic constraint model is established, incorporating constraints such as plot area limits, crop rotation rules, seasonal planting restrictions, and field management requirements. Next, using normal distributions probabilistic modeling methods are introduced to quantify yield fluctuations (±10%) and price fluctuations (±5%). Finally, a solver is employed for Monte Carlo simulation to generate numerous stochastic scenarios. The top ten optimal strategies yield annual profits ranging from 50.43 million to 52.90 million CNY, validating the model's effectiveness. This framework provides dynamic decision support for agricultural management, optimizes resource allocation, reduces uncertainty risks, and enhances economic benefits and sustainable development capabilities in agrarian production.*

Keywords: *Uncertainty Analysis, Monte Carlo Simulation, Stochastic Programming Model, Planting Decision Optimization, Agricultural Risk Management*

1. Introduction

Agriculture is an industry that utilizes the growth and development laws of plants and animals to obtain products through artificial cultivation [1]. It is inherently uncertain, facing various risks such as market fluctuations, climatic hazards, and pest outbreaks [2]. As a foundational sector supporting national economic development, crop farming plays a vital role in ensuring food security, promoting rural economic growth, and maintaining ecological balance [1]. These risks directly affect crop yields and quality, thereby impacting farmers' incomes and agricultural sustainability. Consequently, planting risk management has become a critical component of agricultural practices [3]. By identifying, assessing, and controlling these risks, farmers can scientifically plan crop planting to improve economic efficiency and resilience [2].

Monte Carlo simulation [4], a numerical analysis method based on random sampling, demonstrates unique advantages in agricultural decision optimization. When addressing agricultural uncertainties, Monte Carlo generates extensive random samples to simulate agricultural outputs under diverse scenarios, offering comprehensive and accurate decision-making references [5]. Probability distributions [6], such as normal [7] and Poisson distributions [8], serve as essential tools for describing stochastic events like market fluctuations and climate variability.

Given the uncertainties in agricultural production and the goal of profit maximization, establishing an optimization model for crop planting decisions that accounts for uncertainties is crucial [3]. This study develops a Monte Carlo-based model by integrating random parameters (e.g., normal and Poisson distributions) into a programming framework. The model offers three advantages: (1) it considers multiple uncertainties to enhance decision accuracy; (2) it simulates planting outcomes under various scenarios [9], aiding in the formulation of scientific planting plans; and (3) its algorithm exhibits strong adaptability and scalability, applicable to diverse regions and crop types [10], thereby supporting structural adjustments, risk mitigation, and profit maximization in agriculture [11].

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2. Planning the establishment of the model

The data used in this study are sourced from the "National Undergraduate Mathematical Modeling Competition," specifically farmland and crop information from a mountainous village in North China.

The village has 1,201 acres of open farmland divided into 34 plots of four types: flat dryland (A), terraced fields (B), hillside land (C), and irrigated land (D). Flat dryland, terraces, and hillside land are suitable for one seasonal grain crop annually. Irrigated land can grow one seasonal rice or two seasonal vegetables. Additionally, the village has 16 ordinary greenhouses (E) and 4 smart greenhouses (F), each covering 0.6 acres. Ordinary greenhouses can grow one seasonal vegetable and one seasonal edible mushroom annually, while smart greenhouses support two seasonal vegetables.

The above data is shown in Table 1.

Table 1 Crop Planting Requirements

Crop Name	Category	Suitable Land	Planting Season	Notes
Soybeans,blacek beans,Red beans, mung beans, climbing beans	grain	A,B,C	Single season planting	Legumes
Wheat, corn, millet, sorghum, millet, buckwheat, pumpkin, red, oat, barley				
Rice		D	Single season planting	
Cowpea, sword bean, kidney bean	vegetable	D,E,F	Season 1, Season 1 or Season 2	Legumes
Potatoes, tomatoes, eggplants, spinach, green peppers, cauliflower, cabbage, lettuce, green vegetables, cucumbers, lettuce, peppers, water spinach, yellow cabbage, celery				
Chinese cabbage, white radish, carrot		D	Season 2	
Mushroom, shiitake mushroom, white mushroom, morel	Edible Fungus	E	Season 2	

2.1 Deterministic Constraints

2.1.1 Plot Area Constraints

A_j is the total area of the $j-th$ plot or greenhouse,

X_{ijpt} represents the planting area (mu) of the $i-th$ icrop in the $j-th$ plot or greenhouse in the $p-th$ season of the $t-th$ year.

The total area constraint is:

$$\sum_{t=t_0}^{t_0+2}\sum_{i=1}^{n} X_{ijtp} \leqslant A_j \quad \forall j \tag{1}$$

This constraint ensures that the total planting area of each plot or greenhouse in two seasons each year cannot exceed the total area of the plot.

2.1.2 Seasonal Restrictions

Assumptions:

$$B_{ijtp} = \begin{cases} 0 & \text{Not planted} \\ 1 & \text{Planted} \end{cases} \tag{2}$$

$$Z_{ijpt} = \begin{cases} 0, & \text{for } i \in \{1,2,...,15,17,...,34\} \\ 1, & \text{for } i = 16 \\ 2, & \text{for } i \in \{35,36,37\} \\ 3, & \text{for } i \in \{38,39,40,41\} \end{cases} \tag{3}$$

Ensure that rice cultivation on irrigated land is limited to one crop per year:

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$$(1-Z_i)\cdot B_{16j2t}=0, i=16 \tag{4}$$

Ordinary greenhouses can grow in two seasons, one season of vegetables and one season of edible fungi. The vegetables in the first season cannot be cabbage, white carrots, and red carrots, and only edible fungi can be grown in the second season.

Season 1 (vegetables, except Chinese cabbage, white carrots, and red carrots):

$$B_{ij1t}\cdot(2-Z_i)=0,\quad \forall i\in 35,36,37 \tag{5}$$

Season 2 (Edible Fungi Only):

$$(3-Z_i)\cdot B_{ij2t}\neq 0,\ \forall i\ \in\{38,39,40,41\} \tag{6}$$

Smart greenhouses can only grow vegetables in two seasons each year, and cannot grow cabbage, white carrots, and red carrots.

$$(2-Z_i)\cdot B_{ijpt}=0,\quad \forall i\ \in\{35,36,37\} \tag{7}$$

2.1.3 Crop growth patterns

The same crop cannot be planted on the same plot of land or greenhouse for two consecutive years:

$$\text{Two different seasons:} B_{i,j,p,t}+B_{i,j,p-1,t}\leqslant 1,\quad \forall i,j,t \tag{8}$$

$$\text{Two years are different:} B_{i,j,p,t}+B_{i,j,p,t-1}\leqslant 1,\quad \forall i,j,t \tag{9}$$

Let w_i be the indicator variable of whether the $i-th$ crop is a legume crop (if it is a legume crop, then $B_i=1$, otherwise 0). The legume crop planting constraint is:

$$\sum_{t=t_0}^{t_0+2}\sum_{i=1}^{n} w_i\cdot B_{ijt}\geq 1\quad \forall j \tag{10}$$

Each plot or greenhouse must be planted with pulses at least once in three years.

2.1.4 Field operation management

$$A_j=\min\{Q(i,j,p,2023)\} \tag{11}$$

$$\sum_{i=1}^{n}\sum_{p=1}^{2} X_{ijpt}\geq A_{\min}\quad \forall i,j,p,t \tag{12}$$

Where $A_{\min}$ is the lower limit of the planting area of each crop on each plot.

2.2 Planting decision optimization model with uncertain factors

2.2.1 Identify decision variables

Let $x_{i,j,p,t}$ represent the area (in mu) of the $i-th$ crop planted in the $j-th$ plot or greenhouse in the $t-th$ year and the $p-th$ quarter.

2.2.2 Establish the objective function (total profit)

$$profit=income-\cos t=\sum_{k=1}^{n}(P_k\cdot Y_k-C_k\cdot A_k) \tag{13}$$

Among them, P_i is the unit sales price of the i-th crop (yuan/jin), Y_i Is the actual sales volume of the i-th crop (jin), C_i is the planting cost of the i-th crop (yuan/mu), and X_i is the planting area of the i-th crop (mu).

2.2.3 Uncertainty constraints

Among the uncertain conditions assumed in the question, the expected sales rate of wheat and corn

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is between 5% and 10%, the expected sales of other crops will change by about ±5% relative to 2023, the yield per mu will change by ±10% each year, and the edible fungus change may decrease by 1% to 5% each year. The uncertainties of these constraints vary within a range. This article assumes that these indicators conform to the normal distribution within the range.

$$f(x)=\frac{1}{\sigma\sqrt{2}}e^{-\frac{(x-\mu)^2}{2\sigma^2}} \tag{14}$$

Solution of mean μ:

$$\mu=\frac{\max+\min}{2} \tag{15}$$

Solution of standard deviation σ:

The standard deviation σ indicates the degree of dispersion of fluctuations. Assuming that 95% of our data will fall within a range of variation (i.e., the ± range is a 95% confidence interval with $Z_{\alpha/2}$ =1.96), the formula for calculating the standard deviation is:

$$\sigma=\frac{\text{Fluctuation range}}{2\times Z_{\alpha/2}} \tag{16}$$

Where the fluctuation range is the range of the upper and lower fluctuations. For example, for a fluctuation of $\pm 5\%$, the fluctuation range is 5%.

This paper divides these uncertain constraints in crop production and sales into market volatility factors and extreme climate factors. Through the above normal distribution probability model, the normal distribution is used to describe the fluctuation range of uncertainty factors:

Firstly, Market volatility factors:

Let $D_{i,t}$ be the expected sales volume of the i-th crop in year t. For wheat and corn (crop number $i \in \{6,7\}$) the average annual growth rate of wheat and corn is between 5% and 10%, and we have:

$$D_{i,t}=D_{i,t-1}\cdot(1+r_{it}),\quad r_{it}\sim N(7.5\%;(1.27\%)^2) \tag{17}$$

For other crops (crop number $i \notin \{6,7\}$), other crops have a ±5% fluctuation relative to 2023, including:

$$D_{i,t}=D_{i,2023}\cdot(1+\delta_i),\quad \delta_i\sim N(0;(2.5\%)^2) \tag{18}$$

Secondly, Extreme climate factors:

Let $Y_{i,t}$ be the per-acre yield of the i-th crop in the t-th year. The various crops will fluctuate by ±10% each year. Then:

$$Y_{i,t}=Y_{i,2023}\cdot(1+\gamma_{it}),\quad \gamma_{it}\sim N(0;(5\%)^2) \tag{19}$$

In summary, the planting decision optimization model with the introduction of uncertain factors is obtained:

$$Max\ Profit\ =\ Max\sum_{k=1}^{n}(P_k\cdot Y_k-C_k\cdot A_k) \tag{20}$$

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$$\text{s.t.} \quad \begin{cases} \sum_{t=t_0}^{t_0+2} \sum_{i=1}^{n} X_{ijtp} \leqslant A_j \quad \forall j \\ B_{ijtp} = \begin{cases} 0 & \text{Not planted} \\ 1 & \text{Planted} \end{cases} \\ Z_{ijpt} = \begin{cases} 0, & \text{for } i \in \{1,2,...,15,17,...,34\} \\ 1, & \text{for } i = 16 \\ 2, & \text{for } i \in \{35,36,37\} \\ 3, & \text{for } i \in \{38,39,40,41\} \end{cases} \\ (1 - Z_i) \cdot B_{16j2t} = 0, i = 16 \\ B_{ij1t} \cdot (2 - Z_i) = 0, \quad \forall i \in 35,36,37 \\ \cdots \\ D_{i,t} = D_{i,2023} \cdot (1 + \delta_i), \quad \delta_i \sim N(0;(2.5\%)^2) \\ Y_{i,t} = Y_{i,2023} \cdot (1 + \gamma_{it}), \quad \gamma_{it} \sim N(0;(5\%)^2) \end{cases} \tag{21}$$

3. Results

3.1 Monte Carlo simulation optimization model solution

For the constraint condition where the probability distribution is not a standard normal distribution, we continuously generate random parameter sequences based on their probability distribution functions and substitute them into the planning model. We use the solver to find the planting strategy under the random sequence. By discretizing the distribution function, we can get the probability corresponding to each group of random sequences, and then perturb each planning strategy. Finally, we get the planting planning strategy with the highest economic benefits. The top 10 revenues that we selected to iterate on to get the best strategy are shown in Table 2.

Table 2 Partial results table

Serial number	Serial number	Serial number
1	Variable sequence 1	51397067.98
2	Variable sequence 2	51151854.36
3	Variable sequence 3	52365835.69
4	Variable sequence 4	50430382.96
5	Variable sequence 5	51900609.99
6	Variable sequence 6	51612847.22
7	Variable sequence 7	51871244.50
8	Variable sequence 8	51859868.20
9	Variable sequence 9	52895676.77
10	Variable sequence 10	51488932.56

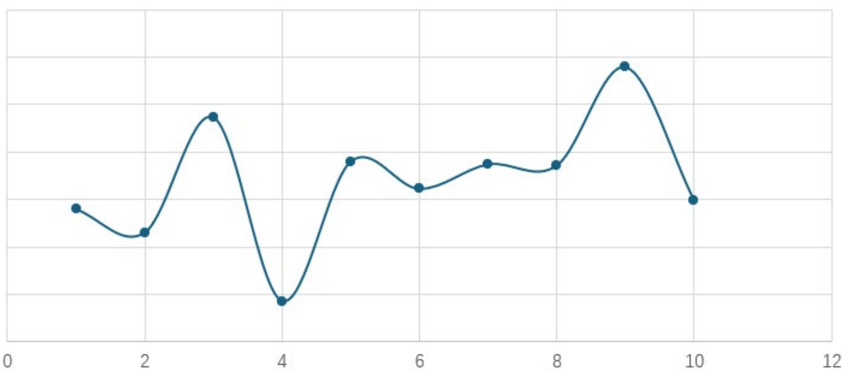

Figure 1 Result data distribution

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Reasonableness of Profit Range:

The data results are shown in Figure 1. The annual profit of the optimal strategies ranges from 50.43 million to 52.90 million CNY, with a variation of approximately 4.9%. This fluctuation range aligns well with the uncertainty parameters defined in the model (price ±5%, yield ±10%), demonstrating the model's capability to effectively quantify the impact of risks on profits. These results confirm the robustness and reliability of the model in identifying optimal strategies under uncertainty.

Stability of Strategies:

The profit difference between Sequence 9 (52.90 million CNY) and Sequence 4 (50.43 million CNY) may stem from the selection of high-risk, high-reward crops (e.g., double-season vegetable cultivation in smart greenhouses) or yield losses under extreme climate scenarios. Further analysis is required to examine the proportion of high-risk crops in these variable sequences, which could reveal the trade-offs between risk exposure and profit maximization.

Coverage of Uncertainties:

While the Monte Carlo simulation covers most probabilistic scenarios through random sampling, it does not explicitly account for extreme events (e.g., consecutive yield reductions). Relying solely on normal distributions might underestimate the risks associated with "black swan" events, such as prolonged market crashes or catastrophic climate impacts. Future iterations of the model should incorporate heavy-tailed distributions or stress-testing frameworks to enhance scenario comprehensiveness.

3.2 Result data visualization

According to the data obtained by the algorithm simulation, the planting of various crops is visualized.

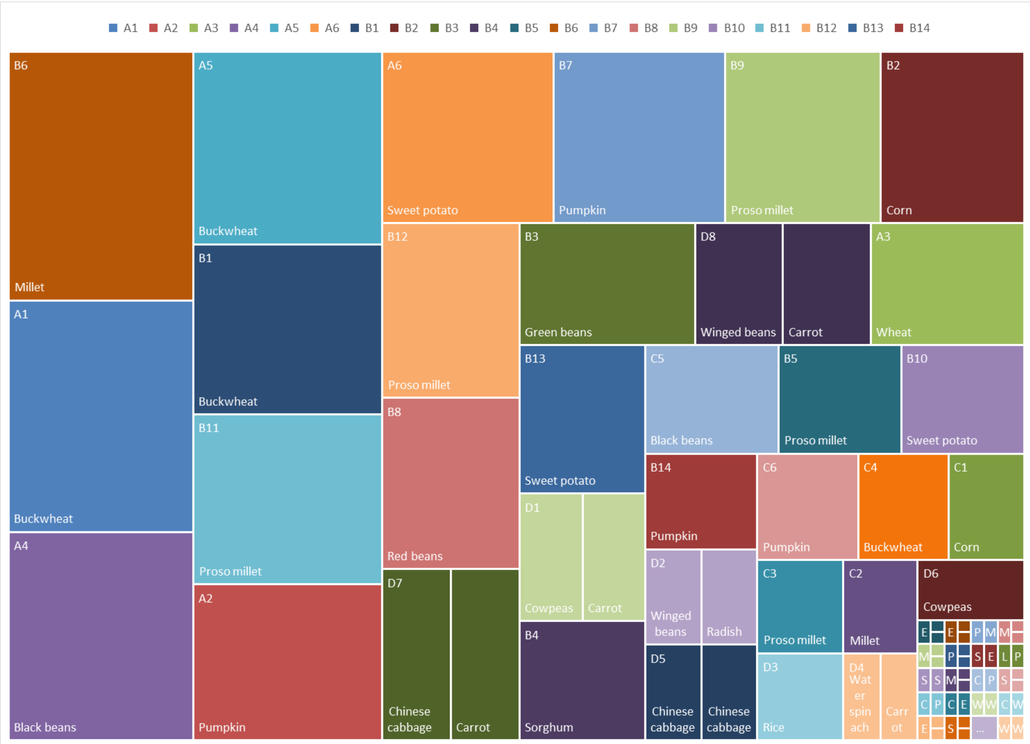

Figure 2 Visualization of crop planting plan

By visualizing the data for the optimal planting strategy, as shown in Figure 2, the relative position and size of the various crops, it is possible to visually compare the different planting strategies for each crop.

4. Conclusions

This study presents a novel approach to optimizing crop planting decisions under uncertainty by

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integrating Monte Carlo simulation with stochastic programming. The proposed model, which incorporates probabilistic elements such as normal and Poisson distributions, effectively addresses the complexities of market fluctuations and extreme climate events. By simulating a wide range of scenarios, the model identifies optimal planting strategies that maximize profits while mitigating risks. The results demonstrate the model's robustness and reliability, as evidenced by the consistent profit range of 50.43 million to 52.90 million CNY across different scenarios. This research not only advances the theoretical understanding of agricultural decision-making under uncertainty but also provides practical tools for farmers and agricultural managers to enhance the sustainability and profitability of agricultural production.

The model developed in this study has significant potential for extension to other agricultural and non-agricultural domains. For instance, similar optimization frameworks could be applied to forestry, animal husbandry, and other agricultural-related industries to address uncertainty issues. Additionally, the methodology could be adapted for use in other fields such as energy investment and supply chain management, where decision-making under uncertainty is crucial. Future research could focus on incorporating more sophisticated probabilistic distributions to better capture extreme events and improve the model's adaptability to different regional and crop-specific conditions. This would further enhance the model's applicability and value in supporting sustainable development and risk management in various industries.

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