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Multi-Period Crop Planting Strategy Optimization Based on Multi-Objective Programming and Monte Carlo Simulation

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Abstract: This study addresses the optimization of crop planting arrangements for the period from 2024 to 2030, with the objective of maximizing the cumulative economic return. A dynamic programming framework is adopted as the primary methodology, while the decision-making logic of the greedy algorithm is incorporated to update the planting strategy year by year. Specifically, the planting decision for each year is determined on the basis of the forecast results and operational outcomes of the preceding year. For the two possible disposal strategies of unsold agricultural products, separate multi-stage optimization models are established and solved, thereby generating corresponding optimal planting plans for the entire planning horizon. In addition, the model takes into account a range of uncertainties associated with agricultural production and market conditions, including historical sales performance, expected demand for different crops, yield per unit area, cultivation costs, and fluctuations in selling prices. These factors are assumed to vary over time rather than remain constant. To evaluate the influence of such uncertainties, Monte Carlo simulation and probabilistic statistical analysis are employed to generate numerous possible scenarios. The expected performance of each planting strategy is then estimated through repeated random sampling, which improves the robustness and risk resistance of the final decision scheme.

Keywords: Multi-objective programming, Monte Carlo simulation, greedy algorithm, crop planting optimization, decision-making under uncertainty.

1. Introduction

Demographic expansion and rising food consumption have placed increasing pressure on agricultural production systems, making the efficient and environmentally responsible use of farmland a critical issue. In many rural communities, the amount of cultivable land is relatively small, and improving the economic output generated by each unit of land is essential for promoting regional development and strengthening rural livelihoods.

This challenge is particularly evident in the mountainous regions of northern China, where uneven terrain, restrictive weather conditions and fragmented plots limit the flexibility of agricultural production. In some locations, climatic constraints permit only a single cultivation cycle each year. Consequently, agricultural planning must coordinate crop selection, land allocation and production scheduling to increase resource utilization, maintain stable output and control operational losses.

Environmentally friendly cultivation provides a possible pathway for balancing agricultural profitability with ecological protection. Such production systems rely primarily on natural inputs and sustainable management techniques while limiting synthetic agrochemicals and genetically modified materials. Crop selection must therefore account for biological suitability, local temperature and precipitation patterns, soil properties and water availability. Different categories of farmland, including dry fields, terraces, sloping plots and irrigated areas, should be assigned crops that match their respective production conditions.

Agricultural decisions are also affected by uncertain events, including extreme weather, demand and price variation, biological hazards and fluctuations in production costs. A well-designed cultivation scheme should therefore pursue economic returns while maintaining sufficient resilience against adverse scenarios. Through location-specific land allocation and scientifically formulated production plans, rural regions can obtain greater economic value from constrained farmland resources and support the long-term improvement of local agricultural income.

2. Planting Strategy Study

To determine a profitable land-use arrangement over the seven-year planning horizon, the cultivation decision is formulated as a sequential optimization process. Rather than solving all annual decisions independently, the allocation adopted at each stage is derived from the production state and feasible choices inherited from earlier stages. A short-term best-response rule is applied when comparing candidate crops and land assignments in a given year, while the cumulative economic performance over the entire horizon is used to assess the final schedule. This procedure links consecutive annual decisions and produces an integrated cultivation plan under intertemporal constraints.

The feasible use of each plot depends strongly on its physical environment and available agricultural facilities. Dry flat fields, terraced areas and sloping fields are generally assigned to a single annual grain-growing cycle. Irrigated plots may support either one rice harvest or two vegetable rotations. Conventional greenhouses accommodate a vegetable crop followed by an edible-fungus crop, whereas smart greenhouses can sustain two vegetable production cycles within one year. These differences in seasonal capacity, crop suitability and facility conditions create a heterogeneous set of planting restrictions.

To reduce the dimensionality and computational burden of the full optimization problem, the decision system is decomposed into two coordinated modules. The first module focuses on grain allocation across dry flat land, terraces and sloping fields, since these land categories share similar annual production patterns and crop compatibility requirements.

The second module handles crops associated with irrigated fields and protected cultivation facilities. It jointly determines the allocation of rice, vegetables and edible fungi under season-specific restrictions. Vegetables such as potatoes, tomatoes, eggplants and legumes may be arranged in irrigated fields or greenhouse facilities during permitted production periods. Conventional greenhouses reserve their subsequent cycle for fungal products such as shiitake and morel mushrooms. When an irrigated plot is used for rice, the land follows a single-harvest pattern; under a two-cycle vegetable arrangement, the later cycle is limited to designated crops such as Chinese cabbage, carrots and white radishes. By solving the two modules separately and subsequently integrating their results, the original large-scale planning task can be handled more efficiently while preserving the principal agronomic constraints.

2.1. Objective Function

The objective function is to maximise the target profit function. In the following, i denotes the ith crop and j denotes the jth plot, where i =1, 2, 3, ..., 15, in turn, represents 15 food crops: soybean, black bean, red bean, mung bean, climbing bean, wheat, corn, grain, sorghum, millet, buckwheat, pumpkin, sweet potato, oat and barley; j =1, 2, ..., 26, in turn, represents A1 flat dry land, ..., A6 flat dry land, B1 terraced land, ..., B14 terraced land, ..., B14 terraced land, ..., B12 terraced land, ..., B12 terraced land. j = 1, 2, ..., 26, representing A1 flat dryland, ..., A6 flat dryland, B1 terrace, ..., B14 terrace, C1 hillside, ..., C6 hillside.)

x_{ij} is the acreage of crop i in plot j in acres. y_{ij} is whether or not crop i is planted in plot j.

$$y_{ij} = \begin{cases} 0, & indicates\ that\ crop\ i\ is\ not\ planted\ on\ plot\ j \\ 1, & indicates\ that\ crop\ i\ is\ planted\ on\ plot\ j \end{cases} \tag{1}$$

Let a_{ij} be the planting unit yield of the ith crop in the jth plot, in kg/mu. b_{ij} be the planting cost of the ith crop in the jth plot, in yuan/mu. c_i be the selling unit price of the ith crop, in yuan/jin. d_i be the predicted selling volume of the ith crop, and f_i be the total production of the ith crop in the current year, and it is easy to compute the expression of f_i.

$$f_i = \sum_{j=1}^{M} x_{ij} y_{ij} a_{ij} \tag{2}$$

Let g_i be the sales of crop i, $g_i = f_i \ c_i$, and the cost of cultivation m, be:

$$m = \sum_i^N \sum_j^M x_{ij} y_{ij} b_{ij} \tag{3}$$

Thus the profit function is easily obtained:

$$maxZ = \sum_i^N g_i - m = \sum_i^N \left[\sum_{j=1}^{M} x_{ij} y_{ij} a_{ij}\right] \cdot c_i - \sum_i^N \sum_j^M x_{ij} y_{ij} b_{ij} \tag{4}$$

2.2. Restrictive Condition

(1) Crop production does not exceed expected sales per season

If the crop production exceeds the expected sales volume, it will result in a loss of profit, thus requiring that the crop production per set does not exceed the expected sales volume:

$$f_i = \sum_{j=1}^{M} x_{ij} y_{ij} a_{ij} \leqslant d_i, i = 1,2,\cdots,15 \tag{5}$$

(2) Crop planting does not exceed the size of the plot

Let e_j be the maximum planting area of the jth plot:

$$\sum_i^N x_{ij} y_{ij} \leqslant e_j, j = 1,2,\cdots,26 \tag{6}$$

(3) Planting plots should not be spread too thinly per crop per season

It is possible to combine different crops on the same plot, but a good planting programme should take into account the ease of field management and cultivation operations. According to the cultivation practice in 2023, only one crop is planted in A1 flat dryland, B1 terraced land and C5 hillside land, which is convenient for crop management. For the sake of appropriate crop combination, this paper stipulates that no more than three crops should be planted in the same plot, namely:

$$\sum_i^N y_{ij} \leqslant 3, j = 1,2,3,\cdots,26 \tag{7}$$

(4) Each crop should not be planted on too small an area in a single plot

According to the planting data in 2023, basically all the flat drylands are fully planted, and 35 acres are planted in the smallest A3 flat dryland, and there is no vacancy in other plots. Based on the above facts, it is assumed that not less than 35 acres of flat drylands, not less than 20 acres of flat terraces and not less than 13 acres of slopes will be planted with crops:

$$\begin{cases} x_{ij} \leqslant 35, j = 1,2,\cdots,6 \\ x_{ij} \leqslant 20, j = 7,8,\cdots,20 \\ x_{ij} \leqslant 13, j = 21,23,\cdots,26 \end{cases} \tag{8}$$

(5) Each crop cannot be planted in the same plot over and over again.

The indicator variable $z_{ij}(t)$ is introduced to denote the actual cultivation of crop i in year t in the jth plot.

$$z_{ij}(t) = \begin{cases} 0, & indicates\ that\ crop\ i\ is\ not\ planted\ on\ plot\ j\ in\ t\ year \\ 1, & indicates\ that\ crop\ i\ is\ planted\ on\ plot\ j\ in\ t\ year \end{cases} \tag{9}$$

Where t = 2023, 2024, ..., 2030.

The indicator variable $zz_{ij}(t)$ is also introduced to denote whether or not crop i can be planted in year c at the jth plot.

$$zz_{ij}(t) = \begin{cases} 0, & indicates\ that\ crop\ i\ can\ not\ be\ planted\ on\ plot\ j \\ 1, & indicates\ that\ crop\ i\ can\ be\ planted\ on\ plot\ j \end{cases} \tag{10}$$

Distinguish from the above equation, here t = 1, 2, ..., 15, denoting the years 2024, 2025, ..., 2030.

It is not difficult to show that $z_{ij}(t)$ and $zz_{ij}(t)$ have the following relationship:

$$\begin{cases} zz_{ij}(t+1) = 0, z_{ij}(t) = 1 \\ zz_{ij}(t+1) = 1, z_{ij}(t) = 0 \end{cases} \tag{11}$$

After adding the variable $zz_{ij}(t)$ again, the above objective function and constraints are modified and the yield is modified as:

$$f_i = \sum_{j=1}^{M} x_{ij} y_{ij} zz_{ij}(t) \cdot a_{ij}, i = 1,2,\cdots,15 \tag{12}$$

Planting costs are modified to:

$$m = \sum_i^N \sum_j^M x_{ij} y_{ij} zz_{ij}(t) \cdot b_{ij} \quad (13)$$

The objective profit function is:

$$maxZ = \sum_i^N f_i c_i - \text{cost} = \sum_i^N \left[\sum_{j=1}^M x_{ij} y_{ij} zz_{ij}(t) \cdot a_{ij}\right] \cdot c_i - \sum_i^N \sum_j^M x_{ij} y_{ij} zz_{ij}(t) \cdot b_{ij} \quad (14)$$

Constraint I is changed as follows:

$$f_i = \sum_{j=1}^M x_{ij} y_{ij} zz_{ij}(t) \cdot a_{ij} \leqslant d_i, i = 1,2,\cdots,15 \quad (15)$$

Constraint II is changed as follows:

$$\sum_i^N x_{ij} y_{ij} zz_{ij}(t) \leqslant e_j, j = 1,2,\cdots,26 \quad (16)$$

(6) Legumes to be planted at least once in three years starting in 2023

Since soil containing rhizobacteria of legume crops is favourable for crop growth, all plots were planted with legume crops at least once in three years from 2023 onwards. The legume crops are only numbered exactly $i = 1, 2, 3, 4, 5$ The five legumes, soybean, black bean, red bean, green bean, and climbing bean, are subject to the constraints V. Revealed, $qq_{ij}(t)$ and $q_{ij}(t)$ are introduced in a similar manner. where $q_{ij}(t)$ denotes the actual cultivation of the ith legume crop on plot j in year t.

$$q_{ij}(t) = \begin{cases} 0, & \textit{indicates that crop i is not planted on plot j in t year} \\ 1, & \textit{indicates that crop i is planted on plot j in t year} \end{cases} \quad (17)$$

Where t = 2023, 2024, ..., 2030.

qqij(t) indicates whether legume crop i must be planted on plot j in year t, where

$$qq_{ij}(t) = \begin{cases} 0, & \textit{indicates that crop i must be planted on plot j} \\ 1, & \textit{indicates that crop i could not be planted on plot j} \end{cases} \quad (18)$$

Since all plots must be planted with legumes within three years, i.e., the planting interval is at least two years, and after an interval of two years without planting legumes, the third year must be planted, so that $t = 2025, 2026, ..., 2030$ is taken, where the condition that the planting of legumes in the years 2023 and 2024 affects the planting of legumes in the year 2025 is implicitly assumed.

There is a relationship equation between these two variables:

$$q_{ij}(t) + q_{ij}(t+1) = qq_{ij}(t+2) \quad (19)$$

If the legume crop is planted in 2023 and not in 2024, q_{ij} (2023) = 1 and q_{ij} (2024) = 0, then:

$$q_{ij}(2023) + q_{ij}(2024) = qq_{ij}(2025) = 1 \quad (20)$$

That is, there is no need to plant legume crop i on plot j in 2025. and then if no legume crop is planted in both 2023 and 2024:

$$q_{ij}(2023) + q_{ij}(2024) = qq_{ij}(2025) = 0 \quad (21)$$

i.e., legume crop i must be grown on plot j in 2025.

Since y_{ij} denotes the cultivation of the crop, thus $qq_{ij}(t)$ affects the value of y_{ij} to get the constraint VI:

$$y_{ij} = \begin{cases} 0, qq_{ij}(t) = 1 \text{ or } 2 \\ 1, qq_{ij}(t) = 0 \end{cases}, i = 1,2,3,4,5,6, j = 1,2,\cdots,26 \quad (22)$$

Combining the above analyses, we obtained the objective profit function, constraints, decision variables, and a multi-stage mathematical planning model with year t as the variable. Also based on the above discussion, the planting interval for the legume crop is at least two years, thus constraint six needs to be considered for 2025 and subsequent years.

The planning model for 2024 crop is as follows:

$$maxZ = \sum_i^N \left[\sum_{j=1}^M x_{ij} y_{ij} zz_{ij}(2024) \cdot a_{ij}\right] \cdot c_i - \sum_i^N \sum_j^M x_{ij} y_{ij} zz_{ij}(2024) \cdot b_{ij} \quad (23)$$

$$\begin{cases} \sum_i^N x_{ij} y_{ij} zz_{ij}(2024) \leqslant e_j, j = 1,2,\cdots,26 \\ f_i = \sum_{j=1}^M x_{ij} y_{ij} zz_{ij}(2024) \cdot a_{ij} \leqslant d_i, i = 1,2,\cdots,15 \\ x_{ij} \leqslant 35, j = 1,2,\cdots,6 \\ x_{ij} \leqslant 20, j = 7,8,\cdots,20 \\ x_{ij} \leqslant 13, j = 21,23,\cdots,26 \\ \sum_i^N x_{ij} \leqslant 3, j = 1,2,3,\cdots,26 \\ zz_{ij}(2024) = 0, z_{ij}(2023) = 1 \\ zz_{ij}(2024) = 1, z_{ij}(2023) = 0 \end{cases} \quad (24)$$

The planning model for 2025 and subsequent years is shown below:

$$maxZ = \sum_i^N \left[\sum_{j=1}^M x_{ij} y_{ij} zz_{ij}(t) \cdot a_{ij}\right] \cdot c_i - \sum_i^N \sum_j^M x_{ij} y_{ij} zz_{ij}(t) \cdot b_{ij} \quad (25)$$

$$\begin{cases} \sum_i^N x_{ij} y_{ij} z_{ij}(t) \leqslant c_{ij}, j = 1,2,\cdots,26, t = 2025,\cdots,2030 \\ f_i(t) = \sum_{j=1}^M x_{ij} y_{ij} z_{ij}(t) \cdot a_{ij} \leqslant d_{ij}, i = 1,2,\cdots,15, t = 2025,\cdots,2030 \\ x_{ij} \leq 35, j = 1,2,\cdots,6 \\ x_{ij} \leqslant 20, j = 7,8,\cdots,20 \\ x_{ij} \leqslant 13, j = 21,23,\cdots,26 \\ \sum_t^N y_{ij} \leq 3, j = 1,2,3,\cdots,26 \\ \begin{cases} zz_{ij}(t) = 0, z_{ij}(t-1) = 1 \\ zz_{ij}(t) = 1, z_{ij}(t-1) = 0 \end{cases}, t = 2025,\cdots,2030 \\ q_{ij}(t-2) + q_{ij}(t-1) = qq_{ij}(t), t = 2025,\cdots,2030 \\ y_{ij} = \begin{cases} 0, qq_{ij}(t) = 1 \textit{ or } 2 \\ 1, qq_{ij}(t) = 0 \end{cases}, i = 1,2,3,4,5,6, j = 1,2,\cdots,26, t = 2025,\cdots,2030 \end{cases} \quad (26)$$

3. Optimisation of Optimal Planting Strategies

Crop production is jointly affected by a wide range of factors, including market demand, yield per unit area, cultivation cost, selling price, and climatic conditions. These parameters generally exhibit substantial uncertainty across different years. If the planning model is constructed solely on the basis of fixed values, the resulting planting scheme may only reflect an idealized situation and may fail to capture the market fluctuations, yield variation, and operational risks that arise in actual agricultural production. Therefore, on the basis of the deterministic crop-planning model established previously, this study introduces random variables and Monte Carlo simulation to further optimize the planting scheme for the period from 2024 to 2030, thereby improving the reliability, stability, and risk resistance of the decision results.

In the crop-planning model, yield per unit area represents the productive capacity of a given crop on a specific plot. Cultivation cost includes the expenditures on seeds, fertilizer, labor, irrigation, and other production inputs per unit area. The selling price reflects the unit revenue obtained when agricultural products enter the market, while the expected sales volume indicates the maximum quantity that the market can absorb for each crop. When the actual output ofa crop in a given year does not exceed its expected sales volume, the entire output is sold at the normal market price. When production exceeds the market demand limit, the excess quantity is sold at 50% of the normal selling price in the previous year. This assumption provides a reasonable representation of discounted sales and unsold inventory caused by oversupply.

Agricultural production conditions and market environments are not constant over the planning horizon. Market demand may vary with population, consumption structure, and the supply of competing products. Yield per unit area may be influenced by precipitation, temperature, soil conditions, and pests or diseases. Cultivation costs may fluctuate because of changes in labor expenses, agricultural input prices, energy costs, and machinery charges. Selling prices may also change in response to market supply and demand. Consequently, expected sales volume, yield per unit area, cultivation cost, and selling price are modeled as random variables. Appropriate variation intervals are assigned to these variables according to the problem conditions, historical observations, and empirical assumptions.

The market demand for maize and wheat is assumed to exhibit a sustained upward trend. Their annual expected sales growth rates are therefore sampled randomly within the range of 5% to 10%. For the remaining crops, whose demand patterns are less stable, annual expected sales volumes are allowed to fluctuate within ±5% of the previous year's reference level. Considering variations in weather and agricultural management, the yield per unit area of each crop is permitted to vary within ±10% of its baseline value. Cultivation costs are adjusted according to a specified annual growth rate or fluctuation interval to reflect inflation and changes in agricultural input prices. Selling prices are generated separately according to the market characteristics of different crop categories. Crops with relatively stable prices are assigned narrower fluctuation ranges, whereas crops with greater market volatility are allowed to vary within wider intervals.

Monte Carlo simulation is a numerical method for analyzing uncertainty through random sampling and repeated computation. Its fundamental idea is to generate a large number of possible production and market scenarios according to the probability distributions or admissible intervals of uncertain variables, and then solve the crop-planning model under each scenario. As the number of simulations increases, the statistical characteristics of the results gradually stabilize and provide an approximation of the probability distribution of crop-planning profits and decisions under real-world uncertainty. Compared with a deterministic model based on a single set of predicted values, Monte Carlo simulation offers a more comprehensive assessment of the influence of uncertainty on planting decisions.

Before the simulation begins, baseline values are first determined for the yield per unit area, cultivation cost, selling price, and expected sales volume of each crop on each type of land. Basic information concerning plot area, land category, crop suitability, seasonal arrangements, and crop-rotation requirements is also entered into the model. Appropriate probability distributions or fluctuation intervals are then specified for all uncertain parameters, and the planning period and total number of simulation trials are established. In this study, 2024–2030 is treated as the complete planning horizon, and each Monte Carlo trial generates a full set of stochastic parameters for all seven years.

At the beginning of each simulation, the algorithm generates random parameters for every year and crop according to the predefined variation rules. For maize and wheat, an annual sales growth rate between 5% and 10% is sampled, and the expected demand for the current year is calculated from the previous year's sales volume. For all other crops, a sales variation rate between −5% and 5% is randomly generated. The yield per unit area of each crop is updated using its baseline yield and a randomly sampled yield deviation. Cultivation costs are adjusted according to the specified growth rule or fluctuation range, and new selling prices are generated according to the corresponding crop-specific assumptions.

Once a complete set of stochastic parameters has been produced, it is substituted into the crop-planning optimization model. The model maximizes total profit over the planning horizon while satisfying constraints on land area, crop suitability, planting seasons, crop rotation, legume cultivation requirements, minimum planting area per plot, and market demand limits. The model output includes the planting area of every crop on every plot in each year, annual production, quantities sold at the normal price, quantities sold at a discount, total sales revenue, total cultivation cost, and net profit.

For annual profit calculation, the total output of each crop is first obtained by multiplying its planting area by its yield per unit area. If the total production does not exceed the expected sales volume, the entire output is valued at the normal selling price. If the total output is greater than the expected demand, the quantity within the sales limit is sold at the normal price, whereas the surplus is sold at the prescribed discounted price. The cultivation cost of the crop across all relevant plots is then subtracted from the total sales revenue to obtain annual net profit. The profits from 2024 to 2030 are accumulated to determine the total return over the entire planning period under the current stochastic scenario.

After one optimization run is completed, the algorithm records the sampled parameter values, optimal planting areas, annual profits, seven-year cumulative profit, and crop-allocation results. A new set of random parameters is then generated, and the full optimization procedure is repeated. To ensure adequate statistical stability, the simulation may be conducted 1,000 times or more. Each trial represents one possible agricultural and market environment, producing a large collection of optimal planting schemes and corresponding profit outcomes.

A feasibility-checking mechanism is also incorporated into the simulation process. If a sampled parameter combination leads to an infeasible optimization problem, for example because market demand is too low, rotation constraints are too restrictive, or land-allocation requirements conflict, the corresponding trial is excluded from the final statistical analysis and a new random scenario is generated. This procedure ensures that all retained planting schemes satisfy the basic agronomic requirements and model constraints.

After all simulation trials have been completed, the resulting outcomes are statistically evaluated. The mean total profit of all valid trials is first calculated to measure the expected economic performance of the planting strategy under typical production and market conditions. The variance and standard deviation of total profit are then computed to quantify income volatility. A smaller standard deviation indicates that the planting scheme is less sensitive to random disturbances and therefore more stable. Minimum profit, maximum profit, and selected profit quantiles are also examined to evaluate performance under adverse and favorable scenarios.

To assess risk more comprehensively, the probability of loss and downside risk may also be calculated. The probability of loss is defined as the proportion of valid trials in which total profit falls below a predefined safety threshold. A scheme with a high expected return but a large probability of loss may involve excessive market risk. By contrast, a scheme with a slightly lower expected profit but consistently positive performance across most scenarios may be more suitable for practical implementation.

The planting frequency and average cultivated area of each crop on each type of land are also summarized. If a particular crop is repeatedly assigned to the same land category in most simulation trials, the corresponding allocation can be regarded as stable and adaptable. If the cultivated area of a crop changes substantially across different scenarios, its planting decision is highly sensitive to fluctuations in demand, price, or yield and should therefore retain greater flexibility in actual production.

The final recommendation is not selected solely according to the highest profit obtained in a single simulation. Instead, multiple indicators are considered jointly, including expected return, profit volatility, minimum return, probability of loss, and stability of crop allocation. For schemes with high returns but excessive risk, the proportion of high-risk crops should be reduced appropriately. For highly stable schemes with insufficient profitability, the area allocated to high-return crops may be increased under acceptable risk constraints. By comprehensively evaluating the large set of simulated outcomes, the strategy that maintains relatively high profit and low risk across most random scenarios is selected as the recommended planting plan for 2024–2030.

From an algorithmic perspective, the Monte Carlo optimization procedure consists of seven consecutive stages: baseline data input, stochastic parameter generation, annual parameter updating, optimization-model solution, result storage, repeated simulation, and statistical evaluation. First, the agricultural data and fluctuation ranges of uncertain variables are entered. Second, a random set of production and market parameters is generated according to the specified distributions. Third, these parameters are updated year by year and substituted into the optimization model. Fourth, the optimal planting areas are obtained while satisfying all constraints. Fifth, the total profit and crop-allocation decisions under the current scenario are saved. Sixth, the above procedure is repeated until the predetermined number of simulations is reached. Finally, the simulation results are analyzed statistically to identify a planting scheme with both strong economic performance and high resistance to uncertainty.

By introducing Monte Carlo simulation, the original deterministic crop-planning model is transformed into a risk-aware decision model capable of handling stochastic disturbances. The method not only provides a planting arrangement under expected conditions, but also characterizes the possible range of profit outcomes under different market and climate scenarios. This offers agricultural decision-makers a more comprehensive basis for planning. Compared with a scheme that merely maximizes theoretical profit, the planting strategy selected through stochastic simulation is better able to adapt to changes in market demand, yield fluctuation, and rising production costs, and therefore demonstrates stronger feasibility and robustness.

(1) Results statistics

Table 1. Planting programme 2024-2030

Year	Parcel Name	Barley	Sorghum	Millet	Sorghum vulgare	Broomcorn millet	Buckwheat	Cucurbit	Sweet potato	Hordeum vulgare
2024	A	44.8	72.5	0	20.3	35.3	0	62.0	133.8	0
	B	114.4	90.2	15.9	35.7	110.1	0	35.5	164.5	6.0
	C	10.2	13.7	14.0	0	6.8	18.0	0	0	16.5
2025	A	33.5	58.6	5.0	38.5	52.0	32.5	51.4	16.4	14.3
	B	41.9	39.6	44.3	37.8	28.2	118.1	111.4	18.3	28.3
	C	0	0	0	0	0	14.1	30.7	14.8	0
2026	A	28.5	31.1	0	21.5	33.8	5.4	93.3	134.1	0
	B	42.2	47.2	14.2	36.5	45.3	21.1	100.4	237.1	6.2
	C	0	0	15.4	0	0	25.3	3.6	15.5	20.4
2027	A	37.1	37.5	8.8	34.3	35.7	4.7	59.1	64.4	5.4
	B	39.8	41.9	31.5	36.6	45.9	75.1	36.8	39.0	15.2
	C	0	0	3.9	0	0	30.5	0	0	13.5
2028	A	83.2	68.9	0	25.1	41.3	0	44.6	52.6	0
	B	82.7	106.1	18.4	46.2	29.6	2.7	102.7	103.4	16.1
	C	13.8	15.3	12.0	0	0	16.8	11.9	16.7	11.6
2029	A	42.6	35.2	9.3	50.8	60.4	10.2	69.5	89.4	5.4
	B	55.0	38.1	13.5	108.8	85.9	29.3	38.3	34.9	14.3
	C	0	0	11.9	14.1	15.5	28.9	0	0	11.5
2030	A	44.0	39.9	9.5	50.4	54.2	9.5	70.6	84.5	4.8
	B	54.0	37.5	13.1	110.7	78.3	30.5	37.2	32.6	15.3
	C	0	0	14.7	17.2	15.7	32.1	0	0	12.8

4. Conclusions

The proposed framework supports a multi-period decision horizon covering 2024–2030, enabling agricultural managers to coordinate present cultivation choices with subsequent production arrangements. Instead of generating an isolated annual schedule, the model links decisions across successive years and allows future plans to be revised in response to updated information. This rolling planning mechanism improves adaptability when actual production conditions deviate from initial expectations and provides a more suitable basis for long-term agricultural management.

The analysis also incorporates several sources of temporal variation that are frequently encountered in practice. These include changing demand for major grain crops, shifts in production conditions caused by environmental variation, fluctuations in commodity prices, and year-specific adjustments in crop performance. By embedding these factors into the decision process, the model avoids relying on a single fixed scenario and can produce cultivation arrangements that remain comparatively stable under different market and production environments.

Nevertheless, several limitations remain. Rare but severe events, such as prolonged drought, flooding, widespread pest outbreaks, or other extreme disturbances, are not explicitly represented in the current formulation. Although such events occur infrequently, their consequences may be substantial and could significantly alter both output and profitability. In addition, future advances in seed breeding, irrigation technology, agricultural machinery, and cultivation practices may change existing yield relationships and production costs. These technological developments are difficult to estimate in advance and may reduce the accuracy of long-range forecasts.

The model also has potential for broader application beyond the original study area. Agricultural suitability, resource availability, and market structure vary considerably across locations, so regional implementation would require recalibration of land attributes, production coefficients, demand parameters, and economic assumptions. After appropriate localization, the framework could be applied to other rural areas to improve the allocation of constrained farmland and coordinate crops with different substitution and complementarity relationships.

The current crop set can also be expanded. In addition to grain, vegetable, and edible-fungus categories, the planning system may incorporate fruit crops, oil-bearing crops, forage crops, and other commercial varieties. A richer crop portfolio would provide more alternatives for land allocation and seasonal rotation, allowing the optimization model to identify more diversified production structures. Such an extension may further improve resource utilization, income stability, and the ability of agricultural systems to respond to changing market conditions.

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