# Research on Optimization Strategies of Agricultural Cultivation Based on Linear Programming Models and Monte Carlo Methods

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**Abstract.** A rural village in China faces multiple challenges, including perennially low temperatures, limitations on the type and amount of arable land, and crop growth patterns. These factors lead to increased difficulty in marketing crops, especially in the stagnant marketing problem, which affects the sustainable development of the agricultural economy. In this paper, a linear programming model is developed for the stagnant marketing problem, and various constraints (e.g., total plot size, minimum cropland area restrictions, crop rotation requirements, etc.) are set to maximize the total return. For uncertainties, the Monte Carlo algorithm is applied to simulate and generate multiple potential scenarios to analyze the optimal planting strategy. By solving the model, this article identified the optimal planting plan under different treatment scenarios, as well as proposed countermeasures to cope with the effects of uncertainties. Overall, this study provides systematic solutions to address the challenges facing rural agriculture in China and valuable cases and references for economic efficiency improvement and sustainable development in the agricultural sector.

**Keywords:** Linear Programming, Monte Carlo Algorithm, Optimal Planting Strategy.

## 1. Introduction

In this paper, a rural area in China is studied and data on its relevant land, crops, and sales in 2023 are collected to form a dataset. The region faces agricultural challenges such as limited land resources, poor crop planning, and difficulties in coping with losses due to uncertainty. These problems have led to difficulties in marketing crops and farmers' incomes not meeting expectations, which have seriously affected the sustainability of the rural agricultural economy. Land resources in the region are limited and different plots have different restrictions on the types of crops and planting areas, for example, flat drylands, terraces, and hillsides can only grow one season of food crops per year, while irrigated land is only suitable for growing one season of rice or two seasons of vegetables per year. In addition, there are corresponding constraints between crops grown locally, for example, due to the limitation of land fertility, crops cannot be planted repeatedly, and specific types of crops (e.g. legumes) need to be planted at certain intervals to maintain soil fertility, and so on. How to make rational use of the limited arable land types and areas to rationally plan the planting strategy to maximize the final income has become a key issue for local development.

Despite the unique farming conditions and crops, the problems faced are common to all rural areas: land resource constraints, crop constraints, climate change, and market changes. Other agricultural regions also need to scientifically optimize local cropping strategies to achieve their positive development. Therefore, this study not only focuses on one rural area in China but also provides a generalized solution for the development of agricultural areas.

In the study of agricultural layout optimization and productivity enhancement, several teams have adopted advanced methods to address the challenges of planting layout optimization and resource utilization. Jiang Yangming's team used web crawlers to obtain agricultural product price data, combined with K-means clustering to analyze price fluctuations, assessed economic benefits and risks through net ROI and Sharpe ratios, and introduced cuckoo search algorithms to optimize crop layout and help farmers stabilize their incomes [1]. Mengmeng Hu's team integrated the MaxEnt model, multi-objective interval parameter planning (MOIPP), life cycle assessment (LCA), and dynamic transformation of land use and its impacts (Dyna-CLUE) model to identify the key variables and optimize the planting structure, taking into account the uncertainty, to provide accurate crop planting layout planning [2]. Jiaying Wang's team proposed a multi-stage planting strategy model based on particle swarm optimization (PSO), which dynamically adjusts to respond to market and climate change, and balances economy and sustainability [3]. Zhang F's team combined the hierarchical analytical process method entropy method (AHP-EW) and partial least squares regression (PLS) to propose a two-stage multi-objective stochastic planning (BMSP) model, which improves irrigation efficiency and reduces pollution for arid regions, showing the advantages of considering both multi-objective planning and stochastic expectation planning in decision making [4]. Jesus David Chaux explores the application of digital twins (DTs) in controlled environment agriculture (CEA) to optimize productivity and contribute to food security through simulation [5]. The application of these methods not only promotes the science and refinement of agricultural management but also provides strong support for the goal of sustainable agriculture. Although all of the above methods have notable performance in practical applications, they all have certain shortcomings. K-means clustering requires a pre-set number of clusters (K-value) and is sensitive to outliers (e.g., uncertainties such as extreme price fluctuations), which may distort the center of clusters; the BMSP model, although considering uncertainty, may have limited prediction and processing ability for extreme events (e.g., extreme weather, market collapse). Be limited, and the AHP-EW therein relies heavily on the subjective judgment of the decision maker, with the risk of subjective bias that may affect the accuracy of the weights, and at the same time, there may be a conflict among economic, environmental, and social objectives in multi-objective optimization (e.g., maximization of the economic benefits may exacerbate the burden on the environment); and from the perspective of cost and resources, constructing and operating the digital twin system requires advanced hardware (e.g., the sensors, controllers) and software (e.g., simulation platforms, data analysis tools), with high initial investment costs; the technology is more suitable for large-scale, capital-intensive CEA systems and is difficult to implement in small-scale or resource-constrained agriculture, and with the rapid development of digital twin technology, agribusinesses may be under pressure for frequent technological upgrades, which can further increase operational costs; MOIPP, LCA, MaxEnt and Dyna-CLUE model integration significantly increases model complexity, resulting in models that are difficult to understand and interpret, making implementation and promotion more difficult. Moreover, complex models usually require high-performance computational resources and long computing time, which limits their applicability in resource-limited areas; PSO algorithm, as a group intelligence optimization method, requires multiple iterations and a large amount of computational resources, which is particularly costly to compute in large-scale problems (e.g., multi-crop, multi-region optimization). In addition, the PSO algorithm may fall into local optimal solutions, especially in high-dimensional, nonlinear problems, which affects the global optimality and model validity of the optimization results. Similarly, the cuckoo algorithm also suffers from the problem of falling into local optimal solutions, and both are sensitive to parameter settings.

Over the past few years, a wide range of mathematical optimization methods based on linear and nonlinear programming methods have been applied to solve a variety of optimization problems in both scientific fields and engineering [6]. At the same time, significant progress has been made in Monte Carlo methods, so-called Monte Carlo (MC) methods, which comprise a large class of stochastic simulation techniques that can be used to solve many optimization and inference problems in science and engineering. Essentially, MC methods proceed by obtaining a large pool of potential values for a desired parameter and replacing the integral with the sample mean. In practice, these parameter values can be obtained either by physically replicating the desired experiment or by probabilistically describing it and generating a set of random realizations [7]. It has nowadays turned into a powerful simulation tool that is widely used in a variety of engineering fields. For many years, Metropolis Monte Carlo has been used to simulate dense phases of polymer systems with great success [8]. In other fields, Yagang Zhang's team incorporates effective modal identification, uses different prediction methods based on modal characteristics, and proposes a new set of optimization algorithms to improve nonlinear prediction. Finally, based on Monte Carlo theory, a set of interval prediction schemes that can adapt to different error characteristics is proposed. The results show that this prediction system significantly outperforms all comparative prediction schemes [9]. Christopher R. John developed Monte Carlo-quoted consensus clustering (M3C) based on Monte Carlo references, which corrects the inherent bias of consensus clustering [10]. In summary, Monte Carlo methods are good at dealing with complex uncertainty; they have high flexibility and adaptability, are suitable for high-dimensional, nonlinear problems, and can reduce the risk of falling into a locally optimal solution to a certain extent; and they can generate probability distributions of the results, visualize the range of potential risks, and help decision makers quantify the risks, which is superior to heuristic algorithms (e.g., Cuckoo's algorithm, PSO) that only provide a single optimal solution. Linear programming, on the other hand, excels in high efficiency, low resource requirements, and multi-objective trade-offs. The combination of the two can make up for the shortcomings of other methods in terms of subjectivity, local optimality, and technology dependence, which is especially suitable for multidimensional, dynamic, and resource-constrained scenarios in agricultural optimization. Therefore, this paper proposes a linear programming model to solve the stagnation problem as well as a simulation applying the Monte Carlo algorithm to cope with the effects of uncertainties.

## 2. Model Establishment

### 2.1. Establishment of the linear programming model

Linear programming aims to maximize or minimize a linear objective function, which, at the same time, satisfies a set of linear constraints. The purpose of this constructed linear programming model is to plan the optimal planting strategy for a rural village in China for the next seven years, so the objective function is to maximize the revenue from planting, maximize the profit, and ensure that the crop sales are within the desired range. The constraints are limited arable land resources: 1201 mu of open arable land, 16 ordinary greenhouses, and 4 intelligent greenhouses. Crop growth pattern: the same piece of land can not be continuously re-cropped for a crop; at least once in three years to plant legumes. Consider the cost price and sales volume of all kinds of crops in 2023, as well as the trend of market demand changes in the next few years.

This article now makes the following premise assumptions:

(1) Assume that the area of each type of cropland is fixed and remains constant for a long time to come.

(2) Assume that the types of crops are fixed and remain the same in the coming years.

(3) Assume that based on the data on market demand in 2023 and the market development trend in the next few years, it is possible to predict the market demand for each type of crop in recent years, i.e., the expected sales volume, cost, and selling price of each crop in the next few years will be the same as that in 2023.

With the expected sales volume, planting cost, mu yield, and sales price remaining stable relative to 2023, this article needs to do two kinds of treatments for the portion of the crop that exceeds the expected sales volume; the first is that the portion of the crop that exceeds the expected sales volume is stagnant, i.e., it results in wastage and no revenue, and the second is that the portion of the crop that exceeds the expected sales volume is sold at half of the sales price. For each of these two scenarios, the optimal cropping program for the countryside for the years 2024 - 2030 is given.

### 2.1.1 The case where the stagnant portion is completely wasted

Construct the objective function:

$$max\sum_{t=2024}^{2030}\sum_{i,j}(C_j * X_{i,j,t} * \min\{P_j * C_j * X_{i,j,t}, L_{j,t}\} - B_j * X_{i,j,t}) \tag{1}$$

Where $C_j$ is the acre yield of the j-th crop; $X_{i,j,t}$ is the area of the j-th crop planted on the i-th plot in year t; $P_j$ is the selling price of the j-th crop; $L_{j,t}$ is the expected sales volume of the j-th crop in year t; and $B_j$ is the cost of cultivation of the j-th crop.

Constraints:

(1) Non-negative constraints: the area planted for each crop cannot be negative.

$$X_{i,j,t} \geq 0 \tag{2}$$

(2) Plot size constraints: each piece of arable land has a finite area, and the area of the planted crop should be less than or equal to the total area of the plot.

$$\sum_{j} x_{i,j,t} \leq S_i \tag{3}$$

Where $S_i$ is the area of the i-th parcel.

(3) Legume constraints: Legumes have beneficial soil fertility factors such as rhizobacteria and need to be planted at least once every three years per plot.

$$\sum_{j \in J_{beans}} x_{i,j,\mathrm{t}} \geq 1, \quad (\forall i \in I) \tag{4}$$

(4) Minimum planting area constraint: To facilitate field management, the planting area of each crop grown on each plot should not be too small.

$$x_{i,j,\mathrm{t}} \geq m_j, (\forall i \in I, \forall j \in J) \tag{5}$$

Where $m_j$ is the minimum planting area of the j-th crop.

(5) Heavy crop planting constraints: due to the land fertility problem, if the same piece of land is planted with the same crop for many seasons in a row, it will make the soil fertility decline, which will lead to a reduction in crop yields, to avoid this situation, it is required that the same piece of land can not be planted in a row.

$$X_{i,j,t} \leq M * (1 - X_{i,j,(t-1)}), (i, j, t > 1) \tag{6}$$

Where $M$ is an arbitrarily large number.

(6) Rice planting constraints: It is appropriate to plant one season of rice or two seasons of vegetables per year on irrigated land, i.e., if rice is planted on irrigated land, no more vegetables can be planted there.

$$x_{i,paddy} * \sum_{j \in I \setminus \{paddy\}} x_{i,j,t} = 0(\forall i \in I_{irrigable\_land}) \tag{7}$$

### 2.1.2 Half-price sale of the unsold portion

Based on the model that exceeds the part of stagnant sales, this article only needs to change the objective function to get the mathematical model that exceeds the part of the half-price sale. That is, this article only needs to change the objective function, decision variables and constraints remain unchanged.

Modified objective function: This article only needs to subtract 50% of the lost sales from the original model's objective function for the production that exceeds the expected sales volume.

$$max\sum_{t=2024}^{2030}\sum_{i,j}(C_j * X_{i,j,t} * (P_j * \min\{C_j * X_{i,j,t}, L_{j,t}\} + 0.5 * P_j * \max\{C_j * X_{i,j,t} - L_{j,t}, 0\}) - B_j * X_{i,j,t}) \tag{8}$$

### 2.2. Planting planning model with uncertainties

According to experience, uncertain factors such as climate, market, and potential planting risks will lead to different degrees of growth or decline in the expected sales volume, mu yield, sales price, and planting cost of various crops. This article needs to consider the impact of these factors on rural development and give the optimal planting plan for crops from 2024 to 2030.

The introduction of risk assessment in problem-solving is important in today's era of smart agriculture and various strategy support systems. Its main purpose is to deal with the problem of uncertainty and volatility in agricultural production due to various factors. Due to the volatility of factors such as yields, prices, costs, and sales volumes, uncertainty can be dealt with through Monte Carlo simulation. Monte Carlo simulation is a numerical method to estimate the expected value of a problem through multiple random sampling. Its steps include:

1) Define the range of fluctuation for each variable (e.g. ±10% for acre yield, ±5% for expected sales volume, etc.).

2) Generate multiple possible planting scenarios: in each simulation, values are randomly selected from the fluctuating range of each variable to construct the complete scenario.

3) Calculate the total return under each scenario. Multiple scenario simulations allow for the calculation of the total return under various possible scenarios and the selection of the planting scenario that maximizes profit.

In this model, the core of the risk assessment is reflected in the setting of the risk coefficient $Q_{j,t}$. This article still considers the acreage of each crop on each plot in each season as the decision variable, and this article also consider $Q_{j,t}$ as the risk of growing each crop in each season. The constraints remain the same as in model 2.1. Next, the objective function is determined: our objective is to maximize the return from planting and minimize the risk of planting, taking into account the varying degrees of future uncertainty on crop yields, costs, and sales:

$$max\sum_{t=2024}^{2030}\sum_{i\in I}\sum_{j\in J}\left(\left(C_{j,t}*P_{j,t}-B_{j,t}\right)*X_{i,j,t}-Q_{j,t}*X_{i,j,t}\right)-100*\sum_{t=2024}^{2030}\sum_{i\in I}\sum_{j\in J}Q_{j,t}*X_{i,j,t} \tag{9}$$

Where $C_j$ is the yield of crop j in year t, which fluctuates by 10% per year; $P_{j,t}$ is the selling price of crop j in year t, which fluctuates according to the corresponding trend; $B_{j,t}$ is the cost of growing crop j in year t, which increases by 5% per year; and $Q_{j,t}$ is the risk score of crop j in year t.

## 3. Model Solving

### 3.1. Solving the linear programming model

The results of the optimization analysis for the stagnant case (only some of the results are shown) are displayed in Table 1:

**Table 1.** Optimization results in the wastage of slow-moving crops

| year | quarter of a year | parcel name | blade bean | cabbage | cucurbit | potato |
|---|---|---|---|---|---|---|
| 2024 | first quarter | A1 | 0 | 0 | 16 | 0 |
| 2024 | first quarter | A2 | 0 | 0 | 0 | 0 |
| 2024 | first quarter | A3 | 0 | 0 | 0 | 0 |
| 2024 | first quarter | A4 | 0 | 0 | 0 | 7.2 |
| 2024 | first quarter | A5 | 0 | 6.8 | 6.8 | 0 |
| 2024 | first quarter | A6 | 5.5 | 0 | 0 | 0 |
| 2024 | first quarter | B1 | 0 | 6 | 0 | 0 |
| 2024 | first quarter | B2 | 0 | 0 | 0 | 0 |
| 2024 | first quarter | B3 | 4 | 4 | 4 | 0 |

The results of the optimization analysis for the case where the overproduction is sold at 50% (only partial results are shown) are presented in Table 2:

**Table 2.** Optimization results for the case of selling 50% of the overproduction

| year | quarter of a year | parcel name | blade bean | cabbage | cucurbit | potato |
|---|---|---|---|---|---|---|
| 2024 | first quarter | A1 | 8 | 0 | 0 | 0 |
| 2024 | first quarter | A2 | 5.5 | 5.5 | 0 | 0 |
| 2024 | first quarter | A3 | 3.5 | 0 | 0 | 3.5 |
| 2024 | first quarter | A4 | 0 | 0 | 7.2 | 0 |
| 2024 | first quarter | A5 | 6.8 | 0 | 0 | 0 |
| 2024 | first quarter | A6 | 0 | 5.5 | 0 | 5.5 |
| 2024 | first quarter | B1 | 0 | 0 | 0 | 0 |

Tables 1 and 2 show the results of some of the optimal planting strategies, and this result can serve as a degree of reference for the planning of the planting industry in this village for the next seven years.

The purpose of the planting strategy represented in Table 1 is to maximize the return within the expected sales volume while minimizing the risk of stagnation, this planting scheme will first strictly adhere to the planting constraints to ensure that the risk of stagnation is minimized, and selecting higher yielding crops within the constraints is a relatively conservative strategy.

In contrast, the planting strategy expressed in Table 2 aims at maximizing the total return, including the expected sales volume return and the half-price return on the stagnant portion of the sale. This planting scheme will be more inclined to increase the acreage of high-yielding crops to obtain higher total returns. Thus the total return may be higher than in the case of wastage of the stagnant portion, but it is also exposed to a higher risk of stagnation.

### 3.2. Solving planting planning models with uncertainties

The linear programming model is solved using the pulp library function in Python to solve for the change in total annual returns.

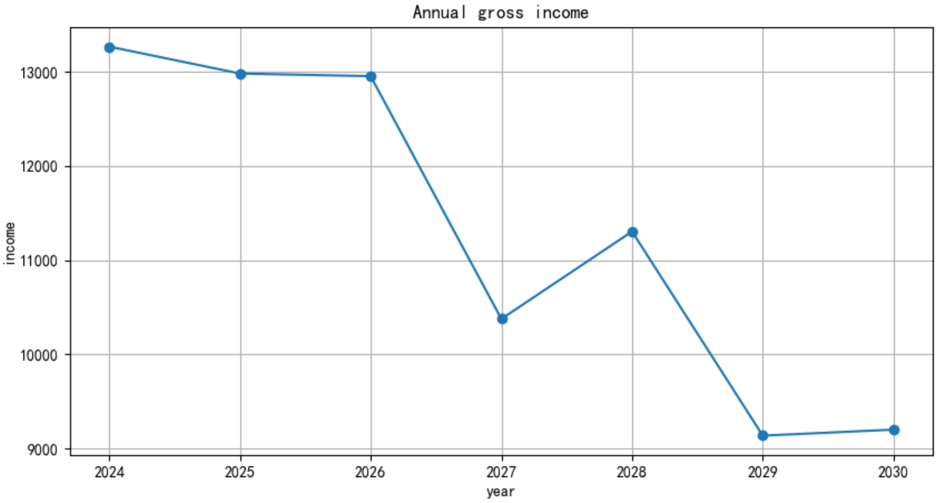

**Figure 1.** Gross proceeds by year

As can be seen in Figure 1, there is a general downward trend in total annual returns in the coming years, and the downward trend in total returns in the coming years may be due to a combination of factors such as fluctuating market demand, unfavorable climatic conditions, rising planting costs, falling selling prices, accumulation of risk factors, and limitations in modeling assumptions.

The change in acreage per year for each crop (presented in seven groups) is shown in Figure 2:

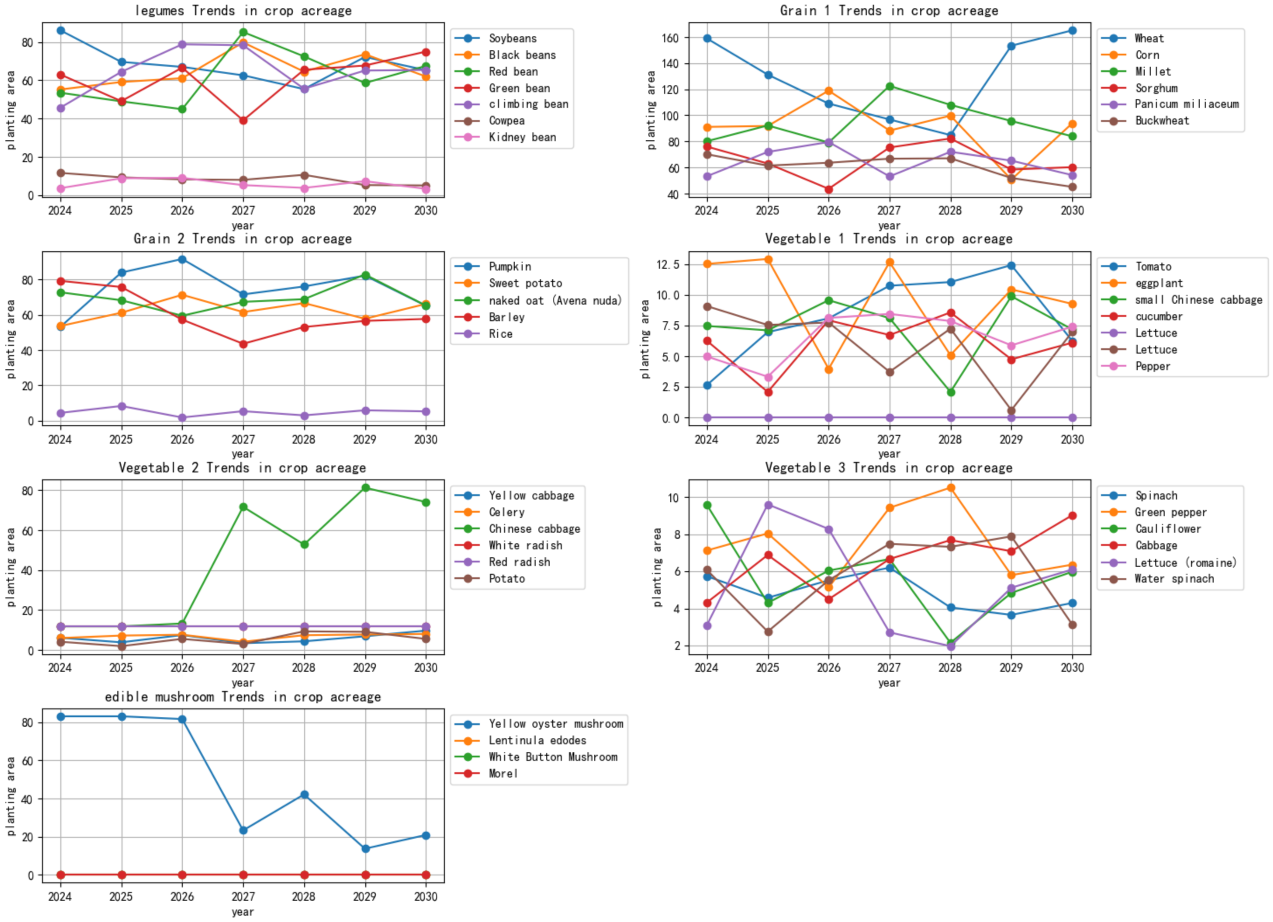

**Figure 2.** Crop cultivation by year

From Figure 2, it can be visualized that to cope with the changes in the expected sales volume, planting cost, and sales unit price caused by climate, market, and other factors. The model gives the corresponding planting strategy to ensure the development of the rural planting industry, improve the economic benefits of the planting industry, and promote the sustainable development of the rural planting Industry.

## 4. Conclusion

This paper investigates crop planting planning in a rural village in China by establishing a linear programming model and applying the Monte Carlo algorithm. Firstly, this paper gives the optimal planting plans for the next seven years under the two situations of the crops being wasted in the stagnant part of the market and the stagnant part of the market being sold at half price. These plans can provide a certain value of reference for the local crop planting industry. It can be inferred that the benefit of selling the stagnant part at half price will be greater than that of wasting the stagnant part, but if planting according to the former plan, it will increase the risk of stagnation. Subsequently, this paper uses the Monte Carlo algorithm to introduce the uncertain factors brought by climate and market changes and gives the crop planting planning for the next seven years under the influence of uncertain factors. The results show a higher income for the next three years of cropping planning, followed by a decline, which may be due to market changes or the continued deterioration of climate change. To cope with the effects of these uncertainties, planting industry practitioners can hedge their risks by appropriately increasing the amount of farmland and introducing crops with higher economic value, among other measures. The results also provide valuable references for other agricultural regions facing similar problems. By taking climate and market uncertainties into account, this study can not only help improve the economic efficiency of agriculture in the region but also support the sustainable development of agriculture globally.

## References

[1] Jiang Y, Wang T, Zhao H, et al. Big data analysis applied in agricultural planting layout optimization [J]. Applied engineering in agriculture, 2019, 35 (2): 147-162.

[2] Hu M, Tang H, Yu Q, et al. A new approach for spatial optimization of crop planting structure to balance economic and environmental benefits [J]. Sustainable Production and Consumption, 2025, 53: 109-124.

[3] Wang J, Wang Y. Multi-stage Crop Planting Strategy Optimization Model Based on PSO Algorithm [C] // 2024 3rd International Conference on Electronics and Information Technology (EIT). IEEE, 2024: 915-919.

[4] Zhang F, Yue Q, Engel B A, et al. A bi-level multiobjective stochastic approach for supporting environment-friendly agricultural planting strategy formulation [J]. Science of The Total Environment, 2019, 693: 133593.

[5] Chaux J D, Sanchez-Londono D, Barbieri G. A digital twin architecture to optimize productivity within controlled environment agriculture [J]. Applied Sciences, 2021, 11 (19): 8875.

[6] Braik M S. Chameleon Swarm Algorithm: A bio-inspired optimizer for solving engineering design problems [J]. Expert Systems with Applications, 2021, 174: 114685.

[7] Luengo D, Martino L, Bugallo M, et al. A survey of Monte Carlo methods for parameter estimation [J]. EURASIP Journal on Advances in Signal Processing, 2020, 2020: 1-62.

[8] Mavrantzas V G. Using Monte Carlo to simulate complex polymer systems: Recent progress and outlook [J]. Frontiers in Physics, 2021, 9: 661367.

[9] Zhang Y, Zhao Y, Shen X, et al. A comprehensive wind speed prediction system based on Monte Carlo and artificial intelligence algorithms [J]. Applied Energy, 2022, 305: 117815.

[10] John C R, Watson D, Russ D, et al. M3C: Monte Carlo reference-based consensus clustering [J]. Scientific Reports, 2020, 10 (1): 1816.