Transactions on Environment, Energy and Earth Sciences
ISSN: 2960-1924, eISSN: 2960-2300 | Volume 4
GEMFE 2024

Research on Optimization of Crop Planting Strategies Based on Linear Programming and Monte Carlo Methods Abstract

Yibo Shang

School of Computer Science and Engineering, Northeastern University, Shenyang, China, 110169

20235769@stu.neu.edu.cn

Abstract. With global population growth and climate change impacting agriculture, optimizing crop planting strategies is essential. This study aims to maximize net returns from limited land and climatic conditions using a linear programming model combined with Monte Carlo simulation. Two scenarios were considered: excess yield either wasted or sold at a reduced price. By simulating various planting strategies, the optimal scheme was identified. The results indicated that the highest total return of 9,323,486.21 was achieved in 2025, while the return in 2028 was lower at 8,695,777.98. This research provides valuable insights into improving agricultural productivity and profitability.

Keywords: Crop planting strategies; Monte Carlo simulation; linear programming.

1. Introduction

With the continuous growth of the global population and the uncertain impact of climate change on agricultural production, how to optimize crop planting strategies and maximizing agricultural production benefits under limited land resources and changing market demands has become a crucial issue. Especially in areas with special climatic conditions, such as the mountainous regions of North China, rational use of limited arable land resources and scientific arrangement of crop cultivation to improve the benefits of agricultural production are the keys to promoting the sustainable development of the rural economy. Traditional agricultural production methods often rely on experience and simple rules, making it difficult to cope with complex market fluctuations and environmental changes. Therefore, it is of great practical significance to optimize agricultural production based on advanced mathematical models and computational methods.

In this paper, a combination of linear programming [1] and Monte Carlo simulation [2-3] is used to address this problem. Linear programming is a mature optimization technique widely used in resource allocation and production planning, while Monte Carlo simulation provides an effective tool for solving complex optimization problems through random generation and statistical analysis. The combination of these two methods can effectively deal with the uncertainty and complexity of agricultural production. On this basis, this study developed a linear programming model to maximize net returns [4-5] and solved it using Monte Carlo simulation [6-7]. The model considers different stunting treatment situations and randomly simulates multiple cropping strategies under constraints such as plot size and crop rotation rules, and finally proposes an optimal crop cultivation scheme.

In this study, this study first carry out data (crop cultivation in 2023 and related statistical data) preprocessing, organize, merge, and standardize the data for different plots in terms of cultivation area, production, sales price, cost, etc., and also select the median sales unit price of each crop as the benchmark price to ensure the accuracy and relevance of the model inputs. Subsequently, a linear programming model was established, with x_{ijt} (the area of the i-th piece of land used for planting the j-th crop in the t-th year) as the decision variable; planting area, land type, season, temperature, etc. as the constraints; according to the two scenarios of overproduction, stagnant sales, and 50% price reduction, the objective function was given; finally, the constraints were added, and the Monte Carlo model was developed according to the requirements of the crops planted in each type of plot and the annual crop rotation limitations, using the Monte Carlo model. For crop rotation restrictions, the Monte Carlo algorithm [8-10] is utilized to solve the linear programming model, which results in the optimal planting scheme from 2024 to 2030, respectively. Through these steps, this study expect to provide a scientific decision-support tool for agricultural production to cope with various challenges in modern agricultural production and ultimately maximize economic benefits.

2. Data sources and crop cultivation analysis

Data for this study was obtained from http://cucmc.cnki.net. The crop cultivation and related data were merged using Python's built-in merge function, connecting the crop cultivation data from Annex 2 with relevant statistics. This study consolidates this information into Table 1.

Table 1. Crop cultivation (partial)

serial number	name	typology	planting area	order of seasons	Type of plot	mu yield	Cost of cultivation	unit price of goods sold	sales volume
6	maize	foodstuff	80	single season	semi-arid	800	450	3.00-4.00	64000
6	maize	foodstuff	80	single season	stepped fields	760	450	3.00-4.00	60800
6	maize	foodstuff	80	single season	hillside	720	450	3.00-4.00	57600
28	bok choy	fruits	0.6	first quarter	wetland	3200	1600	5.00-6.50	1920
28	bok choy	fruits	0.6	first quarter	greenhouse	4000	2000	5.00-6.50	2400
28	bok choy	fruits	0.6	first quarter	intelligent greenhouse	3600	2200	6.00-7.80	2160
23	broccoli	fruits	0.3	second quarter	wetland	2700	2300	4.80-6.70	810
23	broccoli	fruits	0.3	second quarter	greenhouse	3300	2700	4.80-6.70	990
23	broccoli	fruits	0.3	second quarter	intelligent greenhouse	3000	3000	5.80-8.00	900

Due to the volatility of market prices, it is necessary to determine the unit price and sales volume of each crop. Based on the data obtained in (1), the price range in the “unit price/(yuan/column)” is divided into two intervals, and then a function is defined to calculate the actual sales price of each row.

Assuming that the unit sales price of crop j fluctuates between $s_{j,\min}$ and $s_{j,\max}$, the actual sales price s_j is calculated using the following formula:

$$s_j = s_{j.\min} + random \times (s_{j.\max} - s_{j.\min}) \tag{1}$$

random is a random value generated in [0, 1].

Total Sales: $\sum_j q_j$

Average sales unit price:

$$\bar{s} = \frac{\sum_j (s_j \times q_i)}{\sum_j q_i} \tag{2}$$

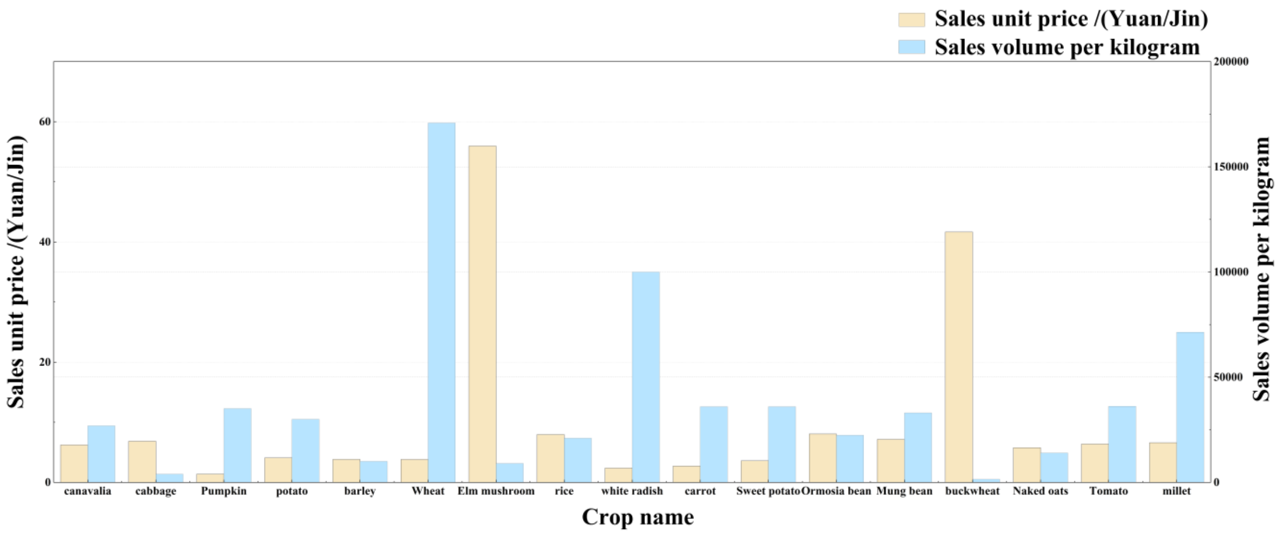

Figure 1. Pre-sale unit prices for sales volume (partial)

Based on the restrictions on crop plots in Figure 1, the data were collated and Table 2 was obtained.

Table 2. Crop cultivation restrictions (partial)

serial number	name	Typology	Semi-arid	Stepped fields	hillside	wetland	First season of watered land	Common shed first season	Smart Shed Season 1
1	soya bean	Grain (legumes)	1	1	1	0	0	0	0
2	black soybean	Grain (legumes)	1	1	1	0	0	0	0
3	azuki bean	Grain (legumes)	1	1	1	0	0	0	0
28	bok choy	fruits	0.6	first quarter	wetland	3200	1600	5.00-6.50	1920
28	bok choy	fruits	0.6	first quarter	greenhouse	4000	2000	5.00-6.50	2400
28	bok choy	fruits	0.6	first quarter	intelligent greenhouse	3600	2200	6.00-7.80	2160
23	broccoli	fruits	0.3	second quarter	wetland	2700	2300	4.80-6.70	810
23	broccoli	fruits	0.3	second quarter	greenhouse	3300	2700	4.80-6.70	990
23	broccoli	fruits	0.3	second quarter	intelligent greenhouse	3000	3000	5.80-8.00	900

3. Modeling and solving

3.1. Modeling linear programming

Linear programming models have a wide range of applications in the field of agricultural production and resource allocation, aiming to maximize economic efficiency by optimizing the use of resources (e.g., land, cost, etc.).

Given constraints such as limited land resources, different types of land, specific cropping methods, market demand, planting order, and season, this study need to determine the optimal area (decision variable denoted as x_{ijt}) of each crop (denoted as j) to be planted on each piece of land (denoted as i) within each year (denoted as t) to maximize the total profit.

For case 1, the overproduced portion of the crop is stagnant and constitutes a direct loss, the objective function is constructed as follows:

$$\max z = \sum_{i=1}^{52}\sum_{j=1}^{41}\sum_{t=1}^{7} x_{ijt} q_j s_j - \sum_{i=1}^{51}\sum_{j=1}^{41}\sum_{t=1}^{7} x_{ijt} c_j \tag{3}$$

For scenario 2, the overproduced portion of the crop is sold at a 50% price reduction and the objective function is changed:

$$\max z = \sum_{i=1}^{51}\sum_{j=1}^{41}\sum_{t=1}^{7} (x_{ijt} q_j s_j - x_{ijt} c_j + x_{ijt} \cdot (p_j - q_j) \cdot s_j \cdot 0.5) \tag{4}$$

This paper follows the crop numbers and plot names in the annex. The given constraints are as follows:

(1) Plot area constraints:

The sum of the crop acreage of each plot (i) in each year (t) must not exceed the total acreage of the plot.

(2) Crops are matched to plot types:

Only food crops numbered 1-15 can be grown on flat and dry land, terraced land, and hillside land; crops numbered 16 and above cannot be grown.

Watered land can grow crops numbered 16 (rice) or two seasons of numbered 17-37 (vegetables) per year.
Ordinary greenhouses can grow vegetables numbered 17-37 in the first season and only edible mushrooms numbered 38-41 in the second season.

Smart greenhouses can grow vegetables numbered 17-37 in both seasons, but are not allowed to grow crops numbered 35 (cabbage), 36 (white radish), or 37 (red radish).

(3) Legume crop rotation constraints:

Legume crops numbered 1,2,3,4,5,17,18,19 shall be planted in each plot at least once in three years.

(4) Crops cannot be planted consecutively in the same plot:

The same crop cannot be planted consecutively in the same plot in the same year (to avoid yield reduction due to heavy cropping).

(5) Limitations on market demand for crops:

The total production (area planted multiplied by unit yield P_j) of each crop per year must not exceed its expected sales volume q_j.

(6) Sequencing constraints for crops grown in watered land:

If two seasons of vegetables are planted in watered land, a variety of vegetables except cabbage, white radish, and carrot may be planted in the first season; only one of cabbage, white radish, and carrot may be planted in the second season, and these three crops may be planted only in the second season of watered land.

(7)Seasonal planting restrictions for greenhouses:

Ordinary greenhouses must grow edibles numbered 38-41 in the second season of each year; smart greenhouses are not allowed to grow cabbage, white radish, or red radish in any season.

In summary, a mathematical model of the problem can be developed as:

Situation 1:

$$\max z=\sum_{i=1}^{52}\sum_{j=1}^{41}\sum_{t=1}^{7}x_{ijt}q_js_j-\sum_{i=1}^{51}\sum_{j=1}^{41}\sum_{t=1}^{7}x_{ijt}c_j \tag{5}$$

Situation 2:

$$\max z=\sum_{i=1}^{51}\sum_{j=1}^{41}\sum_{t=1}^{7}(x_{ijt}q_js_j-x_{ijt}c_j+x_{ijt}\cdot(p_j-q_j)\cdot s_j\cdot 0.5) \tag{6}$$

$$s.t.\begin{cases}\sum_j x_{ijt}\le landarea(i),\forall i,\forall t\\ x_{ijt}=0,\forall j\in\{16,17,...,41\},\forall i\in\{A,B,C\},\forall t\\ \sum_j x_{ijt}^{vegetable}\le 2,\forall i\in D,\forall t\\ x_{ijt}^{s2}=0,\forall j\notin\{38,39,40,41\},\forall i\in E,\forall t\\ x_{ijt}^{s2}=0,\forall j\notin\{35,36,37\},\forall i\in F,\forall t\\ \sum_{t=1}^{3}x_{ijt}\ge 1,\forall i,\forall j\in\{1,2,3,4,5,17,18,19\}\\ x_{ijt}\cdot x_{ij,t+1}=0\qquad \forall i,\forall j,\forall t\\ x_{ijt}^{s2}=0,\forall j\notin\{35,36,37\},\forall i\in D,\forall t\end{cases} \tag{7}$$

3.2. Monte Carlo solution model

The Monte Carlo method is a stochastic simulation technique based on probabilistic and statistical principles, which solves various problems by generating random numbers (or pseudo-random numbers). This method connects the problem to be solved with the corresponding probabilistic model and uses a computer to perform statistical simulation or sampling to obtain an approximate solution to the problem.

To address this problem, this paper applies the algorithm to the optimization of planting strategies, firstly, randomly generating planting strategies, establishing a function with the gain obtained as the objective, and repeating the simulation, generating a large number of random strategies to be compared, and selecting the maximization of the gain planting scheme.

In the Monte Carlo algorithm, each iteration randomly generates the planting area $X_{i,j}$, and net income will also change, and the steps to solve this are as follows:

(1) Initialization

Input data on plot type, crop, and planting rules and set the number of simulations n.

(2) Stochastic simulation cycle

Randomized planting strategies, i.e., generating different crop combinations for each plot, are generated based on crop suitability, crop rotation rules, and plot size.

(3) Calculation of the objective function

$$\max z=\sum_{i=1}^{51}\sum_{j=1}^{41}\sum_{t=1}^{7}(x_{ijt}q_js_j-x_{ijt}c_j+\max(0,x_{ijt}\cdot(p_j-q_j)\cdot s_j\cdot 0.5)) \tag{8}$$

(4) Strategy Screening

Complete n simulations, record the net benefit z for each simulation, and screen for the planting scenario with the highest net benefit.

(5) Determination of optimal program

The option with the highest net return z is selected as the optimal crop planting plan.

4. Model output and benefit analysis

(1) Model convergence iterations

During the convergence iterations of the model, this study not only ensured that the cropping schemes were in line with land types, crop rotation regulations, and seasonal demands but also sought to maximize agricultural returns. By selecting the scenarios with the highest net returns from a large random sample, this study aim to develop an optimal strategy for the crop planting program from 2024 to 2030. Using a village as a case study, this paper designed a multi-season optimal yield cropping scheme, set up 200 iterations, and plotted in Fig. 2 to show the changes in the objective values.

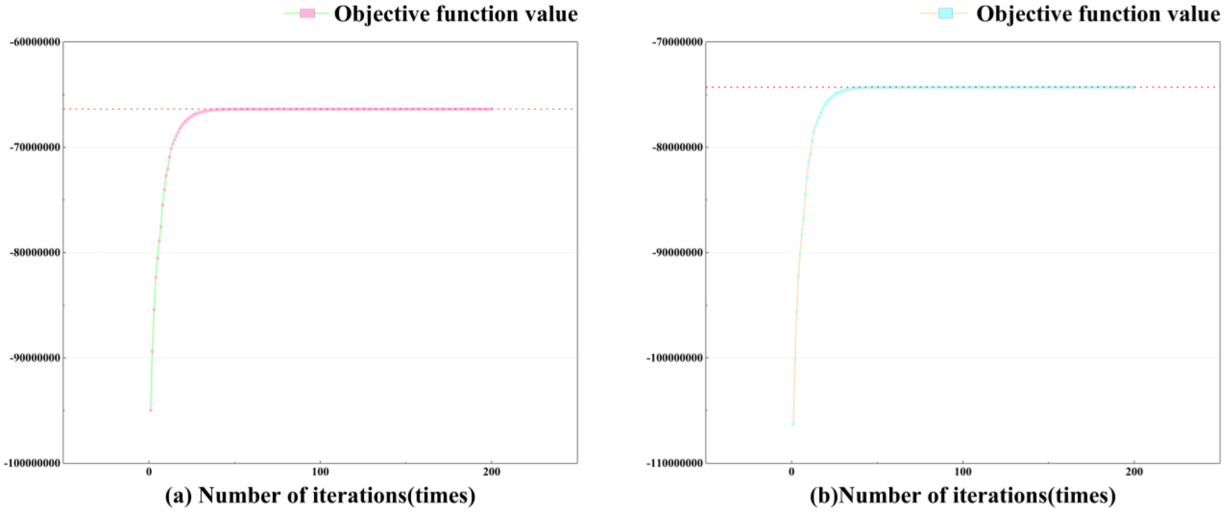

Figure 2. Iterative plot of target value changes under different cases. (a) Case 1. (b) Case 2.

(2) Optimal cropping program for crops from 2040 to 2030

Table 3. Selected planting strategies for the first scenario in 2024 (partial)

tectonic plate	soya bean	black soybean	azuki bean	mung bean	soya bean	shiitake mushroom	enoki mushroom	morel mushrooms
A1	8	8	8	8	0	0	0	0
A2	5.5	5.5	0	0	0	0	0	0
A3	0	0	3.5	0	0	0	0	0
C1	1.5	1.5	1.5	1.5	0	0	0	0
C2	1.3	1.3	0	0	0	0	0	0
C3	0	1.5	0	1.5	0	0	0	0
F1	0	0	0	0	0	0	0	0
F2	0	0	0	0	0	0	0	0
F3	0	0	0	0	0	0	0	0

Table 4. Selected planting strategies for the second scenario in 2024 (partial)

tectonic plate	soya bean	black soybean	azuki bean	mung bean	soya bean	shiitake mushroom	enoki mushroom	morel mushrooms
A1	8	0	0	8	0	0	0	0
A2	5.5	5.5	5.5	0	0	0	0	0
A3	3.5	3.5	3.5	0	0	0	0	0
C1	0	0	1.5	1.5	0	0	0	0
C2	0	0	0	1.3	0	0	0	0
C3	1.5	0	1.5	1.5	0	0	0	0
F1	0	0	0	0	0	0	0	0
F2	0	0	0	0	0	0	0	0
F3	0	0	0	0	0	0	0	0

Table 3 and Table 4 shown the different planting strategies for different case. After optimizing the cropping strategy for the years 2024 to 2030, the yield results for each year were obtained.

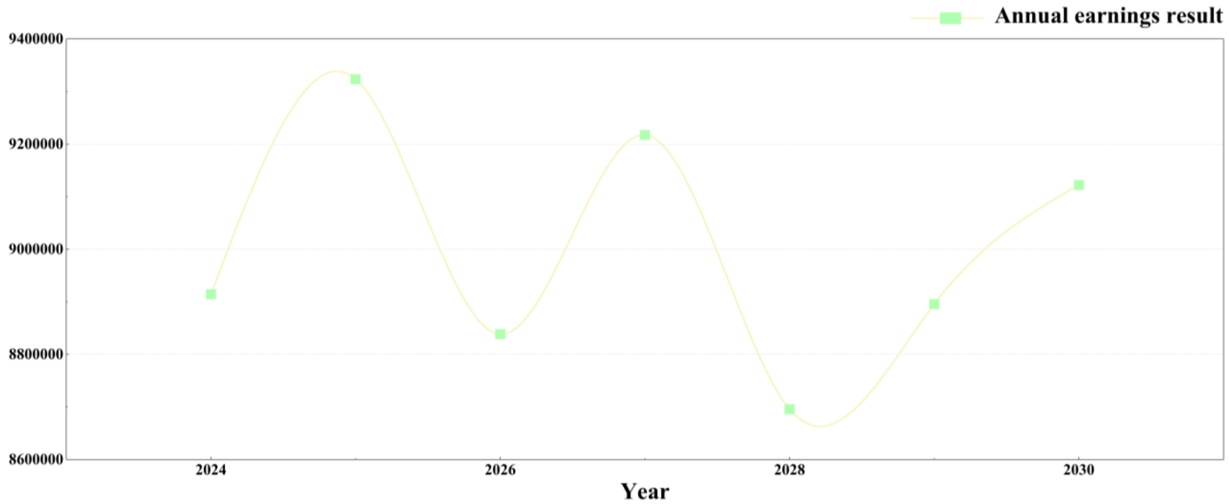

Figure 3. Optimized annual return results

From the results shown in Figure 3, the year 2025 had the highest total return of 9,323,486.21 over the period. In contrast, the year 2028 had a relatively low total return of 8,695,777.98 Overall, the returns fluctuated considerably from year to year, and this fluctuation may be related to adjustments in soybean planting strategies and how the lagging portion of the crop is treated.

5. Conclusion

In this study, crop planting strategies were optimized through an approach based on linear programming and Monte Carlo simulation. The results of the study show that the complexity and uncertainty in agricultural production can be effectively dealt with using this method. The highest total return of 9,323,486.21 was achieved in 2025 considering stunting losses, compared to 8,695,777.98 in 2028. This optimization scheme not only improves the overall economic efficiency but also provides an effective solution strategy when dealing with different stunting scenarios. Through several simulations and iterations, this study arrive at the optimal planting scheme, which provides a scientific basis for decision-making in agricultural production in the coming years. This paper provides a new research idea and framework applied to the field related to agricultural economic optimization and verifies the feasibility of the method. The combined method of linear programming and Monte Carlo simulation is used to effectively optimize resource allocation and cope with the uncertainty of market demand and climate change. This study not only proves the effectiveness of the method used in agricultural economic optimization but also provides an important reference for further research and practice in related fields. The application of this method can help to solve complex problems in agricultural production and maximize economic benefits.

References

[1] Chu Yuhong, Cha Chufan. Optimizing production measures of small fine chemical enterprises based on linear programming [J]. Chemical Management, 2024 (11): 139-141.

[2] Zhang Yongqiao. Reliability analysis of power supply based on Monte Carlo algorithm for distribution network regulation and operation [J]. Automation and Instrumentation, 2024 (6): 136-139.

[3] MA Jialiang, XU Xusong, XUE Yaoyang, et al. Application of Monte Carlo method in tolerance analysis of gearbox [J]. Southern Agricultural Machinery, 2024, 55 (14): 10-14.

[4] Deng Xinguo, Ye Xijin, Chen Jiarui. Combining heuristic algorithms with improved integer linear programming for ordered escape wiring [J]. Computer Integrated Manufacturing Systems: 1-21.

[5] QU Leifei, Dai Xiaoping, Liu Gang, et al. Optimization of diversion flow at the mouth gate based on linear optimization model [J]. Journal of North China University of Water Conservancy and Hydropower (Natural Science Edition): 1-8.

[6] PANG Zhongyuan, LUAN Qitong, XU Endong. Traveling wave fault localization in distribution network cable lines based on evolutionary Monte Carlo method [J]. Light Source and Lighting, 2024 (07): 66-68.

[7] ZHANG Yusheng, ZHANG Satellite, HAO Qiushi, et al. Monte Carlo simulation study of radiation field of carbon ion radiotherapy module based on GATE [J]. Industrial Metrology, 2024, 34 (03): 90-93. DOI: 10.13228/j.boyuan.issn1002-1183.2023.0174.

[8] WANG Yaqi, ZHANG Wen, WANG Jiahui, et al. A prediction method for calculating the cost of electric power project based on Monte Carlo algorithm [J]. Electrical Technology and Economy, 2024 (07): 256-258.

[9] Huang Mingqiao. Research on backgammon game algorithm based on Monte Carlo tree search [J]. Computer Knowledge and Technology, 2024, 20 (18): 15-18, 29.

[10] BAI Min, MA Zhaoyang, ZHOU Zixiang. A denoising method for seismic data based on Monte Carlo chunked pre-training dictionary [J]. Advances in Geophysics: 1-17.