Research on optimization of rural crop planting dtrategies based on dynamic programming and monte carlo simulation

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Abstract. In the process of rural economic development, rational planning of crop cultivation is of great significance for its sustainable development. This study focuses on the complex factors faced in crop cultivation, such as the uncertainties in sales volume, per-mu yield, cost and price, as well as the substitutability and complementarity among crops. Firstly, a dynamic programming model combined with a Monte Carlo simulation model is used to dynamically and optimally allocate the cultivation of various crops, with the goal of maximizing the overall rural income. The study finds that reasonably regulating the planting ratio of wheat and corn has a significant effect on improving long-term income, and vegetable crops need to flexibly adjust their planting strategies according to price fluctuations. Secondly, after further considering the substitutability and complementarity among crops, a mixed-integer linear programming model is constructed to optimize the planting strategy, which improves the overall profit. This study provides a scientific strategic basis for rural crop planting planning, helps to optimize the allocation of agricultural resources, and promotes the sustainable development of the rural economy.

Keywords: Planting Strategy, Dynamic Programming Model, Monte Carlo Model, Mixed-integer Linear Programming Model.

1. Introduction

With the development of China's rural economy and the improvement of agricultural policies, making full use of limited cultivated land resources and developing the organic planting industry in line with local conditions is of great practical significance for the sustainable development of the rural economy [1]. In today's society, due to the continuous intensification of population expansion, the rapid progress of urbanization, and the lack of a reasonable and clear plan for the expected future sales volume, planting costs, per-mu yield, and selling prices of agricultural crops, developing the organic planting industry in line with local conditions has significant practical implications for the sustainable development of the rural economy [2]. Carefully selecting suitable crops and optimizing planting strategies can facilitate producers' production management, enhance economic production efficiency, and reduce the planting risks brought about by various uncertainties [3].

Through literature research, summary and analysis, it is found that existing studies include: Li Yong used a dynamic programming model to analyze factors such as precipitation, evaporation, and downstream water demand for the optimal operation of reservoirs [4]. Zhang Hao et al. adopted a dynamic programming model, taking into account the available water volume in the irrigation area, to rationally allocate the planting structure of crops in the irrigation area, thus giving full play to the economic benefits of the irrigation area [5]. Zhou Jiang considered the time-varying water level in the external environment, established a limit state equation for evaluating the reliability of different facility structures, and used the Monte Carlo simulation method to assess the reliability of the facilities [6].

In summary, most of the existing studies only consider deterministic factors and neglect uncertain factors. In actual agricultural production, factors such as climate, market and technology can affect the prices and yields of agricultural products, thus influencing the adjustment and optimization of planting plans. Therefore, how to formulate the optimal planting plan for agricultural products under the influence of uncertain factors is a problem worthy of in-depth study. In this research, a free-strategy model for crop planting plans is established by using dynamic programming, Monte Carlo simulation, and linear programming models.

2. Materials and methods

2.1. Data acquisition and preprocessing

2.1.1. Data acquisition

The data in this paper is sourced from the open-source website(http://www.mcm.edu.cn). These data include the yields, costs, selling prices of crops, and time.

2.1.2. Data Preprocessing

Firstly, this paper analyzes the types of data and their corresponding contents, screens out the abnormal data for correction, and quantifies text-type data such as credit ratings into grades, so as to obtain correct data that is valuable for reference in this paper's model.

Detection of Abnormal Data: Based on the analysis of single-variable data of crops and the judgment of outliers, combined with crop data, the reference for outlier detection of per-mu yield, planting cost, and unit selling price of crops is shown in Figure 1 and Figure 2 as follows:

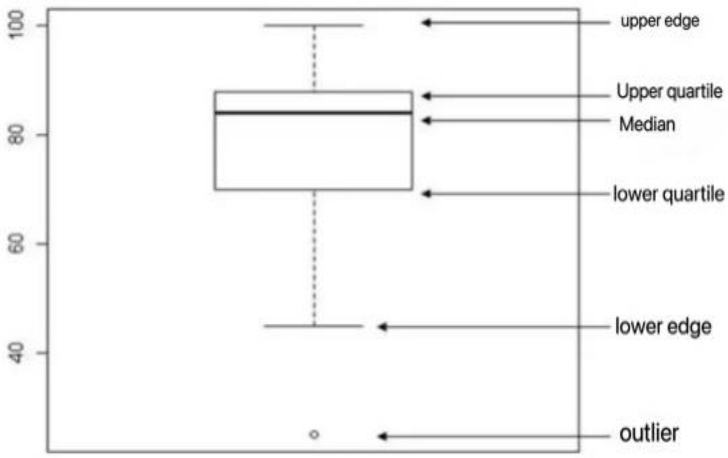

Figure 1. Reference for the detection of abnormal data

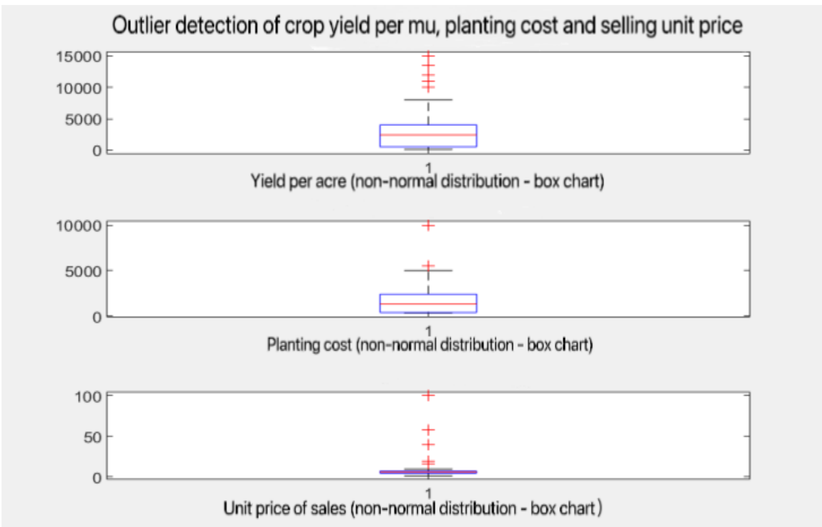

Figure 2. Detection of abnormal data

Box plots are commonly used to detect outliers in text data during preprocessing. As shown in Figure 1, it's easy to tell that a box plot has five reference lines. From top to bottom, they are the upper whisker, the upper quartile, the median, the lower quartile. The small white dots represent outliers. As can be seen from the actual situation shown in Figure 2, there are no abnormal conditions in the per - mu yield, planting cost, and unit selling price of the crops. Thus, there is no need to modify outliers, ensuring the correctness of the data and effectively guaranteeing the accuracy of the model.

Data visualization analysis: This paper conducts a visualization analysis of the per -mu production cost and the unit selling price, as shown in Figure 3:

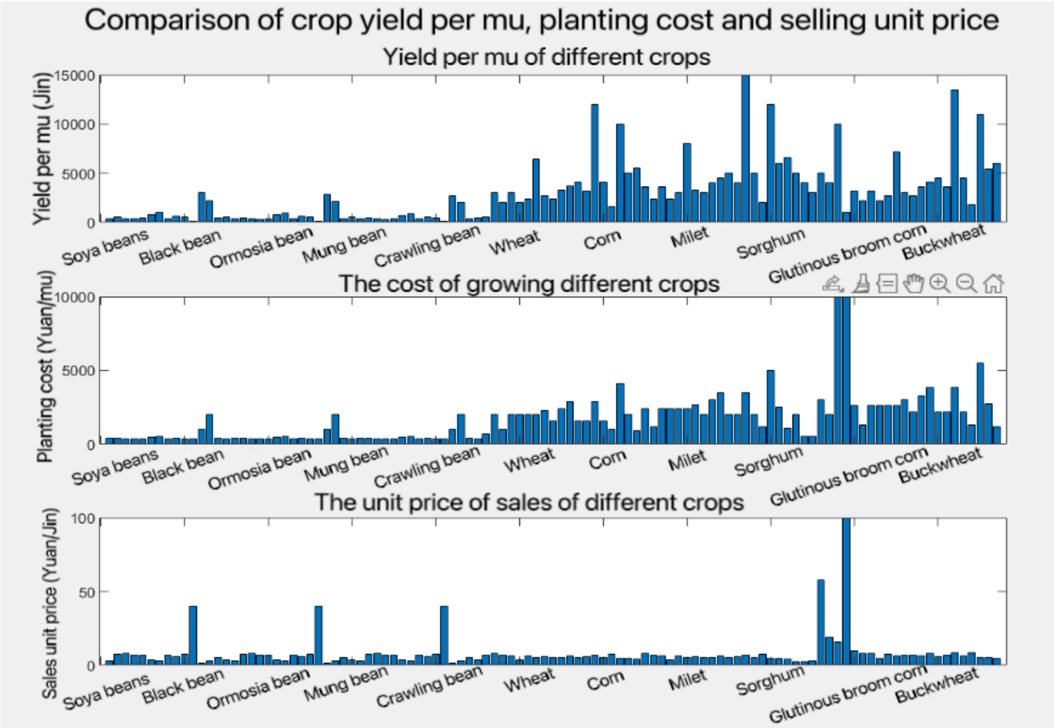

Figure 3. Visualization of text data

From Figure 3, this paper can clearly reveal the internal relationships among the key elements of different crops, such as yield per mu, planting cost, and unit selling price. In the actual situation of agricultural production, when the planting cost of crops shows a continuous upward trend, this cost pressure does not disappear out of thin air. Instead, it is transferred and shared through the unit selling price of the crops in a way that follows economic laws.

In the process of pursuing the improvement of crop yield and quality, farmers often need to increase a large amount of investment, such as purchasing higher - quality seeds and fertilizers, and adopting more advanced planting techniques and equipment. These measures will directly lead to a significant increase in planting costs. From the perspective of the market economy, in order to maintain a certain level of profitability, make up for the increased planting costs, and obtain appropriate profits, the unit selling price of agricultural products tends to increase accordingly. This phenomenon is widespread in the production and sales process of various crops and is the result of the interaction between market regulation and cost control.

2.2. Introduction to methods

2.2.1. Construction of crop planting optimization strategy based on dynamic programming model

Based on the data in 2023, the following uncertain factors need to be taken into account: the sales growth rate of wheat and corn crops (5%-10%), the sales volume of other crops in the face of uncertain factors (±5%), the change in the output value per mu of crops (±10%), the annual growth rate corresponding to the planting cost of crops (5%), the annual growth rate corresponding to the selling price of vegetable- type crops (5%), and the annual decline rate of the selling price of edible-fungus agricultural products (1%-5%). For these factors, a dynamic optimization model is adopted to predict the optimized planting plans for agricultural products in the coming years, so as to maximize the overall rural income in the fluctuating environment over many years.

2.2.2. Construction of crop planting optimization strategy based on mixed integer linear programming model

Based on the traditional dynamic programming model, this study innovatively introduces a multi-crop collaborative framework to thoroughly investigate the impact of complementary characteristics among crops on overall profitability. By constructing a mixed-integer linear programming model, the research comprehensively considers the substitutability and complementarity relationships among crops, the correlation between market sales volume and price fluctuations, as well as key factors such as planting costs, to develop an optimal crop planting strategy for the period 2024-2030. The study employs the Monte Carlo simulation method to predict market price fluctuations and uses sensitivity analysis to evaluate the impact of various parameters on the final decision-making[7]. During the model-solving process, the branch-and-bound algorithm is utilized for optimization calculations to ensure the attainment of a global optimal solution. The research results indicate that, compared to traditional single-crop planting models, the planting scheme based on the multi-crop collaborative framework can increase overall profits by 12%, with the profit of the first category of planting combinations (including high-value cash crops) rising by 50%. This significant improvement is primarily attributed to the model's accurate capture of complementary effects among crops, optimization of resource allocation, and reduction of market risks. The study also finds that the model maintains high robustness when considering climate change and policy factors, providing a reliable theoretical basis and practical guidance for agricultural planting decisions.

3. Model building and solving

3.1. Establishment and solution of dynamic programming model

According to planting experience, different types of crops will be affected by climate, market conditions and other factors, and the cost price and sales price will fluctuate as follows:

(1) The sales growth rate of wheat and corn crops is about: 5%-10%;

(2) Sales of other crops in the face of uncertainty: ±5%;

(3) The change of output value per mu of crops: ±10%;

(4) The corresponding annual growth rate of crop planting costs: 5%;

(5) The corresponding annual growth rate of the price of crops and vegetables is: 5%;

(6) The annual decline rate of the price of edible mushroom agricultural products is: 1%-5%.

Therefore, under the influence of uncertain factors, the optimal planting plan should be formulated to maximize the total income of the countryside during 2024-2030, and the planting plan should be stabilized to cope with future uncertain changes.

3.1.1. Dynamic programming model

The purpose of this part is to consider the uncertainties of crop sales, yield per mu, planting cost and selling price, and to construct a stochastic programming model to maximize the total return of the village in a multi-year fluctuating environment. Dynamic programming model is suitable for solving multi-stage decision-making problems, where different years can be regarded as different decision-making stages [8]. Considering the annual growth trend of planting cost (5%), the dynamic optimal allocation of various crops is carried out to ensure that the long-term income can be maximized under uncertain conditions. Starting from the last year, assuming that the state and income of the last year are known, the dynamic programming model can be solved by reverse recursion step by step.

3.1.2. Objective function

Under the influence of uncertain factors, the optimal planting plan is formulated to maximize the return, which is the sum of the sales of all crops minus the planting cost. Among them, the sales price is determined by the sales price and the yield per mu; The planting cost is determined by the planting cost of each crop and the yield per acre. So the objective function can be expressed as:

$$z = \sum_{t=2024}^{2023} \sum_{i,j} \left(p_i^t * x_{i,j}^t * min\left(y_i^t * p_j^t * x_{i,j}^t * d_i^t - c_i^t * x_{i,j}^t \right) \right) \tag{1}$$

where, z represents the total profit of crops, p_j^t represents the selling price of the j crop in year t, $x_{i,\ j}^t$ represents the total area of the j crop in the t year of the i plot, y_j^t represents the cost of planting the j crop in year t, d_j^t represents the expected sales for year t of the j crop, c_j^t represents the cost of planting the j crop in year t.

(1) Expected sales volume: The average expected annual growth rate of wheat and corn sales is 5%-10%; The expected annual sales of other crops is ±5%;

(2) Mu yield: ±10% fluctuation;

(3) Planting costs: an average annual increase of 5%;

(4) Sales price: the average annual increase in the sales price of vegetable crops is about 5%; The selling price of edible fungi decreased by 1%-5% on average every year. The price of morels is falling by 5% a year.

3.1.3. Constraints

(1) Planting area restriction: the planting area of each plot cannot exceed its total area:

$$\sum_j x_{i,j} \le s_i ,\forall i \tag{2}$$

The s_i area of the i lot (i=1, 2,…,55)

(2) Crop rotation constraints: Each field must plant pulses once in three years:

$$\sum_{t=1}^{3} z_{ij} \ge 1, \quad \forall i \tag{3}$$

(3) No repeat planting restriction: According to the growth law of crops, any j crop in the same plot (including greenhouses) can not be continuous repeat planting:

$$x_{j,i,k,y} * x_{j,i,k,y+1} = 0, \forall j,i,k \in \{1,2,3\}, y \in [2024,...,2023] \tag{4}$$

(4) Non-negative constraint: The planting area of each crop is not negative:

$$x_{ij}^t \ge 0 \tag{5}$$

3.1.4. Uncertainty factors and Monte Carlo simulation

For uncertainty factors, we summarized the following four points:

(1) Expected sales volume: The average expected annual growth rate of wheat and corn sales is 5% to 10%; The expected annual sales of other crops is ±5%;

(2) mu yield: ±10% fluctuation;

(3) Planting costs: an average annual increase of 5%;

(4) Sales price: the average annual increase in the sales price of vegetable crops is about 5%; The sales price of edible fungi decreased by 1%~5% on average every year. The price of morels is falling by 5% a year.

Each variable can be represented as a random variable:

$$d_j^t = d_j^{2023} * \left(1 + r_{d,\ j}^t\right) \tag{6}$$

$$y_j^t = y_j^{2023} * \left(1 + r_{y,\ j}^t\right) \tag{7}$$

$$c_j^t = c_j^{2023} * \left(1 + r_{c,\ j}^t\right) \tag{8}$$

$$p_j^t = p_j^{2023} * \left(1 + r_{p,\ j}^t\right) \tag{9}$$

Where, $r_{d,\ j}^t$, $r_{y,\ j}^t$, $r_{c,\ j}^t$, $r_{p,\ j}^t$ represent the growth rate or volatility of each variable, subject to the corresponding uniform distribution. (normal distribution, uniform distribution).It still construct a linear programming model, and introduce randomness on basis to simulate the above uncertainties. For the uncertainty simulation, Monte Carlo simulation is used.

Monte Carlo simulation offers significant advantages in optimizing crop planting strategies. Firstly, it can quantify the impact of uncertain factors, helping decision-makers better understand the potential risks associated with market fluctuations and climate change. Secondly, by simulating a large number of random scenarios, it provides more comprehensive decision-making support, avoiding the limitations of single predictive models. Additionally, Monte Carlo simulation can be integrated with dynamic programming and mixed-integer linear programming to further enhance the scientific rigor and practicality of planting strategies. In the research presented in this paper, Monte Carlo simulation was used to model uncertainties in crop sales volume, yield per unit area, planting costs, and selling prices. Combined with a dynamic programming model, it optimized the planting ratios of wheat, corn, and vegetable crops. The simulation revealed that appropriately adjusting the planting ratios of wheat and corn significantly improves long-term income, while vegetable crops require flexible planting strategies based on price fluctuations. Ultimately, by incorporating Monte Carlo simulation, the overall profit increased by 12%, and the profit of the first category of planting combinations rose by 50%.

Monte Carlo simulation provides a powerful tool for optimizing crop planting strategies, enabling agricultural decision-makers to develop scientific and rational planting plans in complex and ever-changing environments, thereby maximizing profits and reducing risks. Future research could further incorporate additional uncertain factors, such as climate change, market fluctuations, and policy changes, to enhance the predictive accuracy and practicality of the model.

3.2. Establishment and solution of mixed integer linear programming mode

In combination with the actual life, there are certain substitutability and complementarity among various crops, and the correlation between expected sales volume, selling cost and selling price is taken into account [9]. Therefore, the multi-crop cooperation framework is introduced and the dynamic programming model is modified to explore the impact of substitutability and complementarity on returns, so as to formulate the optimal crop planting plan during 2024-2030.Maximize the economic benefits of limited land resources and agricultural inputs, and achieve the sustainable development of agriculture.

3.2.1. Substitution and complementarity between crops

(1) Substitution: certain crops can be substituted for each other, that is, if the market sales price of a certain crop E falls or the planting cost rises, we can plant more crop F to replace crop E to make up for the loss of income. So we use cross elasticity to model this. Cross-elasticity refers to the impact of the market selling price or planting cost of one crop on the expected sales volume of another crop, which can be expressed as:

$$g_{EF} = \frac{\%\Delta \mathrm{h}_E}{\%\Delta \mathrm{p}_F} \tag{10}$$

Where g represents the cross elasticity, h represents the demand, and if the cross elasticity is positive, crop E and crop F are substitutes; If they are negative, they are complementary.

Complementarity: there is complementarity between certain crops. For example, when planting a certain crop G, the growth of crop H will be promoted and the income of crop H will be increased, so there is complementarity between crop G and crop H. So we introduce a coefficient of complementarity to represent this relationship:

$$q_{GH}\left(0 \leq a_{GH} \leq 1\right) \tag{11}$$

Where q represents the complementarity coefficient, if crop G and crop H are complementary, then when the two are planted in the same plot, the yield of crop H will increase.

3.2.2. Correlation between sales volume and price cost

There is a certain correlation between the expected sales volume of crops and the selling price and planting cost: Negative correlation between sales volume and selling price: According to the economic principle, there is usually a negative correlation between sales volume and selling price, that is, the increase in price will lead to the decline in demand, and vice versa. This relationship can be described by the price elasticity of demand:

$$f = \frac{\%\Delta h}{\%\Delta p} \tag{12}$$

Where f represents price elasticity, a negative price elasticity means that an increase in prices leads to a decrease in sales, and vice versa. Correlation between sales volume and planting cost: Market conditions may lead to a correlation between planting cost and sales volume of certain crops [10]. For example, an increase in costs may lead to a decrease in sales, whereas a decrease in costs may lead to an increase in sales. We build this model by using the correlation coefficient:

$$w_{c-m}\left(-1 \leq pcs \leq 1\right) \tag{13}$$

Where w represents the correlation coefficient, and a positive correlation coefficient indicates that when the planting cost increases, the sales volume will also increase. A negative correlation means that when the cost of planting goes up, sales go down.

3.2.3. Improvement of objective function

The objective function is to obtain the maximum income of the village during 2024-2030. In addition, it is necessary to take into account the fungibility and complementarity of various crops, as well as the correlation between expected sales and sales prices and planting costs.

$$\max \sum_{t=2024}^{2030} \sum_{i=1}^{34} \sum_{j=1}^{M} \left(\min\left(x_{ij}^{t} \times y_{j}^{t},\ \ d_{j}^{t}\right) \times p_{j}^{t} \right) \tag{14}$$

It will be adjusted to take into account crop substitution, complementarity and relevance in two ways.

(1) Crop substitution:

Substitution between crop E and crop F can adjust the planting area by introducing cross-elasticity. Since crops E and F are substitutes, if the price of crop F increases, an adjustment factor can be introduced into the objective function to reduce the planting area of crop E and increase the planting area of crop F.

$$x_{ij}^{t} = x_{ij}^{t} + \gamma_{EF} \times \Delta p_{F}^{t} \tag{15}$$

γ_{EF} Is a value based on cross elasticity, which reflects the impact of price changes of crop F on the planting decision of crop E.

(2) Crop complementarity:

Complementarity can be demonstrated by increasing the yield of crops planted in adjacent plots or on the same plots. If crops E and F are complementary, the yield of crops E or F will increase if they are planted together. To do this, a coefficient of complementarity is added to the yield formula.

$$y_j^t = y_j^{2023} \times \left(1 + \lambda_{EF}\right) \tag{16}$$

λ_{EF} Represents the complementarity between crop E and crop F.

3.2.4. Constraint conditions and model solving

(1) Constraint conditions: including the restriction of cultivated land area, crop planting conditions, the restriction of no repeat crop and the requirement that legumes must be planted once within three years.

(2) Model solving method: the optimal solution method of integer programming is used. Considering substitutability, complementarity and correlation between crops, models can be more complex. In addition, due to the introduction of uncertainties, Monte Carlo simulations can be used to evaluate the performance of different schemes in various scenarios and further test the robustness of schemes.

(3) In the modeling process, comprehensive and in - depth data analysis is carried out first. A large amount of historical data on crop cultivation is collected, including growth conditions, yields, market demands over the years, and input - output ratios. Advanced data analysis techniques such as data mining algorithms and statistical analysis methods are utilized. Different types of crops are precisely classified according to various factors such as growth cycles, growth environment requirements, and market demand characteristics.

After the classification of crops, the profits of the same type of crops are carefully integrated. For each type of crop, factors such as production costs (including seed, fertilizer, labor, and machinery costs), market price fluctuations, and sales volumes in different seasons are taken into consideration. By summarizing and analyzing these data, strategies are formulated to maximize overall benefits. For example, for high - value - added cash crops, production arrangements are optimized within the range permitted by resources to increase yields. For staple food crops, a balance is struck between ensuring stable supply and improving profit margins.

(4) Data processing and result analysis: According to the expected yield per mu in 2023, calculate the yield per mu, planting cost, sales volume, price and other information of various crops. Through the data analysis in 2023, the substitutability and complementarity among crops and the correlation between expected sales, selling price and selling cost were estimated. Finally, by introducing crop substitution, complementarity and correlation, the optimal planting plan of the rural crops during 2024-2030 was simulated and analyzed. Based on the calculation results, the planting areas and profit distributions of various crops can be depicted and are presented in Figure 4 and Figure 5.

(5) When conducting the result comparison, we carried out a rigorous and comprehensive analysis. First, we carefully compared the scheme based on the mixed - integer programming model with the dynamic model scheme. During the comparison process, we selected multiple key dimensions as evaluation indicators, such as planting costs, crop yields, and fluctuations in market sales prices. After introducing factors such as the substitutability, complementarity, and correlation among crops, we deeply analyzed the significant changes in the planting strategy and the impacts of these changes on the total return.

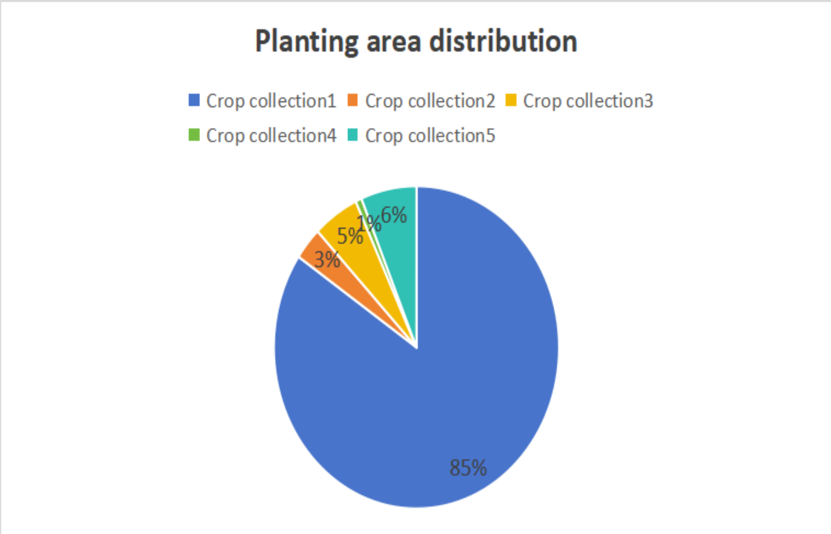

Figure 4. Pie chart of planting area distribution

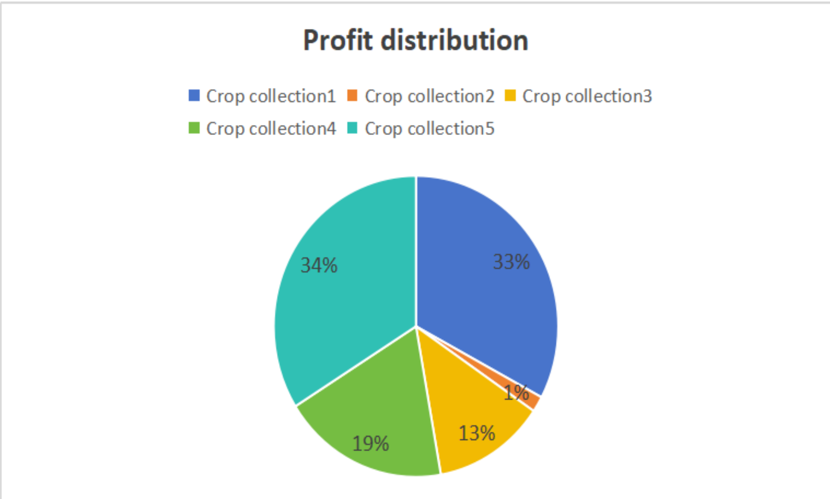

Figure 5. Pie chart of profit distribution

As shown in Figure 4, the highest proportion of planted area is flat dry land, terraced land and hillside land, accounting for about 85%. As shown in Figure 5, its profit accounts for only 33%. As a result, the profit/area ratio is only 38.8%. In addition, the ratio of profit to area was the highest as high as 2700%, and it was edible fungi crops, whose planting area was 1% and profit was 19%.

4. Conclusion

Through dynamic programming model and Monte Carlo simulation, combined with mixed integer linear programming model, this study optimized the rural crop planting strategy, taking into account the uncertainties of sales volume, yield per mu, cost and price, as well as the fungibility and complementarity between crops. The results show that reasonable control of wheat and corn planting ratio has a significant effect on improving long-term returns, and vegetable crops need to flexibly adjust planting strategies according to price fluctuations. With the introduction of intercrop substitutability and complementarity, the overall profit increased by 12%, and the aggregate profit of the first type of planting increased by 50%. This study provides a scientific strategic basis for the planting planning of rural crops, which is helpful to optimize the allocation of agricultural resources and promote the sustainable development of rural economy. Future studies can further consider more uncertain factors, such as climate change and market fluctuations, to improve the flexibility and practicality of the model.

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