The combination of single-objective nonlinear uncertain optimization and particle swarm algorithm for optimization crop selection

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Abstract. In actual agricultural sowing, due to the uncertainty of various concurrent risk types, such as the expected sales volume, yield per mu, planting cost, and selling price of various crops, a single-objective nonlinear uncertainty optimization model is established after comprehensively considering the variation of relevant indicators of various agricultural products within a certain range, to make reasonable decisions for crop planning, rotation, and dense planting. To demonstrate the applicability and feasibility of the method proposed by the model, we use actual cases from the North China region to predict the formulation strategies for agricultural cultivation in the next seven years. The calculation quickly finds the optimal solution within a smaller number of iterations and meets the different requirements under different terrain conditions such as flat and dry land, terraced fields, and hillsides. The practical verification of the model is combined with the application of the particle swarm algorithm, fully demonstrating its potential in agricultural decision-making and helping farmers make scientific planting choices in complex and changeable environments.

Keywords: Particle Swarm Optimization (PSO), crop selection, Uncertainty optimization, Agriculture.

1. Introduction

Rural land resources, as the foundation of agricultural production and the reliance of farmers' lives, their rational utilization and efficient management have become an important issue in current agricultural development. The optimization of agricultural planting strategies is a complex problem caused by the interaction of several factors that need to be considered simultaneously, including limited arable land resources, restrictions on plot types, the influence of market conditions, and specific requirements of farmers.

In order to achieve good economic benefits, it is very necessary to determine production activities based on the actual situation, quantify subjective factors (such as the knowledge and experience accumulated by farmers in planting) and objective factors, and thereby establish a mathematical model to make reasonable decisions for crop planning, rotation and planting density.

When actually conducting agricultural sowing, farmers need to select several crops that meet the planting conditions from many crops and plant them on specific plots of land. The usual purpose is to achieve maximum economic profit. Chongfeng Ren[1] used An improved bi-level programming model to consider the fairness of water resources distribution and the maximization of agricultural economic benefits, and applied the developed model to the case study of Wuwei City, Gansu Province, China. At the same time, suggestions are put forward for decision makers to face similar problems.

Xuan Liang[2], Nilton Willian Pechibilski[3], Albornoz[4] solved different problems by establishing linear programming models. In particular, the model of the last author considered a new linear binary integer program to solve the crop rotation planning problem, and took into account the constraints of different land divisions and the adjacency constraints under the same land. The linear model assumes that the relationship between variables is linear, which may not hold in some applications. For example, when the growth of crops is affected by multiple factors or certain indicators show a nonlinear relationship with time, nonlinear relationships may exist.

According to Carlo Filippi's[5] viewpoint, in order to calculate correctly and have an in-depth understanding of the crop planning problem, various uncertain factors that may cause changes cannot be forgotten. Both Rong Jiang[6] and Junfang Zhao[7] discussed the impact of climate change on corn production and established the Decision Support System for Agrotechnical Technology Transfer Model and regression model respectively.

Many studies only considered the impact of a single factor when dealing with these uncertainties, failing to fully integrate multiple uncertainty factors. These studies either asked how farmers perceived the importance of each risk or focused on conceptual issues, rather than assessing how exposure to all risks quantitatively affected agricultural indicators such as yields or income[8].

When solving optimization problems, there are many intelligent optimization algorithms to choose from. Among them, Particle Swarm Optimization is a swarm-based stochastic optimization algorithm. Compared with other optimization algorithms, it is relatively simple to implement and has a better ability to escape from local optimal solutions, with better global search performance. Magdy Eman [9] applied the particle swarm algorithm to the fund allocation in Pavement management systems to reduce maintenance costs while improving pavement conditions. Ezzatul Akmal Kamaru Zaman[10] used it to determine feature correlation and redundancy during online feature selection.

When farmers actually carry out agricultural sowing, they will integrate a variety of common crops and consider different plot types, and are also affected by a variety of concurrent risks. Therefore, in order to achieve economic profit maximization, it is necessary to establish a mathematical model and use the particle swarm optimization algorithm to solve it. This study needs to comprehensively consider the changes of relevant indicators of each agricultural product within a certain range, such as expected sales volume, planting cost, per mu output and selling price, which may be volatile or monotonic over time. Under such uncertain factors, the formulation strategies for predicting future agricultural planting are given.

2. Problem Description

We consider a general agricultural system. The existing open farmland is divided into multiple plots of different sizes, and some plots belong to different types. Different plots allow for the cultivation of different crops. In addition, in addition to open farmland, there are indoor greenhouses, and the greenhouses also have different types. Different greenhouses allow for the cultivation of different crops. Each plot and greenhouse has its own planting area limit, and different crops can be combined in the same plot (containing greenhouse) in each season.

In addition to the above objective factors and conditions, farmers also have their own knowledge and experience accumulated from years of planting.

(1) Crop rotation effect: Each crop cannot be continuously grown in the same plot (including greenhouses) to avoid reduced yields.

(2) Alternate planting: It is required that all the land in each plot (including greenhouses) plant leguminous crops at least once within three years. The nitrogen fixation of the rhizobial bacteria of leguminous crops can release excess nitrogen into the soil. This improvement in fertility has a positive impact on the subsequent cultivation of many crops (such as corn, wheat, etc.)

(3) Reasonable dense planting: The planting area of each crop in a single plot (including greenhouse) should not be too small.

3. An Expected Profit Maximization Model

The research objective of the problem is to maximize the profit of agricultural products, and it is necessary to establish a mathematical programming model with the planting area of crops as the decision variable. The output, expected sales volume, cost and selling price of crops change over time.

To accurately describe such minor changes, it is necessary to consider the comprehensive factors such as the characteristics of the crops themselves, the growth environment and the local economic development level.

3.1. Establishment of the single-objective programming model

Suppose x_{ijt} represents the proportion of the area of the $i-th$ plot where the $j-th$ crop is grown during the $t-th$ period, and I, $T$and T are respectively the maximum values of their ranges.

3.1.1. Calculate the expected sales volume

Since the actual sales volume data for 2023 is unknown, the slowdown rate r is introduced. Then, for the $i-th$ plot and the $j-th$ type of agricultural product in 2023, the expected sales volume per mu is

$$Q_{ij} = q_{ij}(1-r) \tag{1}$$

Among them, q_{ij} represents the output per mu of the $j-th$ agricultural product in the $i-th$ plot.

3.1.2. Establish the objective function

The objective of this planning model is to maximize profits, and the objective function is as follows

$$max \sum_t \sum_i \sum_j x_{ijt} S_i \left(P_j - c_{ij}\right) \tag{2}$$

Among them, S_i represents the area of the ith plot, and P_j and c_{ij} respectively represent the sales volume and planting cost of the $j-th$ crop on the $i-th$ plot per mu of land.

3.1.3. Decision variables

The area of each plot is constant. And all plots will be used for growing crops, and based on the above, the profit when all crop yields are sold is known. Therefore, the total profit is determined by the value of x_{ijt}.

3.1.4. Establish constraint conditions

•Area constraint: The total area of crops in each plot shall not exceed the area of the plot.

$$\sum_j S_i x_{ijt} \le S_i \ \forall i,t \tag{3}$$

•Seasonal constraints on land: Flat and dry land, terraced fields and hillsides can only grow one season of crops each year.

$$x_{ijk} = 0 \tag{4}$$

•Crop rotation rule constraint: The same kind of crop cannot be grown in adjacent quarters. There is

$$min\left(x_{ijt}, x_{ijt+1}\right) = 0 \ \forall i,j \tag{5}$$

•Constraint on the number of bean plantings: According to the condition, the same plot must be planted with beans at least once within three years.

Suppose $E = \{a|Plot\ A\ planted\ beans\ in\ the\ first\ year\}$, $F = \{a|Crop\ A\ is\ beans\}$, we have

$$\begin{cases} x_{ijt} + x_{ijt+1} + x_{ijt+2} > 0, i \in E \text{ and } t \ge 3 \\ x_{ij1} > 0 \qquad , i \notin E \text{ and } j \in F \\ x_{ijt} \ge 0 \qquad ,\text{else} \end{cases} \tag{6}$$

• Planting proportion constraint: According to the above analysis, when a certain plot is planted with only one crop, $x_{ijt} \in \{0,1\}$; when two crops are planted, assuming X_{inf} represents the lower bound of the planting proportion of a certain crop, then $x_{ijt} \in \{a | X_{inf} \leq a \leq 1\}$.

3.2. The variation law of agricultural indicators

3.2.1. Crop yield per acre

Crop yield per acre is affected by factors such as climate, resulting in a ±10% variation each year. Precipitation is influenced by many factors such as temperature, humidity, and time. It can be assumed that the precipitation on a certain day follows a normal distribution. Additionally, precipitation is closely related to the season, so the distribution parameters should be a function of time, and the expression of this function is solved based on actual data. Let the precipitation on the $\tau - th$ day be

$$P_w \sim N\left(\mu_1(\tau), \sigma_1^2(\tau)\right) \tag{7}$$

Among them, $\mu_1(\tau), \sigma_1^2(\tau)$ are parameters, which are functions of time τ. Additionally, it is necessary to limit $\mu_1(\tau) > 3\sigma_1(\tau)$, because the case where $P < 0$does not conform to the physical laws, and the probability $P(P_w < \mu_1 - 3\sigma_1) = 0.003$ can be ignored.

Next, the weather judgment of each day of the year is given. Let $W_e(\tau)$, where $W_e = 0$ indicates no precipitation and $W_e = 1$ indicates precipitation. When it precipitates, the precipitation amount is P_w; otherwise, it is 0. According to physical laws, if there is no precipitation for many consecutive days, the surface water such as rivers and oceans evaporates into water vapor and accumulates in the atmosphere, which will increase the precipitation probability in the following days; conversely, if it precipitates continuously, the water vapor in the atmosphere decreases and the thickness of the cloud layer reduces, which will decrease the precipitation probability in the following days. Since $P(W_e(0) = 0) = 1 - P(W_e(0) = 1)$, only $P(W_e(0) = 1)$ is studied. Based on the above analysis, assume that the probability of precipitation on a certain day is

$$P(W_e(\tau) = 1) = \frac{1}{\pi} arctan(\beta n) + \frac{1}{2} \ (n = 0,1,2 \dots \dots) \tag{8}$$

Among them, the parameters determine the probability of precipitation on the current day based on the precipitation conditions in the previous few days. Suppose $n = 0$ on day τ. On day $\tau + 1$, if it rains, n is reduced by 1; otherwise, it is increased by 1. β reflects the influence of n $(0 \leq \beta \leq 1)$.

There are upper and lower boundaries for the single day precipitation that keeps the crops neither dry nor flooded, which are assumed to be represented by $supP_w$ and $infP_w$. Considering artificial irrigation, then there is

$$infP_w = 0 \tag{9}$$

As the precipitation gradually increases from 0, the growth status of the crops experiences normal growth, slightly excessive moisture to flooding.If the daily rainfall requirements of each crop WR and $supP_w$ can be determined, then for each mu of land on that day The rate of change in output is

$$\Delta q_{ij\tau} = \left(0.1 - 0.2\, max(P_w - WR, 0) / (supP_w - WR)\right) \times 100\% \tag{10}$$

Then it can be known that the per mu output of each crop in the following years.

$$q_{ijT} = q_{ij} \times \Delta q_{ijT} \quad \forall i \in E^i, j \in E^j \tag{11}$$

Among them, T corresponds respectively to the number of predicted years, and $\Delta q_{ijT} = \sum_\tau \Delta q_{ij\tau} / 360$

3.2.2. The per mu planting cost of crops

The per mu planting cost of crops: The per mu planting cost increases by 5% every year.

$$c_{ijt} = c_{ij}(1 + 0.05)^{t/2} \ \forall i \in E^i, \forall j \in E^j, \forall t \in E^t \tag{12}$$

3.2.3. Selling prices of crops

①The selling price of grains remains stable;②The selling price of vegetables increases by 5% every year. In conclusion,

$$\begin{cases} p_{ijt} = p_{ij} \ \forall i \in E^i,, \forall t \in E^t \\ p_{ijt} = p_{ij}(1 + 0.05)^{t/2} \ \forall i \in E^i, \forall t \in E^t \end{cases} \tag{13}$$

3.2.4. Expected sales volume of crops

It can be known by referring to the relevant materials that the relationship between price and sales volume is as follows:

$$lg(Average\ monthly\ sales) = -0.169 \times \text{Average monthly unit price} + 3.620 \tag{14}$$

Among them, the unit of sales volume is kg, and the unit of unit price is yuan/kg. Suppose the above relationship can reflect the changes in the current regional market relationship, the relationship between the changes in annual sales volume and the changes in the average annual selling price is as follows

$$\Delta Q_{ijt} = 10^{-0.338\Delta p_{ijt}} \tag{15}$$

Among them, ΔQ_{ijt} represents the ratio of sales volume in the (t + 1)th year to that in the tth year, and Δp_{ijt} is the difference in sales price between the (t + 1)th year and the tth year.

3.3. The finally established model

The decision variables and constraints remain unchanged. Let P_{ij} and q_{ij} represent the price and output per mu of the corresponding crops respectively (the same below). If $q_{ij} \geq Q_{ij}$, then the actual sales volume is Q_{ij}; otherwise, if $q_{ij} < Q_{ij}$, then the actual sales volume is q_{ij}. Therefore, the actual sales amount is

$$P_{ij} = p_{ij}\, min(q_{ij}, Q_{ij}) \tag{16}$$

Substitute it into Formula (2) to obtain the objective function

$$max \sum_t \sum_i \sum_j x_{ijt} S_i \left[p_{ijt}\, min(q_{ijt}, Q_{ijt}) - c_{ijt}\right] \tag{17}$$

4. Particle Swarm Optimization

4.1. Basic Idea

The basic idea of Particle Swarm Optimization (PSO) is to simulate the process of information sharing and transfer in the foraging activities of birds. It is a search algorithm based on group collaboration: During the search process, particles rely on the evaluation function to determine the distance to the best quality. Each particle, based on the optimal position it has been in the past and the optimal position of the entire group, will decide the next movement position with random disturbance. The basic solution process of the model is shown in Table 1:

Table 1. Particle Swarm Optimization Algorithm Flow

The basic process of Particle Swarm Optimization (PSO)
Step 1: Initialization: Initialize parameters and randomly initialize the positions and velocities of the particle swarm
Step 2: Preliminary evaluation of particles: Calculate the initial fitness
Step 3: Update particles: Update the velocity and position of the particles recursively. If the velocity and position exceed the maximum limit, It needs to be adjusted.
Step 4: Re-evaluate the particles: 1) Compare the fitness of the particle with its historical optimal value and update the best position. 2) Based on the fitness of the particles and the global optimum value of the population, update the best position found so far for all particles.
Step 5: Termination condition: If the error of two adjacent iterations is less than the threshold or the maximum number of iterations is reached.

As shown in Figure 1, it is the flowchart

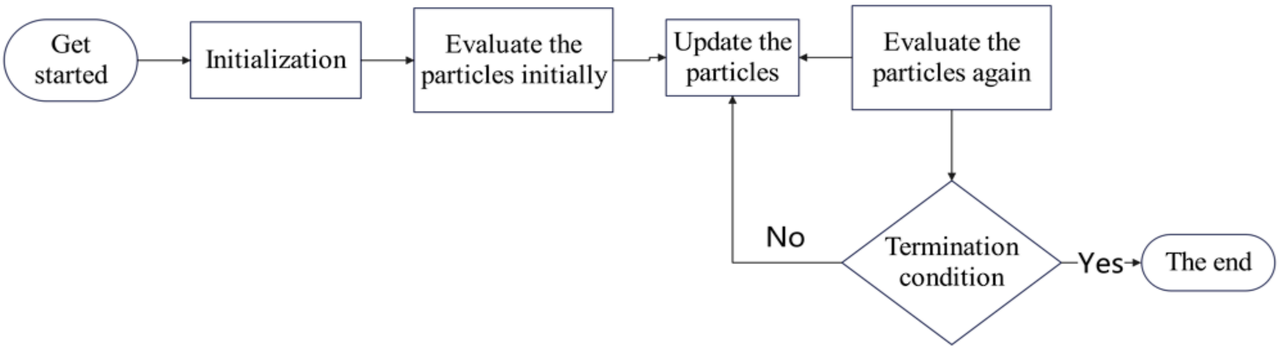

Figure 1. Flow chart of particle swarm optimization

4.2. Specific Integration

First, initialize the population, population size, the velocity and size of each particle. Judge the quality of the particles based on the fitness function, that is, determine whether the particles are good solutions. Then enter the algorithm iteration. The particles generated in each iteration represent a solution within the feasible domain. In this problem, random generation is adopted for the four dimensions of each particle, namely the number of crops, the number of lands, the number of seasons, and the number of years.

The iterative formula of the particle swarm algorithm is

$$v_i^d = wv_i^{d-1} + c_1 r_1 \left(pbest_i^d - x_i^d\right) + c_2 r_2 \left(gbest^d - x_i^d\right) \tag{18}$$

$$x_i^{d+1} = x_i^d + v_i^d \tag{19}$$

In the formula, c_1 is the individual learning factor, representing the size of the particle affected by "self". c_2 is the group learning factor, which represents the size of the particle affected by "inter-group information sharing". The inertia weight w represents the size of the particle affected by the previous moment due to inertia. These three parameters correspond to different directions respectively, and their combined action determines the velocity change of the particle. The velocity of the particle is obtained by adding these three parts together, while the position is generated by iterative updating recursively.

In this problem, after calculating the objective function to obtain the individual best position and the group best position, the velocity and position of the particles can be updated. In each iteration process, the constraint conditions need to be applied to the movement of the particles. For example, on each plot, the plantable area of each crop needs to be less than the area of the plot, and the total area of the crops planted on each plot is less than the area of the plot itself.

5. A Real Case Study

5.1. Input data and parameters setting

Data from the North China region was collected. The village is located in the mountainous area of North China, where the temperature is consistently low throughout the year. Most of the arable land can only grow one season of crops each year. The open arable land in this area is divided into 34 plots of different sizes, including four types: flat and dry land, terraced fields, hillsides, and irrigated land. Flat and dry land, terraced fields, and hillsides are suitable for growing one season of food crops each year; irrigated land is suitable for growing one season of rice or two seasons of vegetables each year.

The village also has 16 ordinary greenhouses and 4 smart greenhouses, each with an arable land area of 0.6 mu. Ordinary greenhouses are suitable for growing one season of vegetables and one season of edible fungi each year, while smart greenhouses are suitable for growing two seasons of vegetables each year.

In cases where data has been collected in specific circumstances:

5.1.1. Reclarify the parameter domain

Each plot is numbered from 1 to 53 in the order o $A1, A2, \dots, B1, B2 \dots, F4$; for the two seasons of a year, it is numbered from 1 to 14 in the order of the first quarter of 2024, the second quarter of 2024,..., the second quarter of 2030 (for the plots planted in a single season, it is considered that no crops are grown in the second season). Suppose x_{ijt} represents the proportion of the area of the $j-th$ crop grown on the $i-th$ plot in the $t-th$ period, it can be known that the range of values

$$\begin{gathered} E^i = \{1,2,\dots,54\} \\ E^j = \{1,2,\dots,41\} \\ E^t = \{1,2,\dots,14\} \end{gathered} \tag{20}$$

5.1.2. The proportion of the planting area of a certain crop in a certain plot

Based on the collected data, the number of crop types planted in each plot in each season in 2023 is statistically shown in Figure 2.

It was found that in each plot during the same season, either only one type of crop was grown, or both crops were grown at a ratio of one-half each. When two crops were grown, the planting ratio of the two crops could not simultaneously exceed one-half. Therefore, the planting strategy in 2023 was a special case. Although the actual situation might be difficult to achieve, following the planting strategy of 2023 could effectively simplify the model.

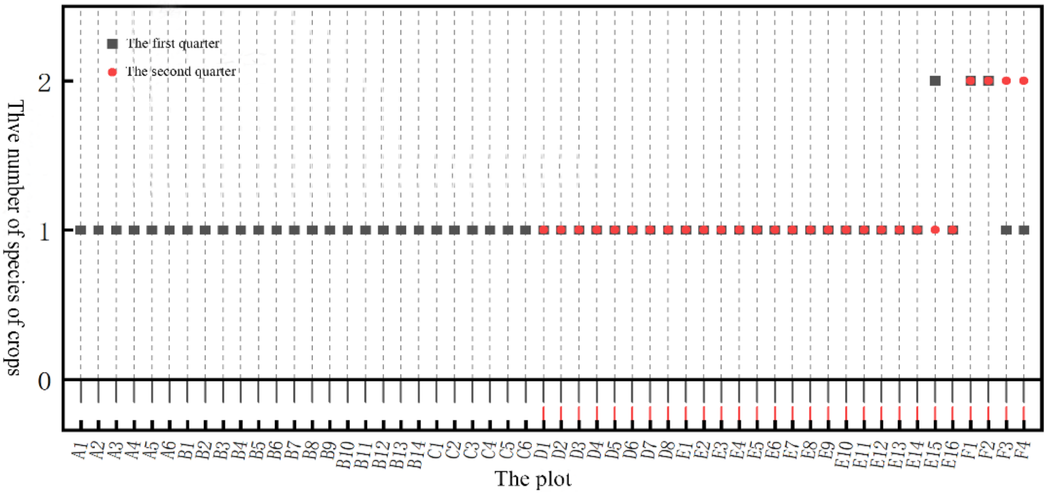

Figure 2. The number of crop types planted in each season of each plot in 2023

5.1.3. Re-establish the constraint conditions

- Area constraint: The total area of crops in each plot shall not exceed the area of the plot.

$$\sum_{j} S_i x_{ijt} \leq S_i \ \forall i, t \tag{21}$$

•Seasonal constraints on land: Flat and dry land, terraced fields and hillsides can only grow one season of crops each year.

$$x_{ij(2n)} = 0 \ \forall i \in \{1,2, \dots ,26\}, \forall j \in E^j, \forall n \in \{1,2,3,4,5,6,7\} \tag{22}$$

•Season of Crops and Land Constraints: ①Rice can only be grown in a single season on irrigated land②Chinese cabbage, white radish and carrot can only be grown in the second season on irrigated land, and vice versa③Common greenhouses can only grow edible fungi in the second season, and vice versa④Vegetables cannot be grown on flat and dry land, terraced fields and hillsides

$$\forall n \in \{1,2,3,4,5,6,7\}$$
$$\begin{cases} x_{i16(2n-1)} = 0 \quad \forall i \in \{1,2, \dots ,26,35, \dots ,54\} \\ x_{ij(2n-1)} = 0 \quad \forall i \in \{1,2, \dots ,26,35, \dots ,54\}, \forall j \in \{35,36,37\} \\ x_{ij(2n-1)} = 0 \quad \forall i \in \{27, \dots ,34\}, \forall j \in \{1, \dots ,34,38, \dots ,41\} \\ x_{ij(2n-1)} = 0 \quad \forall i \in \{1,2, \dots ,35,51, \dots ,54\}, \forall j \in \{38,39,40,41\} \\ x_{ij(2n-1)} = 0 \quad \forall i \in \{36, \dots ,50\}, \forall j \in \{1, \dots ,37\} \\ x_{ijt} = 0 \quad \forall i \in \{17, \dots ,34\}, \forall j \in \{1 \ , \dots ,26\} \forall t \in E^t \end{cases} \tag{23}$$

•Crop rotation rule constraint: The same kind of crop cannot be grown in adjacent quarters. There is

$$min\left(x_{ijt}, x_{ijt+1}\right) = 0 \ \forall i, j \tag{24}$$

•Constraint on the number of bean plantings: According to the conditions, the same plot must be planted with beans at least once within three years. And assuming that there are no plots planted with bean plants in 2023, they must be planted in 2024.

Suppose $E = \{a | \text{Plot A planted beans in the first year}\}$, $F = \{a | \text{Crop A is beans}\}$, we have

$$\begin{cases} x_{ijt} + x_{ijt+1} + x_{ijt+2} > 0, i \in E \text{ and } t \geq 3 \\ x_{ij1} > 0 \qquad , i \notin E \text{ and } j \in F \\ x_{ijt} \geq 0 \qquad ,\text{else} \end{cases} \tag{25}$$

•Planting proportion constraint: To simplify the model, data from 2023 can be referred to. It should be noted that there is no intercropping in flat and dry land, terraced fields, and hillsides. The greenhouse and smart greenhouse plots that implement intercropping are divided into two equal parts. The following assumptions are made:

Firstly, all plots can be intercropped, and the two crops will evenly divide the plot. Secondly, if any plot does not adopt the above-mentioned mixed planting strategy, only a single type can be used. Therefore, the constraint conditions are

$$x_{ijt} \in \{0,0.5,1\} \tag{26}$$

Such a planting proportion strategy is not a replication of 2023, but a supplement to 2023 to enhance the persuasiveness of the results.

•Sales prices of crops: ①The selling price of grains remains stable②The selling price of vegetables increases by 5% annually;③ It is known that for edible mushrooms other than morel mushrooms, the selling price drops by approximately 1% to 5% annually. Considering that the cultivation cost of white spirit mushrooms is relatively high, while the profits of yellow elm mushrooms and shiitake mushrooms are relatively high, if there is an unexpected price drop, the resulting losses will be significant. Therefore, for the robustness of the model, it is stipulated that the selling prices of all edible mushrooms decrease by 5% annually. In conclusion,

$$\begin{cases} p_{ijt} = p_{ij} & \forall i \in E^i, \forall j \in \{1,2,\dots,16\}, \forall t \in E^t \\ p_{ijt} = p_{ij}(1+0.05)^{t/2} & \forall i \in E^i, \forall j \in \{17,\dots,37\}, \forall t \in E^t \\ p_{ijt} = p_{ij}(1-0.05)^{t/2} & \forall i \in E^i, \forall j \in \{38,\dots,41\}, \forall t \in E^t \end{cases} \tag{27}$$

•Expected sales volume of crops: After having specific crops, the original formula will be specified, that is, the relationship between the change in annual sales volume and the change in the average annual selling price is transformed as follows

$$\Delta Q_{ijt} = 10^{-0.338\Delta p_{ijt}} \ i \in \{17,\dots,41\} \tag{28}$$

Among them, ΔQ_{ijt} represents the ratio of sales volume in the (t + 1)th year to that in the tth year, and Δp_{ijt} is the difference in sales prices between the (t + 1)th year and the tth year.

Finally, in order to demonstrate the robustness of the model, assuming that the average annual growth rate of the expected sales volume of wheat and corn is 5%, then

$$Q_{ijt} = Q_{ij}(1+0.05)^{t/2} \ i \in \{6,7\} \tag{29}$$

5.2. Data preprocessing

5.2.1. Crop Profit Analysis

Based on the data, it was found that the price ranges were the same except for the crops grown in the intelligent greenhouse. However, for the same type of crop in different plots of land, the per mu yield and the cost per mu would also vary. To ensure the comprehensiveness of the statistics, first, without considering the intelligent greenhouse, the average per mu yield and the average selling price of the same type of crop in various types of plots were taken. Secondly, the profit calculation formula was used.

$$Profit = output \ x \ selling \ price - cost \tag{30}$$

The average profit per mu of the 41 kinds of crops is shown in Figure 3.

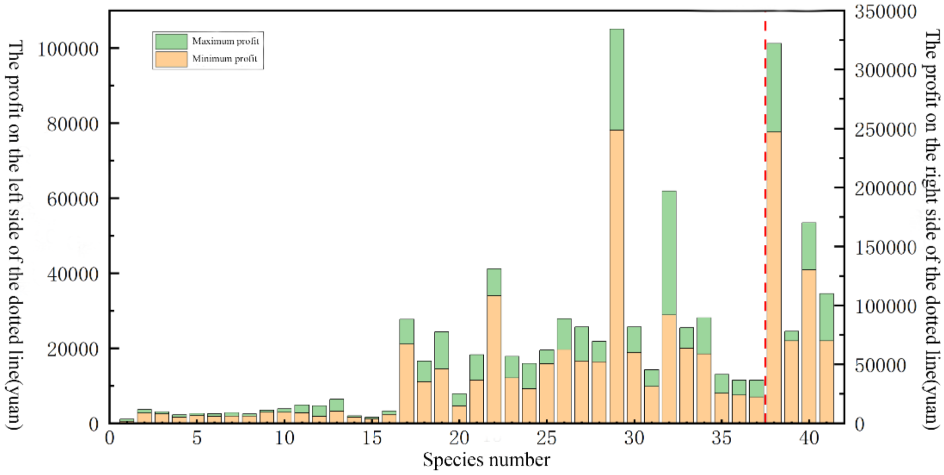

Figure 3. Profit per mu of each crop

It can be found that the high-profit crops are generally vegetables and edible fungi. For example, cucumbers, Lepiota brunneoincarnata, Pleurotus ostreatus and morel mushrooms have relatively high profits; conversely, the profits of food-type crops such as soybeans, black soybeans, wheat and corn are relatively low.

5.2.2. Outlier Analysis (Taking Cucumbers as an Example)

Regarding the cost of cucumber cultivation, by referring to relevant materials, it is known that in 2021, the cost per mu of cucumber in China ranged from 4,800 yuan to 14,500 yuan per mu, which was more than the 3,200 yuan per mu used in the above data. Considering that the research site is a certain village in the North China region, on the one hand, there is a lack of statistics; on the other hand, the economic development level of rural areas is generally lower than that of cities. Therefore, the relatively low material costs, labor costs, etc. in rural areas are acceptable.

Regarding the per mu yield of cucumbers, the national average per mu yield of cucumbers from 2015 to 2020 is presented in Table 2.

Table 2. National average output per mu of cucumbers from 2015 to 2020

Year	2015	2016	2017	2018	2019	2020
Unit yield	11420.36	11611.1	10678.4	11368.04	11194.7	12136.86

It can be seen that the data in the table is relatively close to the original data, so the fallacy of the output per mu of cucumbers is excluded. Regarding the sales price of cucumbers, by referring to the statistical data, the average daily sales price of cucumbers across the country in 2023 was obtained. 24 days were randomly selected and Figure 4 was drawn.It was found that the actual data did not fall within the sales price range of cucumbers. It can be considered that there was an error in the price of cucumbers in the data, resulting in the profit of cucumbers being much higher than that of other vegetables of the same type. Based on the above analysis, in this paper, the correct minimum and maximum sales prices of cucumbers in 2023 will be used to replace the lower and upper limits of the interval in the data.

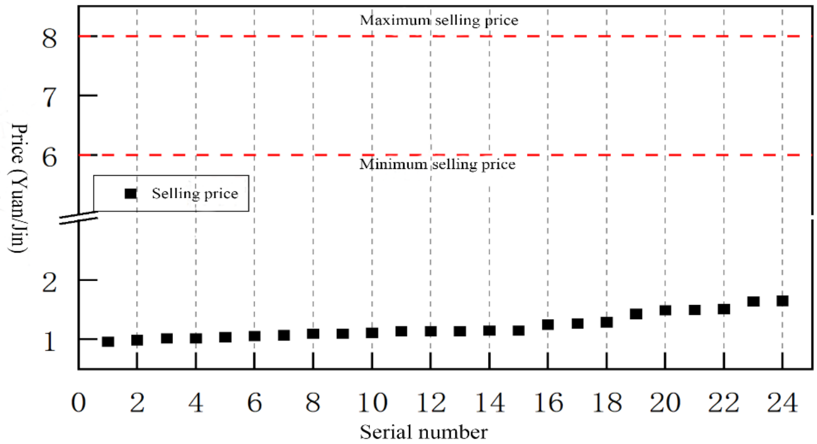

Figure 4. Cucumber Price and Actual Cucumber Price in 2023

5.3. Solving for the expected sales volume

By referring to the official website of the National Meteorological Bureau, it is known that the monthly average precipitation data of Shanxi Province in 2022 is shown in Figure 5**.**

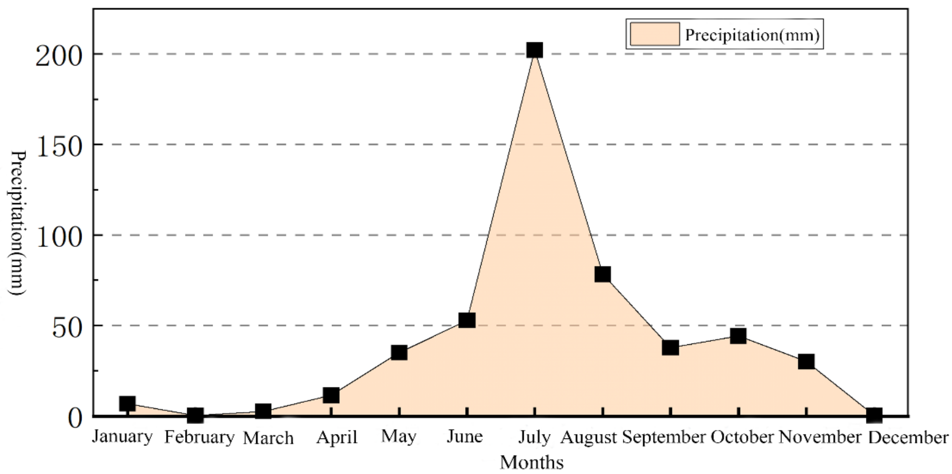

Figure 5. Filled map of monthly precipitation in Taiyuan City, Shanxi Province in 2022

The figure shows that the peak rainfall in Shanxi Province occurs in summer, reflecting the temperate monsoon climate with concurrent rain and heat in the North China region. Next, taking the precipitation situation of Taiyuan, Shanxi Province as an example, we study the value of the per mu yield of crops. Further make an assumption that each month has 30 days. The total number of days in December is close to a whole year. For the convenience of solving the problem, assume that $\mu_1(\tau)$ =precipitation of each month / 30, and $\sigma_1(\tau) = \frac{\mu_1(\tau)}{3}$ Among them, $\tau = 0,1,2, \dots ,360.$

Consult relevant materials and set

$$\begin{cases} WR &= 0.3 \\ supP_w &= 0.8 \end{cases} \tag{31}$$

The results of five solutions are shown in Table 3.

Table 3. Results of Monte Carlo Simulation

Number of simulations	1	2	3	4	5	6	Mean value
Rate of change	0.042	0.041	0.042	0.043	0.043	0.043	0.042

After the above calculation, except for corn and wheat, the expected annual sales volume of other crops is expected to increase by approximately 4.2% compared with 2023.By observing the data in the table, it is found that although at the micro level, an extremely large number of random factors have been incorporated, the fluctuation range of the rate of change is not very large, and there is no decrease. This is not a chance factor. Quite a number of random factors acting together on a variable often produce macro effects. This is where the charm of micro random simulation of macro variables lies.

5.4. Computational results

The result of 2027 is shown in the following Table 4 and Table 5:

Table 4. Partial Results of the First Quarter of 2027

	Soybeans	Black bean	Red bean	Mung bean	Climb bean	Wheat	Corn	Millet	Sorghum
A1	1.3	5.1	6.4	0	3.4	0	7.1	0	0
A2	10.7	0	0	3	0	1.6	3.5	7.4	0.1
A3	0.3	0.2	0	1.6	0.3	1.7	1.1	3.7	2.4
A4	1.1	5.9	0	0.1	0.5	5.8	0	1.7	0
A5	0	0	0.2	4.5	0	0.2	0	1	0

Table 5. Partial Results of the Second Quarter of 2027

	Soybeans	Black bean	Red bean	Mung bean	Climb bean	Wheat	Corn	Millet	Sorghum
A1	0	0	0	0	0	0	0	0	0
A2	0	0	0	0	0	0	0	0	0
A3	0	0	0	0	0	0	0	0	0
A4	0	0	0	0	0	0	0	0	0
A5	0	0	0	0	0	0	0	0	0

After solving the model using Particle Swarm Optimization (PSO), after approximately 60 iterations, the change in fitness was less than 0.2%, and the final optimal profit value reached 11012919.06 yuan. This result not only demonstrates the efficiency of the algorithm but also proves the reliability of the model in practical applications. From the comparison between Table 4 and Table 5, it is clear that the calculation results are consistent with expectations and meet all constraints. This indicates that the model is not only feasible in theory but also produces practical benefits in practice. Specifically, the model successfully meets the requirements for annual suitable single-season cultivation of food crops under different topographic conditions such as flat and dry land, terraced fields, and hillsides, which is crucial for ensuring the stability of food production.

6. Conclusions

After verification through practical problems, the model has shown a certain degree of applicability and feasibility, indicating that it can effectively deal with the complex decision-making problems existing in agricultural production. By using the Particle Swarm Optimization (PSO) algorithm to solve the established single-objective nonlinear uncertain optimization model, the optimal solution can be quickly found within fewer iterations, which gives it a great advantage in practical applications. This global search ability allows the model to avoid falling into local optimum, thereby better adapting to the complex agricultural environment.

In addition, the model can not only handle multiple uncertain factors (such as climate change, market fluctuations, etc.), but also flexibly respond to the planting needs of different crops, providing personalized decision support. This enables agricultural producers to make more scientific planting decisions based on market demand and resource conditions, increasing yield and economic benefits.

In summary, the practical verification of this model, combined with the application of particle swarm optimization algorithm, fully demonstrates its potential in agricultural decision-making, providing an effective solution for improving agricultural production efficiency and sustainable development.

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