Optimizing Crop Planting Strategy Based on Goal Programming and Differential Genetic Algorithm

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Abstract. The formulation of crop planting strategy is of great significance to effectively utilize rural cultivated land resources and promote the sustainable development of rural economy. The optimal planting strategy is to make full use of cultivated land resources to plant crops in order to obtain the maximum expected profit under the premise of following the law of crop growth. Based on the given rural planting conditions, the growth law of various crops, the expected sales volume of various crops, the yield per mu, the planting cost and the uncertainty of the selling price, this paper constructs a single objective programming model to maximize the expected total profit of crops as the objective function, and introduces conditional value at risk to carry out robust optimization of the objective function. The uncertainty parameters were simulated by Monte Carlo method, and their expectation and variance were estimated by kernel density estimation method. Finally, differential genetic algorithm was used to solve the model, and the optimal planting strategy was obtained.

Keywords: Agricultural Economic Benefits, Sustainable Development, Differential Genetic Algorithms, Monte Carlo Simulation.

1. Introduction

Agricultural land resources play a pivotal role in the socio-economic development of China, especially in ensuring food security and supporting the country’s economic and social growth. As a fundamental component of the rural economy, farmland is central to the production of staple crops, which are crucial for feeding the nation’s vast population. However, with the limited availability of arable land and the varying suitability of different land types for specific crops, the efficient use of agricultural land becomes a significant challenge. Janouek, Z., et al. [1] shows which natural conditions (general soil and climate characteristics) were considered when creating crop rotation models. Understanding the potential and limitations of the regional context is key to making land use decisions objective. Rumpel, C., et al. [2] also emphasizes the necessity of developing regional strategies to increase soil carbon (organic matter) levels.

In many developing countries, crop planting planning is becoming a research hotspot, and more and more scholars have gradually applied various intelligent optimization algorithms to planting planning [3]. Von Lucken et al. [4] adopted a variety of multi-objective evolutionary algorithms such as non-dominated Sorting Genetic Algorithm III (NSGA III) to solve a multi-objective crop rotation planning problem. Including cost minimization, crop diversification, nutrient balance, profit maximization, etc. Fenz et al. [5] developed a new data-driven method for crop rotation planning using reinforcement learning, which has better flexibility and scalability. Hajimirzajan et al. [6] adopted a multi-stage mixed integer linear programming model and comprehensively considered supply chain cost, yield, efficient use of arable land and water resources, etc., to build a strategic framework for sustainable planting at a national scale. Luo Dan, et al. [7] aims at the unbalanced supply of tomato raw materials in tomato sauce production season, multi-objective particle swarm biogeography algorithm was proposed to solve the tomato planning model. The algorithm performed better than the traditional evolutionary algorithm and was able to obtain a reasonable planting planning scheme. Zhang Hao, et al. [8] takes Luga irrigation District, Senegal as an example, combined the advantages of deterministic dynamic programming and stochastic programming to establish an optimization model of planting structure of tropical grassland climate irrigation district based on stochastic dynamic programming, and the research results are conducive to making reasonable farmland management and planting decisions in the irrigation district. Jia Hansi, et al. [9] based on the AquaCrop model, analyzes the optimal planting density of maize in the rain-fed agricultural area of western Yunnan under different rainfall years. The results can provide data support and theoretical reference for improving maize planting structure, ensuring food security, improving resource utilization efficiency and promoting agricultural sustainable development.

The above studies have provided many innovative ideas in applying intelligent optimization algorithms to solve the problem of crop planting planning. However, there are also some possible shortcomings.

(1) Trade-off issue in multi-objective optimization: In multi-objective optimization, how to balance different objectives (such as cost, output, resource utilization efficiency, environmental impact, etc.) remains a difficult point. There may be conflicts among different objectives, and choosing appropriate weights and solutions is still a challenge, especially in complex agricultural environments.

(2) Lack of dynamic data procession: Most of above studies may rely on static historical data without considering real-time monitoring and dynamic changes. In actual agricultural production, situations such as weather, market demand, and resource supply are constantly changing. Therefore, models need to have stronger dynamic adaptability and the ability to update real-time data.

This study delves into the field of crop planting decision-making, employing mathematical modeling and computer simulation techniques to address the inherent complexity challenges in agricultural planning. By establishing planning models, it quantifies uncertainties such as land type, crop growth patterns, and sales indicators, and utilizes mathematical methods to solve for the optimal values of the model, aiming to optimize planting strategies. This not only enhances the economic efficiency of agriculture in rural areas but also provides significant support for the integrated development of the agricultural industry. Through methods such as multi-objective particle swarm optimization, Monte Carlo simulation, and conditional value-at-risk, this study optimizes planting schemes under different scenarios, aiming to provide scientific basis and decision support for the sustainable development of agriculture in our country.

2. Overview of the Research Area

2.1. Background of the problem

A village is located in the mountains of North China, the temperature is low all the year round, and most of the farmland can only grow one season of crops every year. The village has 1201 mu of open farmland, scattered into 34 plots of different sizes, including flat dry land, terraced land, hillside land and irrigated land 4 types. Flat drylands, terraces and hillsides are suitable for planting grain crops one season a year. Irrigated land is suitable for growing one season of rice or two seasons of vegetables per year. The village also has 16 ordinary greenhouses and 4 smart greenhouses, each of which has a cultivated area of 0.6 mu. Ordinary greenhouses are suitable for planting one season of vegetables and one season of edible fungi every year, and smart greenhouses are suitable for planting two seasons of vegetables every year. The same plot (including greenhouses) can be combined to grow different crops each season.

2.2. Dataset description

Dataset 1 is a dataset of farmland and crop information, consisting of two tables. The first table provides the types and areas of each of the 54 plots of land in the village. The second table describes the crop types of the 41 types of crops in the village, their suitability for farmland cultivation, and the corresponding cultivation constraints.

The plots suitable for planting each crop in each quarter of this village are shown in Figure 1, and the plots area and other information are detailed in Dataset 1 which can be available at:

https://www.mcm.edu.cn/html_cn/block/8579f5fce999cdc896f78bca5d4f8237.html

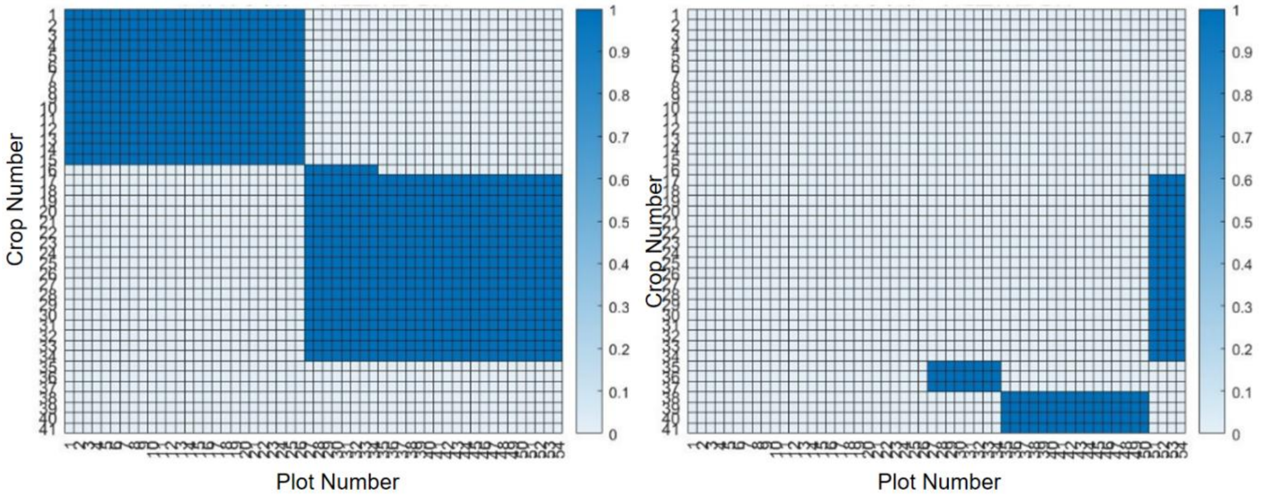

Figure 1. Distribution of plots suitable for planting (a) 1st season (b) 2nd season

According to the growth law of crops, each crop can not be planted in the same plot (including greenhouses), otherwise it will reduce production; Since soil containing rhizobacteria of legume crops is conducive to the growth of other crops, from 2023 all land in every plot (including greenhouses) will be required to plant legume crops at least once in three years. At the same time, the planting plan should take into account the convenience of farming operations and field management, such as: the planting area of each crop in each season should not be too scattered, the area of each crop in a single plot (including greenhouses) should not be too small, and so on.

Crop planting and related statistics for 2023 are detailed in Dataset 2 which can be available at the same website with the source of Dataset 2. Dataset 2 provides detailed records of the crop planting situation in this village in 2023, with a total of 86 pieces of planting record data. Each piece of planting record data contains six elements: planting plot, crop number, crop name, crop type, planting area, and planting season.

By integrating the information of this rural cultivated land plot with the crop planting and relevant statistical data in 2023, we can obtain the suitable planting plots of each crop and the planting season, etc. Some rural cultivated land plots and crop information are shown in Table 1.

Table 1. Information of some farmland plots and crops in the certain rural area

Plot	Crop Number	Crop Name	Crop Type	Plant Area(mu)	Plant Season	Plot Type
A1	6	Wheat	Grain	80	Single	Flat dry land
A2	7	Corn	Grain	55	Single	Flat dry land
A3	7	Corn	Grain	35	Single	Flat dry land
…	…	…	…	…	…	…
F4	23	Spinach	Vegetable	0.3	2nd Season	Greenhouse

2.3. Research Objective

According to experience, the future expected sales of wheat and corn have a trend of growth, with an average annual growth rate between 5% and 10%, and the future expected sales of other crops have a change of about ±5% per year compared to 2023. The per mu yield of crops is often affected by climate and other factors, and there will be a change of ±10% per year. Due to the influence of market conditions, the cost of growing crops increases by about 5% per year on average. The selling prices of grain crops were basically stable. The sales price of vegetable crops has a growing trend, with an average annual increase of about 5%. The sales price of edible mushrooms is stable and has fallen, about 1% to 5% per year, especially the sales price of morel mushrooms has fallen by 5% per year.

The problem to be solved in this paper is as follows: considering the expected sales volume, yield per mu, uncertainty of planting cost and selling price of various crops as well as potential planting risks, the optimal planting plan for the rural crops in 2024~2030 is given.

3. Methodology

3.1. Estimation of uncertainty parameter distribution

Monte Carlo simulation [10] is a statistical method using random sampling to solve problems. It generates a large number of random samples to simulate and analyze the uncertainty in the system, so as to evaluate the results under different scenarios. In this problem, this method can be used to simulate the changes of various uncertain parameters, such as sales volume, yield per mu, planting cost, and selling price, so as to help predict the effect of crop planting strategies. The steps include defining the probability distribution of the parameters, generating a random sample, running the model, and analyzing the statistical properties of the results. The ultimate goal of this approach is to obtain a reliable estimate and risk assessment of the outcome of the decision.

This paper has simulated the annual growth rate of sales volume, per mu yield, planting cost and selling price of each crop by Monte Carlo simulation method. Based on this, KDE kernel density estimation method is used here to estimate the distribution of each uncertainty parameter.

KDE is a nonparametric method for estimating the probability density function of a random variable. It constructs a smooth density estimate by applying a kernel function through logarithmic data points and weighted averaging all data points. The core of KDE is to choose the appropriate kernel function and bandwidth parameters, where the bandwidth determines the degree of smoothing. Through this method, the distribution characteristics of data can be effectively visualized and understood.

KDE kernel density estimation is performed as follows:

Considering one-dimensional data, there are the following sample data $x_1, x_2, x_3, \ldots, x_n$, assuming that the cumulative distribution function of the sample data is $F(x)$, and the probability density function is $f(x)$, then:

$$F(x_{i-1} < x < x_i) = \int_{x_{i-1}}^{x_i} f(x)dx \tag{1}$$

$$f(x_i) = \lim_{h \to 0} \frac{F(x_i + h) - F(x_i - h)}{2h} \tag{2}$$

After introducing the empirical distribution function, we have:

$$f(x_i) = \lim_{h \to 0} \frac{1}{2nh} \sum_{i=1}^{n} l_{x_i - h \le x_j \le x_i + h} \tag{3}$$

Kernel function is introduced, and Gaussian kernel function is adopted in this paper, we have:

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K_0(\frac{|x - x_i|}{h}) \tag{4}$$

In this paper, the KDE kernel density function estimation method is used to estimate the uncertainty parameter distribution of each crop. The KDE estimation of the expected annual sales growth rate distribution of each crop is shown in Figure 2(a)(b), from which the expectation and variance of each crop uncertainty parameter can be calculated.

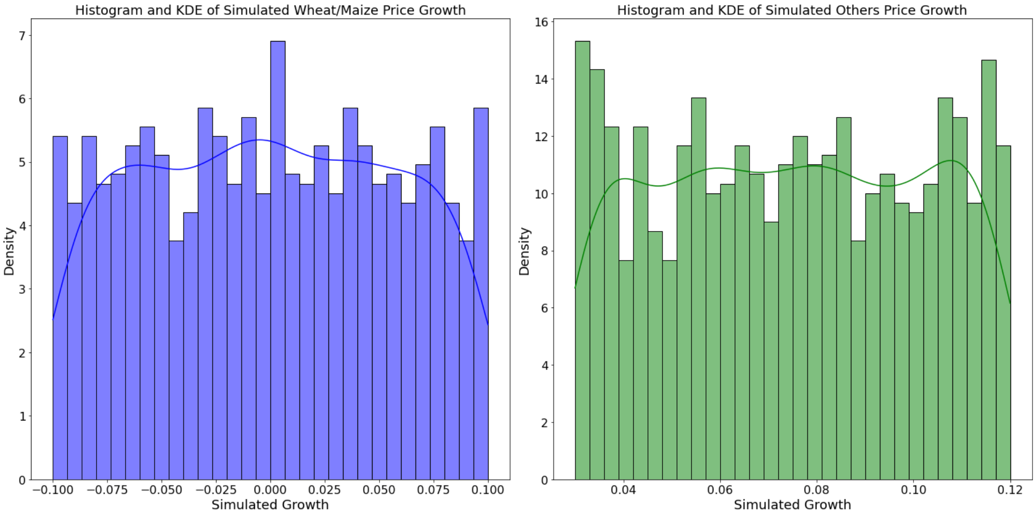

Figure 2. Estimates of the distribution of expected sales growth rates (a)wheat, maize (b) others

3.2. Target planning based on maximizing expected total profit

In Section 3.1, the trends of future expected sales, per mu yield, planting cost and selling price of various crops are given. Accordingly, the planning model is established:

Decision variable: In the t season, the area of the j crop planted on the i arable land is:

$$x_{jit} \tag{5}$$

Meanwhile, $1 \le j \le 41, 1 \le i \le 54, 1 \le t \le 14$.

Objective function:

Considering the uncertainty of the expected sales volume, per mu yield, planting cost and annual change rate of selling price of each category, this paper selects the right and potential planting risk, and the maximum profit can be obtained as follows:

$$\max\ f = E(Z) - \lambda \cdot CVaR_{\alpha}(Z) \tag{6}$$

The calculation formula of each parameter is as follows:

$$\alpha = 0.99 \tag{7}$$

$$Z = \sum_{j=1}^{41}\sum_{t=1}^{14} P_{jt} \cdot \min\left(\sum_{i=1}^{54} x_{jti} \cdot y_{ji}, S_{jt}\right) - \sum_{j=1}^{41}\sum_{t=1}^{14}\sum_{i=1}^{54} x_{jti} \cdot C_{jit} \tag{8}$$

$$E(Z) = \sum_{j=1}^{41}\sum_{t=1}^{14} E(P_{jt}) \cdot E\left[\min\left(\sum_{i=1}^{54} x_{jti} \cdot y_{ji}, S_{jt}\right)\right] - \sum_{j=1}^{41}\sum_{t=1}^{14}\sum_{i=1}^{54} x_{jti} E(C_{jti}) \tag{9}$$

$$VaR_{\alpha}(Z) = E(Z) - \varepsilon_{\alpha} \cdot \sqrt{D(Z)}, \tag{10}$$

$$\begin{aligned} D(Z) &= D\left(\sum_{j=1}^{41}\sum_{t=1}^{14} P_{jt} \cdot \min\left(\sum_{i=1}^{54} x_{jti} \cdot y_{ji}, S_{jt}\right) - \sum_{j=1}^{41}\sum_{t=1}^{14}\sum_{i=1}^{54} x_{jti} \cdot C_{jti}\right) \\ &= \sum_{j=1}^{41}\sum_{t=1}^{14} D(P_{jt}) \cdot D\left[\min\left(\sum_{i=1}^{54} x_{jti} \cdot y_{ji}, S_{jt}\right)\right] \\ &\quad - C_{jit}^{2}\left[\sum_{j=1}^{41}\sum_{t=1}^{14}\sum_{i=1}^{54} D(x_{jti}) + 2\sum_{j_1 \ne j_2} \rho\left(\sum_{i=1}^{54} x_{ij_1t}, \sum_{i=1}^{54} x_{ij_2t}\right) \cdot \sqrt{D\left(\sum_{i=1}^{54} x_{ij_1t}\right) \cdot D\left(\sum_{i=1}^{54} x_{ij_2t}\right)}\right] \end{aligned} \tag{11}$$

$$CVaR_{\alpha}(Z) = E(Z \mid Z \le VaR_{\alpha}(Z)) \tag{12}$$

Among them, Z is total profit, $VaR_{\alpha}(Z)$ is the value at risk of Z at α confidence level, $CVaR_{\alpha}(Z)$ is the conditional value at risk of Z at α confidence level, λ is an acceptance of risk, ε_{α} is the upper α quantile of Z .

Constraints:

① Land area constraint: that is, the planting area of each crop in a certain land can not exceed the total area of this land. This constraint can be expressed as:

$$\sum_{j=1}^{41} x_{jti} \leq Q_i \tag{13}$$

Among them, Q_i is the cultivable area of the i arable land; $1 \leq i \leq 54, 1 \leq t \leq 14$

② Repeated cropping restriction: each crop can not be continuously cropping in the same plot (including greenhouses). This constraint can be expressed as:

$$x_{jti} \cdot x_{j(t+1)i} = 0 \tag{14}$$

Among them, $1 \leq j \leq 41, 1 \leq i \leq 54, 1 \leq t \leq 13$.

③ Legume planting constraints: Starting from 2023, all land in each plot (including greenhouses) is required to plant legume crops at least once in three years. This constraint can be expressed as:

$$\sum_{k=0}^{5} x_{j(t+k)i} > 0 \tag{15}$$

Among them, $j \in [1,5] \cup [17,19], 1 \leq i \leq 54, 1 \leq t \leq 9$.

④ Crop suitable plots and seasonal constraints: for a certain crop, it can only be planted in a certain season of a certain plot type. This constraint can be expressed as:

$$x_{jti} = 0 \tag{16}$$

Among them, $t \in \mathbf{T_j}$ or $i \in \mathbf{I_{jt}}$.

⑤ Sales growth constraints: the expected sales of wheat and corn in the future have a growing trend, with an average annual growth rate between 5% and 10%, and the expected sales of other crops in the future have a change of about ±5% compared with 2023. This constraint can be expressed as:

$$S_{jt} = (1 + g_{sj}) \cdot S_{j(t-2)} \tag{17}$$

Among them, $3 \leq t \leq 14$, g_{sj} is the average sales growth rate of the j crop. The value of g_{sj} ranges from:

$$g_{sj} \in \begin{cases} [5\%, 10\%], \ j \in \{6,7\} \\ [-5\%, 5\%], \ j \in [1,5] \cup [8,41] \end{cases} \tag{18}$$

⑥ Yield per muchange constraint: the annual change rate of crop yield per mu is ±10%. This constraint can be expressed as:

$$y_{jit} = (1 + g_{yj}) \cdot y_{j(t-2)i} \tag{19}$$

Among them, $3 \leq t \leq 12$, g_{yj} is the average per mu yield change rate of the j crop, and we have $g_{yj} \in [-10\%, 10\%]$, $\forall j \in [1,41]$.

⑦ Cost change constraints: the average annual growth rate of crop planting costs is about 5%. This constraint can be expressed as:

$$C_{jit} = (1 + g_{cj}) \cdot C_{j(t-2)i} \tag{20}$$

Among them, $3 \le t \le 12$, g_{cj} is the average rate of change of the planting cost of the j crop, and we have $g_{cj} = 5\%$, $\forall j \in [1, 41]$.

⑧ Constraints on the change of selling prices: the selling prices of grain crops are basically stable; The selling price of vegetable crops is on the rise, with an average annual growth rate of about 5%. Edible mushroom sales prices remained stable, but slightly decreased, the annual decline rate of about 1% to 5%, especially morels, whose sales prices fell by about 5% per year. This constraint can be expressed as:

$$P_{jti} = \begin{cases} P(1+g_{pj}) \cdot P_{j(t-2)i}, t = 2k+1, 1 \le k \le 6 \\ P_{j(t+1)i}, t = 2k, 1 \le k \le 7 \end{cases} \tag{21}$$

Among them, g_{pj} is the rate of change in the average selling price of crop number j. The value of g_{pj} ranges from:

$$g_{pj} \in \begin{cases} \{0\}, 1 \le j \le 16 \\ \{5\%\}, 17 \le j \le 37 \\ [-5\%, -1\%], 38 \le j \le 40 \\ \{-5\%\}, j = 41 \end{cases} \tag{22}$$

In summary, the planning model for solving the optimal planting scheme is as follows:

$$\max f = E(Z) - \lambda \cdot CVaR_{\alpha}(Z)$$

$$s.t. \begin{cases} \sum_{j=1}^{41} x_{jti} \le Q_i, 1 \le i \le 54, 1 \le t \le 14 \\ x_{jti} \cdot x_{j(t+1)i} = 0, 1 \le j \le 41, 1 \le i \le 54, 1 \le t \le 13 \\ \sum_{k=0}^{5} x_{j(t+k)i} > 0,\ j \in [1,5] \cup [17,19], 1 \le i \le 54, 1 \le t \le 9 \\ x_{jti} = 0,\ t \in \mathbf{T_j} or i \in \mathbf{I_{jt}} \\ S_{jt} = (1+g_{sj}) \cdot S_{j(t-2)}, 3 \le t \le 14 \\ y_{jit} = (1+g_{yj}) \cdot y_{j(t-2)i}, 3 \le t \le 12 \\ C_{jit} = (1+g_{cj}) \cdot C_{j(t-2)i}, 3 \le t \le 12 \\ P_{jti} = \begin{cases} P(1+g_{pj}) \cdot P_{j(t-2)i}, t = 2k+1, 1 \le k \le 6 \\ P_{j(t+1)i}, t = 2k, 1 \le k \le 7 \end{cases} \\ g_{sj} \in \begin{cases} [5\%, 10\%], j \in \{6, 7\} \\ [-5\%, 5\%], j \in [1,5] \cup [8, 41] \end{cases} \\ g_{yj} \in [-10\%, 10\%] \\ g_{cj} = 5\% \\ g_{pj} \in \begin{cases} \{0\}, 1 \le j \le 16 \\ \{5\%\}, 17 \le j \le 37 \\ [-5\%, -1\%], 38 \le j \le 40 \\ \{-5\%\}, j = 41 \end{cases} \end{cases} \tag{23}$$

3.3. Differential Genetic Algorithm (DGA)

Differential Genetic Algorithm (DGA) [11] is a variation strategy that combines Differential Evolution (DE) with traditional Genetic Algorithm (Genetic Algorithm). GA) combined with hybrid optimization algorithm. The core idea is to enhance the global search capability of GA by using differential variation operation in differential evolution, while preserving the selection, crossover and population renewal mechanism of GA.

The overall process of DGA is similar to genetic algorithm, but the mutation operation is replaced by differential mutation strategy in differential evolution. The basic steps are as follows:

(1) Initialize population: Generate initial population randomly.

(2) Selection operation: Select high-quality individuals through fitness evaluation.

(3) Differential variation: Differential variation is performed on individuals to generate variant individuals.

- **Basis vector selection:** Randomly select an individual from the population as the base vector (e.g.x_{r_1})
- **Difference vector generation:** Select two or more different individuals (e.g.x_{r_2},x_{r_3}) and compute their difference vectors.
- **Scale factor (F):** The effect of the difference vector is controlled by scaling factor F:

$$v_i = x_{r_1} + F * (x_{r_2} - x_{r_3}) \tag{24}$$

(4) **Cross operation:** the mutation individual and the original individual are cross-generated test individuals.

(5) **Generation of new populations:** retention of better individuals through greedy selection.

(6) **Repeat iteration:** until the termination condition (such as the maximum number of iterations or the convergence threshold) is met.

To sum up, the differential genetic algorithm (DGA) pseudo-code is as follows:

Algorithm 1 Differential Genetic Algorithm(DGA)

Require: Population size NP, Scaling factor F, Crossover probability CR, Maximum iterations T
Ensure: Optimal solution $\mathbf{x}_{\text{best}}$

```
Initialize population:
for i = 1 to NP do
  Randomly generated individual x_i = (x_{i,1}, x_{i,2}, ..., x_{i,D}) {D is dimension}
end for
Calculate the fitness of all individuals f(x_i)
x_best ← arg min f(x_i) {Record the global optimal solution}
for t = 1 to T do
  for i = 1 to NP do
    Difference variation:
    Choose three different individuals at random r_1 ≠ r_2 ≠ r_3 ≠ i
    Generate a mutant v_i = x_{r_1} + F · (x_{r_2} − x_{r_3})
    Cross operation:
    Generating test unit u_i:
    for j = 1 to D do
      if rand ≤ CR or j = j_rand then
        u_{i,j} ← v_{i,j} {Binomial crossing}
      else
        u_{i,j} ← x_{i,j}
      end if
    end for
    Greedy choice:
    if f(u_i) < f(x_i) then
      x_i^new ← u_i
      if f(u_i) < f(x_best) then
        x_best ← u_i {Update the global optimal solution}
      end if
    else
      x_i^new ← x_i
    end if
  end for
  {x_i} ← {x_i^new} {Regeneration population}
end for
return x_best
```

Figure 3. Principles of Differential Genetic Algorithm (DGA)

4. Results and Discussions

In this paper, genetic algorithm is used to solve the above planning model. When the termination condition is met, the iteration is stopped and the planting plan is recorded at this time. Some of the results are shown in Table 2. The expected quarterly profits of different types of crops were counted and the stacked bar chart as shown in Figure 3 was drawn.

Table 2. Planting plan for the second season of 2024 (Partial)

Crop Name	Plot Name	Plant Area	Crop Name	Plot Name	Plant Area
Soya beans	A1	0	…	…	…
Soya beans	A2	0	Cauliflower	F2	0.06
…	…	…	Cauliflower	F3	0.06
Cowpea	F2	0	…	…	…
Cowpea	F3	0.12	Morel	F3	0
Cowpea	F4	0	Morel	F4	0

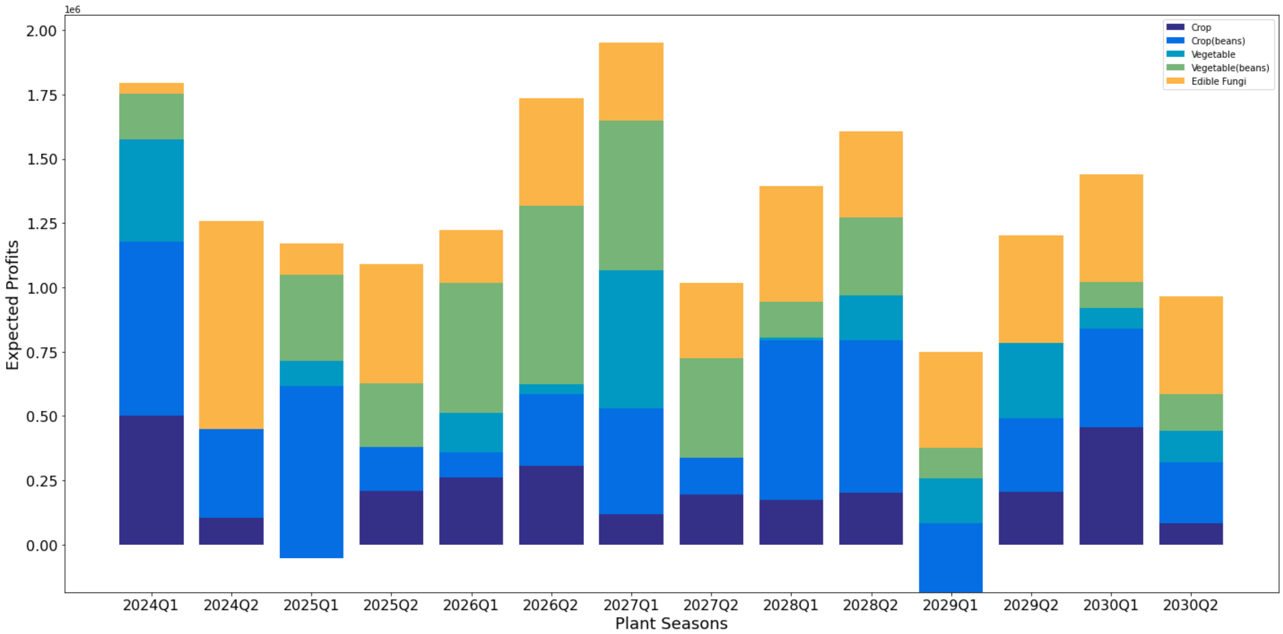

Figure 4. Expected quarterly profits for different types of crops by quarter

Figure 4 shows the distribution of expected profits from planting various crops in different seasons:

(1) The expected profit in the second quarter of each year is significantly higher than that in the first quarter, and the expected profit brought by the cultivation of edible fungi is the largest;

(2) Although vegetable crops can be grown in both seasons, the expected profit of planting vegetables in the second season is much higher than that in the first season.

Under the background of the certain question, according to the optimal planting scheme obtained by genetic algorithm, the sum of the maximum expected total profit for 7 years is 22332184.68 yuan and the corresponding conditional VAR is 7886172.54 yuan at 0.2 risk acceptance level and 0.99 confidence level. The maximum annual total profit from 2024 to 2030 is 3244,568.82 yuan, and the corresponding conditional value at risk is 7886,172.54 yuan. The average annual profit is 3190312.10 yuan. The average dispersion was 1.1116.

5. Conclusion

This research constructs a single-objective programming model to conduct in-depth analysis on the effective utilization of rural cultivated land resources and the optimization of crop planting strategies. In the research, based on the planting conditions of rural areas, the growth patterns of crops, sales volume, per-acre yield, planting costs, and sales prices, the expected total profit of crops is maximized as the objective function, and Conditional Value at Risk (CVaR) is introduced for robust optimization. Through Monte Carlo simulation, the uncertainty parameters are fully simulated, and the expected values and variances of the parameters are estimated using kernel density estimation. Finally, the differential genetic algorithm is used to solve the optimization model, and the optimal planting strategy is obtained. The study shows that after comprehensively considering various uncertainty factors, the optimized planting strategy can effectively increase the expected profit of crop planting, and at the same time reduce the risks brought by market fluctuations and changes in natural conditions, enabling farmers to maximize their income in a complex and changing environment. This study has important theoretical value and practical significance for promoting the transformation and upgrading of rural economy, promoting agricultural modernization, and increasing farmers' income.

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