ISSN 2616-5775 Vol. 8, Issue 1: 38-47, DOI: 10.25236/AJCIS.2025.080106

A mixed integer 0-1 planning crop planting strategy model based on robust optimization

Shuchang Wang[1,a,#], Jiayi Zeng[1,b,#], Yingshi Wu[2,c], Houmin Wang[1,d,*]

[1]*School of Computer Science and Engineering, Guangdong Ocean University, Yangjiang, 529500, China*
[2]*School of Mechanical Energy and Engineering, Guangdong Ocean University, Yangjiang, Guangdong, 529599, China*
[a]*ayratswa408700@foxmail.com*, [b]*zjy0106190006@stu.gdou.edu.cn*, [c]*13570421927@163.com*, [d]*hmwang@gdou.edu.cn*
[#]*Co-first author*
[*]*Corresponding author*

Abstract: *In modern agricultural production, crop cultivation strategies play a crucial role in sustainable agricultural development. In the context of precision agriculture, this paper tackles the issue of formulating the optimal planting scheme for existing crops. By utilizing historical farming data and crop planting information, etc., a mixed-integer 0-1 programming crop planting strategy model (ROPS) based on the robust optimization method is established. This model aims to maximize the economic returns of all plots while considering constraints such as the area of cultivated land and the degree of discrete planting areas. It also integrates the uncertainties in indicators such as crop yields and expected sales volume. The methodology can incorporate the uncertain information embedded in the indicators into the modelling and produce reasonable model results that allow decision-makers to weigh the risks and benefits to develop optimal solutions. The results indicate that the model was employed to solve the optimal cropping scheme for crops from 2024 to 2030. Through analysis, it was discovered that the average return for the seven years is $8,680,100, which is 35% higher than the initial profit in 2023. The adjusted optimal planting program for crops has significantly improved economic efficiency, and is more beneficial for improving production efficiency and developing organic agriculture, which is of practical significance for promoting the sustainable development of the rural economy.*

Keywords: *Planting Strategies, Robust optimization models, Mixed-integer 0-1 planning, Crop cultivation, Parametric uncertainty*

1. Introduction

Arable land, crucial for food production, sets the red line for food security for 1.4 billion Chinese. A country's food production capacity hinges on two main factors: the quantity and quality of its arable land. However, in recent years, the total amount of arable land in China has decreased and the quality of arable land has declined[1].In addition, reducing hunger and improving food security have become key priorities of the Sustainable Development Goals (SDGs) of the 2030 Agenda[2].Continuing threats to global food security as a result of intensifying climate change, rising food demand, and frequent armed conflicts[3]. Food security remains a key challenge, especially in smallholder agricultural systems[4].To ensure stable food production and self-sufficiency, limited arable land must be fully utilized by selecting suitable crops, optimizing strategies, reducing risks, and developing tailored planting programs.

Currently, there are more mature methods for the study of optimal planting programs for crops. Commonly used optimization methods at home and abroad include traditional empirical methods, linear programming methods, and dynamic programming methods[5].For instance, Yang Xiaoli et al. optimized Pingliang City's cropping structure in Gansu using a multivariate linear function, significantly increasing potato planting and boosting the total output value of main crops by 13.5% to 21.5%[5];Wu Menghan et al. created a multi-objective model to optimize crop planting in an irrigation area, boosting carbon sequestration by 0.8 tons, economic benefit by 584.5 million yuan, and saving 1.1 million cubic meters of irrigation water[6].Roberto et al. used MOMILP and a weighted approach to optimize crop diversity by 60% on average, while limiting net income reduction to 5%[7].Liu Mingchun et al. used linear programming to adjust Minqin County's crop structure, changing the summer-to-autumn crop ratio to 1:1.81. This increased net output value by 68.39 million yuan compared to 2000[8].Yang Yijiang et al. used dynamic and linear programming to determine the optimal crop planting scheme for a village[9].

However, Challenges remain in multi-objective crop optimization. Traditional algorithms may not handle complex problems due to real-world factors. The linear weighting method, for instance, can be sensitive to small parameter changes and yield similar solution vectors with different weights, lacking diversity. In addition, a uniform distribution of the set of weights generally does not produce a uniformly distributed set of Pareto solutions[10]-[11].Secondly, uncertainty treatment: applying multi-objective planning in real problems often ignores the impact of some uncertainties on the optimization problem[12]. Meanwhile, in current research, there has been relatively little reporting on optimal allocation in agriculture based on multi-objective linear programming involving multi-objective weight uncertainty methods[13].Therefore, it is necessary to introduce a multi-objective optimization method that can effectively handle weighting uncertainty and difficult solutions to improve the reliability of the optimization results.

Consequently, this paper introduces a robust mixed-integer 0-1 programming model (ROPS) for crop planting, addressing multi-objective uncertainty and solution difficulties. It considers sales, acreage, cost/price uncertainties, and growth risks. Conditional mutually exclusive variables avoid local optima, and solution process optimizations enhance accuracy and efficiency, providing a reference for modern crop cultivation strategies.

2. Robust optimization-based mixed-integer 0-1 planning approach

In crop planting optimization, mismatch between expected sales and actual yield can lower prices. Multi-objective planning addresses this, but solutions are complex, often leading to local optima. Fluctuating costs and yields make traditional linear weighting approaches inadequate. This paper introduces a robust mixed-integer 0-1 planning method (ROPS) to solve multi-objective planning complexity and parameter uncertainty, optimizing planting strategies under fluctuating indicators.

The ROPS model's general form is provided:

With x as the decision variable, ω as the uncertainty value, and U_i as the uncertainty set, the general optimization model is:

$$\begin{cases} \min f(x) \\ g(x,\omega) \le 0, \forall \omega \in U_i, i = 1,2,...,m \\ x \in R^n \end{cases} \tag{1}$$

Robust optimization models are built with optimization results that are relatively sensitive to the selection of the uncertainty set, and when the uncertainty set is more detailed, the complexity of the model is higher and the solution is more difficult. When the uncertainty set is wider, the optimal solution derived is more conservative, thus greatly limiting the practical application value and decision-making guidance[14], so the accuracy of the uncertainty set will determine the model's solution time and the validity of the results[15].The collected information and review of the literature shows that there are interval variations in the indicators such as acre yield and planting cost of crops per year with the year, so the box uncertainty set, also called interval set, is chosen in this paper:

$$U = \left\{ \omega \mid e^T = 0, \omega_{\min} \le \omega \le \omega_{\max} \right\} \tag{2}$$

Where: e is the unit vector and ω is the perturbation variable.

The establishment of the robust optimization model is roughly divided into the following three steps; in the first step, the decision variables, constraints, and objective function of the uncertain optimization model are first established. In the second step, the uncertainty set is selected. In the third step, the pairwise transformation is carried out, and the conservatism of the model is adjusted through the introduction of parameters Γ_t based on the pairwise theory. Assuming that the number of uncertainty parameters does not exceed the number of introduced parameters, the model must be solvable, and even if it does, there is a high probability of obtaining a robust solution[16].

ISSN 2616-5775 Vol. 8, Issue 1: 38-47, DOI: 10.25236/AJCIS.2025.080106

3. Empirical applications

3.1. Overview of the study area

This paper focuses on a mountainous region in North China with low annual temperatures and single-crop seasons. The area has 1,201 acres of farmland, 41 crop types, and 34 plots of varying sizes (flat, terraced, hillside, irrigated). Plot areas are detailed in Table 1.Flat lands, terraces, and hillsides support one food crop season; watered land supports one rice or two vegetable seasons. The area has 16 regular and 4 smart sheds (each 0.6 acres), suitable for one vegetable and mushroom season (regular) or two vegetable seasons (smart). Land (including sheds) can be used for different crops each season.

Table 1: Area of regional plots

Type of plot	Plot size(areas)
Terraced land	619
Flat dry land	365
Irrigated land	109
Hillsides land	108
Ordinary greenhouses	9.6
Smart greenhouses	2.4
Total	1213

The main crops in the region are classified into five major crop types: edibles, vegetables (pulses), vegetables, grains (pulses), and cereals. Figure 1 presents information on average acreage yields for the five major crop types in the region. During the forecast period, it is assumed that the expected sales volume is related only to the acreage yield, without considering other influencing factors, and that the plots of the same type are mostly concentrated in the same area with a more concentrated distribution. Also for cases where the acreage of the crop exceeds the expected sales volume, the excess is sold at a reduced price of 50 percent of the 2023 sales price.

Taking into account the actual planting situation in the study area and the growth patterns of crops, each of these crops cannot be planted in the same plot (including greenhouses) in consecutive heavy plantings; otherwise, the yield will be reduced. Since the soil containing rhizobacteria of legume crops is beneficial to the growth of other crops, it is required to plant legume crops at least once in three years on all the land of each plot (including greenhouses) starting from 2023. At the same time, the planting program should consider the convenience of farming operations and field management. For example, each crop should not be too widely scattered in each season, and the area of each crop planted in a single plot (including greenhouses) should not be too small.

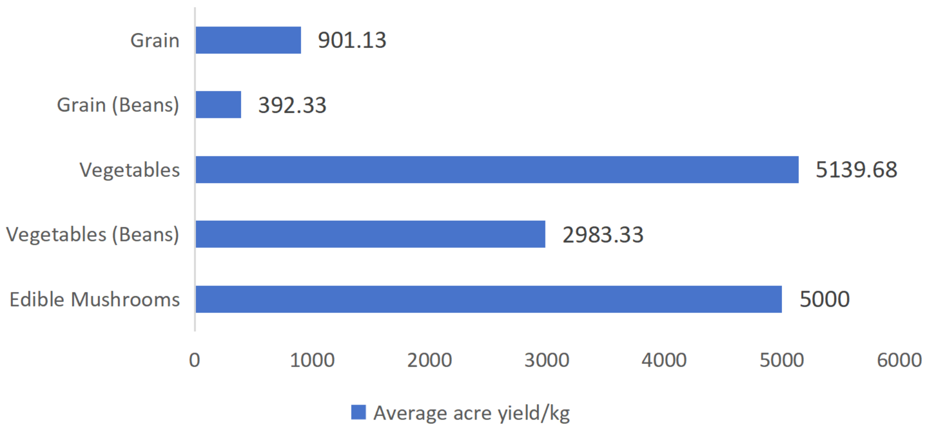

Figure 1: Average yield per acre for the five major crop types

3.2. Data sources

The research data sources of this paper mainly include the National Bureau of Statistics, the China Grain Statistical Yearbook, the National Ecological Data Centre Resource Sharing Service Platform, and the spatio-temporal Three-Level Environmental Big Data Platform.

ISSN 2616-5775 Vol. 8, Issue 1: 38-47, DOI: 10.25236/AJCIS.2025.080106

3.3. Model Construction

3.3.1. Determination of the objective function

Without considering the parameter fluctuation, the total return calculation of all plots in this mountainous area is divided into two cases: when the total production of arable land is less than the expected sales volume, the profit consists of the actual acreage revenue and planting costs; when the total production of arable land is greater than the expected sales volume, the profit consists of the expected sales volume revenue, the oversold portion of the revenue and the cost of planting, in this paper, we will consider the two cases together, and for the crop oversold sales volume part of the income is expressed by the segmentation function $f(q)$ The specific formula is as follows:

$$Max \sum_{t=2024}^{2030} \sum_{i} \sum_{j} (P_j \times G_{i,j} \times M_{i,j,t}) - \sum_{t=2024}^{2030} \sum_{i} \sum_{j} (M_{i,j,t} \times C_{i.j}) + f(q) \tag{3}$$

Where P_j denotes the selling price of the j crop, $G_{i,j}$ denotes the acre yield of the j crop in the i plot, $M_{i,j,t}$ denotes the area of the j crop planted on the i plot in the t year, and $C_{i,j}$ denotes the cost of planting the crop of the j crop in the i plot of the crop.

$f(q)$ represents income from crop over sales, with discounted sales over expected sales:

$$f(q) = \begin{cases} 0.5P_j \times (q_{j,t} - w_j) & \mathrm{q}_{j,t} > w_j \\ 0 & \mathrm{q}_{j,t} \le w_j \end{cases} \tag{4}$$

Where $q_{i,j}$ denotes the total acre yield of crop j crop in the t year.

From the point of view of the model solution, although the objective function only adds the expression of discounted sale, from the nature of the model, due to the introduction of the segmentation function, the single-objective linear planning model, transformed into a multi-objective planning model.

To solve the segmented function problem more efficiently and avoid the interference of the local optimal solution as much as possible, this paper proposes an improved method-introducing two 0-1 variables, transforming them to represent the constraints, and constructing a mixed-integer 0-1 linear programming model on this basis. This approach aims to optimize the solution process of the segmented function by introducing discrete decision variables to improve the accuracy of the solution and the efficiency of obtaining the global optimal solution[17]-[18].

Step 1: Decompose the total planting amount of the crop q into two variables, i.e., use q_1, q_2 to represent the two cases in which the total planting amount of the crop is less than or equal to w and is greater than w_j respectively so that the over-selling portion of the crop generates revenue $f(q) = 0 \times q_1 + 0.5 \times P_j q_{2i,j,t}$. For the segmented function, the over-production of the crop can be sold at the selling price $0.5 p_j$ only if the total amount of crop planted $q_1 = w_j$. To this end, the constraints are as follows:

$$\begin{cases} (q_1 - w_j) \times q_2 = 0 \\ 0 \le q_1, q_2 \le w_j \end{cases} \tag{5}$$

Step 2: Since the constraint $(q_1 - w_j) \times q_2 = 0$ is a multi-objective constraint, this paper constructs a linear constraint by introducing two 0-1 variables k_1, k_2. Where k_1 denotes selling the excess at 0 yuan per catty and k_2 denotes selling the excess at $0.5 p_j$ Yuan per catty, corresponding to the constraints that need to be satisfied after the modification are as follows:

ISSN 2616-5775 Vol. 8, Issue 1: 38-47, DOI: 10.25236/AJCIS.2025.080106

$$\begin{cases} k_2 \times W_j \le q_{1,j,t} \le k_1 \times W_j \\ q_{2,j,t} \le k_2 \times W \\ k_1 + k_2 = 1 \end{cases} \tag{6}$$

After going through the above steps, the fluctuation of the parameters is considered and the uncertainty information of the parameters is incorporated into the modelling process to construct the ROPS model, i.e., to find the maximum value of the economic efficiency in the environment of the worst value of the objective function. Finally, a mixed integer 0-1 planning crop planting strategy model based on robust optimization is constructed, and the minimum value variable of this model is used to solve the objective function under the influence of uncertainty. That is, when the resulting annual profit is greater than the annual profit in 2023, then the result of this objective function is always greater than the annual profit in 2023, regardless of the value of the variable. The final expression combining discounted sales and parametric uncertainty is as follows:

$$\max_{M_{i,j,t}} \min_{G_{i,j},W_j} \sum_{t=2024}^{2030} \sum_i \sum_j (P_j(t) \times G_{i,j}(t) \times M_{i,j,t}) - \sum_i \sum_j \sum_t (M_{i,j,t} \times C_{i,j,t}(t)) + 0.5 p_j q_{2j,t} \tag{7}$$

3.3.2. Determination of constraints

a) Cropland area limitations

In the actual process of crop cultivation, there is a limit to the area that can be cultivated on each piece of land, and the area of crop cultivation cannot exceed the area of that piece of land. Exceeding the area of arable land may lead to over-utilization of land resources and ecological balance, which is not conducive to improving the production efficiency of arable land. There are constraints between the area under cultivation and the area of arable land as follows:

$$\sum_{j=1}^{41} M_{i,j,t} \le A_i \tag{8}$$

$M_{i,j,t}$ denotes the area of the j crop, planted on the i plot in year t, and A_i is denoted as the area of the i planted plot.

In addition, the planting program should take into account the convenience of ploughing operations and field management, i.e. the area of each crop planted in a single plot is not too small, and the planting density α is introduced to measure the relationship between the area planted in a single plot and the overall cultivated area, which can be expressed as the following formula:

$$\sum_{j=1}^{41} M_{i,j,t} \ge \alpha \times A_i \tag{9}$$

b) Total production limit

If the total production of a crop per season exceeds the corresponding expected sales volume, for the excess that is not sold, the excess is sold at a reduced price of 50 per cent of the 2023 sales price. Therefore, to maximize revenue, the expected sales volume is the top line of the total crop production, with the following constraints:

$$\sum_{i=1}^{54} G_{i,j} \times M_{i,j,t} \le W_j \tag{10}$$

Where $C_{i,j}$ denotes the acre yield of the j crop on the i plot, $M_{i,j,t}$ denotes the acreage of the j crop, planted on the i plot, in year t, and W_j denotes the predicted sales volume of the j crop.

c) Limit of at least one legume planting in three years

Because soil containing legume crop rhizobacteria helps other crops grow, each plot is required to be planted with a legume crop at least once every three years starting in 2023. Splitting the problem into sub-problems, it is important to consider whether there is any planting of legume crops in the years before and after, and to use the idea of dynamic programming to achieve continuous updating of the

ISSN 2616-5775 Vol. 8, Issue 1: 38-47, DOI: 10.25236/AJCIS.2025.080106

planting of legume crops, with the following constraints:

$$y_{i,j,t} + y_{i,j,t+1} + y_{i,j,t+2} \ge 1 \tag{11}$$

$$y_{i,j,t} = \begin{cases} 0, \textit{No legumes on plot } i \textit{ in year } t \\ 1, \textit{Legumes on plot } i \textit{ in year } t \end{cases} \tag{12}$$

Where $y_{i,j,t}$ denotes the type of crop, whether or not it is a legume, grown on the i plot in the year t.

d) Continuous heavy cropping limit

According to the growth pattern of crops, each crop cannot be ploughed on the same piece of land for two consecutive years. Because the growth of different crops needs to draw different nutrients in the soil, when the continuous cultivation of the same crop for two years will cause some nutrient deficiencies in the soil, resulting in a reduction in yield. Using the idea of dynamic programming, we need to fully consider the planting situation before and after two years, so we split the problem into relatively simple sub-problems to explore the planting situation shortly. The planting relationship of the same crop in the same field is as follows:

$$X_{i,j,t} + X_{i,j,t+1} \le 1 \tag{13}$$

Where $X_{i,j,t}$ denotes the j crop, whether or not it was planted on the i plot in year t, and, $X_{i,j,t+1}$ denotes species j whether or not it was planted on the i plot in year $t+1$.

e) Limit the degree of dispersal of the cultivation area

In the program of crop cultivation, the convenience of farming operations and field management should be taken into account, for example, for each crop each season, the planting land can't be too dispersed, from the assumption that the same type of regional planting area distribution is more concentrated, add constraints to limit the same type of crop planting area in the neighbouring plots: g. Model conservativeness constraints:

$$\left| M_{i,j,t} - M_{i',j,t} \right| \le \phi \tag{14}$$

$M_{i,j,t}$ denotes the area of the j crop, planted on the i plot in year t, and ϕ is the permitted regional variation in cultivation.

f) Model conservatism constraints

The conservatism of the model is regulated by introducing the parameters $W_{j,t}$, $G_{i,j,t}$.

$$\begin{cases} L_{W_{j,t}} \le W_{j,t} \le U_{W_{j,t}} \\ L_{G_{i,j,t}} \le G_{i,j,t} \le U_{G_{i,j,t}} \end{cases} \tag{15}$$

Where $W_{j,t}$ denotes the expected acres of the j crop in year t, and $G_{i,j,t}$ denotes the acres of the j crop in year t of the i plot.

3.3.3. Selection of robust optimization uncertainty sets

a) Growth and fluctuation of sales

It is clear from social development that with the rapid growth of the secondary sector, wheat and maize can be used not only to supply the needs of the population but also as raw materials for industry. With the global emphasis on renewable energy, the production of biofuels is expanding and the demand for maize and wheat will increase accordingly. The average growth rate of their sales is predicted to be between 5 and 10 per cent, and the expression is given below:

ISSN 2616-5775 Vol. 8, Issue 1: 38-47, DOI: 10.25236/AJCIS.2025.080106

$$W_j(t) = W_j(2023) \times (1 + a_{j,t})^{t-2023}$$
$$a_{j,t} \in [0.05, 0.10], \forall j \in \{6,7\}, t \in [2024, 2030] \tag{16}$$

where $W_j(t)$ denotes the expected acres produced by crop j in year t, and $a_{j,t}$ denotes the expected average growth rate of sales volume of the crop j in year t.

For the other crops, the expected future sales volume for each year of their sales volume varies by approximately ±5 per cent relative to 2023. The expression is given below:

$$W_j(t) = W_j(2023) \times (1 + a_{j,t})$$
$$a_{j,t} \in [-0.05, 0.05], \forall j \in \{6,7\}, t \in [2024, 2030] \tag{17}$$

b) Fluctuations in acreage production

In a complex and changing natural environment, crop yield per acre shows fluctuations from year to year within a relatively large range, which can be found in the range of about ± 10 per cent. The expression is as follows:

$$G_j(t) = G_j(2023) \times (1 + b_{j,t})^{t-2023}$$
$$b_{j,t} \in [-0.1, 0.1], \forall j, t \in [2024, 2030] \tag{18}$$

Where $G_j(t)$ denotes the acre yield of the j crop in year t and $b_{j,t}$ denotes the acre yield of the j crop in year t.

c) Fluctuation in discount strength

Discounting of agricultural products usually refers to the reduction of a certain percentage of the original selling price during the sales process to promote sales, clear inventory or because the product is close to its shelf life. In the sale of agricultural products, discounting may be related to seasonal supply changes, market demand fluctuations or policy adjustments. Therefore, the discount fluctuation variable λ is introduced to replace the oversold portion sold at 50 per cent of the original price.

$$f(q) = \lambda p_j q_{2i,j,t} \tag{19}$$

d) Growth in planting costs

With the booming economy and the overall progress of society, the standard of living of the people has steadily risen, and the price of labour has also risen. Against this background, the cost of growing crops has increased by an average of 5 per cent per year, as shown in the following expression:

$$G_j(t) = C_j(2023) \times (1 + 0.05)^{t-2023}, \forall j, t \in [2024, 2030] \tag{20}$$

e) Change in selling price

For food crops, where prices are essentially stable and not adjusted, the expression is as follows:

$$p_j(c) = p_j(2023) \quad , \forall j \in [2024, 2030] \tag{21}$$

where $p_j(t)$ denotes the price of the j crop in year t.

For vegetable crops, where prices increase by 5 per cent per year, the expression is as follows:

$$p_j(t) = p_j(2023) \times (1 + 0.05)^{t-2023}$$
$$\forall j \in Vegetables, \quad t \in [2024, 2030] \tag{22}$$

For which the price of morel mushrooms falls by 5 per cent per year, the expression is as follows:

$$p_j(t) = p_j(2023) \times (1 - 0.05)^{t-2023}, t \in [2024, 2030] \tag{23}$$

For edible mushroom crops, the expression is as follows, assuming that prices decline by 1 to 5 per

ISSN 2616-5775 Vol. 8, Issue 1: 38-47, DOI: 10.25236/AJCIS.2025.080106

cent per year:

$$p_j(t) = p_j(2023) \times (1 - d_{j,t})^{t-2023}$$
$$d_{j,t} \in [0.01, 0.05], \forall j \in mushrooms,\ t \in [2024, 2030] \tag{24}$$

4. Analysis of results

The model outputs the optimal crop cultivation scheme from 2024-2030, analyzed macro (total income, cultivation in North China's mountains) and micro (terrace planting scheme) perspectives to test planting strategy rationality.

4.1. Macro perspective: changes in overall regional economic benefits from 2024 to 2030

For the assessment and analysis of the overall economic benefits of the mountainous region, the changes and trends of the annual benefits from 2024 to 2030 are calculated and analyzed from the perspective of the year, and the following table shows the changes in the annual benefits of the mountainous region in eight years under the scenario of the optimal planting strategy of crops.

Table 2: Profit gain for the year

Year	Profit/yuan
2023	6957922.5
2024	8826375.053
2025	8755609.378
2026	8774259.309
2027	8776908.907
2028	8757118.7
2029	8807099.684
2030	8762875.114

As can be seen in Table 2, mountain revenue is rising, up 35% in 2024 vs. 2023 through resource integration and crop mixing. Declines in 2025 and 2028 were followed by increases, likely due to natural disasters or pests. This shows the model's reasonableness and supports better planting decisions.

4.2. Macro perspective: Changes in economic benefits of the six major land parcels from 2024 to 2030

The annual profits of the North China Mountain region are analyzed over seven years based on parcel types. The annual profits over seven years are analyzed for three land parcel types, as shown in Figure 2.

Figure 2: Annual Profit Gains over Seven Years for the Parcel

As can be seen in Figure 2, annual profits from plot terraces surpass those of hillsides and greenhouses, trending upwards. Terraces cover the largest acreage, while Smart Sheds Season 1 have the

ISSN 2616-5775 Vol. 8, Issue 1: 38-47, DOI: 10.25236/AJCIS.2025.080106

least. Hill slopes have more space but similar crop options as dry lands. This comparison shows plot size affects annual profit.

4.3. Microcosmic perspective: Terrace crop cultivation strategy, 2024-2030

From the above analyses, it can be found that the terraces produce the largest annual profit gain among the seven years' gain in the whole study area, so the planting strategies of crops corresponding to the terraces were explored during the planning period to test the reasonableness of the planting strategies, as shown in Table 3.

Table 3: Crop cultivation in terraces from 2024 to 2023

Year	Crops	Plantation(areas)
2024	sorghum	31.00
	Avena nuda	7.89
	Barley	21.11
2025	Crawler bean	29.32
	Wheat	30.68
2026	Red beans	60.00
2027	Crawler bean	36.20
	Wheat	3.45
	Sorghum	20.35
2028	Wheat	60.00
2029	Sorghum	32.50
	Avena sativa	8.90

Over seven years, data analysis shows terraced areas had the highest average annual profit in the study area. Their crop choices exhibited regularity and profit orientation:

1) Terraces focus on high-yield crops like wheat and sorghum, planted extensively in 2025, 2027, 2028, and 2030, covering at least 50% of land. This high planting area directly correlates with high yearly profits, showing that planting large amounts of high-yield crops boosts plot economic benefits.

2) Ensuring robustness: Yearly crop structure adjustments show adaptability to returns. Alternating sorghum and wheat between 2024 and 2030 maximizes area in some years, reflecting responsiveness to market and crop adaptation. This robust structure ensures consistent terrace returns, mitigating risks from mono-cropping yield fluctuations.

3) Promoting diversification: Terrace cropping includes sorghum, wheat, and other crops like barley, oats, and red beans. Diversified patterns reduce market and climate risks, ensuring steady annual profit growth.

5. Conclusion

This study establishes a mixed integer 0-1 planning crop planting model using robust optimization for multi-objective planning and parameter uncertainty. Robust optimization addresses index uncertainty, while two conditionally exclusive variables tackle multi-objective planning, providing support for solving crop planting strategy under complex uncertainty.

In mountainous North China, robust optimization was used to maximize crop economic benefits. Results showed annual profit increases, with a 35% rise in 2024 vs. 2023. Terraced plots were most profitable, planting seven crop types including high-yield wheat and sorghum, demonstrating strategy effectiveness.

Results show that crop planting adjustments based on robust optimization's mixed integer 0-1 planning are valuable. Given North China's mountainous land diversity and crop variety, the research model offers a methodology for villages to decide future crop planting areas, structures, and other methods, providing suitable decision-making programs.

References

[1] YU Zhenguo, HU Xiaoping. Study on the relationship between food security and quantity and quality of arable land in China[J]. Geography and Geographic Information Science,2003,19(3):45-49

ISSN 2616-5775 Vol. 8, Issue 1: 38-47, DOI: 10.25236/AJCIS.2025.080106

[2] Urfels A, Mausch K, Harris D, et al. Farm size limits agriculture's poverty reduction potential in eastern India even with irrigation-led intensification[J]. Agric Syst, 2023, 207: 103618.

[3] Bentley A R, Donovan J, Sonder K, et al. Near- to long-term measures to stabilize global wheat supplies and food security[J]. Nat Food, 2022, 3: 483-486.

[4] Cui Z, Zhang H, Chen X, et al. Pursuing sustainable productivity with millions of smallholder farmers[J]. Nature, 2018, 555: 363-366.

[5] YANG Xiaoli, YIN Dong, LI Xiaojuan, et al. Research on the optimisation scheme of crop planting structure in Pingliang City[J]. Research on Agriculture in Arid Areas,2003,(03):65-68

[6] Wu Menghan, Wang Yi. Optimal adjustment of multi-objective planting of crops in Shache Irrigation District, Xinjiang [J]. People's Yellow River, 2024, 46(1): 120-125, 131.

[7] Pontes R S G, Brandão D N, Usberti F L, et al. Multi-objective models for crop rotation planning problems[J]. Agricultural Systems, 2024, 219: 104050.

[8] Liu Mingchun,Xue Shengliang. Crop cultivation structure adjustment programme along the desert area in the eastern part of Hexi Corridor[J]. Journal of Nanjing Meteorological Institute, 2003,(01): 124-129.DOI:10.13878/j.cnki.dqkxxb.2003.01.018.

[9] YANG Yijiang,YANG Yiwen. Dynamic planning model and its application in determining the best planting scheme for crops[J]. Guangdong Chemical Industry, 2013, 40(14):70-71+84.

[10] P. Gao, North China Electric Power University, School of Electrical and Electronic Engineering, Beijing, China. A review of multi-objective optimisation algorithms[C]//North China Electric Power University. North China Electric Power University, 2011.

[11] Xu Bingkun. An improved weighted summation algorithm for solving multi-objective optimisation problems[D]. Xi'an University of Electronic Science and Technology, 2010.DOI: 10.7666/ d. y1866941.

[12] Karimia N, Feylizadeh MR, Govindan K, Bagherpour M. Fuzzy multi-objective programming: A systematic literature review[J]. Expert Systems With Applications, 2022, 196: 116663.

[13] TAN Qian, TIAN Gou, ZHANG Tianyuan, et al. A multi-objective optimal allocation model of agricultural water resources based on robust planning method[J]. Journal of Water Resources, 2020, 51(01): 56-68.DOI:10.13243/j.cnki.slxb.20190449.

[14] Liu Yankui, Liu Ying. New advances in robust plausibility optimisation[J]. Journal of Hebei University (Natural Science Edition),2021,41(5):457-462. DOI:10.3969/j.issn.1000-1565.2021.05.002

[15] Pengfei Zhang, Gupta D. Robust optimization with order statistic uncertainty set[J]. European Journal of Operational Research, 2023, 311(1023-1039): 1-17. DOI: 10.1016/j.ejor.2023.05.024.

[16] Y. Q. Li. Study on several models of robust linear optimisation [D]. Shandong University of Science and Technology,2009.DOI:10.7666/d.D299344.

[17] Asghari M, Fathollahi Fard A M, Mirzapour Al-e-hashem S M J, Dulebenets M A. Transformation and Linearization Techniques in Optimization: A State-of-the-Art Survey[J]. Mathematics, 2022, 10(283). DOI: 10.3390/math10020283.

[18] MirHassani S A, Hooshmand F. Linearization of Nonlinear Functions[C]// Methods and Models in Mathematical Programming. Springer International Publishing: Cham, 2019: 115-204. DOI: 10.1007/978-3-030-27045-2_4.