Crop planting strategy by robust particle swarm optimized-algorithm

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Abstract. With the rapid transformation of rural economies, optimizing crop planting structures has become a key strategy to address limited resources, market volatility, and environmental risks. This issue is especially critical in the mountainous regions of North China, where arable land is scarce and topographic constraints pose serious challenges to traditional agriculture. This study develops a multi-objective mathematical model that comprehensively considers key uncertain factors, including yield per mu, planting costs, and sales volume. By integrating Particle Swarm Optimization (PSO) with Robust Optimization techniques, the model identifies an optimal crop planting scheme for the period 2025–2030. The proposed solution remains stable under uncertainty and meets practical requirements for adaptability and feasibility. The results provide valuable theoretical and decision-making support for improving land use efficiency, reducing planting risks, and promoting sustainable agricultural development in resource-constrained mountainous areas. This research offers practical guidance for policymakers and agricultural planners seeking data-driven strategies in the context of rural economic transformation.

Keywords: Robust Optimization, Particle Swarm Optimization, Crop Planting.

1. Introduction

Under the accelerated global agricultural modernization, rural economies are undergoing profound structural transformations, where optimizing crop planting structures has become a key strategy for enhancing agricultural productivity, increasing farmers income, and addressing resource constraints, market fluctuations, and environmental challenges.

As a typical dry farming area, the cultivated land resources in the mountainous area of North China are restricted by terrain fragmentation and soil erosion, and the soil organic carbon (SOC) content has decreased by 30-40% compared with the early stage of reclamation. In recent years, extreme climate events have occurred frequently in this region. Statistics show that the fluctuation range of effective accumulated temperature in the key growth period of maize is ±15%, and the interannual variation coefficient of precipitation is more than 25%. Under the current planting system, farmers often face seasonal oversupply of outdoor vegetables due to synchronized harvesting, while facility agriculture is vulnerable to energy cost fluctuations. This dual uncertainty complicates optimal resource allocation through traditional planning methods. Studies have shown that energy price volatility negatively impacts agricultural production and increases carbon emissions, while the spatial concentration of vegetable production can lead to market price volatility [1-2]. Therefore, understanding and adjusting crop planting structures under limited arable land conditions, informed by spatiotemporal patterns of crop phenology and cropping systems, has become a critical issue for achieving sustainable agricultural development and maximizing economic benefits [3].

In recent years, research on optimizing crop planting structures has primarily focused on data-driven agricultural planning, intelligent optimization algorithms, and sustainable agricultural development. However, traditional optimization methods mainly rely on mathematical modeling techniques such as linear programming (LP) and weighted goal programming (WGP) [4]. Due to the numerous uncertainties in agricultural production, such as market price fluctuations and changes in input costs, these conventional approaches struggle to effectively adapt to dynamic adjustment requirements in complex environments. In contrast, the particle swarm optimization (PSO) algorithm, known for its strong global search capability and fast convergence, has been widely applied in agricultural optimization problems. Nevertheless, the standard PSO tends to fall into local optima when handling multi-constrained problems and exhibits weak adaptability to external environmental changes. Robust optimization, as an effective approach to managing uncertainty, builds decision-making models that ensure solutions maintain reliable performance even under worst-case scenarios. In the context of crop planting structure planning, where climate variability, market volatility, and resource constraints introduce significant uncertainty, applying robust optimization can greatly improve the stability and practicality of agricultural decisions. Similar to its application in energy management for hybrid electric vehicles—where integrating digital twin models with Particle Swarm Optimization (PSO) has proven effective—robust optimization offers valuable insights for enhancing the resilience of agricultural planning systems [5].

This study addresses the crop planting demands in rural areas of North China by comprehensively considering multiple uncertain factors, including sales volume, planting costs, and yield per unit area. A corresponding mathematical model is established, and a robust particle swarm optimization (RPSO) algorithm is employed to develop an optimized planting structure model that adapts to uncertain environments. The study proposes optimal planting schemes for the period from 2025 to 2030. The research not only provides scientifically grounded crop planting strategies for mountainous regions in North China but also contributes novel insights into the application of intelligent algorithms in agricultural planting optimization.

2. The robust particle swarm model

2.1. Robust particle swarm algorithm

Particle Swarm Optimization (PSO), proposed by J.Kennedy and R.C.Eberhart in 1995, is a heuristic optimization method based on swarm intelligence. The algorithm simulates the foraging behavior of birds and uses the cooperation between particles to search for the global optimal solution. PSO has the advantages of simple operation, fast convergence speed and few parameters, which can effectively overcome the shortcomings of traditional optimization methods (such as linear programming) in parameter complexity and computational complexity. In the standard PSO, each particle updates its speed and position according to its historical optimal position (individual optimal) and group optimal position (global optimal). The update formula is as follows:

$$\mathrm{v}_\mathrm{i}^{\mathrm{t}+1} = \mathrm{w}\mathrm{v}_\mathrm{i}^\mathrm{t} + \mathrm{c}_1\mathrm{r}_1(\mathrm{p}_\mathrm{i} - \mathrm{x}_\mathrm{i}^\mathrm{t}) + \mathrm{c}_2\mathrm{r}_2(\mathrm{g} - \mathrm{x}_\mathrm{i}^\mathrm{t}) \tag{1}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{2}$$

Where, v_{it} and x_{it} denote the velocity and position of the *i-th* particle at iteration *t*, *w* is the inertia weight,c_1 and c_2 are acceleration coefficients, r_1,$r_2 \in [0,1]$ are random factors, pi is the individual best, and g is the global best.

However, standard PSO faces multiple challenges in the planning of rural crop planting in mountainous areas of North China. Due to the uncertainty of factors such as sales volume, planting cost and yield per mu, PSO is easy to fall into local optimum and is sensitive to environmental changes, resulting in insufficient stability of the optimization scheme. To this end, this study introduces robust optimization, whose core idea is to find robust solutions in uncertain environments to ensure that the optimization results are still reliable in the worst case [6]. Combined with PSO, a robust particle swarm optimization algorithm (Robust PSO, RPSO) is formed.

The process of robust optimization is shown in Figure 1.

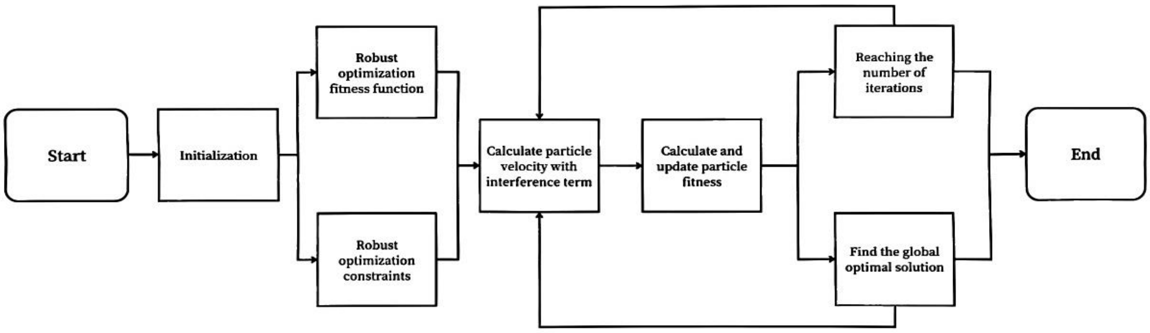

Figure 1. Robust particle swarm optimization algorithm

RPSO enhances the adaptability of the algorithm to fluctuation factors by introducing uncertain disturbance terms into the fitness function. The improved speed update formula is:

$$v_i^{t+1} = wv_i^t + c_1r_1(p_i - x_i^t) + c_2r_2(g - x_i^t) + c_3\delta \quad (3)$$

where δ represents the uncertainty perturbation, and $c_3$is a hyperparameter controlling its impact.

A penalty function is introduced in Equation (4) to enforce constraints on land use and crop rotation, punish solutions that violate these restrictions, and guide the group to a feasible area.

$$F(x_i) = f(x_i) + \lambda\sum max(0, g_j(x_i)) \quad (4)$$

where $f(x_i)$ is the original objective function, λ is the penalty factor, and $g_j(x_i)$ represents constraint violations.

In crop planting planning, RPSO can effectively deal with the problems of sales growth trend, cost fluctuation and yield uncertainty, and provide a more robust optimization scheme.

2.2. Model Establishment

Aiming at the crop planting planning of a village in the mountainous area of North China, this study constructs a model that comprehensively considers the uncertainties of open-air farmland and greenhouse resources, including expected sales volume, planting cost, mu yield and sales price]. The goal of the model is to maximize the total annual profit while dealing with unsalable or reduced-price sales situations that exceed sales.

2.2.1. Decision Variables and Uncertainty Factors

The decision variable is defined as x_{ijk}^t , which represents the planting area (mu) of the *i* crop in the *t* year on the *k* cultivated land of the *j* class.

The decision variables accurately describe the crops planted on specific plots in different years and their areas through the four dimensions of time *t*, crop type *i*, cultivated land type *j* and plot number *k*.

According to literature research [7], the main sources of uncertainty in crop planning include fluctuations in expected sales volume, yields, costs, and prices. Specifically, wheat and corn exhibit an annual sales growth of 5%–10%, while other crops vary by ±5%. Yields per mu are influenced by climate, with a typical fluctuation of ±10%. Planting costs increase annually by approximately 5% due to inflation. Sales prices remain stable for food crops, rise by about 5% for vegetables, and decline by 1%–5% for edible fungi.

2.2.2. Objective Function

The objective is to maximize the total profit over the next five years. Excess production beyond sales is sold at 50% to simulate real market dynamics.

Let $P_{t,i,j}$be the profit of the *i-th* crop planted on the *j-th* farmland, we have:

$$P_{t,i,j} = S_{t,i,j}Q_{i,j}x_{ijk}^t - C_{i,j}x_{ijk}^t \quad (5)$$

where $S_{t,i,j}$ is the sales price, $Q_{i,j}$ is the yield per mu, and $C_{i,j}$ is the cost per mu.

The objective function is:

$$maxF = \sum_{t=2025}^{2030} \sum_{i} \sum_{j} \sum_{k} P_{t,i,j} \tag{6}$$

2.2.3. Constraints

In crop planting planning, constraints define the boundaries that must be run for the best planting plan to ensure feasibility and sustainability. The following constraints are tailored to the geographical, resource and agricultural conditions of the North China Mountains to guide crop allocation across plots and years [7].

(1) Total Land Area Constraint:

The availability of land is a fundamental limitation of any planting plan. This constraint ensures that the total area allocated to crops on a given plot does not exceed its physical capacity [8], thereby maintaining the reality and feasibility of the plan. The mathematical expression is shown in formula (7).

$$\sum_{i} x_{ijk}^{t} \leq A_{j,k}, \forall t, j, k \tag{7}$$

where $A_{j,k}$ is the area of plot k of land type j.

(2) Legume and Crop Rotation Requirements:

Sustainable agriculture relies on practices such as crop rotation to maintain soil health and minimize the risk of pests and diseases [9].

This limitation has two parts: it requires the inclusion of legumes, which can naturally supplement soil nitrogen and prevent the continuous planting of the same crop on the same plot to avoid soil depletion and pest accumulation.

Beans requirements: In order to ensure soil fertility, each plot must be planted at least once every 3 years. As expression (8) described:

$$\sum_{t=t}^{t+2} \sum_{i \in \text{legumes}} x_{ijk}^{t} \geq 1, \forall j, k \tag{8}$$

Crop rotation requirements: In order to promote biodiversity and reduce pest pressure, the same crop cannot be planted on the same plot for several years in a row. As expression (9) described:

$$x_{ijk}^{t} x_{ijk}^{t+1} = 0, \forall t, i, j, k \tag{9}$$

(3) Rice Planting Restriction:

As a water-consuming crop, rice requires specific conditions and careful resource management. This constraint limits the irrigated land, and each irrigated plot only allows one season of rice crops per year to adapt to the natural growth cycle of crops and the need to effectively protect water resources. As expression (10) described:

$$x_{abk}^{t} = 0 \text{ or } 1, \forall t, k \tag{10}$$

where, a and b are specific constants.

(4) Crop Distribution and Minimum Area:

Effective management and economic profitability depend on simplifying planting decisions and ensuring sufficient scale [10].

This limitation limits the number of crop types per plot to two per year, reduces complexity, and requires that any crop planted covers at least 0.5 mu, ensuring that the area is economically viable and manageable. As expression (11) described:

$$\sum_{i} x_{ijk}^{t} \leq 2, x_{ijk}^{t} \geq 0.5 \text{ or } 0 \tag{11}$$

2.2.4. Robust Optimization

Uncertain parameters are modeled as random variables ξ with defined ranges (Table 1).

Table 1. Uncertainty Ranges

Factor	Range
Wheat Sales Volume	$[S_{2023}1.05^{t}, S_{2023}1.10^{t}]$
Yield per Mu	$[Q_{i,j}0.9, Q_{i,j}1.1]$
Planting Costs	$[C_{i,j}1.05^{t}]$

The robust objective function minimizes the worst-case impact:

$$maxF_{\text{robust}} = \min_{\xi} \sum_{t=2024}^{2030} \sum_{i} \sum_{j} \sum_{k} P_{t,i,j}(\xi) \tag{12}$$

3. Results

3.1. Data Descriptive Statistics

The data set used in this study is derived from the 2024 Chinese Undergraduate Mathematical Contest in Modeling (CUMCM), which provides simulated data on land types, crop varieties, and economic indicators for rural agricultural planning in mountainous areas of North China. The dataset includes 67 sample plots, a total of 1,253 acres, covering flat dry land, terraced fields, irrigated land, ordinary greenhouses and smart greenhouses, as well as 41 crop types and related economic indicators such as yield (500-12000 gold / mu), cost (1000-10000 yuan / mu), price (1-120 yuan / gold) [7].

Statistical data organization:

(1) Land Types and Areas: 67 plots totaling 1253 mu, comprising flat dry land, terraces, irrigated land, ordinary greenhouses, and smart greenhouses.

(2) Crop Types: 41 crops, including 15 grains, 18 vegetables, 5 grain legumes, 4 vegetable legumes, and 4 edible fungi.

(3) Planting Seasons: Single-season for grains (except rice), dual-season for greenhouse vegetables.

(4) Economic Indicators: Yields range from 500 to 12,000 jin/mu, costs from 1,000 to 10,000 yuan/mu, and prices from 1 to 120 yuan/jin.

3.2. Simulation and Optimization Results

Simulation was implemented by python codes.

RPSO was implemented with parameters: swarm size $N = 50$, maximum iterations $T = 200$, inertia weight $w = 0.8$, acceleration coefficients $c_1 = c_2 = 2$, and perturbation coefficient $c_3 = 0.1$. Key findings include:

Planting Plan: Optimized crop allocations across land types (Table 2).

Table 2. Partial 2025 Optimization Results

Crop	Flat Dry Land (mu)	Irrigated Land (mu)	Greenhouse (mu)
Crop	300	150	0
Cucumber	0	0	50

Economic Impact: As shown in Table 3 and Figure 2, the robust optimization approach (Scheme 1) consistently produced more stable and higher annual profits compared to standard PSO optimization (Scheme 2) across the eight-year period. On average, Scheme 1 achieved a 15% increase in total profit, 8% cost reduction, and a 20% decrease in profit volatility, indicating significantly improved economic resilience under uncertainty.

Comparative Analysis: RPSO outperformed standard PSO by 30% in stability under uncertainty.

Table 3. Total profit of crop planting after robust optimization (million yuan)

Year	2023	2024	2025	2026	2027	2028	2029	2030
Scheme1	5.89	5.91	5.9	5.84	5.83	5.91	6.02	5.98
Scheme2	5.89	5.75	5.93	5.41	5.75	5.71	6.06	5.75

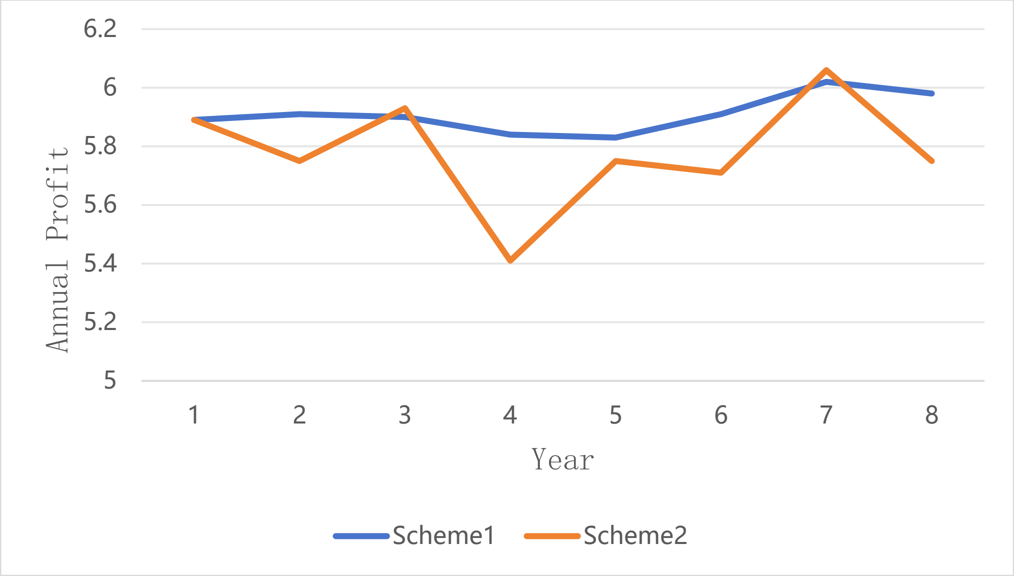

Figure 2. Annual Profit Comparison between Robust Optimization and Standard PSO

4. Conclusion and Outlooks

This study proposes a method based on robust particle swarm optimization (RPSO) for optimizing crop planting structure in rural areas of North China mountainous region. This method combines the global search capability of classical particle swarm optimization algorithm with the stability of robust optimization in dealing with uncertainty. It can effectively handle various uncertain factors such as environment and economy, and is superior to traditional optimization methods in performance. The simulation results show that the optimized planting plan from 2025 to 2030 not only significantly improves the total agricultural profit, but also enhances land use efficiency and promotes sustainable agricultural development. The robustness of RPSO also enables it to provide more stable and reliable decision support in the face of weather changes and market fluctuations. In addition, this model has strong practical value in practical applications and can provide a scientific tool for local governments and rural cooperatives to formulate agricultural strategies. This method is not only suitable for optimizing planting structures, but can also be extended to rural planning fields such as irrigation scheduling and fertilizer distribution. Overall, this study is innovative in methodology and has guiding significance in practice, contributing to rural revitalization and sustainable land use development in complex geographical environments.

Despite the promising results, this research still has limitations. Notably, it does not consider long-term environmental dynamics such as climate change, soil degradation, or evolving policy impacts, which could influence agricultural performance over time. Future research will focus on integrating these dynamic and uncertain factors into the optimization framework to make the model more comprehensive. In addition, incorporating artificial intelligence technologies, such as neural networks, reinforcement learning, or hybrid metaheuristics, could further improve the model's adaptability and predictive power. These improvements would support the development of intelligent agricultural decision-support systems that enable precision farming and contribute to long-term rural sustainability.

Acknowledgements

The authors gratefully acknowledge the financial support from Maynooth University.

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