ISSN 2522-3488 Vol. 9, Issue 2: 41-45, DOI: 10.25236/IJNDES.2025.090207

Research on Crop Planting Strategy Problem Based on Multi Objective Dynamic Linear Programming Model

Wenqing Yu, Wentao Yi, Deyi Xie

College of Science, Shandong Jianzhu University, Jinan, China, 250101

Abstract: *In order to achieve sustainable development of rural economy, effectively utilize limited arable land resources, and develop according to local conditions. The organic farming industry is of great significance. This article is based on the existing planting experience in a certain rural area, and establishes a mathematical model analysis to improve the production efficiency of agricultural products and reduce the negative impact of uncertain factors on planting. Establish Single-Objective Programming model, Spearman correlation analysis, Multi-objective Optimization Problem, Nonlinear Programming model. There is a significant correlation between yield per acre and crop type, plot type, and planting season, and considering the expected sales volume, yield per mu, planting cost, and sales price of various crops. The influence of factors has important strategic significance for rural revitalization and China's economic development.*

Keywords: *Single-Objective Programming, Spearman Correlation Analysis, Multi-Objective Optimization (MOP)*

1. Introduction

The phrase "the land is the foundation of the people" underscores the critical role of arable land as a fundamental resource for rural development. Enhancing the production efficiency of farmland crops, reducing management costs, and mitigating the impact of external uncertainties are essential for achieving rural revitalization and sustainable economic growth in China. Despite the increasing diversification and modernization of agricultural practices, challenges remain in aligning crop types, planting seasons, and plot characteristics with market demand, production costs, and environmental variability. Therefore, selecting appropriate crop varieties, planting seasons, and plot types is crucial for optimizing agricultural outcomes.

Recent research has made significant strides in crop planting strategies. For instance, Hervé Vanderschuren et al. [2] investigated the role of proteomics in crop cultivation, highlighting its contributions to understanding protein composition, regulation, and modification in plant systems. Similarly, Wu et al. [1] utilized a CPSO (Chaotic Particle Swarm Optimization) model to optimize crop planting structures in irrigation areas, achieving efficient water resource utilization. In the context of crop pricing, Jiang et al. [3] developed a multi-objective chaotic game optimization algorithm for energy futures price prediction, providing valuable insights into the impact of market dynamics on crop planting strategies. Additionally, Roy et al. [4] systematically evaluated land degradation caused by climate change and geo-environmental factors, offering a comprehensive framework for addressing sustainability challenges in agriculture. Finally, Peng et al. [5-7] examined the resilience of agricultural strategies to geological disasters, emphasizing the importance of adapting to natural and climatic uncertainties.

However, their studies often overlook critical constraints that influence crop planting strategies. For example, Vanderschuren et al. [2] focused primarily on proteomics without considering key factors such as yield limitations relative to expected sales volume, restrictions on the number of plots allocated per crop, minimum planting area requirements for individual crops, and the interplay between crop yield, geological conditions, and market dynamics. Building on the foundational work of Vanderschuren et al. [2] and Wu et al. [1], this study addresses these gaps by integrating multi-objective optimization, Spearman correlation analysis, and nonlinear programming. Our approach aims to refine crop planting strategies, balancing productivity, cost efficiency, and risk mitigation in dynamic agricultural systems. By incorporating these constraints, we propose a comprehensive framework for optimizing crop planting plans under conditions of uncertainty, contributing to the sustainable development of rural economies.

ISSN 2522-3488 Vol. 9, Issue 2: 41-45, DOI: 10.25236/IJNDES.2025.090207

2. Optimization Models and Algorithms

2.1 Linear Programming model

The linear programming model is a type of mathematical optimization framework that deals with linear objective functions and linear constraints. Its primary goal is to find the optimal solution that either maximizes or minimizes the objective function while satisfying all constraints. This model is extensively utilized in areas such as resource allocation, production planning, and logistics, where efficient and optimal solutions are critical.

To address agricultural challenges, we propose a modeling framework using Spearman correlation to analyze planting season, yield, crop type, and land parcel relationships, guiding optimization models.

2.2 In the case of considering unsold waste, establish a linear programming model for calculation

Based on the analysis results of the Spearman model above, we have established a linear programming model to further study the relationship between the four elements.

The Linear Programming (LP) model is a mathematical optimization technique used to maximize or minimize a linear objective function subject to a set of linear equality or inequality constraints. It is widely applied in fields such as operations research, economics, logistics, and resource allocation. The general form of an LP model is

$$\text{Max f} = \sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{2} \left(x_{i,j,k} \cdot Y_j \cdot P_j - x_{i,j,k} \cdot C_j \right) \tag{1}$$

$$\text{Min g} = x_{i,j,k} \cdot Y_j - D, \forall j \tag{2}$$

Where $x_{i,j,k}$ is the area of planting the j-th crop on the i-th plot of land in the k-th season (acre), Y_{j-th} is acre yield of crop j (jin/acre),P_{j-th} is Sales unit price of the j-th crop (yuan/jin),and c_{j-th} is the planting cost of the j-th crop (yuan/acre).

Constraint 1: Production does not exceed expected sales volume:

$$x_{i,j,k} \cdot Y_j \leq D \tag{3}$$

Constraint 2: Constraint on the planting area of the plot:

$$\sum_{j=1}^{m} x_{i,j,k} \leq 1201, \forall i = 1,2,\ldots,n, \forall k = 1,2 \tag{4}$$

Where $x_{i,j,k}$ is the area of planting the j-th crop on the i-th plot of land in the k-th season (acre).

Constraint 4: Constraints on planting leguminous crops within three years:

$$\sum_{k=1}^{6} x_{i,j_{\text{legume}},k} \geq 1, \forall i = 1,2,\ldots,n \tag{5}$$

Where j_{legume} is a collection of all leguminous crops,$k = 1,2,\ldots,6$ is Six seasons in three years.

Constraint 5: The area of a single planting plot should not be too small as a constraint:

$$\begin{array}{l} mm \\ \Sigma\Sigma D_{i,i'} \cdot x_{i,j} \cdot x_{i',j} \leq C \\ i = 1 i' = 1 \end{array} \tag{6}$$

Where $D_{i,i'}$ is The distance between plot i and plot i`,$X_{i,j}$ and $X_{i'}, j'$ is Planting area of two blocks.

2.3 Differential Evolution

Differential Evolution (DE) is a population-based stochastic optimization algorithm that uses mutation, crossover, and selection to solve complex, nonlinear, and multimodal optimization problems efficiently. To further analyze and obtain the optimal planting plan for the rural crops from 2025 to 2030, we have chosen the following algorithm Genetic inheritance:

$$\mathbf{v}_i^{(g+1)} = \mathbf{x}_{rn}^{(g)} + F \cdot \left(\mathbf{x}_{r(n+1)}^{(g)} - \mathbf{x}_{r(n+2)}^{(g)} \right) (2024 \leq g < 2030) \tag{7}$$

Where Xrn(g) is initial annual output, Xr(n+1)(g) is initial year sales unit price per acre, Xr(n+2)(g) is initial year sales cost, Vi(g+1) is expected planting quantity.

ISSN 2522-3488 Vol. 9, Issue 2: 41-45, DOI: 10.25236/IJNDES.2025.090207

F: (1 0 0 1) An indicator vector that can be inherited, with values ranging from 0 to 1, is used to mark whether to plant or not, in order to prevent repeated planting constraint

$$x_{i,j,1} \times x_{i,j,2} = 0, \forall i = 1,2,\dots,n, \forall j = 1,2,\dots,m \quad (8)$$

Where $x_{i,j,1}$ is season 1 planted a certain crop,$x_{i,j,2}$ is season 2 planted a certain crop.

3. Result

3.1 Spearman correlation

Using Spearman correlation analysis, analyze the correlation between planting season, yield per mu, crop type, and plot type.

Table 1 Spearman correlation

	Planting season_x	yield per acre/jin	Crop type	Land type
Planting season_x	1 (0.000***)	0.753 (0.000***)	0.814 (0.000***)	0.747 (0.000***)
yield per acre/jin	0.753 (0.000***)	1 (0.000***)	0.614 (0.000***)	0.693 (0.000***)
Crop type	0.814 (0.000***)	0.614 (0.000***)	1 (0.000***)	0.753 (0.000***)
Land type	0.747 (0.000***)	0.693 (0.000***)	0.753 (0.000***)	1 (0.000***)

Explanatory: ***, **, *represent significant levels of 1%,5%, and 10%respectively

The results showed that the significant P-values of all four were less than 0.05, indicating a significant relationship between yield per mu and crop type, plot type, and planting season in the Table 1. This indicates a good correlation between yield per mu and these three factors.

3.2 The Linear Programming (LP) model

Table 2 Optimal Crop Planting Strategy (partial) from 2024 to 2030

	Parcel name	soybean	Black beans	Red beans	mung bean	Climbing beans
Season 1	A1	0	0	0	0	0
	A2	0	0	0	0	0
	A3	0	0	0	0	0
	A4	0	0	0	0	0
	A5	0	0	0	0	0
	A6	0	0	0	0	0
	B1	0	0	60	0	0
	B2	0	0	0	0	0
	B3	0	0	0	0	0
	B4	0	0	0	0	0
	B5	0	0	0	0	0
	B6	0	0	0	0	0
	B7	0	0	0	0	0
	B8	0	0	0	0	0
	B9	0	0	0	0	0
	B10	0	0	0	0	25
	B11	0	0	0	0	0
	B12	0	45	0	0	0
	B13	0	0	0	0	0
	B14	0	0	0	0	0
	C1	0	0	0	0	0
	C2	15	0	0	0	0
	C3	0	0	0	0	0
	C4	0	0	0	0	0

Subsequently, a linear programming model was used for analysis, with constraints including: based on the planting area of the plot, preventing replanting, planting legumes at least once within three years, and ensuring that the area of a single planting plot is not too small. By further processing the data, the optimal planting plan for 2024 to 2030 is shown in Table 2.

ISSN 2522-3488 Vol. 9, Issue 2: 41-45, DOI: 10.25236/IJNDES.2025.090207

3.3 Differential Evolution

Table 3 Crop yields (partial) from 2024 to 2030.

	Parcel name	soybean	Black beans	Red beans	mung bean	Climbing beans
Season 1	A1	0	0	0	0	0
	A2	0	0	0	55	0
	A3	0	0	0	0	0
	A4	0	0	0	0	0
	A5	0	0	0	0	0
	A6	0	0	0	0	0
	B1	0	0	0	0	0
	B2	0	0	0	0	0
	B3	0	0	0	0	0
	B4	0	0	0	0	0
	B5	0	0	0	0	0
	B6	0	0	0	0	0
	B7	0	0	0	0	0
	B8	0	45	0	0	0
	B9	0	0	0	0	0
	B10	0	0	0	0	0
	B11	0	0	0	0	0
	B12	0	0	0	0	0
	B13	0	0	0	0	0
	B14	0	0	0	0	0
	C1	0	0	0	0	0
	C2	15	0	0	0	0
	C3	0	0	0	0	0
	C4	0	0	0	0	18

Finally, a differential evolution (DE) algorithm was employed to optimize the planting plan for the rural area. This algorithm was configured by setting four key variables: the expected planting amount, the initial year yield, the initial year unit price per acre, and the initial year planting cost. These variables were chosen to comprehensively capture the economic and agricultural dynamics of the region. The differential scaling factor FF, which controls the mutation and crossover operations in the DE algorithm, was carefully tuned to a range between 0.5 and 1 to ensure a balance between exploration and exploitation during the optimization process. This range was selected based on preliminary experiments to avoid premature convergence while maintaining efficient search capabilities.

The DE algorithm iteratively refined the solution by generating new candidate solutions through mutation, crossover, and selection operations. The mutation operation introduced diversity by combining differences between randomly selected individuals in the population, while the crossover operation blended the mutated solutions with the current population to create trial solutions. The selection operation then compared the trial solutions with the current population, retaining the better-performing individuals for the next generation. This process continued until convergence criteria were met, ensuring that the final solution was robust and near-optimal.

Building on the results of the DE algorithm and integrating insights from the previously applied genetic algorithm, the optimal planting plan for the rural area from 2024 to 2030 was derived. This plan, illustrated in Table 3, provides a detailed roadmap for maximizing agricultural productivity and economic returns over the specified period. The Table highlights key trends, such as the recommended crop distribution, projected yield improvements, and cost-effective strategies for scaling production. The integration of these two algorithms ensured a comprehensive exploration of the solution space, accounting for both short-term constraints and long-term sustainability goals. The final planting plan serves as a valuable decision-making tool for stakeholders, enabling them to allocate resources efficiently and adapt to changing market and environmental conditions.

4. Conclusions and outlooks

This study comprehensively analyzed the influencing factors associated with the planting and sales of seven different crops, focusing on the significant relationships between four major elements of crop cultivation: plot type, planting season, crop type, and yield per mu. By employing a combination of Spearman correlation analysis, linear programming (LP) models, and differential evolution (DE) algorithms, the research successfully identified the optimal planting plan for a rural area from 2024 to

2030. The findings revealed that yield per mu is significantly correlated with crop type, plot type, and planting season, highlighting the importance of these factors in agricultural planning. The LP model, constrained by factors such as planting area, crop rotation, and minimum plot size, provided a robust framework for optimizing crop selection and distribution. Additionally, the DE algorithm, which considered variables like expected planting amount, initial year yield, unit price, and planting cost, further refined the planting strategy, ensuring a balance between productivity, cost efficiency, and risk mitigation. However, our model and approach still have some limitations that need to be improved. For instance, the method used in this study is relatively simplistic and lacks innovation when addressing prediction problems, and it does not provide a comparative analysis of multiple algorithmic models. A deeper analysis of the economic aspects of different crops in the data should be conducted to develop a more optimal crop planting strategy tailored to the specific rural context.

The results demonstrated that integrating multi-objective optimization techniques with correlation analysis can effectively improve agricultural productivity, reduce management costs, and mitigate the impact of external uncertainties. This approach not only enhances the economic viability of farming but also contributes to sustainable rural development by aligning crop cultivation with local environmental and market conditions.

While this study provides valuable insights into optimizing crop planting strategies, there are several areas for future improvement and exploration:

Incorporation of Multiple Prediction Models: The current study primarily relied on linear programming and differential evolution algorithms. Future research should consider integrating additional prediction models, such as machine learning algorithms, simulation-based approaches, and statistical models. By comparing the results of different models, more accurate and adaptable planting strategies can be developed, particularly in the face of climate variability and market fluctuations.

Integration of Technological Advancements: Future research should explore the integration of emerging technologies, such as precision agriculture, remote sensing, and IoT (Internet of Things), to enhance data collection and decision-making processes. These technologies can provide real-time monitoring and predictive analytics, further improving the accuracy and efficiency of crop planning.

In conclusion, while this study lays a solid foundation for optimizing crop planting strategies, there is significant potential for further research to address its limitations and explore new avenues. By leveraging advanced modeling techniques, economic analysis, and technological innovations, future studies can develop more robust and adaptive agricultural strategies that contribute to the sustainable development of rural economies.

References

[1] Wu L, Tian J, Liu Y, et al. Multi-Objective Crop Planting structure optimisation based on game theory[J]. Water, 2022, 14(13): 2125.
[2] Vanderschuren H, Lentz E, Zainuddin I, et al. Proteomics of model and crop plant species: status, current limitations and strategic advances for crop improvement[J]. Journal of proteomics, 2013, 93: 5-19.
[3] Jiang P, Liu Z, Wang J, et al. Decomposition-selection-ensemble forecasting system for energy futures price forecasting based on multi-objective version of chaos game optimization algorithm[J]. Resources Policy, 2021, 73: 102234.
[4] Roy P, Pal S C, Chakrabortty R, et al. RETRACTED: A systematic review on climate change and geo-environmental factors induced land degradation: Processes, policy-practice gap and its management strategies [J]. Geological Journal, 2023, 58(9): 3487-3514.
[5] Peng L, Tan J, Deng W, et al. Understanding the resilience of different farming strategies in coping with geo-hazards: A case study in Chongqing, China[J]. International journal of environmental research and public health, 2020, 17(4): 1226.
[6] Shekhawat K, Almeida-Trapp M, García-Ramírez G X, et al. Beat the heat: plant-and microbe-mediated strategies for crop thermotolerance [J]. Trends in plant science, 2022, 27(8): 802-813.vzj2011.0173.
[7] Kamran M, Imran Q M, Ahmed M B, et al. Endophyte-mediated stress tolerance in plants: A sustainable strategy to enhance resilience and assist crop improvement[J]. Cells, 2022, 11(20): 3292.