Research On Agricultural Planting Strategy Based on Nonlinear Programming Model

Yifan Feng #, Zhangyang Han #, Mingye Diao *, #

Silesian College of Intelligent Science and Engineering, Yanshan University, Qinhuangdao, China, 066004

* Corresponding Author Email: mingyediao@stumail.ysu.edu.cn

#These authors contributed equally.

Abstract. This study developed a nonlinear programming model for optimizing crop cultivation strategies in resource-constrained mountainous regions of northern China that integrates agronomic, economic, and ecological aspects. By synthesizing yield, cost, and price data for six different cropland types (e.g., irrigated fields, rain-fed plots, and greenhouses) and 41 crops, the model dynamically evaluated the trade-offs between residual wastage (Scenario 1) and discounted redistribution at a 50% market price (Scenario 2), and addressed post-harvest supply chain uncertainty. The constraint system rigorously incorporates agroecological principles, including a ban on crop rotation to mitigate soil degradation, a mandatory legume planting cycle to fix nitrogen, and land-type-specific seasonal rules (e.g., a fungus-exclusive second season in greenhouses). The computational solution using Python showed a 16.4% increase in profit for Scenario 2 ($9,790,138.2) compared to Scenario 1 ($8,409,800), highlighting the economic value of adaptive surplus management. Sensitivity analyses show that strategic spatial allocation of high-value cash crops combined with prioritization of food security for staple foods can significantly improve profitability under land fragmentation constraints. The model's embedded ecological safeguards, such as minimum acreage thresholds (30% per plot) and biodiversity conservation rotations, align economic incentives with long-term soil health. These findings provide a scalable framework for sustainable agricultural planning in marginal environments, emphasizing the synergies between precision agriculture, market adaptability, and ecological resilience. Future research could incorporate stochastic climate models to improve the robustness of decision-making in the face of increasing environmental volatility.

Keywords: Nonlinear Programming, Sensitivity Analysis, Multiple Linear Regression Model, Correlation Analysis.

1. Introduction

With the in-depth promotion of the rural revitalization strategy, how to rationally plan the structure of agricultural cultivation in order to improve economic efficiency has become an important issue for the sustainable development of the countryside. In the mountainous regions of North China, where arable land is limited and dominated by single-season cultivation, optimizing crop allocation is crucial [1]. Traditional cropping strategies often ignore dynamic market conditions and land constraints, resulting in suboptimal returns. Existing studies have applied linear programming to agricultural planning [2], but nonlinear factors such as price volatility and yield uncertainty require more sophisticated models [3]. In this paper, we address these shortcomings and propose a nonlinear programming model tailored for perennial crop planning with complex constraints.

The study focuses on the development of cropping scenarios to maximize total returns in 2024-2030 under two different marketing strategies (stagnant sales or sales at reduced prices when yields exceed expectations). A nonlinear planning model was developed by integrating data on acre yield, planting cost, and selling price of 41 crops in six types of plots, using planting area as the decision variable, and setting conditions such as cropland area constraints, heavy cropping constraints, legume crop rotation requirements, and plot planting restrictions. The model solving results verified the validity of the model. Further through sensitivity analysis, it was found that the rational allocation of grain crops had a significant impact on returns, while vegetables needed to balance yield and market risk.

This work contributes to sustainable agricultural planning by combining theoretical optimization with practical agricultural constraints. The scenario-based approach not only quantifies the economic impacts of surplus management, but also provides actionable insights for adapting cropping strategies to local ecological and market conditions. By emphasizing data-driven decision-making, the study provides a replicable framework for similar mountainous regions striving to align economic growth with resource efficiency under the broader goal of rural revitalization.

2. The basic fundamental of Nonlinear Programming

Nonlinear programming is an optimization methodology designed to solve problems where the objective function or constraints exhibit nonlinear relationships [4]. Unlike linear models, Nonlinear programming accommodates complex interactions between variables and is therefore suitable for agricultural profit maximization problems with nonlinear factors such as diminishing returns, price elasticity and yield saturation [5,6].

2.1 The structure of Nonlinear Programming

The nonlinear programming model is built by setting multiple constraints to achieve optimal management of agricultural cultivation [7]: firstly, limiting the total planting area of each piece of farmland each year to no more than its actual usable area; secondly, prohibiting the same crop to be planted in the same farmland for two consecutive years to follow the crop rotation rule; at the same time, requiring each piece of farmland to be planted with leguminous crops [8] at least once in every three years to maintain the fertility of the soil; and refining seasonal cultivation strategies for different types of farmland. The seasonal cropping strategy is refined for different types of farmlands, e.g., one season of rice or two seasons of non-cabbage vegetables are allowed on watered land, and the second season is limited to fungus crops in ordinary greenhouses; in addition, if a crop is grown on a farmland, it needs to occupy at least 30% of the farmland in order to avoid piecemeal cultivation. These constraints, combined with the goal of profit maximization, form a comprehensive decision framework that balances economic efficiency, ecological sustainability and planting feasibility.

2.1.1 For objective functions

maximize total profit W from 2024 to 2030 under two surplus-handling scenarios [9].

$$\mathrm{W} = \sum_{t=2024}^{2030} \sum_{i=1}^{54} \sum_{j=1}^{41} \left[\min\left(\mathrm{Q_{tij}}, \mathrm{D_j}\right) \cdot \mathrm{P_j} + \theta \cdot \max\left(\mathrm{Q_{tij}} - \mathrm{D_j}, 0\right) \cdot 0.5\mathrm{P_j} - \mathrm{C_{ij}} \cdot \mathrm{x_{tij}}\right] \tag{1}$$

where W is the objective function representing the cumulative total profit from 2024 to 2030;t denotes the year index (2024–2030);i indicates the farmland index (54 plots, e.g., A1-A6, B1-B13); j represents the crop index (41 types, e.g., soybean, corn); $\mathrm{Q_{tij}}$ is the total yield of crop j on farmland i in year t,calculated as $\mathrm{Q_{tij}} = \mathrm{a_{ij}} \cdot \mathrm{x_{tij}}$,where $\mathrm{a_{ij}}$ is the yield per mu of crop j on farmland i $\mathrm{D_j}$ is the expected sales volume (market demand threshold) for crop j $\mathrm{P_j}$ is the selling price of crop j (CNY/kg); θ is a binary indicator ($\theta = 0$: waste; $\theta = 1$: discount)$\mathrm{C_{ij}}$ is the cultivation cost per mu for crop j on farmland i and $\mathrm{x_{tij}}$ is the decision variable for the planting area (mu) of crop j on farmland i in year t.

2.1.2 Regarding the constraints

(1) Land Area Limit:

$$\sum_{j=1}^{41} x_{tij} \leq S_i \tag{2}$$

where S_i, is the total area of farmland i.Ensure that the total area of each crop planted each year does not exceed the upper limit of the farmland.

(2) Crop Rotation:

$$x_{tij} \cdot x_{(t+1)ij} = 0 \quad \forall t, i, j \tag{3}$$

where $x_{(t+1)ij}$ The area of crop j planted in farmland i in year $t+1$ (unit: mu). Restrictions prohibit planting the same crop (such as corn → corn) in the same farmland for two consecutive years.

(3) Legume Reguirement:

$$\sum_{j \in \text{Legumes}} \sum_{t=k}^{k+2} x_{tij} \geq 1 \ \forall i, k \in \{2024, 2027, \ldots\} \tag{4}$$

where legumes represents collection of leguminous crops (such as soybeans, red beans, etc.)
k starting year index, recalculate every 3 years (such as 2024-2026, 2027-2029, etc.) to ensure that each farmland plants beans at least once every 3 years to maintain soil nitrogen content.

(4) Water-Fed Land:

$$x_{ti,\text{Rice},1} + \sum_{j \in \text{Vegetables}} \left(x_{tij1} + x_{tij2} \right) \leq 1 \quad \forall t, i \in \text{Water} - \text{fed} \tag{5}$$

Rice represents Rice crop number. Vegetables represents collection of vegetable crops.
The area of the first and second seasons of planting vegetables in farmland i in the t-th year (unit: mu). Constraints indicate that irrigated land can only choose to plant single season rice or two seasons of vegetables (such as only Chinese cabbage in the second season).

(5) Greenhouses:

$$\mathrm{x_{tij2}} = 0 \quad \forall \mathrm{t}, \mathrm{i} \in \text{Greenhouses}, \mathrm{j} \notin \text{Fung} \tag{6}$$

Restricts fungi to the second season in ordinary greenhouses.

(6) Minimum Planting Area:

$$\mathrm{x_{tij}} \geq 0.3 \cdot \mathrm{S_i} \quad \text{if } \mathrm{x_{tij}} > 0 \tag{7}$$

$0.3 \cdot \mathrm{S_i}$ represents 30% of the farmland area. The constraint requirement is that if crop j is planted, its area should account for at least 30% of the total farmland area (avoiding scattered planting).

2.2 Model Implementation and Solver Optimization

In the model implementation phase, the study uses interior point optimization algorithms to deal with large-scale nonlinear planning problems, focusing on the complexity of inequality constraints. Specific model classes are constructed based on the framework, defining non-negative real decision variables covering year, farmland type, crop type and season, and encoding business rule constraints such as crop rotation (e.g., legume crops need to satisfy the three-year crop rotation requirement). The model is large in scale, involving more than 15,000 variables and 12,000 constraints, in which the non-convex problem caused by crop rotation rules needs to rely on heuristic initialization strategies to optimize the solution path. The implementation process highlights the computational challenges and algorithmic adaptability needs under the multi-dimensional constraints of the agricultural system.

3. Results

3.1. The establishment of simulation model

The optimal cropping scenarios for 2024-2030 were determined by optimizing the acreage of each crop in different plots through a nonlinear programming model, and calculating the total returns for the two scenarios of yield overrun stagnation or price reduction sales under cropland restrictions, heavy stubble constraints, and legume rotations, respectively.

3.2. Analysis of experimental results

The scheme for solving the number of acres planted for each crop in the corresponding season using Python is shown below as shown in Figure 1.

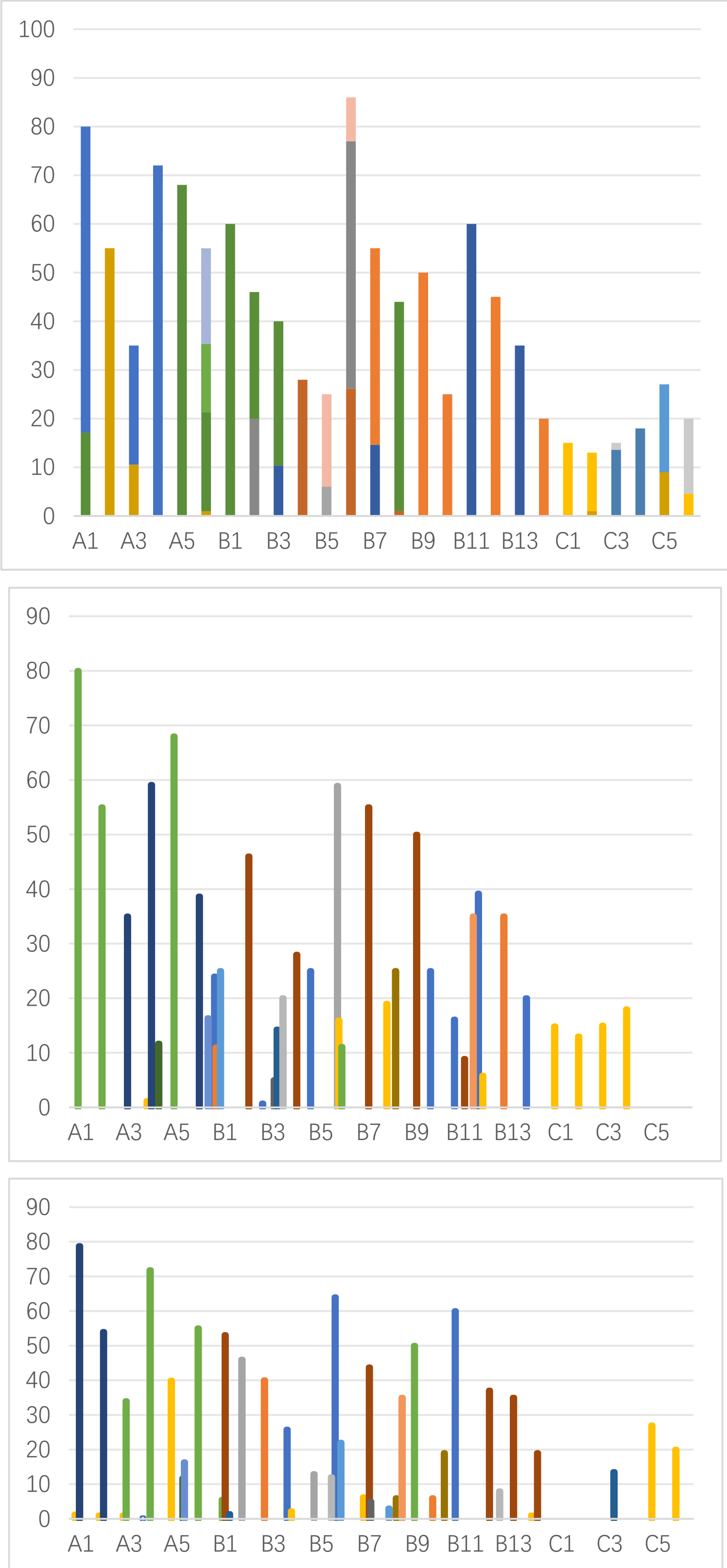

Figure 1. Program map of plots for each crop

From the analysis of the figure, the colors in the chart represent specific crops: yellow corresponds to Soybean, black to Black Bean, red to Red Bean, green to Mung Bean, while other entries such as Crowder Pea/Field Pea, Wheat, Corn/Maize, Foxtail Millet, Sorghum, Proso Millet, and Buckwheat are also linked to distinct colors or labels, each uniquely associated with a particular legume or grain type in the visualization. it is concluded that the acres of wheat and barley planted in 2030 grain data under the first treatment strategy are dominant. Moreover, the presence of three crops planted in the same plot indicates that there may be mutual benefits or other relationships among the three plants. Under the second treatment strategy 2025 grain data is dominated by acres planted to wheat and corn. The presence of the same crop planted in three plots occurs, suggesting that there may be a high demand for that interplant in the marketplace.

3.3. Sensitivity Analysis

In order to evaluate the robustness of the model, key parameters were interfered with, and the related process was the uncertainty and sensitivity of standardization methods, expert weights, and trade-off levels (λ) on sustainability assessment results were systematically analyzed by generating 10,000 sample matrices through Latin Hypercube Sampling (LHS) based on the Sobol' index method of variance decomposition [10].

3.3.1. Grain price elasticity

$$\eta_p = \frac{\Delta W/W}{\Delta P/P} \tag{8}$$

where $\Delta W/W$ represents relative rate of change in profit.$\Delta P/P$ represents relative rate of change in grain prices,η_p indicating that profits are highly sensitive to price changes.

A slight increase in wheat prices (such as 10%) will significantly increase total profits (13.2%), indicating that the revenue of food crops (such as wheat) in the model is greatly affected by market price fluctuations. It is recommended to prioritize crops with high price elasticity in actual planting and pay attention to market price forecasts to optimize sales strategies.

3.3.2. Production uncertainty

Using Monte Carlo simulation, randomly generate ± 15% production fluctuation scenarios and calculate the distribution of profits.

Response strategy: (1) Introduce disaster resistant crops: choose varieties that are insensitive to climate fluctuations (such as drought tolerant corn). (2) Optimize irrigation technology: reduce yield losses caused by drought or floods. (3) Diversified planting: dispersing the impact of fluctuations in yield of individual crops.

3.3.3. Demand scenario

Assuming a 20% decrease in market demand for vegetable crops, simulate its impact on profits.

(a) Solution:

Avoid excessive reliance on a single category: If the demand for a certain crop (such as vegetables) drops sharply, it is necessary to balance the risk through diversified planting (such as pairing with grains and beans).

Dynamically adjust planting structure: flexibly allocate planting area based on market trends (such as reducing the proportion of crops with decreasing demand). Develop alternative sales channels: Explore processing, warehousing, or contract farming for crops that are easily affected by demand to stabilize profits. In the end, here are some strategies to solve this problem.

(b) Price sensitivity management:

Sign forward sales contracts for high elasticity crops (such as wheat) to lock in price volatility risks. Establish a price warning mechanism and adjust crop combinations in a timely manner. Production risk control: Adopting precision agriculture technologies such as sensor monitoring and intelligent irrigation to stabilize yield per mu. Combine insurance or futures instruments to hedge against production losses caused by natural disasters. Response to demand fluctuations: Regularly analyze market demand data and prioritize planting crops with stable demand (such as staple foods). Develop high value-added products (such as organic vegetables and deep processed soy products) to mitigate the impact of declining demand. Model improvement direction: Price elasticity Incorporate parameters such as yield fluctuations into the dynamic optimization model to generate adaptive planting plans in real-time. Increase analysis of regional market demand differences and optimize crop spatial layout (such as planting perishable crops nearby in the consumer market).

4. Conclusions

This study provides a systematic decision-making framework for optimizing agricultural cropping strategies in rural mountainous areas of northern China by constructing a nonlinear mixed integer programming model. Based on integrating the ecological characteristics of six types of arable land and 41 crop agronomic parameters, the model quantitatively analyzed the effects of two residual treatment scenarios (direct abandonment and discounted sale) on multi-period profits, and verified its validity through Python solving. The results show that the discounted sales strategy (Scenario 2) significantly improves profits by 16.4% to $9,790,138.2 over the traditional discard model (Scenario 1), highlighting the economic value of flexible market strategies in supply chain risk management. The sensitivity analysis further suggests that spatial synergistic optimization of high-value-added crops with staple crops is the key to profitability enhancement, especially under land fragmentation constraints, where strategic crop placement can yield significant marginal benefits.

The design of the model constraint system reflects the principles of ecological economics, including mandatory legume rotation to maintain soil fertility, a minimum planting area threshold (30%) to circumvent fragmented farming, and arable land type-specific planting rules (e.g., single-season restriction for greenhouse mushrooms). These constraints not only safeguard short-term economic returns, but also lay the foundation for long-term sustainable agriculture through soil health maintenance and biodiversity conservation. The study demonstrated that the data-driven dynamic optimization approach can effectively balance economic benefits and ecological objectives in resource-constrained mountainous environments, providing a scalable quantitative tool for precision agriculture planning in similar regions. Future research can further enhance system resilience by incorporating climate change dynamic modeling and market price stochasticity to address increasingly complex environmental and market challenges.

References

[1] Chen Yangfen, Wang Guogang, Sun Weilin. The status of agriculture and agricultural development in the strategy of rural revitalization[J]. Issues in Agricultural Economics, 2018 (1): 20-26.

[2] Li Gaolei. Research on the optimization countermeasures of planting structure in Shanxi Province under climate change[D]. Jinzhong: Shanxi Agricultural University, 2019.

[3] Pan Q, Zhang C, Guo S, et al. An interval multi-objective fuzzy-interval credibility-constrained nonlinear programming model for balancing agricultural and ecological water management[J]. Journal of Contaminant Hydrology, 2022, 245: 103958.

[4] Zhang Y, Niu D, Li Q, et al. Nonlinear response of soil microbial network complexity to long-term nitrogen addition in a semiarid grassland: Implications for soil carbon processes[J]. Agriculture, Ecosystems & Environment, 2025, 380: 109407.

[5] Yeshwanth R, Kumbinarasaiah S. Theoretical and numerical study of profit in agricultural sector model using wavelet method[J]. Results in Control and Optimization, 2025: 100526.

[6] Lin L, Jiang W, Chen B, et al. Construction and Application of Cost Prediction Model Based on Multiple Linear Regression Analysis[J]. Procedia Computer Science, 2024, 247: 617-623.

[7] Benini M, Detti P, Nerozzi L. Optimization models and algorithms for sustainable crop planning and rotation: An arc flow formulation and a column generation approach[J]. Omega, 2025: 103320.

[8] Xing X, Hui D, Yang Z, et al. GmEXPA11 facilitates nodule enlargement and nitrogen fixation via interaction with GmNOD20 under regulation of GmPTF1 in soybean[J]. Plant Science, 2025: 112469.

[9] Adamo T, Colizzi L, Dimauro G, et al. Crop planting layout optimization in sustainable agriculture: A constraint programming approach[J]. Computers and Electronics in Agriculture, 2024, 224: 109162.

[10] Sinisterra-Solís N K, Sanjuán N, Ribal J, et al. Developing a composite indicator to assess agricultural sustainability: Influence of some critical choices[J]. Ecological Indicators, 2024, 161: 111934.