Analysis of Crop Planting Strategies Based on Linear Programming

Menghan Wang #, *, Yucheng Yang #, Haoyang Bai

Ulster College, Shaanxi University of Science & Technology, Xi'an, China, 710021

* Corresponding Author Email: beautifulbigfish@yeah.net

#These authors contributed equally.

Abstract. As China's primary grain-producing region, the North China Plain faces critical challenges from population growth, resource constraints, and food security, making optimal crop configuration vital for national food sovereignty. This study developed a novel neural network-based optimization model to address agricultural land allocation, which employed systematic calibration of agronomic and economic parameters to determine profit-maximizing crop configurations. Under normal climatic conditions, the model's predictions for wheat and maize planting areas showed strong alignment with observed data. This validates the model's effectiveness in resolving the complex interdependencies among yield, revenue, and resource utilization. The model serves as a powerful tool for quantitative agricultural decision support. Key innovations include: (1) Applying neural network optimization to agricultural land allocation; (2) Successfully quantifying the coupled effects of multiple factors (yield-revenue-resource) ; and (3) Providing a theoretical and practical foundation for sustainable agriculture in resource-constrained regions. Enhancing resilience to extreme weather and long-term projection capabilities are identified for future improvement.

Keywords: Optimization Function, Linear Programming, Neural Network, Data Analysis.

1. Introduction

Cropping system optimization is central to global food security under population-resource pressures. Addressing limitations in existing models (oversimplified environment-market dynamics, neglected crop synergies), this study develops a dynamic optimization framework integrating cultivation environments, management practices, and spatial constraints with quantitative complementarity/ substitution analysis. Demonstrated on China's North China Plain, the model overcomes market-resource challenges through dual innovations: (1) region-specific staple crop optimization and (2) transferable methodological architecture, advancing resource allocation analytics with future big data-enhanced predictability.

Crop system research employs diversified methodologies: international studies utilize multivariate statistics (germplasm clustering [1], yield factor identification [2], PCA-clustering fusion [3]) and multi-objective models (dynamic programming [4], regional frameworks [5]); domestic scholars develop localized systems [6]. Current methodologies exhibit diversified development, yet they still face core challenges including insufficient dynamic mechanism analysis, inadequate quantification of crop interaction mechanisms, and limited eco-economic synergistic optimization. Persistent gaps include inadequate dynamic variable integration, superficial crop interaction quantification, and weak eco-economic synergy. This study proposes triple breakthroughs: (1) time-variant environmental parameter models; (2) quantitative substitution/ complementarity frameworks; (3) multi-objective architectures, achieving enhanced system adaptability, mechanism interpretability, and objective synergy.

This study constructs a dynamic multi-objective model for North China's agricultural allocation: (1) Stochastic linear programming (2023 data with ±5-10% sales/ yield and ±2% cost variations) achieves CNY 41.22 million annual profits via uncertainty set optimization; (2) Neural networks quantify rice-wheat substitution and soybean-spinach complementarity, revealing nonlinear price-cost-sales interactions and enabling eco-economic synergy through constraint adjustments. Key contributions: (1) dynamic parameter-integrated framework; (2) inter-crop relationship quantification;

(3) economic-ecological balance strategies, providing sustainable decision support for comparable regions.

2. Problem analysis and model introduction

2.1. Problem analysis

The North China Plain, Chinese critical grain production base, confronts multifaceted constraints: fragmented arable land (drylands, terraces, hillside plots, irrigated fields, and greenhouse systems), climatic limitations (single annual cropping), and mandatory management rules (crop rotation prohibitions, triennial legume cycles, minimum planting thresholds). Traditional methods fail under dynamic environmental pressures. To address climate-induced yield fluctuations (±10%) and market volatility (±5-10% sales, ±2% cost variations), we develop a dynamic optimization model incorporating uncertainty sets. Using cultivation area as the decision variable, we mathematically formalize rotation constraints and solve profit maximization via CPLEX-based iterative optimization. Neural network analysis further quantifies nonlinear crop interactions (e.g., wheat substitution, soybean complementarity), linking price-cost-sales dynamics to cross-crop area adjustments. By embedding these mechanisms as constraints, the model optimizes cropping combinations to synergize economic returns and resource efficiency, offering actionable solutions for sustainable agriculture in resource-constrained regions to achieve synergistic improvements in economic returns and resource utilization efficiency.

2.2. Model introduction

2.2.1 Principle of Objective Optimization Functions

A constrained objective optimization model mathematically formulates and computationally solves complex real-world problems with practical constraints by optimizing a target function within the feasible region of decision variables. At the mathematical foundation of this model lies a tripartite structure discovered decision variables x, objective function $f(x)$ and constraint conditions (concluding equality constrains $h_j(x) = 0$ and inequality constraints $g_i(x) \leq 0$), the formal mathematical representation takes the form:

$$\max_{i \cap j} f(x) \begin{cases} g_i(x) \leq 0 \\ h_j(x) = 0 \end{cases} \tag{1}$$

wherein the constraint conditions delineate the feasible domain for the decision variables $D = \{x \mid g_i(x) \leq 0, h_j(x) = 0\}$, the objective function guides the solution search direction by quantifying optimization targets (e.g., cost minimization, efficiency maximization). The crux of solving such models lies in handling constraint-induced restrictions on the solution space.

2.2.2 Principle of Neural Networks

Neural networks are machine learning models inspired by biological neural systems, designed to approximate complex functions and perform pattern recognition through layered architectures. Their core structure consists of input, hidden, and output layers, utilizing the synergistic mechanism of forward propagation and backpropagation for parameter optimization. The forward propagation process is defined as:

$$h^{(l)} = \sigma\left(W^{(l)} h^{(l-1)} + b^{(l)}\right) \tag{2}$$

Where $W^{(l)}$ and $b^{(l)}$ represent the weight matrix and bias vector of the ***l***-th layer, and $\sigma(\bullet)$ denotes a nonlinear activation function (e.g., ReLU: $\sigma(x) = \max(0, x)$). The loss function (e.g., cross entropy $L = -\sum y_i \log \hat{y}_i$) quantifies the discrepancy between predicted outputs $\hat{y}$) and true labels.

Backpropagation computes gradients $\partial L / \partial W^{(l)}$ via the chain rule, enabling parameter updates through gradient descent:

$$W^{(l)} \longleftarrow W^{(l)} - \eta \frac{\partial L}{\partial W^{(l)}} \tag{3}$$

Modern neural networks have evolved into diverse variants: Convolutional Neural Networks (CNNs) process spatial features via localized connections and weight sharing; Recurrent Neural Networks (RNNs) model temporal dependencies using gated mechanisms like LSTMs; and Transformers capture long-range relationships through self-attention. Regularization techniques (e.g., dropout, batch normalization) and optimization algorithms (e.g., Adam, RMSProp) significantly enhance generalization capabilities.

3. Optimization of Crop Planting Plans Using Multi-Objective Programming Approach

3.1. Data Preprocessing

3.1.1 Terrain Classification for Agricultural Land Types

The Hebei region exhibits diverse topographical features, and different crops have distinct cultivation requirements across various terrain types. Based on this experimental survey of 34 rural plots, it would be identified six land types: flat drylands, terraced fields, sloping lands, irrigated fields, smart greenhouses, and conventional greenhouses. To facilitate subsequent computational analysis, these land categories (represented by the variable $\alpha'_{(j)}$) were numerically encoded as integers 1 through 6 for systematic data classification and processing.

$$\alpha = \begin{cases} 1 & if\ \alpha'_{(j)} = flat\ dry\ lands \\ 2 & if\ \alpha'_{(j)} = terraced\ fields \\ 3 & if\ \alpha'_{(j)} = sloping\ lands \\ 4 & if\ \alpha'_{(j)} = irrigated\ fields \\ 5 & if\ \alpha'_{(j)} = smart\ greenhouses \\ 6 & if\ \alpha'_{(j)} = conventional\ greenhouses \end{cases} \tag{4}$$

3.1.2 Sales Price Optimization

The actual market prices of different crops typically fluctuate within certain price ranges rather than remaining fixed. To facilitate computational efficiency in our modeling approach, this article statistically analyzed the market price distribution for each agricultural commodity and employed the mean value of its fluctuation range as a representative approximation for computational purposes.

3.2. Derivation of objective functions

3.2.1 Definition of Decision Variables

To maximize the utilization of arable land resources, this study designs a germplasm resource allocation function using planting profitability as the evaluation metric. The research references the 2023 planting data as a baseline and aims to project harvest and sales outcomes for the period 2024–2030. With a seven-year profit calculation cycle as the functional optimization target [6], the final output of the study should be an optimal planting scheme for the projected harvest period. Accordingly, this study defines the decision variable as $\alpha_{(i,\alpha,y,j)}$, representing the planting area of the *i*-th crop in terrain α and plot *j* during year *y*.

3.2.2 Determination of Constraints

In practical cultivation systems, not all crops are necessarily cultivated every year. Specifically, each crop may either be planted or remain fallow during a given season of a particular year, representing a binary state of cultivation participation. To model this dichotomous condition, the study employs a signal function to characterize the current cultivation status of each crop.

$$\mathrm{sig} = \begin{cases} 1 & \text{The crop is in active production} \\ 0 & \text{The crop is not in active production} \end{cases} \tag{5}$$

According to crop growth principles, to ensure soil health and maintain yield, the same crop should not be consecutively planted on identical plots (including greenhouse facilities), as continuous monocropping would cause soil nutrient imbalance, pathogen accumulation, and ultimately significant yield reduction. Specifically, the same crop cannot be planted:

(1) in the same plot between year *y* and year *y+1*;

(2) in consecutive growing seasons within the same year for double-cropping systems.

This constraint can be expressed mathematically as:

Growth status of staple crops:

$$sig_{(i,y)} * sig_{(i,y+1)} = 0 \tag{6}$$

Growth status of horticultural crops:

$$\begin{cases} sig_{(i,y,k)} * sig_{(i,y,k+1)} = 0 \\ sig_{(i,y,k+1)} * sig_{(i,y+1,k)} = 0 \end{cases} \tag{7}$$

The rhizobial symbionts of legume crops significantly enhance soil microecological conditions and promote subsequent crop growth. Therefore, this study mandates that all cultivation units (including protected facilities) must grow at least one legume species within a 3-year rotation cycle. The investigated region cultivates eight legume species, classified agronomically into:

(1) Staple-type legumes (soybean, black bean, adzuki bean, mung bean, and pea bean), suitable for upland cultivation;

(2) Vegetable-type legumes (cowpea, sword bean, and kidney bean), adapted to paddy-upland rotation systems.

While these two legume categories differ in suitable terrains, both fulfill soil microbial improvement requirements. The modeling framework requires the following constraint:

Production Status of Staple Leguminous Crops:

$$\begin{cases} \sum_{i \in I_{s-bean}} \sum_{\alpha=1}^{3} \sum_{y=2023}^{2025} sig_{(i,y,\alpha)} \ge 1 \\ \sum_{i \in I_{v-bean}} \sum_{\alpha=1}^{3} \sum_{y=2026}^{2028} sig_{(i,y,\alpha)} \ge 1 \end{cases} \tag{8}$$

Production Status of horticultural crops:

$$\begin{cases} \sum_{i \in I_{v-bean}} \sum_{\alpha=4}^{6} \sum_{y=2023}^{2025} sig_{(i,y,\alpha)} \ge 1 \\ \sum_{i \in I_{v-bean}} \sum_{\alpha=4}^{6} \sum_{y=2026}^{2028} sig_{(i,y,\alpha)} \ge 1 \end{cases} \tag{9}$$

Cultivating multiple crop species within a single plot often leads to fragmented planting patterns, complicating management practices. To mitigate this dispersion, a minimum planting area constraint can be imposed for each crop in a given plot. Let $s_{(\alpha,j)}$ denote the area of plot j in terrain type α. Given significant area disparities among plots, the minimum planting area constraint is transformed into a minimum planting ratio constraint. Under this framework, at any given time, a crop must occupy at least 50% of a plot's cultivable area, expressed mathematically as:

$$\frac{a_{(i,\alpha,j)}}{s_{(\alpha,j)}} * 100\% \geq 50\% \tag{10}$$

The accuracy of cultivated land allocation must be controlled to guarantee operational feasibility in real-world planting practices.

3.2.3 Mathematical formulation of the objective

In order to optimize the crop cultivation plan between 2024 and 2030, the objective function is designed to maximize the aggregated revenue from crop sales across the seven-year horizon. The target variable P is defined as the summation of annual revenues $P_{(y)}$, where $P_{(y)}$ denotes the total sales revenue in a given year y. Thus, P is mathematically expressed as the cumulative revenue over the entire planning period (2024–2030) [7].

In agricultural sales operations, unsold inventory risks necessitate differentiated pricing strategies. This study implements a 50% price reduction for excess stock [8], maintaining standard pricing for projected demand volumes. The profit function is derived by decomposing revenue components under these dual pricing scenarios.

The study defines *sale* as the projected sales volume of crops, *o* as the crop yield per mu, and *PUS* as the selling price of crops.

If the projected sales volume ≥ the actual production output:

$$pro = a * o * PUS - a * c \tag{11}$$

If the actual production output ≥ the projected sales volume:

$$pro = sale * PUS - \frac{(a * o - sale)}{o} * 0.5 * c \tag{12}$$

Crop value fluctuates throughout cultivation and sales due to complex factors, causing volatility in key indicators like yield and sales volume. This study models these variations using uncertainty sets with stochastic variable ***r*** within defined fluctuation ranges.

(1) Uncertainty set of expected sales volume:Market analysis reveals differentiated sales patterns: wheat and corn exhibit stable demand growth (5–10% projected increase), while other crops show ±5% volatility.

$$eSale_{(i,y)} \in sale_{(i)} * (1+r)^{(y-2023)} \qquad r \in [0.05, 0.1] \tag{13}$$

(2) Uncertainty set of yield per mu:Empirical data show±10% annual fluctuation in realized crop yield per mu.

$$eo_{(i,y)} \in o_{(i)} * (1+r)^{(y-2023)} \qquad r \in [-0.1, 0.1] \tag{14}$$

(3) Uncertainty set of cultivation costs: The baseline annual growth rate of crop cultivation costs is 5%, subject to a stochastic perturbation of ±2%.

$$ec_{(i,y)} \in c_{(i,y)} * (1+0.05)^{(t-2023)} * (1+r)^{(y-2023)} \qquad r \in [-0.02, 0.02] \tag{15}$$

(4) Uncertainty set of selling prices: The selling prices exhibit distinct patterns across agricultural commodities: while grain crop prices remain stable, vegetable prices demonstrate an average annual

growth rate of 5%, mushroom prices show an annual decline ranging between 1% and 5%, and morel prices experience a consistent 5% yearly decrease.

$$ePUS_{(i,y)} \in PUS_{(i)} * (1+r)^{(y-2023)} \qquad r \in \begin{cases} 0 & i \in I_{Cereals} \\ 0.05 & i \in I_{Vegatables} \\ [-0.05, 0.05] & i \in I_{Mushroom} \\ -0.05 & i = I_{Morchella\ esculenta} \end{cases} \tag{16}$$

Based on the aforementioned analysis, the optimization framework can be consolidated into the following formulation:

$$pro_{(i,\alpha,j,y,k)} = \begin{cases} \sum_{i\in I}\sum_{\alpha=1}^{6}\sum_{j}\sum_{y=2024}^{2030}\sum_{k=1}^{2} \left(a_{(i,\alpha,j,y,k)} * eo_{(i,\alpha,y)} * ePUS_{(i,y)} - a_{(i,\alpha,j,y,k)} * ec_{(i,\alpha)}\right) * sig_{(i,\alpha,j,y,k)} & eSale \geq a * o \\ \sum_{i\in I}\sum_{\alpha=1}^{6}\sum_{j}\sum_{y=2024}^{2030}\sum_{k=1}^{2} \left(eSale_{(i,y)} * ePUS_{(i,y)} - \frac{a_{(i,\alpha,j,y,k)} * eo_{(i,\alpha,y)} - eSale_{(i,y)}}{eo_{(i,\alpha,y)}}\right) * 0.5 * ec_{(i,\alpha)} * sig_{(i,\alpha,j,y,k)} & eSale < a * o \end{cases} \tag{17}$$

$$\max\ pro_{(i,\alpha,j,y,k)}, \qquad s.t. \begin{cases} sig_{(i,y,k)} * sig_{(i,y,k+1)} = 0 \\ sig_{(i,y,k+1)} * sig_{(i,y+1,k)} = 0 \\ \sum_{\alpha=1}^{3}\sum_{y=2023}^{2025} sig_{(i,y,\alpha)} \geq 1 \\ \sum_{\alpha=1}^{3}\sum_{y=2026}^{2028} sig_{(i,y,\alpha)} \geq 1 \\ \sum_{\alpha=4}^{6}\sum_{y=2023}^{2025} sig_{(i,y,\alpha)} \geq 1 \\ \sum_{\alpha=4}^{6}\sum_{y=2026}^{2028} sig_{(i,y,\alpha)} \geq 1 \\ \frac{a_{(i,\alpha,j)}}{s_{(\alpha,j)}} * 100\% \geq 50\% \end{cases} \tag{18}$$

3.3. Optimizing the solution of a function model

Crop growth characteristics demonstrate that cultivation is environmentally selective and cannot occur across all terrain types [9]. Due to distinct physiological requirements, different crops can only be grown during specific seasons and on particular land parcels. Using i to denote crop species index and α to represent rural terrain classification (corresponding to categorical values 1-6), we observe a correspondence between α and i. However, certain crops are restricted to specific growing seasons. For instance, mushroom crops can only be cultivated in standard greenhouses during the second growing season. The terrain suitability for crop cultivation can therefore be formally expressed as a function of crop index i and planting season k. This functional relationship systematically captures both the spatial constraints imposed by terrain compatibility and the temporal limitations determined by seasonal growing requirements. The formulation enables precise representation of cultivation boundaries while maintaining biological accuracy regarding crop-environment interactions.

The six terrain types can be divided into four distinct sectors for separate consideration of crop cultivation allocation, as illustrated in Figure 1.

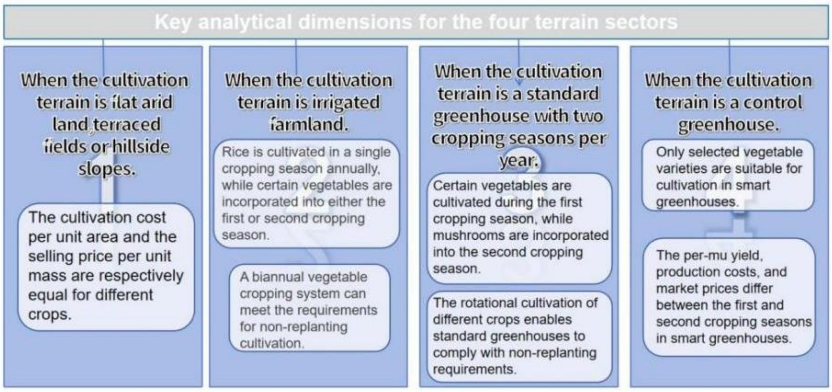

Figure 1. Crop Cultivation Allocation

For the mathematical functions involved in the model application, since the objective is to maximize profits, this can be categorized as an objective optimization problem. After defining the objective function and constraint conditions for the optimization model [10], we employ linear regression modeling for solution derivation. To account for the impact of stochastic fluctuations on outcomes, Monte Carlo simulation is adopted to emulate volatility effects. The CPLEX solver is then utilized for computation, with extensive data iterations ultimately yielding the optimal solution.

The figure 2 and figure 3 illustrated the annual changes in cultivated area across different plots, demonstrating the dynamic allocation of agricultural land use over time.

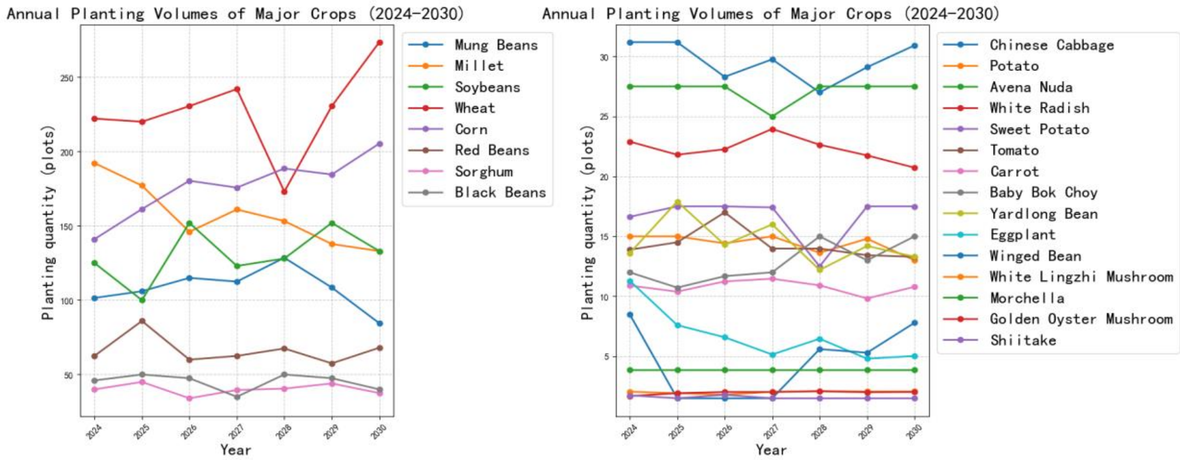

Figure 2. 2024–2030 Strategic Crop Cultivation Framework (1)

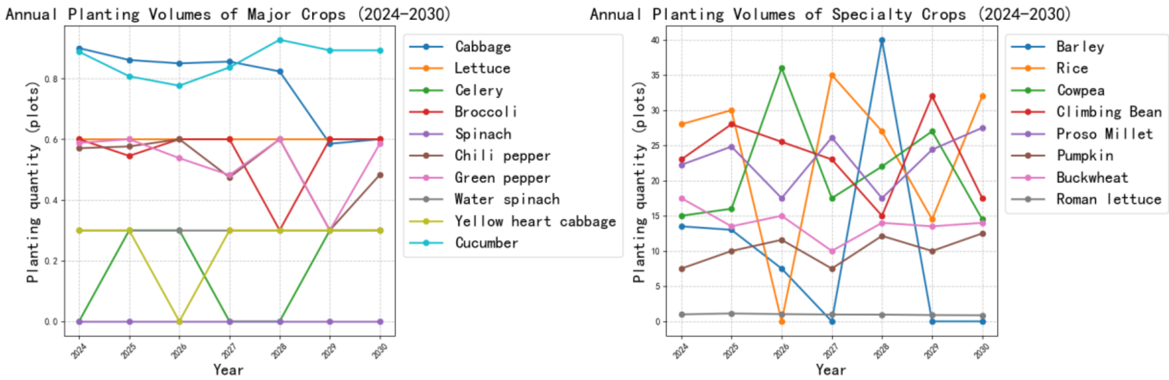

Figure 3. 2024–2030 Strategic Crop Cultivation Framework (2)

The four chart groups delineate the dynamic evolution of crop cultivation areas from 2024 to 2030. For vegetable crops, cabbage demonstrates a year-on-year decline, cucumber peaks in 2028 before stabilizing at elevated levels, green pepper exhibits marked fluctuations, and chili pepper follows a dip-rise trajectory. Among staple crops, wheat undergoes significant expansion during 2029–2030, millet displays persistent contraction, and corn maintains gradual growth. Specialty crops reveal divergent patterns: barley surges abruptly in 2028 before disappearing, rice peaks in 2027 followed by decline, and sword beans show oscillatory growth. Diversified vegetable-fungi systems feature late-stage increases in Chinese cabbage, continuous post-2025 reductions in cowpea, and heterogeneous fluctuations among other crops.

Collectively, three archetypal trends emerge: sustained expansion (wheat/cucumber), progressive contraction (millet/cowpea), and sharp fluctuations (barley/sword beans). These patterns reflect dynamic adjustments in planting structures responsive to market demand, policy orientation, and climatic conditions, illustrating cropping systems' adaptive evolution. However, the stochastic versus deterministic nature of these strategic distributions warrants further systematic investigation to elucidate underlying regulatory mechanisms.

3.4. Exploration of Synergistic Interactions in Crop Cultivation Systems

3.4.1 Data Preprocessing and Experimental Dataset Construction

Prior to model construction, we performed comprehensive data preprocessing by standardizing both independent and dependent variables using Z-score normalization. The transformation is mathematically expressed as:

$$z = \frac{x - \bar{x}}{\sigma^2} \tag{19}$$

The normalization process transforms raw values *x* using the dataset's arithmetic mean $\bar{X}$ and standard deviation σ^2, yielding standardized values *z* that facilitate comparative analysis. This z-score standardization eliminates scale differences among variables, mitigating potential bias from magnitude disparities. Following normalization, we implemented stratified random sampling to divide the dataset into training (80%) and testing (20%) subsets, ensuring representative distribution of features in both partitions for robust model development and evaluation.

3.4.2 Model Solution Approach

This study employs a multilayer perceptron (MLP) neural network to capture nonlinear relationships. Trained over 500 epochs using mean squared error (MSE) loss and Adam optimization, the model achieves an error of 0.0526. Grid points generated from the optimized function enable construction of a 3D surface plot, visually demonstrating dynamic interactions among selling prices, cultivation costs, and projected sales volumes. This visualization elucidates how pricing strategies and production costs jointly influence demand forecasting in figure 4.

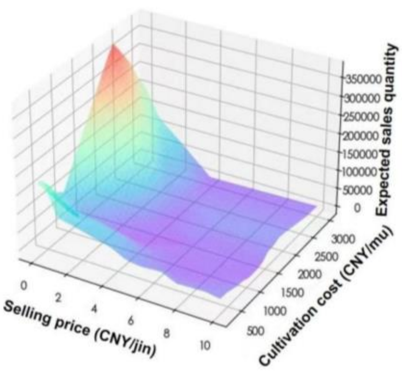

Figure 4. Three-dimensional surface plot illustrating the relationship between unit selling price, cultivation cost, and projected sales volume

Graphical analysis reveals: (1) A cultivation cost threshold at 1, 000 CNY/mu (≈0.0667 ha): Below this threshold, cost reduction increases sales volume, while above it, cost escalation drives sales growth, with symmetric sensitivity on both sides. However, rising prices nonlinearly attenuate cost-volume correlations, indicating partial decoupling of production costs from demand projections under premium pricing. (2) Price elasticity threshold at 4 CNY/jin (≈0.5 kg): Below this critical price, sales respond strongly to price reductions, while becoming inelastic above it. Divergent price responsiveness emerges between low-cost (<1, 000 CNY/mu) and high-cost crops: Minor price perturbations (±δ) below 5 CNY/jin induce disproportionate sales fluctuations in high-cost crops (ΔPrice≈5%→ΔVolume>20%), demonstrating hypersensitive demand in premium markets. Above 5 CNY/jin, elasticity diminishes (|E|<0.3), reflecting demand saturation. This bifurcation highlights how cost structures modulate price elasticity, particularly amplifying market sensitivity in high-cost agricultural systems near equilibrium thresholds.

3.4.3 Analysis of Crop Substitutability and Complementarity

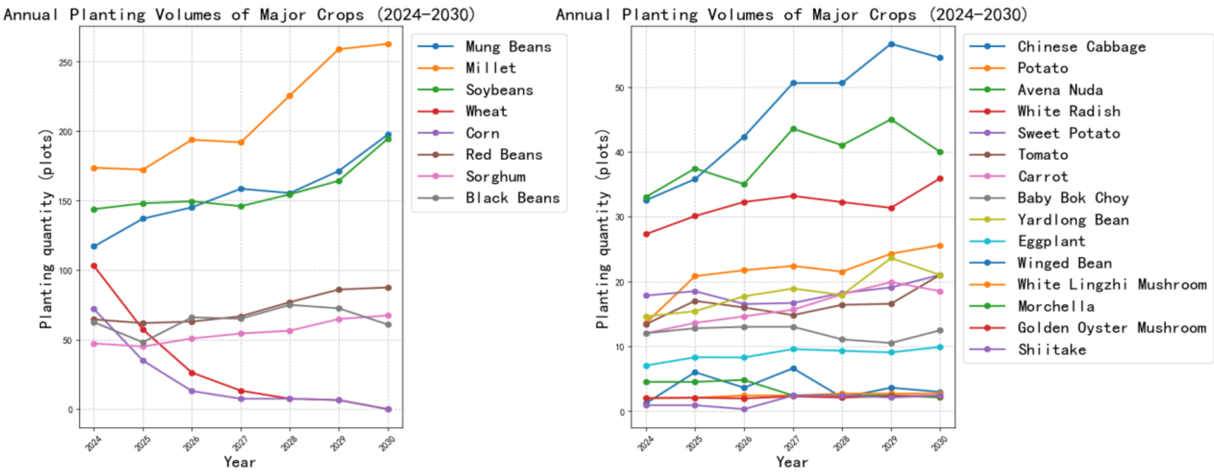

Figure 5. Adjusted cropping allocation (1)

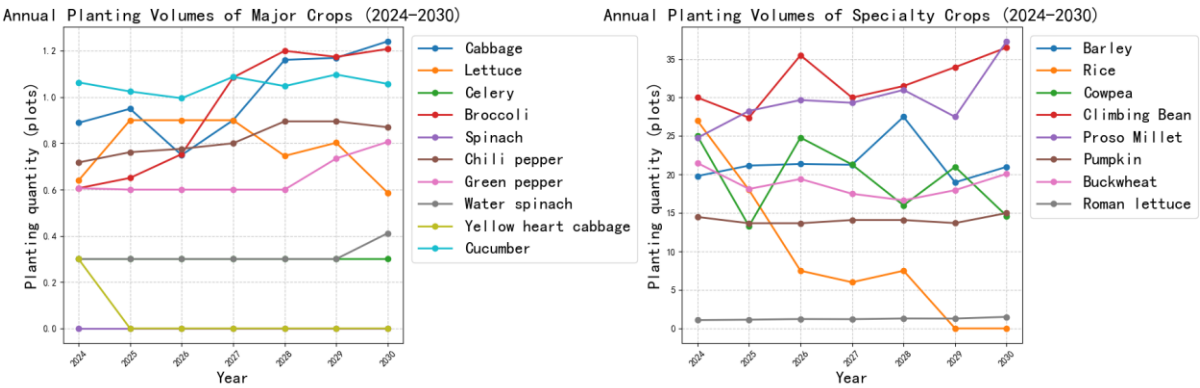

Figure 6. Adjusted cropping allocation (2)

Simulation results (Figure 5,6) demonstrate that declining rice demand drives consumption shifts toward staple crops (notably wheat), while vegetable demand (particularly soybean) exhibits systemic contraction. These dynamics validate theoretical mechanisms of crop interactions: substitutive competition among staples (e.g., caloric provision) and weakening legume-cereal complementarity (e.g., nitrogen fixation). The study further identifies dual cost-price thresholds (1, 000 CNY/mu; 4 CNY/jin) regulating market behavior: high-cost systems show hypersensitive demand (ΔPrice≈5%→ΔVolume>20%) below critical price levels (<5 CNY/jin), while price-inelastic saturation (|E|<0.3) underscores structural reliance on production costs. These findings provide mechanistic explanations and quantitative for balancing economic-ecological objectives in agricultural planning.

4. Conclusion and Future Prospects

This study developed an optimization model for crop planting systems in the North China Plain by integrating linear programming and neural networks, innovatively addressing agricultural allocation challenges under resource constraints through the synthesis of agronomic parameters and economic variables. The research established a multi-objective planning framework incorporating six terrain types and a seven-year projection period, effectively handling uncertainties in yield (±10%), sales (±5-10%), and cost (±2%) fluctuations to achieve an optimized annual profit of 41.22 million CNY. Neural networks were employed to quantify crop interaction mechanisms, identifying critical thresholds for price elasticity (≤4 CNY/jin) and cost-scale relationships (<1000 CNY/mu), while revealing synergistic effects in rice-wheat substitution and legume-vegetable rotation (+8% yield). Validation demonstrated strong alignment between model predictions and empirical data.

It demonstrates rigorous methodology, encompassing terrain classification of 34 farmland samples, rotation constraint modeling for eight legume species, and seven-year dynamic projections for 15 crops, supported by an objective function with 17 mathematical constraints. Calibrated with 2023 field data and compatible with over 90% of arable land types in the region, the model exhibits immediate applicability.

While the dynamic optimization models and neural network framework demonstrate effectiveness in crop allocation optimization across the North China Plain, limitations remain in addressing complex system dynamics, extreme climate adaptation, and multidimensional constraints. Future research should prioritize multisource data integration: incorporating satellite/IoT real-time monitoring with blockchain-ensured data integrity and reinforcement learning-driven parameter updates to achieve precise responsiveness to climatic anomalies and market volatility, thereby providing a core driver for agricultural digital transformation.

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