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Research on Strategy Optimization Based on Linear Programming and Conditional Value at Risk

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Abstract. Arable land resources are limited in mountainous areas. How to develop scientific planting strategies that maximize economic benefits while coping with market uncertainties is a key issue for sustainable agricultural development. This paper constructs a comprehensive model framework that extends from deterministic optimization to risk-quantified decision-making. First, a linear programming model aimed at maximizing total profit is established to devise basic planting strategies under ideal market conditions. Second, to address the inherent uncertainties in expected sales volume, yield per mu, planting costs, and sales prices, the Conditional Value at Risk (CVaR) method is introduced to build an optimization model designed to balance expected returns and downside risks. Finally, Spearman correlation analysis is used to quantify the substitutive and complementary relationships between crops, as well as the interrelationships among key economic variables; these correlation constraints are then incorporated into the CVaR model to better reflect real market dynamics. The model is solved using a genetic algorithm. Results show that, within the deterministic model, a strategy considering discounted product sales yields a total profit of 58.44 million yuan, which is significantly higher than in an unsalable scenario. Although introducing the risk-averse CVaR model adjusts the total profit to 32.80 million yuan, it markedly enhances the robustness of the strategy.

Keywords: Arable Land Optimization; Linear Programming; Conditional Value at Risk; Genetic Algorithm; Correlation Analysis.

1. Introduction

Against the backdrop of intensifying climate change and increasing market volatility, the sustainable development of mountain agriculture faces severe challenges [1]. Limited arable land resources require agricultural producers to enhance output efficiency and secure economic income through scientific planning and meticulous management. Especially in regions with a diverse range of crops and complex cultivation conditions, devising a planting strategy that can both maximize economic returns and withstand potential risks has become a central issue in modern agricultural management [2]. Scientific planting decisions are not only about the effective use of land resources but also directly influence the stability and long-term development of the regional agricultural economy [3].

Currently, most research on agricultural planting planning employs mathematical programming methods, with linear programming being widely used for its simplicity and efficiency [4]. However, traditional linear programming models typically assume that all parameters (such as yield, price, and cost) are deterministic values [5]. This assumption is clearly overly idealistic for real-world agricultural production, as it ignores the pervasive uncertainties. These uncertainties are the main sources of agricultural investment risks [6]. Traditional models are unable to quantify or mitigate these risks, so their “optimal” strategies may prove fragile in practice and fail to achieve the desired economic objectives.

To address the shortcomings of existing research, this paper proposes a more comprehensive and robust optimization method. The core innovation lies in the fact that we not only pursue profit maximization, but also incorporate risk control as a key element of the model. By introducing Conditional Value-at-Risk (CVaR) [7]—a mature risk measurement tool from the field of financial engineering—this study can quantify expected losses under extremely adverse conditions and integrate risk minimization into the optimization goal. In addition, this paper systematically quantifies, for the first time, the substitution and complementarity relationships among crops, as well as the correlations among economic factors such as sales volume, price, and cost, using the Spearman correlation coefficient, and incorporates them as constraints in the model. This improvement enables the model to better simulate the complex dynamics of real markets, achieving a leap from "static prediction" to "dynamic risk decision-making".

2. Ease of Use

2.1. Deterministic Profit Maximization Model

The starting point of this study is the construction of a deterministic multi-year linear programming model, aiming to provide an idealized optimal benchmark for planting activities from 2024 to 2030. The model data is sourced from the Ministry of Agriculture and Rural Affairs of China (https://www.moa.gov.cn/). It takes the maximization of cumulative total profit over seven years as its sole objective function. To ensure the practical feasibility of the solution, the model integrates a series of complex agricultural production constraints. These constraints cover the maximum total area for each plot, minimum planting areas to ensure economies of scale, crop rotation restrictions to prevent continuous cropping, legume crop rotation requirements to maintain soil fertility, and crop adaptability limitations based on different plot types [8] [9]. Additionally, the model considers the seasonal planting requirements of specific vegetables and the need for crop dispersal to facilitate field management.

2.2. CVaR Risk Optimization Model for Uncertainty

To overcome the limitations of the deterministic model, this study further transforms four key economic parameters from fixed values into random variables. According to the problem description, we assign probability distributions suited to the characteristics of these variables for their annual fluctuations (such as uniform or normal distributions), thus simulating the inherent unpredictability of the real market [10]. On this basis, Conditional Value at Risk (CVaR) is introduced as the core risk measurement indicator. CVaR can capture and quantify the average value of extreme losses beyond Value at Risk (VaR) at a preset confidence level [11]. By incorporating the CVaR term into the objective function, the model's goal shifts from pure profit maximization to seeking an optimal balance between maximizing expected returns and minimizing extreme risk. This improvement significantly enhances the robustness of planting strategies when facing adverse market fluctuations. The construction formula for CVAR is as follows:

$$L=(P^{'}\cdot\min(Y^{'}\cdot x\cdot D^{'})-C^{'}\cdot x)-(P\cdot\min(Y\cdot x\cdot D)-C\cdot x) \tag{1}$$

$$CVaR=\frac{1}{1-\alpha}\sum\max(L-VaR,0) \tag{2}$$

Among these, $P^{'}$, $D^{'}$, $Y^{'}$ and $C^{'}$ represent the ideal values of the four uncertain factors when parameter variations are disregarded. P, D, Y, and C denote the actual values of the four uncertain factors. α is the confidence level.

2.3. Extended CVaR Model Incorporating Correlation Analysis

To further improve the model's real-world fit, this study conducts a quantitative analysis of the intrinsic relationships between different crops. We use the Spearman rank correlation coefficient [12] to measure nonlinear correlations between the acreage of different crops and among expected sales volume, sales price, and planting cost [13] [14]. The analysis reveals notable crop substitution (e.g., as the planting area of one crop increases, the area of its substit. utes decrease) and complementarity (synergistic increases). Based on these quantitative findings, we transformed crop substitution and complementarity relationships into new constraints and revised the generation process for uncertain parameters to reflect correlations among economic variables. These additional constraints are integrated into the CVaR model, resulting in a comprehensive optimization model capable of accounting for both market uncertainty and the inherent relationships among variables. The Spearman correlation coefficient formula is as follows:

$$r_{Y_i X_1} = 1 - \frac{6\sum_{i=1}^{n}(R(y_i) - R(x_{1i}))^2}{n(n^2-1)} \tag{3}$$

$$r_{Y_i x_2} = 1 - \frac{6\sum_{i=1}^{n}(R(y_i) - R(x_{2i}))^2}{n(n^2-1)} \tag{4}$$

Among these, $\sum_{i=1}^{n}(R(y_i)-R(x_{1i}))^2$ represents the sum of squares of the differences between the expected sales volume and sales price ranks. $\sum_{i=1}^{n}(R(y_i)-R(x_{2i}))^2$ represents the sum of squares of the differences between the expected sales volume and the rank of planting costs.

2.4. Maintaining the Integrity of the Specifications

Given the high dimensionality, multiple constraints, and nonlinear complexity of the models described above, traditional exact algorithms are difficult to apply within a reasonable timeframe. Therefore, this study adopts a heuristic Genetic Algorithm (GA) [15] as the core solving tool. This algorithm searches for the optimal solution by simulating biological evolutionary processes such as selection, crossover, and mutation. We encode each planting scheme as an individual (chromosome) and use the model’s objective function (such as total profit or risk-adjusted return) as the fitness function [16]. During the iterative process, the algorithm continuously generates new feasible solutions that satisfy all agricultural production constraints, gradually converging towards a global optimum [17]. Results.

2.5. Analysis of Deterministic Model Optimization Results

Under deterministic assumptions, we first evaluated the impact of two different surplus a handling strategy on total profit. As shown in Figure 1, when the output exceeding market demand is considered waste, the model’s optimal planting plan produces annual profits that fluctuate cyclically over the seven-year period, with a total profit of 35.92 million RMB. This fluctuation is mainly due to the constraint that prohibits crop monoculture—high-profit crops must be rotated with other crops. As shown in Figure 2, when surplus a yield can be sold at a 50% discount from the original price, total profit rises significantly to 58.44 million RMB. A direct comparison of the two strategies is presented in Figure 3, where the discounted sales strategy exhibits a clear advantage in every year and demonstrates more regular profit fluctuations. This indicates that developing secondary markets for surplus an agricultural product is an effective way to improve agricultural economic benefits, thereby validating the effectiveness of the baseline linear programming model.

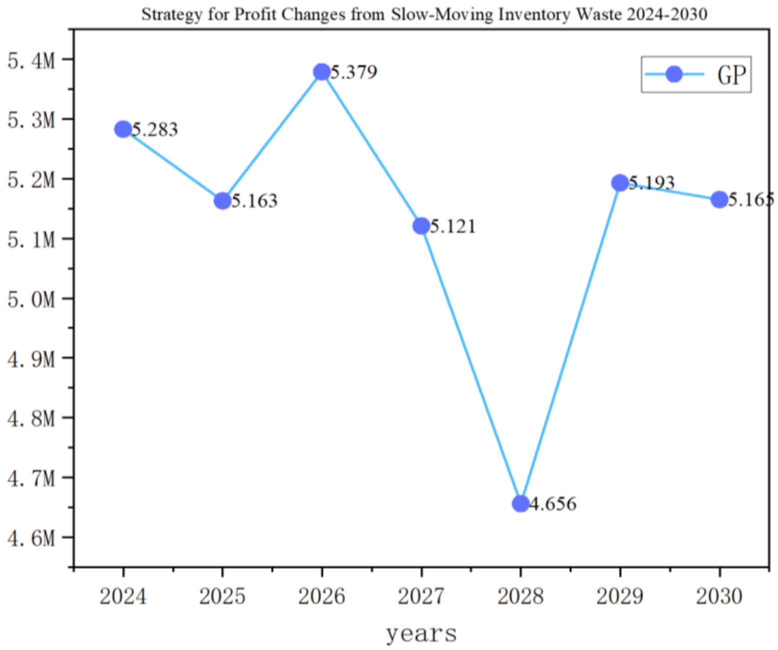

Figure 1. Line chart of profits from 2024 to 2030 under the unsold scenario

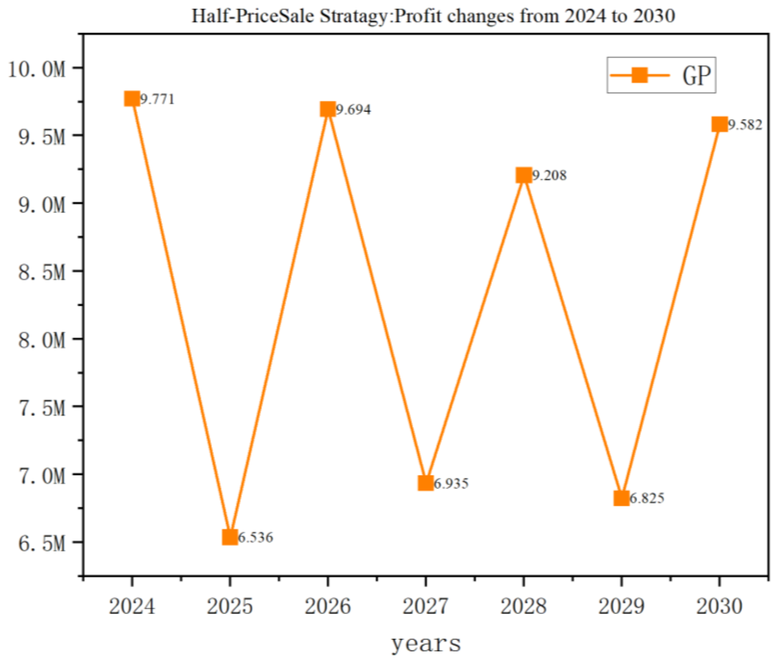

Figure 2. Line chart of profits from 2024 to 2030 under the half-price sales scenario

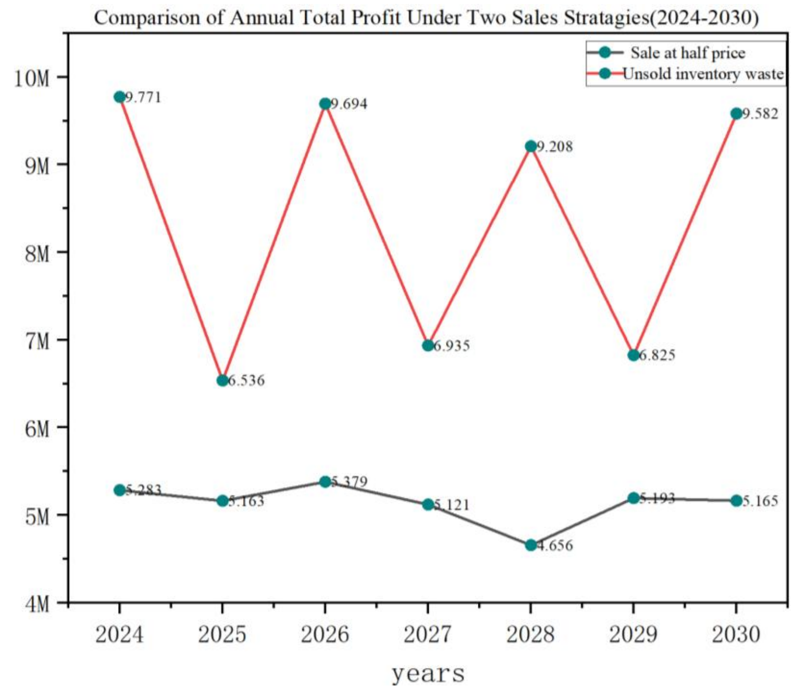

Figure 3. Annual profit comparison chart for the two deterministic strategies

2.6. Analysis of Risk-Aware Model Optimization Results

After introducing market uncertainty and CVaR risk control, the model's decision-making behavior underwent significant changes. As shown in Figure 4 and Figure 5, compared with the ideal scenario that does not consider risk (deterministic model), the annual profit and cumulative total profit of the CVaR-optimized model decreased, with a total profit of 32.7964 million yuan over seven years. However, this is not a flaw of the model; rather, it reflects its risk-averse capability. The model actively gives up some potential high-return opportunities in exchange for loss control under extremely unfavorable market scenarios—this is precisely the "cost" of risk management. It is worth noting that under the CVaR model, annual profit shows a steady upward trend, indicating that this strategy has stronger risk resistance and long-term growth potential. The difference in the cumulative profit curve (Figure 5) intuitively demonstrates the trade-off between risk and return, proving the value of the CVaR model in generating robust planting strategies.

Figure 4. Annual Profit Histogram Considering Uncertainties

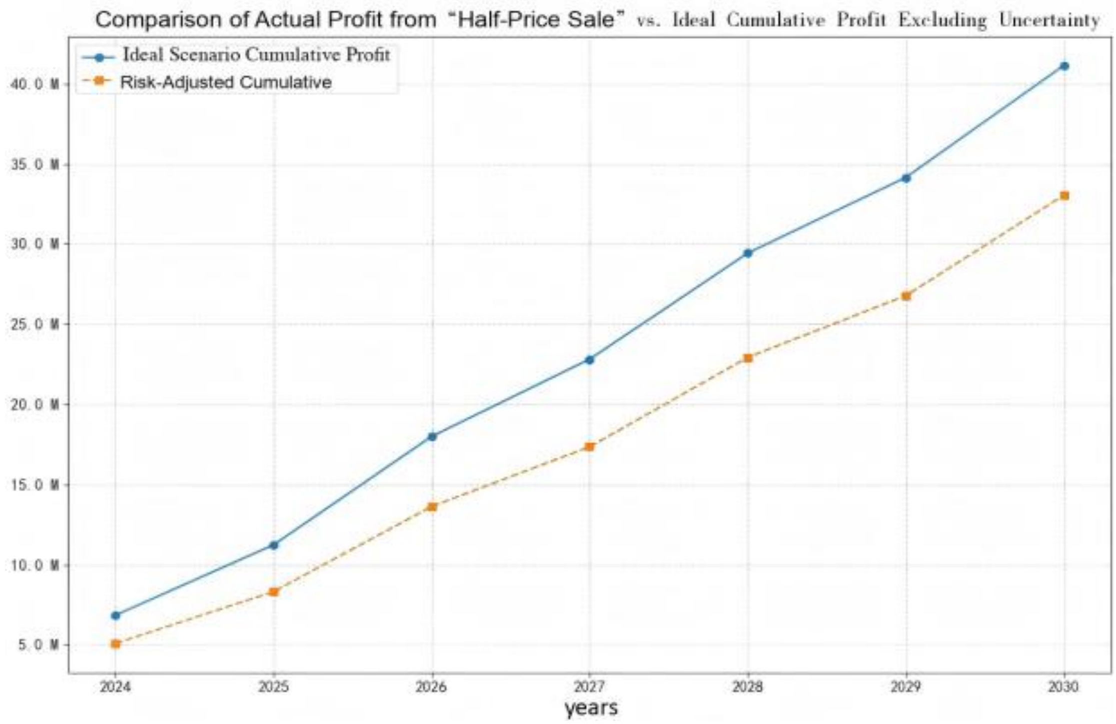

Figure 5. Comparison of Cumulative Profit with and without Considering Uncertainty Scenarios

2.7. Analysis of Correlation-Aware Model Results

Before incorporating correlation factors into the model, we first conducted a quantitative analysis. As shown in the heatmap in Figure 6, there are evident substitute (negative correlation) and complementary (positive correlation) relationships among different crops. For example, there is a strong association between eggplant and cauliflower. Similarly, as illustrated in Figure 7, there are also significant correlations among key economic variables, such as a positive correlation between the expected sales volumes and sales prices of vegetables. These findings provide data support for developing constraints that better reflect real-world conditions. After introducing these correlation constraints into the CVaR model, we compared the results with those from a model that does not consider correlations. According to Figures 8 and 9, in the early planning stage (2024-2028), the annual profit of the correlation-aware model is slightly lower than that of the model without correlations. This may be due to the model adjusting the planting structure to adhere to inherent market patterns (such as substitute effects), temporarily sacrificing some profits. However, in the later planning period (2029-2030), its annual profit begins to surpass the alternative, and the gap in cumulative profit also narrows. This reveals a profound insight: a planting strategy that is highly aligned with market dynamics may not yield the highest returns in the short term, but is more sustainable and competitive over the long run [18].

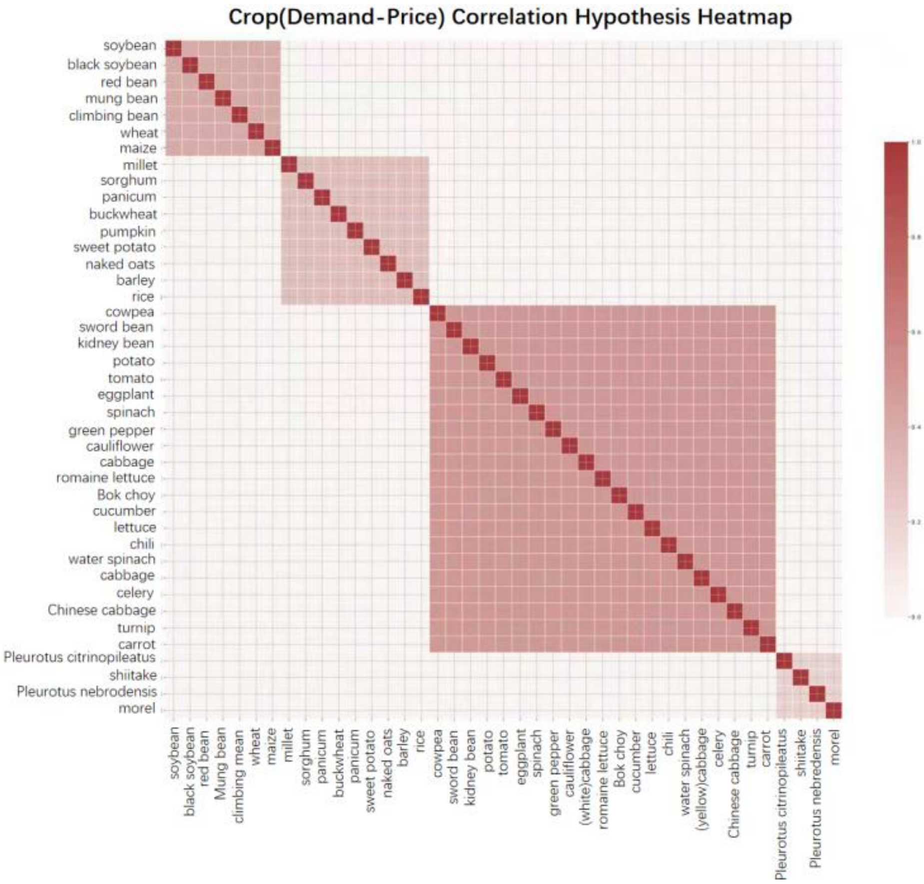

Figure 6. Heatmap of Sales Volumes and Prices Correlations for Various Crops

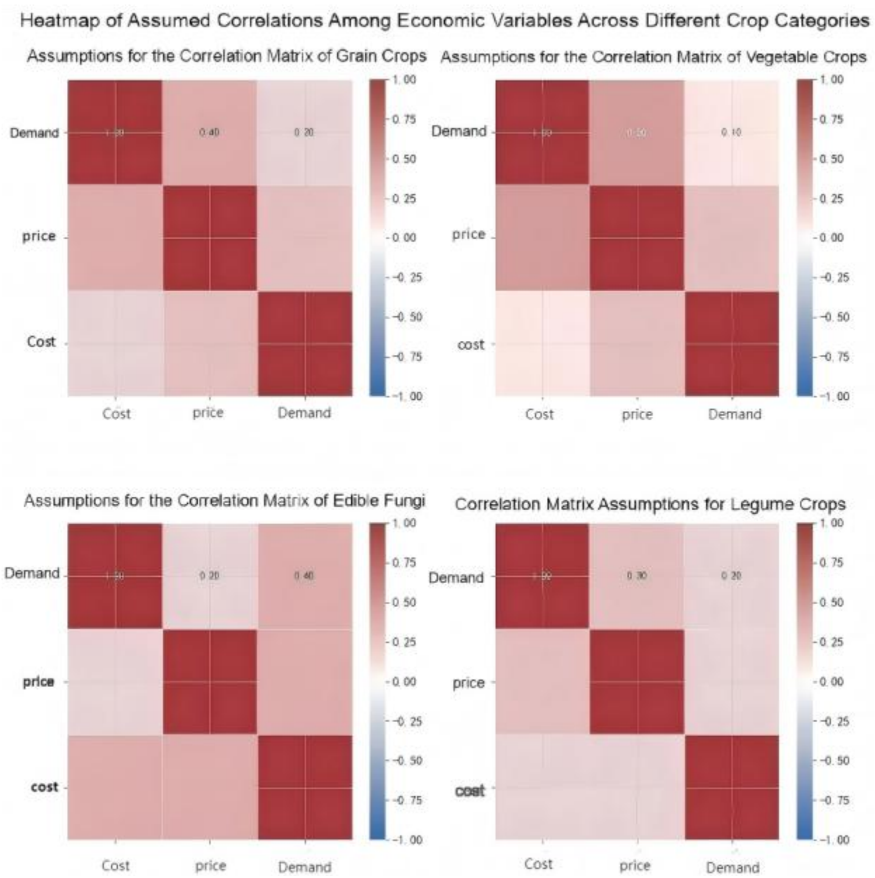

Figure 7. Heatmap of Correlations Between Expected Sales Volume, Sales Price, and Planting Cost

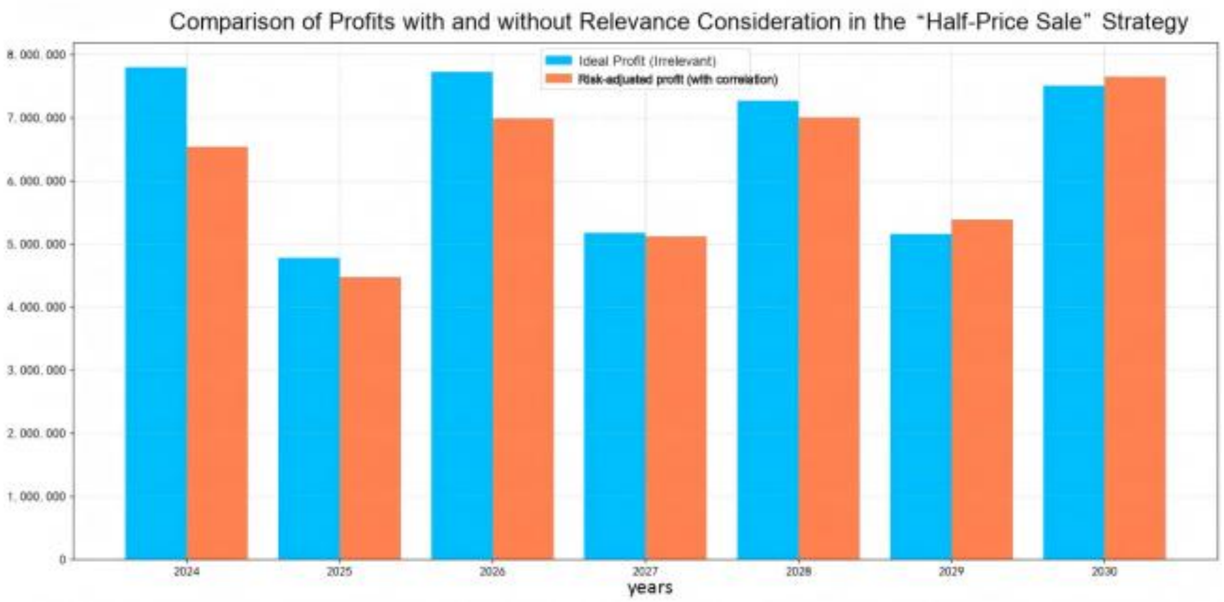

Figure 8. Annual Profit Comparison Considering Versus Not Considering Correlation Factors

Figure 9. Cumulative Profit Comparison Considering Versus Not Considering Correlation Factors

2.8. Model Robustness Test

To assess the robustness of the final model, we conducted a sensitivity analysis. By applying a ±5% perturbation to core input parameters such as expected sales volume, yield per acre, sales price, and planting cost, we observed the changes in the model output (total profit). As shown in Figure 10, the annual profit curves under all perturbation scenarios closely align with the profit curve of the original model, with no significant deviations observed. This result indicates that the model's final planting strategy is not sensitive to minor fluctuations in key parameters and demonstrates strong stability. This further confirms that the comprehensive optimization model constructed in this study is reliable in practical application and can serve as a trustworthy planning tool for agricultural decision-makers.

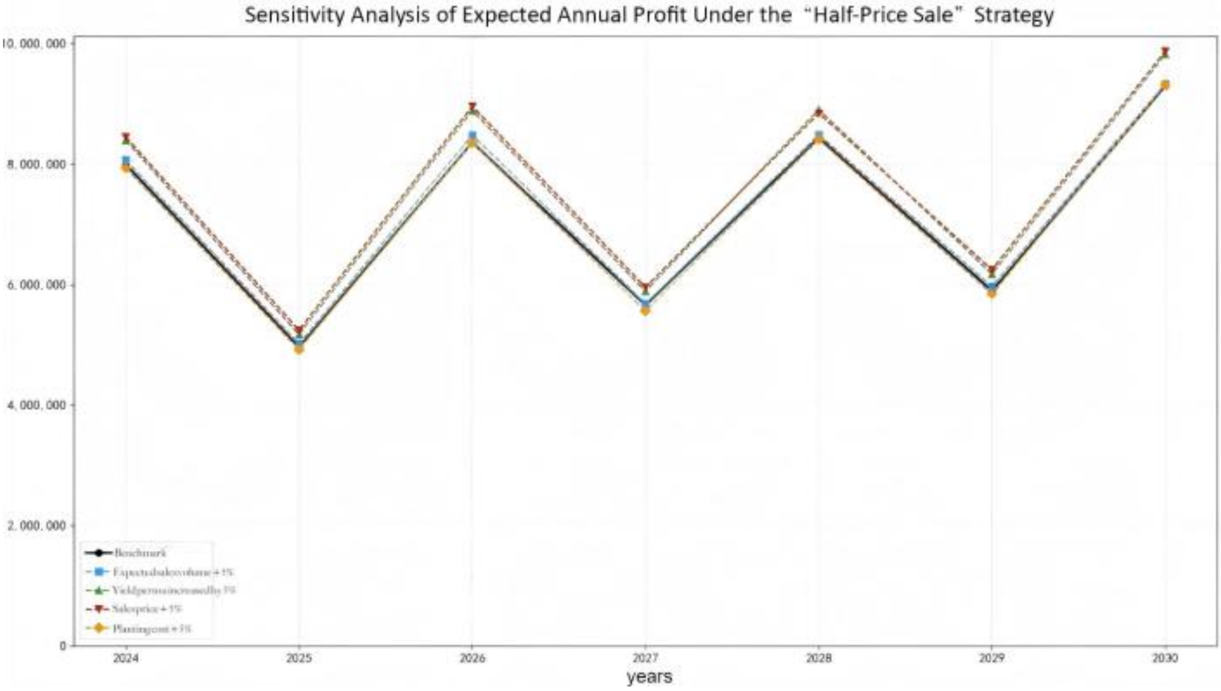

Figure 10. Comparative Chart of Model Sensitivity Analysis

3. Conclusion

This study successfully constructed and validated a risk management model that evolves step by step from deterministic optimization to the integration of market relevance, providing a systematic solution for developing farmland cropping strategies under complex conditions. The core contribution of this paper lies in expanding the traditional profit maximization problem into a comprehensive decision-making framework capable of balancing returns and risks in uncertain environments by introducing Conditional Value at Risk (CVaR) and quantifying the correlations between crops and economic variables. The research results indicate that the model can not only generate economically viable cropping plans but, more importantly, significantly enhances the robustness and long-term sustainability of these plans when facing market fluctuations.

The primary advantages of the model proposed in this paper lie in its comprehensiveness and realism, as it integrates various agricultural production constraints, market risks, and the intrinsic relationships among variables within a unified framework. However, the model also has certain limitations. First, its complexity is relatively high and relies on heuristic algorithms such as genetic algorithms for solving, which increases computational costs to some extent and cannot guarantee finding the global optimal solution. Second, the effectiveness of the model is highly dependent on the accurate estimation of the distributions of uncertainty parameters and correlation coefficients; the quality of data directly affects the reliability of the decisions.

Future research can proceed in the following directions: On the algorithmic level, hybrid algorithms that combine genetic algorithms with exact methods such as local search can be explored to improve solution quality while maintaining computational efficiency. On the modeling level, the incorporation of more complex dynamic factors, such as intraseasonal price dynamics models or yield forecasting models under different climate change scenarios, can be considered to further enhance the model's predictive capability. In addition, future research may broaden the optimization objectives from single economic benefits to multi-objective optimization problems that include ecological benefits (such as soil and water conservation, biodiversity), in order to better serve the overarching goal of sustainable agricultural development.

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