Research on Optimization of Regional Agricultural Planting Strategy Based on Sequential Mixed-Integer Linear Programming

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Abstract. In the context of global food security and rural revitalization strategies, developing efficient and sustainable modern agriculture has become a core issue in the agricultural sector. This paper addresses the optimization of agricultural production under specific geographical and market conditions by constructing a multi-year, multi-constraint Sequential Mixed Integer Linear Programming (SMILP) model. The model explores optimal arable land resource allocation schemes that balance economic benefits and ecological sustainability. With long-term economic returns maximization as the objective function, it systematically integrates crop sales revenue, planting costs, and implicit management costs arising from dispersed planting. At the same time, it rigorously incorporates constraints such as plot-crop suitability matching, annual crop rotation systems, and legume crop soil fertility maintenance. To quantify the impact of market risks on planting decisions, the model innovatively sets up two scenarios: "complete unsaleability" and "discounted sales," simulating uncertainties in the agricultural product market. Experimental results demonstrate that the model can dynamically generate annual planting plans for the 2024-2030 planning period, effectively balancing economic benefits and ecological constraints. Comparative analysis shows that the "discounted sales" strategy, with flexible sales channels, can significantly enhance overall profitability and reduce operational risks, providing a scientific and practical intelligent decision-making tool for agricultural production decisions. The findings of this study hold significant theoretical value and practical guidance for the intelligent transformation and sustainable development of modern agricultural management.

Keywords: Agricultural Optimization, Planting Strategy, Mixed Integer Linear Programming, Crop Rotation, Sustainable Development.

1. Introduction

The With the rapid advancement of digital technology and intelligent sciences, their deep integration with traditional agriculture is sparking an industrial revolution centered on "smart agriculture." Facing global population growth, arable land resource scarcity, and multiple challenges posed by climate change, optimizing agricultural production through modern means to ensure food security and increase farmers' income has become a core issue concerning national economy and people's livelihood. In this context, using data-driven mathematical modeling to intelligently regulate agricultural planting structures for optimal resource allocation and maximum output is not only an inevitable trend of technological development but also a key pathway to solving the dilemmas of modern agricultural development.

In recent years, Mixed Integer Linear Programming (MILP) has been widely applied due to its ability to handle both continuous variables (e.g., planting area) and discrete decisions (e.g., whether to plant a certain crop), enabling more precise depiction of complex real-world constraints. Research trends in the past five years (2020-2025) have further propelled the field toward greater refinement, dynamism, and adaptability. For instance, in water and fertilizer resource management, García-Galiano et al. [1] proposed a multi-objective MILP model for optimizing irrigation water and nitrogen fertilizer application strategies in intensive citrus farming in Spain. In adapting to climate change, Murakami and Iizumi [2] combined optimization algorithms with crop growth models (WOFOST) to provide optimal solutions for crop rotation calendars under climate change. Randall et al. [3] developed a robust temporal optimization method, ensuring that generated crop planning schemes remain feasible and stable across various future climate change predictions.

In addressing uncertainty, Li and Hu [4] constructed a multi-stage stochastic programming model capable of handling random factors such as crop prices and precipitation, significantly enhancing farm expected profits. Amiry et al. [5] optimized crop planting plans considering uncertainties in water resources and market demand through a two-stage stochastic programming approach. In expanding optimization dimensions, studies are no longer limited to single economic objectives. Acosta-Alba et al. [6] incorporated energy consumption and greenhouse gas emissions into their model to promote the ecological transition of agricultural systems. Esteso et al. [7] creatively added a social fairness objective of "minimizing inequality among farmers" in their model. Additionally, Hosseini-Eshkiki et al. [8] developed a decision support system integrating crop planting and irrigation scheduling to maximize water productivity. Lü et al. [9] built a land use optimization model considering ecosystem service values.

Although these studies have made progress on specific issues, the Sequential Mixed Integer Linear Programming (SMILP) model presented in this paper, which systematically integrates long-cycle dynamic rotation, legume soil fertility maintenance, planting dispersion management costs, and diverse market risk scenarios, still holds significant innovative value and practical significance. Addressing the shortcomings in existing agricultural production optimization research regarding multi-constraint coordination and market dynamic response, this paper proposes a multi-dimensional integrated sequential optimization method. The innovations of this study are threefold: First, constructing a highly realistic SMILP model that integrates key agronomic rules such as crop-plot suitability matching, annual rotation systems, and periodic legume rotation for systematic constraint integration; Second, innovatively introducing a "dispersion penalty term" in the objective function to quantify the discreteness of plot planting layouts, optimizing field management efficiency and filling the gap in quantifying implicit management costs; Finally, by constructing "complete unsaleability" and "discounted sales" market scenarios, systematically simulating the impact of market uncertainty on agricultural production decisions, quantitatively revealing the critical role of sales channel flexibility in agricultural economic benefits. The generated refined planting schemes for the seven-year period from 2024 to 2030, validated through multi-dimensional data visualization, perform excellently in balancing economic benefits and ecological sustainability, providing a replicable and promotable scientific decision-making paradigm for similar regional agricultural planning, with important reference significance for advancing intelligent and precise modern agricultural development.

2. Theory and Methods

The optimization object of this study is agricultural production activities in a rural area in the North China mountainous region. This rural area possesses various types of arable land, including open dryland, terraced fields, irrigated land, and ordinary and smart greenhouses, each with specified suitable crops and seasons for planting. The core optimization goal is to formulate optimal annual planting plans for all plots over the seven-year planning period from 2024 to 2030 to maximize cumulative economic benefits. These plans must strictly adhere to the following core constraints:

(1) Suitability constraints: Each crop can only be planted in suitable plot types and seasons.

(2) Crop rotation constraints: The same crop planted in a plot in the previous year cannot be planted again the following year (no continuous cropping).

(3) Legume rotation constraints: Starting from 2023, any plot must plant at least one legume crop within any consecutive three years to maintain soil fertility.

(4) Management convenience: Planting areas for each crop should not be overly dispersed, and the planting area on a single plot should not be too small.

(5) Market sales constraints: Total crop yield is limited by expected sales volume, with excess handled according to two scenarios: complete waste or half-price sales.

Based on this, we constructed a sequential solving Mixed Integer Linear Programming model. The model solves iteratively on a yearly basis, with each year's optimization decisions based on the previous year's planting results, forming a dynamic, forward-looking optimization chain. For modeling convenience, the required variables are defined as shown in Table 1:

Table 1 Symbol Definitions

Symbol	Meaning	Unit
I	Set of all plots, $i \in I$	
J	Set of all crops, $j \in J$	
J_{legume}	Set of all legume crops, $J_{legume} \subset J$	
S	Set of all planting seasons (here 1 or 2), $s \in S$	
T	Set of planning years (2024, …, 2030), $t \in T$	
A_i	Total area of plot i	mu
P_j	Unit sales price of crop j	yuan/kg
C_{ij}	Unit area cost of planting crop j on plot i	yuan/mu
Y_{ij}	Unit area yield of crop j on plot i	kg/mu
D_j	Annual expected market sales upper limit for crop j	kg
$H_{i,t-1}$	Crop planted on plot i in year t-1	
$L_{i,t-1}$	Binary parameter, 1 if plot i planted a legume crop in year t-k, otherwise 0	
α	Surplus product sales discount rate (α=0 for scenario one, α=0.5 for scenario two)	
λ	Planting dispersion penalty coefficient	
ε	Minimum allowable planting area on a single plot	mu
M	A sufficiently large positive number (for "Big M" method)	
$x_{ijst} \geq 0$	Area of crop j planted on plot i, season s, in year t	mu
$z_{ijst} \in \{0,1\}$	Binary variable, 1 if $z_{ijst}>0$, otherwise 0	
$Q_{jt}^{normal} \geq 0$	Normal sales volume of crop j in year t	kg
$Q_{jt}^{surplus} \geq 0$	Surplus sales volume of crop j in year t	kg

The model's optimization objective is to maximize annual net profit, consisting of total revenue, total costs, and dispersion penalty:

$$\text{Maximize} \quad Z_t = \sum_{j \in J} (P_j \cdot Q_{jt}^{\text{normal}} + \alpha \cdot P_j \cdot Q_{jt}^{\text{surplus}}) - \sum_{i,j,s} C_{ij} \cdot x_{ijst} - \lambda \sum_{i,j,s} z_{ijst} \tag{1}$$

This objective function aims to maximize annual economic benefits [9]. The first part, $\sum_{j \in J}(P_j \cdot Q_{jt}^{\text{normal}} + \alpha \cdot P_j \cdot Q_{jt}^{\text{surplus}})$ is total sales revenue, consisting of two components: income from normal market price sales and income from excess (surplus) sold at a discount rate α. The second part, $\sum_{i,j,s} C_{ij} \cdot$

x_{ijst} is the total cost of planting all crops on all plots. The third part, $\lambda \sum_{i,j,s} z_{ijst}$ is an innovative "dispersion penalty term" [6]. By penalizing the number of crop-plot planting decisions (counted by binary variables), this term guides the model toward concentrating planting areas for the same crop, reducing implicit field management costs from excessive dispersion.

To ensure that the planting strategies generated by the optimization model are not only mathematically optimal but also scientifically feasible, practical, and sustainable in agricultural practice, we have established the following series of core constraints. These conditions translate the basic physical limits of agricultural production, core agronomic principles, and ecological sustainability requirements into rigorous mathematical language, collectively forming the decision boundaries of this model.

Plot area constraint:

$$\sum_{j \in J} x_{ijst} \leq A_i, \quad \forall i \in I, s \in S \tag{2}$$

This formula stipulates that in any year and season, the sum of areas planned for all crops ($j \in J$) on any plot i must not exceed the actual total area A_i of that plot. This is the most fundamental physical limit in the model, ensuring all planting plans are within the carrying capacity of land resources, avoiding unrealistic "armchair" planning. It guarantees the physical feasibility of the model outputs, serving as a basic premise for agricultural planning.

Production-sales balance constraint:

$$\sum_{i \in I, s \in S} Y_{ij} \cdot x_{ijst} = Q_{jt}^{\text{normal}} + Q_{jt}^{\text{surplus}}, \quad \forall j \in J \tag{3}$$

This constraint establishes a bridge between production and sales. It stipulates that the total yield of any crop (obtained by summing planting areas x_{ijst} . on each plot multiplied by corresponding unit yields Y_{ij}) must equal the sum of its normal sales volume and surplus sales volume. This is an accounting balance principle, ensuring all outputs are accounted for, providing an accurate basis for subsequent total revenue calculations.

Market demand constraint:

$$Q_{jt}^{\text{normal}} \leq D_j, \quad \forall j \in J \tag{4}$$

This constraint reflects market capacity limits. It stipulates that the quantity Q_{jt}^{normal} sold at normal prices for each crop cannot exceed its annual expected market sales upper limit D_{jt}. This makes the model's decisions more aligned with market realities, avoiding production surpluses and potential economic losses due to overly optimistic market demand estimates.

Annual rotation constraint:

$$\sum_{s \in S} z_{ijst} = 0, \quad \forall i \in I, j = H_{i,t-1} \tag{5}$$

This is a key agronomic constraint aimed at achieving sustainable agricultural production. It prohibits planting the same crop on the same plot for two consecutive years (i.e., no continuous cropping). This rule is crucial in agricultural practice as it helps break pest and disease lifecycles, balance soil nutrient consumption, and suppress certain associated weeds, thereby maintaining soil health and long-term stable crop yields.

Legume rotation constraint:

$$\sum_{j \in J_{\text{legume}}, s \in S} z_{ijst} + L_{i,t-1} + L_{i,t-2} \geq 1, \quad \forall i \in I \tag{6}$$

This constraint embodies the principles of ecological agriculture and land conservation. It mandates that any plot must have planted at least one legume crop in the past consecutive three years (calculated from 2023). Legume crops possess rhizobial nitrogen-fixing biological characteristics, converting atmospheric nitrogen into soil nitrogen fertilizers, serving as natural "soil fertility enhancers." Adhering to this rule helps maintain and enhance soil fertility, reducing dependence on chemical nitrogen fertilizers.

Logical association constraints:

$$x_{ijst} \le M \cdot z_{ijst}, \quad \forall i, j, s \tag{7}$$

$$x_{ijst} \ge \varepsilon \cdot z_{ijst}, \quad \forall i, j, s \tag{8}$$

This set of constraints uses the "Big M" method to link decision variables (whether to plant) with quantity variables (how much to plant). Equation (7) ensures that the planting area x_{ijst} can only be greater than zero when the model decides to plant a certain crop on a plot (i.e., $z_{ijst}=1$). Equation (8) serves the "management convenience" requirement, stipulating that once planting is decided, the area must be at least a minimum threshold ε, avoiding overly fragmented "patch" plots that are inconvenient for mechanized operations and field management.

Suitability and surplus handling constraints:

$$Q_{jt}^{surplus} = 0 \tag{9}$$

The model also ensures through parameter settings that planting area variables x_{ijst} can only take non-zero values for suitable crop-plot-season combinations. Additionally, to distinguish the two market scenarios, in the simulation of scenario one (complete unsaleability), an additional constraint $Q_{jt}^{surplus}=0$ is added, meaning any yield exceeding the market demand upper limit is considered waste, generating no economic value, providing a comparative benchmark for evaluating the value of market channels.

3. Analysis of experimental results

3.1. Scenario One: Rigid Market with Surplus Unsold

The Sequential Mixed Integer Linear Programming (SMILP) model adopted in this study is implemented using Python and the PuLP optimization library, based on attachment data provided in the competition. With 2023 planting history as the initial condition, it employs a year-by-year iterative solving strategy to generate dynamic optimal planting schemes for the seven-year planning period from 2024 to 2030.

This scenario simulates a rigid demand market environment. Its core feature is that when the total yield of a certain crop exceeds its annual expected sales volume, the excess part cannot enter market circulation, i.e., it is completely unsold. This surplus yield not only generates no revenue but also means the complete loss of previously invested planting costs (including land, seeds, fertilizers, labor, etc.). In the mathematical model, this is represented by a sales discount rate α of 0 for surplus yield. This scenario represents a high-risk agricultural operation environment, requiring extremely cautious planting decisions to strictly avoid overproduction, as any production exceeding market absorption capacity will directly translate into net losses. Therefore, under this scenario, the optimization model's objective function strongly favors formulating a relatively conservative planting plan.

3.2. Scenario Two: Flexible Market with Surplus Discounted

This scenario simulates a more elastic market structure, assuming the existence of secondary markets or alternative sales channels. Its core feature is that after meeting expected sales volumes, surplus agricultural products can still be sold at 50% of the original sales price. This means that although the profit margin for surplus yield is compressed, it can still recover partial value, effectively offsetting some production costs. In the mathematical model, this corresponds to a sales discount rate α of 0.5 for surplus yield. This scenario represents a relatively low-risk operation environment, providing a buffer zone for over-expected production and reducing losses from yield fluctuations or market forecast deviations. Therefore, this scenario allows and encourages the model to adopt more aggressive planting strategies to maximize potential total economic benefits by fully utilizing land resources.

First, regarding overall economic benefits, Figure 1 illustrates the trajectory of annual total profit changes under the two scenarios, visually presenting the dynamic evolution of annual total profits over the seven-year planning period. The orange curve represents scenario two (allowing discounted sales of surplus products), while the cyan curve represents scenario one (complete unsaleability of surplus products). It is evident that the annual profits in scenario two (surplus discounted sales) are significantly higher than in scenario one (surplus unsold). Over the entire planning period, profits in scenario two remain stable above approximately 2.4 million RMB, while those in scenario one fluctuate around 2.3 million RMB with greater volatility. This quantitative result powerfully demonstrates that opening flexible sales channels for surplus agricultural products, even at substantial discounts, can greatly enhance the overall economic efficiency and stability of agricultural production, serving as an effective means to mitigate market risks.

Second, in terms of economic stability and risk resilience, scenario two exhibits superior robustness. Its profit curve shows smaller fluctuations, demonstrating stronger annual consistency. In contrast, scenario one's profit trajectory has greater volatility, implying greater vulnerability to endogenous (e.g., yield forecast deviations) or exogenous (e.g., minor market demand changes) disturbances. The discounted sales mechanism acts as an "economic buffer" here, effectively smoothing sharp profit declines from overproduction by providing value realization channels for excess yield, thereby enhancing the economic resilience of the entire agricultural system.

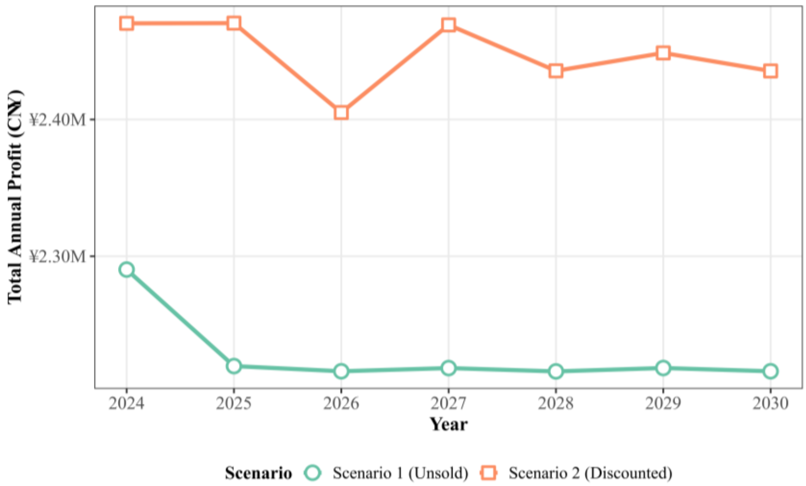

Figure 1: Projected Annual Profit Trajectories for 2024-2030

Next, regarding dynamic land utilization structures, Figure 2 compares the total planting area changes for three major crop categories—grains, vegetables, and edible fungi—under the two scenarios. The figure shows that grain crops occupy the vast majority of planting areas (approximately 900-1000 mu), while vegetables and edible fungi have much smaller scales. This structural feature aligns highly with the problem background setting of "the rural area dominated by flat dryland and terraced fields," proving that the model can accurately match land plot types with crop suitabilities, achieving reasonable resource allocation at the macro level.

Under both scenarios, grain crops remain the primary planting category, occupying most of the arable land, consistent with the region's land structure dominated by dryland and terraced fields. Vegetables and edible fungi have much smaller planting areas, mainly limited to irrigated land and greenhouses. In most years, the red curve representing scenario two is slightly higher than or equal to the blue curve representing scenario one. This indicates that in scenario two, with lower market risks (i.e., existence of surplus product sales channels), the model tends to adopt an aggressive "full resource utilization" strategy. Since the punitive consequences of overproduction are significantly weakened, the model dares to allocate more land resources to production to explore the upper limits of total output and profits. Conversely, under the high-risk deterrence of scenario one, the model exhibits a conservative "risk-averse" strategy, potentially reducing planting areas strategically to build safety margins, ensuring total yields are strictly controlled within expected sales volumes to avoid any unsold losses.

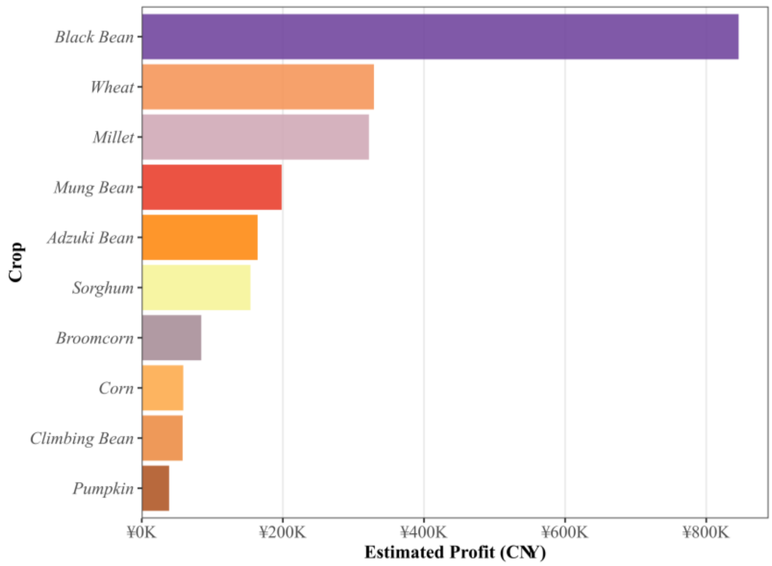

Figure 2: Comparative Land Utilization Dynamics by Crop Type

Then, regarding economic contributions of key crops, to delve deeper into profit composition, we analyzed the projected profit contributions of each crop in 2024 under scenario two (Figure 3). The results show that black beans are the absolute core engine of this rural agricultural economy, with projected profit contributions exceeding 800,000 RMB, more than twice that of wheat, the second-highest. Wheat and millet together form the second tier of profit contributions. This finding has extremely high strategic value, clearly indicating that in situations with limited resources (e.g., water, fertilizers, high-quality plots), priority should be given to ensuring the production of these "star crops."

The distribution of crop profit contributions exhibits a typical Pareto distribution (or 80/20 rule), where a few high-value crop varieties contribute the majority of profits. This reveals the intrinsic structure of the agricultural economic system. Understanding this is crucial for managers, meaning that management efforts should follow the same principle, with refined management of high-contribution crops to ensure their yields and quality.

Although profits are highly concentrated, the existence of the "long tail" of other diversified crops (e.g., sorghum, corn, various beans) in the figure is equally indispensable. While their individual profit contributions are low, their collective presence is necessary to meet the model's complex agronomic constraints (especially rotation and legume rotation). This diversity is not only for agronomic sustainability considerations (e.g., maintaining soil fertility, breaking pest cycles) but also economically builds a risk-diversified crop portfolio, reducing the risk of systemic collapse from single-crop market or disease issues.

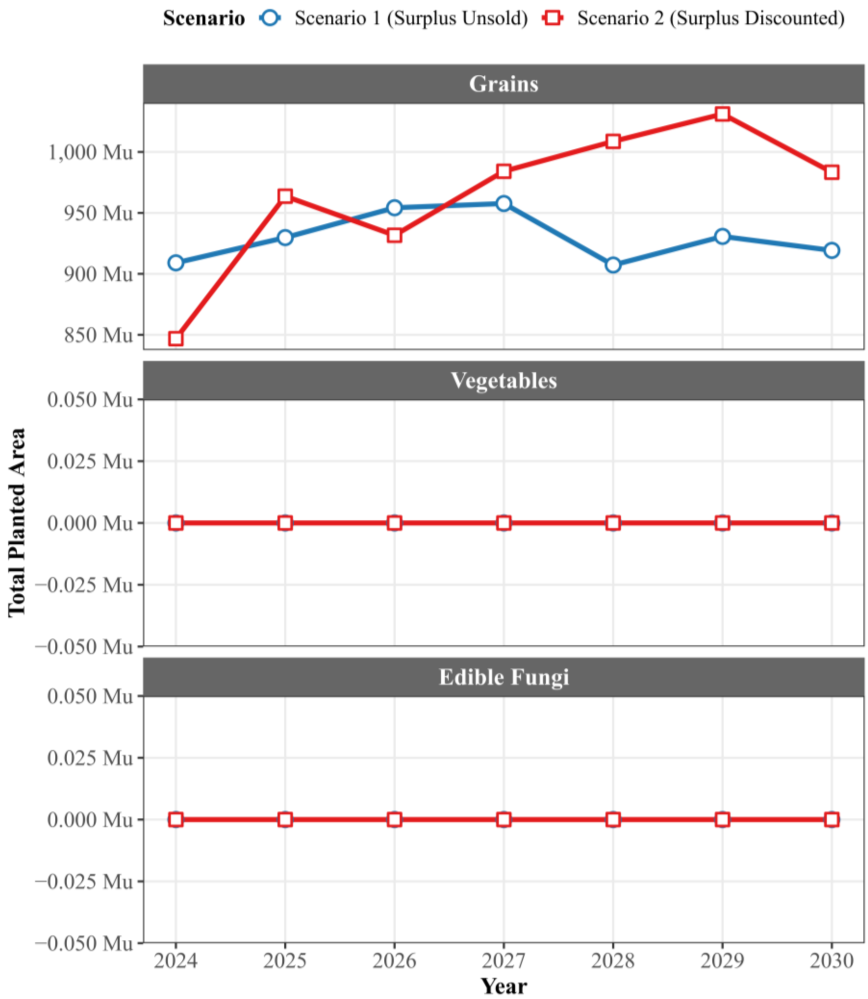

Figure 3: Economic Contributions of Each Crop in 2024 under Scenario Two

Finally, this paper presents optimal rotation visualizations. Specifically, Figures 4 and 5 use heatmaps to intuitively display detailed planting plans for selected representative plots from 2024 to 2030 under the two scenarios (values in the figures represent planting areas in mu). These charts are not only the final outputs of the model but also visually verify strict adherence to rotation rules. For example, tracing any plot horizontally (row), such as plot A2 in Figure 5 with the sequence "black beans -> wheat -> mung beans -> wheat...", shows different colors and crop types in adjacent years, perfectly proving the model's strict enforcement of "annual rotation on the same plot." Similarly, observing any consecutive three-year planting window, such as plot B1 in Figure 5 (wheat -> mung beans -> wheat), inevitably includes one legume crop (e.g., black beans, mung beans, red adzuki beans). This intuitively verifies the model's satisfaction of the "at least one legume crop in three years" requirement for maintaining soil fertility and ecological sustainability.

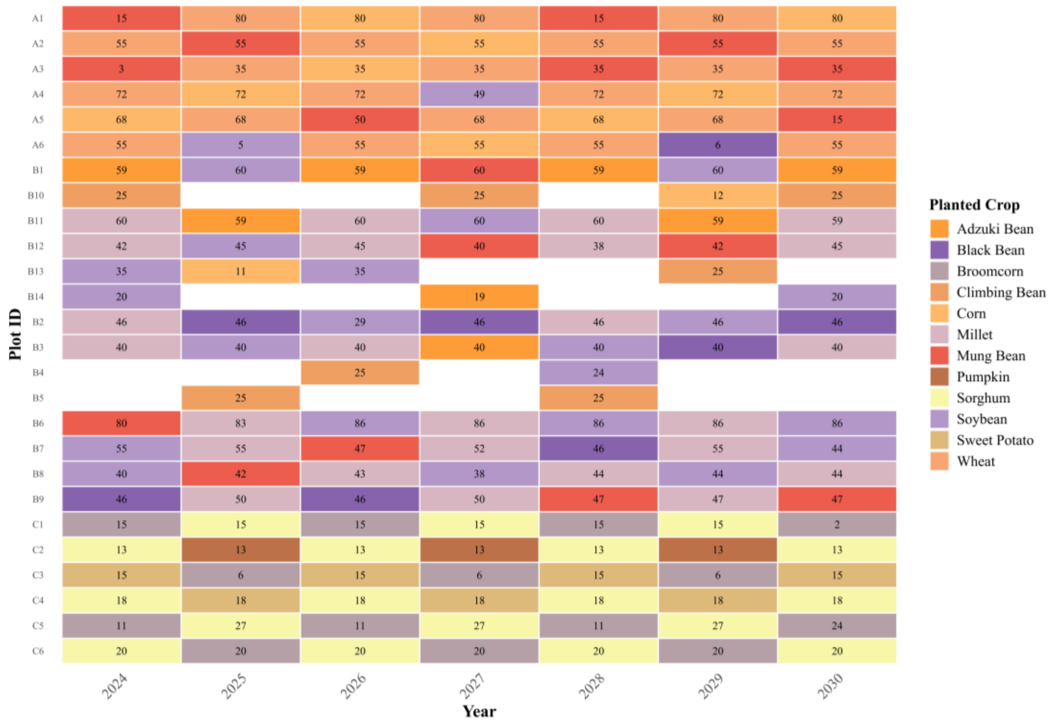

Figure 4: Data-Driven Rotation Strategy under Scenario One (Surplus Discounted Sales)

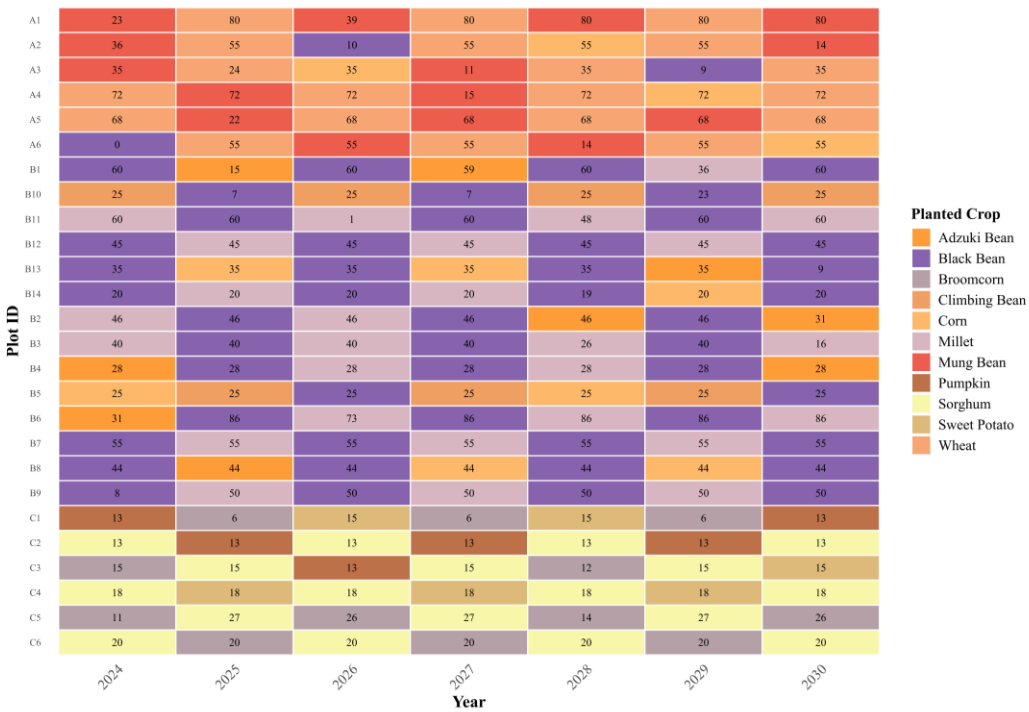

Figure 5: Data-Driven Rotation Strategy under Scenario Two (Surplus Unsold)

A detailed comparison of the two figures reveals differences in planting schemes for the same plots under different scenarios. For instance, plot B14 in 2027 is left idle in scenario one but planted with 20 mu of crops in scenario two. This reaffirms the earlier analysis that the model dynamically adjusts its micro-level planting decisions based on external market environments (scenarios). The scheme is not a fixed, infinitely repeatable rotation table but a vibrant, year-by-year adaptive and optimized dynamic plan.

Beyond academic validation, these visualization results demonstrate significant practical utility as operational references for intelligent agricultural production. By translating abstract optimization outcomes into specific, quantifiable, and executable guidance, they provide farm managers with actionable insights without requiring deep understanding of the underlying mathematical models. This approach exemplifies the effective implementation of precision and smart agriculture in rural contexts.

3.3. Discussion and Implications

The experimental results from both scenarios demonstrate the effectiveness of the Sequential Mixed Integer Linear Programming (SMILP) model in optimizing regional agricultural planting strategies under complex constraints. The main conclusions derived from this study are as follows:

1. The SMILP model effectively integrates complex agronomic requirements (e.g., crop rotation, soil fertility maintenance) and operational management needs (e.g., reducing dispersed planting costs) into a unified optimization framework. This ensures that the generated planting plans are not only mathematically optimal but also agriculturally feasible and sustainable.

2. Through comparative analysis of the two market scenarios, the study quantifies the immense value of market flexibility to agricultural economic benefits. The "discounted sales" scenario consistently outperforms the "complete unsaleability" scenario in terms of profitability and risk resilience, proving that diversified sales channels are key to modern agriculture in mitigating risks and enhancing profitability.

3. The model outputs not only provide macro-level trends in profits and land utilization but also deliver specific, executable planting plans down to the "plot-crop-year" level, combining strategic guidance with tactical operability. This makes the model a practical tool for farmers and decision-makers.

These findings highlight the potential of the SMILP model as a scientific and dynamic decision-support system for agricultural planning. For future research directions, we suggest expanding in the following areas: First, introducing more complex uncertainty models, such as stochastic programming or robust optimization, to more precisely characterize risks from climate change and market price fluctuations [3,4,5,10] Second, extending the model's optimization objectives to build a multi-objective optimization model encompassing economic, ecological, and social benefits[1,6,7,9,11], such as minimizing water resource consumption, carbon footprint, and maximizing biodiversity. Third, integrating the optimization model with broader agricultural supply chains to achieve full-chain optimization "from farm to table"[12,13]. Finally, with the development of IoT and sensor technologies, future models can combine with real-time data streams [14,15] to realize higher-level smart agricultural decisions from "advance planning" to "real-time dynamic adjustment."

4. Conclusions

This research presents a novel and systematic solution to the optimization of regional agricultural planting strategies through the construction of a dynamic Sequential Mixed-Integer Linear Programming (SMILP) model. The core value of this model lies in its high degree of integration and realism. It moves beyond mere profit maximization by fusing complex agronomic rules, ecological sustainability requirements, and market uncertainties, thereby achieving a crucial transition from "mathematical optimum" to "agronomic feasibility" and "economic rationality."

The salient contributions of this work are threefold. Methodologically, the innovative introduction of a "dispersion penalty term" quantifies hidden management costs, making the optimized plans more aligned with the practical realities of farm management. In terms of risk response, the framework's incorporation of two distinct market scenarios provides a quantitative analysis of the decisive impact that sales channel flexibility has on agricultural profitability and risk resilience, offering critical insights for policy and operational decisions. Finally, regarding the output, the model generates not a static plan but a dynamic, multi-year, plot-specific scheduling strategy. The visualization of these plans transforms them into an actionable "intelligent operational manual" for farmers, significantly enhancing the practical applicability and deployment potential of the research.

In summary, this study not only validates the effectiveness of advanced operational research methods in optimizing complex agricultural systems but, more importantly, successfully translates abstract mathematical models into concrete action guides that balance economic and ecological objectives, and reconcile long-term strategy with short-term operations. It thereby provides a replicable and scalable paradigm to advance the intelligent transformation and sustainable development of agriculture. Future work will focus on incorporating climate and price uncertainties through stochastic programming and expanding the model to multi-objective optimization considering environmental impacts.

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