A Hybrid PSO-GA Model for Optimizing Crop Planting Strategies

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Abstract. In the context of rural revitalization, optimizing crop planting strategies is essential for promoting sustainable agricultural development and enhancing rural economic benefits. This paper proposes a novel multi-objective optimization model that hybridizes Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to overcome the individual limitations of these widely used algorithms. The model uniquely integrates multiple practical constraints—including crop types, yield per unit area, market demand, selling price, planting costs, and soil suitability—into a comprehensive framework aimed at maximizing overall economic returns. By effectively combining PSO's fast convergence with GA's robust global search ability, the hybrid algorithm enhances convergence stability and solution accuracy in complex, high-dimensional agricultural planning problems. Furthermore, this study introduces a tailored constraint-handling mechanism to better reflect real-world agricultural scenarios. Extensive experiments on actual agricultural data demonstrate that the proposed model outperforms traditional single-algorithm approaches in both efficiency and effectiveness, providing reliable decision support for optimizing crop planting strategies. The innovative fusion of PSO and GA, coupled with practical constraint integration, distinguishes this research and contributes significantly to the advancement of intelligent agricultural decision-making under rural revitalization initiatives.

Keywords: Particle Swarm Optimization, Genetic Algorithm, Big Data, Crop Planting Strategies, Multi-Objective Optimization.

1. Introduction

Rural revitalization has heightened the importance of optimizing crop planting strategies as a key driver for sustainable agricultural growth. To enhance crop yield efficiency, optimize resource allocation, and improve agricultural economic benefits, researchers have increasingly turned to intelligent optimization algorithms. Among these, Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have been widely applied due to their robust global search capabilities and rapid convergence, respectively [1][2]. However, when applied independently, GA and PSO exhibit certain limitations. GA may suffer from premature convergence and high computational costs, especially in complex, high-dimensional problems. PSO, while efficient, is prone to getting trapped in local optima in multimodal or dynamic environments. To overcome these challenges, hybrid algorithms combining GA and PSO have been proposed, leveraging the strengths of both to enhance performance in complex optimization problems. Such hybrid approaches have shown promise in various applications, including agricultural planning and resource management [3].

In recent years, the application of intelligent optimization algorithms in agriculture has attracted growing attention. Genetic Algorithms (GA) have been widely employed in tasks such as land-use planning, crop yield optimization, and agricultural resource allocation. Ding et al. (2021) summarized the use of GA in land-use decision-making, demonstrating its advantages in solving complex spatial optimization problems [4]. Vie et al. (2020) reviewed the general development of GA, emphasizing its adaptive nature and highlighting challenges such as parameter tuning and convergence stability [5]. Meanwhile, Particle Swarm Optimization (PSO) has also been extensively used due to its simplicity and rapid convergence. Chen et al. (2022) reviewed the applications of PSO in experimental design optimization, pointing out its high efficiency in multi-objective search tasks [6]. Liu et al. (2021) provided a comprehensive review of recent advancements in PSO, focusing on dynamic adjustment mechanisms and hybridization strategies that enhance algorithmic performance in complex optimization problems [7]. These studies illustrate the increasing interest in GA and PSO for solving agricultural optimization problems.

Although both Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have been widely adopted in agricultural optimization, they each present notable limitations when used independently. GA, while having strong global search capability, often suffers from premature convergence and high computational cost, especially when dealing with complex and high-dimensional problems [8]. Moreover, its performance is highly sensitive to the setting of control parameters such as crossover and mutation rates, which may lead to instability and suboptimal results if improperly tuned [9]. PSO, on the other hand, is recognized for its simplicity and fast convergence. However, it is prone to falling into local optima, particularly in multimodal or dynamic environments [10]. This tendency reduces its reliability in finding global solutions for intricate agricultural models.

To address these challenges, recent studies have explored hybrid optimization strategies combining GA and PSO to leverage their complementary strengths. However, most existing hybrid models focus on theoretical benchmarking or simplified scenarios, and lack application to real-world agricultural decision-making under multiple constraints, such as land suitability, cost-efficiency, and market dynamics. In contrast, this study proposes a novel PSO-GA fusion model specifically tailored for multi-objective crop planting strategy optimization. The model integrates practical agricultural constraints—including crop yield per unit area, planting cost, market price, and soil compatibility—into the optimization framework. Moreover, the proposed model is designed to enhance convergence stability and global search efficiency in high-dimensional, constrained agricultural environments, which is rarely addressed comprehensively in prior work [11]. Therefore, this study fills a gap in the integration of theoretical and practical optimization in agriculture and offers a novel methodological framework for solving complex agricultural decision problems.

2. The basic fundamental of hybrid PSO-GA model

2.1. The structure of Particle swarm optimization

In the field of computational science, particle swarm optimization (PSO) is an algorithmic technique that addresses optimization problems by iteratively refining a set of candidate solutions based on a predefined quality metric. The algorithm operates by maintaining a population of candidate solutions, referred to as particles, which explore the search space by updating their positions and velocities according to a set of simple mathematical equations. The velocity and position update mechanisms in particle swarm optimization incorporate factors such as inertia weight, learning coefficients, and stochastic components. The algorithm typically involves several key steps: initializing the population, evaluating the fitness of particles, updating individual and global best positions, and adjusting velocities and positions iteratively until a termination criterion is met. PSO is favored for its simple structure, fast convergence, and strong global search capabilities. However, it also faces certain limitations, including susceptibility to local optima, sensitivity to parameter settings, and reduced efficiency when dealing with large-scale problems. To address these challenges, numerous improved variants have been developed to enhance its performance, leading to its widespread application across a variety of optimization tasks.

2.2. Genetic algorithm

In computer science and operations research, a genetic algorithm (GA) is a metaheuristic inspired by the process of natural selection that belongs to the larger class of evolutionary algorithms (EA). Genetic algorithms are commonly used to generate high-quality solutions to optimization and search problems via biologically inspired operators such as selection, crossover, and mutation. Some examples of GA applications include optimizing decision trees for better performance, solving sudoku puzzles, hyperparameter optimization, and causal inference.

2.3. GA-PSO

In the analysis of seasonal crop production where the total yield exceeds the anticipated sales volume, the surplus is managed through a discounted sale strategy. To achieve the goal of maximizing total crop revenue, it is crucial to allocate land plots and greenhouses rationally and to determine an optimal planting scheme.

Therefore, this study constructs an integrated Genetic Algorithm–Particle Swarm Optimization (GA-PSO) model to develop an optimal crop cultivation strategy. The hybrid GA-PSO model leverages the global search capability of the Genetic Algorithm and the fast convergence characteristics of Particle Swarm Optimization. By combining the evolutionary operators of GA (such as selection, crossover, and mutation) with the information-sharing and adaptive search behavior of PSO, the model effectively addresses the limitations of each individual algorithm. This integration enhances both the solution accuracy and the convergence speed, making it well-suited for solving complex agricultural optimization problems involving multiple constraints and decision variables. The algorithmic process is shown in Figure 1.

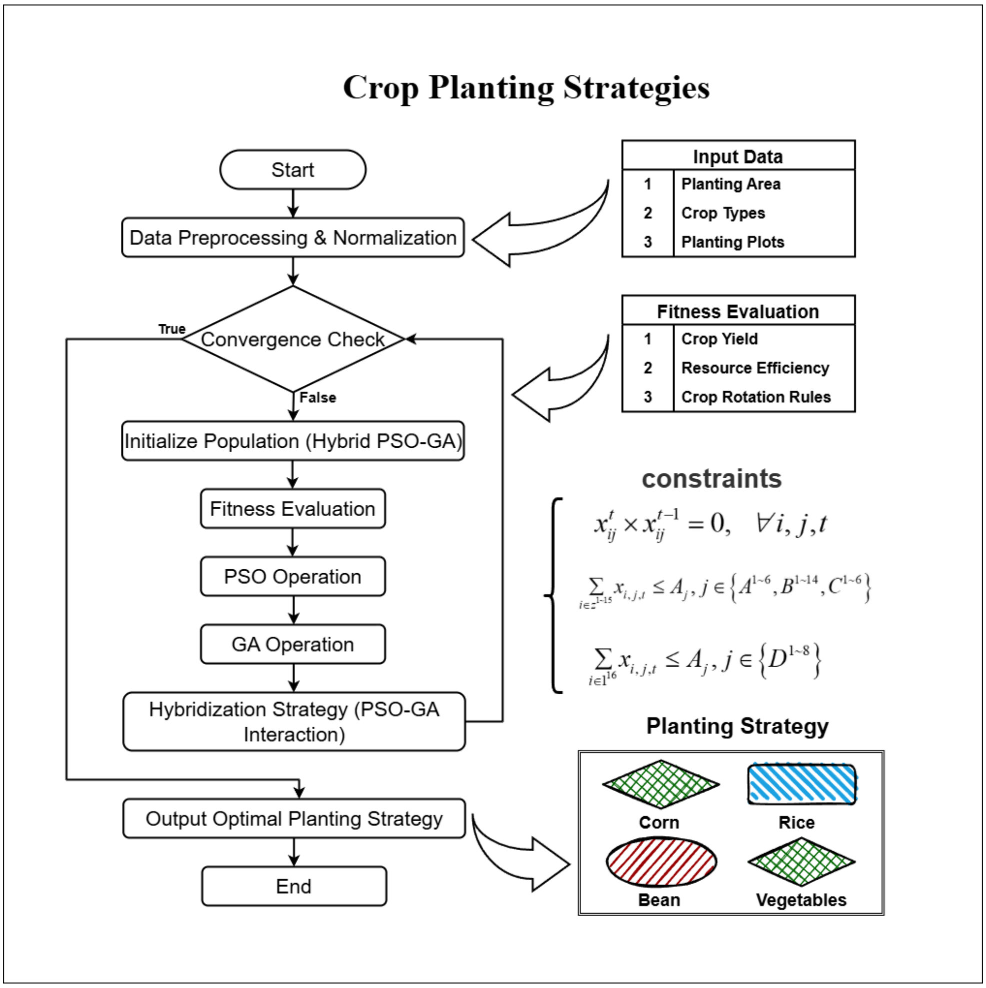

Figure 1. PSO-GA Hybird Algorithmic Process

The PSO-GA hybird model is subsequently constructed through a three-step process:

(1) Price reduction strategy:

$$V_j^t = (P_j \times \min(x_{ijt} \times q_j, D_j)) + (0.5 \times P_j \times \max(0, x_{ijt} \times q_j - D_j)) - (c_j \times x_{ijt}) \tag{1}$$

where V_j^t means the revenue generated by crop j in year t, P_j represents the unit price of crop j, x_{ijt} is the area of land plot i used to cultivate crop j in year t, q_j means the yield per mu of crop j, D_j is the planting cost per mu of crop j, and c_j denote the planting cost per mu of crop j.

(2) Objective function is to maximize the total revenue.

The first step involves summing the revenues of all individual crops:

$$MaxV=\sum_{j}^{M}\left(P_j\times\min\left(x_{ijt}\times q_j,D_j\right)\right)+\left(0.5\times P_j\times\max\left(0,x_{ijt}\times q_j-D_j\right)\right)-\left(c_j\times x_{ijt}\right) \tag{2}$$

Secondly, the crop allocations across all land plots are aggregated:

$$MaxV=\sum_{1}^{34}\sum_{j}^{M}\left(P_j\times\min\left(x_{ijt}\times q_j,D_j\right)\right)+\left(0.5\times P_j\times\max\left(0,x_{ijt}\times q_j-D_j\right)\right)-\left(c_j\times x_{ijt}\right) \tag{3}$$

Finally, the results are aggregated over the years 2024 to 2030:

$$MaxV=\sum_{2024}^{2030}\sum_{1}^{34}\sum_{j}^{M}(P_j\times\min(x_{ijt}\times q_j,D_j))+(0.5\times P_j\times\max(0,x_{ijt}\times q_j-D_j))-(c_j\times x_{ijt}) \tag{4}$$

The above formulation represents the objective function required for this study.

2.4. Constraints

(1) Cultivated Land Area Constraint: The planting area on each plot must not exceed its actual area.

$$\sum_{j=1}^{M}x_{ij}^{t}S_i,\forall t,\forall i \tag{5}$$

where S_t means the area of land plot i.

(2) Crop Rotation Constraint: The same crop cannot be planted consecutively on the same land plot.

$$x_{ij}^{t}\times x_{ij}^{t-1}=0,\quad \forall i,j,t \tag{6}$$

(3) Flat dry land, terraced fields, and hillside land are suitable for the single-season cultivation of grain crops (excluding rice) each year.

$$\sum_{i\in z^{1\sim15}}x_{ijt}\le A_j,\ j\in\{A^{1\sim6},B^{1\sim14},C^{1\sim6}\} \tag{7}$$

where A means flat dryland, B represents terraced fields, and C is sloped land.

(4) Constraint on Concentrated Planting Areas: To prevent excessive dispersion of planting areas for each crop, a constraint can be introduced to limit the distribution of the same crop across adjacent land plots.

$$\left|x_{ij}^{t}-x_{i'j}^{t}\right|\le\delta,\quad \forall i \tag{8}$$

where i is the adjacent plots.

(5) Irrigated land is suitable for single-season rice cultivation each year.

$$\sum_{i\in 1^{16}}x_{ijt}\le A_j,\ j\in\left\{D^{1\sim8}\right\} \tag{9}$$

(6) Ordinary greenhouses are suitable for growing two seasons of vegetables each year

$$\sum_{i\in z^{1\sim34}}x_{ijt}\le 2A_j,\ j\in\left\{F^{1\sim4}\right\} \tag{10}$$

This is the set of all constraints in the problem:

$$Constraints\begin{cases}\sum_{j=1}^{M} x_{ij}^{t} S_i, \forall t, \forall i \\ x_{ij}^{t} \times x_{ij}^{t-1} = 0, \quad \forall i, j, t \\ \sum_{i \in z^{1\sim15}} x_{ijt} \le A_j, \, j \in \left\{ A^{1\sim6}, B^{1\sim14}, C^{1\sim6} \right\} \\ \left| x_{ij}^{t} - x_{i'j}^{t} \right| \le \delta, \quad \forall i \\ \sum_{i \in 1^{16}} x_{ijt} \le A_j, \, j \in \left\{ D^{1\sim8} \right\} \\ \sum_{i \in z^{1\sim34}} x_{ijt} \le 2A_j, \, j \in \left\{ F^{1\sim4} \right\} \end{cases} \tag{11}$$

In summary, the PSO-GA hybird model can be established to define the objective function under the discounted sale scenario.

$$MaxV = \sum_{2024}^{2030} \sum_{1}^{34} \sum_{j}^{M} (P_j \times \min(x_{ijt} \times q_j, D_j)) + (0.5 \times P_j \times \max(0, x_{ijt} \times q_j - D_j)) - (c_j \times x_{ijt}) \tag{12}$$

3. Results

The dataset analyzed in this research was sourced from publicly available databases, including https://github.com/spMohanty/PlantVillage-Dataset and https://github.com/pratikkayal/PlantDoc-Dataset. These datasets have been validated and widely used in previous studies.

3.1. Algorithm Implementation

We employed Python as the development tool to implement the PSO-GA hybrid algorithm. Python offers a powerful suite of mathematical libraries that significantly enhance the efficiency of solving optimization problems. In our implementation of the PSO-GA hybird algorithm, we configured each component of the algorithm, including the following aspects:

(1) Fitness Function Calculation

The fitness function is defined based on the specific optimization problem. For instance, in the case of crop cultivation planning, the fitness function can be formulated as the total revenue generated by a given planting strategy. This calculation takes into account factors such as the planting area, crop yield, market price, and production cost of various crops.

(2) Population Initialization

The swarm size, i.e., the number of particles, is first determined. Each particle’s position and velocity are then randomly initialized within the defined search space. In the context of the crop cultivation problem, a particle's position represents the allocation of planting areas for various crops across different plots. The velocity is initialized with small random values, which correspond to the step sizes for adjusting the planting area allocations.

(3) Velocity and Position Update

The velocity and position of each particle are updated based on the standard PSO update equations. Parameters such as inertia weight, cognitive and social learning factors, and random coefficients can be adjusted and optimized according to the specific characteristics of the problem.

(4) Genetic algorithm selects the optimal solution

To enhance global exploration and avoid premature convergence, genetic algorithm operators are subsequently applied to the updated population. Specifically, particles with higher fitness values are selected through a selection mechanism, and crossover and mutation operations are performed to generate new candidate solutions. This hybrid update process allows the algorithm to maintain diversity in the population and effectively balance exploration and exploitation, thus improving optimization performance in complex, multi-constraint agricultural planning tasks.

(5) Control of the Iterative Process

A maximum number of iterations or other termination criteria, such as a fitness value precision threshold, are set to control the iterative process. During each iteration, the fitness calculation, individual best and global best updates, as well as velocity and position updates, are repeatedly executed.

3.2. Analysis of experimental results

The convergence analysis of hybrid PSO-GA algorithm are shown in Figure 2.

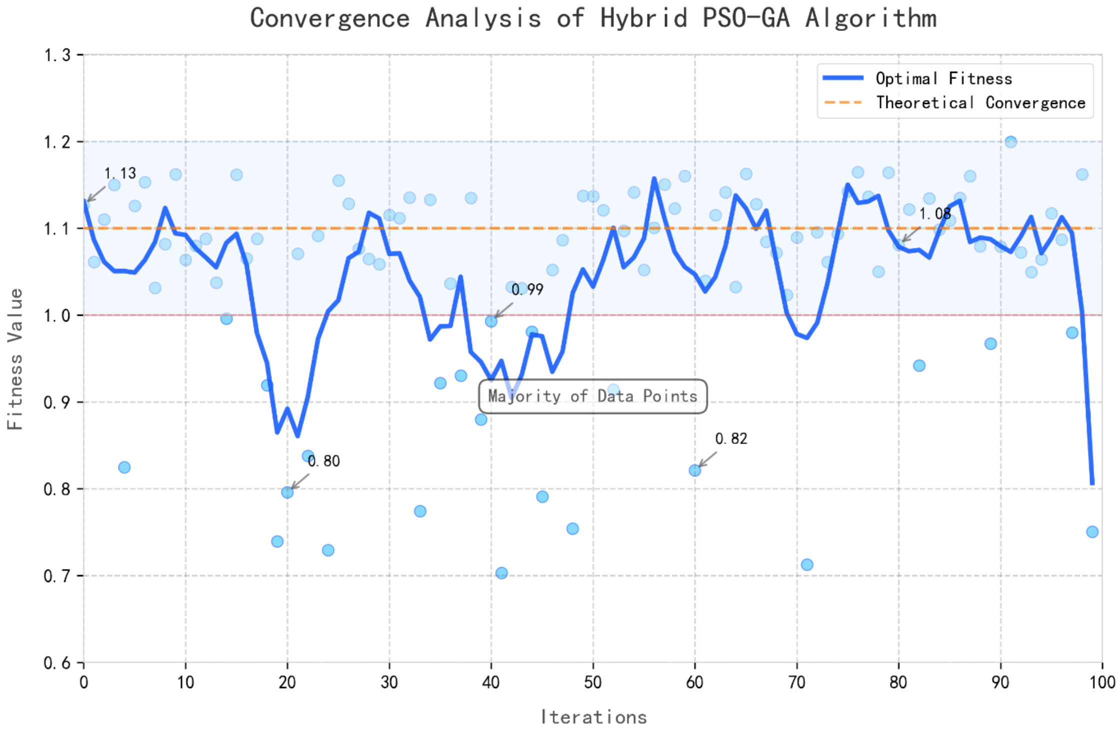

Figure 2. Convergence Analysis of Hybrid PS0-GA Algorithm

The figure illustrates the hybrid algorithm's stable convergence to theoretical optima, with most iterations yielding near-optimal fitness, underscoring its efficiency and reliability for crop planning optimization. The correlation matrix of vegetables is shown in Figure 3 and correlation matrix of grain can see in Figure 4.

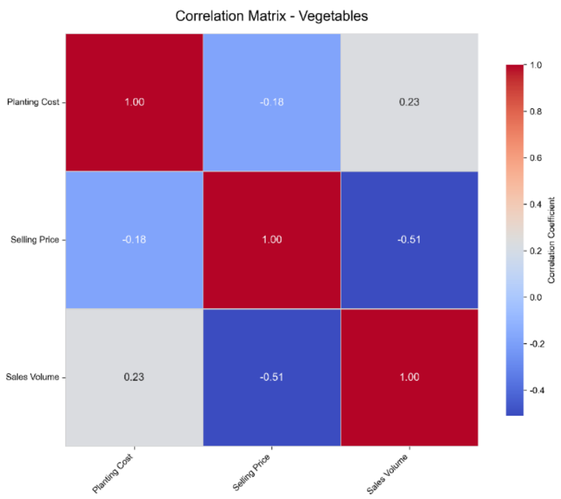

Figure 3. Correlation Matrix of Vegetables

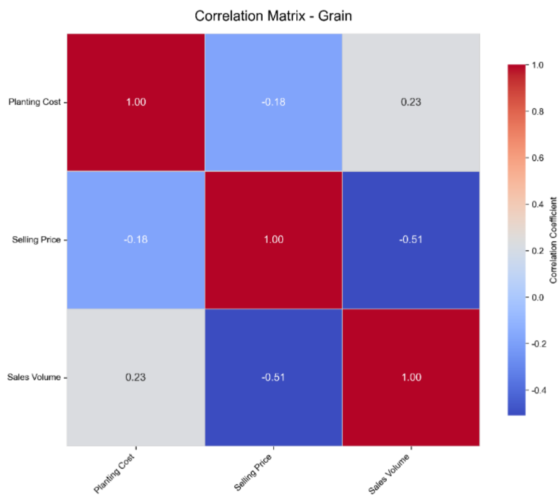

Figure 4. Correlation Matrix of Grain

The correlation matrices for vegetables show weak negative (planting cost–selling price, -0.18), weak positive (planting cost–sales volume, 0.23), and moderate negative (selling price–sales volume,

-0.51) relationships. These embed real-world economic dynamics (e.g., price elasticity, cost-volume synergy) into the hybrid PSO-GA model, enabling data-driven crop strategy optimization. This integration enhances the model’s ability to balance profit and agricultural feasibility, validating its practical utility in planning. Based on the model solution results, we verify the correctness of the basic solution by applying the previously established constraints. The types of crops suitable for planting in various land and greenhouse categories are summarized as follows:

(1) Flat dry land, terraced fields, and hillside land: single-season grain crops (excluding rice);

(2) Irrigated land: single-season rice or two-season vegetables;

(3) On irrigated land in the second season: one of Chinese cabbage, white radish, or red radish;

(4) Ordinary greenhouses: only edible fungi can be cultivated in the second season;

(5) Smart greenhouses: two-season vegetables (excluding Chinese cabbage, white radish, and red radish);

(6) The total planting area of crops must not exceed the size of the respective land plots.

The land Area Distribution by Type and Season are shown in Figure 5.

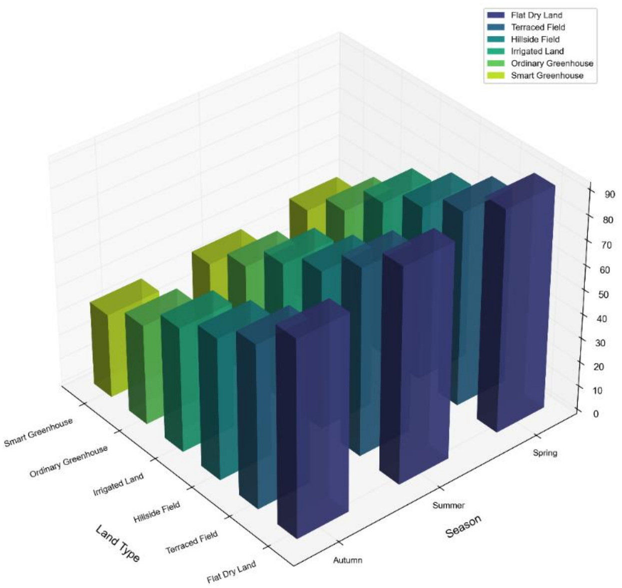

Figure 5. Land Area Distribution by Type and Season

By applying the above constraints to analyze the model’s solution results, it is confirmed that all constraints are satisfied, indicating the correctness of the model solution. The crop planting strategy under the discounted sale scenario is shown in Table 1. Due to the large volume of data, only a partial display is presented.

Table.1. Crop planting strategy under the discounted sale scenario

Season	Plot name	Soybean	Black bean	Red bean	Rice	Whea t	Maiz e
First season	Flat dryland	7.85	21.65	52.42	0	13.75	77.6
First season	Terraced field	14.1 5	7.85	0	12.5	6.25	0
First season	Sloped land	45.2 5	37.25	32.25	0	37.25	45.25
First season	Irrigated land	0	0	0	75.5 6	0	0
First season	Conventional greenhouse	7.85	12.5	7.65	12.5	15.65	21.42

4. Conclusions and Outlooks

Under the rural revitalization strategy, optimizing crop planting strategies remains a challenging task due to multi-dimensional constraints. While Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) have been widely used individually, each has limitations—PSO may converge prematurely, and GA often faces slow convergence and parameter sensitivity. These issues reduce their effectiveness when applied separately to complex agricultural optimization problems. In this study, a hybrid PSO-GA multi-objective optimization model was proposed to address the crop planting strategy problem, aiming to maximize economic returns while satisfying various agricultural and environmental constraints. By integrating the rapid convergence of PSO with the global search capability of GA, the proposed model demonstrates superior performance in both efficiency and accuracy. Experimental results confirm the robustness and practical applicability of the model in real-world agricultural planning, indicating its strong potential for broader application.

Future research will focus on incorporating dynamic environmental factors such as weather variability, market fluctuations, and pest infestations to further enhance model adaptability. Additionally, the integration of the model with geographic information systems (GIS) and remote sensing data will be explored to enable spatially-aware and large-scale optimization in smart agriculture scenarios.

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