

A Multi-objective Decision Framework for Agricultural Insurance-Futures Policy Optimization Considering Farmer Utility and Fiscal Constraints

Jiayi Wang^{1,a}, Yile Wang^{2,b,*}

¹Digital College, Beijing Technology and Business University, Beijing, China

²School of Economics, Beijing Technology and Business University, Beijing, China

^awjy06wang@163.com, ^bwyl13393401611@126.com

**Corresponding author*

Keywords: Agricultural insurance-futures; Multi-objective optimization; Farmer utility; Risk management

Abstract: To address the challenge of balancing coverage levels, fiscal subsidies, and risk control in agricultural "insurance plus futures" policies, this paper proposes a multi-objective decision-making framework that accounts for farmer utility and fiscal constraints. First, a Constant Relative Risk Aversion (CRRA) utility function is employed to characterize farmers' income preferences under price uncertainty, integrating fiscal subsidy costs and wealth fluctuation risks into a unified evaluation system. Subsequently, a tri-objective optimization model is established—aiming to maximize farmer utility, minimize fiscal costs, and minimize risk exposure—with coverage levels, subsidy ratios, and premium rates serving as decision variables; the Non-dominated Sorting Genetic Algorithm II (NSGA-II) is then used to solve for the Pareto-optimal policy set. Using a corn "insurance plus futures" case study, policy analysis is conducted based on parameters derived from existing research and actual projects, alongside comparisons with other optimization algorithms. The results demonstrate that the proposed method yields a well-distributed set of policy solutions and clearly illustrates the trade-offs between farmer utility, fiscal expenditure, and risk control. Further sensitivity analysis reveals that fiscal budgets, market volatility, and farmers' risk preferences significantly influence optimal coverage levels and subsidy allocations. This paper offers a practical analytical approach for transitioning agricultural "insurance plus futures" policy formulation from empirical settings to multi-objective, quantitative decision-making.

1. Introduction

In recent years, agricultural product prices have fluctuated frequently due to factors such as supply-demand dynamics, climatic conditions, international markets, and production costs, creating significant uncertainty regarding farmers' operating income [1,2]. For small-scale farmers with limited risk-bearing capacity, relying solely on spot market sales often proves insufficient to cope with income losses caused by price declines [3]. Against this backdrop, the "Insurance + Futures"

model has emerged as a vital tool for agricultural risk management. Its fundamental approach involves using insurance mechanisms to provide price protection for farmers while leveraging futures and related derivatives to transfer the market risks assumed by insurers, thereby establishing a risk-sharing arrangement among farmers, insurance institutions, and the futures market [4,5]. Compared to reliance on fiscal subsidies or traditional agricultural insurance alone, this model enhances risk transfer efficiency to some extent and offers a more flexible pathway for managing agricultural price risk. As these projects are increasingly promoted, determining appropriate levels of coverage, premium rates, and subsidy ratios has evolved from a mere product design issue into a complex decision-making challenge involving farmers' interests, fiscal burdens, and risk control [6].

In the practical implementation of "Insurance + Futures" projects, coverage levels and subsidy ratios are often determined based on historical data, regional conditions, or existing program frameworks. While this approach is highly practical, it can lead to conflicts between competing objectives. For instance, raising coverage levels strengthens farmers' resilience against price drops but typically entails higher insurance costs and greater fiscal expenditure; increasing the subsidy ratio reduces the financial burden on farmers but may strain government finances [6,7]. Pursuing high coverage solely from the farmers' perspective risks overlooking fiscal affordability, whereas overemphasizing subsidy limits may undermine the risk-protection function of the insurance instrument itself. Consequently, neither the highest coverage level nor the largest subsidy ratio is necessarily optimal; the core challenge lies in striking a reasonable balance among farmers' returns, fiscal costs, and risk control. Integrating these interdependent factors into a unified decision-making framework is crucial for enhancing the scientific rigor of "Insurance + Futures" policy design.

Extensive research has already established a robust theoretical foundation regarding agricultural insurance, farmers' risk preferences, and policy optimization. One stream of research focuses primarily on insurance product pricing, coverage levels, and payout mechanisms, specifically examining the risk compensation effectiveness of insurance schemes under varying price volatility conditions [8]. Another stream approaches the issue from the perspective of farmers' decision-making, employing the Constant Relative Risk Aversion (CRRA) utility function to characterize farmers' risk preferences regarding uncertain income and evaluating various coverage schemes based on expected utility [8,9]. Additionally, some studies have begun to address the efficiency of fiscal subsidies and the sustainability of agricultural risk management policies [6,7]. However, existing research often relies on single-indicator evaluations—such as maximizing farmer utility or minimizing fiscal costs—as the optimization objective. When multiple policy objectives coexist, a single optimal solution fails to fully capture the interplay of interests among stakeholders or provide policymakers with alternatives that offer varying risk-cost profiles. Consequently, there is a need to transition from traditional single-objective decision-making to a multi-objective framework that simultaneously accounts for coverage effectiveness, fiscal expenditure, and farmers' interests [10].

To address these issues, this paper proposes a multi-objective decision-making framework for agricultural "insurance + futures" programs that incorporates farmer utility, fiscal constraints, and risk exposure. The framework treats policy parameters—such as coverage levels and subsidy rates—as primary decision variables; it evaluates the extent to which insurance schemes improve farmers' income and risk-bearing capacity while calculating associated fiscal subsidy costs and measuring residual risk under various policy combinations. The solution process employs the Non-dominated Sorting Genetic Algorithm II (NSGA-II) to identify Pareto optimal solutions across objectives, thereby avoiding the oversimplification inherent in aggregating multiple objectives into a single indicator. Unlike approaches that yield only a single "optimal coverage level," this study emphasizes the trade-offs between competing policy objectives and identifies representative policy combinations based on criteria such as low cost, balanced outcomes, and low risk. Parameter settings and case analyses draw upon existing literature, public data, and typical operational ranges found in actual

"insurance + futures" projects to ensure the economic validity of the results. Through this approach, the paper aims to provide a more intuitive, quantifiable analytical tool to facilitate collaborative decision-making among governments, insurance institutions, and farmers, while offering a reference for the future design of differentiated coverage schemes and fiscal subsidy policies.

2. Mathematical Formulation

2.1. Agricultural Income Model

Let W_0 denote the farmer's initial wealth, P_t the realized agricultural product price, Q the production quantity, P_0 the reference price, and h the coverage level. Under a given coverage level, the corresponding guaranteed price is hP_0 . When the realized market price falls below this level, the insurance mechanism compensates for the price shortfall; otherwise, no indemnity is paid. Therefore, the farmer's final wealth depends not only on agricultural sales revenue, but also on insurance compensation and the premium actually borne by the farmer.

Considering the insurance premium rate f and the fiscal subsidy ratio s , the farmer pays only the portion of the total premium that is not covered by the government subsidy. Accordingly, the farmer's terminal wealth under price scenario t can be expressed as

$$W_t = W_0 + QP_t + Q \max(hP_0 - P_t, 0) - (1-s) f h P_0 Q \quad (1)$$

Equation (1) incorporates price variation, coverage level, premium cost, and fiscal subsidy into a unified wealth formulation. A higher coverage level can increase compensation when market prices decline, but it also raises insurance costs. Meanwhile, a higher subsidy ratio reduces the premium directly paid by the farmer. Therefore, the effects of the coverage level and subsidy ratio are interdependent, as both jointly influence the farmer's final wealth. Since final wealth alone cannot fully reflect the farmer's preference toward uncertain income, a utility-based evaluation is further introduced.

2.2. Farmer Utility Objective

Farmers generally exhibit a certain degree of risk aversion when facing uncertain agricultural income. To describe this preference, the Constant Relative Risk Aversion (CRRA) utility function is adopted. Let γ denote the coefficient of relative risk aversion [11-12]. The utility associated with terminal wealth is defined as

$$U(W_t) = \frac{W_t^{1-\gamma}}{1-\gamma}, \quad \gamma \neq 1 \quad (2)$$

Since a single price scenario cannot fully represent the overall performance of an insurance policy, the average utility across multiple price scenarios is used to evaluate farmer welfare. Suppose that M price scenarios are considered. The first optimization objective is therefore formulated as

$$\max F_1(h, s, f) = \frac{1}{M} \sum_{t=1}^M U(W_t) \quad (3)$$

A larger value of γ implies that the farmer places greater emphasis on income stability and protection against unfavorable price movements. Under such conditions, a higher coverage level may become more attractive. However, if policy design focuses only on maximizing farmer utility, the resulting solution may favor excessive coverage or subsidy levels and thereby increase fiscal expenditure. For this reason, fiscal cost is introduced as an independent policy objective.

2.3. Fiscal Subsidy Cost Model

Fiscal subsidies play an important role in reducing farmers' direct premium burden and encouraging participation in agricultural "Insurance + Futures" programs. Nevertheless, government financial resources are limited. Let N denote the number of participating farmers. Given the insured value hP_0Q , premium rate f , and subsidy ratio s , the total fiscal subsidy expenditure can be expressed as

$$F_2(h, s, f) = C_s = NsfhP_0Q \quad (4)$$

Accordingly, the fiscal objective is formulated as

$$\min F_2(h, s, f), \quad C_s \leq B \quad (5)$$

where B denotes the maximum government budget available for the program.

The above relationship shows that increases in the coverage level, premium rate, or subsidy ratio may all lead to higher fiscal expenditure. Therefore, a natural conflict exists between farmer utility and fiscal cost. Policy design should not simply maximize one side of this relationship, but should seek an appropriate balance between farmer protection and fiscal affordability. In addition, whether greater fiscal expenditure actually produces better risk protection needs to be further evaluated from the perspective of income stability.

2.4. Risk Exposure Objective

One of the primary purposes of agricultural insurance is to mitigate the adverse impact of price fluctuations on farmers' income. Therefore, in addition to farmer utility and fiscal cost, this study evaluates the volatility of terminal wealth under different policy combinations. Let $\bar{W}$ denote the average terminal wealth across all price scenarios. Risk exposure is measured by the dispersion of terminal wealth around its mean and is expressed as [13-14]

$$F_3(h, s, f) = R = \frac{1}{M} \sum_{t=1}^M (W_t - \bar{W})^2, \quad \bar{W} = \frac{1}{M} \sum_{t=1}^M W_t \quad (6)$$

The third optimization objective is therefore given by

$$\min F_3(h, s, f) \quad (7)$$

A lower value of R indicates more stable farmer wealth across different market conditions and therefore stronger risk-buffering performance. In general, increasing the coverage level can reduce losses under unfavorable price conditions, but it may also result in higher premiums and greater fiscal expenditure. Hence, farmer utility, fiscal cost, and risk exposure do not move consistently in the same direction, which makes the problem more suitable for multi-objective optimization rather than a single weighted objective.

2.5. Multi-objective Decision Model

Based on the three objectives described above, the coverage level h , fiscal subsidy ratio s , and insurance premium rate f are combined into the policy decision vector

$$\mathbf{x} = (h, s, f) \quad (8)$$

Since the optimization algorithm adopted in the following section is formulated in a unified minimization form, the farmer utility maximization objective is transformed into the minimization of its negative value [15]. The final multi-objective optimization model is therefore expressed as

$$\begin{aligned}
\min_{\mathbf{x}} \mathbf{F}(\mathbf{x}) &= [-F_1(\mathbf{x}), F_2(\mathbf{x}), F_3(\mathbf{x})] \\
h_{\min} &\leq h \leq h_{\max}, s_{\min} \leq s \leq s_{\max} \\
f_{\min} &\leq f \leq f_{\max}, NsfhP_0Q \leq B
\end{aligned} \tag{9}$$

Here, $h_{\min}$ and $h_{\max}$ represent the lower and upper bounds of the coverage level, $s_{\min}$ and $s_{\max}$ denote the feasible range of the fiscal subsidy ratio, while $f_{\min}$ and $f_{\max}$ define the allowable premium rate interval. The corresponding parameter ranges will be determined with reference to existing studies and commonly adopted values in agricultural “Insurance + Futures” programs.

Rather than combining the three objectives through fixed weights, the proposed framework preserves the inherent conflicts among farmer welfare, fiscal sustainability, and risk reduction. Pareto-optimal solutions are therefore identified to generate policy combinations with different preferences. This makes it possible to evaluate the fiscal cost associated with improvements in farmer utility, as well as the policy expenditure required for further risk reduction. The resulting solution set also provides the basis for selecting low-cost, balanced, and risk-control-oriented policy schemes. In the following section, the NSGA-II is introduced to obtain the Pareto frontier and support the final policy selection.

3. Multi-objective Optimization Method

The previous section established a three-objective optimization model involving farmer utility, fiscal subsidy cost, and risk exposure. These objectives are inherently conflicting. For example, a higher coverage level may reduce farmers’ exposure to price risk, but it usually increases fiscal expenditure. Therefore, it is difficult to obtain a unique solution using conventional single-objective optimization methods. In this study, the NSGA-II is adopted to solve the proposed model.

3.1. NSGA-II Algorithm Framework

In the proposed optimization problem, each individual represents a complete “Insurance + Futures” policy scheme. The decision variables include the coverage level h , fiscal subsidy ratio s , and insurance premium rate f . Accordingly, the i -th candidate policy can be expressed as

$$\mathbf{x}_i = (h_i, s_i, f_i), i = 1, 2, \dots, N_p \tag{10}$$

where N_p denotes the population size. The algorithm first generates an initial population within the feasible ranges of the decision variables. Each candidate solution is then evaluated according to the objective functions established in Section 2, including farmer utility, fiscal subsidy cost, and risk exposure. To maintain a unified minimization form, the objective vector is written as

$$\mathbf{F}(\mathbf{x}_i) = [-F_1(\mathbf{x}_i), F_2(\mathbf{x}_i), F_3(\mathbf{x}_i)] \tag{11}$$

After objective evaluation, NSGA-II ranks candidate policies according to their non-dominated levels and uses crowding distance to preserve well-distributed solutions. Selection, crossover, and mutation are then performed to generate new candidate policy combinations. The offspring population is combined with the parent population and screened again for the next generation. This process continues until the maximum number of generations is reached or the Pareto solution set becomes sufficiently stable. The overall optimization procedure can therefore be summarized as policy initialization, objective evaluation, non-dominated sorting, crowding-distance calculation, genetic operations, elitist preservation, and Pareto solution output, as illustrated in Fig. 1.

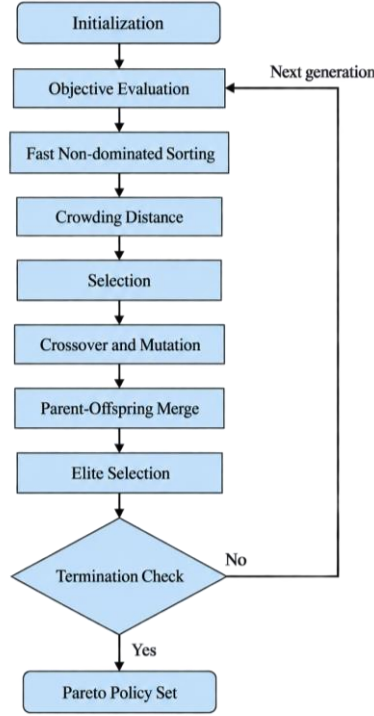


Figure 1: NSGA-II flowchart

3.2. Non-dominated Sorting and Crowding Distance

For any two candidate policy schemes x_a and x_b , x_a is considered to dominate x_b if it is no worse than x_b for all objectives and strictly better for at least one objective. This relationship can be expressed as

$$F_m(\mathbf{x}_a) \leq F_m(\mathbf{x}_b), \forall m, \exists k : F_k(\mathbf{x}_a) < F_k(\mathbf{x}_b) \quad (12)$$

Based on this principle, individuals in the population are divided into different non-dominated fronts. The first front contains solutions that are not dominated by any other candidate and therefore represents the best trade-off policies in the current population. After removing the first front, the same procedure is repeated to obtain the second, third, and subsequent fronts. Compared with directly combining farmer utility, fiscal cost, and risk exposure through weighted summation, this approach preserves the original conflicts among the objectives and reduces dependence on subjective weight settings.

However, relying only on non-dominated ranks may cause a large number of candidate solutions to concentrate in a limited region of the Pareto frontier. To improve the distribution of the solution set, crowding distance is introduced to measure the local density around each individual within the same non-dominated front. For the i -th individual, the crowding distance is defined as

$$d_i = \sum_{m=1}^3 \frac{F_m^{i+1} - F_m^{i-1}}{F_m^{\max} - F_m^{\min}} \quad (13)$$

where F_m^{i+1} and F_m^{i-1} denote the objective values of the two neighboring individuals after sorting according to the m -th objective. $F_m^{\max}$ and $F_m^{\min}$ are the maximum and minimum values of the corresponding objective within the current front. A larger crowding distance indicates that the individual lies in a relatively sparse region. When two individuals have the same non-dominated rank, the one with the larger crowding distance is given priority.

Through the joint use of non-dominated sorting and crowding distance, the algorithm maintains both solution quality and the coverage of the Pareto frontier. After this screening process, new candidate policies must still be generated to explore regions of the decision space that have not yet been sufficiently searched. This is achieved through genetic operations.

3.3. Selection, Crossover, and Mutation

In each generation, parent individuals are selected according to both non-dominated rank and crowding distance. When two candidate individuals are compared, the solution with the better non-dominated rank is selected first. If both belong to the same front, the individual with the larger crowding distance is preferred. This strategy increases the probability that high-quality policies are retained while preventing the population from converging prematurely to a narrow region.

Since the coverage level, subsidy ratio, and premium rate are continuous variables, real-valued encoding is adopted in this study. Crossover generates new policy combinations from two parent solutions and explores the region between their parameter values. For the j -th decision variable, a simplified crossover operation can be written as

$$x_j^c = \alpha x_j^{p_1} + (1 - \alpha) x_j^{p_2}, 0 \leq \alpha \leq 1 \quad (14)$$

where $x_j^{p_1}$ and $x_j^{p_2}$ denote the j -th decision variables of two parent policies, and x_j^c is the corresponding offspring variable. Crossover mainly exploits promising regions identified by the current population, whereas mutation expands the search range and helps prevent premature convergence. For a selected decision variable, mutation can be implemented as

$$x_j' = x_j + \delta_j (x_j^{\max} - x_j^{\min}) \quad (15)$$

where δ_j is a random variable controlling the direction and magnitude of the perturbation. After crossover and mutation, the feasibility of each candidate policy is checked again. If the coverage level, subsidy ratio, or premium rate exceeds its feasible interval, the corresponding variable is adjusted to the nearest boundary. If the resulting fiscal subsidy cost exceeds the budget limit B , the candidate is treated as infeasible and excluded from the preferred policy set.

3.4. Elitist Preservation and Pareto Policy Set

Let P_g denote the parent population at generation g , and Q_g the corresponding offspring population. The two populations are first merged into a combined candidate population as

$$R_g = P_g \cup Q_g \quad (16)$$

The combined population R_g is then subjected to fast non-dominated sorting. Individuals are sequentially selected according to their non-dominated ranks until the population size of the next generation reaches N_p . If a non-dominated front cannot be fully retained, individuals within that front are sorted by crowding distance in descending order, and those with larger crowding distances are selected first. This elitist preservation mechanism ensures that high-quality solutions remain available in subsequent generations while sufficient diversity is maintained for further exploration.

When the maximum number of generations is reached, the first non-dominated front of the final population is regarded as the Pareto-optimal policy set and can be defined as

$$\mathcal{P}^* = \{ \mathbf{x} \mid \nexists \mathbf{y} \text{ such that } \mathbf{y} \prec \mathbf{x} \} \quad (17)$$

Here, $\mathcal{P}^*$ does not represent a single optimal policy, but rather a set of efficient policy combinations

for which one objective cannot be further improved without sacrificing at least one other objective. In the context of this study, the Pareto frontier directly reflects the trade-offs among farmer utility improvement, fiscal expenditure, and risk reduction.

4. Case Study and Experimental Setup

4.1. Case Scenario

In this study, the reference price for corn is set at 2,500 yuan/t, and the policy coverage encompasses 10,000 participating households. With an insured quantity of 10 t per household, the total volume of agricultural products covered by the project under baseline conditions is 100,000 t. The coverage level is adjustable between 0.60 and 1.00, the fiscal subsidy ratio is constrained to the 0.30–0.70 range, and the insurance premium rate is set between 0.03 and 0.06. Compared to simply prescribing a fixed policy combination, these parameter ranges provide the NSGA-II algorithm with sufficient search space to generate a continuous Pareto policy frontier that balances lower fiscal expenditure against higher risk protection.

In the baseline scenario, the price volatility is set at 0.25, the farmers' risk aversion coefficient at 3, and the fiscal budget cap at 5 million yuan. Subsequent sensitivity analyses expand the ranges for volatility, the risk aversion coefficient, and the fiscal budget to examine how changes in external market risks and policy constraints affect the optimal policy combination. Specific parameter settings are detailed in Table 1.

Table 1: Parameter settings for the corn Insurance-Futures case

Parameter	Symbol	Value
Agricultural product	—	Corn
Reference price	P_0	2500 yuan/t
Number of farmers	N	10000
Insured quantity per farmer	Q	10 t
Initial wealth	W_0	80000 yuan
Coverage level	h	0.60–1.00
Subsidy ratio	s	0.30–0.70
Premium rate	f	0.03–0.06
Baseline volatility	σ	0.25
Volatility range	σ	0.20–0.35
Baseline risk-aversion coefficient	γ	3
Risk-aversion range	γ	1–5
Baseline fiscal budget	B	5 million yuan
Budget range	B	3–8 million yuan
Number of price scenarios	M	10000

4.2. Comparison of Algorithms

To evaluate the performance of NSGA-II in addressing this policy problem, the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Multi-objective Particle Swarm Optimization (MOPSO) were selected as benchmark methods. GA and PSO derive a single compromise solution using a normalized, equal-weight objective function, with the weight for each of the three objectives fixed at 1/3; in contrast, MOPSO and NSGA-II directly solve the three-objective model presented in Chapter 3 without aggregating the objectives via weighting.

To avoid bias arising from differences in computational scale, the population size and maximum number of iterations were set to 100 and 200, respectively, for all four methods. Each method was run independently 30 times, and the same set of price scenarios was used to evaluate the objective functions. Specific algorithm configurations are listed in Table 2.

Table 2: Parameter settings of the compared optimization algorithms

Method	Population	Iterations	Main parameter settings
GA	100	200	Crossover rate = 0.90, mutation rate = 0.10
PSO	100	200	$w = 0.70, c_1 = 1.50, c_2 = 1.50$
MOPSO	100	200	$w = 0.70, c_1 = 1.50, c_2 = 1.50$, archive size = 100
NSGA-II	100	200	Crossover rate = 0.90, mutation probability = $1/3$

Table 2 shows that the four methods utilize consistent population sizes and generation counts, ensuring comparable search scales for each optimization run. For NSGA-II, the mutation probability is set to $1/3$ —corresponding to the three continuous policy variables—to allow for potential perturbations in the coverage level, subsidy ratio, and insurance premium rate. The external archive capacity for MOPSO is set to 100, matching the final population size retained by NSGA-II, thereby ensuring comparability between the two multi-objective algorithms regarding the size of the Pareto solution set.

GA and PSO are primarily used to illustrate the policy outcomes resulting from a single compromise objective, whereas MOPSO serves as a direct multi-objective counterpart to NSGA-II. Consequently, the subsequent analysis compares the utility, cost, and risk associated with representative policy points from each algorithm, while also evaluating the quality of the Pareto fronts obtained by MOPSO and NSGA-II.

4.3. Evaluation Metrics

The experimental evaluation consists of two parts: an assessment of policy outcomes and an evaluation of multi-objective search performance. The assessment of policy outcomes directly aligns with the study's objectives, covering household utility, fiscal subsidy costs, and risk exposure; additionally, the risk reduction rate is calculated to quantify the extent to which the insurance policy mitigates wealth fluctuations compared to an uninsured scenario. Fiscal costs are uniformly expressed in millions of yuan to prevent differences in numerical magnitude from affecting the presentation of results.

Table 3: Evaluation metrics used in the experiments

Metric	Evaluation target	Preferred direction
Farmer utility	Farmer welfare	Higher
Fiscal subsidy cost	Government expenditure	Lower
Risk exposure	Income stability	Lower
Risk reduction rate	Insurance effectiveness	Higher
HV	Pareto coverage	Higher
IGD	Pareto convergence	Lower
Spread	Pareto distribution	Lower

For the multi-objective algorithms, the Pareto solution sets are further evaluated using three metrics: Hypervolume (HV), Inverted Generational Distance (IGD), and Spread. A higher HV value

indicates broader coverage of the obtained frontier within the objective space; a lower IGD value signifies that the solution set is closer to the reference Pareto frontier; and Spread measures the uniformity of the non-dominated solutions' distribution along the frontier, with a lower value indicating a more stable distribution. All evaluation metrics are listed in Table 3.

In the subsequent analysis of results, GA and PSO are primarily compared based on three economic indicators of their final compromise policies; for MOPSO and NSGA-II, in addition to comparing representative policies, metrics such as HV, IGD, and Spread are also evaluated. Each stochastic optimization algorithm was executed 30 times; consequently, the reported performance metrics represent the average values across these 30 runs, with standard deviations also included to avoid reliance on the results of a single optimal run.

4.4. Experimental Procedure

The entire experiment was conducted according to a standardized procedure. First, the corn price, insurance coverage scale, and policy variable boundaries were fixed, and 10,000 price scenarios were generated. Subsequently, the GA, PSO, MOPSO, and NSGA-II algorithms were executed to calculate farmers' utility, fiscal subsidy costs, and risk exposure for each candidate policy. Policy combinations exceeding the benchmark budget of 5 million yuan were immediately deemed infeasible and excluded from the final policy selection process.

After 200 generations of searching, the GA and PSO each yielded a single final compromise policy, while MOPSO and NSGA-II produced sets of non-dominated policies. Three representative policies were then selected from the final Pareto front of the NSGA-II algorithm: the Low-cost Policy, the Balanced Policy, and the Low-risk Policy. Specifically, the Low-cost Policy was identified as the non-dominated solution with the lowest fiscal subsidy cost, and the Low-risk Policy as the one with the lowest risk exposure; the Balanced Policy was determined based on the principle of minimizing the Euclidean distance from the three normalized objectives to the ideal point, without manual weight adjustment.

Therefore, the selection criterion for the Balanced Policy is defined as follows:

$$D_i = \sqrt{\tilde{F}_{1,i}^2 + \tilde{F}_{2,i}^2 + \tilde{F}_{3,i}^2} \quad (18)$$

Specifically, all three objectives are converted into normalized loss metrics aligned in the same direction, and the Pareto solution minimizing D_i is ultimately selected as the comprehensive equilibrium policy. This approach ensures a unique selection rule for the equilibrium solution and avoids the need for subjective selection of an intermediate point based on graphical visualization.

5. Results and Discussion

5.1. Pareto Optimal Policy Frontier

Figure 2 illustrates the three-dimensional Pareto policy frontier obtained via NSGA-II, where the horizontal axis represents farmer utility, the vertical axis represents fiscal cost, and the depth axis represents risk exposure; color intensity is used to further indicate risk levels. The utility indices of the final non-dominated solutions range from approximately 0.736 to 0.861, fiscal subsidy costs primarily fall between 2.88 and 4.98 million yuan, and risk exposure decreases from 2.18 to 1.39. The frontier exhibits a continuous distribution without significant clustering of solutions in any single region, demonstrating the algorithm's ability to simultaneously preserve effective policy combinations across the dimensions of low cost, high utility, and low risk.

The trends along the Pareto frontier show that when fiscal investment increases from 2.88 million

yuan to approximately 4.22 million yuan, the utility index rises from 0.736 to 0.829 (an increase of about 12.6%) and risk exposure drops from 2.18 to 1.58 (a decrease of about 27.5%). In contrast, when fiscal investment is further increased to 4.98 million yuan, the utility index rises only to 0.861, while risk exposure falls to 1.39. In other words, beyond the 4.2 million yuan mark, further increases in fiscal expenditure can still improve policy outcomes, but the magnitude of this improvement diminishes significantly.

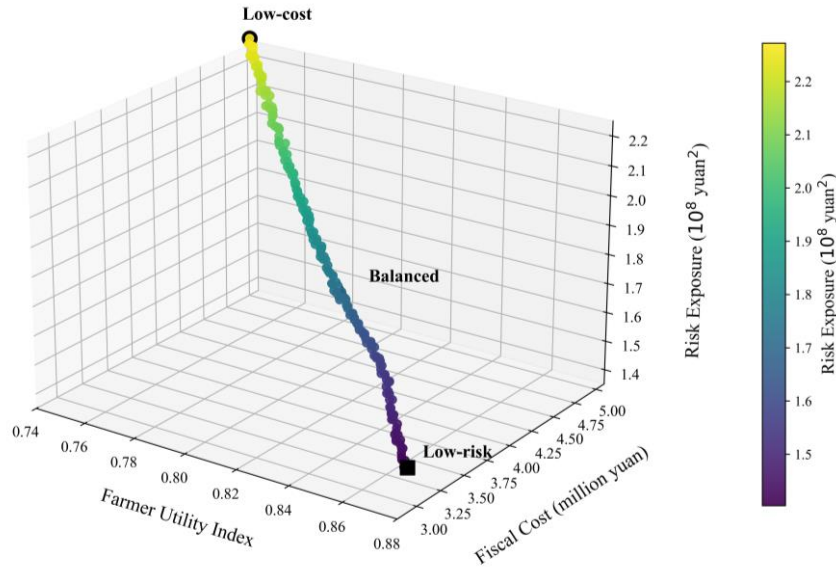


Figure 2: Three-dimensional Pareto frontier of the NSGA-II policy solutions

5.2. Algorithm Performance Comparison

Representative results from the various optimization methods are summarized in Fig. 3. The GA yielded a utility index of 0.756, a fiscal cost of 4.63 million yuan, and a risk exposure of 2.03; the PSO improved the utility index to 0.774, reduced the fiscal cost to 4.49 million yuan, and lowered the risk exposure to 1.91. Moving to multi-objective optimization, the MOPSO achieved a utility index of 0.807 and a risk exposure of 1.72, with a fiscal cost of 4.36 million yuan. Finally, the representative solution from NSGA-II reached a utility index of 0.829 and a fiscal cost of approximately 4.21 million yuan, with risk exposure further reduced to 1.58.

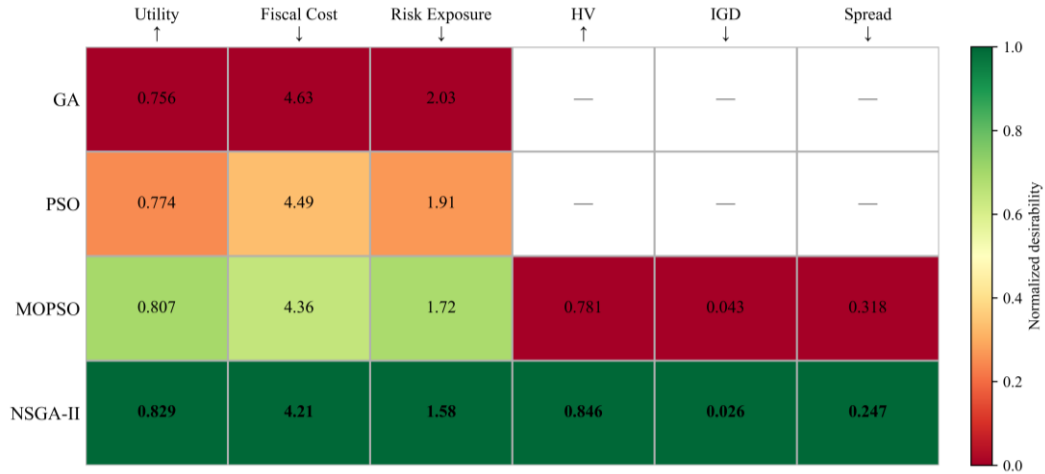


Figure 3: Performance comparison among GA, PSO, MOPSO, and NSGA-II

Compared to the GA, the NSGA-II increased the utility index by approximately 9.7%, reduced fiscal expenditure by about 9.1%, and lowered risk exposure by 22.2%. Compared to the MOPSO, the NSGA-II further improved the utility index by approximately 2.7%, reduced risk exposure by about 8.1%, and lowered the fiscal cost by approximately 0.15 million yuan. These results demonstrate that the advantages of the NSGA-II were not gained through increased fiscal investment; rather, the algorithm achieved higher utility and lower risk at comparable or even lower fiscal costs.

5.3. Analysis of Representative Policies

From the complete Pareto frontier, this paper selects three policy points with distinct decision-making implications—the Low-cost Policy, Balanced Policy, and Low-risk Policy—and compares them in Fig. 4.

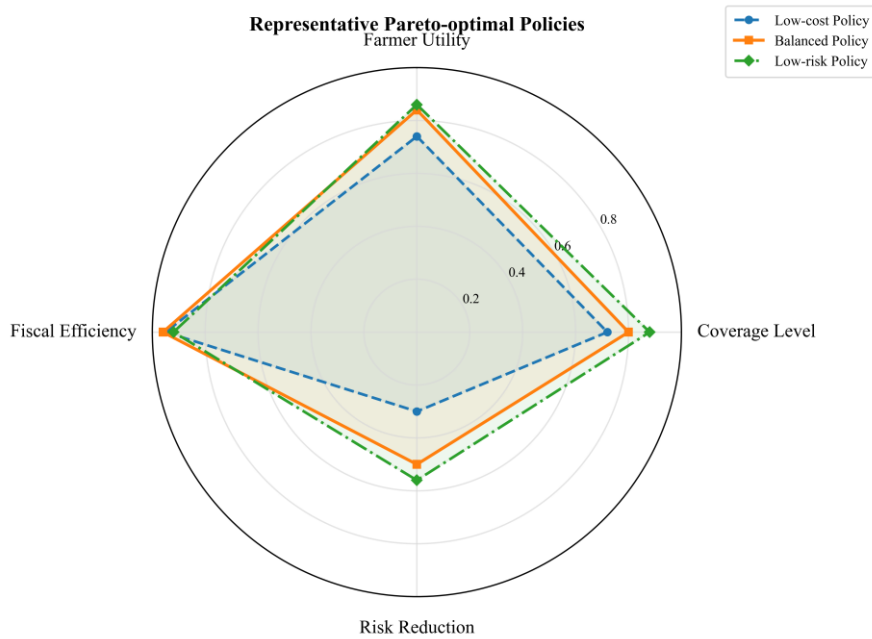


Figure 4: Comparison of three representative Pareto-optimal policies

The Low-cost Policy features a coverage level of 0.72, a subsidy ratio of 0.40, and an insurance premium rate of 0.040, resulting in a fiscal cost of 2.88 million yuan. While this scheme entails the lowest fiscal expenditure, its utility index is only 0.736, with a risk exposure of 2.18 and a risk reduction rate of approximately 30.1%. Consequently, its primary advantage lies in fiscal savings, whereas its risk protection capability is relatively limited.

Under the Balanced Policy, the coverage level rises to 0.84, the subsidy ratio is 0.49, and the insurance premium rate is approximately 0.041. The fiscal cost stands at 4.22 million yuan, the utility index reaches 0.829, and risk exposure drops to 1.58, yielding a risk reduction rate of about 49.4%. Compared to the Low-cost Policy, fiscal investment increases by 1.34 million yuan; however, risk exposure decreases by 27.5% and the utility index rises by 0.093, indicating that the additional fiscal investment at this stage yields significant policy improvements.

The Low-risk Policy further raises the coverage level to 0.94 and the subsidy ratio to 0.53, with a fiscal cost approaching 4.98 million yuan. This scheme reduces risk exposure to 1.39 and achieves the highest utility index of 0.861, yet it nears the benchmark fiscal budget ceiling of 5 million yuan. Compared to the Balanced Policy, the fiscal cost increases by approximately 0.76 million yuan, while the utility index rises by only 0.032 and risk exposure drops by 0.19, demonstrating a notably diminishing marginal improvement.

Therefore, in the baseline scenario, the Balanced Policy is better suited as a comprehensive policy choice. Rather than pursuing the lowest risk or merely minimizing fiscal costs, it achieves a risk reduction rate of nearly 50% at a coverage level of approximately 84%, while retaining a budget margin of about 0.78 million yuan.

5.4. Sensitivity Analysis

To further analyze the impact of changes in external conditions on policy choices, Figures 5 and 6 illustrate the optimal policy adjustments resulting from variations in the fiscal budget, market volatility, and farmers' risk aversion.

As shown in Figure 5, when the fiscal budget increases from 3 million yuan to 5 million yuan, the optimal level of protection rises from 0.73 to 0.84 and the utility index improves from 0.768 to 0.829, while risk exposure drops from 1.98 to 1.58. In other words, a budget increase of 2 million yuan at this stage reduces risk exposure by approximately 20.2%.

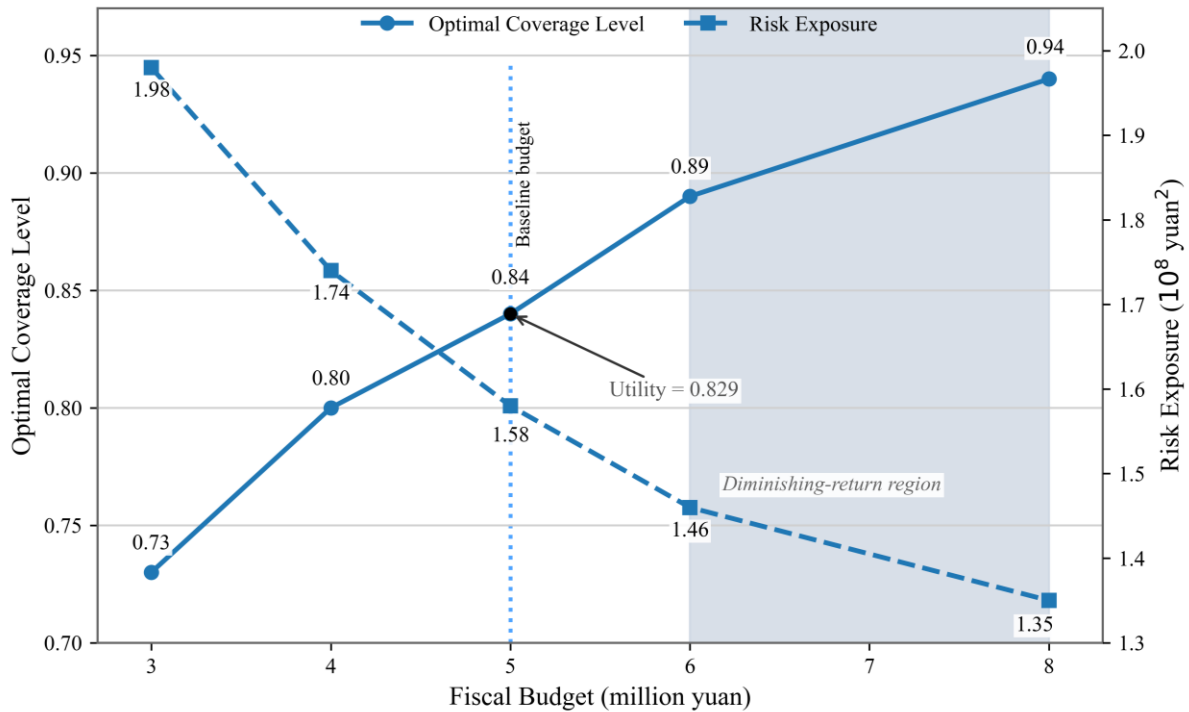


Figure 5: Sensitivity of the optimal policy to fiscal budget

When the budget is further raised to 6 million yuan, the level of protection increases to 0.89 and risk exposure falls to 1.46; at a budget of 8 million yuan, the level of protection reaches approximately 0.94, with risk exposure dropping to 1.35. Although fiscal space continues to expand, the utility index rises only from 0.848 to 0.862—an increase of less than 2%—when the budget moves from 6 million yuan to 8 million yuan. Consequently, significant diminishing marginal returns begin to appear once the budget exceeds the 5–6 million yuan range.

As shown in Figures 6(a) and 6(b), when price volatility increases from 0.20 to 0.35, the optimal coverage level rises gradually from 0.80 to 0.91, and fiscal expenditure increases from approximately 3.76 million yuan to 4.89 million yuan. Meanwhile, risk exposure rises from 1.24 to 2.37. This indicates that when external market risk intensifies significantly, raising the coverage level can mitigate some losses but cannot fully offset the increase in risk caused by price volatility itself.

When the farmers' risk aversion coefficient increases from 1 to 5, the optimal coverage level rises from 0.77 to 0.90, the subsidy ratio increases from 0.45 to 0.52, and risk exposure decreases from

1.82 to 1.44. Unlike price volatility, an increase in risk aversion primarily drives the policy to shift toward a higher coverage zone along the existing Pareto frontier, rather than directly expanding market risk.

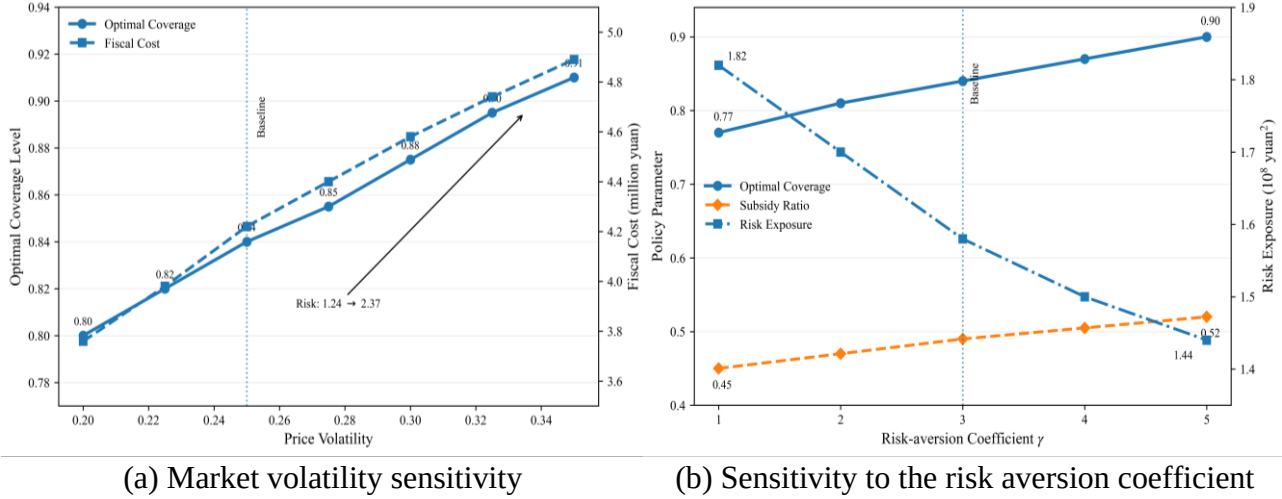


Figure 6: Sensitivity of policy decisions to market volatility and farmer risk aversion

6. Conclusion

To address the challenge of simultaneously balancing farmers' utility, fiscal costs, and risk control in the design of agricultural "insurance + futures" policies, this paper constructs a multi-objective decision-making framework and employs the NSGA-II algorithm to jointly optimize coverage levels, subsidy ratios, and premium rates. The study reveals that there is no single, fixed optimal parameter set for these policies; rather, different policy combinations entail distinct trade-offs between costs and risks. Pareto optimization preserves a range of efficient decision alternatives, shifting policy formulation from the selection of a single outcome to a comprehensive balancing of farmer welfare, fiscal affordability, and risk protection effectiveness. Furthermore, the study finds that as fiscal investment increases, improvements in protection exhibit diminishing marginal returns. Consequently, policy design should not focus solely on raising coverage levels but rather on identifying policy ranges where risk mitigation aligns better with fiscal expenditure, while allowing for dynamic adjustments based on market volatility and shifts in farmers' risk preferences.

This study has certain limitations. The current model focuses primarily on price risk, with insufficient consideration given to yield risk, basis risk, extreme market shocks, and the operational constraints of insurance institutions; additionally, variations in farm scale and risk preferences among farmers have not been fully disaggregated. Therefore, the findings are best suited as tools for policy optimization and mechanism analysis rather than as direct substitutes for the design of actual projects in specific regions. Future research could integrate yield risk, basis risk, and tail risk into a unified framework; incorporate multiple agents—such as diverse farmer types, various agricultural products, and insurance institutions; and conduct external validation using data from actual "insurance + futures" projects to enhance the model's applicability to differentiated policy design and practical decision-making.

References

- [1] Zmami M, Ben-Salha O. What factors contribute to the volatility of food prices? New global evidence[J]. *Agricultural Economics/Zemědělská Ekonomika*, 2023, 69(5): 171.
- [2] Guo K. How are climate risk shocks connected to agricultural markets?[J]. *Journal of Commodity Markets*, 2023,

32: 100367.

- [3] Shin S. Demand for weather index insurance among smallholder farmers under prospect theory[J]. *Journal of Economic Behavior & Organization*, 2022, 202: 82-104.
- [4] Wang H, Xu S. Income allocation of ‘insurance+ futures’ with risk modified Shapley value method[J]. *Applied Economics Letters*, 2023, 30(6): 740-750.
- [5] Han J. The Poverty Alleviation Role of the “Insurance+ Futures” Pattern—Evidence from 10 Chinese Provinces[J]. *Risks*, 2025, 13(4): 75.
- [6] Zhong L. Optimal design of agricultural insurance subsidies under the risk of extreme weather[J]. *International Journal of Production Economics*, 2023, 263: 108920.
- [7] Gong X, Hennessy D A, Feng H. Systemic risk, relative subsidy rates, and area yield insurance choice[J]. *American journal of agricultural economics*, 2023, 105(3): 888-913.
- [8] Biram H D. Mitigating price and yield risk using revenue protection and agriculture risk coverage[J]. *Journal of Agricultural and Applied Economics*, 2022, 54(2): 319-333.
- [9] Peng P, Xu Z. Price expectations, risk aversion, and choice of sales methods for large-scale farmers under incomplete market conditions[J]. *Agribusiness*, 2022, 38(4): 1012-1031.
- [10] Sánchez M V, Cicowiez M. Optimising policies to achieve agricultural transformation objectives: an application for Ethiopia[J]. *Journal of Applied Economics*, 2022, 25(1): 765-783.
- [11] Solibakke P B. Constant relative risk aversion utility and consumption CAPM: discount factors and risk aversions for Norway, Sweden, and the UK[J]. *Cogent Economics & Finance*, 2024, 12(1): 2299609.
- [12] Phelps C E. A user’s guide to economic utility functions[J]. *Journal of Risk and Uncertainty*, 2024, 69(3): 235-280.
- [13] Dang D M, Chen C. Multiperiod Mean-Buffered Probability of Exceedance in Defined Contribution Portfolio Optimization[J]. *SIAM Journal on Financial Mathematics*, 2026, 17(3): 1220-1278.
- [14] De Nardi M. Why do couples and singles save during retirement? Household heterogeneity and its aggregate implications[J]. *Journal of Political Economy*, 2025, 133(3): 750-792.
- [15] Singh V P. A novel approach based on TOPSIS method to solve Fermatean fuzzy multi-objective optimization problem[J]. *Engineering Computations*, 2026: 1-32.