RESEARCH ARTICLE

Reasonable allocation of agricultural water resources and adjustment of planting structure based on multi-objective optimization model

Meijian Yu*

Shandong Research Center on Town Development, Yantai Institute of Science and Technology, Yantai, Shandong, China.

Received: January 22, 2025; **accepted:** May 1, 2025.

Water scarcity is an important issue in current agricultural development. Reasonably utilizing water resources and improving local agricultural economic benefits is an important issue. This study proposed a water resource allocation model based on multi-objective optimization to address the poor agricultural water resource allocation and unreasonable crop planting structure. The model took the simplex aggregation algorithm to optimize water resource allocation and added the simplex aggregation backtracking algorithm to adjust the carbon footprint backtracking of planting structure. The results showed that, after using the water resource optimization model among 13 regions of testing area, the planting area in region 1 decreased by 0.30 × 10^5 m^3, while region 6 increased the cotton planting area. The total volume of crop trade in the region increased by 0.59 × 10^8 m^3. After optimizing the carbon emission model, the carbon emission decreased by 0.5 × 10^9 kg and the economic trade volume increased by ¥2 × 10^9 CNY. After model optimization, the local planting area and water resource allocation had been effectively managed, improving the economic and trade capacity of the region and reducing carbon emissions. This study had important guiding significance for future water resource allocation and agricultural structure adjustment.

Keywords: water resources; economic performance; planting structure; multi-objective optimization; planting area.

***Corresponding author:** Meijian Yu, Shandong Research Center on Town Development, Yantai Institute of Science and Technology, Yantai 265600, Shandong, China. Email: yumeijian1980@126.com.

Introduction

Water scarcity has become a major resource issue worldwide, especially in agricultural production. The utilization and rational allocation of water resources are crucial for sustainable agricultural development [1]. With the current population growth and economic development, the demand for agricultural products continues to increase, making water scarcity a major issue in current social development [2]. Reasonable allocating water resources and optimizing agricultural planting structure under limited water resources conditions have become an important direction for current agricultural production and development [3]. Multi-objective optimization model is an effective mathematical tool, which can provide the best resource allocation plan based on considering multiple factors and objectives. By establishing a multi-objective optimization model, multiple objectives such as economic benefits, resource utilization efficiency, and environmental protection can be considered simultaneously, seeking a balance point among these objectives to allocate water resources reasonably and optimize agricultural planting structure adjustment [4].

In most studies, multi-objective models have been widely applied in multiple fields. Sawik *et al*. proposed a multi-objective optimization conceptual model and introduced practical methods to optimize spatial task planning. The results indicated that the model could effectively balance risk, sustainability, and supply chain objectives, reduce task risk through systematic decision-making methods, improve resource utilization efficiency, and meet environmental sustainability requirements [5]. Seyednouri *et al*. proposed a multi-objective optimization model to optimize the multi-energy and multi-microgrids, which included cost and profit analysis. The results indicated that the new model based on Mixed-Integer Linear Programming (MILP) scene reduction and ε-Constraint Mixed-Integer Nonlinear Programming (MINLP) effectively solved uncertainty and obtained a Pareto optimal solution set for cost-profit equilibrium [6]. Zhang *et al*. developed a multi-objective fast optimization method to optimize Solid Fuel Ramjet (SFRJ) engines, which combined non-uniform rational B-splines, Levy motion gradient descent, and support vector regression. The results showed that the new method predicted quickly and had low errors, significantly reducing Total Pressure Loss (TPL) through multi-objective optimization while maintaining thrust [7]. Sun *et al*. proposed a multi-objective optimization technique for underground logistics systems based on subways to alleviate urban congestion, which constructed an entropy fuzzy technique for order preference by similarity to an ideal solution (TOPSIS) evaluation model and a mixed integer programming model and combined with Particle Swarm Optimization (PSO) and A* algorithm to optimize Logistics Network Planning (LNR) decisions. The results showed that the method could efficiently plan M-ULS networks and provide economically feasible and environmentally friendly Pareto optimal solutions [8]. Multi-objective optimization models can effectively improve practical performance in various fields. Currently, some researchers have conducted research focusing on the allocation and management of agricultural water resources. Ouyang *et al*. developed a research framework consisting of functional analysis, international review, policy evolution evaluation, and successful factor exploration to evaluate the effectiveness of China's water resource tax policy pilot and found that water resource tax improved water use efficiency, optimized water use structure, and helped promote rational water policies and governance decisions [9]. Martínez-Valderrama *et al*. proposed a new analysis gap mechanism and solution to address the widening gap between agricultural water use and water resource supply and found that combining the eight action lines and implementing comprehensive water resources management could address the severe challenges of widespread water scarcity in the future [10]. Ma *et al*. proposed a comprehensive evaluation method combining crop model and CGE model to compensate for the impact of climate change on agriculture and found that climate change might lead to a reduction in the area of food cultivation in ecologically fragile regions, an increase in cash crops, and intensifying challenges to food security [11].

Although multi-objective models can effectively improve the data solving and rational allocation of target problems, there are still significant practical issues that need to be addressed in water resource management and planting structure adjustment to improve management efficiency and economic benefits. This research innovatively used multi-objective algorithms to adjust and analyze water resource management and crop planting structure by introducing a simplex aggregation algorithm based on multi-objective model to enhance the water resource data management capability and water resource data processing efficiency in water resource management and allocation. Further, a simplex aggregation backtracking algorithm was added to the multi-objective model to enhance its backtracking and data analysis capabilities for the adjustment of planting structure.

Materials and methods

Analysis of agricultural water resources and crop carbon footprints

In agriculture, water footprint analysis usually adopts a “top-down” or “bottom-up” approach to water allocation. The “top-down” approach can analyze and allocate multiple different industries and regions in agriculture, which is simple to account for water resources. However, this method cannot provide better recommendations for water resource management and allocation. The “bottom-up” approach can clarify the current allocation of water resources in different regions and provide better recommendations. This study used a "bottom-up" approach to water management to analyze agricultural water resources [12]. Agricultural water resource analysis requires analyzing the water resource usage of different crops that absorb both surface water and groundwater when utilizing water resources. Surface water mainly comes from two sources including rainfall and irrigation. Meanwhile, crops also release some water resources into the atmosphere through their leaves due to transpiration and then return to the surface through rainfall. During this process, when the surface water resources are insufficient, the crops absorb groundwater. Therefore, when analyzing crop water resources, the transpiration and water use efficiency of crops were thoroughly analyzed. The crop water demand was calculated as follows [13].

$$GWR = 10 * \sum_{m=1}^{cgp} [\min(ET_c, P_e)] \tag{1}$$

where GWR was the crop water demand, which was the amount of water resources absorbed by crops from the ground. P_e was the rainfall. ET_c was the amount of water evaporated by crops through transpiration. cgp was the growth cycle of crops. m was the month of crop growth. The crop transpiration was shown in equation (2).

$$\boldsymbol{P_c} = \begin{cases} \boldsymbol{P \times (125 - 0.6 \times P)/125} \\ \boldsymbol{41.7 + 0.1 \times P} \end{cases} \tag{2}$$

when P was greater than the critical value of 83.3, the rainfall calculation at this time was $P \times (125 - 0.6 \times P)/125$. When P was less than the critical value, the rainfall at this time was $41.7 + 0.1 \times P$. The transpiration rate of crops was then determined as below [14].

$$\begin{aligned} ET_c = {} & K_c * \left(0.408 * \Delta * (R_n - G)\right) / \left(\Delta + \gamma * (1 + 0.34 * U_2)\right) + \\ & K_c * 900 * \gamma * U_2 * (e_s - e_a) / (T + 273) / \left(\Delta + \gamma * (1 + 0.34 * U_2)\right) \end{aligned} \tag{3}$$

where K_c was the crop coefficient. Δ was the slope of saturated vapor pressure. R_n was the net radiation level of crops. G was the soil heat flux density of crops. γ was the ventilation coefficient. U_2 was the wind speed at a height of 2 meters. e_s was the saturated vapor pressure of crops. e_a was the actual vapor pressure of the crop. T was the air temperature. The water requirements of different crops in different regions may vary. Therefore, water resources need to be allocated according to the growth and development of crops and irrigation needs. The requirement of crop irrigation water was calculated as follows [15].

$$B = 10 * \sum_{m=1}^{cgp} [\max(ET_c - P_e, 0)] \tag{4}$$

where B was the surface water irrigation demand of crops. The unit water demand of crops in the region was shown in equation (5).

$$\begin{cases} \boldsymbol{GWF = \frac{GWR}{S}} \\ \boldsymbol{BWF = \frac{B}{S}} \end{cases} \tag{5}$$

where GWF was the groundwater demand footprint of crops. S was the unit yield area of crops. BWF was the footprint of crop irrigation water demand. Crop carbon footprint analysis is an important method for analyzing the planting situation and structure of crops. The changes in crop carbon footprint can reflect the changes in crop resources and adjust the planting structure reasonably through resource changes. The systematic quantitative evaluation was used to analyze the carbon components of crops. When analyzing the carbon footprint of crops, there are several major pathways of change including production and processing, irrigation, fertilization, farmland, crop burning, crop roots, and other carbon cycle patterns. In carbon footprint analysis, the boundary of carbon cycling in crop systems was first determined. Then, data on crop carbon cycling processes was collected to calculate changes in crop carbon footprint before the final evaluation and analysis of the crops. The crop carbon footprint boundary was determined by analyzing crop carbon footprint changes and collecting crop data through boundary determination. Due to the varying yields and carbon footprint changes of different crops, this study processed and analyzed crop data through models.

Construction of multi-objective optimization model for crop resource optimization

Due to the wide variety of crops in actual production and differences in regional and resource allocation, a multi-objective optimization model was used to analyze the water resources and carbon footprint of crops, which was established with the goals of actual crop economic benefits and water resource conservation. The economic and trade objective function was shown in equation (6) [16].

$$\max F_1 = \sum_{j=1}^{p}[(Y_j * \sum_{i=1}^{q} x_{ij} - M_j) * UP_j] + \sum_{j=1}^{p}[(\min(Y_j * \sum_{i=1}^{q} x_{ij}, M_j) * OP_j] \quad (6)$$

where F_1 was the economic benefits of the crop. Y_{ij} was the total production of crop j in water resource area i. x_{ij} was the resource allocation of crop j in water resource area i. M_j was the minimum demand for crop j in local production. UP_j and OPj were the export and import prices of crop j in the current region, respectively. The water resource utilization of crops in the current region was shown in equation (7) [17].

$$\min F_2 = \sum_{j=1}^{p}\sum_{i=1}^{q}(B_{ij} * Y_j * x_{ij}) \quad (7)$$

where F_2 was the water resource demand of crops in the current region. B_{ij} was the demand for surface irrigation water resources for crop j in water resource area i. The model needed to constrain different resource conditions when allocating resources. The water resource constraint condition was shown in equation (8).

$$\sum_{j=1}^{p} x_{ij} = H_i^{all} \quad (8)$$

where H_i^{all} was a constant representing the total demand for land resources. The land constraint condition was shown in equation (9) [18].

$$\sum_{j=1}^{p}\sum_{i=1}^{q}(B_{ij} * Y_j * x_{ij} / \eta_i) \le V \quad (9)$$

where η_i was the water resource conversion efficiency in region i. V was the water resource threshold in region i. The multi-objective optimization model required control variables to constrain water resource objective function of the current region when analyzing water resource allocation to maximize local economic trade and minimize water resource consumption. In addition, constraints were imposed on the local water and land resources. Further, the objective function and constraints were used to achieve the maximum objective constraints of the model. However, during the resource constraint process, the model was prone to dimensional disasters due to dimensional changes. Therefore, the simplex aggregation algorithm was added to transform different crop objectives into a single objective at different stages, which reduced the dimensionality and enhanced the data processing capability of the model. Based on this algorithm, the model first converted multiple target aggregate models into a series of constrained target sub-models. Then, a series of constrained objective sub-models were converted into a single objective model based on the constraints of different objectives. The single objective model was then analyzed and solved using a geometric algorithm. The

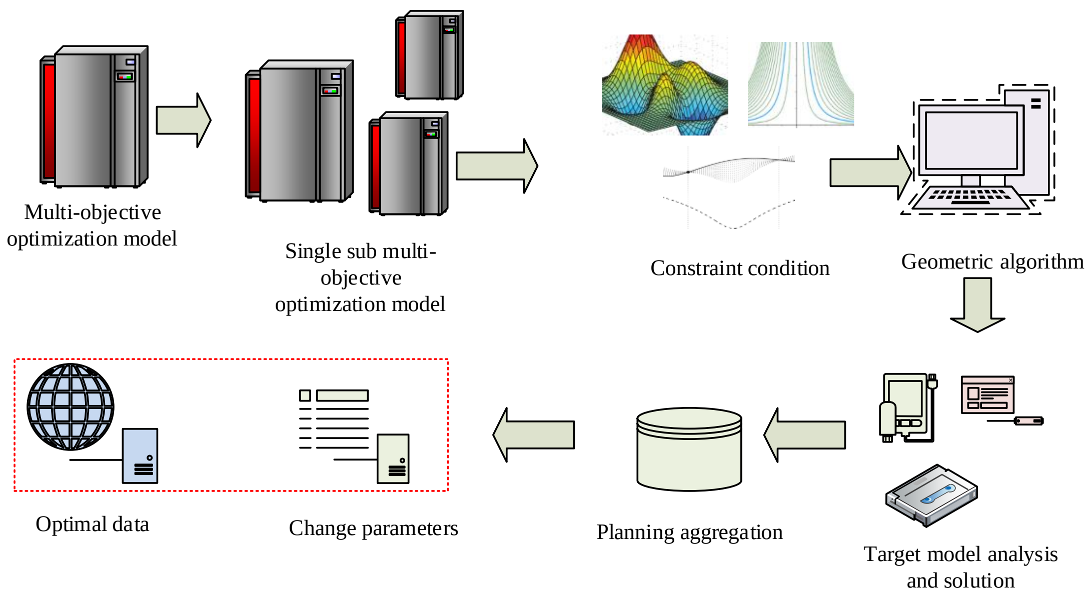


Figure 1. Multi-objective model crop planting structure adjustment model.

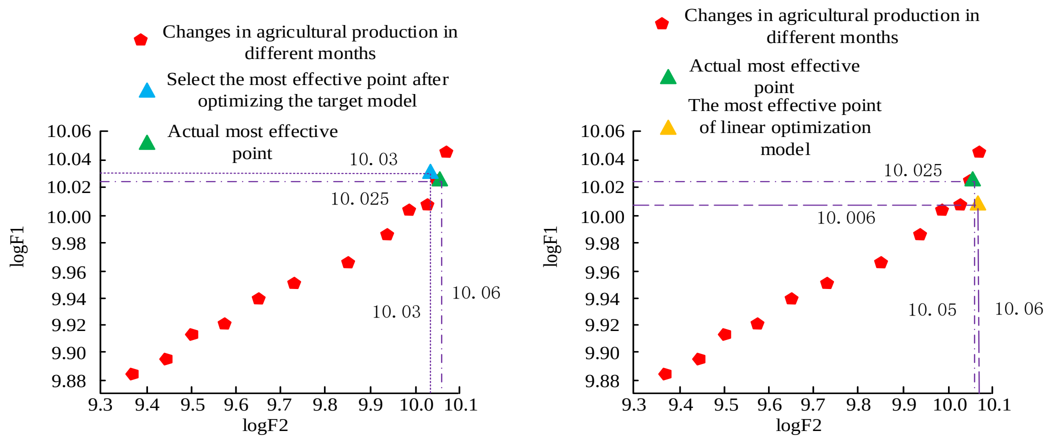
obtained single-objective solutions were planned and aggregated. The optimal solution in the current sequence was finally selected from the aggregated data. Meanwhile, the model selected a priority point after obtaining the optimal solution and analyzed it through multi-objective decision-making to obtain the most efficient point. The current most effective point was the optimal point after optimization. The changes in crop planting structure were analyzed through the changes in crop carbon footprint distribution. In the distribution of crop carbon footprint, with the low-carbon situation of crops as the target, the annual emissions of crop carbon changes in the current region were determined as the target. The low-carbon objective function was obtained as follows [19].

$$\min F_3 = \sum_{j=1}^{p}(C_j * Y_j) * \sum_{i=1}^{q}(x_{ij}) \tag{10}$$

where F_3 was the carbon index objective function. C_j was the carbon footprint of crop j. The objective function was agricultural production competition under low-carbon conditions as shown in equation (11) [20].

$$\min F_3^{'} = \sum_{j=1}^{p}(C_j * Y_j) * \sum_{i=1}^{q}(x_{ij}) / \sum_{j=1}^{p}\sum_{i=1}^{q}(Y_{ij} * B_{ij} * x_{ij} * E_i / \eta_i) \tag{11}$$

where $F_3^{'}$ was the agricultural competitiveness under low-carbon conditions. E_i was the agricultural water revenue in region i. The less competitive agriculture is, the more competitive it is with similar constraint situation in the model. Unlike the previous model that adjusting the carbon footprint and planting structure of crops was a large-scale data optimization process, this study used a simplex aggregation backtracking algorithm for multi-objective problem analysis, which transformed a large-scale multi-objective optimization problem into a single process multi-stage optimization problem (Figure 1). In the carbon footprint and crop planting structure, the multi-objective optimization model of carbon footprint was the same as the water resource optimization model. The carbon footprint process of crops was first transformed into a single sub-objective through the model. The target model was constrained and then aggregated to compute a single solution between sub-single targets. However, unlike the multi-objective model for water resources, the multi-objective model for carbon footprint calculated the optimal solution for crop planting structure.



(a) The most effective point of multi-objective optimization

(b) The most efficient point of linear programming

Figure 2. Comparison of optimal points between two models.

The x_{ij} value was then changed to fully solve the entire process, and new solution values were obtained again. Ultimately, the optimal solution for crop planting structure was completed.

Validation of multi-objective optimization model

The data from the planting areas of rice, wheat, corn, and cotton in 13 districts and counties (designated as regions 1 to 13) of Henan Province, China were employed to validate the proposed model. The data collection period was from January 2023 to July 2023. The practical application of two different structural allocation models were explored. The multi-objective model for water resources was analyzed and optimized using MATLAB (MathWorks, Natick, MA, USA). The computational hardware was Intel Core i7 with 4 cores, NVIDIA GPU, 32 GB RAM, 512 GB SSD hard drive, and Windows 10 system. The weight size of the model was set based on the actual multiple runs with weight sizes of 0.79 and 0.21, respectively. The impact of multi-objective modeling-based water allocation on crop planting area was analyzed.

Statistical analysis

The one-way ANOVA was performed with inter regional water resource benefits (¥/m³) as the dependent variable and crop type as the independent variable.

Results and discussion

Resource allocation of multi-objective model for water resources

Different water resource implementation plans were analyzed based on the current economic and trade goals and water resource usage goals of the selected area. The minimum agricultural water consumption was 65 × 10^8 m^3, and the minimum agricultural economic and trade benefit (F1) was ¥30 × 10^8 (CNY). The maximum agricultural water consumption (F2) was 110 × 10^8 m^3, and the maximum agricultural economic and trade benefit (F1) was ¥800 × 10^8. If there were more F2, F1 would be even larger. The research compared the changes in the most effective point between the linear optimization model and the multi-objective model to determine the optimal situation of the current model. The results demonstrated that, when using the multi-objective algorithm for calculation, the optimal logF1 value of the multi-objective model was 10.03, which was closer to the actual optimal logF1 value of 10.025 with a difference of 0.005 between the two points. The logF2 value of the multi-objective optimization model was 10.03, while the actual optimal point was 10.06, which had a difference of 0.03 between the two points (Figure 2a). Further, the logF1 value of the linear optimization model was 10.006, which differed from the actual point by

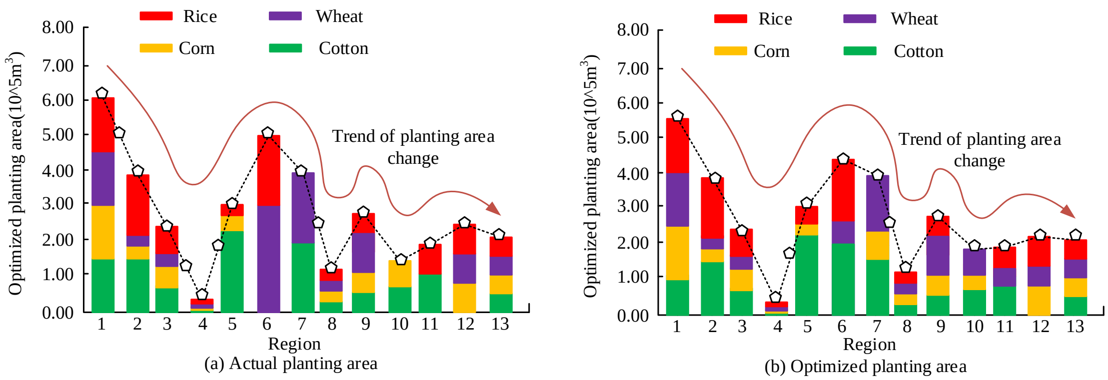


Figure 3. Changes in planting areas in different regions before and after optimization.

Table 1. Comparison of water resource trade before and after optimization.

Crop/minimum requirement	Total output ($\times 10^4$ t)		Irrigation water volume ($\times 10^6$ m^3)		Water resource trade volume ($\times 10^8$ m^3)	
	Before	After	Before	After	Before	After
Rice/1,251.15	1,161.258	1,251.15	3,215.84	3,184.74	+2.64	0
Corn/257.35	234.510	257.35	201.54	246.18	+0.18	0
Wheat/47.18	94.350	87.54	274.65	246.24	-1.54	-0.95
Cotton/9.66	16.540	9.66	252.31	143.05	-2.06	0
Total	-	-	3,944.34	3,820.21	-0.78	-0.95

0.019, while the logF2 value was 10.05 with the difference from the actual point by 0.01 (Figure 2b). The results confirmed that multi-objective optimization model was closer to the actual water resource optimization situation, indicating that using the multi-objective optimization model could better optimize the regional water resource allocation. After regional optimization, the model showed some changes in planting areas in certain regions. The cotton planting area in region 1 decreased from 1.20 × 10^5 m^3 before optimization to 0.90 × 10^5 m^3 after optimization with the planting area decreased after optimization by 0.30 × 10^5 m^3. Meanwhile, the rice planting area was reduced in region 5 with the planting area decreased from 3.00 × 10^5 m^3 to 2.80 × 10^5 m^3, resulting in an overall decrease of 0.20 × 10^5 m^3. In region 6, the cotton planting area increased by 2.00 × 10^5 m^3. The wheat planting area in region 11 increased by 1.30 × 10^5 m^3. The planting area of rice, wheat, and corn also reduced in region 12 (Figure 3). These increased areas might be due to some crops not being able to be planted well in the current region based on water resource allocation. Meanwhile, the crops that were conducive to planting had been mobilized and allocated. The optimization model could effectively allocate water resources in the current region and enhance the water resource utilization efficiency. To investigate the actual trade situation of water resources utilization in the optimized model, the water resources trade situation in the area before and after optimization was compared with positive trade volume indicating imports and negative trade volume indicating exports. In practical applications, optimizing water resource allocation can ensure regional grain planting and regional water resource utilization, increase grain production, and promote actual economic trade in grain. The results showed that, when using the multi-objective model for water resource optimization, the actual grain trade of all four crops increased after optimization (Table 1).

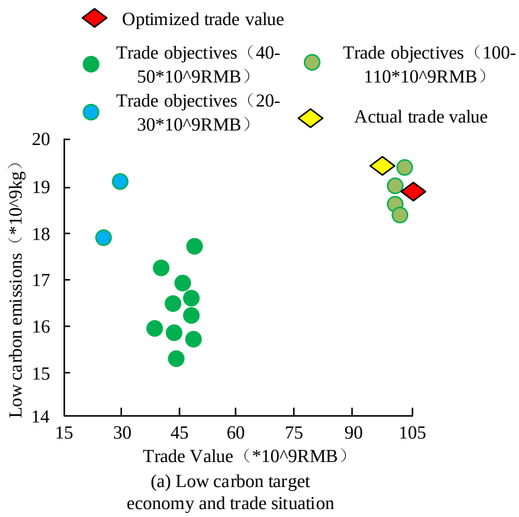


Figure 4. Economic and trade changes before and after optimization.

After optimization, the planting and trade volume of rice, wheat, and cotton achieved self-sufficiency. The trade volume of corn increased by 0.59 × 10^8 m^3 after optimizing water resources, which might be due to optimized water resource allocation increasing crop cultivation. The results indicated that optimizing water resources could achieve economic growth of certain crops in different regions and also improve regional water resource utilization efficiency.

Analysis of multi-objective model planting structure adjustment results

The changes in planting structure and carbon footprint in the area were analyzed based on the results of the water resource allocation situation. The water efficiency of different regions in Henan Province, China was compared, and the water efficiency reflected the cost of water resources in that region. The results showed that regions 1 to 13 had a water yield of 25.51, 22.54, 17.32, 21.28, 18.15, 21.98, 20.15, 16.84, 16.88, 17.02, 16.12, 17.25, 16.45 ¥/m³, respectively. There were differences in water resource benefits in different regions. Some regions had significant differences in overall regional water resource benefits based on the size of planting area and water demand. The maximum water resource benefit in region 1 was 25.51 ¥/m³, while the minimum water resource benefit in region 11 was 16.12 ¥/m³, which might be due to the high demand for water resources or the growing of crops in region 1, resulting in higher water resource cost. The economic and trade changes of the province before and after optimizing the multi-objective model under low-carbon conditions were compared, and the results demonstrated that, from the carbon emissions and economic and trade changes, the actual carbon emission was 19.2 × 10^9 kg, while the optimized carbon emission was 18.7 × 10^9 kg. After optimization, the carbon emission decreased by 0.5 × 10^9 kg, which might be an optimized planting structure adjustment to reduce carbon emissions. The economic and trade volume before optimization was ¥102 × 10^9. After optimization, it reached ¥104 × 10^9 with an increase of ¥2 × 10^9 in economic and trade volume (Figure 4a). This result might be because the model adjusted the structure of crop cultivation. The carbon competitiveness before optimization reached 0.055, while the optimized carbon competitiveness was only 0.053 with a decrease of 0.02. The economic and trade volume before optimization was only ¥100 × 10^9, while the optimized economic and trade volume reached ¥105 × 10^9 with a trade volume growth of ¥5 × 10^9 (Figure 4b). The results indicated that the multi-objective optimization model could

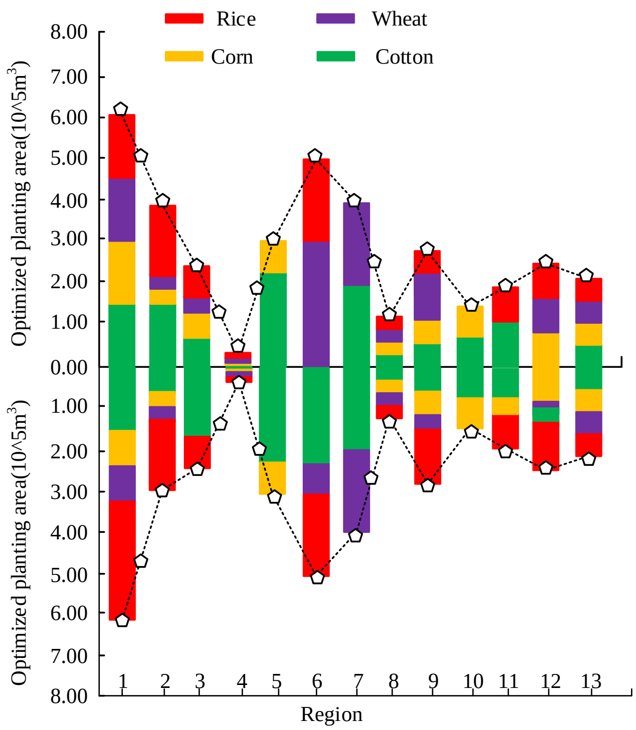


Figure 5. Changes in planting area before and after carbon footprint optimization.

promote agricultural economic and trade growth while reducing regional carbon emissions. To analyze the planting structure after multi-objective optimization of carbon footprint, a comparative analysis was conducted on the planting areas of 13 regions before and after optimization. The results showed that there were changes in the planting area and crop types in some areas optimized through carbon footprint optimization. In region 1, the corn planting area decreased from 3.00×10^5 m^3 to 2.29×10^5 m^3, while the rice planting area increased from 6.00 $\times 10^5$ m^3 to 6.20×10^5 m^3, which might be because in the carbon footprint analysis of the region, rice cultivation was more suitable for regional carbon cycling. Meanwhile, some crops were planted in certain areas. Regions 6, 11, and 12 respectively increased their planting areas for wheat, corn, and cotton, which might be because these crops were more suitable for regional carbon footprint changes in the carbon cycle and carbon emissions of the region (Figure 5). The multi-objective optimization model for carbon footprint could analyze the carbon footprint of different regions and adjust the planting structure, which not only coordinated the local agricultural economy, but also reduced regional carbon emissions.

The crop economic and trade changes before and after optimization demonstrated that, except for cotton, the other three crops increased, while the cotton decreased by about 0.40×10^8 m^3. Carbon emissions decreased from 175.95×10^8 kg to 168.94×10^8 kg with an overall decrease of 7.01×10^8 kg (Table 2). The multi-objective optimization model for carbon footprint could effectively reduce regional carbon emissions and improve economic and trade conditions, which had good effects on the local economic development and crop cultivation adjustment. After optimization, the planting area of rice in region 5 decreased from 3.00×10^5 to 2.80×10^5 m³, while it increased from 6.00×10^5 to $6.20 \times$ 10^5 m³ in region 1. The overall average change in planting area was $-0.15 \times 10^5 \pm 0.23$ m³. The planting area of wheat in region 11 significantly increased by 1.30×10^5 m³, while it decreased in region 12 with an average change amplitude of

Table 2. Changes in crop economic trade before and after carbon footprint optimization.

Crop/minimum requirement	Total output ($\times 10^4$ t)		Irrigation water volume ($\times 10^6$ m^3)		Water resource trade volume ($\times 10^8$ m^3)		Carbon emission ($\times 10^8$ kg)	
	Before	After	Before	After	Before	After	Before	After
Rice/1,251.15	1,161.258	1,251.15	3,215.84	3,248.65	2.64	1.54	73.54	69.58
Corn/257.35	234.510	257.35	201.54	251.26	0.18	-0.16	21.62	18.65
Wheat/47.18	94.350	87.54	274.65	257.64	-1.54	-2.68	9.45	10.35
Cotton/9.66	16.540	69.54	252.31	153.19	-2.06	-1.66	71.35	70.36
Total	-	-	3,944.34	3,910.74	-0.78	-2.96	175.96	168.94

$0.45 \times 10^5 \pm 0.61$ m^3. The corn planting area in region 1 decreased from 3.00×10^5 to 2.29×10^5 m^3, while it increased in regions 6 and 11 with the average change amplitude of $-0.12 \times 10^5 \pm 0.35$ m^3. In region 1, cotton plating area decreased by -0.30×10^5 m^3, while it in region 6 increased significantly by 2.00×10^5 m^3 with the average change amplitude as $0.85 \times 10^5 \pm 1.02$ m^3. After optimization, the total water trade volume increased by ¥2×10^9. The total carbon emissions in the area dropped by 7.01×10^8 kg from 175.95×10^8 kg before optimization to 168.94×10^8 kg after optimization with an average reduction of 12.5% in carbon emissions per hectare.

Different crops showed significant impacts on water resource efficiency ($F = 6.32$, $P < 0.01$). Cotton had the highest water resource efficiency with the average of ¥22.8/m^3, while corn had the lowest one with the average of ¥17.2/m^3. There was a significant difference among regions ($F = 4.15$, $P < 0.05$) with region 1 (¥25.51/m^3) significantly higher than the other regions (average ¥18.6/m^3). The results of planting area and carbon emissions showed that rice planting area was significantly positively correlated with carbon emissions ($r = 0.72$, $P < 0.01$), while cotton planting area was negatively correlated with carbon emissions ($r = -0.58$, $P < 0.05$). Water resource benefits were strongly positively correlated with economic trade volume ($r = 0.85$, $P < 0.001$), indicating that efficient water use could significantly improve economic benefits. In terms of water trade volume, the rice trade volume decreased by 2.64×10^8 m^3, while the wheat trade volume increased by 0.59×10^8 m^3. In terms of carbon footprint optimization, the optimized carbon emission was significantly reduced by 0.5×10^9 kg from 19.2×10^9 kg to 18.7×10^9 kg, while the economic trade volume changed from ¥102×10^9 to ¥104×10^9 with an increase of ¥2×10^9. In addition, the carbon competitiveness also decreased after optimization from 0.055 to 0.053, which indicated that optimizing the model promoted economic and trade development while reducing carbon emissions.

Overall, the multi-objective optimization model achieved better results in both water resource optimization and carbon footprint optimization, which could effectively improve the rational deployment of local water resources and planting structure, reduce planting costs, and improve planting efficiency. This research mainly focused on insufficient water resource management and utilization in different regions, which led to a decrease in regional economic crop yields and an increase in regional carbon emissions. A water resource allocation model based on multi-objective optimization was proposed, which combined different algorithm structures to improve the efficiency of water resource management and carbon footprint data analysis and processing. The results revealed that the optimal solution obtained after applying the water resources optimization model was close to the theoretical optimum. Overall, due to model optimization, the total trade of crops in the region increased by 0.59×10^8 m^3. There were differences in water resource benefits among different regions with region 1 showing the most significant benefits. The comparative analysis of carbon footprint optimization models showed that the planting area in region 1 decreased after optimization, while the rice planting area increased, which indicated that the planting area and structure of several regions were more reasonable after adjustment. Taken together, the model optimization reduced carbon emissions by 7.01×10^8 kg and achieved an increase in trade volume, proving the effectiveness of the multi-objective optimization model in rationally allocating local water resources and planting structure, and reducing planting costs and improving planting efficiency. Although some achievements have been made in this research, there are still some shortcomings, which include that the research only analyzed the spatial water resources and planting structure. Further analysis of temporal structure is needed. Meanwhile, future research also needs to analyze specific crops grown in specific regions to improve the adaptability of the model.

References

1. Liu Z, Han Z, Shi X, Liao X, Leng L, Jia H, *et al*. 2023. Multi-objective optimization methodology for green-gray coupled runoff control infrastructure adapting spatial heterogeneity of natural endowment and urban development. Water Res. 233(6):119759-119760.
2. Chen Y, Wang M, Zhang Y, Lu Y, Xu B, Yu L, *et al*. 2023. Cascade hydropower system operation considering ecological flow based on different multi-objective genetic algorithms. Water Resour Manage. 37(8):3093-3110.
3. Davoudkhani IF, Zishan F, Mansouri S, Abdollahpour F, Grisales-Noreña LF, Montoya OD. 2023. Allocation of renewable energy resources in distribution systems while considering the uncertainty of wind and solar resources via the multi-objective Salp Swarm algorithm. Energies. 16(1):474-475.
4. Tamashiro K, Omine E, Krishnan N, Mikhaylov A, Hemeida AM, Senjyu T. 2023. Optimal components capacity based multi-objective optimization and optimal scheduling based MPC-optimization algorithm in smart apartment buildings. Energ Build. 278(1):112616-112617.
5. Sawik B. 2023. Space mission risk, sustainability and supply chain: review, multi-objective optimization model and practical approach. Sustainability. 15(14):11002-11003.
6. Seyednouri SR, Safari A, Farrokhifar M, Ravadanegh SN, Quteishat A, Younis M. 2023. Day-ahead scheduling of multi-energy microgrids based on a stochastic multi-objective optimization model. Energies. 16(4):1802-1803.
7. Zhang N, Zhao D, Shi J, Huang H, Zhang Y, Sun D. 2023. Characterizing and predicting bluff-body solid fuel ramjet performances *via* shape design and multi-objective optimization model. Phys Fluids. 35(12):125150-125151.
8. Sun X, Hu W, Xue X, Dong J. 2023. Multi-objective optimization model for planning metro-based underground logistics system network: Nanjing case study. J Ind Manag Optim. 19(1):170-171.
9. Ouyang R, Mu E, Yu Y, Chen Y, Hu J, Tong H, *et al*. 2024. Assessing the effectiveness and function of the water resources tax policy pilot in China. Environ Dev Sustain. 26(1):2637-2653.
10. Martínez-Valderrama J, Olcina J, Delacámara G, Guirado E, Maestre FT. 2023. Complex policy mixes are needed to cope with agricultural water demands under climate change. Water Resour Manage. 37(6):2805-2834.
11. Ma M, Huang D, Hossain SS. 2023. Opportunities or risks: Economic impacts of climate change on crop structure adjustment in ecologically vulnerable regions in China. Sustainability. 15(7):6211-6212.
12. Eryiğit M, Sulaiman SO, Najm AB, Mhedi NM. 2023. Optimal management of multiple water resources by a heuristic optimization for a water supply in the desert cities of western Iraq. Desalin Water Treat. 281(1):7-14.
13. Tansar H, Duan HF, Mark O. 2023. A multi-objective decision-making framework for implementing green-grey infrastructures to enhance urban drainage system resilience. J Hydrol. 620(5):129381-129382.
14. Cheraghi R, Jahangir MH. 2023. Multi-objective optimization of a hybrid renewable energy system supplying a residential building using NSGA-II and MOPSO algorithms. Energ Convers Manage. 294(10):117515-117516.
15. Sabale R, Venkatesh B, Jose M. 2023. Sustainable water resource management through conjunctive use of groundwater and surface water: A review. Innov Infrastruct Solut. 8(1):17-18.
16. Jangir P, Buch H, Mirjalili S, Manoharan P. 2023. MOMPA: Multi-objective marine predator algorithm for solving multi-objective optimization problems. Evol Intel. 16(1):169-195.
17. Ahmad M, Zeeshan M. 2023. Multi-objective optimization of concentrated solar power plants from an energy-water-environment nexus perspective under distinct climatic conditions—Part B: Environ-economic analysis. J Clean Prod. 385(1):135689-135690.
18. Zhang F, Cui N, Guo S, Yue Q, Jiang S, Zhu B, *et al*. 2023. Irrigation strategy optimization in irrigation districts with seasonal agricultural drought in southwest China: A copula-based stochastic multiobjective approach. Agr Water Manage. 282(5):108293-108294.
19. Ooi JK, Hoy ZX, Hossain MU, Zhang Z, Khan M, Woon KS. 2024. An integrated multi-objective optimization framework for municipal solid waste management and emissions trading scheme. Clean Technol Environ Policy. 26(5):1383-1397.
20. Usman AM, Abdullah MK. 2023. An assessment of building energy consumption characteristics using analytical energy and carbon footprint assessment model. Green Low Carbon Econ. 1(1):28-40.