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A Full-Scale Optimization of a Crop Spatial Planting Structure and its Associated Effects

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ABSTRACT

Driven by the concept of agricultural sustainable development, crop planting structure optimization (CPSO) has become an effective measure to reduce regional crop water demand, ensure food security, and protect the environment. However, traditional optimization of crop planting structures often ignores the impact on regional food supply–demand relations and interprovincial food trading. Therefore, using a system analysis concept and taking virtual water output as the connecting point, this study proposes a theoretical CPSO framework based on a multi-aspect and full-scale evaluation index system. To this end, a water footprint (WF) simulation module denoted as soil and water assessment tool–water footprint (SWAT-WF) is constructed to simulate the amount and components of regional crop WFs. A multi-objective spatial CPSO model with the objectives of maximizing the regional economic water productivity (EWP), minimizing the blue water dependency (BWF_{rate}), and minimizing the grey water footprint (GWF_{grey}) is established to achieve an optimal planting layout. Considering various benefits, a full-scale evaluation index system based on region, province, and country scales is constructed. Through an entropy weight technique for order preference by similarity to an ideal solution (TOPSIS) comprehensive evaluation model, the optimal plan is selected from a variety of CPSO plans. The proposed framework is then verified through a case study of the upper–middle reaches of the Heihe River Basin in Gansu province, China. By combining the theory of virtual water trading with system analysis, the optimal planting structure is found. While sacrificing reasonable regional economic benefits, the optimization of the planting structure significantly improves the regional water resource benefits and ecological benefits at different scales.

1. Introduction

Water resources play an irreplaceable role in China's agricultural production. Against a background of water shortages, agricultural water consumption accounts for more than 60% of total water consumption, while the water used for crop production accounts for 85% of total water consumption [1,2]. China's uneven distribution of water resources sets up a contradiction between agricultural water use and the water use of other industries in China, which is particularly prominent in the arid north region [3–6]. Meanwhile, population growth and economic development are putting greater pressure on food security in China [7–9].

Confronted by the dual challenges of water shortages and food security, researchers are exploring possible solutions from different perspectives, including water-conservation measures, agronomic measures, planting structure adjustment, physical and virtual water transfers, biological breeding, and so forth [10–14]. Among these, crop planting structure optimization (CPSO) can bring multiple benefits to a region and play an important role in ensuring the sustainable development of regional agriculture [15]. The optimization in CPSO is aimed to establish an optimal relation between water resources and agricultural production, while maximizing regional benefits by reasonably optimizing and adjusting the planting proportion and spatial distribution of various crops in the region [16,17]. Many cases of planting structure

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adjustment have been carried out using optimization models [18–20]. This research field has also gradually shifted from focusing on a single optimization objective to focusing on multi-objective models that consider economic, resource, and ecological benefits [21–23].

The concept of virtual water trading provides a new perspective on how to enable regions that lack water resources to reduce their water scarcity [24,25]. Virtual water [26] represents the amount of water consumed in the production of goods or services; that is, virtual water exists in goods or services in an "intangible" form. Virtual water trading is a commodity strategy for water-poor areas to ensure the security of their water resources by importing water-intensive products instead of using limited local water resources to produce them [27,28]. Virtual water can be divided into blue water footprint (BWF_{blue}), green water footprint (GWF_{green}), and grey water footprint (GWF_{grey}), according to the source and usage of water [29,30]. In agricultural production, BWF_{blue} is defined as the consumption of surface water and groundwater, while GWF_{green} refers to the consumption of rainwater that will not be runoff [31]. These two footprints are closely related in the hydrological system, which can be determined by means of a soil–water balance model [32,33]. GWF_{grey} refers to the amount of freshwater required to dilute a load of pollutants so that the quality of the receiving water body remains within environmental water-quality standards. It is mainly used to characterize the water pollution intensity of production [34].

Previous studies have shown that the composition of a crop's virtual water depends not only on the characteristics of the crop but also on the regional planting environment. This finding indicates that the planting advantage of crops can be reflected by different compositions of crops' virtual water content in different regions [35]. Therefore, studies have incorporated water footprints (WFs) into the CPSO model to provide managers with reasonable agricultural management strategies. For example, with the aim of conserving agricultural water, reducing pollution, and increasing economic output, Yu et al. [1] optimized the agricultural planting structure in north China under water-saving scenarios of 15%, 20%, and 30%, respectively. Through a comparison of the comprehensive benefits, they found that the 15% water-saving plan was the best. Guo et al. [36] introduced the concept of WFs into a multi-objective optimization model and a multi-objective decision evaluation model to optimize a crop planting structure from the four aspects of society, economy, resources, and ecology.

The previously mentioned studies optimized a regional planting structure by integrating the concept of WFs into regional benefits, with the objective of maximizing regional benefits. However, a regional crop planting structure affects the actual output of various local crops, which affects the balance between the supply and demand of food, and then affects inter-regional trade [37]. Lack of consideration of the associated effects outside the region will lead to an incomplete optimization of a regional planting structure. Therefore, the optimization of a planting structure should take into account regional benefits, supply–demand balance, and the food trading closely related to the planting structure adjustment. This is the key innovation of our study. In addition, taking virtual water trading as an entry point broadens the horizons of CPSO research, which is the feature of this study.

Motivated by the above mentioned research gaps, this study proposes a theoretical framework for the comprehensive consideration of regional CPSO and a full-scale associated benefit evaluation, which is connected with the virtual water trading of different crops in the region. Under the proposed framework, this study takes the upper–middle reaches of the Heihe River Basin in northwest China as a case to implement the CPSO and benefits evaluation. The research content includes three parts: ① The balance between the supply and demand of each provincial-level administrative region (PLAR) is analyzed, and the interprovincial food trade is quantified; ② based on food security, the object of virtual water trading is determined, and then the multi-objective CPSO model is operated under different CPSO plans; and ③ an evaluation index system based on the three levels of region, province, and country is constructed, and the entropy weight technique for order preference by similarity to an ideal solution (TOPSIS) comprehensive evaluation model is used to select the optimal regional planting structure plans.

2. Material and methods

This study proposes a theoretical framework for the comprehensive consideration of regional CPSO and a full-scale associated benefits evaluation. The overall procedure followed in this study is summarized in Fig. 1, and a detailed description is provided below. The case study area is described in detail in Section S1 in Appendix A.

2.1. Quantification of the food supply and demand and interprovincial food trading

A spatial mismatch between food production and demand is the main impetus of food trading. On the premise of meeting their own food needs, each provincial administrative region sends surplus food to other PLARs. The calculation formula for provincial food surplus is as follows:

$$T_{i,j} = G_{i,j} + \left(\mathrm{im}_{i,j} - \mathrm{ex}_{i,j}\right) - C_{i,j} \quad (1)$$

where i and j represent the crop type and province, respectively. $T_{i,j}$ is the surplus of food i in province j. $T_{i,j} > 0$ means there is food i output in province j, $T_{i,j} < 0$ means that there is food i input in province j, and $T_{i,j} = 0$ means there is no interprovincial trade of crop i in province j. G and C respectively refer to the volume of production and the consumption of crop i in province j, while im and ex respectively represent the import and export volume of crop i in province j.

A balance analysis of the food supply and demand in 31 PLARs in China is the premise for exploring the food trading relationship among the provinces in China. Based on the regional division method adopted in the China Rural Household Survey Annual Inspection and China Economic Annual Inspection, this study divides 31 PLARs (excluding Hong Kong, Taiwan, and Macao) into three economic regions according to the regional and economic development level, as follows: the eastern region, central region, and western region (Fig. S1 in Appendix A). The PLAR abbreviations are provided in Table 1. Among them, the production data of the main food in all PLARs in China can be obtained from the *China Statistical Yearbook*. The consumption data of various crops, which was obtained from the Brick database[†], was downscaled to the provincial level. The consumption channels of China's food industry include ration consumption, feed consumption, industrial consumption, seed consumption, and losses. The four main crops (corn, wheat, barley, and canola) in the Heihe River Basin are the objects of this study. Based on the relevant statistical data, the consumption proportions of corn and wheat crops in the central, western, and eastern regions are shown in Table 2. Data on the barley consumption proportion was obtained from Ref. [38]. Data on the corresponding consumption components of each PLAR was calculated according to the proportion of the urban and rural population, the output of livestock products and aquatic products, the output of the main byproducts of crops, and crop outputs. Canola is primarily used to obtain oil, so its consumption in each PLAR was calculated according to the proportion of the population.

[†] https://www.agdata.cn/.

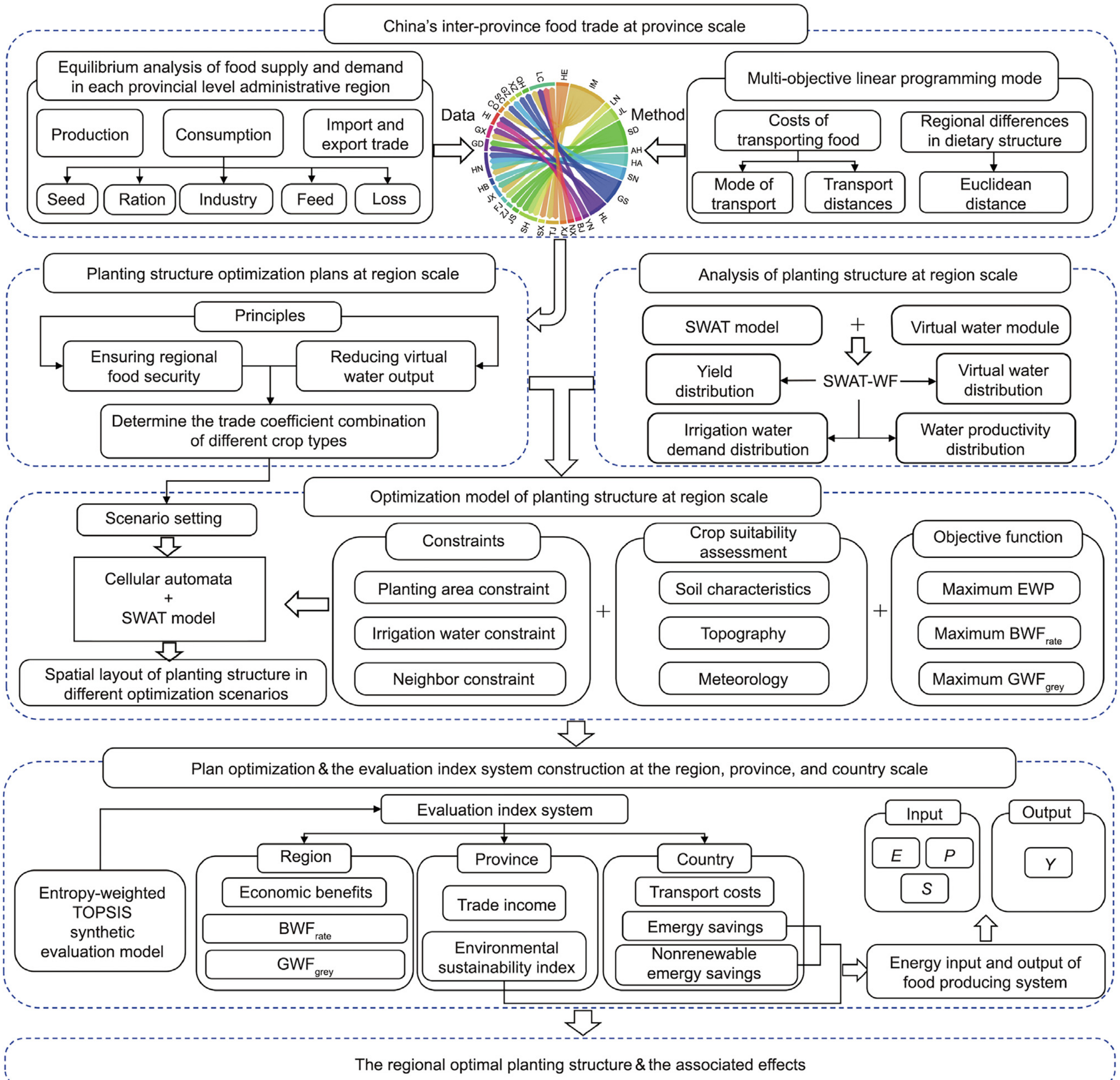

Fig. 1. Research framework for optimal regional crop planting from a region–province–country nexus perspective. EWP: economic water productivity; BWF_{rate}: blue water dependency; *P*, *S*, and *E* respectively represent the emergy flows of total purchased materials, services, and environmental resources; and *Y* is the crop yield, SWAT: soil and water assessment tool.

Table 1
Abbreviated names of each PLAR.

PLAR	Abbreviation	PLAR	Abbreviation	PLAR	Abbreviation
Anhui	AH	Hubei	HB	Shanxi	SX
Beijing	BJ	Hunan	HN	Shaanxi	SN
Fujian	FJ	Jilin	JL	Shanghai	SH
Gansu	GS	Jiangsu	JS	Sichuan	SC
Guangdong	GD	Jiangxi	JX	Tianjing	TJ
Guangxi	GX	Liaoning	LN	Tibet	XZ
Guizhou	GZ	Inner Mongolia	IM	Xinjiang	XJ
Hainan	HI	Ningxia	NX	Yunnan	YN
Hebei	HE	Qinghai	QH	Zhejiang	ZJ
Henan	HA	Shandong	SD	Chongqing	CQ
Heilongjiang	HL				

Only 31 PLARs in China are listed in this study. Taiwan, Hong Kong, and Macao are not included in the investigation.

Table 2
Consumption proportion of corn and wheat crops in the central, western, and eastern regions of China, and barley consumption proportion in China.

Crop	Region	Ration consumption		Feed consumption	Industrial consumption	Seed consumption	Losses
		Rural	Urban				
Corn	Eastern	7.69%	2.12%	70.97%	15.59%	0.66%	2.98%
	Central	14.11%	1.41%	72.04%	7.31%	0.91%	4.22%
	Western	15.13%	1.52%	72.92%	4.61%	1.13%	4.70%
Wheat	Eastern	44.55%	25.62%	10.09%	11.77%	4.20%	3.77%
	Central	58.22%	20.88%	5.86%	6.04%	4.85%	4.15%
	Western	72.56%	15.70%	3.25%	2.00%	4.30%	2.20%
Barley	China	2.45%	0	3.67%	89.71%	3.43%	0.73%

Data sources: Statistical Yearbooks of all provinces and cities; National Costs and Returns of Agricultural Products; Market Statistical Yearbook of China; China Feed Industry Yearbook. All consumption proportion data do not take into account Taiwan, Hong Kong, and Macao.

This study quantifies the provincial food trade pattern by constructing a multi-objective linear optimization model of China's interprovincial trade. The model takes the global minimum of food transportation cost and dietary structure difference as the objective function and the conservation of food surplus and shortage as the constraint condition. The dietary structure difference is characterized by the Euclidean distance of the consumption of rations and animal products in each PLAR. The food transportation cost considers the distance and mode simultaneously, as obtained from Gao et al. [39]. The weights of the transportation cost and difference of dietary structure between PLARs used in the model are 0.665 and 0.335, referring to the research of Qian et al. [40]. The multi-objective linear optimization model is as follows:

$$\begin{cases} \text{Objective function}: \min F(x_{i,a,b}) = \\ \quad \sum_{a=1}^{M}\sum_{b=1}^{N}(0.665t_{i,a,b}\times x_{i,a,b}+0.335s_{i,a,b}\times x_{i,a,b}) \\ \text{Constraints}: \\ \quad \forall(a,b):\ x_{i,a,b}\geq 0;\ \forall(a,a):\ x_{i,a,a}=0; \\ \quad \sum_{a=1}^{M} x_{i,a,b} = X_a \\ \quad \sum_{b=1}^{N} x_{i,a,b} = X_b \end{cases} \tag{2}$$

where $t_{i,a,b}$ and $s_{i,a,b}$ respectively represent the transport cost and the difference in the dietary structure of crop i between provinces a and b. M and N respectively represent the number of all exporters and importers of crop i, and $x_{i,a,b}$ is the mass of crop i transferred between provinces a and b.

2.2. Water footprint estimates

The soil and water assessment tool (SWAT) model is a process-based, semi-distributed hydrological and water-quality mode. In this study, we coupled the SWAT model with a WF simulation module, in what we called soil and water assessment tool-water footprint (SWAT-WF). The WFs of raw crops is the ratio of water used for production to crop yield, which was estimated by using the improved SWAT-WF. The operating procedures and a detailed description of the SWAT-WF module are presented in Section S2 in Appendix A.

Before the application of SWAT-WF in the present study, a SWAT model over the upper–middle reaches of the Heihe River Basin was established and calibrated, as described by Niu et al. [41] and Liu et al. [42]. The area was discretized into 1613 hydrological response units (HRUs) in 34 sub-basins, while the model was calibrated and validated for streamflow, evapotranspiration, and the yield of four main crops. In the present study, the NSGA-II algorithm was used to further improve the calibration accuracy of the model; the simulation performance of the model for soil moisture content was also validated, as detailed in Section S2 in Appendix A.

Blue water dependency (BWF_{rate}) is the proportion of crop BWF_{blue} to total WF. The closer the BWF_{rate} value is to 0, the lower the dependence of crop production is on agricultural irrigation [43]. Lowering BWF_{rate} can alleviate the competition pressure of water resources. The calculation formula can be expressed as follows:

$$BWF_{rate} = \frac{BWF_{blue}}{WF} \tag{3}$$

We simulate the WF of an HRU with different crops planted by replacing the crop planting type and related management measures on that HRU. This process is completed by means of Python programming. The WFs of different crops planted on each cultivated land HRU in the whole study area are then obtained, providing a data basis for regional CPSO.

2.3. Regional planting structure optimization model

With the SWAT-WF module, the WFs of the main crops in the study area are simulated, and the objects of virtual water trading are determined. On the basis of ensuring regional food security, various trade combination plans are formed by setting trade coefficients for multiple trade objects. In this study, a trade coefficient refers to the reduction ratio of the planting area beyond the regional demand. That is, with an increase in the trade coefficient of a crop, the planting proportion of this crop in the study area decreases, which is accompanied by a decrease in yield. However, the state of the regional supply exceeding demand is not changed until the trade coefficient is equal to 1, at which a balance of supply and demand is reached. In this way, the planting proportion of crops with high WFs is reduced, and the crop planting structure in the region is changed.

In order to optimize the crop planting structure in different trade combinations, an optimization model based on SWAT and cellular automata was developed in a previous study by Liu et al. [42]. Their optimization model takes the crop planting area, available irrigation water, and crop planting suitability as the constraint conditions. In the study by Liu et al. [42], a reasonable optimal planting structure was found with maximum regional economic water productivity (EWP) in the upper–middle reaches of the Heihe River Basin. Thus, from an economic perspective, this study chooses EWP as the optimization objective. The BWF_{rate} can also effectively reflect water resource-use efficiency, while the GWF_{grey} quantifies ecological benefits. Accordingly, the model in the present study takes the maximum EWP, the minimum BWF_{rate}, and the minimum regional GWF_{grey} as the optimization objectives, and changes the single objectives of the model to multiple objectives.

The whole optimization model was implemented using MATLAB (R2016a; the MathWorks Inc., USA). A flow chart of the

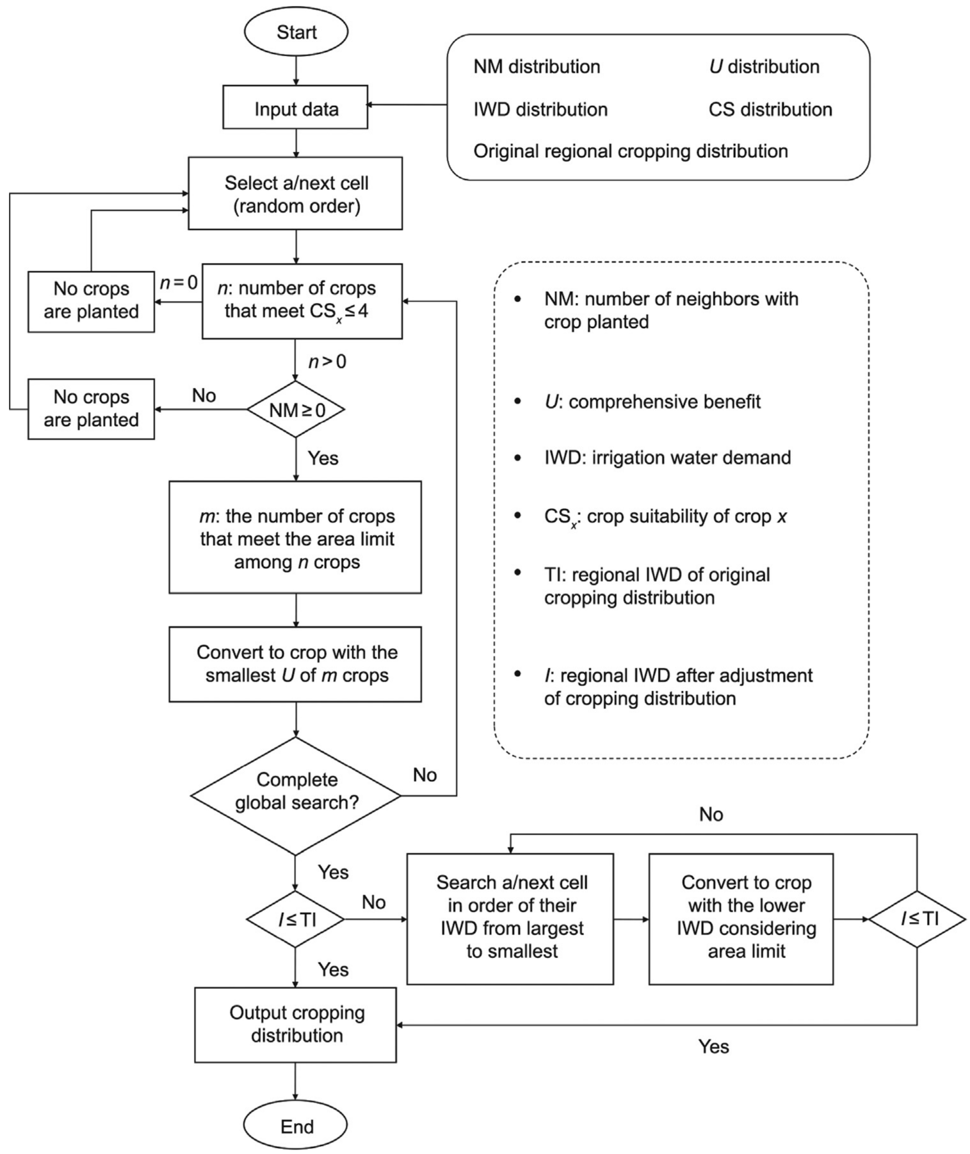

Fig. 2. Flow chart of the regional planting structure optimization model.

CPSO model is summarized in Fig. 2, and the mathematical expression of model is given in Section S3 in Appendix A.

2.4. Evaluation and optimization of plans

After inputting the different trade coefficient combinations into the optimization model, the optimal planting structure and corresponding optimal benefit indexes under each plan are obtained. To select the optimal plan from different trade combinations, in terms of which combination possesses the best benefits within the region and minimum negative effects on food trade outside the region, this study establishes an evaluation index system at the three scales of region, province, and country. An entropy weight TOPSIS comprehensive evaluation model is used to select the optimal plan, with the closeness coefficient as the comprehensive score of each plan. The detailed processes of this method are presented in Section S4 in Appendix A.

The top layer of the evaluation index system is the target layer—that is, the regional trade plans. The second layer is the criterion layer, which includes the regional benefits, provincial benefits, and country benefits. The third layer is the index layer, which is composed of the relevant benefit indexes of each scale. CPSO is a key scientific issue that is internally related to agricultural sustainability and externally related to the food trade [36,37]. Agricultural sustainability must be coordinated with economic feasibility, resource-use efficiency, and environmental concerns [44]. Economic income represents the most intuitive economic benefits of agriculture and is an important indicator for evaluating economic feasibility. Improving water use efficiency is an effective way to alleviate regional water resource shortages. The BWF_{rate} reflects the regional water use efficiency, characterizing resource benefits. The GWF_{grey} effectively reflects the degree of agricultural non-point source pollution, representing the ecological benefits of farmland systems. Therefore, these three indicators are selected to comprehensively quantify the regional benefit level.

In regard to the principle of ecological and economic benefits [45], the food trade income and environmental sustainability index are selected as the benefit indexes at the province level, to show the impact of regional planting structure changes on the advantages of provincial agricultural economic development and the health of the farmland ecological environment. The trade cost accounts for 30%–35% of China's grain sales price [39], which is an important index affecting the grain trade volume and trade orientation. Emergy savings and nonrenewable emergy savings define

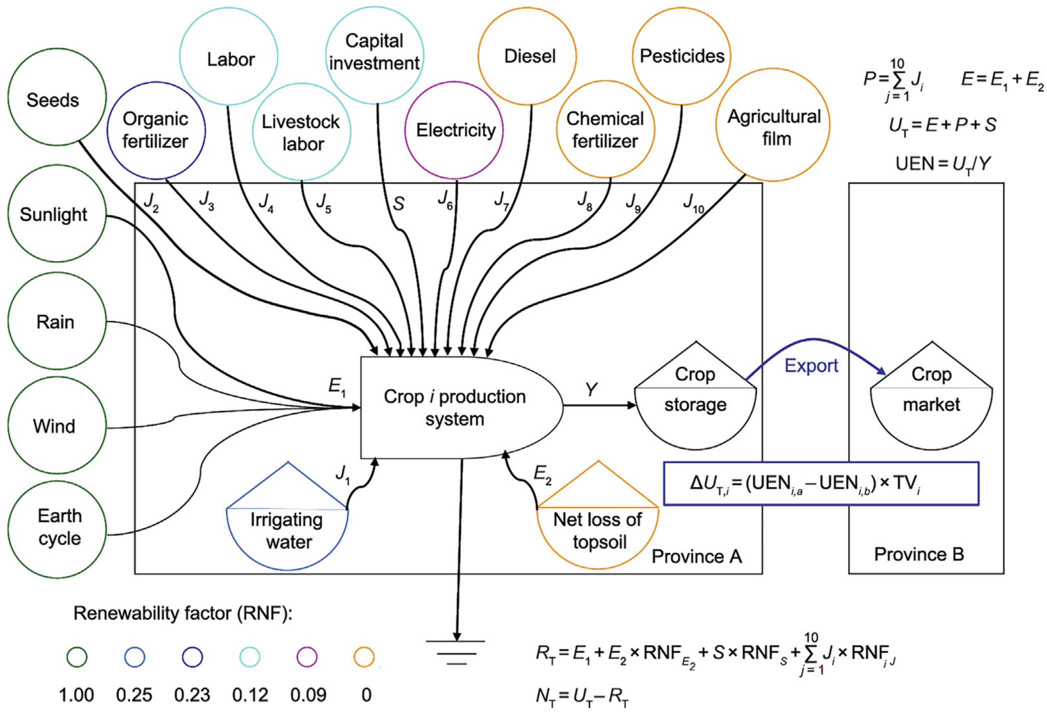

Fig. 3. Emergy systems language diagrams illustrating the operation of the crop production and interprovincial trade systems. U_T is the total emergy flow for crop i; R_T and N_T are the total renewable and nonrenewable emergy flows of the systems, respectively; Y is the crop yield of the production systems for crop i; UEN is the emergy value per unit yield; and TV is the amount of food traded between PLARs; J_i is the ith element of E.

the impact of trade changes on ecological resource conservation from the perspective of the comparative environmental advantage. Therefore, the total transport costs, emergy savings, and nonrenewable emergy savings of trade are selected into an evaluation index system.

Among these, the environmental sustainability index, emergy saving, and nonrenewable emergy saving are all related to the emergy system. The core of an emergy analysis is to quantitatively analyze the emergy value transformation process of the ecosystem and socioeconomic system by using a unified emergy currency expression. Based on the Emergy Systems Language proposed by Odum [46], Fig. 3 presents an overview of the system's emergy flow, money flow, and boundaries. In this study, the crop system is divided into the crop production and trade processes. Environmental resources, purchased materials, and services are the primarily input sources driving the crop system. Through the interprovincial crop trade, emergy flows between PLARs. These two processes make up the whole crop system. The unit emergy value (UEV) is the solar emergy directly or indirectly required to make 1 g, 1 J, or 1 USD of input. The global emergy baseline of the UEV used in this paper is the 1.20×10^{25} sej·a^{-1} standard. According to the renewability factors (RNFs), the input emergy of the crop system is divided into renewable and nonrenewable parts. The input data, UEVs, and RNFs used in this study are summarized in Table S1 in Appendix A.

Adjusting the planting structure of the region results in a change in the emergy input and output of the crop production system in the province where the region is located, and the corresponding emergy indexes also change. We use the environmental sustainability index (ESI) to quantify the ecological benefits for the province. The calculation formula is as follows:

$$\mathrm{ESI} = \frac{U_T/(P+S)}{N_T/R_T} \tag{4}$$

where P and S are the emergy flows of the total purchased materials and services, respectively; U_T is the total emergy flow; and R_T and N_T are the total renewable and nonrenewable emergy flows of the systems, respectively.

The change in the regional planting structure leads to a change in the interprovincial trade pattern, along with a change in the interprovincial emergy flow. Trading crops from a province with a low production emergy value to a province with a high production emergy value results in emergy saving. This change in the trade pattern will change the trade emergy savings of the whole country. Therefore, we take emergy saving and nonrenewable emergy saving, respectively, as indexes to measure the rationality of trades.

$$U_{\mathrm{saving}} = -\sum_{i=1}^{X}\sum_{a=1}^{M}\sum_{b=1}^{N}(\mathrm{UEN}_{i,a} - \mathrm{UEN}_{i,b}) \times \mathrm{TV}_{i,a,b} \tag{5}$$

$$\mathrm{UN}_{\mathrm{saving}} = -\sum_{i=1}^{X}\sum_{a=1}^{M}\sum_{b=1}^{N}(\mathrm{UENN}_{i,a} - \mathrm{UENN}_{i,b}) \times \mathrm{TV}_{i,a,b} \tag{6}$$

where U_{saving} and $\mathrm{UN}_{\mathrm{saving}}$ respectively represent the total emergy savings and the total nonrenewable emergy savings of various crop trade patterns. X is the total number of crop types, which is four in this study. $\mathrm{UEN}_{i,a}$ and $\mathrm{UEN}_{i,b}$ represent the emergy value per unit yield of crop i produced in province a and province b, respectively, and UENN represents the unit nonrenewable emergy. $\mathrm{TV}_{i,a,b}$ represents the trade volume of crop i from province a to province b.

3. Results

3.1. China's interprovincial-level food trade

The supply–demand status of each of the main crop types in the study area (corn, wheat, barley, and canola) was calculated for each PLAR in China; the results are shown in Fig. 4 and Fig. S2 in Appendix A (spatial distribution). Fig. 5 presents trade flow information on these four food crops among provincial-level regions,

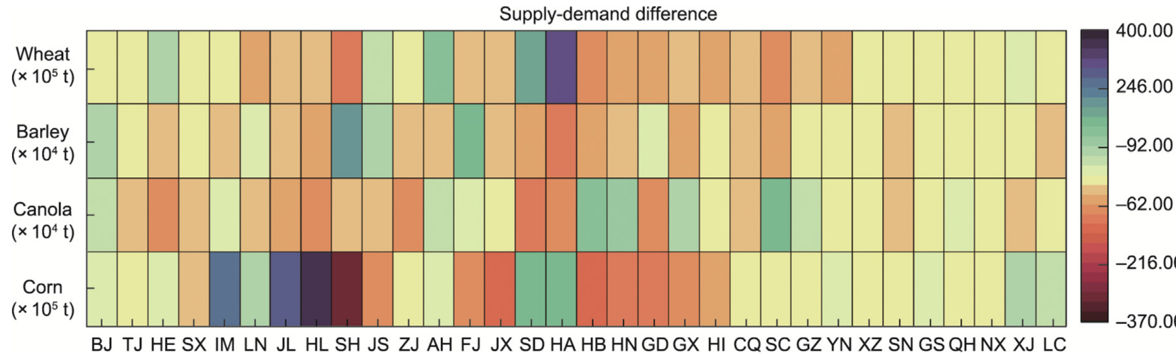

Fig. 4. The supply–demand difference of wheat, barley, canola, and corn crops in China's PLARs. LC represents grain depots.

obtained according to the linear optimization model. It is clear that food-surplus PLARs are mainly concentrated in northeast China. Corn shows typical north–south differences. The corn yield in northern PLARs is greater than its demand. Inner Mongolia, Jilin, and Heilongjiang are the main corn-export PLARs. Most PLARs in the south are unable to meet self-sufficiency, with Shanghai,

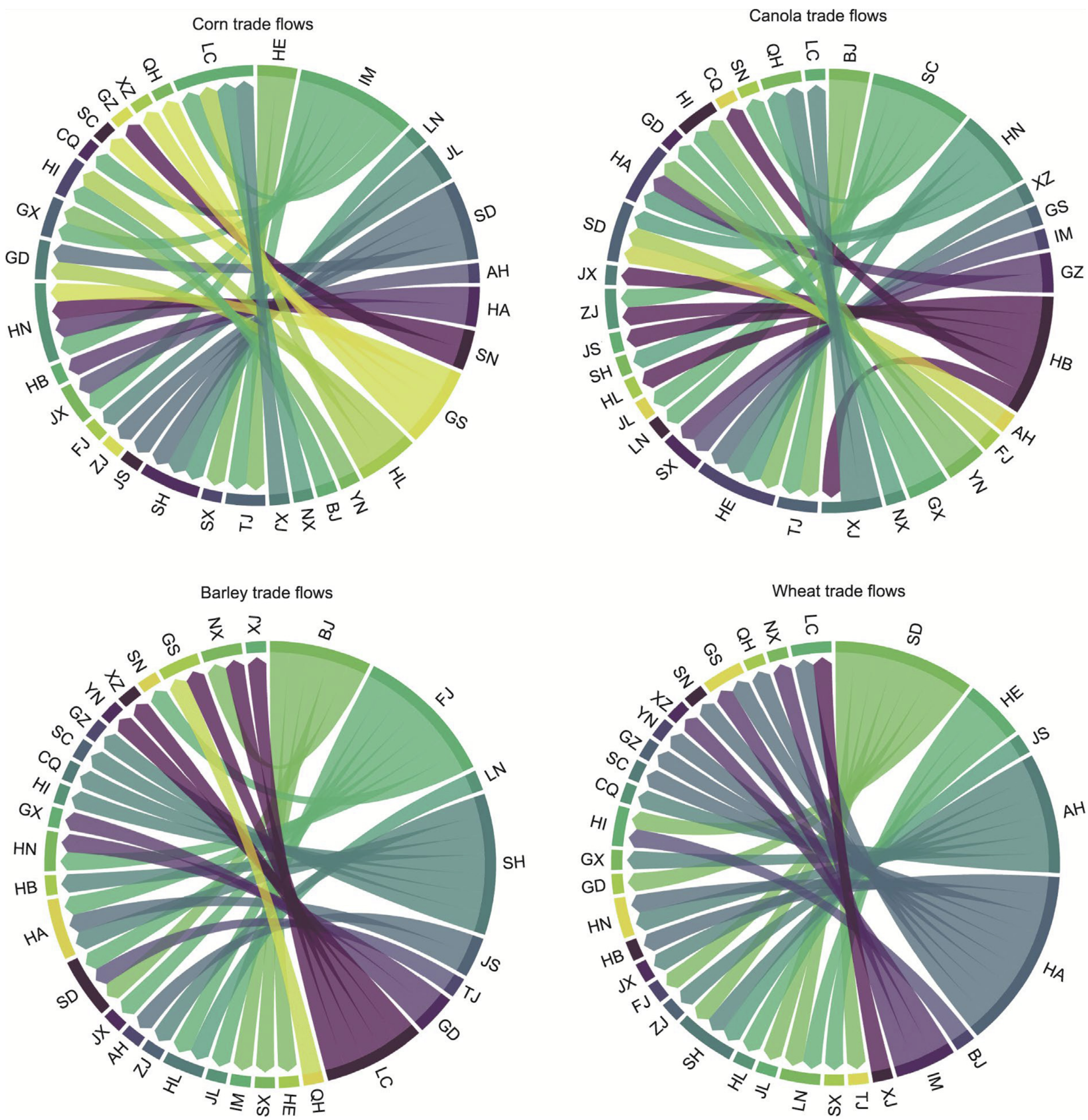

Fig. 5. Trade flows of corn, canola, barley, and wheat between PLARs.

Hubei, and Jiangsu being the main importers of corn. Most PLARs' corn imports fulfill part of their food shortage, while Beijing's corn imports alter the regional surplus–deficit status. The PLARs in which canola crop production exceeds demand are mainly concentrated in Western China. In addition, in the central region, Hubei, Hunan, Anhui, and Fujian are the main surplus PLARs for canola. Shandong is the province with the largest canola deficit. Qinghai is the only province that produces more barley than it needs when barley imports are not taken into account, and all its surplus is transported to Gansu province. After barley imports, Beijing, Tianjin, Liaoning, Shanghai, Jiangsu, Fujian, and Guangdong become supply zones, with Shanghai and Fujian having the largest supply of more than 1 million tons. The main supply belt of wheat is in the North China Plain, while Xinjiang and Inner Mongolia in the north also have a small amount of production surplus after meeting their own demand. Henan is China's largest wheat-producing region.

Since crop inventory data is not published, we used the national annual balance to represent the crop amounts obtained from or stored in grain depots. The results of a supply–demand balance analysis of these four crops show that the annual balance of corn and wheat crops in China is positive; that is, the supply of corn and wheat exceeds the demand, and the surplus crops are stored in depots. However, the annual balance of barley and canola in China is negative, so barley and canola must be obtained from depots to meet the national consumption demand.

3.2. Water footprint and virtual water trade of major crops

To specifically illustrate the WFs and virtual water trade of the major crops, the agricultural land over the Heihe River Basin in northwest China was selected for investigation. The WF of regional crop production and its component distribution in the upper-middle reaches of the Heihe River Basin were simulated, and the results are shown in Fig. 6. It is clear that the total WF of canola is the largest (1743.19 $m^3 \cdot t^{-1}$), followed by that of corn (1002.03 $m^3 \cdot t^{-1}$), while the WFs of barley and wheat are relatively small (620.78 and 529.62 $m^3 \cdot t^{-1}$). The BWF_{blue} of the four crops in most counties accounts for the highest proportion of the total WF, which is consistent with the characteristics of crop planting in the northwest arid area, which mainly depends on irrigation. We simulated the WFs of different crops planted on each cultivated land HRU in the whole region using the constructed SWAT-WF module through Python; the characteristic values of the crop WFs in each county are shown in Table 3.

The main planting areas of corn are concentrated in the middle reaches of the Heihe River Basin. The total WF of corn in the western region of the middle reaches is greater than that in the eastern region of the middle reaches. Shandan county has the lowest WF of corn, at only 752.61 $m^3 \cdot t^{-1}$. The proportions of the BWF_{blue} and GWF_{green} of corn gradually decrease from east to west across the middle reaches of the Heihe River basin, with the proportion of the GWF_{grey} increasing by degrees. This finding indicates that more pressure on the ecology has been induced by planting corn in the western region of the middle reaches. The results in Table 3 indicate that the mean WF in most counties increases by 10.00–75.00 $m^3 \cdot t^{-1}$ when the cultivated land in the region is planted with corn, which indicates that increasing the planting areas of corn will further increase the total corn WF in each county.

Canola is mainly planted in Qilian county in the upper reaches of the Heihe River Basin and in Minle and Shandan counties in the middle reaches. The total WF of canola in all the studied counties exceeds 1000.00 $m^3 \cdot t^{-1}$, among which Minle has the lowest WF, at 1637.13 $m^3 \cdot t^{-1}$. The results show that the total WF of canola in Ganzhou and Linze counties can be controlled at 1550.99 and 1408.91 $m^3 \cdot t^{-1}$, while expanding the planting area of canola in Shandan county can reduce the average WF in Shandan by 694.92 $m^3 \cdot t^{-1}$. This finding well demonstrates that optimizing the canola planting area is an effective way to reduce the canola WF.

The WFs of wheat and barley are more in the eastern part of the Heihe River Basin and less in the western part of the Heihe River Basin. The WFs of barley and wheat in the western part of the river basin are below 500.00 and 680.00 $m^3 \cdot t^{-1}$, respectively. The WFs in the eastern part of the river basin (i.e., Shandan and Minle counties) are about 200.00 $m^3 \cdot t^{-1}$ higher than those in the western part. The proportion of grey water has similar distribution characteristics, except in Gaotai county. Therefore, it can be inferred that the western region of the middle reaches of the Heihe River Basin is more suitable for the cultivation of barley and canola crops in terms of WF. Furthermore, expanding the wheat planting in Ganzhou and central Sunan, and adjusting barley planting regions in Minle and central Sunan can effectively reduce crop WF.

Through the analysis of the WFs above, it can be concluded that canola and corn crops are the targets of virtual water trading in the studied area. On the basis of ensuring regional food security, we set trade coefficients (with a trade coefficient change between 0 and

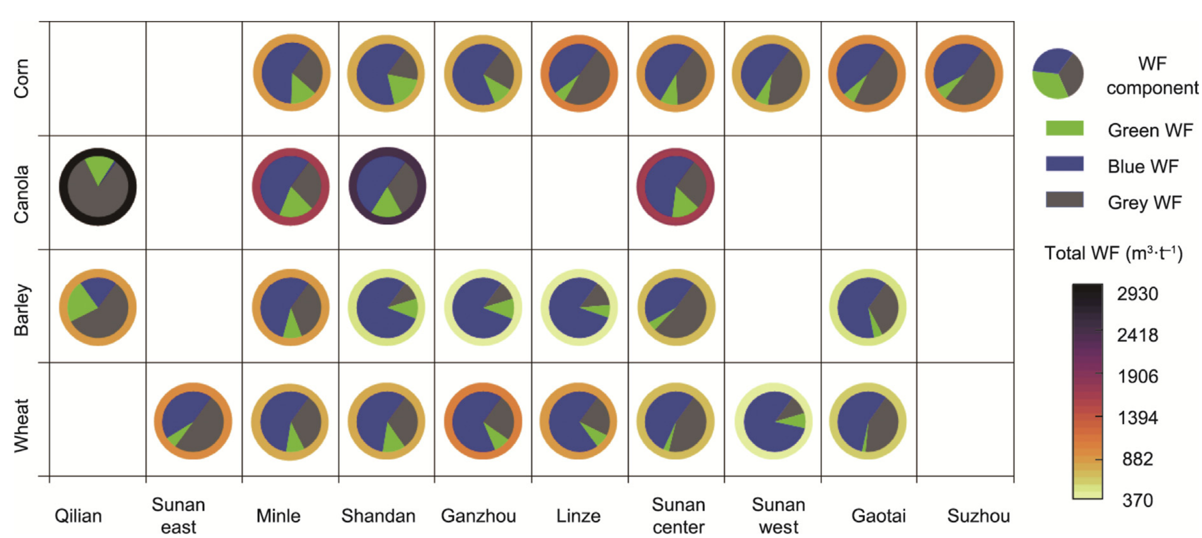

Fig. 6. Total WF and WF components of the four main crops in the upper–middle reaches of the Heihe River Basin.

1.00, with 0.05 increments) for the two crops. The different trade coefficient combinations of the two crops constituted a total of 441 change plans for the regional planting structure. The all 441 plans were brought into the established CPSO model to determine the optimal spatial distribution under different plans.

3.3. Determination of optimal planting structure

With an increase in the trade coefficient of corn and canola, the yield deficit of wheat demand gradually decreases from 2.74×10^{-2} million tons to 2.20×10^{-3} million tons. While the supply–demand status of barley crops in the study area changes from a deficit of 2.87×10^{-2} million tons to a surplus of 0.23 million tons.

Through the crop emergy system constructed in this study, we calculated the crop production emergy of each PLAR in the country; the results are shown in Fig. 7 and in Fig. S3 in Appendix A (spatial distribution). We find that the emergy of corn production in southern China is significantly higher than that in northern China, while the emergy nonrenewable ratio (ENR) shows the opposite distribution trend. This distribution feature also exists in the production emergy system of wheat crops. It can be seen that corn and wheat production in the southern region is more dependent on renewable water and heat resources, while that in the northern region is more dependent on nonrenewable emergy inputs. The average production emergy of canola is the greatest among the four crops, and the canola production emergy in Gansu province is the highest, with a value of more than 3.74×10^9 sej·g^{-1}. Areas with a lower unit emergy of canola production are mainly distributed in the North China Plain. Areas with a lower production emergy of barley crops are mainly distributed in the central region, the Three Northeastern Provinces (Heilongjiang, Jilin, and Liaoning), and the coastal areas, but this lower production emergy has a higher ENR. Among them, the barley supply in the coastal area mainly comes from imports, and the imported crops are recognized as non-emergy consumption production; this is the main reason for the low emergy value of barley in the coastal area. Meanwhile, the ENR of barley in the central and northern regions is significantly higher than that in other regions. Comparing the production emergy of four crops in Gansu with those in other provinces, it can be seen that barley has the lowest emergy consumption and a low ENR, and thus can effectively reduce the use of local nonrenewable emergy. This result demonstrates the rationality of our plans.

Fig. 8 shows the regional, provincial, and country benefit changes of the optimal planting structure under the 441 CPSO plans in the study area. Figs. 8(a)–(c) presents the change in the regional benefit index with the changes in the corn and canola trade coefficients. The change in regional economic income is a positive index,

Table 3
Mean values of total WF data for various crops in different counties under the original planting structure and the equivalent values when all cultivated land HRUs are planted the corresponding crop.

County	Item	CANP ($m^3 \cdot t^{-1}$)	CORN ($m^3 \cdot t^{-1}$)	BARL ($m^3 \cdot t^{-1}$)	SWHT ($m^3 \cdot t^{-1}$)
Qilian	HRU[a]	3200.05	1500.07	950.11	910.09
	ORI[b]	3300.00	—	853.95	—
Sunan east	HRU	3149.21	1495.58	690.13	902.29
	ORI	—	—	—	920.21
Minle	HRU	1786.12	860.41	615.33	706.96
	ORI	1637.13	800.37	835.17	761.31
Shandan	HRU	1702.13	826.33	511.23	662.85
	ORI	2397.05	752.61	522.78	748.13
Ganzhou	HRU	1550.99	769.33	433.71	478.58
	ORI	—	758.36	398.55	681.90
Linze	HRU	1408.91	999.54	454.85	540.52
	ORI	—	1030.04	419.03	502.44
Sunan center	HRU	1729.29	930.31	490.88	533.76
	ORI	—	865.67	686.94	707.61
Sunan west	HRU	1357.43	734.05	1136.32	454.77
	ORI	—	749.94	—	371.51
Gaotai	HRU	1847.95	991.04	613.39	481.80
	ORI	—	966.83	500.07	550.38
Suzhou	HRU	1731.27	986.83	924.97	429.84
	ORI	—	955.45	—	—

[a]HRU represents the data characteristics when the same crop is planted on the cultivated land HRU of the whole county.
[b]ORI represents the mean values of total WF under the original planting structure.
— indicates that there is no corresponding crop planted in that county; BARL: spring barley; CANP: spring canola-polish; CORN: corn crop; SWHT: spring wheat.

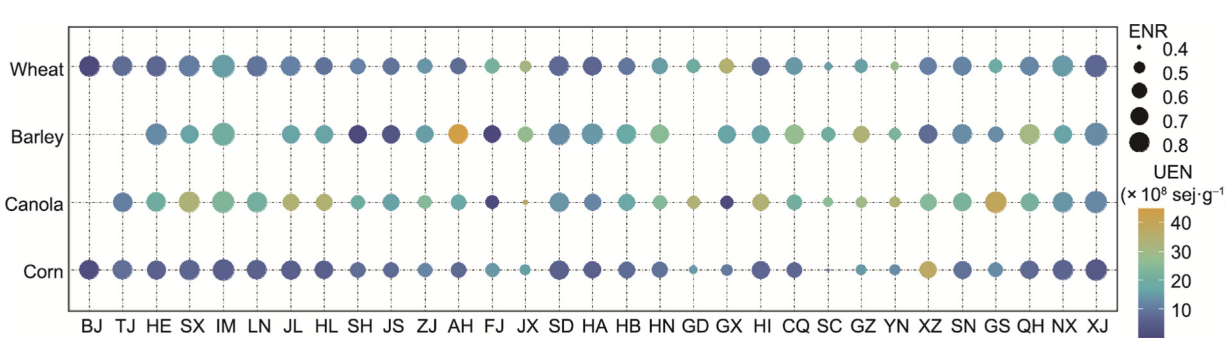

Fig. 7. UEN and emergy nonrenewable ratio (ENR) of wheat, barley, canola, and corn crops in the PLARs of China.

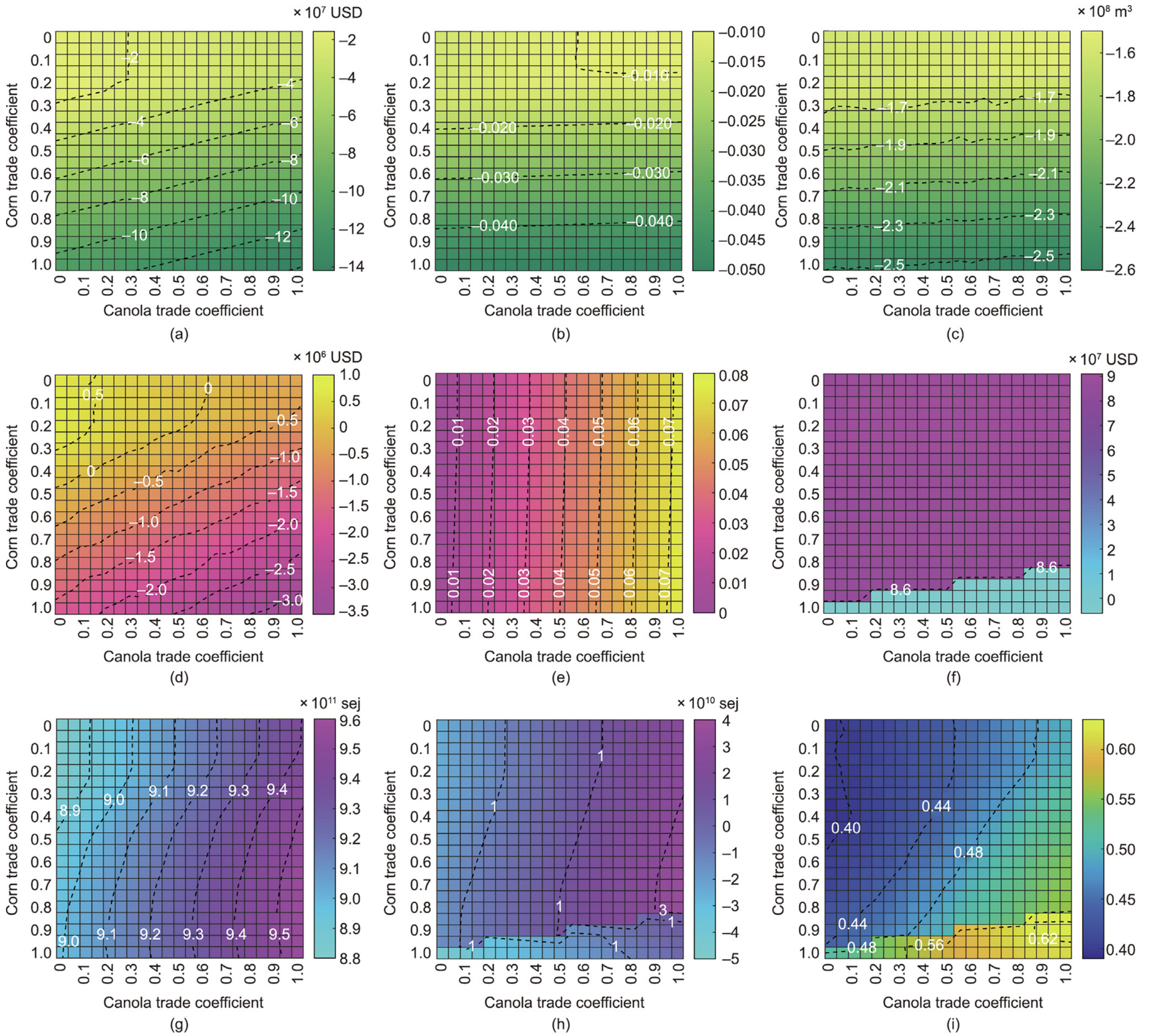

Fig. 8. Changes in each evaluation index such as (a) economic income, (b) BWF_{rate}, (c) GWF_{grey}, (d) trade income, (e) environmental sustainability index, (f) transport costs, (g) emergy saving, (h) nonrenewable emergy saving, and (i) the change in the closeness coefficient with a change in the trade coefficient of corn and canola.

while the changes in BWF_{rate} and GWF_{grey} are negative indexs. With an increase in the trade coefficient, the regional economic income, BWF_{rate}, and GWF_{grey} all exhibit a downward trend. Figs. 8(d) and (e) shows the provincial benefits. In all optimization plans, the change in the total trade income in Gansu province varies from -3.31×10^6 to 7.10×10^5 USD. As a whole, the total trade income gradually decreases as the trade coefficient increases. The change in ESI in Gansu province is basically not affected by the corn trade coefficient in the study area; rather, it gradually increases with the increase of the canola trade coefficient. It is clear that reducing the canola planting areas in the study area improves the sustainability of the agricultural system in Gansu.

The changes in the country benefits are shown in Figs. 8(f)–(h). The change in trade costs displays polarizing characteristics, as shown in Fig. 8(f). When the trade coefficient of corn crops is large enough, the total trade costs of the four crops among the provinces are reduced, with the largest reduction being 5.60×10^6 USD. Both the trade emergy savings and the trade nonrenewable emergy savings increase with an increase in the canola trade coefficient, but show little response to a change in the corn trade coefficient. However, when the corn trade coefficient is greater, a change in nonrenewable emergy saving showed the same differentiation as that in trade costs. Compared with the original trade pattern, the nonrenewable emergy saving under the segmentation line only slightly increases, or even decreases. The main reason for the differentiation is that, with the gradual increase in the total yield of barley in Gansu province, the production and marketing status of barley in the country change. According to the minimization of costs, the trade among PLARs has been redistributed.

Fig. 8(i) shows the results of the optimal selection of all plans by means of the entropy weight TOPSIS comprehensive evaluation model. The results suggest that, when the trade coefficient of corn is 0.85 and that of canola is 0.95, the closeness coefficient of the plan is the greatest, reaching 0.62. This is the best plan to change the crop planting structure in the study area, based on a comprehensive consideration of multiple benefits at the region, province, and country levels. The values of each index before and after the change of planting structure are shown in Table 4.

Table 4
Value of eight evaluation indexes before and after optimizing the crop planting structure.

Index	Economic income (USD)	BWF_{rate}	GWF_{grey} (m^3)	Trade income (USD)	Environmental sustainability index	Transport costs (USD)	Emergy saving (sej)	Nonrenewable emergy saving (sej)
Original	3.61×10^9	0.600	6.25×10^8	9.89×10^8	0.48	5.254×10^9	1.053×10^{13}	6.434×10^{12}
Optimal	3.48×10^9	0.560	3.86×10^8	9.86×10^8	0.55	5.249×10^9	1.148×10^{13}	6.438×10^{12}
Change	-1.30×10^8	−0.040	-2.39×10^8	-3.00×10^6	0.07	-4.800×10^6	9.500×10^{11}	4.900×10^9

3.4. Analysis of the associated effects of the optimal crop planting structure

The optimal crop planting distribution in the study area under the optimal trade coefficient combination is shown in Fig. 9 and in Fig. S4 in Appendix A. The crops are no longer planted intensively after optimization, but are scattered throughout the whole study area. The planting areas of wheat and canola are transferred to Ganzhou, Linze, and Gaotai counties in the western region. Barley crops are still intensively planted in the eastern region, mainly in the south of Shandan and Minle counties. In addition to canola, Ganzhou county has the largest planting proportion of major crops. Canola is still mainly planted in Minle county, where the planted area accounts for about 25% of the total canola area in the study area.

Fig. S4 also shows the distribution of EWP, BWF_{rate}, and GWF_{grey} after the optimization of the planting structure. EWP in the eastern region is significantly lower than in the western region, while the distribution trend of BWF_{rate} and GWF_{grey} is the opposite. Ganzhou county and the northern region of Shandan county have the highest BWF_{rate} and the lowest GWF_{grey}. Fig. 10 presents a comparison of three indexes before and after CPSO at the county scale. The results indicate that the regional benefit to most counties is effectively improved by the optimization of the planting structure, and the reduction in GWF_{grey} is the greatest benefit. In Qilian and Linze counties, the average GWF_{grey} reduction of crops is the largest, at 245 and 107 $m^3 \cdot t^{-1}$, respectively. Except for Sunan county in the western region, the BWF_{rate} of most counties obviously decreases, indicating that the water use efficiency in the region has been improved after optimization. The increase in EWP is the smallest among the three benefits. On the whole, the optimal plan effectively improves multiple regional benefits, which is reasonable and meaningful for the study area.

The trade flow direction in Gansu province is drawn in Fig. S5 in Appendix A. In Gansu province, the crops trade structure has changed significantly, with the greatest changes occurring in the barley trade pattern. Under the original planting structure, Gansu needed barley crops from Qinghai province and grain depots to meet its food deficit. The change of the planting structure transforms Gansu into a surplus province of barley. After meeting its own needs, driven by the minimization of trade costs, Gansu province transports barley to its surrounding four provinces, among which the largest trade volume is transported to Xinjiang Autonomous Region, reaching 6.28×10^{-2} million tons. This adjustment changes the nonrenewable emergy savings of the relevant barley trade flows in Gansu province from negative to positive. After optimizing the planting structure, the trade flow directions of corn, canola, and wheat crops in Gansu province do not change. Only the transportation volume changes, with a decrease of 0.26 million tons of corn from Gansu to Hunan provinces, a decrease of 6.90×10^{-3} million tons of canola from Gansu to Hebei provinces, and a decrease of 2.36×10^{-2} million tons of wheat from Henan to Gansu provinces. These changes in the trade volume of canola and corn crops reduce the amount of nonrenewable emergy transfer from high consumption areas to low consumption areas, which is more conducive to sustainable development.

In general, the optimized crop planting structure in the study area not only benefits the regional economic and environmental sustainability but is also effective for the sustainable development of the country. The successful demonstration of this case demonstrates the rationality of our proposed research framework.

4. Discussion

CPSO and resource allocation has attracted a great deal of attention in recent years. Most studies have presented innovated topics from the perspective of optimization models or optimization algorithms [47,48], such as interval fuzzy robust fractional programming [49], a maximum entropy model [50], and an elite

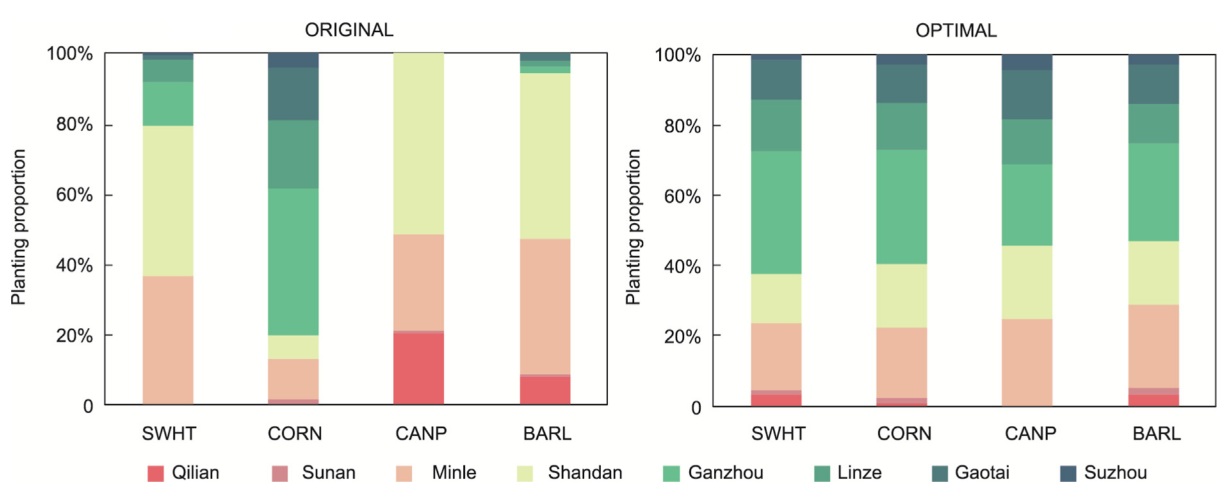

Fig. 9. Proportion of the planting area of the main crops in each county to the planting area of the whole basin before and after crop planting structure optimization. BARL: spring barley; CANP: spring canola-polish; CORN: corn crop; SWHT: spring wheat; ORIGINAL: the original planting structure; OPTIMAL: the optimal planting structure.

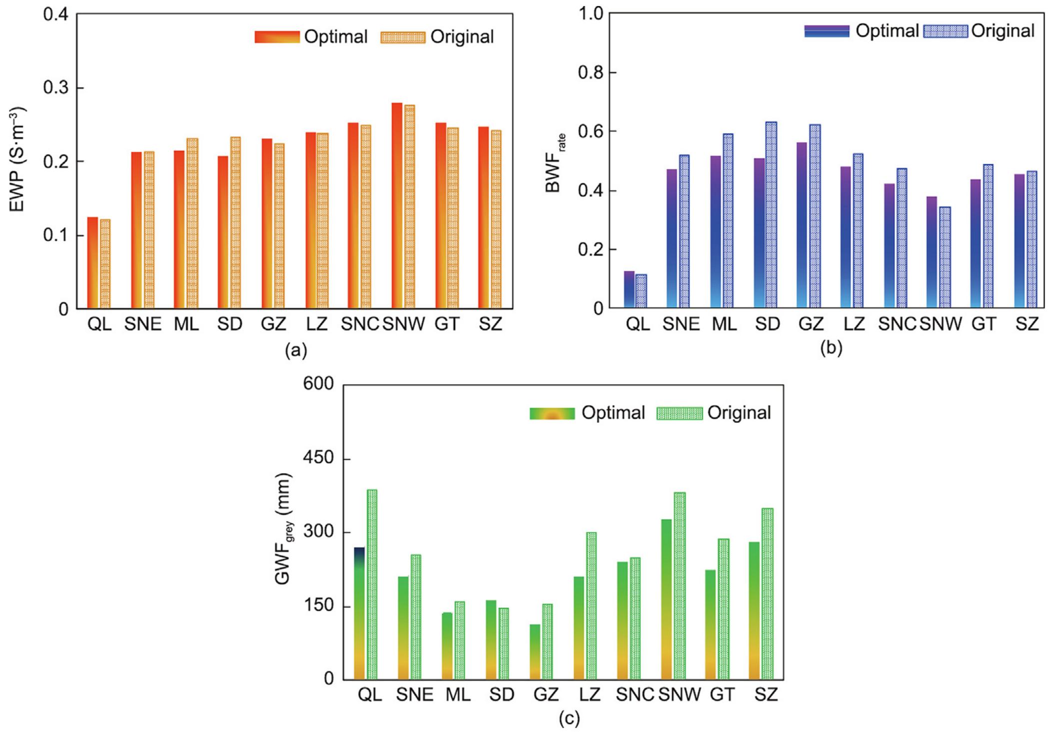

Fig. 10. (a) EWP, (b) BWF_{rate}, and (c) GWF_{grey} of the optimal crop planting structure and a comparison of three benefit indexes at the county scale before and after planting structure optimization. QL: Qilian; SNE: eastern Sunan; ML: Minle; SD: Shandan; GZ: Ganzhou; LZ: Linze; SNC: central Sunan; SNW: western Sunan; GT: Gaotai; SZ: Suzhou.

nondominated sorting genetic algorithm [13]. As the WF of crop production can effectively represent environmental benefits, it has been widely introduced into multi-objective optimization models to achieve the improvement of multiple regional benefits [51,52]. However, all studies on the optimization of planting structure have only focused on the change and improvement in the benefits of the study area within a closed space, and ignored the impact on the benefits at all levels outside the region. Therefore, this study takes the virtual water output as a connection point and puts forward a CPSO theory based on a region–province–country full-scale evaluation index system for the first time.

Evaluating the rationality of a system or optimization plan from multiple aspects by establishing an evaluation index system has been widely done in many industries [53–55]. A comprehensive index system usually involves multi-aspect benefits, such as benefits to the economy and the environment, and specific evaluation indexes are selected in corresponding benefit layers [56,57]. Thus far, no research has proposed a comprehensive evaluation index system from multiple scales and combined it with the optimization of crop planting structure. In this study, the comprehensive benefit of the planting structure is taken as the target layer, and the region-, province-, and country-scale benefits are taken as the criterion layer. Eight basic evaluation indexes are set at the index layer. The innovation of this study is to optimize and evaluate the regional crop planting structure from multiple scales and perspectives at the same time.

Population growth, rapid urbanization, and rapid economic development have greatly challenged the sustainability of the agricultural system. The concept of sustainable development has gradually become the first choice on the agenda of researchers, governments, industries, and national conferences. As an important part of human survival, food production depends on the sustainable support of natural ecosystems. Therefore, whether a change in a regional crop planting structure aligns with the sustainable development of the agricultural system is a level that must be considered. Crop production is a system involving the input of the natural ecosystem dimension, the economic dimension, and the social dimension. It is difficult to directly quantify production efficiency. However, emergy is a "common currency" that can convert the input of these three dimensions into the same unit of measurement and creatively quantify the direct and indirect contributions of crop production from the perspective of energetics and system ecology. The division of the renewable emergy value and the nonrenewable emergy value in production input has become an effective method to evaluate the sustainability and emergy efficiency of complex systems. This study creatively puts forward the concept of emergy saving, which is represented by the emergy value of the output PLAR being lower than that of the input PLAR. The nonrenewable part in emergy saving can be expressed as the savings in nonrenewable emergy. This study only takes emergy saving as a benefit index to evaluate the rationality of regional planting structure change. However, this concept makes it possible to quantify the sustainability of interprovincial trade. Based on the emergy difference of the crop planting system among PLARs, the crop planting area can be adjusted to improve the resource utilization efficiency.

As grain reserve data is not accessible [58] and the available studies fail to estimate the size of the grain reserve in detail [59], this study identifies grain depots as virtual producers or virtual consumers when quantifying interprovincial food trade, which weakens the influence of the reserve scale and reserve area layout. In addition, we optimize the regional planting structure by considering the impact of planting structure changes on full-scale domestic benefits, so the change in international food trade construction is not included in the model. These are the uncertainties and limitations of this study. A bi-level programming model considering international trade [60] and a commodity storage model [61] could be incorporated for a more complex environment.

At present, the forcing data for driving the full-scale optimization of the crop spatial planting structure includes statistical data, such as grain reserves, dietary structure, food production, and food consumption structure. Data with higher spatial and temporal resolution will be favorable to the optimization results. The use of more dynamic data, such as sub-scale food deposits or trade amount, will increase the frequency of the performed optimization. An ideal optimization plan should consider both the available/ dynamic data and the practicability/operability, which presents a challenge in obtaining an effective optimization.

5. Conclusions

This study is the first to propose a theoretical framework for regional CPSO based on a full-scale and multi-aspect benefit evaluation. It not only maximizes the regional benefits through a regional spatial CPSO model but also evaluates and analyzes the associated benefits of CPSO at the province and country levels. The proposed theoretical framework for regional CPSO was applied to the upper–middle reaches of the Heihe River Basin in Gansu province, China, which provided a reasonable planting layout for the study area and verified the rationality of the theoretical framework.

Considering food import and export, this study analyzed the supply–demand relationship of corn, wheat, canola, and barley crops in various provinces of China. Through a multi-objective linear optimization model with a global minimum of food transportation cost and dietary structure difference as the objective function, the direction and volume of food trade among PLARs were quantified. The results show that corn and wheat are basically transported from north to south, while barley supply is mainly dependent on foreign imports, and the overall pattern of barley transportation is from port cities to inland area. Canola is transported from the central and western regions to the eastern regions. This analysis of trade patterns is the data on which the benefit evaluation was based. The supply of corn and canola in Gansu province exceeds the demand, while that of wheat and barley is the opposite.

Based on green–blue water accounting and the calculation method of GWF_{grey}, this study constructed a WF simulation module based on a SWAT model, denoted the SWAT-WF module, to simulate the total amount and components of the WFs of regional crop production. The simulation results indicate that canola has the largest WF, followed by corn, while wheat and barley have relatively small WFs in the study area. A total of 441 regional planting structure change plans were formed by different trade coefficient combinations, and the optimal planting structure in different plans was obtained.

Combined with emergy analysis and economic indexes, a multi-aspect benefit-evaluation index system based on the region, province, and country scales was constructed. Through an entropy weight TOPSIS comprehensive evaluation model, the optimal planting structure for the case study area was found when the trade coefficient of corn and canola are 0.85 and 0.95, respectively. This planting structure not only effectively reduces the regional GWF_{grey}, as well as improving the water use efficiency and EWP, but also improves the sustainability index of Gansu province and the emergy and nonrenewable emergy savings of interprovincial trade. The proposed planting structure is effective for the sustainable development of the region and the country.

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Compliance with ethics guidelines

Qi Liu, Jun Niu, Taisheng Du, and Shaozhong Kang declare that they have no conflict of interest or financial conflicts to disclose.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eng.2023.03.012.

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