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Cropping pattern optimization considering water shadow price and virtual water flows: A case study of Yellow River Basin in China

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ABSTRACT

Cropping pattern determines the agricultural water use requirement and efficiency, as well as economic benefits of crop production. Agricultural water resources include blue water (irrigation water) and green water (soil moisture from precipitation), which have different shadow prices. The virtual water (VW) flow embedded in the interregional food trade causes burden shifts of water resources pressures in space. However, these intertwined economic and social effects have been neglected in regional cropping structure management. Using the case of the Yellow River Basin in China, here, we propose a two-stage multi-objective cropping pattern optimization scheme to maximize crop economic output, while minimize blue water scarcities (the first stage), and considered the criteria of maximum economic benefits of the interprovincial crop-related VW flows based on the shadow prices of crop green and blue water use (the second stage). Results show considerable differences in shadow prices of crop water use by colures, crops and location. With the optimized cropping pattern, which appropriately expands the planting scale of vegetables with higher water shadow price and comparative advantage and reduces the crop planting with lower water shadow price and intensive blue water consumption (e.g., soybean and wheat), blue water scarcity can be alleviated by ~20%, combined with a ~5% increase in crop economic output and up to ~3% (800 million USD) higher benefits of VW flows. The premise to achieve above goals is to improve crop water resources utilization efficiency and break down the barriers of dietary preferences and trade policy.

1. Introduction

Agriculture accounts for 92% of the global freshwater consumption and is expected to continue to grow in the future (Hoekstra and Mekonnen, 2012). The competitive use of water resources in agriculture and other sectors has intensified water scarcity in many places around the world. Factors such as population growth, urbanization, diet changes and climate changes have exacerbated water pressures in certain water scarce regions (Mekonnen and Hoekstra, 2016; Rodell et al., 2018; Tove A. Larsen et al., 2016; Tuninetti et al., 2022; Vörösmarty et al., 2000). Due to the spatial heterogeneity of crop water productivity, regional cropping pattern should be optimized and water resource management across sectors should be coordinated to alleviate regional water pressures (Chouchane et al., 2020). Cropping pattern optimization should comprehensively consider the pressure of water resources, food production and economic benefits (Yao et al., 2020; Ren et al., 2021). Moreover, with increased interregional crop trade and logistics, the optimization of cropping patterns could alleviate local physical water scarcities and change the virtual water (VW) flow patterns embedded in crop trades across the regional boundaries to bring social and economic benefits (Ye et al., 2018). To quantify the benefits of VW flow, it is vital to assess the economic value of water used to produce the traded crops, which can be measured by the shadow price of crop water use (Bierkens et al., 2019). The crop water shadow price indicates the marginal benefits obtained by using an additional cubic meter of water for crop production and reflects the scarcity of resources (Angulo et al., 2014; Liu et al., 2009). Quantifying the specific value of the crop water shadow price is conducive to a more rational allocation of agricultural water resources and alleviate local water shortage (Novo et al., 2009; Grammatikopoulou et al., 2020).

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Numerous studies have investigated regional cropping pattern optimization with increasingly comprehensive optimization objectives and diverse methods. In terms of optimization objectives, maximum crop production or crop economic benefits and minimum irrigation water consumption are traditional objectives (e.g., Davis et al., 2017; Márquez et al., 2011; Morankar et al., 2013; Osama et al., 2017; Varade and Patel, 2019). With improvements in knowledges of integrations between crop production, water resources and human societal sustainability, more factors related to environment and society have been incorporated in the cropping pattern optimization program. For instance, environmental factors such as crop water productivity (Fan et al., 2021; Ren et al., 2019), water resource carrying capacity (He et al., 2021), groundwater extraction (Ma et al., 2022; Varade and Patel, 2019), fertilizer use (Jain et al., 2021; Wang et al., 2022; Xie et al., 2023), carbon emissions (Li et al., 2023; Wang et al., 2022; Xie et al., 2023), and biodiversity (Wen and Chen, 2023). Water footprint of crop production has the advantage of distinguishing between blue water and green water consumed during crop growth period (Hoekstra and Mekonnen, 2012). Therefore, the minimizing crop water footprint has been placed in the cropping pattern optimization targets (Balezentis et al., 2020; Chouchane et al., 2020; Liu et al., 2022; Liu et al., 2021b; Sedghamiz et al., 2018; Wang et al., 2021; Wen and Chen, 2023). Chouchane et al. (2020) and Liu et al. (2021b) carried out a global and Chinese crop redistribution scheme with minimal blue water scarcity and minimum blue water footprint as one of the optimization objectives, respectively. Some studies took the maximum proportion of crop green water footprint as objective (Liu et al., 2022; Sedghamiz et al., 2018; Zhang et al., 2021). In terms of methods (Table 1), existing methods include linear programming (Balezentis et al., 2020; Wang et al., 2022; Xie et al., 2023), fuzzy programming (Morankar et al., 2013; Wang et al., 2021; Zhang et al., 2021), two-layer optimization (Liu et al., 2022). However, these algorithms have drawbacks such as computational complexity and strong subjectivity in the process of solving the optimal solution (Sedghamiz et al., 2018). Recently, evolutionary algorithms have received widespread attention, such as genetic algorithm (Deb et al., 2002), ant colony algorithm (Shaikh et al., 2015), and particle swarm algorithm (Jain et al., 2021). The second-generation genetic algorithm (NSGA-II) with the advantages of fast non-dominated sorting process, elite strategy, non-parameter, and effective constraint processing methods, has been widely applied in research cases of multi-objective cropping pattern optimization (Ma et al., 2022; Márquez et al., 2011; Sedghamiz et al., 2018; Zhang et al., 2023).

However, even though it has been acknowledged that the interregional VW flow is an indispensable part of the hydrological cycle under the influence of human activities in the context of open economy and society (D'Odorico et al., 2019), the existing scheme of regional cropping pattern optimization still focuses on local impacts from producer aspects, largely ignoring remote economic and environmental impacts driven by traders and consumers (Table 1). Another visible defect is that most of the current optimization schemes focus on environmental and economic impacts, and the social aspects are largely ignored. Several studies have shown that VW flows bring benefits in terms of water saving (Chapagain et al., 2006), economic return (Oki et al., 2017) and social equity (Xin et al., 2022) mainly in recipiant regions. However, other studies have highlighted the negative effects of VW flows on the origin regions, which forego their water resources but retain environmental pollutions due to the production excess products for export (Zhao et al., 2015; Dalin et al., 2017). It is essential to incorporate the benefits and negative effects of VW flows into the cropping pattern optimization framework to ensure the efficiency and fairness of regional agricultural water resources utilization. Currently, the water price of crop production rarely reflects its real economic value and scarcity due to various reasons such as insufficient water rights, governmental price protection. One of the main methods to evaluate the real value of water is to assess its shadow price (i.e., the marginal value generated by water resources, which is related to the optimal allocation of resources). The benefit of

Table 1
Representative literatures on regional cropping pattern optimization.

References	Objectives	Methodology	Study area	Consideration of virtual water
Márquez et al. (2011)	Maximizing gross margin; Minimizing water consumption	NSGA-II	Spain	No
Morankar et al. (2013)	Maximizing net benefits, crop production, labor employment	Fuzzy optimization	India	No
Davis et al. (2017)	Maximizing food production; Minimizing blue water use	Replacement analysis	Global	No
Sedghamiz et al. (2018)	Maximizing profits, share of green water	NSGA-II	Iran	No
Najafabadi et al., (2019)	Maximizing profit, virtual water import, use of labor; Minimizing cost	Robust optimization	Iran	Yes
Balezentis et al. (2020)	Maximizing water footprint, Shannon equitability index, total output	Linear optimization	Lithuania	No
Chouchane et al. (2020)	Minimizing blue water scarcity	Linear optimization	Global	No
Liu et al. (2021b)	Maximizing calorific production; Minimizing blue water footprint	NSGA-II	China	No
Liu et al. (2022)	Maximizing calorific value, blue water use benefits, ratio of the green water footprint, net crop benefit; Minimizing ecological effect,	Two-layer optimization	Northwest China & Central Asia	Yes
Ma et al. (2022)	Maximizing net profits; Minimizing groundwater extraction, food reduction	NSGA-II	Baoding, China	No
Li et al. (2023)	Maximizing net economic benefits, nutritional water productivity; Minimizing carbon emissions	NSGA-III	Hetao Irrigation District, China	No
Zhang et al. (2023)	Maximizing economic benefits, net carbon sink, water use efficiency; Minimizing soil	NSGA-II	Heihe River Basin, China	No

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Table 1 (*continued*)

References	Objectives	Methodology	Study area	Consideration of virtual water
	loss, nitrogen loss			
Xie et al. (2023)	Maximizing farmer incomes; Minimizing water demand, carbon emissions, fertilizer use, pesticide use	Linear optimization	China	No
This study	Maximizing crop economic output, benefit of virtual water; Minimizing blue water scarcity	NSGA-II	Yellow River Basin, China	Yes

VW flow is the combination of the shadow price of unit water resource and interregional VW flow, which can effectively reflect the equity and benefit (i.e., social impact) of water resource redistribution. Therefore, considering the benefits of VW flow in the optimization of cropping pattern helps broaden the scope of current concerns: enrolling social impact and involving the new perspective on traders and consumers.

The current study aims to coordinate multiple trade-offs among resources, economy and society in regional cropping patterns by proposing a two-stage multi-objective cropping pattern optimization scheme that incorporates the benefits of crop-related VW flows. Using the Yellow River Basin (YRB), China over 2004–2014 as a case study, the cropping pattern was optimized at provincial scale considering two goals: maximum crop economic output while minimum blue water scarcities (the first stage), and then the optimal cropping scheme was obtained by considering the maximum benefits of the interprovincial crop-related VW flows based on the shadow prices of crop green and blue water use (the second stage). This study provides two contributions. First, this is the first analysis to consider the impact of VW flow (trade) in the cropping pattern optimization, which is conducive to formulating optimization strategies from a more comprehensive and systematic perspective. Second, social impacts are considered in the optimization scheme. We considered ten crops (i.e., apple, cabbage, cotton, groundnut, maize, potato, rapeseed, soybean, tomato, and wheat) that are mainly cultivated in the watershed, while other staple crops (e.g., rice) in other regions outside the YRB were excluded. The optimization objectives were set based on the estimation and evaluation of shadow prices of green and blue water consumed in crop production in time and space by crops in the YRB (covering all provinces of Shanxi, Inner Mongolia, Shandong, Henan, Sichuan, Shaanxi, Gansu, Qinghai, and Ningxia). Finally, in order to fully consider the environmental, economic and social effects and potential of cropping pattern optimization, we selected and compared the optimization results under three typical hydrological years of the YRB: dry year (2006), normal year (2010), and wet year (2012).

The YRB was selected as a case study for three reasons. First, the YRB produces 13% of China's food with only 2% of blue water resource in the country (YRCC, 2013). The mismatch between water and land for crop production led to moderate or severer water scarcity (Omer et al., 2020; Ringler et al., 2010; Xie et al., 2020; Zhang et al., 2008). Second, the interprovincial crop-related VW flows have become intensive in the basin and over 40% of the water used for crop production is currently embedded in traded crops (Liu et al., 2021a; Zhao et al., 2022; Zhuo et al., 2022). Third, there are visible spatial heterogeneities in the harvested area and cropping structure among provinces within the YRB (Fig. 1).

2. Methods and data

The cropping pattern in the YRB was optimized by a two-stage optimization. In the first stage, the evolutionary algorithm was used to coordinate the trade-offs between natural and economic impacts caused by crop production, and a set of optimal solutions was obtained. In the second stage, the economic effect was considered as criteria to screen

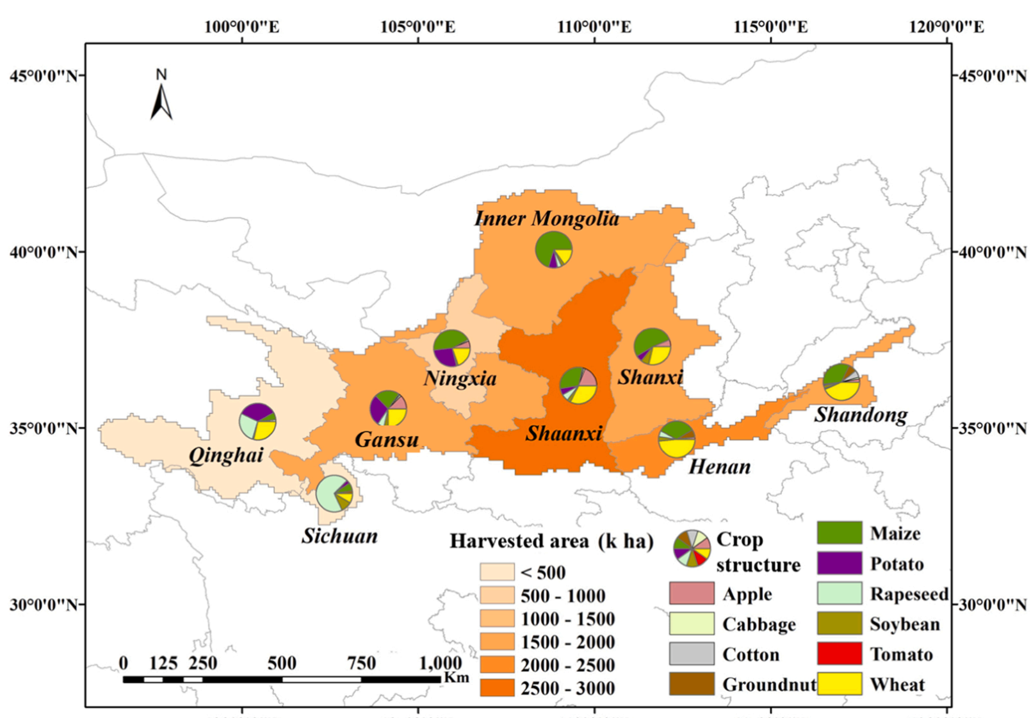

Fig. 1. Location and cropping structure of nine provinces within the Yellow River Basin by the year 2014.

the optimal cropping pattern from the optimal solution set. The flow chart of this study is shown in Fig. 2.

2.1. Two-stage optimization of cropping patterns in the YRB

The first stage was a nonlinear optimization for two objectives based on the NSGA-II proposed by Deb et al. (2002), which is an efficient multi-objective evolutionary algorithm, and has been widely used in the optimization of crop spatial redistribution (Abdelkader and Elshorbagy, 2021; Liu et al., 2021b; Márquez et al., 2011; Sedghamiz et al., 2018). In the multi-objective optimization of this study, the crop harvested areas were taken as decision variables, totaling 180 decision variables (i.e., the harvested area of each crop (totaling ten crops) in each province (totaling nine provinces) under irrigated or rain-fed conditions is a decision variable). Additionally, the harvested area of all the ten crops and the production of grain crops (wheat and maize) were the constraints, and the cropping structure of the 180 decision variables was optimized for the three hydrological years (i.e., dry year 2006, normal year 2010 and wet year 2012, which were identified by sorting frequency on the recent 30 years of annual precipitation within YRB) to measure the optimization potential of different hydrological years.

The first objective was to minimize the scarcity of blue water of the YRB. Blue water scarcity (BWS) is defined as the ratio of blue water consumption to blue water availability in the YRB. The water consumption of the agricultural sector was determined by the unit blue water footprint of specific crop, crop production (i.e., the yield multiplied harvested area of each crop) under irrigated environment.

$$\min BWS = \frac{\sum_{n=1}^{3} D_n + \sum_i \sum_c A_{ir}(i,c) \times Y_{ir}(i,c) \times uBWF(i,c)}{BWA} \tag{1}$$

where BWS is the overall blue water scarcity degree of the YRB, dimensionless; D_n (n = 1, 2, 3) is the water consumption of household, industry, and environment , respectively, m^3. $i = 1, 2.\ 9$ are the nine provinces in the YRB; c= 1,2. 10 are the ten crops in the YRB; $A_{ir}(i,c)$ (in ha) and $Y_{ir}(i,c)$ (in t/ha) are the area and yield of crop c in province i under irrigation, respectively; $uBWF(i,c)$ is the blue water footprint per unit yield, m^3/t; BWA is the blue water resources availability in the YRB, m^3. The methodology of $uBWF(i,c)$ was used according to Zhuo et al. (2016).

The second objective was the maximum economic output of crops in the YRB, that is, the product of crop market price and crop production.

$$\max \text{ Economic output } = \sum_i \sum_c Price_{i,c} \times P_{i,c} \tag{2}$$

where *Economic output* is the economic output obtained by selling crops at the local market price, *USD*; $Price_{i,c}$ indicates the market price of crop c in province i within the YRB, USD/t; and $P_{i,c}$ is crop production of crop c in province i including irrigated and rain-fed conditions, t. We selected crop production rather than crop sales as produced crops have economic value regardless of their subsequent use (e.g., self-consumption, loss, waste, seeds, storage, etc.).

We created constraints from two aspects: harvested area and crop production of grain crops (wheat, maize), to solve the above two objective functions.

2.1.1. (1) Constraints on harvested area of each crop

For the crop harvested area, the total cropping area in the YRB could not exceed that before optimization. Moreover, the rain-fed or irrigated area of crops in the basin was allowed to expand, but it could not exceed the maximum allowable area expansion coefficient α (expressed as the maximum ratio of the irrigated or rain-fed area of a crop in specific province after optimization to the area before optimization). We here took the value of α as 1.3 following the settings in the previous relevant literature by Chouchane et al. (2020). We created similar constraints for any crop c.

$$\begin{cases} \sum_{i,c} A_{rf}(i,c) + \sum_{i,c} A_{ir}(i,c) \le A_{ref} \\ \sum_{i,c} A_{rf}(i,c) \le \alpha \sum_{i,c} A_{ref,rf}(i,c) \\ \sum_{i,c} A_{ir}(i,c) \le \alpha \sum_{i,c} A_{ref,ir}(i,c) \\ \forall c, \sum_i A_{rf}(i,c) \le \alpha \sum_i A_{rf,ref}(i,c) \\ \forall c, \sum_i A_{ir}(i,c) \le \alpha \sum_i A_{ir,ref}(i,c) \end{cases} \tag{3}$$

where A_{ref} is sum of harvested areas of each crop in the YRB before

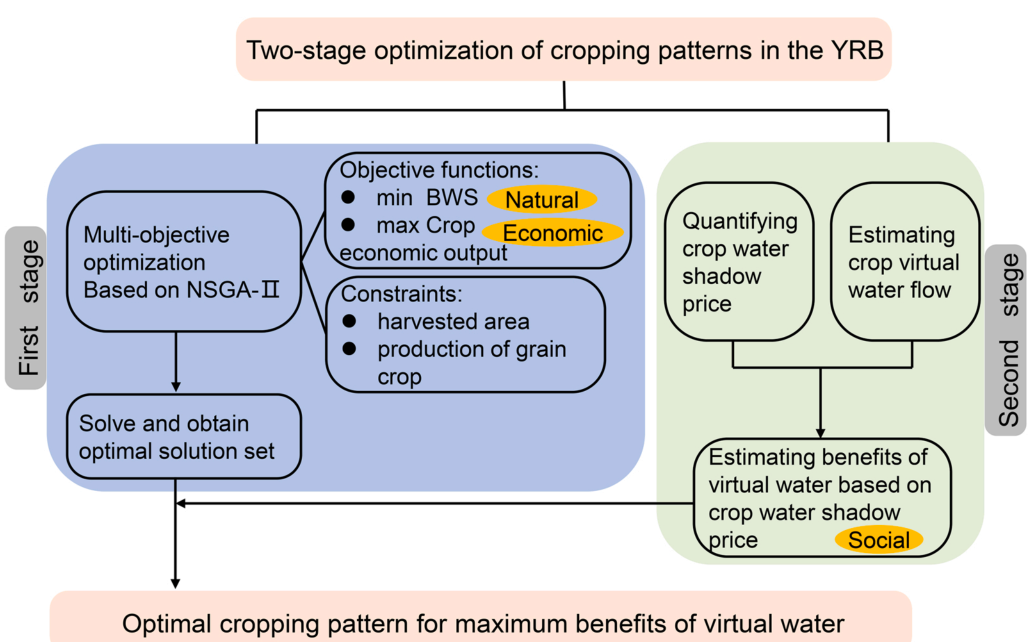

Fig. 2. Flow chart used in this study.

optimization, *ha*; $A_{rf}(i,c)$ and $A_{ir}(i,c)$ are rain-fed and irrigated areas after optimization for crop *c* in province *i*, *ha*; and α is the upper threshold of area expansion coefficient, which was mainly used to avoid excessive expansion of crop irrigated or rain-fed areas and ensure the changes within a reasonable range.

2.1.2. (2) Constraints on production of grain crops

Given the importance of grain crops (wheat, maize) for food security in the basin, this study further limited that the optimized production of wheat and maize could not be lower than the previous figure.

$$\begin{cases} \sum_i P_{i,wheat} \geq \sum_i P_{i,wheat,ref} \\ \sum_i P_{i,maize} \geq \sum_i P_{i,maize,ref} \end{cases} \tag{4}$$

where P_i (in *t*) is the production of wheat or maize in province *i* within the YRB, which was obtained from the product of crop harvested area and unit yield.

The second stage was to quantify the social benefits caused by VW flow. Specifically, the maximum benefits of crop-related VW flows based on water shadow price was taken as the criteria to screen the optimal solution set (i.e., cropping pattern). In the Sections 2.2 and 2.3, more details on the methods of quantifying crop water shadow price and benefits of crop related VW flows based on water shadow price would be introduced, respectively.

2.2. Quantification of crop water shadow price

The shadow price of water reflects the value of crops that can be produced by a marginal unit of water consumption (Bierkens et al., 2019). For better management, water resources are usually divided into blue (including surface water and groundwater) and green water resources (water from rainfall, stored in unsaturated soil and utilized by plants) (Falkenmark and Rockström, 2010; Rockström et al., 2009). Owing to the heterogeneity of provinces in terms of water resources and crop structures, the blue and green water shadow price of ten crops in the nine provinces in the YRB were quantified separately, which was divided into the following three main steps.

First, the contribution of blue and green water to crop production under irrigated and rain-fed conditions was distinguished following Zhuo et al. (2022) and Shang et al. (2021).

$$\begin{cases} P_b = \dfrac{Y_{ir} - Y_{rf}}{Y_{ir}} \times P_{ir} \\ P_g = P_{g,ir} + P_{rf} \\ P_{g,ir} = P_{ir} - P_b \end{cases} \tag{5}$$

where P_b and P_g are the crop production contributed by blue water and green water, respectively, *t*; Y_{ir} and Y_{rf} are the crop yield per unit area under irrigated and rain-fed conditions, respectively, t/ha; $P_{ir}$and P_{rf} refer to the crop production under irrigated and rain-fed conditions, respectively, *t*; and $P_{g,ir}$ is the crop production attributed to green water footprint under irrigated condition, *t*.

Second, the Cobb-Douglas production function was used for the regression analysis to obtain the regression coefficient β ($0 < \beta < 1$). The exponential and natural logarithm forms of Cobb-Douglas production function used in this study were as follows:

$$\begin{cases} P_g = \beta_0 \times A^{\beta A} \times X^{\beta X} \times GW^{\beta GW} \\ P_b = \beta_1 \times A^{\beta A} \times X^{\beta X} \times BW^{\beta BW} \\ \ln P_g = \ln\beta_0 + \beta_A \ln A + \beta_X \ln X + \beta_{GW} \ln GW \\ \ln P_b = \ln\beta_1 + \beta_A \ln A + \beta_X \ln X + \beta_{BW} \ln BW \end{cases} \tag{6}$$

where *A* is the cropping area, *ha*; *X* is the market input, including X_1, X_2, X_3, which are raw material, labor force and land input, respectively; *GW* and *BW* are the green and blue water footprint, m^3/y; β_{GW} and β_{BW} is the regression coefficient for the green and blue water footprint.

Third, the blue and green water shadow price of crops was calculated.

$$\begin{cases} MP_{green} = \beta_{GW} \times \dfrac{P}{GW} \\ MP_{blue} = \beta_{BW} \times \dfrac{P}{BW} \\ SP_{green} = Price \times MP_{green} \\ SP_{blue} = Price \times MP_{blue} \end{cases} \tag{7}$$

where MP_{blue} and MP_{green} are the marginal productivity of blue water and green water respectively, t/m^3; *Price* is the price corresponding to the crop per unit yield, USD/*t*; SP_{blue} and SP_{green} are the shadow prices of blue and green water, respectively, USD/m^3.

2.3. Estimation of associated benefits of crop-related interprovincial VW flows based on crop water shadow price

The associated benefits of crop-related inter-provincial VW flows of the YRB (*EVW*, in USD/*y*) were quantified according to the weighted water shadow price of crops in the basin after the optimization of cropping pattern, which was determined by the product of crop-related inter-provincial VW flows and crop water shadow prices. Here, we assumed the overall crop trade structure of the YRB remained unchanged before and after the optimization.

$$EVW = \sum_c VW_c \times SP_c \tag{8}$$

where VW_c is the VW flow of crop *c*, m^3; SP_c is the weighted water shadow price of specific crop *c* in the YRB, USD/m^3.

VW_c was obtained from the trade volume multiplying crop unit water footprint. Specifically, we first simulated the crop trade relationship among 31 provinces in China, and then downscaled the trade volume of the nine provinces within YRB. The crop trade volume among 31 provinces within China was quantified by the linear optimization algorithm proposed by Dalin et al. (2014), which was established on the principles of minimum trade cost and supply-demand relationship.

$$\begin{cases} \min\left(Cost_c = \sum_{i=1,j=1}^{i=31,j=31} T_{i,j,c} \times cost_{i,j,c} \right) \\ \sum_{j=1}^{j=31} T_{i,j,c} \leq S_{i,c}, i = 1\ldots31 \\ \sum_{i=1}^{i=31} T_{i,j,c} = D_{j,c}, j = 1\ldots31 \\ T_{i,j,c} \geq 0 \end{cases} \tag{9}$$

where $Cost_c$ is the total trade cost of crop *c*, *USD*; $T_{i,j,c}$ is the crop trade volume transported from province *i* to province *j*, t/y; $cost_{i,j,c}$ is the cost of transporting unit crops from province *i* to province *j*, USD/t; $S_{i,c}$ is the quantity of crop *c* used for export producing in province *i*, t/y; $D_{j,c}$ is the total demand for crop *c* in province *j*, t/y.

After obtaining the trade volume of crops among 31 provinces in China, we acquired the trade relations of province complete located in the YRB (only Ningxia). Then, for provinces partly located in the YRB (other eight provinces), the trade data were scaled down according to the proportion of the population within the basin and the whole province, following Zhuo et al. (2020). Finally, we multiplied the trade data by the unit production water footprint of the producing province to obtain the VW flows pattern of ten crops in the nine provinces in the YRB.

2.4. Data sources

The data on population, crop yield, and harvested area of the nine provinces in the YRB were obtained from the National Bureau of Statistics (CNKI, 2022); data on rainfall, domestic, industrial, and environmental water were obtained from the Water Resources Bulletin (MWRC, 2022); and data on material input, labor force and land used to calculate the shadow price of crop blue and green water were collected from China Agricultural Statistical Yearbook (CNKI, 2022). The market price of each crop came from the Compilation of Costs and Benefits of Agricultural Products (CNKI, 2022); The agricultural production data such as the effective irrigation area of crops and the irrigation area of irrigation mode at the provincial level were derived from the Yearbook of China's Agricultural Machinery Industry (CNKI, 2022). For provinces only partially located in the YRB, the yield and crop harvested area were aggregated within the basin scale based on grid data. The consumption data were distributed to the YRB based on the grid scale population distribution proportion of the YRB. The 2.5′ grid unit resolution population distribution in the YRB was obtained from the NASA Socio-Economic Data and Application Center (SE-DAC) (NASA, 2022); and the distribution proportion of irrigation area and rain-fed area of each crop grid scale was taken from mirca2000 database (Portmann et al., 2010). To ensure comparability and avoid the impact of price changes, economic related data were converted to constant prices based on the initial year of this study in 2004.

3. Results

3.1. Blue and green water shadow price in crop production

The blue and green water shadow prices of ten crops in nine provinces of the YRB from 2004 to 2014 are shown in Fig. 3. Overall, the shadow prices of blue and green water of staple food crops with larger production scale were markedly lower than those of cash crops. The blue and green water shadow prices of maize, wheat and soybean were less than 1 USD in all provinces. While the blue and green water shadow prices in vegetables (including cabbage, potato and tomato) were two orders of magnitude higher than those of staple food crops. This can be explained as vegetables have higher water use efficiency and market price than wheat and maize.

As the shadow price of blue water for apple and rapeseed was 0, blue water could not be the restriction for these two crops. Therefore, we focused on their green water shadow price. The multi-year average green water shadow price of apple in Shandong province was the highest (8.4 USD/m^3), since Shandong province belongs to the northern region with less rainfall, while the market price of apple was higher than that of other crops. This result indicates that the additional green water resources will bring more marginal benefits to apple production in Shandong province. The multi-year average green water shadow price of rapeseed was much lower than that of apple (the largest is 0.2 USD/m^3 in Sichuan province), which implied that the economic benefits of rapeseed selection will be less when both crops can be planted.

We selected representative crops from three categories (staple foods, oils, and vegetables) for further analyze. The multi-year average blue and green water shadow price of wheat were the highest in Henan (0.3 and 0.4 USD/m^3 for blue and green water, respectively) (Fig. 3a). Henan, as the main wheat producing area, has natural resource endowment and advanced production technology (e.g., advanced agricultural mechanization and field management). The multi-year average blue water shadow price of soybean was the highest in Inner Mongolia (0.1 USD/m^3 for blue or green water), as Inner Mongolia has Hetao Irrigation Area (the largest designed irrigation area in China) with advanced irrigation technology. Additional investment in irrigation in these areas can produce higher economic returns. The multi-year average green water shadow price of soybean in Shandong was the highest (0.1 USD/m^3), which was caused by the scarcity of green water

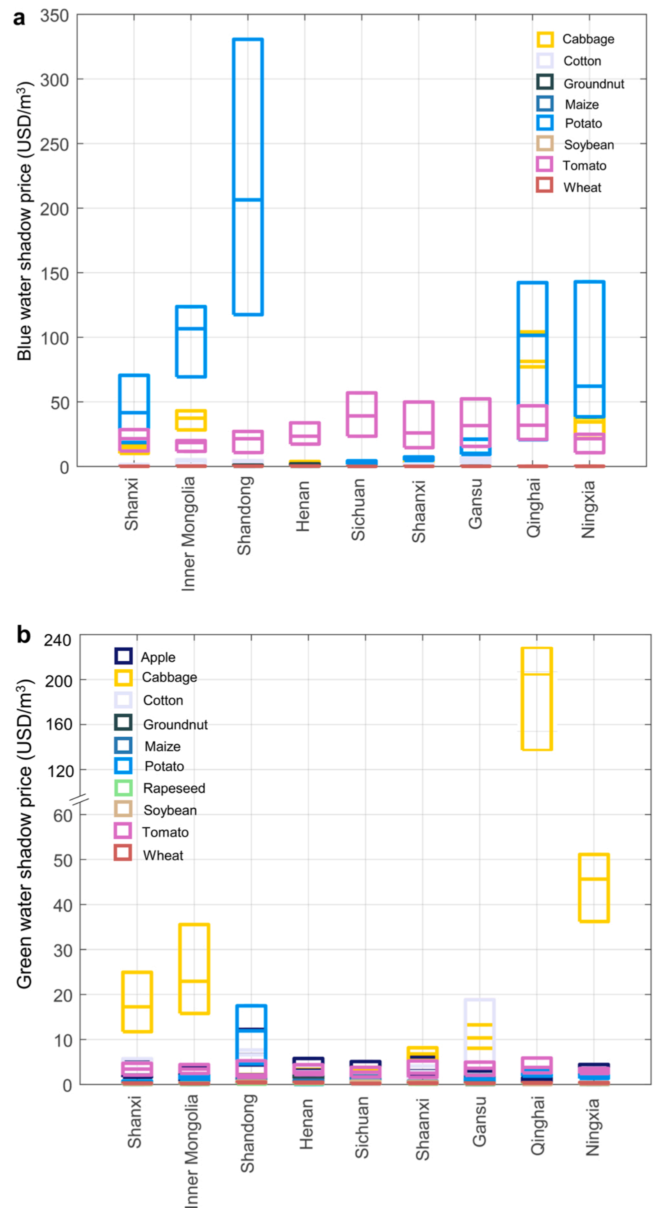

Fig. 3. Shadow prices of blue (a) and green water (b) of ten crops in nine provinces within the Yellow River Basin from 2004 to 2014.

in Shandong (Fig. 3b). The multi-year average shadow price of blue and green water of Chinese cabbage in Qinghai province was much higher than that in the other eight provinces, where the shadow price of green water exceeded 160 USD/m^3, while most provinces were less than 16 USD/m^3. As Qinghai province has the lowest annual average temperature of the YRB, which is conducive to the production of Chinese cabbage.

3.2. Multi objective cropping structure optimization results and benefits of crop-related interprovincial VW flows

Fig. 4 shows the Pareto optimal solution set of optimizations of cropping pattern in the YRB based on NSGA-II algorithm in dry year (2006), normal year (2010) and wet year (2012). The optimized blue water scarcity in dry, normal, and wet year decreased by 14.1–15.6%, 16.0–16.8% and 24.8–25.4%, respectively, while the economic output increased by 1.1–7.3%, 2.2–8.7% and 1.1–7.2%, respectively. In addition, the optimized crop harvested area decreased by 0.1–5.4% (Fig. 4). This phenomenon proved the possibility of adjusting cropping pattern

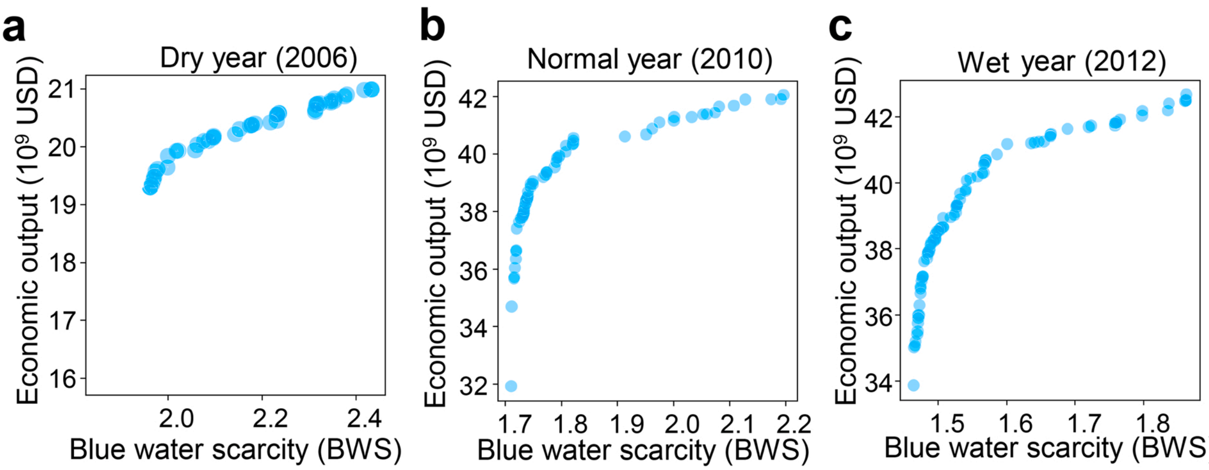

Fig. 4. The Pareto solution set of minimum blue water scarcity (BWS) and maximum crop economic output in three typical hydrological years based on the NSGA-II algorithm. Each point represents an optimization result.

by using multi-objective optimization algorithm to reduce the shortage of blue water and achieve economic outputs without the limitation of crop area expansion.

Compared with the value before optimization, the optimized benefits of VW flow of crops in the YRB based on the water shadow price surged in different hydrological years (Fig. 5). The benefits of crop VW flow in

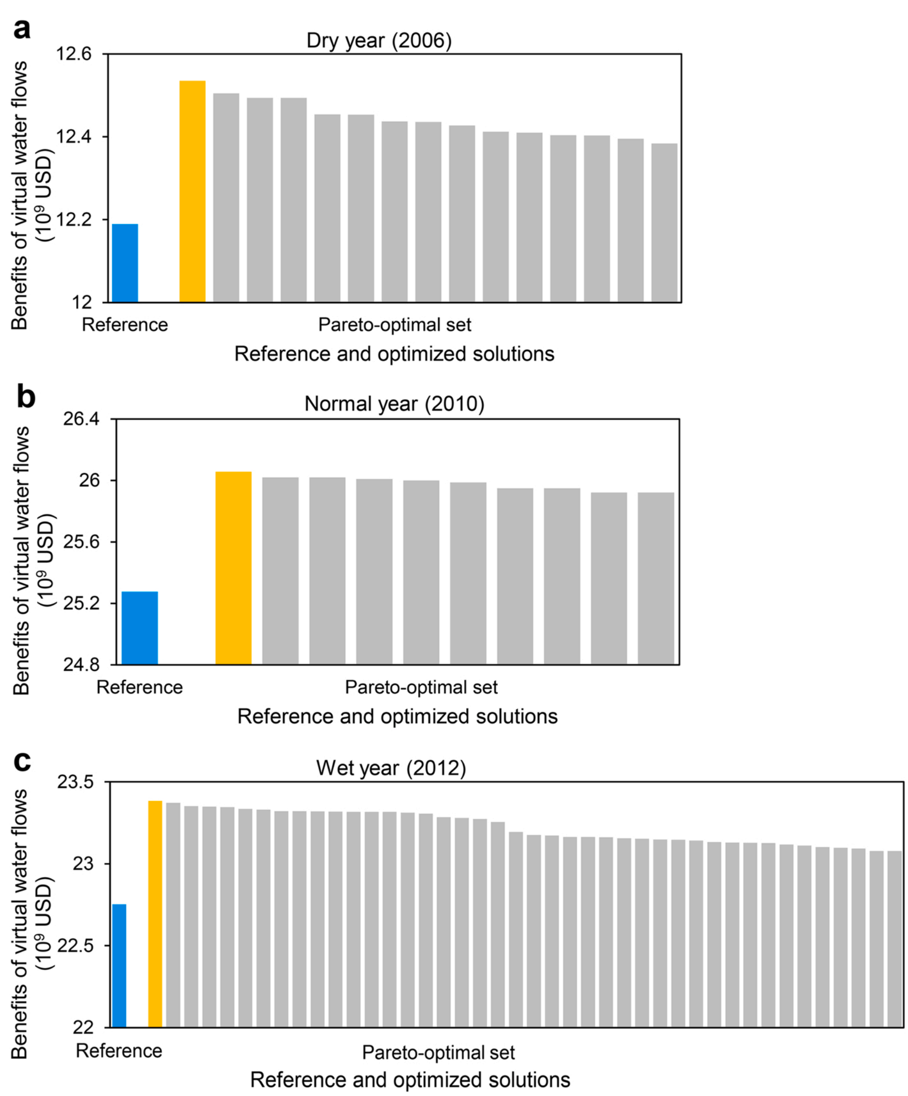

Fig. 5. Benefits of crop-related interprovincial virtual water flows based on crop water shadow price before (Reference) and after optimization (Pareto optimal set) in the Yellow River Basin.

dry, normal, and wet year increased by 1.6%– 2.8%, 2.6%– 3.1% and 1.4%– 2.8%, respectively. The sum of maximum benefits of VW flow of the crops after optimization was 12.53, 26.06 and 23.39 billion USD, respectively, in the three years. The benefit of VW flow decreased slightly in wet year as the planting proportion of staple crops (wheat and maize) with relatively low water shadow prices increased in wet year. The benefits of crop VW flow in the YRB in the normal year increased by 800 million USD after optimization, demonstrating that the benefits of VW trade in the whole YRB could be increased by adjusting the current cropping pattern.

We compared the provincial crop harvested area before (Fig. S1) and after (Fig. 6) optimization and the benefits based on the VW flows. Shaanxi and Henan had the largest wheat production areas and were the main wheat export provinces. The benefits of wheat VW exported by Shaanxi to Sichuan during wet year were up to 337 million USD. After optimization, Inner Mongolia, Shanxi and Sichuan were the provinces with the largest decline in wheat harvested area, decreasing by 77%, 72% and 61%, respectively, in wet year, whereas Henan, Shandong and Gansu increased slightly. After optimization, the maize harvested area in Qinghai, Sichuan and Inner Mongolia decreased by ~50%, whereas that in Gansu, Ningxia and Shanxi increased by 25%. After optimization, Shaanxi and Henan had become the largest contributors of maize VW import in Sichuan. The benefits of maize-related VW flow in wet year reached 503 and 230 million USD, respectively. Inner Mongolia shifted from a province mainly exporting maize to a self-sufficient province, which alleviates its pressure on blue water resource scarcity.

3.3. Redistribution scheme of cropping patterns of the YRB incorporating benefits of crop-related interprovincial VW flows

Fig. 7 illustrates blue water scarcity, economic output, harvested area and crop production under before optimization and optimized solutions with the greatest benefit of VW flow in different hydrological years. Compared with that before optimization, the optimized blue water scarcity and harvested area in the YRB dropped sharply, especially the blue water scarcity and harvested area in the wet year decreased by 25.3% and 4.3%, respectively (Fig. 7a and Fig. 7c). Economic output and crop production showed the opposite trend, increasing by 7.2% and

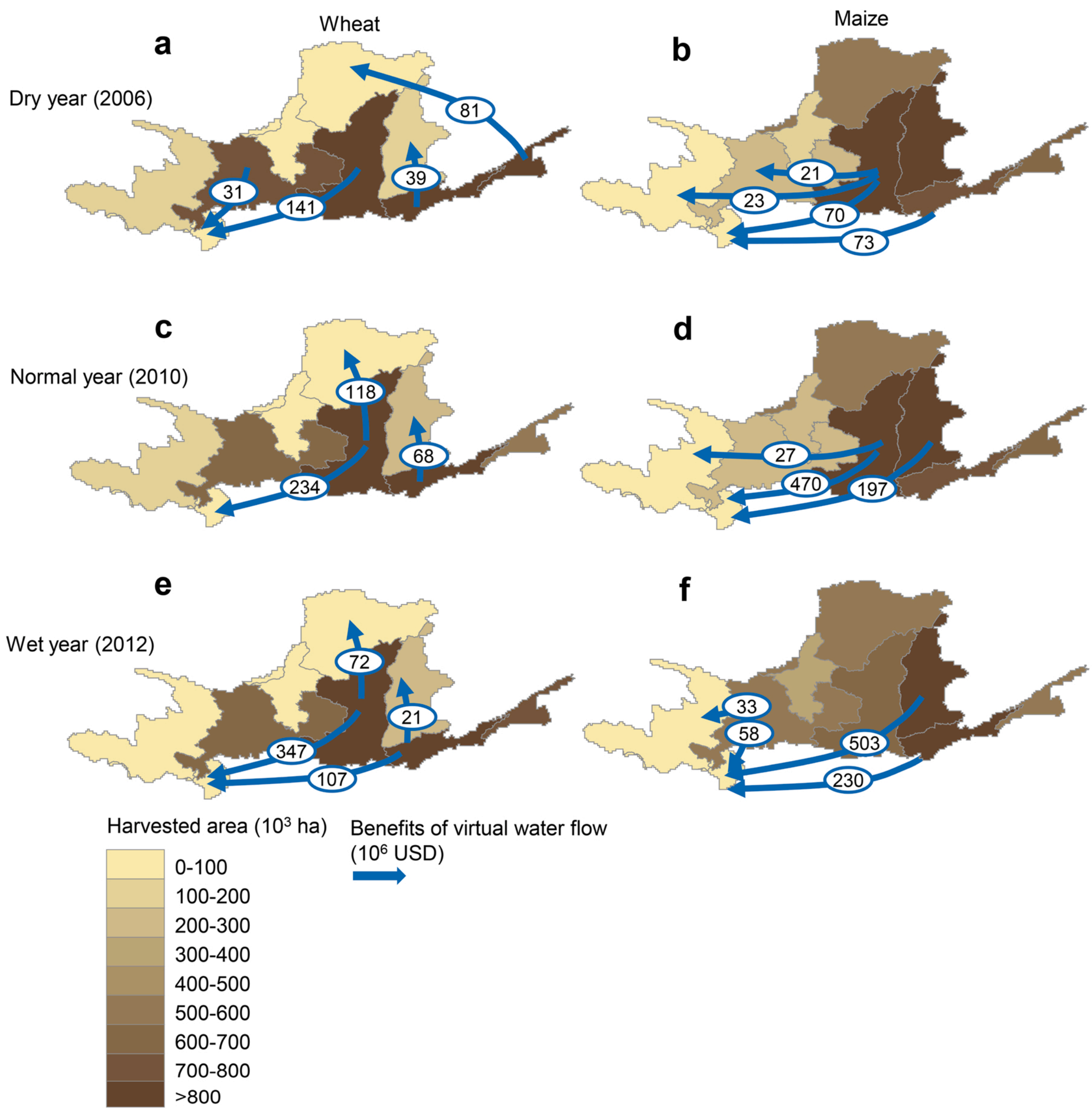

Fig. 6. Optimized provincial crop harvested area and the benefits of crop-related interprovincial virtual water flows based on crop water shadow price of wheat and maize. The background indicates the crop harvested area of the optimal scheme screened under the condition that the maximum benefit of virtual water flows, and the blue arrow indicates the benefit of the virtual water flows in terms of the optimal scheme. Here, values lower than 20 million USD were omitted for simplicity.

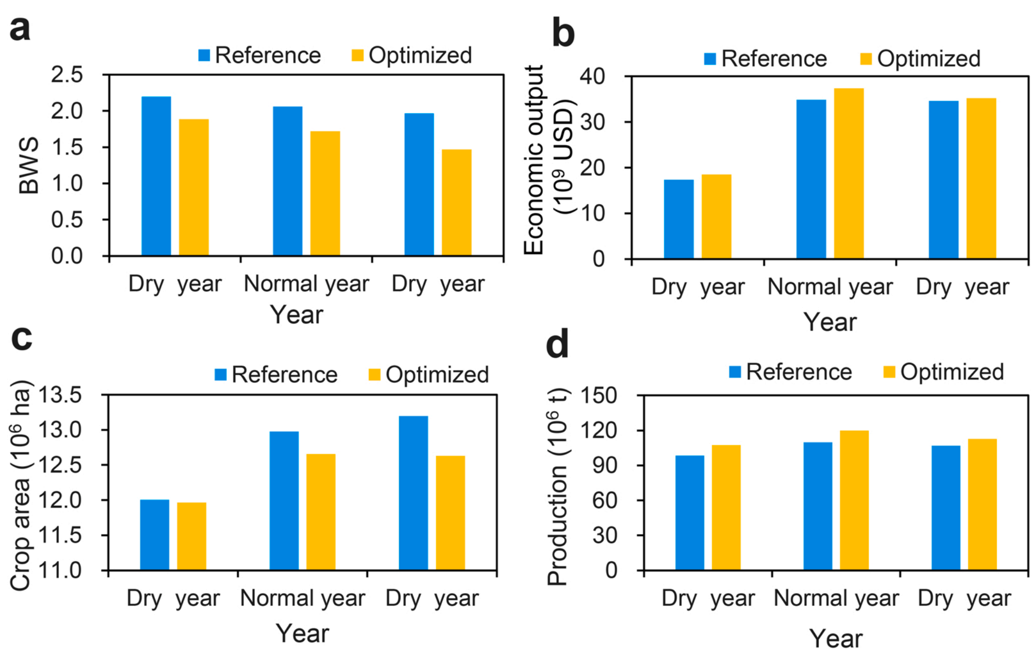

Fig. 7. Comparison of (a) blue water scarcity (BWS), (b) crop economic output, (c) crop harvested area and (d) crop production before and after cropping structure optimization under different hydrological years.

9.2%, respectively, in normal year (Fig. 7b and Fig. 7d).

Furthermore, more information on optimized irrigation, rain-fed areas, and crop production of each crop was observed in terms of the irrigation mode and specific crops (Table 2). The overall characteristics of the optimized irrigation and rain-fed area in different hydrological years were similar. The recommended strategy is to reduce the irrigation area and appropriately expand the rain-fed harvested area, especially the crops with low water shadow price. Furthermore, the irrigation area of soybean (63%) should be substantially reduced in dry year as its water shadow price was relatively low (Table 2). The water resources saved by reducing soybean production could be used to slightly expand the irrigation area of maize (2%) and potato (18%) in dry year, as these crops have higher crop yield. Appropriately expanding their irrigation area could increase their production by 2% and 26%, respectively, which is conducive to meeting the restriction that no reduction for the total crop production in the YRB. Although the optimized irrigation area of wheat in dry year was only 17% lower than that before optimization, wheat has the largest reduction in irrigation area (516 thousand ha) due to its largest irrigation area base.

From dry year to wet year, the most remarkable characteristic was that the cropping pattern shifted to expanding grain crops (wheat and maize) and compressed cash crops with the increase in rainfall. The irrigation areas of maize and wheat increased markedly (119 and 35 thousand ha, respectively) with the increased rainfall. Accordingly, crop production increased by 7 and 1 million tons, respectively. Another visible change was that the irrigation scale of cash crops in the wet year was considerably lower than that in the dry year. For instance, the irrigated areas of cotton, apple, and peanut decreased by 113 (55%), 57 (53%) and 32 (48%) thousand ha, respectively, in the wet year compared with the dry year.

Table 3 further exhibits the changes in the harvested area of crops in different hydrological years in specific province before and after the optimization based on the maximum benefit of VW flow. We found that the harvested area of the dominant producing areas of each crop expand after optimization. In contrast, provinces with low productivity showed compress the harvest area. For instance, the major apple-producing areas in Shaanxi and Gansu increased by 148 (31%) and 55 (24%) thousand ha, respectively, after the optimization in the normal water

Table 2
Optimized crop area and production of each crop based on the maximum benefit of virtual water flow at different hydrological years.

	Apple	Cabbage	Cotton	Groundnut	Maize	Potato	Rapeseed	Soybean	Tomato	Wheat
Dry year (2006)										
Irrigated area (10^3 ha)	107 (−45%)	21 (−31%)	204 (−8%)	66 (−33%)	2518 (2%)	57 (18%)	25 (−88%)	85 (−63%)	22 (6%)	2454 (−17%)
Rainfed area (10^3 ha)	706 (24%)	81 (14%)	226 (0%)	240 (26%)	1546 (18%)	1082 (9%)	313 (12%)	346 (−9%)	45 (−9%)	1822 (27%)
Production (10^6 t)	10 (5%)	15 (1%)	0.1 (2%)	1 (1%)	21 (2%)	38 (26%)	0.1 (−28%)	0.2 (−39%)	3 (1%)	19 (2%)
Normal year (2010)										
Irrigated area (10^3 ha)	190 (−2%)	26 (−18%)	66 (−65%)	20 (−81%)	2590 (−1%)	52 (−1%)	40 (−84%)	42 (−81%)	21 (−5%)	2482 (−18%)
Rainfed area (10^3 ha)	902 (22%)	81 (−6%)	112 (−2%)	222 (10%)	1953 (7%)	1448 (19%)	294 (−12%)	339 (−2%)	60 (0%)	1715 (27%)
Production (10^6 t)	15 (15%)	18 (7%)	0.2 (−50%)	1 (−38%)	25 (2%)	39 (24%)	0.1 (−41%)	0.3 (−48%)	4 (−3%)	19 (0%)
Wet year (2012)										
Irrigated area (10^3 ha)	50 (−75%)	18 (−45%)	91 (−46%)	34 (−69%)	2637 (−2%)	55 (1%)	38 (−84%)	33 (−84%)	20 (−11%)	2489 (−17%)
Rainfed area (10^3 ha)	1036 (30%)	115 (22%)	80 (−4%)	242 (21%)	1856 (−9%)	1468 (19%)	316 (−4%)	312 (−4%)	69 (6%)	1671 (28%)
Production (10^6 t)	16 (3%)	18 (6%)	0.2(−43%)	1 (−19%)	28 (1%)	27 (21%)	0.1 (−36%)	0.3 (−39%)	4 (−4%)	20 (0%)

Note: the values in the parentheses represent the percentage change of the optimized crop area or production compared to that before optimization.

Table 3
Optimized crop area of each crop for specific province based on the maximum benefit of virtual water flow at different hydrological years.

	Apple	Cabbage	Cotton	Groundnut	Maize	Potato	Rapeseed	Soybean	Tomato	Wheat
Dry year (2006)										
Shanxi	-13 (−13%)	0 (−1%)	20 (13%)	27 (19%)	0 (−3%)	-112 (−83%)	-80 (−71%)	-1 (−57%)	-1 (−39%)	0 (0%)
Inner Mongolia	-4 (−67%)	4 (19%)	-12 (−16%)	0 (−19%)	66 (8%)	154 (33%)	-6 (−8%)	-2 (−28%)	-341 (−69%)	0 (0%)
Shandong	1 (2%)	-8 (−42%)	0 (−91%)	-16 (−79%)	40 (18%)	10 (28%)	0 (−59%)	0 (−1%)	-208 (−91%)	0 (0%)
Henan	7 (16%)	0 (22%)	-51 (−61%)	0 (−78%)	0 (4%)	9 (6%)	2 (1%)	-1 (−65%)	163 (25%)	343 (31%)
Sichuan	0 (−97%)	1 (3%)	10 (21%)	0 (32%)	-18 (−10%)	1 (26%)	-19 (−20%)	0 (2%)	343 (31%)	0 (−42%)
Shaanxi	25 (7%)	4 (23%)	0 (−36%)	0 (−85%)	15 (18%)	9 (16%)	-28 (−63%)	-2 (−14%)	0 (−42%)	-58 (−6%)
Gansu	45 (25%)	1 (24%)	0 (−14%)	132 (19%)	18 (12%)	-1 (−32%)	-75 (−63%)	0 (−69%)	-58 (−6%)	163 (27%)
Qinghai	0 (15%)	-1 (−22%)	2 (24%)	-194 (−28%)	6 (25%)	-1 (−1%)	0 (−29%)	3 (15%)	163 (27%)	10 (8%)
Ningxia	-11 (−56%)	16 (20%)	-3 (−63%)	133 (27%)	0 (−47%)	-2 (−86%)	-55 (−41%)	-2 (−17%)	10 (8%)	-197 (−79%)
Normal year (2010)										
Shanxi	-19 (−20%)	1 (25%)	-38 (−28%)	-37 (−24%)	0 (−12%)	4 (3%)	-102 (−75%)	0 (−14%)	-3 (−56%)	0 (0%)
Inner Mongolia	-3 (−51%)	-3 (−12%)	-29 (−59%)	0 (−94%)	217 (25%)	92 (18%)	16 (20%)	-5 (−30%)	-313 (−57%)	0 (0%)
Shandong	5 (13%)	-14 (−70%)	0 (−36%)	-20 (−85%)	-71 (−19%)	18 (22%)	0 (−19%)	0 (0%)	-260 (−97%)	0 (0%)
Henan	-10 (−23%)	0 (−19%)	-41 (−83%)	0 (12%)	-2 (−32%)	70 (31%)	-13 (−10%)	0 (27%)	-84 (−13%)	361 (32%)
Sichuan	0 (−76%)	-1 (−3%)	-11 (−37%)	0 (−22%)	-18 (−8%)	-3 (−67%)	-18 (−22%)	-1 (−5%)	361 (32%)	0 (−21%)
Shaanxi	148 (31%)	3 (17%)	0 (−11%)	0 (5%)	6 (6%)	1 (1%)	-23 (−60%)	-1 (−5%)	0 (−21%)	201 (21%)
Gansu	55 (24%)	1 (24%)	0 (10%)	210 (24%)	35 (20%)	0 (−18%)	-53 (−54%)	0 (−66%)	201 (21%)	74 (13%)
Qinghai	0 (3%)	0 (−5%)	-4 (−53%)	-342 (−38%)	6 (23%)	-15 (−11%)	0 (−4%)	1 (7%)	74 (13%)	19 (23%)
Ningxia	-19 (−46%)	-8 (−19%)	-1 (−17%)	103 (20%)	0 (−49%)	-2 (−68%)	-43 (−33%)	1 (9%)	19 (23%)	-172 (−82%)
Wet year (2012)										
Shanxi	-4 (−4%)	-2 (−90%)	-51 (−42%)	17 (11%)	0 (−53%)	-59 (−40%)	-110 (−85%)	0 (−55%)	-4 (−67%)	0 (0%)
Inner Mongolia	-1 (−20%)	-10 (−42%)	-8 (−31%)	0 (9%)	-259 (−30%)	138 (25%)	16 (22%)	-6 (−48%)	-315 (−61%)	0 (0%)
Shandong	-16 (−38%)	1 (7%)	0 (−86%)	-23 (−93%)	126 (32%)	2 (3%)	0 (−4%)	1 (8%)	-222 (−77%)	0 (0%)
Henan	-6 (−14%)	0 (−17%)	-18 (−39%)	0 (−13%)	-8 (−61%)	67 (31%)	-63 (−47%)	-1 (−60%)	127 (19%)	264 (23%)
Sichuan	0 (−81%)	4 (12%)	9 (30%)	0 (7%)	56 (23%)	1 (23%)	-14 (−23%)	4 (24%)	264 (23%)	0 (−72%)
Shaanxi	54 (11%)	8 (34%)	0 (−45%)	0 (−92%)	27 (27%)	-35 (−64%)	-25 (−70%)	3 (19%)	0 (−72%)	29 (3%)
Gansu	79 (32%)	1 (20%)	-1 (−59%)	146 (16%)	53 (30%)	0 (−22%)	-54 (−53%)	0 (−5%)	29 (3%)	118 (23%)
Qinghai	0 (14%)	2 (20%)	-5 (−67%)	-461 (−44%)	7 (30%)	-20 (−14%)	0 (−26%)	2 (9%)	118 (23%)	-26 (−34%)
Ningxia	-13 (−32%)	-11 (−43%)	-4 (−61%)	77 (15%)	0 (−10%)	-2 (−75%)	-21 (−17%)	-1 (−9%)	-26 (−34%)	-117 (−65%)

Note: the values in the parentheses represent the percentage change of the optimized crop area compared to that before optimization.

year. In dry year, the harvested area of potatoes in Inner Mongolia increased by 154 (33%) thousand ha due to the higher water productivity, while that in Shanxi decreased by 112 (83%) thousand ha. More details on optimized crop harvested area are given in Tables S2-S4.

Fig. 8 depicts the spatial distributions of the percentage changes in the blue water footprint and economic output of grain crops (wheat and maize) based the maximum benefit of VW flow in different hydrological years. Spatial analysis showed that multi-objective optimization considerably reduced the crop blue water footprint in water-scarce provinces. Shanxi, Inner Mongolia and Ningxia province had the substantial reductions (1309.2, 1004.1 and 767.7 million m^3, respectively) in wheat blue water footprint after optimization in the dry year. A consistent trend was also observed in normal year and wet year. On the contrary, the blue water footprint of Henan and Shandong province increased by 657.1 and 570.0 million m^3, respectively, in the dry year. This was caused by the differences in wheat economic productivity per unit of water resources in these provinces. The increase in the wheat blue water footprint in Henan was only half the reduction in Shanxi, while the economic output of wheat in Henan (~450 million USD) was 1.5-fold higher than that of Shanxi (~300 million USD).

However, the opposite trend was observed for maize. The blue water footprint of Shanxi in different hydrological years increased by 135.5, 167.1 and 57.9 million m^3, respectively, compared to that before optimization. With these increases, the corresponding crop economic output increased by 250, 400 and 240 million USD, respectively, indicating that Shanxi province had a comparative advantage in maize production. Inner Mongolia, a province with water scarce, also showed the maximum potential of 700 million m^3 for reducing the blue water footprint of grain crops.

4. Discussion

In the current study, we considered the maximum crop economic output while minimum blue water scarcities. We employed NSGA-II to optimize the cropping patterns of ten crops in nine provinces within the YRB in different hydrological years, especially considering the

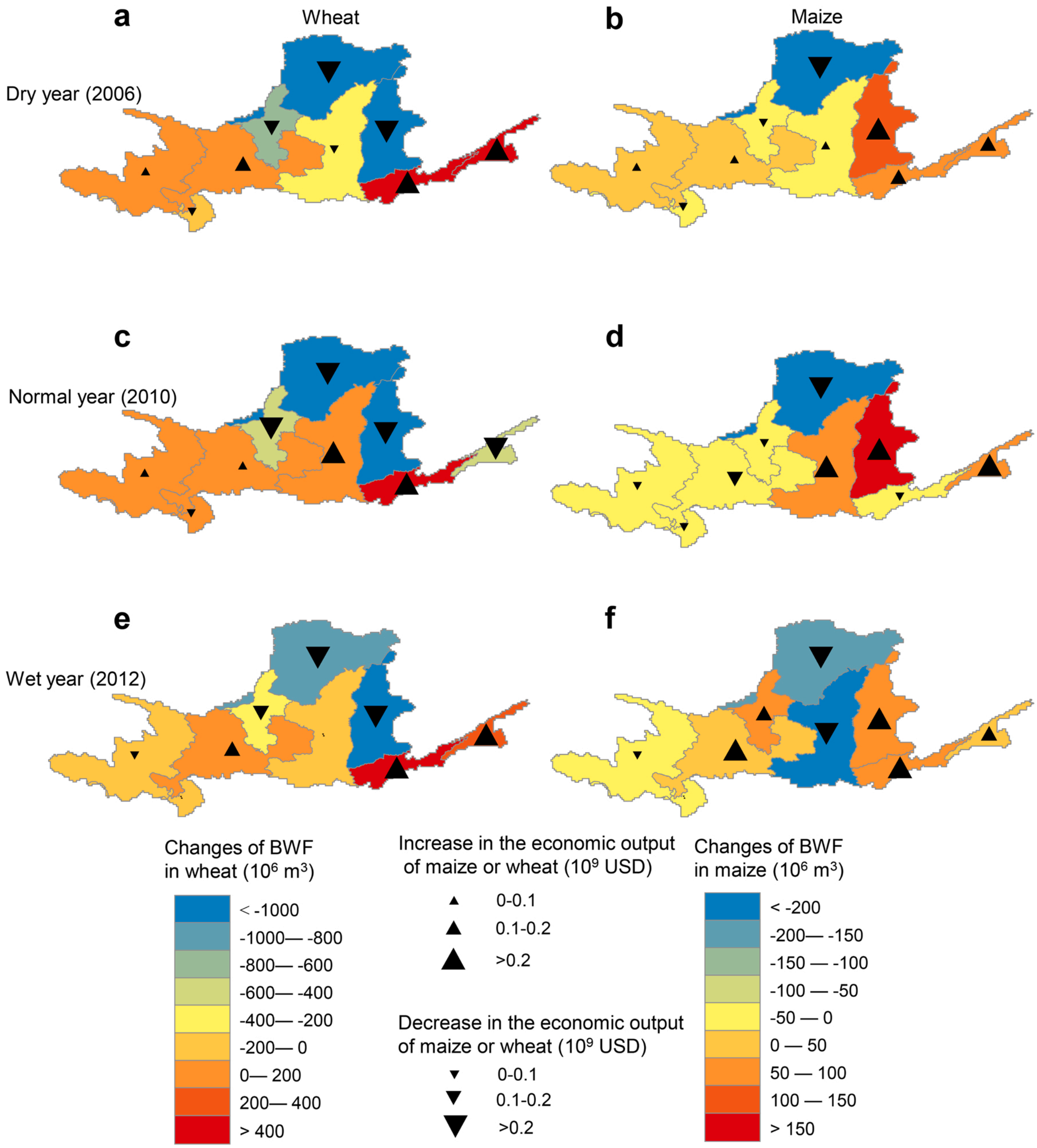

Fig. 8. Spatial distribution of changes in blue water footprint (BWF) and crop economic output in (a) wheat and (b) maize in different hydrological years after cropping structure optimizations. The black positive triangle and inverted triangle represent the increase and decrease of economic output compared with that before optimization, respectively.

maximum benefits of crop-related interprovincial VW flows based on crop water shadow price to evaluate the optimized solutions for the first time. The results demonstrate that the YRB can realize multiple environmental, economic and social benefits without expanding the existing cultivated land area through the optimization of cropping structure.

We found an evident trade-off between reducing blue water scarcity and increasing crop economic output. Nevertheless, the optimization of cropping pattern in the YRB can alleviate the shortage of blue water by ~20% and increase crop-related economic output by ~5% compared with the current crop production pattern. These findings support previous research results on the benefit of crop redistribution on blue water savings, crop production and economic output increase at different scales (Davis et al., 2017; Liu et al., 2021b; Liu et al., 2022; Xie et al., 2023). As such, regional cropping pattern optimization can serve as a potential supplementary solution to bridge the gap between technology and yield in crop production, which requires significant financial expenditures (Davis et al., 2017). However, this study has insufficient advantages in terms of crop production and economic output compared to previous studies, mainly for two reasons. First, the optimization area of this study is limited to the basin scale, and the spatial heterogeneity of agricultural production within the basin is smaller than that in global and national scale. Secondly and more importantly, this study incorporated VW flows into the regional cropping pattern optimization scheme by considering the benefits of crop-related inter-provincial VW flows based on the crop water shadow price. Considering the benefits of VW flows, it may weaken the performance of other objectives. In the current study, the benefits of VW flows showed that the adjustment of cropping mode could increase the benefit related to VW flows of up to 800 million US dollars (~3%) in the YRB, which provides a new possibility for alleviating regional water pressure and improving the benefits related to crop trade through VW trade. These potential benefits can be realized owing to the spatial heterogeneity of crop characteristics, water or land resource endowment and agricultural technology. In terms of crops, the principal change before and after optimization is that wheat is greatly converted from irrigation to rain-fed cultivation, and the harvested area of potato and apple with high water use efficiency is appropriately expanded. These changes not only ensure food security, but also maximize benefits. Spatially, Gansu and Ningxia have significantly lower water use efficiency than other provinces within the YRB due to relatively backward production technology and higher crop evapotranspiration. In contrast, Henan, Shandong and Inner Mongolia have comparative advantages in wheat and maize production as the better land, light and heat resource endowments and technical advantages brought about intensive production. (Table 4).

The dominant strategy to reduce the blue water scarcity and increase crop economic output is to substantially reduce the irrigation area of most crops while accordingly expand the rain-fed area, which is similar to the results obtained by Chouchane et al. (2020) on a global scale. Especially in dry year, as the huge heterogeneity of crop water shadow prices in different crops and regions, the recommended measures are reduction of the irrigation area of crops with relatively low shadow price of blue water (e.g., rapeseed and soybean), and use the saved blue water to produce crops with higher benefits or unit yield (e.g., maize or potato). Such a shift means that feasible, dynamic adjustment of cropping pattern is also a measure worthy of consideration. In addition, the wheat harvested area in the YRB has been compressed in recent years while the production scale of cash crops (apples, cotton, and peanuts) is growing annually. Although this will certainly alleviate the shortage of blue water and bring higher economic outputs, it may undermine regional food security. Therefore, it is imperative to consider the multiple trade-offs between blue water shortage, economic interests and food security into account.

Spatial analysis demonstrated that the specific optimization strategy of cropping patterns has regional heterogeneity. For instance, it is recommended that Shanxi province, which has water scarcity, should shift the current pattern of wheat production to maize, which would reduce the blue water consumption of the province. Furthermore, the increase in maize production in Shanxi could effectively alleviate the increasing crisis of feed crop self-sufficiency under the general trend of transformation to meat of dietary structure in China (Liu et al., 2021b). Note that not all provinces benefit equally after optimization. Wheat production in Henan province and Shandong province is not only dominant in the YRB, but in the whole China. However, the optimized results show that the blue water footprint of wheat production in Henan province has increased by 657.1 and 570.0 million m^3 compared with that before optimization, which is closely related to the higher water and the economic productivity in Henan province. It is necessary to expand the harvested area as much as possible in the provinces with higher crop productivity, as the optimal solution set on the premise of the maximum benefit of VW flow. The water economic productivity of wheat in Henan province is much higher than that of other provinces. Optimization brought considerable benefits but resulted in a remarkable increase in the blue water footprint of Henan province.

Table 4
Comparison of maximum blue water savings, production increase, economic output increase, and benefit of virtual water with previous study.

Reference	Blue water savings	Production increase	Economic output increase	Benefit of virtual water increase
Davis et al. (2017)	12%	19%	-	-
Liu et al. (2021b)	16%	12%	-	-
Liu et al. (2022)	23%	8%	18%	-
Xie et al. (2023)	19%	0%	8%	-
This study	20%	9%	5%	3%

Several realistic factors should be considered to achieve the above objectives. Previous studies have shown that agricultural production and trade policies, agricultural infrastructure development and human capital may be more crucial restrictive factors affecting cropping patterns and VW trade than water or soil resources endowments (Chouchane et al., 2020; Huang et al., 2021; Wang et al., 2021; Yu et al., 2021; Zhao et al., 2019). The possibility of achieving the dual objectives of resource conservation and social benefits has been proved to be technologically feasible. However, the constraint condition of this study only included the two factors of cultivated land area and crop production, while crop distribution is also affected by natural resource endowment, climate conditions, local culture, regional dietary preference, labor force, technology, capital, and other factors (Abdelkader and Elshorbagy, 2021; Davis et al., 2017; Reed et al., 2013; Smilovic et al., 2019), which will hinder the realization of the goal of this study. For instance, we found that transformation from wheat to maize production in Shanxi province can effectively alleviate the shortage of blue water and increase the benefits of VW flow. However, the optimization scheme is probably blocked by historical background of diet as Shanxi is a typical flour-based province. Therefore, actual cropping pattern adjustment needs to consider more dimensional factors to ensure its feasibility.

This study had three major limitations. First, this study took the provincial scale of the YRB as the basic spatial research unit, which is limited by data availability and computing cost. However, crop productivity has spatial heterogeneity within provinces, which was not considered in this study. Additionally, blue water scarcity was based on the provincial unit, which would mask the water shortage in specific space or time in the province (Mekonnen and Hoekstra, 2016). Nevertheless, the provincial-level information provided in this study is effective because this would be as the fundamental decision-making unit on crop structure redistribution or VW trade. Second, this study took the YRB as a whole when considering the benefits of VW flow and assumed that the trade pattern between the basin and the outside basin remains unchanged before and after optimization. Such assumptions slightly increase the uncertainty in estimating the benefits of the VW flow. However, this assumption was conducive to capturing the dynamic information of cropping structure adjustment of provinces within the basin, and in favor of the direct comparison of the results before and after optimization. Third, the resource effect of this study only considers the blue water, ignoring the impact of green water and grey water (water quality). Green water contributes 60% of the water used for global crop production (Schyns et al., 2019), and water quality is closely related to human activities (Hansen et al., 2021) and should thus be considered in future research. However, the major findings of the current study are still of policy significance. Studies focusing on the optimization of cropping pattern at a smaller scale is highly recommended and more sensible objectives and constraints need to be incorporated to ensure the feasibility of the optimization scheme in the future research.

5. Conclusion

This study established a two-stage optimization scheme of regional cropping pattern of ten crops in nine provinces within the YRB, which reconciled three goals for maximum crop economic output while minimum blue water scarcities (the first stage), and evaluated the optimal scheme by the maximum benefits of the interprovincial crop-related VW flows based on the shadow prices of crop green and blue water use (the second stage). The results showed that the shadow price of crop blue and green water is affected by crop types, natural resource endowment and market prices. There is a huge heterogeneity across crops and regions. Compared with the current cropping pattern, the optimized scheme can alleviate blue water scarcity by ~20%, increase the crop-related economic output by ~5%, and increased the benefit of crop VW flow up to

~800 million US dollars. To achieve these goals, the key pathway is to transform irrigation area of water-intensive crops while lowering water shadow price to rain-fed production. We suggest appropriately expanding the production scale of vegetable crops with higher water shadow price and comparative advantage in the YRB, such as cabbage, potato, and tomato, and reducing the harvested area of crops with lower shadow price of blue water and more water consumption, such as soybean and wheat, to simultaneously consider regional water resources security and higher economic outputs. Future research will consider more optimization objectives and verify the practical effects of these optimization schemes on different spatial scales to ensure the stability and feasibility of optimization. This study provides a scientific reference for the YRB and other regions to realize sustainable crop production and water resources management through crop spatial redistribution, as well as a new insight into the benefits of VW in the optimization of cropping patterns.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agwat.2023.108339.

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