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Socioeconomic drivers of provincial-level changes in the blue and green water footprints in China

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ABSTRACT

Socioeconomic development has led to increased consumption of both blue and green water. Consequently, China is facing serious water scarcity issue. However, few studies have investigated interactions of blue and green water footprints, as well as driving forces underlying the changes in water footprints across provinces and sectors. To fill in this knowledge gap, we quantified the spatial-temporal dynamics of the blue and green water footprint (BWF and GWF, respectively), and analyzed the key factors that drive the provincial-level changes in BWF and GWF from 2002 to 2012. The analysis is facilitated by the approaches of multi-region input-output analysis and structural decomposition analysis, and we developed one decoupling index to quantify the water-economy relation and substitution between green and blue water. The results show that China's BWF averaged at 161 billion m^3/yr, about one-third the size of the GWF. In addition, water scarce provinces in Northern China were moving towards decoupling between economic growth and blue water consumption, with GWF playing an increasingly important role. The changes in the WFs were mainly influenced by changes in affluence (final demand per capita), technological improvements (decreased direct water consumption intensity), and consumption pattern (composition of the final demand) rather than changes in the population and export. Technology improvement, consumption pattern shift and industrial structure adjustment contribute to WF reductions, thus help improve water security and sustainability in China. This study provides a new approach to analyze water-economy relations for water scarce countries.

1. Introduction

Water is an indispensable resource for all forms of life and for production activities of human society (World Economic Forum, 2017). Global water withdrawal has increased to 4436 km^3/yr by 2010, from 500 km^3/yr in 1900 (Wada and Bierkens, 2014; Wada et al., 2013), and the rate of demand for water has been growing at more than double the rate of population growth (Connor, 2015; Wada et al., 2013; Soligno et al., 2019). Freshwater scarcity, a temporal or spatial imbalance between water endowments and demands, has become a threat to the sustainable development of human society, globally, more than 1.5 billion people live under conditions of severe water deficiency (Gosling and Arnell, 2016; Liu et al., 2017; Kummu et al., 2010; Cai et al., 2017). This problem is particularly serious in some rapidly developing countries such as China. The per capita available water resources in China are approximately 2100 m^3, only one fourth of the global average, making it one of the 13 countries with the most serious water shortage (Gu et al., 2017; Liu et al., 2017). Increasing population, improving living standards, shifting consumption patterns, and expanding economic activities have been responsible for the rising water demand in China (Chen et al., 2017). Furthermore, a substantial portion of local water resources is consumed to produce goods and services for exporting to other regions, meaning that the impact of trade on local water can be high (Godfray et al., 2010; Sun et al., 2017). To fulfill future water security needs and to find the most effective strategies for water management, it is essential to understand the socioeconomic mechanisms that drive the spatial and temporal trends in water consumption and the distribution of this consumption among various sectors of the economy.

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Freshwater consists of both blue water and green water. Blue water refers to water resources in rivers, lakes, ponds, and aquifers. Such resources can be used for purposes such as irrigating, drinking, manufacturing, and washing. Green water is the precipitation that falls on land and is stored in the soil or remains on the surface of the soil or vegetation (Hoekstra, 2019). Worldwide, green water use accounts for 80% of total water use, which is a crucial resource for sustainable water development (Liu and Yang, 2010; Zang and Liu, 2013). Crops or vegetation always dominate green water consumption in the form of evapotranspiration. However, green water is often ignored in water resources management and regulations due to its "invisibility" in the landscape and difficulty in using for other purposes except indirect allocation through land-use change (Schyns et al., 2019). The concept of water footprint (WF) has played an essential role in linking economic production, human consumption and water resources. WF refers to the total amount of water consumed by the production of commodities or services through the whole supply chain (Allan, 1996; Hoekstra, 2003). The blue water footprint (BWF) represents the consumption of surface and groundwater along production chains. In contrast, the green water footprint (GWF) is primarily the consumption of soil moisture in agricultural production (Guan and Hubacek, 2007; Zhao et al., 2010; Hoekstra et al., 2011). A few studies have provided comprehensive WF assessments for economic sectors at the regional, national, and global scales with both bottom-up and top-down approaches (Chapagain and Hoekstra (2008); ; Lenzen et al., 2013; Feng et al., 2014; Feng and Hubacek, 2015; Zhao et al., 2017; Chen et al., 2018; Zhang et al., 2019).

Although water footprint studies based on a bottom-up approach have shown some progress in assessments and policy implications (Haghighi et al., 2018; Marston et al., 2018; Xu et al., 2019; Liu et al., 2020), they are known to have the double counting problems and the difficulty in distinguishing water use in intermediate products from its use in final products (Feng et al., 2011). The multiregional input-output model approach (MRIO) is a widely used top-down approach, which can overcome these drawbacks and to trace the complex pathways of virtual water through the economic systems (Lenzen, 2009; Cazcarro et al., 2013; Zhang and Anadon, 2014; Yang et al., 2018; Garcia et al., 2020).

In China, several pioneering water related MRIO studies have been carried out, influential examples including Feng et al. (2014), Zhang and Anadon (2014) , Zhao et al. (2015), Zhao et al., (2020), Zhang et al. (2019), Zhang et al. (2019b) and Chen et al., (2017). These works identified a considerable diversity in BWF among provinces and quantified virtual blue water flows between them. However, these studies focused on BWF with little attention to GWF, and furthermore, the interactions between the two WFs were generally ignored. Hou et al., (2018) applied the WIOD (World Input-Output Tables) database to calculate China's GWF on the national scale but being unable to describe GWF on a higher spatial resolution like state or provincial levels. We highlight that if blue water consumed to sustain crop growth can be replaced by green water, and there are potentials to increase green water for food production, the saved blue water can be allocated to other purposes, such as producing commodities with much higher productivity per unit of water use or sustaining environmental flows to restore the functioning of ecosystems. From this perspective, increasing green water use and saving blue water in agriculture are important for improving water sustainability. In addition, some previous studies that quantified the driving forces of WFs in China rarely consider the heterogeneous effects of various driving factors across different regions and socioeconomic sectors (e.g., Guan et al., 2014; Liang et al., 2014; Yang et al., 2016 and Fan et al., 2019). Cai et al., (2019) and Gao et al., (2021) quantified the driving forces of changes in interregional blue water flows or water usage embodied in interregional trade at the subnational level but fell short in reporting WFs and driving forces deeply. In fact, enormous differences exist across the provinces in China in terms of water quantity, water availability, population and the development level, and these differences cannot be ignored. Thus, a spatial-temporal analysis of the various socioeconomic drivers of China's complex dynamics of BWF and GWF as well as their interactions at the province scale provides a substantial addition to the current knowledge of water research. Such knowledge enrichment will help policy makers to better understand the water use situation and improve water management by accounting for heterogeneity in the driving forces in different provinces and economic sectors.

In this study, we investigate driving forces of the spatial-temporal changes in BWF and GWF of China at the provincial level (excluding Tibet, Hong Kong, Macao, and Taiwan due to data unavailability) over 2002, 2007, and 2012 within a multi-regional input-output (MRIO) framework. Then we developed one decoupling index to quantify the water-economy relation and substitution between green and blue water. Lastly, structural decomposition analysis (SDA) was applied to decompose the factors that affect WF and then assess the contributions of these driving forces to BWF and GWF. The key questions we are going to answer are as follows: How do both BWF and GWF vary in spatial-temporal scale, especially at the provincial scale? How are these two WFs substituted over time and distributed among sectors such as agriculture and food processing industry? How much is the contribution of each driver to the change of WFs over time? To what extent BWF and GWF are interlinked? Based on in-depth analyses, some policy implications are drawn for sustainable water management across regions and economic sectors.

2. Methods and data

2.1. Calculating the WF of provincial economic production using the MRIO framework

Two approaches are frequently used to calculate WF of the production of commodities and services, either consumed by the inhabitants of a region, or other regions if traded: the bottom-up approach and the top-down approach. The former estimates water consumption by multiplying the amount of water used per unit of production by the amount of these products traded, based on detailed trade data (Chapagain and Hoekstra, 2008; Orlowsky et al., 2014; Zhuo et al., 2016). This approach allows us to assess water consumption for individual products at the spatial-temporal scales (raster, city, basin, yearly etc.), especially for agricultural and food commodities. But it is rarely used to calculate WF in industry or service sectors because of their complex processing stages and the difficulty in distinguishing between intermediate water use and final water use. In the top-down approach, WF is calculated by tracing the supply chains throughout the economy using a monetary transaction matrix, and consumed water will be allocated to each economic sector rather than the intermediate-use segments. This approach typically aggregates processes and products by economic sectors and has been extensively used in the form of input-output studies at regional, national, and global scales (Feng et al., 2014; Hubacek and Feng, 2016; X. Zhao et al., 2017; P. Zhang et al., 2020). We choose the top-down approach for this study because of its advantages on the sectoral level and the greater availability of data.

The MRIO modeling is one tool for assessing the environmental impacts of production or consumption based on the flow of materials between sectors and economic regions (Miller and Blair, 2009) (often using the monetary value of the materials as a proxy for the materials). It has been widely used to assess embodied resource consumption at each processing stage (Feng et al., 2013; Feng et al., 2014; Chen et al., 2019). The IO technique was developed by Leontief in the late 1930s (Leontief, 1951; Leontief, 1986). In the MRIO table, different regions are connected through inter-regional monetary transactions. The core linear equations used in the MRIO analysis are as follows:

$$\begin{bmatrix} X_1 \\ \vdots \\ X_r \\ \vdots \\ X_p \end{bmatrix} = \begin{bmatrix} A_{11} & \cdots & A_{1r} & \cdots & A_{1p} \\ & \vdots & \ddots & \vdots & \vdots \\ A_{r1} & \cdots & A_{rr} & \cdots & A_{rp} \\ & \vdots & \vdots & \ddots & \vdots \\ A_{p1} & \cdots & A_{pr} & \cdots & A_{pp} \end{bmatrix} \begin{bmatrix} X_1 \\ \vdots \\ X_r \\ \vdots \\ X_p \end{bmatrix} + \begin{bmatrix} y_{11} + \sum_{s\neq 1} f_{1s} + e_1 \\ \vdots \\ y_{rr} + \sum_{s\neq r} f_{rs} + e_r \\ \vdots \\ y_{pp} + \sum_{s\neq p} f_{ps} + e_p \end{bmatrix} \tag{1}$$

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_r \\ \vdots \\ X_p \end{bmatrix}, A = \begin{bmatrix} A_{11} & \cdots & A_{1r} & \cdots & A_{1p} \\ & \vdots & \ddots & \vdots & \vdots \\ A_{r1} & \cdots & A_{rr} & \cdots & A_{rp} \\ & \vdots & \vdots & \ddots & \vdots \\ A_{p1} & \cdots & A_{pr} & \cdots & A_{pp} \end{bmatrix}, F = \begin{bmatrix} y_{11} + \sum_{s\neq 1} f_{1s} + e_1 \\ \vdots \\ y_{rr} + \sum_{s\neq r} f_{rs} + e_r \\ \vdots \\ y_{pp} + \sum_{s\neq p} f_{ps} + e_p \end{bmatrix} \tag{2}$$

Where $X = (X_r^i)$ is the vector of gross economic output and X_r^i is the gross economic output of sector i in province r. The technical coefficient submatrix $A_{rp} = (a_{rp}^{ij})$ is given by $a_{rp}^{ij} = \frac{z_{rp}^{ij}}{x_p^j}$, in which z_{rp}^{ij} represents the intersectoral monetary flows from sector i in province r to sector j in province p, and x_p^j is the total output of sector j in province p. $y_{rp} = (y_{rp}^i)$ is the final demand matrix and y_{rp}^i is the final demand of province p for the goods of sector i produced in province r. When $r = =p$, this represents the final demand produced by economic sector i in the province, f_{ps} is the net trading flow of final goods from province p to province s, and e_p is the net export vector from province p to the rest of the world. Thus, Eq. (1) can be rewritten as follows:

$$X = AX + F \tag{3}$$

L, the Leontief inverse matrix $(I - A)^{-1}$, which captures both direct and indirect effects. Solving Eq. (3) for X gives:

$$X = L \cdot F = (I - A)^{-1} \cdot F \tag{4}$$

The MRIO table is extended with water-use coefficients of individual sectors in each province. In order to calculate WF across the supply chains as being triggered by the final consumption F, the diagonal matrix of water-use coefficients W is multiplied with the Leontief matrix L and final demand vector F, as presented in Eq. (5):

$$WF = W \cdot (I - A)^{-1} \cdot F \tag{5}$$

Each water-use coefficient in W is equal to the direct WF of each economic sector in province p (DWF_p^i) divided by the total economic output of each sector in the same province (X_p^i).

Then the production water footprint could be rewritten as:

$$WF_p = W_p \cdot X_p = W_p \cdot L_p \cdot F_p = \left(\frac{DWF_p^i}{X_p^i}\right) \cdot (I - A_{pp})^{-1} \left(y_{pp} + \sum_{s\neq p} f_{ps} + e_p\right) \tag{6}$$

Where WF_p is the vector for the total provincial-level WF for the production of commodities and services along supply chain triggered by final demand(in this study, the BWF and GWF) of province p; W_p is the vector for provincial-level direct water consumption intensity (i.e., water consumption per unit gross output) for each sector in province p, which is equal to the direct WF in province p (DWF_p) divided by the total economic output of each sector in the same province (X_p); $y_{pp} y_{pp} + \sum_{s\neq p} f_{ps}$ is domestically produced products to fulfill demand (including domestic and other provinces of China), regardless of how the flows are used (i.e., final demand or intermediate demand). e_p constitutes the exporting volume to the rest of the world.

2.2. Quantifying the water-economy relation and substitution between green and blue water

By comparing the movements of two measurements – water intensity (WI, i.e., water footprint per unit of GDP) and GWF proportion in total water footprint (GWFP), we are able to distinguish four types of water-economy relationships which characterize the substitution between GWF and BWF. Basically, WI is an indicator that represents water use efficiency, and GWFP indicates the role of green water in food production. Thus, a decoupling index based on WI and GWFP could characterize water-economy relation and substitution dynamics between GWF and BWF. In theory, changes of water-economy relation and substitution can be categorized into four types (Table 1).

2.3. Structural decomposition analysis (SDA)

After we obtained the WF of provincial economic production through MRIO technique, we decomposed factors affecting WF into several components using the SDA technique. These drivers include the direct water consumption intensity effect, the industrial structure effect, the composition of the final demand bundle effect, the per capita final demand effect, the population effect. SDA has the advantage of evaluating the effects of the overall general equilibrium system instead of the independent variation in each factor compared with an index decomposition analysis. It has been widely combined with the IO model to investigate the key determinants of energy use (Lan et al., 2016; Su and Ang, 2017; Zhao et al., 2018), CO_2 emissions (Feng et al., 2015; Dong et al., 2018), atmospheric $PM_{2.5}$ (Guan et al., 2014), SO_2 (Jiao et al., 2017), and blue water use (Fan et al., 2019; Liu et al., 2018; Zhang et al., 2020).

To calculate the drivers of BWF and GWF, we need to further decompose Eq. (5) as follows:

$$WF = W \cdot L \cdot F = W \cdot L \cdot c \cdot y \cdot p \tag{7}$$

Where W indicates the direct water consumption involved in producing one unit of economic output, and it reflects the impacts of technological innovation on water efficiency (Zhang et al., 2012). The Leontief inverse matrix (L) reflects the industrial structure of the economy. Final demand (F) is subdivided into three drivers: c, y, and p, where

Table 1
The water-economy relation and substitution principles of green and blue water footprints.

	Low level	High level
Decoupling *WI decreases*	**Both water intensity (WI) and green water footprint proportion (GWFP) decrease: Low-level decoupling** Water efficiency improvement is accompanied by declining share of green water of total WF. Although the water efficiency improvement is desirable, increasing dependency on blue water is not preferred.	**WI decreases but GWFP increases: High-level decoupling** Water efficiency improves along with a larger share of green water in total WF. Because the comparative advantage and adverse environmental side effects of green water are generally smaller than those of blue water, such contrast movements are highly desirable.
Coupling *WI increases*	**Both WI and GWFP increase: Low-level coupling** The situation is not good but better than case in which WI increases but GWFP decreases.	**WI increases but GWFP decreases: High-level coupling** Water efficiency worsens with higher dependency on blue water, leading to intensifying blue water stress and is not desirable.

$c = \frac{y^{i}_{rp}}{\sum_{i=1}^{n}\sum_{p=1}^{m} y^{i}_{rp}}$ is the $n \times m$ matrix (30 × 30 in this case) for total final demand by the industrial sectors and represents the commodity structure of final demand; $\boldsymbol{y}$ is the final demand per capita by province (30 × 1); and p refers to population (1 × 1); thus, $F = c \times y \times p$. From Eq. (6), we know that $y_{pp} + \sum_{s \neq p} f_{ps}$ is the local consumption, $\boldsymbol{e_p}$ is the export, and the sum of these, F, represents the total final demand; thus we can separate exports from final demand to assess export effect. Thus, Eq. (7) can be rewritten as follows:

$$WF = W \cdot L \cdot F = W \cdot L \cdot (c \cdot y \cdot p + e) \tag{8}$$

The central idea of SDA is that the change in the WF can be decomposed into the changes in its driving factors (determinants) from time 0 to time 1. By calculating the difference in the WF between the two time points, the dominant factors that influence the WF can be investigated using the following equation:

$$\begin{aligned} \Delta WF &= \Delta WF^1 - \Delta WF^0 = W^1 \cdot L^1 \cdot (y^1 + e^1) - W^0 \cdot L^0 \cdot (y^0 + e^0) \\ &= W^1 \cdot L^1 \cdot (c^1 \cdot y^1 \cdot p^1 + e^1) - W^0 \cdot L^0 \cdot (c^0 \cdot y^0 \cdot p^0 + e^0) \end{aligned} \tag{9}$$

Furthermore, the change in the WF (ΔWF) is decomposed into the following six effects:

$$\Delta WF = \Delta dW + \Delta dL + \Delta dC + \Delta dY + \Delta dP + \Delta dE \tag{10}$$

Where ΔdW is the direct water consumption intensity effect, which represents technology improvement, ΔdW will change over time, being triggered by the change in water consumption and economic output. ΔdL is the industrial structure effect, which represents changes in the structure of China's economy. ΔdC is the composition of final demand bundle effect, which illustrates changes in human's consumption structure or pattern. ΔdY is the level of final demand per capita (affluence effect), ΔdP is the population effect, and ΔdE is the export effect. Each of the six drivers in Eq. (10) represents the contribution of that driver to change in the WF while keeping the rest of the variables constant.

In studies of absolute changes in resources, most authors choose additive decomposition instead of multiplicative one because the former is easier to interpret. In a comparative review, some scholars have described the problems with multiplicative decomposition (Su and Ang, 2012; Hoekstra and Bergh, 2003). The six drivers in our SDA model have 6! = 720 decomposition results and different approaches have different results. Su and Ang (2012) summarized four SDA methods and compared their advantages and disadvantages.

In this study, we followed the method in previous publications and used the average of two polar decompositions (Malik and Lan, 2016; Dietzenbacher and Los, 1998). This method starts by changing the first variable first, while holding the other variables constant, and so on until the sixth variable is analyzed, thereby obtaining the first polar form. Then we derived the second polar form by repeating this process in reverse (i.e., starting by changing the sixth variable first, while holding the other variables constant, and so on until we reach the first variable). We then obtained the SDA results based on the arithmetic average of the two polar forms with the following equations:

$$\Delta dW = \frac{1}{2}\left[(W^1 - W^0) \cdot L^0 \cdot (c^0 \cdot y^0 \cdot p^0 + e^0) + (W^1 - W^0) \cdot L^1 \cdot (c^1 \cdot y^1 \cdot p^1 + e^1)\right] \tag{11}$$

$$\Delta dL = \frac{1}{2}\left[W^1 \cdot (L^1 - L^0) \cdot (c^0 \cdot y^0 \cdot p^0 + e^0) + W^0 \cdot (L^1 - L^0) \cdot (c^1 \cdot y^1 \cdot p^1 + e^1)\right] \tag{12}$$

$$\Delta dC = \frac{1}{2}\left[W^1 \cdot L^1 \cdot (c^1 - c^0) \cdot y^0 \cdot p^0 + W^0 \cdot L^0 \cdot (c^1 - c^0) \cdot y^1 \cdot p^1\right] \tag{13}$$

$$\Delta dY = \frac{1}{2}\left[W^1 \cdot L^1 \cdot c^1 \cdot (y^1 - y^0) \cdot p^0 + W^0 \cdot L^0 \cdot c^0 \cdot (y^1 - y^0) \cdot p^1\right] \tag{14}$$

$$\Delta dP = \frac{1}{2}\left[W^1 \cdot L^1 \cdot c^1 \cdot y^1 \cdot (p^1 - p^0) + W^0 \cdot L^0 \cdot c^0 \cdot y^0 \cdot (p^1 - p^0)\right] \tag{15}$$

$$\Delta dE = \frac{1}{2}\left[W^1 \cdot L^1 \cdot (e^1 - e^0) + W^0 \cdot L^0 \cdot (e^1 - e^0)\right] \tag{16}$$

Due to the complexity of the Leontief inverse matrix L, we provide two hypothetical examples in the SI to demonstrate the framework of the input-output table and explain how the industrial structure influences the change in resource consumption. The assessment framework is shown in Fig. 1.

In addition, some scholars may argue that climate variations will influence the relative shares of the blue and green WF within the total; we used the precipitation anomaly index (PAI) (Keyantash and Dracup, 2002) to evaluate the influence of climate variation over space and time. The precipitation anomaly percentage refers to the average state of the deviation over a certain period, as regional rainfall conditions will change over time. Therefore, it is a relative indicator that compares variations over time and space. In meteorology, the precipitation anomaly index is often used as a classified index of drought and flood, expressed as:

$$\frac{H_x = (p_x - p_x')}{p_x' \times 100\%} \tag{17}$$

Where $H_x$is the precipitation anomaly percentage in economic region x, p_x is the precipitation in a specific year, and p_x' is the average rainfall over many years—here it is 33 years (from 1980 to 2012). The drought and flood grades are shown in supplementary Tables S2 and S3.

2.4. Data sources

China publishes national and provincial IO tables every 5 years. China's MRIO tables for 2002, 2007, and 2012 were compiled by previous researchers (State Information Center, 2005; Liu et al., 2014; Mi et al., 2017). It should be noted that Zheng et al. (2020) constructed the 2015 China MRIO table based on the entropy theory because of the lack of provincial single regional input-output tables. This MRIO table has different technological assumptions in terms of production structure and trading patterns compared with the previous China MRIO tables. Hence, combining MRIO 2015 with the other MRIO data will produce biased results when doing time series analysis. In this study, all economic data in the IO tables were converted to the 2010 constant prices (1RMB = 0.15 USD) using the government's official mean annual inflation rates, which is aggregated to about 1.45 for the year 2002, 1.15 for 2007, and 0.90 for 2012. Supplementary Table S1 in the supporting information (SI) lists 30 industrial sectors for which data was available.

To calculate BWF and GWF of provincial economic production, we need the direct BWF and GWF at the sectorial and provincial levels. Liu et al. (2020) simulate the provincial direct BWF and GWF for the main crops (maize, wheat, soybean, rice, millet, and sorghum) with the help of GIS-based Environmental Policy Integrated Climate model (GEPIC). Here we extracted crop WFs as the main inputs for our MRIO analysis. Some detailed simulation procedures, parameters selection and data requirements can be found in Liu et al. (2020), Zhao et al. (2017), Liu and Yang (2010) and Liu et al. (2007). Finally, the direct BWF and GWF of total crops is obtained by dividing the blue and green WFs for the six major crops by their area proportion to the total cultivated area at the provincial level.

Water use in the other agriculture sectors (forestry, livestock husbandry, fishery), secondary and urban domestic sectors was obtained from Provincial Water Resource Bulletin of China (2003, 2008, 2013). For the water use by tertiary sectors, we obtained the data through multiplying urbanization rates by the urban domestic water use in each province (see supplementary Table S4). Liu (2016) provided details of this procedure. Then multiplying water use data for each sector by the

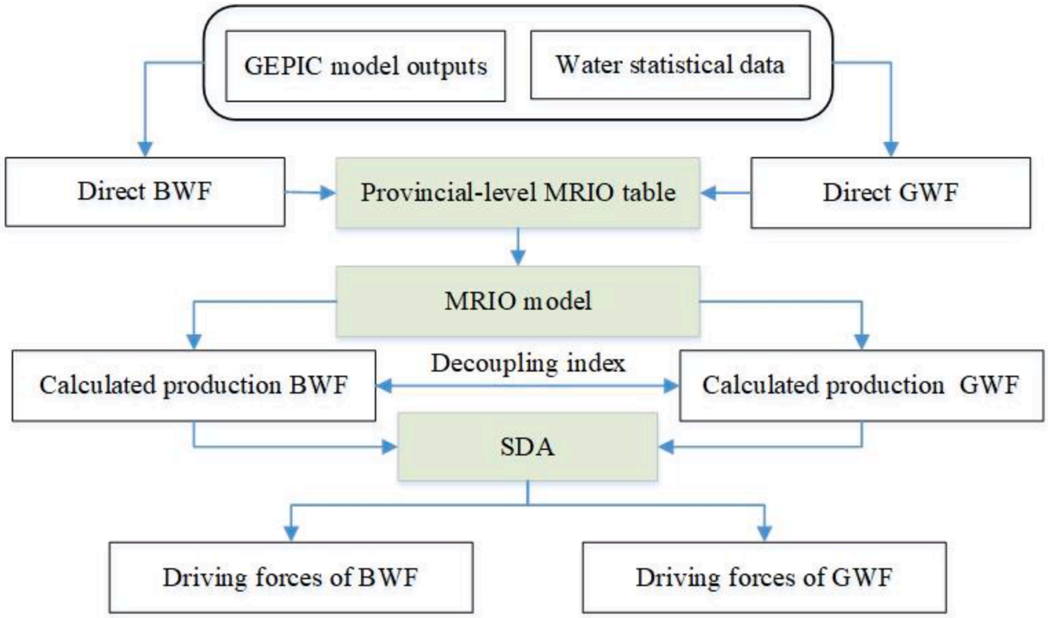

Fig. 1. The assessment framework of this study.

water consumption coefficient, we obtain the BWF (Ministry of Water Resources of China, 2003, 2013). We disaggregated the total BWF in the secondary and tertiary sectors into 29 sectors based on the direct water consumption intensity for the same sectors in 30 provinces in 2007, which were survey-based data recorded in the China Economic Census Yearbook 2008 for industrial sectors (National Bureau of Statistics of China, 2008a) and Zhao et al. (2015)'s dataset for tertiary sectors. All required direct BWF and GWF are listed in Supplementary Tables. Population and gross domestic production (GDP) data were obtained from the Chinese Statistical Yearbook (National Bureau of Statistics of China, 2003, 2008b, 2013). We downloaded the spatial interpolation dataset of annual precipitation in China from 1980 to 2012 (resolution: 1 km $\times$ 1 km) from the Resource and Environment Data Cloud Platform (Chinese Academy of Science).

3. Results

3.1. WFs, water-economy relation and substitution between BWF and GWF on the provincial scale

China's production side BWF increased from 143 billion m^3 to 174 billion m^3 from 2002 to 2007, then decreased to 167 billion m^3 in 2012, averaging at 161 billion m^3 during the study period (Supplementary Table S5). Conversely, China's GWF decreased from 599 billion m^3 to 544 billion m^3 from 2002 to 2007, then increased to 584 billion m^3 in 2012, averaging at 576 billion m^3. In sum, total WF (BWF + GWF) reduced to 718 billion m^3 in 2007 from 742 billion m^3 in 2002, then increase to 751 billion m^3 in 2012. BWF is about one-third of GWF, and the average proportion of GWF is about 78% during the study period.

Fig. 2 shows that the low-level decoupling trend of water-economy relations (see Table 1) were prevalent across provinces during 2002–2007 and the high-level decoupling trend became dominant during 2007–2012. Considering the environmental benefits of substituting blue water by green water, this development is very encouraging. In more details, only five provinces (Heilongjiang, Jilin,

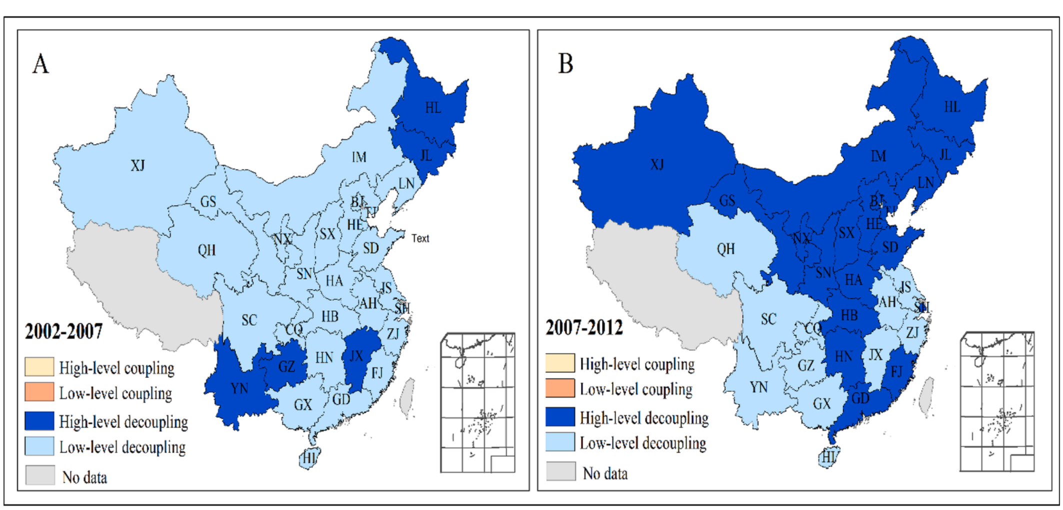

Fig. 2. Water-economy relation and substitution between BWF and GWF on the provincial level during 2002–2012.

Jiangxi, Guizhou and Yunnan) had high-level decoupling trend (Fig. 2 (A), and supplementary Table S5) during the first period. This number increased to 19 after 2007, and most of the new provinces entering this category were located in northern regions, where the scarcity of blue water has been an increasing concern. Supplementary Table S5 reports more information on the annual dynamics of the substitution between GWF and BWF in 20 out of 30 provinces. It shows that the function of blue water can be substituted by green water to varying extents across these provinces and over time. Nevertheless, GWFP continued decreasing in the remaining provinces (Jiangsu, Zhejiang, Anhui etc.), which indicated that the relative importance of green water utilization in these regions become smaller than in the past.

3.2. WF per capita and WF per GDP at the provincial scale

The national average per capita BWF (Fig. 3 (A–C), Table S5) increased from 113 m^3 in 2002 to 124 m^3 in 2012, but BWF per unit GDP (at constant 2010 prices) decreased from 8.1 $m^3/10^3$ yuan to 3.2 $m^3/10^3$ yuan during the same period. The provinces with the largest BWF per capita and per unit GDP were mainly in western regions with a relatively low level of socioeconomic development and low population density (e.g., Xinjiang, Ningxia, Inner Mongolia), whereas those with the lowest values were mostly in the more affluent and more densely populated eastern regions (e.g., Shanghai, Beijing, Tianjin). The western provinces mainly produced water-intensive products; for example, Xinjiang had the largest BWF both in absolute value and per unit terms of population and GDP. It is one of China's key providers of cotton, accounting for 51.8% of the country's cotton production in 2012 (Ministry of Agriculture, 2013). Its water consumption per unit GDP was 37.2 $m^3/10^3$yuan in 2012, which was nearly 12 times the national average. In comparison, Shanghai usually produces products with low water intensity, and its water consumption per unit GDP was 0.4 $m^3/10^3$yuan, which is just one-eighth of the national average.

China's average per capita GWF decreased from 471 m^3 in 2002 to 435 m^3 in 2012 (Fig. 3 (D–F), supplementary Table S5). The GWF per unit GDP also decreased during the same period, from 33.8 $m^3/10^3$yuan to 11.2 $m^3/10^3$yuan. GWF per unit GDP was greatest in the provinces with abundant water resources, such as Jiangxi, Hunan, and Guangxi, as well as in regions with a lower population density, such as Heilongjiang and Guizhou. In contrast, the provinces with the lowest GWF were mainly water-deficient regions, such as Beijing, Tianjin, Shanghai, and Xinjiang. The GWF intensities in these water-poor regions were usually lower because of the smaller share of agriculture production in the local economy, lower precipitation and thus dependency on irrigation for agricultural production, or both. For example, the lowest values of per capita GWF were 34 m^3 and 76 m^3 in Beijing and Tianjin, respectively, as these two cities were characterized by extreme water scarcity and low share of agricultural GDP in the total.

3.3. Changes in sectoral BWF and GWF from 2002 to 2012

Fig. 4 illustrates the total BWF and GWF of the different socioeconomic sectors in the eight economic regions categorized by previous research (Feng et al., 2013; Mi et al., 2017). We aggregated the provincial scale results into the regional scale based on a combination of the provincial geographical locations and their development levels so that we could better illustrate the WF at sectoral and temporal scales. Supplementay Table S1 lists the 30 sectors used in our analysis, and supplementay Table S6 lists the provinces included in each regional group. Supplementay Tables S7 and S8 provide the BWF and GWF, respectively, for each socioeconomic sector.

The Northwest region had the largest share of BWF, accounting for 27% of the total, followed by the Central and North regions, each having a 21% share. Beijing-Tianjin had the smallest volume, at only 2.1 billion m^3. The distribution of the BWF among the other economic regions was relatively uniform, with a proportion ranging from 6% to 8%. The agricultural sector dominated the total BWF, but its contribution decreased both in proportion of the total and in absolute volume, from 59% in 2002 to 40% in 2012, and from 84 billion m^3 to 66 billion m^3 during the same period. The food and tobacco-processing sector ranked

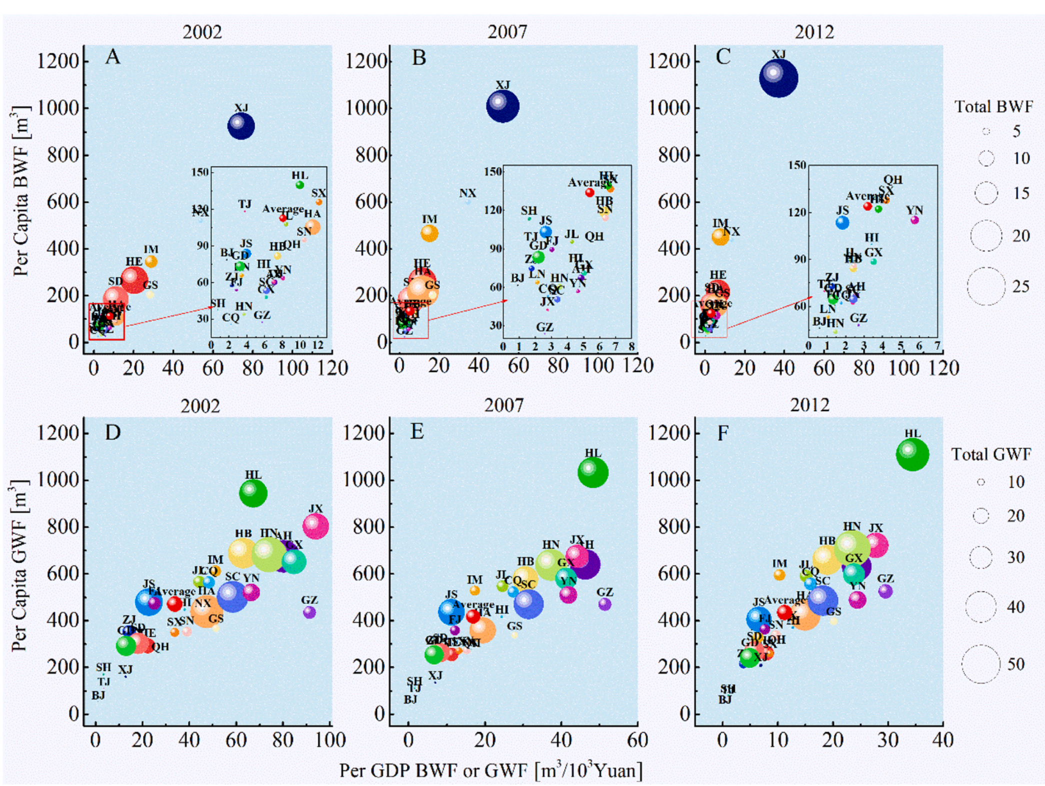

Fig. 3. Relationships between the blue water footprint (BWF) and the green water footprint (GWF) for China's 30 provinces from 2002 to 2012.

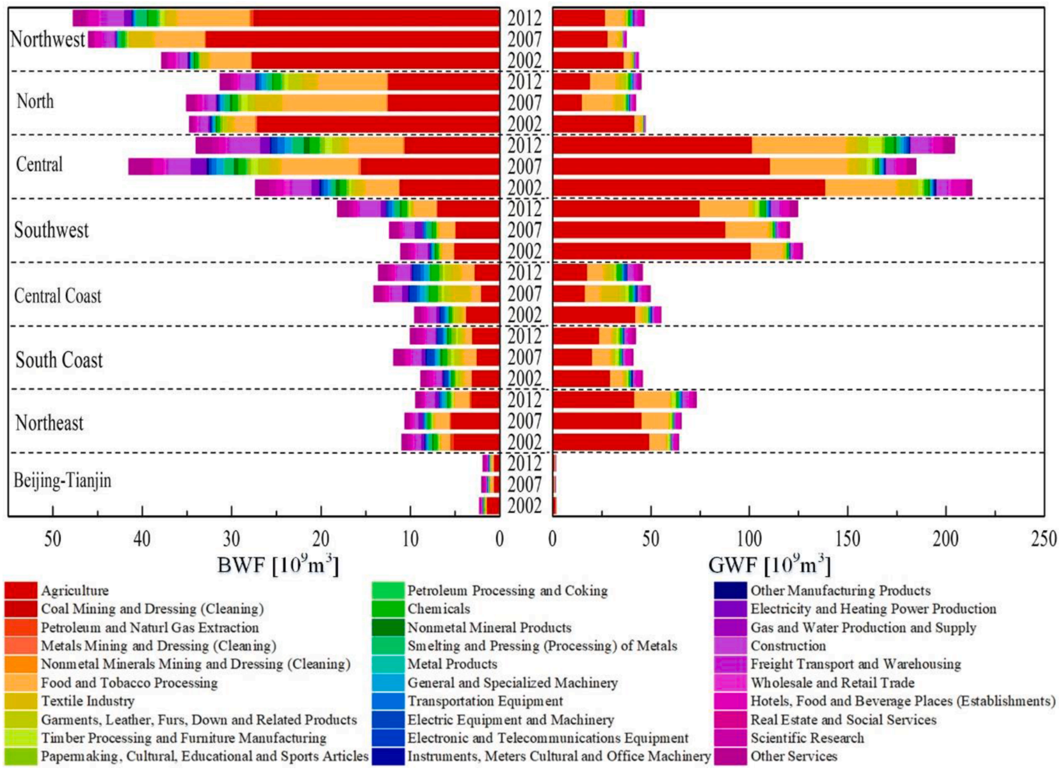

Fig. 4. The water footprints for the 30 sectors in the eight economic regions of China in 2002, 2007 and 2012. The provinces included in each group are listed in supplementary Table S6.

2nd. Its proportion of the total BWF increased from 10% in 2002 to 20% in 2012, and its absolute BWF increased from 14.6 billion m^3 to 29 billion m^3. Thus, agriculture-related commodities still accounted for the majority of blue water consumption although parts of them have been transferred to other non-agricultural sectors through supply chains. The contributions of the non-agricultural sectors to the total BWF were relatively small (< 6%), but in some highly industrialized regions (such as the Central Coast and South Coast), this ratio reached 60%, which was approximately 40% higher than the corresponding figure in the Northwest region. Thus, there was an enormous variation in blue water consumption, depending on the economic composition of each economic region.

Fig. 4 (right) shows the distribution of GWF among regions and sectors in 2002, 2007, and 2012. As we noted in the introduction, the direct GWF stems only from agriculture, and the green water can be redistributed to other industries through the supply chain. The Central region had the largest proportion of the total (35%, at 201 billion m^3), followed by the Southwest region (22%, 124 billion m^3), and Beijing-Tianjin had the smallest GWF with only 1.7 billion m^3 (0.3% of the total). The Northwest region, as the biggest consumer of blue water, had the second-lowest GWF, at 42.7 billion m^3 (7.4% of the total). Agriculture still has the highest consumption, but it decreased throughout the study period—from 73% of the total in 2002 to 52% in 2012—and the agricultural GWF averaged at 355 billion m^3. The proportion of the food and tobacco processing sector increased from 13% in 2002 to 22% in 2012, reaching 130 billion m^3 in 2012. Agriculture-related commodities still played the largest role in the green water market, accounting for more than 74% of the total. The other sectors accounted for a smaller proportion of the total GWF than they did for the BWF, and the pathways of green water consumption by production activities showed no obvious differences among the eight economic regions.

3.4. Changes in regional BWF and GWF and the contributions of the driving forces

The BWF embodied in China's production increased from 143 billion m^3 to 167 billion m^3 from 2002 to 2012. China's BWF increased by 21.7% from 2002 to 2007. It then remained higher in 2012 than in 2002, despite a 4.3% decrease in water consumption from 2007 to 2012 (Fig. 5A). Blue water consumption increased in all regions from 2002 to 2007, except in the Northeast and Beijing-Tianjin regions; the Central and Northwest regions contributed the most to the total. From 2007 to 2012, the BWF decreased in all regions except in the Northwest and Southwest regions. Overall, the regions that contributed the most to the BWF growth were mainly in western China. The BWF in the Northwest and Southwest regions increased by 9.9 billion m^3 and 7.1 billion m^3, respectively, from 2002 to 2012. However, the North regions contributed to a decrease in China's BWF by 3.4 billion m^3.

The increase in China's BWF from 2002 to 2012 mainly resulted from the increased final demand per capita (dY) and the industrial structure (dL). However, the reduction in direct water use intensity (dW) and improvement in the composition of the final demand bundle (dC) were two key factors that drove the decrease in China's BWF (Fig. 5B). The growth in final demand per capita would have increased the BWF by 70.9 billion m^3 (equivalent to 2.29 times the net increase of 30.96 billion m^3) from 2002 to 2007 and by 58.7 billion m^3 (7.85 times the net decrease of 7.48 billion m^3) from 2007 to 2012 while keeping all other factors constant. From 2002 to 2007, the composition of the final demand bundle (dC) was the strongest factor offsetting China's blue water expansion, decreasing the BWF by 43.7 billion m^3 (–1.41 times the net increase), followed by direct water consumption intensity (dW). However, from 2007 to 2012, direct water consumption intensity (dW) surpassed the composition of the final demand bundle (dC) and became the strongest driver that reduced the BWF. The dW and dC decreased the BWF by 76.1 billion m^3 (10.47 times the net increase) and 11.5 billion m^3 (–1.45 times the net increase), respectively. We also found that

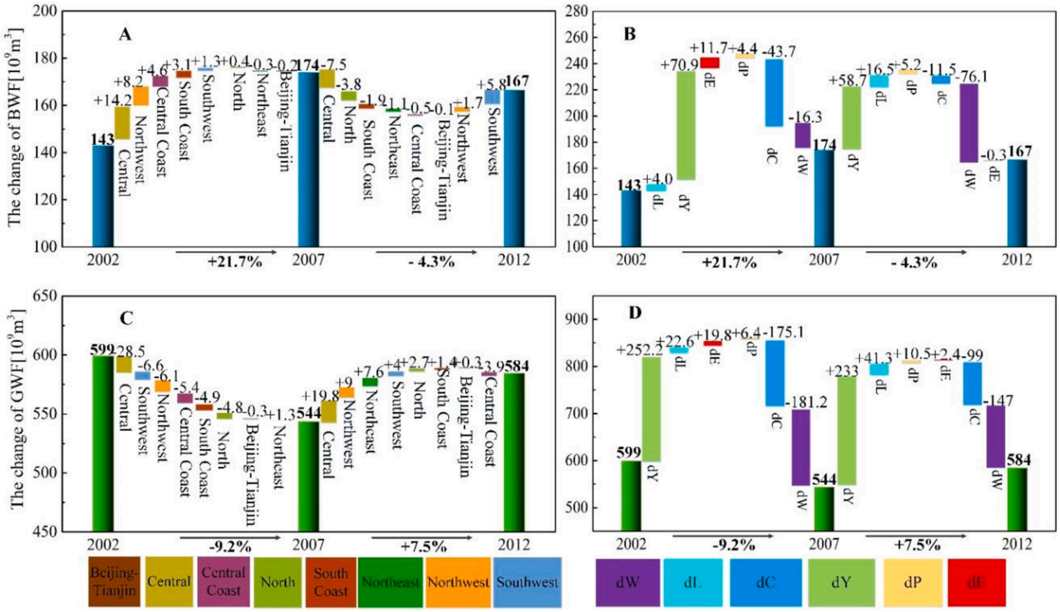

Fig. 5. Changes in (A,B) the blue water footprint (BWF) and (C,D) the green water footprint (GWF) in the years 2002, 2007, and 2012: (A,C) Changes in China's eight regions. (B,D) Contributions of key driving factors: dW, direct water use intensity; dL, industrial structure; dC, composition of final demand bundle; dY, final demand per capita; dP, population; dE, exports.

exports (dE) and population (dP) had a limited effect on the changes in the BWF at the national scale in 2007–2012.

China's GWF declined from 599 billion m^3 in 2002 to 584 billion m^3 in 2012. It decreased by 9.2% from 2002 to 2007 and did not return to the 2002 level, despite an increase of 7.5% from 2007 to 2012 (Fig. 5C). GWF in all regions except the Northeast regions decreased from 2002 to 2007. The Central, Southwest, and Northwest regions contributed the most to this decrease. From 2007 to 2012, the GWF increased in all regions except the Central Coast region. Overall, the regions that contributed most to the reduction in the GWF were the Central and Central Coast regions, which decreased their GWF by 8.7 billion m^3 and 5.1 billion m^3, respectively, from 2002 to 2012. However, the Northeast and Northwest regions contributed greatly to the increase, accounting for a total increase of 11.8 billion m^3.

Of the driving forces behind the reduction of China's GWF from 2002 to 2012, direct water use intensity (dW) and composition of the final demand bundle (dC) had the most pronounced effects, but the final demand per capita (dY) and the industrial structure (dL) also contributed strongly to the increase (Fig. 5D). From 2002 to 2012, direct water consumption intensity (dW) had the strongest effect on reducing China's GWF, followed by the composition of the final demand bundle (dC), which together reduced the GWF by 356.3 billion m^3 (6.44 times the net decrease) from 2002 to 2007 and by 246.6 billion m^3 (6.04 times the net decrease) from 2007 to 2012, keeping all other factors constant. The growth in final demand per capita (dY) increased GWF by 252.2 billion m^3 (−4.58 times the net decrease) between 2002 and 2007 and by 233

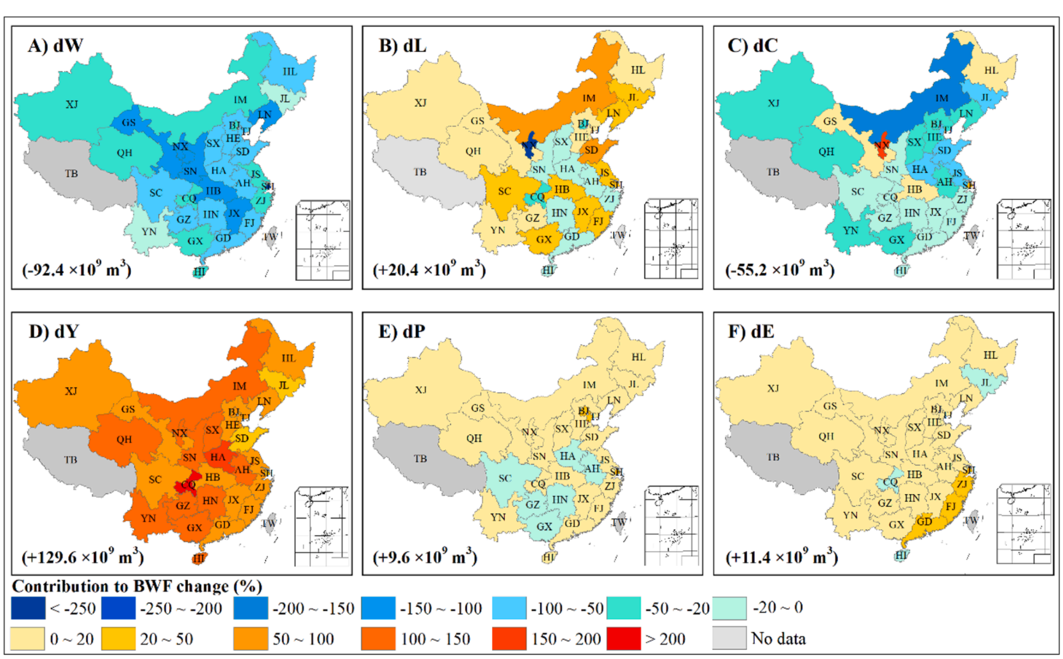

Fig. 6. Structural decomposition analysis of the driving factors to the changes in blue water footprint (BWF) from 2002 to 2012 at the provincial level.

billion m^3 (−5.71 times the net decrease) from 2007 to 2012. However, exports (dE) and population (dP) had a limited impact on the changes in GWF at the national scale since 2007, showing a trend similar to that for BWF (Fig. 5B).

3.5. Contribution of the drivers to provincial-level BWF changes

Fig. 6 and supplementary Table S9 show the provincial-level overview of the drivers for the changes in BWF from 2002 to 2012. During this period, China's BWF increased by 23 billion m^3. Increased affluence (final demand per capita, dY) was the most important driver of the increase, which is similar to the national results. This impact of increased affluence was dominant in all provinces, particularly some northern and central provinces, such as Chongqing (+ 211% of the net change measured in percentage points, hereafter 1.54 billion m^3), Henan (+ 171%, 17.3 billion m^3), and Inner Mongolia (146%, 12 billion m^3). Holding all other variables constant, Jilin had the lowest value at + 29.7% (0.86 billion m^3), followed by Shanghai (+ 45.4%, 0.3 billion m^3). The ratio of the highest to the lowest contribution reached 7 to 1. The other three drivers (dE, dP, dL) also have a positive effect on the BWF, except in some central and southern provinces (e.g., Anhui, Henan, Hunan). The reduction in water intensity (dW) somewhat counteracted this increase in all provinces, particularly in Shanghai (-208%, -1.3 billion m^3), Shaanxi (-134%, -4.6 billion m^3), Ningxia (-127%, -3.8 billion m^3) and Hubei (-125%, -5.8 billion m^3). The lowest contributions were by Yunnan (-15.7%, -0.4 billion m^3), Jilin (-16.3%, -0.5 billion m^3), Inner Mongolia (-25.6%, -2.1 billion m^3), and Chongqing (-32%, 0.2 billion m^3). Changes in the composition of the final demand bundle also contributed to the decrease, except in Gansu, Ningxia, Heilongjiang, and Shanghai. In summary, there were obvious regional disparities in terms of the contributions of the driving forces to the change in BWF.

3.6. Contribution of the drivers to provincial-level GWF changes

Fig. 7 and supplementary Table S10 show the proportions of the decrease in the GWF from 2002 to 2012 caused by the six driving factors at the provincial level. China's GWF went down by 15 billion m^3. Water efficiency improvement (the reciprocal of dW) promoted this decrease in all provinces except Jilin and Beijing. The largest decreases took place in Shaanxi (-108%, -14 billion m^3), Ningxia (-91%, -2.3 billion m^3), Qinghai (-86%, 0.2 billion m^3), and Heilongjiang (-85%, 30.6 billion m^3), whereas Shanghai (-2.4%, -0.07 billion m^3), Tianjin (-6%, -0.07 billion m^3), and Xinjiang (-15.3%, -0.5 billion m^3) had much lower values. Except for Ningxia and Heilongjiang, changes in the composition of the final demand bundle (dC) also contributed strongly to the decrease. The increased final demand per capita (dY) was the most important driver of the increase in GWF, showing a dominant role in all provinces. While higher values were present in Shanxi (+ 122%, 14 billion m^3), Anhui (+ 117%, 48.5 billion m^3), and Ningxia (+ 116%, 2.9 billion m^3), the lowest value at 8.7% (+ 0.3 billion m^3) was present in Shanghai, followed by that in Jilin (+ 20%, + 3.0 billion m^3). In contrast, dL, dE, and dP had a negative effect on GWF in some provinces (e.g., Beijing, Shanghai, Henan). In summary, our analysis revealed obvious regional differences in the contribution of the different driving forces to the change in GWF.

4. Discussion

4.1. Comparison with the literature

Our estimated BWF is very close to the 142 billion m^3 per year estimated by Mekonnen and Hoekstra (2011) for the annual average for 1996–2005. GWF is estimated at 599 billion m^3 in this study, about 18% smaller than the estimate of 706 billion m^3 in the study by Mekonnen and Hoekstra (2011). Different calculation methods and study periods are the two main reasons for these differences. Another reason is that our calculations concentrated on crop production and excluded the GWF in the grazing system. In Mekonnen and Hoekstra (2011), the GWF for crop production was 624 billion m^3 per year, which was very close to our estimate. Zhang and Anadon (2014) assessed BWF for individual 30 provinces in 2007 (see supplementary Table S11). Their estimation of the total BWF was 336 billion m^3/y, which is almost twice our estimate of 174 billion m^3/y for the year 2007. This difference can be fully explained by the fact that BWF was assumed to be equal to water withdrawal in Zhang and Anadon (2014), and China's water consumption accounted for about 52% of water withdrawal in 2012 (Ministry of Water Resources of China, 2013). Furtherly, estimates in this study were BWF of economic production, while Zhang and Anadon (2014)'s BWF is calculated from the consumption side. Consumption-based WF will

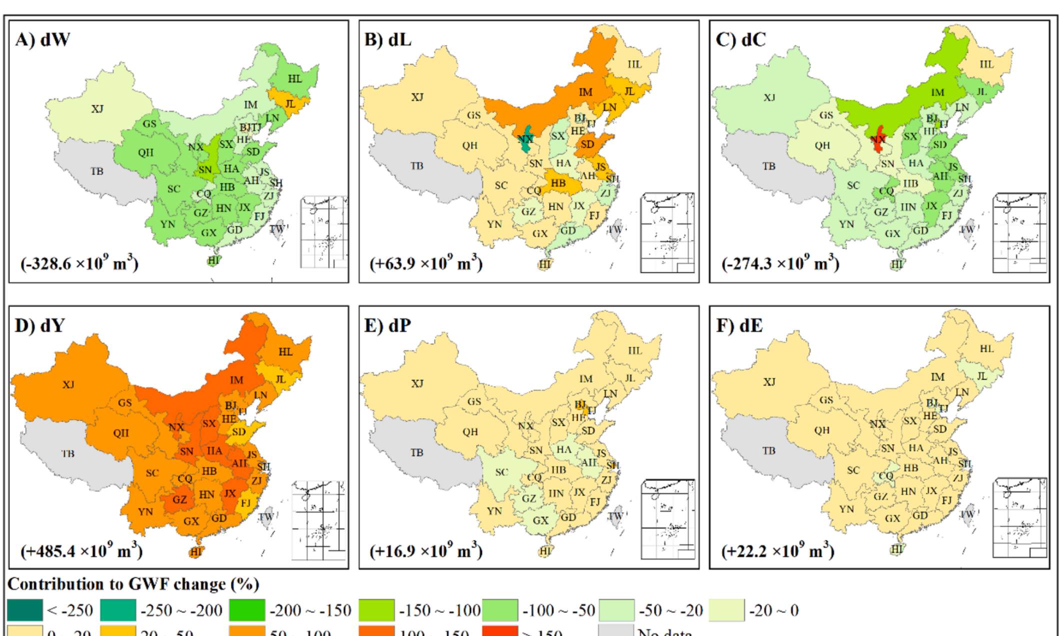

Fig. 7. Structural decomposition analysis of the driving factors to the changes in the green water footprint (GWF) from 2002 to 2012 at the provincial level.

redistribute imported virtual water among regions, For example, Beijing was a typical virtual water importer (Zhao et al., 2017). Hence, our results on the provincial level were different from Zhang et al. (2014). In addition, Xiong et al., (2020) indicated that decoupling trends between BWF and economic growth are appeared in almost all the provinces from 2007 to 2012. Their estimates are consistent with our results, which means China's economy is achieving fast economic growth with lower rates of growth or even decline in water footprints.

4.2. The substitution between green water and blue water

The time series results (Figs. 2,5 (A,C)) demonstrated that the decoupling trend is in the growth. Besides, the decrease of BWF proportion was accompanied by an increase in GWF proportion at the national and regional levels. These provincial water-economy relations imply that certain policies aiming for improving water efficiency or conserving water resources should be promoted in agreement with the spatiotemporal changes of WFs. And further, this substitution is interesting since it suggests that the function of blue water can be substituted by green water to some extent. Actually, green water could be allocated through land use conversion without changing catchment hydrology, as long as evaporation does not change markedly. For example, in the last two decades, many farmers in the North China Plain have gradually changed their planting system from double planting (summer maize + winter wheat) to single planting (spring maize) to cope with the challenges posed by the increasing water shortage and rising opportunity cost of agricultural labor. The consequent reduction in wheat planting is compensated by increased wheat planting in central and southern provinces (Anhui, Jiangsu, Hubei, Henan etc.) with a lower water constraint (Zhong et al., 2017, 2019; Ministry of Agriculture, 2013; Ministry of Agriculture, 2003). The emergence and extension of the "spring corn planting belt" have promoted the shift in agricultural water consumption from irrigated blue water to rain-fed green water (Zeitoun et al., 2010). Chinese statistics (Ministry of Agriculture, 2013; Ministry of Agriculture, 2003) also showed that the area of rain-fed maize in the northern provinces increased from 18.6 million hectares in 2002 to 28 million hectares in 2012. As a result, the blue water saved has been partly released to improve the ecosystem sustainability and partly utilized in non-agricultural and high-valued products to improve the blue water outputs. This finding also provides inspirations for other countries which are facing the similar water scarcity problems, such as India, Central Asia (Varis, 2014; Liu et al., 2021), Middle-East and North Africa (Varis and Abu-Zeid, 2009). They could design incentive mechanisms and adopt policies to enhance the utilization of green water resources in exchange for the minimization of blue water usage, so as to achieve the water sustainability alongside the economic development. This paper represents the first attempt to systematically quantify the extent of mutual substitution between green water and blue water across the economic sectors at both the national and regional levels.

Considering both the virtual water content and the proportion of the GWF in WF, it is found that producing food and feed is mainly relied on green water, and mankind's reliance on green water resources is much bigger than blue water, thus, rain-fed agriculture is extremely important for improving water security (Zeitoun et al., 2010; Schyns et al., 2019). We recommend promoting less irrigation-dependent and rain-fed agriculture—including spring maize, soybean, potatoes, or non-timber forestry—as effective adaptation options for agriculture in northern China, where severe water shortage has become the leading bottleneck for sustainable development (Zhong et al., 2017, 2019). Usually, crops with a low WF have higher water productivity, and planting structure adaptation can reduce the dependence of the agricultural sector on irrigation (Zhao et al., 2014b). Therefore, we also recommend replacing some rice planting in some northern regions with summer maize, and also replacing "summer maize + winter wheat" with spring maize to cope with different degrees of water scarcity (Meng et al., 2012). Because replacing blue water with green water can promote more sustainable water use and the reverse substitution would suppress sustainable water use, policy makers should pay more attention to these substitution implications when they propose a water use strategy. In addition, human appropriation on green water will squeeze natural ecosystem supporting services, e.g. food provision, biodiversity, climate regulation and others (Costanza et al., 1997), human's changing behaviors (energy consumption mix, lifestyle, and dietary transition etc.) will also exacerbate the trade-offs between green water for mankind versus nature in the near future. Considering green water utilization under the maximum sustainable green water resource, and balancing its allocations between supporting ecosystem and supplying for human's basic needs are significant for sustainable water cycles and sustainable development of human society.

4.3. Technological improvement (dW) had the strongest effect on reducing WF

Fig. 8 highlights the dominant role played by the key driving factors in shaping WFs at the provincial level. Technological improvement (dW) had the strongest effect on reducing WF, which is consistent with studies from Zhou et al., (2020), Liu et al., (2018) and Huang et al. (2017). This reflected the adoption of water-saving technology by both the agricultural and non-agricultural sectors from 2002 to 2012. Actually, nearly all the sectors experienced a decrease in their water intensity, especially in food-related sectors with the larger water intensity. The government proposed a series of water conservation measures, including national long-term water saving strategic plan, water-saving transformation in large-size irrigation districts, and national standards of water volume quota system for 193 crops to upgrade technology and equipment for promoting water efficiency improvements. For example, irrigation systems based on sprinkler or drip irrigation have been increasingly implemented, and this implementation should save huge volumes of blue water compared to traditional flood irrigation. Agronomic techniques—such as the use of plastic film mulches and water-retaining agents—have been forcefully promoted during this period, and these techniques can reduce the loss of green water by a significant margin. In fact, these water policy interventions in agriculture have increased the ratio of water-conserving irrigation technology in sown area from 35% in 2002 to 39% in 2012 (National Bureau of Statistics of China, 2003, 2013). In non-agricultural industries, many water-saving measures also have been enforced, such as the use of condensation equipment to recapture steam and the recycling and reuse of water. Some changes in cooling type also contribute to the water intensity reduction. For example, large-size thermoelectric power plants usually have a lower unit freshwater demand due to the adoption of air- or seawater-cooling technologies that was used widely in China since 2008 (Zhang et al., 2017; Sanders, 2015). All these advancements pushed the improvements in water efficiency within these sectors significantly, indicating that improved water use efficiency can make significant contributions to WFs reduction in China. As a result, it is vital to continue improving water efficiency in response to the rapid growth of China's economy in the future. We suggest that the improvement of water efficiency is treated as the key performance indicator of local governments and companies, some water policies like "Three Red Lines", "Water saving society development", "Water volume quota management" also should be involved into the quantitative assessment of city governance. Moreover, more attention should be paid to the less-developed regions, as well as key sectors with high water intensity. Practical measures could include technology transfer from advanced regions and increasing investment to upgrade infrastructure. In addition, the changes in the composition of the final demand bundle (dC) had surpassed the technological improvement (dW) and became the most important factor that drove the decrease in the WF in several provinces (e.g., Beijing, Tianjin, Shandong.). This might reflect the fact that with rising living standards, expenditures in services and high-tech products (which are much less water-intensive than traditional consumer goods) had significantly

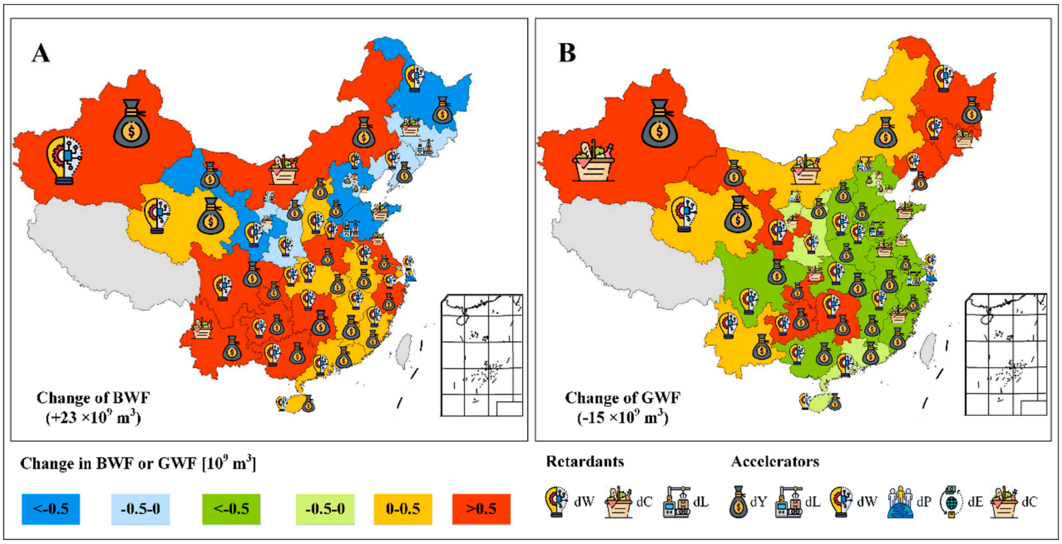

Fig. 8. Changes between 2002 and 2012 in the key driving factors responsible for the changes in the BWF and GWF.

increased their share of the total expenditure (consumption) by consumers, and this change in the structure of consumption expenditure had helped to reduce the WF in these regions (Cai et al., 2016).

4.4. Growing affluence (dY) as the greatest accelerating factor that drove up WF

We quantified the growing affluence (dY) as the greatest accelerating factor that drove up WF from 2002 to 2012. Growing affluence means growing per capita income and consumption levels, which are driven by unprecedented urbanization processing and mass emigration of rural population to urban areas to seek higher income through engaging in industrial and service sectors in urban areas (Liu et al., 2017). Consumers tend to increase their consumption expenditures as their disposable income rises. This is particularly true in a developing country like China, where more affluence people consume more products, which in turn drives up water consumed in the production and use of these products and impose an elevated pressure on freshwater resources. However, an inverted-U curve between environment pressure and wealth (also known as the environmental Kuznets curve) will appear when the affluence per capita reaches the critical consumption level (Cavlovic et al., 2000), after which water consumption will benefit from economic growth due to increasing efficiency. Although China has not reached this turning point, the fact that growth rate of WFs is much lower than that of the affluence level during the study period indicated that great efforts have been done to strengthen water productivity (Zhao et al., 2014). Given the substantial effect of the growth of affluence on water consumption, we advocate the use of low-water intensity products and increase the recycling of materials.

Furthermore, to offset the negative shock of the 2008 global financial crisis to the Chinese economy, the central government implemented the 4 trillion RMB stimulus program (News, 2008). This program expanded domestic demand and thus added weight to a greater WF after 2007 (Fig. 5). China joined the World Trade Organization (WTO) in 2002. The WTO membership provides greater market access to other WTO member nations. Tariff barriers were significantly lowered, restrictions on trade and foreign direct investment were largely removed, and measures promoting trade were implemented under the rules and regulations of the WTO. China's increasing integration into the global market boosted China's exports, and this led to a significant increase in the WF triggered by exports up to 2007 (OECD, 2009). The 2008 global financial crisis resulted in a decline in China's export volume by 3.6% between 2008 and 2012, and this in turn led to a moderate decrease in the WF triggered by export. In addition, the proportion of high value-added products and services in China's total exports has increased since the financial crisis. This change further reduces the power of exports in driving up the WF.

4.5. Adjusting the consumption and production structure could be a key measure to improve water security and sustainability

Our findings revealed that the changes of consumption pattern (dC) also counteracted the WFs, which indicated that the ratio of food-related expense to the total is decreasing over time, consumers' preferences are transforming to high value-added commodities with lower water intensity from basic life necessities with high water-intensity, this transformation alleviated stress on limited water resource to some extent. This finding also suggested the necessity to promote water-saving by changing consumer behavior and structure. It is important to guide individuals to rationally estimate the water consumption along the supply chain of their consumed products, leans towards purchasing water-saving products, and strengthen their responsibility to water conservation as final consumers (Fan et al., 2019; Gao et al., 2021). Some simple things, such as using water-saving toilets and showering for five minutes instead of ten and attaching a water label for each commodity can help. A more effective structural adjustment is to eat less red meat and rice given that red meat is the most water-intensive proteins and rice is the most water intensive staple food.

Additionally, although nation-wide changes in the industrial structure (dL) led to an increase in the WF, such changes reduced the WF in several provinces (e.g., Beijing, Tianjin, Jiangsu; see Figs. 6–8, supplementary Tables S9 and S10). This exceptional effect is due to production recipes have changed in these provinces to incorporate fewer water-intensive inputs due to an improvement in processing. The local government accelerates industrial restructuring and limits industries with high water consumption and low efficiency, indeed, the share of water-intensive agriculture in the GDP of these provinces decreased from 10% in 2002 to 7% in 2012; at the same time, the GDP share for other manufacturing sectors has increased from 90% in 2002 to 93% in 2012. These developed regions have become importers of agricultural-related products, and the import volume is increasing (Zhao et al., 2015; Feng et al., 2014). This finding implies that in the future—if the intensity of direct water consumption in individual sectors becomes harder to reduce—efforts to adjust the industrial structure will be a feasible strategy for reducing the consumption of water resources in areas with water shortage. Specifically, the comparative advantages between provinces and economic sectors should continue to pay a substantial role in future allocation of production activities in China.

4.6. Limitations and uncertainties

Some limitations of our study should be taken into consideration when interpreting the results. First of all, an aggregated agriculture sector in MRIO table may lead to biased result on calculating production-based BWF and GWF, since agriculture includes crop, forestry, livestock husbandry and fishery. However, only 2012 MRIO for raw single IO tables of each province has the disaggregated data for individual subsectors in agriculture. It is not possible to disaggregate agricultural sector in China's MRIO tables for the other two years. Similar situation is also seen in previous studies (Cai et al., 2020; Zhao et al., 2015; Zhang and Anadon, 2014). Nevertheless, our study focuses on spatiotemporal changes in WFs and the driving forces, the consistent in aggregated agricultural sector for different years will reduce the possible bias caused by the disaggregation in the results.

The additive form of the SDA model we used is under the assumption that all the considered determinants were fully independent from each other. This assumption is required to permit the additive decomposition. However, in the real world, these determinants are likely to be related with each other to some extent. This assumption may lead to biases in the decomposition results. We would like to mention that this study did not include gray WF. By definition, gray WF is the freshwater volume that is required to dilute pollutants sufficiently to meet existing ambient water quality standards or achieve natural background concentrations (Zhao et al., 2017). Based on this definition, the gray WF assesses the water pollution induced by domestic and economic activities; it is not a real water consumption indicator. In this study, we wanted to analyze the driving forces of the water consumption in production. Gray WF is therefore not considered.

The quality of the available data may cause some distortions in the results. The used MRIO tables used were from different sources, and were therefore potentially based on different assumptions and simplifications. Also, we relied on official Chinese statistics on water at the national and provincial levels. The reliability of the water statistics has often been questioned (Zhao et al., 2015). Nevertheless, they still represent the best available comprehensive datasets for addressing our research questions. In addition, the need to estimate some missing data on water use in the secondary and tertiary sectors may also affect the results.

There are some uncertainties in our assessment. We selected 6 major crops (wheat, maize, rice, soybean, millet, and sorghum) to simulate water consumption in the agricultural sector. If more primary crops are included in GEPIC model, our values would be more accurate, but the uncertainty caused by limited crops may be not significant based on the fact that the proportion of simulated crops to total food production in China was over 90% (Liu et al., 2014). In addition, MIRCA 2000 data was used to obtain the ratios of irrigated areas to total sown areas for each major crop at the provincial level (Portmann et al., 2010). This dataset is the primary input for calculating direct BWF and GWF in the GEPIC model across China. Working at the provincial level, we estimated the missing data based on newly added cultivated land areas over time. As a result, the changing trends of direct BWF and GWF in crop production will be correct in our study, however, the values have potentials to be improved when actual irrigation situations are included, especially in water scarce northern China (Wang et al., 2020). The GWF in the agricultural sector did not consider livestock grazing, timber production and bioenergy crops due to the lack of data. This underestimates GWF to some extent.

Variation in precipitation could affect the annual green water use in agriculture. We therefore investigated the precipitation anomalies in 8 economic regions for the year 2002, 2007 and 2012 (see supplementary Table S2 and S3). The results do not show significant difference in terms of rainfall or drought/flood magnitude in each region over 2002, 2007 and 2012. This means that precipitation anomalies had limited effect on the substitution between blue and green WF categories during the study period. Finally, when conducting temporal and driving forces analysis for both BWF and GWF, the data of three time points (2002, 2007 and 2012) were used. They have been the only data available in China for such analysis. We consider that the time period over 10 years can reflect the trends in changes in WFs across regions and sectors. The same data were commonly used in similar SDA studies (Deng et al., 2016; Mi et al., 2017; Cai et al., 2019).

Last but not lease, because the calculations of water footprint using the MRIO framework involve tracing the indirect (embodied) water-use across the networks of the supply chains throughout the economy, it would become too complicate to differentiate between water footprint trends that emerged spontaneously from those which were the result of deliberate policy measures, without imposing strong assumptions and introducing new error margins.

5. Conclusions

This study investigated the spatial-temporal distribution of blue water footprint (BWF) and green water footprint (GWF) in China for the years 2002, 2007 and 2012 within the framework of multi-region input-output (MRIO) analysis. We included green water in the analysis of water footprint (WF) and introduced the structural decomposition analysis (SDA) technique to study the driving forces behind BWF and GWF changes at the provincial level, and we developed one decoupling index to quantify the water-economy relation and compared the relative movements of water intensity per unit of gross domestic product (GDP) and GWF proportion in total WF. The following conclusions were drawn:

- The average BWF in China was approximately 161 billion m^3/yr during 2002–2012, equivalent to about one-third of GWF. Agriculture-related commodities accounted for the majority of China's WF, but their proportion decreased gradually during the study period. The Northwest region accounted for the largest proportion of BWF but the second smallest GWF.
- Water scarce provinces in Northern China were moving towards decoupling between economic growth and blue water consumption, with GWF playing an increasingly important role.
- The changes of WF were mainly influenced by changes in affluence (dY), technology (dW) and the consumption pattern (dC), rather than changes in population and exports. Striking differences in WFs distribution and the roles of its socioeconomic determinants highlight the different challenges that stakeholders in different sectors and provinces are facing in their efforts to ensure water security and sustainability.
- At the provincial scale, economic structure effect (dL) has changed from an accelerator of WF change to a decelerator in several provinces, implying that efforts to adjust the industrial structure will be a feasible strategy for reducing water consumption in areas with water scarcity problems in the future.
- The results show that technology improvement, consumption pattern shift and industrial structure adjustment contributed to WF reductions, thus helped improve water security and sustainability in China.
- Our work can inspire other countries to enhance the utilization of green water resources in exchange for the minimization of blue water usage, via both market incentives and regulatory policies, with the aim to achieve water sustainability without compromising economic development.

Data availability statement

Datasets are supplied by this paper and its supplementary information files, all the data is available for the public.

CRediT authorship contribution statement

Dandan Zhao: Conceptualization, Data curation, Methodology, Investigation, Visualization, Writing – original draft, Writing – review & editing. **Junguo Liu:** Conceptualization, Supervision, Investigation, Writing – review & editing. **Hong Yang:** Supervision, Investigation, Writing – review & editing. **Laixiang Sun:** Supervision, Investigation, Writing – review & editing. **Olli Varis:** Supervision, Investigation, Writing – review & editing.

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.

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Supplementary materials

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References

Allan, J.A., 1996. Water use and development in arid regions: environment, economic development and water resource politics and policy. Rev. Eur. Community Int. Environ. Law 5 (2), 107–115.
Cai, B., Hubacek, K., Feng, K., Zhang, W., Wang, F., Liu, Y., 2020. Tension of agricultural land and water use in China's trade: tele-connections, hidden drivers and potential solutions. Environ. Sci. Technol. 54 (9), 5365–5375.
Cai, B., Zhang, W., Hubacek, K., Feng, K., Li, Z., Liu, Y., et al., 2019. Drivers of virtual water flows on regional water scarcity in China. J. Clean. Prod. 207, 1112–1122.
Cai, J., Yin, H., Varis, O., 2016. Impacts of industrial transition on water use intensity and energy-related carbon intensity in China: a spatio-temporal analysis during 2003–2012. Appl. Energy 183, 1112–1122.
Cai, J., Varis, O., Yin, H., 2017. China's water resources vulnerability: a spatio-temporal analysis during 2003–2013. J. Clean. Prod. 142, 2901–2910.
Cavlovic, T.A., Baker, K.H., Berrens, R.P., Gawande, K., 2000. A meta-analysis of environmental Kuznets curve studies. Agric. Res. Econ. Rev. 29, 32–42.
Cazcarro, I., Duarte, R., Sanchez, J., 2013. Multiregional input–output model for the evaluation of Spanish water flows. Environ. Sci. Technol. 47 (21), 12275–12283.
Chapagain, A.K, Hoekstra, A.Y., 2008. The global component of freshwater demand and supply: an assessment of virtual water flows between nations as a result of trade in agricultural and industrial products. Water international 33 (1), 19–32.
Chen, S., Tan, Y., Liu, Z., 2019. Direct and embodied energy-water-carbon nexus at an inter-regional scale. Appl. Energy 251, 113401.
Chen, W., Wu, S., Lei, Y., Li, S., 2017. China's water footprint by province, and inter-provincial transfer of virtual water. Ecol. Indic. 74, 321–333.
Chen, W., Wu, S., Lei, Y., Li, S., 2018. Virtual water export and import in china's foreign trade: a quantification using input-output tables of China from 2000 to 2012. Resour. Conserv. Recycl. 132, 278–290.
Chinese Academy of Science. Spatial interpolation dataset of annual precipitation in China. (2021) http://www.resdc.cn/(Chinese).
Connor, R., 2015. The United Nations World Water Development Report 2015: Water For a Sustainable World, 1. UNESCO publishing.
Costanza, R., d'Arge, R., De Groot, R., Farber, S., Grasso, M., Hannon, B, et al., 1997. The value of the world's ecosystem services and natural capital. Nature 387 (6630), 253–260.
Deng, G., Ma, Y., Li, X., 2016. Regional water footprint evaluation and trend analysis of China—based on interregional input–output model. J. Clean. Prod. 112, 4674–4682.
Dietzenbacher, E., Los, B., 1998. Structural decomposition techniques: sense and sensitivity. Econ. Syst. Res. 10 (4), 307–324. https://doi.org/10.1080/09535319800000023.
Dong, F., Yu, B., Hadachin, T., Dai, Y., Wang, Y., Zhang, S., Long, R., 2018. Drivers of carbon emission intensity change in China. Resour. Conserv. Recycl. 129, 187–201.
Fan, J., Wang, J., Zhang, X., Kong, L., Song, Q., 2019. Exploring the changes and driving forces of water footprints in China from 2002 to 2012: a perspective of final demand. Sci. Total Environ. 650, 1101–1111. https://doi.org/10.1016/j.scitotenv.2018.08.426.
Feng, K., Chapagain, A., Suh, S., Pfister, S., Hubacek, K., 2011. Comparison of bottom-up and top-down approaches to calculating the water footprints of nations. Econ. Syst. Res. 23 (4), 371–385.
Feng, K., Hubacek, K., 2015. A multi-region input–output analysis of global virtual water flows. Handbook of Research Methods and Applications in Environmental Studies. Edward Elgar Publishing.
Feng, K., Davis, S.J., Sun, L., Li, X., Guan, D., Liu, W., et al., 2013. Outsourcing CO_2 within China. Proc. Natl. Acad. Sci. USA. 110 (28), 11654–11659. https://doi.org/10.1073/pnas.1219918110.
Feng, K., Hubacek, K., Pfister, S., Yu, Y., Sun, L., 2014. Virtual scarce water in China. Environ. Sci. Technol. 48 (14), 7704–7713.
Feng, K., Davis, S.J., Sun, L., Hubacek, K., 2015. Drivers of the US CO 2 emissions 1997–2013. Nat. Commun. 6 (1), 1–8.
Gao, C., Xie, R., Zhang, Y., Zhu, K., 2021. Drivers of dynamic evolution in provincial production water usage: perspective of regional relevance. Environ. Sci. Pollu. Res. 28 (12), 15130–15146.
Garcia, S., Rushforth, R., Ruddell, B.L., Mejia, A., 2020. Full domestic supply chains of blue virtual water flows estimated for major US cities. Water Resour. Res. 56 (4), e2019WR026190.
Godfray, H.C., Beddington, J.R., Crute, I.R., Haddad, L., Lawrence, D., Muir, J.F., et al., 2010. Food security: the challenge of feeding 9 billion people. Science 327 (5967), 812–818. https://doi.org/10.1126/science.1185383.
Gosling, S.N., Arnell, N.W., 2016. A global assessment of the impact of climate change on water scarcity. Clim. Change 134 (3), 371–385. https://doi.org/10.1007/s10584-013-0853-x.
Gu, S., Jenkins, A., Gao, S.J., Lu, Y., Li, H., Li, Y., et al., 2017. Ensuring water resource security in China; the need for advances in evidence-based policy to support sustainable management. Environ. Sci. Policy 75, 65–69.
Guan, D., Hubacek, K., 2007. Assessment of regional trade and virtual water flows in China. Ecol. Econ. 61 (1), 159–170. https://doi.org/10.1016/j.ecolecon.2006.02.022.
Guan, D., Hubacek, K., Tillotson, M., Zhao, H., Liu, W., Liu, Z., Liang, S., 2014a. Lifting China's water spell. Environ. Sci. Technol. 48 (19), 11048–11056.
Guan, D., Su, X., Zhang, Q., Peters, G.P., Liu, Z., Lei, Y., He, K., 2014b. The socioeconomic drivers of China's primary PM2.5 emissions. Environ. Res. Lett. 9 (2), 024010 https://doi.org/10.1088/1748-9326/9/2/024010.
Haghighi, E., Madani, K., Hoekstra, A.Y., 2018. The water footprint of water conservation using shade balls in California. Nat. Sustain. 1 (7), 358–360.
Hoekstra, A.Y., 2019. Green-blue water accounting in a soil water balance. Adv. Water Resour. 129, 112–117.
Hoekstra, A.Y., 2003. Virtual water trade: a quantification of virtual water flows between nations in relation to international crop trade. Proceedings of the International Expert Meeting on Virtual Water Trade 12. Delft, pp. 25–47, 2003.
Hoekstra, A.Y., Chapagain, A.K., Mekonnen, M.M., Aldaya, M.M., 2011. The Water Footprint Assessment manual: Setting the Global Standard. Routledge.
Hoekstra, R., van der Bergh, J.C., 2003. Comparing structural and index decomposition analysis. Energy Econ 25 (1), 39–64. https://doi.org/10.1016/S0140-9883(02)00059-2.
Hou, S., Liu, Y., Zhao, X., Tillotson, M.R., Guo, W., Li, Y., 2018. Blue and Green Water Footprint Assessment for China—A Multi-Region Input–Output Approach. Sustainability 10 (8), 2822.
Huang, Q., Wang, J., Li, Y., 2017. Do water saving technologies save water? Empirical evidence from North China. J. Environ. Econ. Manage. 82, 1–16.
Hubacek, K., Feng, K., 2016. Comparing apples and oranges: some confusion about using and interpreting physical trade matrices versus multi-regional input-output analysis. Land Use Policy 50, 194–201. https://doi.org/10.1016/j.landusepol.2015.09.022.
Jiao, J., Han, X., Li, F., Bai, Y., Yu, Y., 2017. Contribution of demand shifts to industrial SO_2 emissions in a transition economy: evidence from China. J. Clean. Prod. 164, 1455–1466. https://doi.org/10.1016/j.jclepro.2017.07.060.
Keyantash, J., Dracup, J.A., 2002. The quantification of drought: an evaluation of drought indices. Bull. Am. Meteorol. Soc. 83 (8), 1167–1180.
Kummu, M., Ward, P.J., de Moel, H., Varis, O., 2010. Is physical water scarcity a new phenomenon? Global assessment of water shortage over the last two millennia. Environ. Res. Lett. 5 (3), 34006.
Lan, J., Malik, A., Lenzen, M., McBain, D., Kanemoto, K., 2016. A structural decomposition analysis of global energy footprints. Appl. Energy 163, 436–451. https://doi.org/10.1016/j.apenergy.2015.10.178.
Leontief, W., 1986. Input-output Economics. Oxford University Press.
Leontief, W., 1951. The structure of American economy, 1919-1939: an empirical application of equilibrium analysis. Rev. Économique 4 (1), 124–125.
Liang, S., Liu, Z., Crawford-Brown, D., Wang, Y., Xu, M., 2014. Decoupling analysis and socioeconomic drivers of environmental pressure in China. Environ. Sci. Technol. 48 (2), 1103–1113.

Liu, J., Yang, H., 2010. Spatially explicit assessment of global consumptive water uses in cropland: green and blue water. J. Hydrol. 384 (3–4), 187–197. https://doi.org/10.1016/j.jhydrol.2009.11.024.

Liu, J., Wiberg, D., Zehnder, A.J.B., Yang, H., 2007. Modeling the role of irrigation in winter wheat yield, crop water productivity, and production in China. Irrig. Sci. 26 (1), 21–33. https://doi.org/10.1007/s00271-007-0069-9.

Liu, J., Yang, H., Gosling, S.N., Kummu, M., Flörke, M., Pfister, S., et al., 2017a. Water scarcity assessments in the past, present, and future. Earth's Futur. 5 (6), 545–559. https://doi.org/10.1002/2016EF000518.

Liu, J., Zhao, X., Yang, H., Liu, Q., Xiao, H., Cheng, G., 2018. Assessing China's "developing a water-saving society" policy at a river basin level: a structural decomposition analysis approach. J. Clean. Prod. 190, 799–808.

Liu, J., Zhao, D., Mao, G., Cui, W., Chen, H., Yang, H., 2020. Environmental sustainability of water footprint in mainland China. Geogr. Sustain. 1 (1), 8–17.

Liu, W., Tang, Z., Chen, J., Yang, B., 2014. Multi-regional Input-output model for 30 Provinces of China in 2007. China Statistics Press, Beijing.

Liu, Y., Zhuo, L., Varis, O., Fang, K., Liu, G., Wu, P., 2021. Enhancing water and land efficiency in agricultural production and trade between Central Asia and China. Sci. Total Environ. 780 (146584) https://doi.org/10.1016/j.scitotenv.2021.146584.

Liu, Y., 2016. The Analysis of Water Footprint Changes and Driving Mechanism in Beijing-Tianjin-Hebei. Beijing Forestry University. (in Chinese).

Liu, Z., Liu, S., Jin, H., Qi, W., 2017b. Rural population change in China: spatial differences, driving forces and policy implications. J. Rural Stud. 51, 189–197.

Lenzen, M., 2009. Understanding virtual water flows: a multiregion input-output case study of Victoria. Water Resour. Res. 45 (9), W09416. https://doi.org/10.1029/2008WR007649.

Lenzen, M., Morana, D., Bhadurib, A., Kanemotoa, K., Bekchanovb, M., Geschkea, A., et al., 2013. International trade of scarce water. Ecol. Econ. 94, 78–85. Retrieved from. http://www.sciencedirect.com/science/article/pii/S0921800913002176%5Cnfiles/459/S0921800913002176.html.

Malik, A., Lan, J., 2016. The role of outsourcing in driving global carbon emissions. Econ. Syst. Res. 28 (2), 168–182. https://doi.org/10.1080/09535314.2016.1172475.

Marston, L., Ao, Y., Konar, M., Mekonnen, M.M., Hoekstra, A.Y., 2018. High-resolution water footprints of production of the United States. Water Resour. Res. 54 (3), 2288–2316.

Mekonnen, M.M., Hoekstra, A.Y., 2011. National water footprint accounts: the green, blue and grey water footprint of production and consumption.

Meng, Q., Sun, Q., Chen, X., Cui, Z., Yue, S., Zhang, F., et al., 2012. Alternative cropping systems for sustainable water and nitrogen use in the North China Plain. Agric. Ecosys. Environ. 146 (1), 93–102.

Mi, Z., Meng, J., Guan, D., Shan, Y., Song, M., Wei, Y.M., et al., 2017. Chinese CO_2 emission flows have reversed since the global financial crisis. Nat. Commun. 8 (1), 1–10. https://doi.org/10.1038/s41467-017-01820-w.

Miller, R.E., Blair, P.D., 2009. Input-Output Analysis: Foundations and Extensions. Cambridge University Press.

Ministry of Agriculture, 2003. Chinese Agricultural Yearbook, 2013. China Agriculture Press (Chinese).

Ministry of Water Resources of China, 2003. Provincial Water Resource Bulletin, 2008 and 2013. China Water Power Press (Chinese).

National Bureau of Statistics of China, 2003. China Statistical Yearbook, 2008 and 2013. China Statistics Press, Beijing (Chinese).

National Bureau of Statistics of China, 2008a. China Economic Census Yearbook. China Statistics Press, Beijing (Chinese).

OECD, 2009. China in the World economy: an OECD Economic and Statistical Survey. Organization for Economic Co-operation and Development.

Portmann, F.T., Siebert, S., Döll, P., 2010. MIRCA2000—Global monthly irrigated and rain-fed crop areas around the year 2000: a new high-resolution data set for agricultural and hydrological modeling. Glob. Biogeochem. Cycles 24 (1).

Orlowsky, B., Hoekstra, A.Y., Gudmundsson, L., Seneviratne, S.I., 2014. Today's virtual water consumption and trade under future water scarcity. Environ. Res. Lett. 9 (7), 074007 https://doi.org/10.1088/1748-9326/9/7/074007.

Schyns, J.F., Hoekstra, A.Y., Booij, M.J., Hogeboom, R.J., Mekonnen, M.M., 2019. Limits to the world's green water resources for food, feed, fiber, timber, and bioenergy. Proc. Natl. Acad. Sci. USA. 116 (11), 4893–4898.

Sanders, K.T., 2015. Critical review: uncharted waters? The future of the electricity-water nexus. Environ. Sci. Technol. 49 (1), 51–66.

Soligno, I., Malik, A., Lenzen, M., 2019. Socioeconomic Drivers of Global Blue Water Use. Water Resour. Res. 55 (7), 5650–5664.

State Information Center, 2005. Multi-regional Input–output Model for China. Social Science Academic Press (Chinese).

Su, B., Ang, B.W., 2012. Structural decomposition analysis applied to energy and emissions: some methodological developments. Energy Econ. 34 (1), 177–188. https://doi.org/10.1016/j.eneco.2011.10.009.

Su, B., Ang, B.W., 2017. Multiplicative structural decomposition analysis of aggregate embodied energy and emission intensities. Energy Econ. 65, 137–147. https://doi.org/10.1016/j.eneco.2017.05.002.

Sun, S., Fang, C., Lv, J., 2017. Spatial inequality of water footprint in China: a detailed decomposition of inequality from water use types and drivers. J. Hydrol. 553, 398–407. https://doi.org/10.1016/j.jhydrol.2017.08.020.

Varis, O., 2014. Curb vast water use in central Asia. Nature 514 (7520), 27–29. https://doi.org/10.1038/514027a (02 October 2014).

Varis, O., Abu-Zeid, K., 2009. Socio-economic and environmental aspects of water management in the 21st century: trends, challenges and prospects for the MENA region. Inter. J. Water Res. Dev. 25, 507–522.

Wada, Y., Wisser, D., Bierkens, M.F.P., 2013. Global modeling of withdrawal, allocation and consumptive use of surface water and groundwater resources. Earth Syst. Sci. Data Discuss. 5 (1), 15–40. https://doi.org/10.5194/esdd-4-355-2013.

Wada, Y., Bierkens, M.F.P., 2014. Sustainability of global water use: past reconstruction and future projections. Environ. Res. Lett. 9 (10), 104003 https://doi.org/10.1088/1748-9326/9/10/104003.

Wang, X, Xin, L, Tan, M, Li, X, Wang, J, 2020. Impact of spatiotemporal change of cultivated land on food-water relations in China during 1990–2015. Sci. Total Environ. 716, 137119.

World Economic Forum, 2017. Global Risks 2017. World Economic Forum, Geneva, 12th Ed.

Xinhua News., 2008. China's 4 trillion yuan stimulus to boost economy.

Xiong, Y., Tian, X., Liu, S., Tang, Z., 2020. New patterns in China's water footprint: analysis of spatial and structural transitions from a regional perspective. J. Clean. Prod. 245, 118942.

Xu, Z., Chen, X., Wu, S.R., Gong, M., Du, Y., Wang, J., et al., 2019. Spatial-temporal assessment of water footprint, water scarcity and crop water productivity in a major crop production region. J. Clean. Prod. 224, 375–383.

Yang, Y., Ingwersen, W.W., Meyer, D.E., 2018. Exploring the relevance of spatial scale to life cycle inventory results using environmentally-extended input-output models of the United States. Environ. Model. Softw. 99, 52–57.

Yang, Z., Liu, H., Xu, X., Yang, T., 2016. Applying the water footprint and dynamic structural decomposition analysis on the growing water use in China during 1997–2007. Ecol. Indic. 60, 634–643.

Zang, C., Liu, J., 2013. Trend analysis for the flows of green and blue water in the Heihe River basin, northwestern. China. J. Hydrol. 502, 27–36. https://doi.org/10.1016/j.jhydrol.2013.08.022.

Zeitoun, M., Allan, J.A.T., Mohieldeen, Y., 2010. Virtual water 'flows' of the Nile Basin, 1998–2004: a first approximation and implications for water security. Glob. Environ. Change 20 (2), 229–242.

Zhang, C., Anadon, L.D., 2014. A multi-regional input–output analysis of domestic virtual water trade and provincial water footprint in China. Ecol. Econ. 100, 159–172.

Zhang, P., Zou, Z., Liu, G., Feng, C., Liang, S., Xu, M., 2020a. Socioeconomic drivers of water use in China during 2002–2017. Resour. Conserv. Recycl. 154, 104636.

... Zhang, X., Liu, J., Tang, Y., Zhao, X., Yang, H., Gerbens-Leenes, P.W., Yan, J., 2017. China's coal-fired power plants impose pressure on water resources J. Clean. Prod. 161, 1171–1179.

Zhang, X., Liu, J., Zhao, X., Yang, H., Deng, X., Jiang, X., Li, Y., 2019a. Linking physical water consumption with virtual water consumption: methodology, application and implications. J. Clean. Prod. 228, 1206–1217.

Zhang, S, Taiebat, M, Liu, Y, Qu, S, Liang, S, Xu, M, 2019. Regional water footprints and interregional virtual water transfers in China. J. Clean. Prod. 228, 1401–1412.

... Zhang, X., Zhao, X., Li, R., Mao, G., Tillotson, M.R., Liao, X., Yi, Y., 2020b. Evaluating the vulnerability of physical and virtual water resource networks in China's megacities Resour. Conserv. Recycl. 161, 104972.

Zhang, Y., Chen, Y., Huang, M., 2019b. Water Footprint and virtual water accounting for China using a multi-regional input-output model. Water 11 (1), 34.

Zhang, Z., Shi, M., Yang, H., 2012. Understanding Beijings water challenge: a decomposition analysis of changes in Beijings water footprint between 1997 and 2007. Environ. Sci. Technol. 46 (22), 12373–12380. https://doi.org/10.1021/es302576u.

Zhao, C., Chen, B., Hayat, T., Alsaedi, A., Ahmad, B., 2014a. Driving force analysis of water footprint change based on extended STIRPAT model: evidence from the Chinese agricultural sector. Ecol. Indic. 47, 43–49.

Zhao, D., Tang, Y., Liu, J., Tillotson, M.R., 2017a. Water footprint of Jing-Jin-Ji urban agglomeration in China. J. Clean. Prod. 167, 919–928.

... Zhao, H., Qu, S., Liu, Y., Guo, S., Zhao, H., Chiu, A.C., Xu, M., 2020. Virtual water scarcity risk in China Resour. Conserv. Recycl. 160, 104886.

Zhao, N., Xu, L., Malik, A., Song, X., Wang, Y., 2018. Inter-provincial trade driving energy consumption in China. Resour. Conserv. Recycl. 134, 329–335.

Zhao, Q., Liu, J., Khabarov, N., Obersteiner, M., Westphal, M., 2014b. Impacts of climate change on virtual water content of crops in China. Ecol. Inform. 19, 26–34. https://doi.org/10.1016/j.ecoinf.2013.12.005.

Zhao, X., Tillotson, M.R., Liu, Y.W., Guo, W., Yang, A.H., Li, Y.F., 2017b. Index decomposition analysis of urban crop water footprint. Ecol. Modell. 348, 25–32. https://doi.org/10.1016/j.ecolmodel.2017.01.006.

Zhao, X., Yang, H., Yang, Z., Chen, B., Qin, Y., 2010. Applying the input-output method to account for water footprint and virtual water trade in the Haihe River basin in China. Environ. Sci. Technol. 44 (23), 9150–9156. https://doi.org/10.1021/es100886r.

Zhao, X., Liu, J., Liu, Q., Tillotson, M.R., Guan, D., Hubacek, K., 2015. Physical and virtual water transfers for regional water stress alleviation in China. Proc. Natl. Acad. Sci. USA. 112 (4), 1031–1035.

Zheng, H., Zhang, Z., Wei, W., Song, M., Dietzenbacher, E., Wang, X., et al., 2020. Regional determinants of China's consumption-based emissions in the economic transition. Environ. Res. Lett. https://doi.org/10.1088/1748-9326/ab794f.

Zhong, H., Sun, L., Fischer, G., Tian, Z., van Velthuizen, H., Liang, Z., 2017. Mission Impossible? Maintaining regional grain production level and recovering local groundwater table by cropping system adaptation across the North China plain. Agric. Water Manag. 193, 1–12.

Zhong, H., Sun, L., Fischer, G., Tian, Z., Liang, Z., 2019. Optimizing regional cropping systems with a dynamic adaptation strategy for water sustainable agriculture in the Hebei Plain. Agric. Syst. 173, 94–106.
... Zhou, F., Bo, Y., Ciais, P., Dumas, P., Tang, Q., Wang, X., Wada, Y., 2020. Deceleration of China's human water use and its key drivers Proc. Natl. Acad. Sci. USA. 117 (14), 7702–7711.
Zhuo, L., Mekonnen, M.M., Hoekstra, A.Y., 2016. Consumptive water footprint and virtual water trade scenarios for China - With a focus on crop production, consumption and trade. Environ. Int. 94, 211–223. https://doi.org/10.1016/j.envint.2016.05.019.