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Spatiotemporal Evolution and Driving Mechanisms of Water Footprint with Input-Output Paradigm: A Case Study of China

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Abstract: The evaluation and quantification of water consumption based on water footprint (WF) is important for sustainable utilization of water resources and is becoming one of the key bases for formulating water resources management policies. However, there are few systematic assessments of both temporal changes and spatial patterns of WF in China, and the driving of water footprint intensity (WFI) is rarely reported. Based on the research background, this paper takes China, the world's largest developing country, as an example to analyze the spatiotemporal evolution of WF through the input–output model. The total WF in China increased by 11.76% from 2002 to 2017. National WFI decreased from 550 $m^3/10^4$ yuan (2002) to 152 $m^3/10^4$ yuan (2017). The regions found to have the highest WF in China include Shandong, Henan, and Hebei, and regions with higher WFI are distributed in East China. From 2002 to 2017, the total WF of each province in China changed significantly. Guangdong, Fujian, and Zhejiang provinces' total WF decreased markedly during the study period. The results show that the grain output per capita and GDP per capita have a significant driving effect on WFI. By adjusting the agricultural structure and improving the comprehensive ability of scientific and technological innovation, it is possible to reduce the WFI in China.

Keywords: water footprint; input-output analysis; driving mechanism; China

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1. Introduction

Water scarcity has been a key environmental issue globally [1], which is a limitation to the realization of the Sustainable Development Goals (SDGs) by 2030 [2]. Human activities consume a lot of water while producing various products and services. China, as the world's largest developing country, is an area with one of the most serious water shortages in the world [3,4]. Thus, the sustainable utilization of water resources is key to China's sustainable development. The assessment of water consumption and the understanding of underlying mechanisms in China are the prerequisites for solving water problems and proposing water-related policies.

Water footprint (WF) is considered to be a reasonable indicator of water consumption in each sector [5], referring to the amount of water consumed in the production of goods or services throughout the supply chain [6]. The wider applications of WF demonstrate its increasingly recognized relevance to policy [7]. Many scholars and institutions have conducted studies on global WF accounting. Hoekstra conducted the first research study on crop WF in 2002 [8] and produced a water footprint calculation manual [9], which proposed WF calculation methods for several products. In the context of China, Zhao et al. [10] calculated China's national water footprint in 2002 and evaluated intersectoral trade, suggesting sectors with high net virtual water exports as a focus for future water conservation in China. Some scholars have calculated WF in specific sectors, mainly in agricultural chains, industry, and food processing [11]. There are two widely accepted methods to assess the regional WF. One is to multiply the water consumption per unit of the production process by the trade volume of the commodity (bottom-up method) [12,13]. The bottom-up method (B-U) is complex when dealing with water consumption in the industrial and service sectors, and is incapable of distinguishing between intermediate and final demand [14]. Hoekstra et al. [14] used the B-U method to assess only direct water consumption during production in 2017.

Another is the top-down (T-D) method [10,15], which calculates WF by tracking the supply chain of the Chinese provincial economy through a monetary transaction matrix. Using an input–output analysis (IOA) to calculate WF is an example of the T-D approach which some scholars have used to measure and assess water resources. By performing a multi-regional input–output (MRIO) analysis, Wang et al. [16] found that 90% of China's WF is reflected in trade, and pointed out that China is subject to both increasing environmental pollution and resource pressure in the global supply chain. Liu et al. [17] tracked trade in three specific regions through MRIO, and confirmed that the growth of value in chain-related trade is a vital factor in the increase of water use. Some scholars have attempted to identify the driving factors behind the increased WF of specific sectors. Zhao et al. [18] explored impacts on WF associated with agricultural products, including population, through an extended Stochastic Impacts by Regression on Population, Affluence, and Technology (STIRPAT) model. Yang et al. [19] studied water use from 1997 to 2007 through WFs in China and derived the determinants of increased water use through the structural decomposition analysis (SDA) method. Zhang et al. [20] assessed virtual water trade between the Yellow River Delta and other provinces through an MRIO analysis, and showed that virtual water (VW) trade exacerbates local water scarcity. There are few reports on the spatiotemporal evolution of various sectors and total WF, as well as the impact of different social and economic factors on the WF of different sectors.

Accordingly, the present study calculated the volume of WF in China and defined the following goals: (1) to analyze the spatiotemporal evolution of WF at the provincial level in China from 2002–2017 and identify the key thermal zones and sectors; and (2) to explore and analyze the driving factors of WFI in different sectors in China. This paper aims to provide a theoretical reference for the sustainable management of water resources in China and other developing countries worldwide.

2. Materials and Methods

2.1. IO Table-Based WF Calculation

The calculation of WF based on IO consists of three parts. Firstly, we accounted for the direct water consumption of each sector across 16 categories. Secondly, the IO tables were processed to fit them into the appropriate form. Finally, we calculated the sectoral WF and WFI, as shown in Figure 1.

First, we consolidated IO table data for each province from 2002 to 2017 into 16 different sectors. Sector abbreviations are shown in Table 1.

Table 1. Sector Abbreviations.

Sector	Abbreviation	Sector	Abbreviation
Agriculture	AGR	Transportation Equipment	TRE
Mining Industry	MIN	Other Sanufacturing	OMA
Food and Beverage	FAB	Water, Electricity and Gas	WEG
Textile	TEX	Construction	CON
Wood and Paper	WAP	Transport, Post and Communications	TPC
Petroleum, Chemical and Non-Metallic Products	PCN	Sale	SAL
Metal Products	MET	Hotels and Restaurants	HRA
Electronics and Machinery	EAM	Other Services	OSE

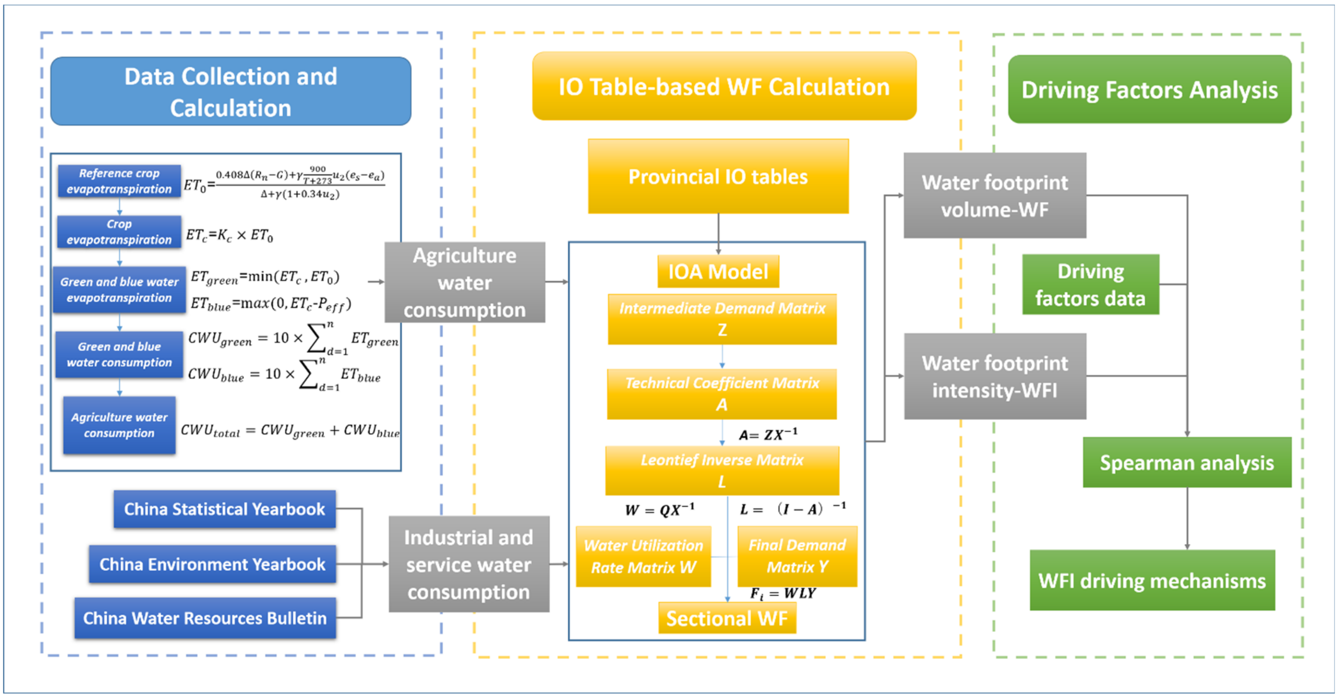

Figure 1. Model and calculation methods.

We then reset IO tables, at which point the effects of imports were eliminated and the outputs were corrected for calculation (as shown in Supplementary Material 1).

Based on the equilibrium relationship and contents of each quadrant, we entered the Water Resources Satellite Account Matrix U. We could then obtain the Technical Coefficient Matrix A, i.e., as shown in Equation (1), where Z is n G n Intermediate Demand Matrix and X is n G 1 Total Output Column Matrix in Equation (2).

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} = \begin{bmatrix} Z_{11} & \cdots & Z_{1n} \\ \vdots & \ddots & \vdots \\ Z_{n1} & \cdots & Z_{nn} \end{bmatrix} \cdot \left[(x_1 \cdots x_r \cdots x_n)^T \right]^{-1} \tag{1}$$

$$(x_1 \cdots x_r \cdots x_n)^T = X, \begin{pmatrix} Z_{11} & \cdots & Z_{1n} \\ \vdots & \ddots & \vdots \\ Z_{n1} & \cdots & Z_{nn} \end{pmatrix} = Z \tag{2}$$

The Leontief inverse Matrix L is obtained by matrix operations, i.e., as shown in Equation (3), where I_n is n G n identity matrix.

$$L = \begin{bmatrix} l_{11} & \cdots & l_{1n} \\ \vdots & \ddots & \vdots \\ l_{n1} & \cdots & l_{nn} \end{bmatrix} = \left\{ \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & 1 \end{bmatrix} - \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \right\}^{-1} \tag{3}$$

Before entering Water Resources Satellite Account, we calculated sectoral water consumption, which consists of three components, including agricultural production, manufacturing, and services.

Agricultural production is composed of crop and animal production. The water consumption of crop production CWU_{total} includes blue water consumption CWU_{blue} and green water consumption CWU_{green}. CWU_{blue} and CWU_{green} are equal to the daily evapotranspiration of crops from planting date to harvest date. Blue water evapotranspiration ET_{blue} is the difference between the total evapotranspiration ET_C and the effective precipitation

P_{eff} (when $(ET_c\text{-}P_{eff})$ was less than zero, it was set as 0). Green water evapotranspiration ET_{green} is a smaller value between total evapotranspiration ET_C and effective precipitation P_{eff}. Total evapotranspiration ET_C is obtained by multiplying the crop coefficient K_C with the reference crop evapotranspiration ET_0.

The animal production water consumption consists of two main parts: water consumption during the entire life cycle, from birth to slaughter; and water consumption during manufacturing. The water consumed during the life cycle consists of three parts: water for processing feed, drinking, and cleaning services. The water consumption in fresh water farming mainly takes the amount of water used for evaporation and cleaning of the water body into account. The data on livestock production used in the calculations were obtained from the China Statistical Yearbook and the compilation of national agricultural product income data.

The water consumption of the industrial and service sectors are much smaller than agriculture in terms of processing primary products, which accounts for approximately a quarter of agricultural water consumption. Therefore, for calculation for WF we mainly considered the blue water volume consumed in the process, which is based on the Water Resources Bulletin from every province.

We entered the calculated water consumption by sector to obtain the Satellite Account Matrix $\hat{U}$ and Water Utilization Rate Matrix $\hat{W}$ in Equation (4), where $w_i = \frac{u_i}{x_i}$.

$$\begin{bmatrix} u_1 & 0 & \cdots & 0 \\ 0 & u_2 & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & u_n \end{bmatrix} = \hat{U}, \begin{bmatrix} w_1 & 0 & \cdots & 0 \\ 0 & w_2 & & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & w_n \end{bmatrix} = \hat{W} \quad (4)$$

According to the Leontief model, we combine $\hat{W}$, L, and Final Demand Matrix Y to find WF in production of the sector F_i in billions of m^3, as shown in Equation (5):

$$F_i = (F_1 \cdots F_r \cdots F_n)^T = \hat{W}L\hat{Y} \quad (5)$$

The provincial total WF of each sector can be summed to obtain the total WF F in a given year in billions of m^3, as shown in Equation (6):

$$F = \sum_{i=1}^{n} F_i \quad (6)$$

By combining the sectoral WF F_i and total WF F, we correspondingly divided by the value added of each sector with the province's gross regional product to obtain the provincial WFI FI in $m^3/10^4$ yuan, as shown in Equation (7).

$$FI = \frac{F^i_{pro}}{v} \quad (7)$$

Here, v is the added value of a sector in 10^4 yuan. When it comes to provincial WFI, the v represents the regional GDP of each province in that year in 10^4 yuan.

The IO table is a macroeconomic analysis tool proposed by Leontief [21,22]. The original IO tables used in this paper were obtained from the China National Bureau of Statistics.

2.2. Driving Factors and Mechanisms

In this paper, 12 economic and social factors were selected [14,23–25] as independent variables, and analysis of the impact of these factors on WFI across sectors was performed using Spearman's correlation analysis method. Factors were selected based on economic conditions (F1 et al.), social situation (F2 et al.), living standards (F4 et al.), and scientific level (F11 and F12). The driver data were obtained from the China Statistical Yearbook, China Environmental Statistical Yearbook, etc. The data resources are displayed in Table 2. The codes and abbreviations are shown in Table 3.

Table 2. Data Resources.

Main Data	Data Resources
Agricultural Water Consumption	China Statistical Yearbook Compilation of National Agricultural Product Income China Meteorological Administration
Manufacturing Water Consumption	China Statistical Yearbook China Statistical Yearbook on Environment
Service Water Consumption	China Statistical Yearbook China Statistical Yearbook of the Tertiary Industry
IO Tables	National Bureau of Statistics
Driving Factors	China Statistical Yearbook China Environmental Statistical Yearbook

Table 3. Driving factors and codes.

Code	Driving Factor	Code	Driving Factor
F1	GDP per Capita	F7	Proportion of Agricultural Output
F2	Urban Population Density	F8	Industrial Output per Capita
F3	Groundwater Supply Ratio	F9	Urbanization Ratio
F4	Urban Engel's Coefficient	F10	Grain Yield per Capita
F5	Rural Engel's Coefficient	F11	Technical Innovation Index
F6	Proportion of Industrial Output	F12	Education Level

3. Results and Analysis

3.1. Changes in China's Water Footprint Volume and Intensity

WF and WFI in China were calculated, and the total national WF showed an increasing trend during the study period (Figure 2a). At the national level, the volume of WF increased from 982.67 billion m^3 in 2002 to 1098.19 billion m^3 in 2017. The largest component among the sectors was *agriculture*, for which the WF proportion decreased from 55.79% to 52.2%. *Food and Beverage* was the sector with the second largest share of the WF volume, which raised from 18.15% (2002) to 27.24% (2017). The *Petroleum, Chemical and Non-Metallic Products* and *Textile* manufacturing industries had the largest share, changing from 1.4% and 5.84% (2002), respectively, to 2.2% and 3.84% (2017). The composition of the tertiary sector decreased from 13.6% (2002) to 12% (2017), where *Hotel and Restaurants* was responsible for the vast majority of the 0.51% improvement during the study period.

The national WFI had a declining trend from 550 m^3/10^4 yuan to 152 m^3/10^4 yuan in 2017, a decrease of 72.36% during the study period. The *Agriculture* and *Food and Beverage* sectors had the largest WFIs in 2002, with 435 m^3/10^4 yuan and 487 m^3/10^4 yuan, respectively, which decreased by 76% and 78% from 2002 to 2017. The sector with the smallest WFI during the study period was the *Hydropower and Gas* sector, which decreased from 1.32 m^3/10^4 yuan (2002) to 0.65 m^3/10^4 yuan (2017).

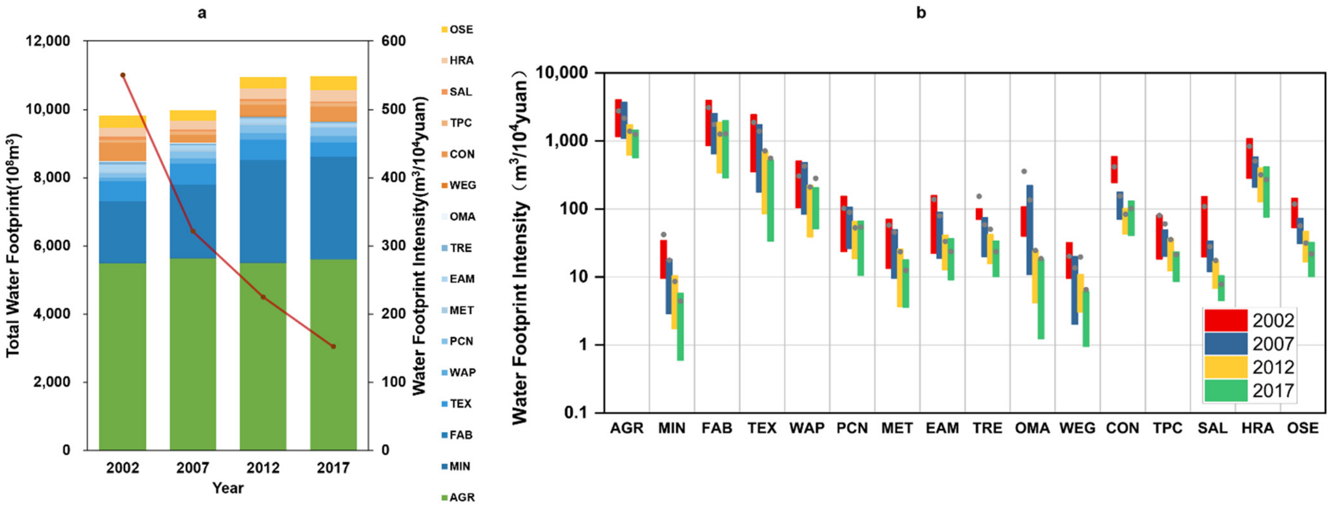

Figure 2. The water footprint and water footprint intensity from 2002–2017. Here, (**a**) shows the water footprint in 2002, 2007, 2012, and 2017 across all sectors, and (**b**) is water footprint intensity of each sector from 2002 to 2017.

3.2. Spatial Distribution and Evolvement of WF and WFI at Provincial Level in China

As shown in Figure 3. The volume of WF and WFI of human activities at the provincial level in China was also calculated and the spatiotemporal evolution was analyzed. In terms of spatial distribution, the regions with higher WF volume in China are located in North China. In 2002, Shandong, Henan, and Hebei had the highest WF volumes with 104.49, 15.79, and 84.566 billion m^3, respectively, which account for nearly 30% of the national WF. The regions with lower WF volumes are mainly distributed in the south of China, among which Shanghai, Beijing, and Qinghai have the lowest WFs with 3.6 (0.37%), 4.3 (0.44%), and 4.52 (0.46%) billion m^3. By 2017, Shandong, Henan, and Heilongjiang had the highest WF volumes with 107.9 (9.83%), 104.18 (9.49%), and 93.16 (8.48%) billion m^3.

As for WFI, volumes were higher in the northwest of China. In 2002, the highest WFIs were 2042.85, 1600.53, and 1425.17 $m^3/10^4$ yuan in Ningxia, Gansu, and Xinjiang, respectively. The lower WFIs were mainly in southern regions, among which Shanghai and Zhejiang had the lowest, with only 7.97% and 20.74% of the national average WFI. In 2017, the WFIs of Xinjiang, Inner Mongolia, and Heilongjiang rose to the top, with 824.01, 739.46, and 719.67 $m^3/10^4$ yuan, respectively.

3.3. Evolvement of Provincial and Sectoral WF Volume in China

As seen in Figure 4, Inner Mongolia, Xinjiang, and Heilongjiang had the largest WF volume change of 174.6%, 100.3%, and 42.3%, respectively, from 2002 to 2017. Beijing, Shanghai, and Fujian saw the largest decreases in WF volume, by 39.75%, 34.62%, and 38.85%, respectively, as the WFs decreased by 1.71, 1.24, and 3.89 billion m^3.

From 2002 to 2017, the WFI decreased by more than 60% in the *Agriculture* sector, except in Inner Mongolia, where it increased by 80%. The WFI decreased by 9.7%, 10.5%, and 17.6% in the *Food and Beverage* sector in Hainan, Liaoning, and Inner Mongolia, respectively, and exceeded 50% in all other provinces. The *Wood and Paper* and *Petroleum, Chemical and Non-Metallic Products* sectors in Heilongjiang as well as the *Hotel and Restaurants* sector in Hebei increased significantly, reaching 80.4%, 78.4%, and 63.2%, respectively. Eight provinces, including Beijing and Fujian, witnessed their WFI decrease by more than 80%. More than half of the provinces and municipalities directly under the central government saw their WFI decrease by somewhere between 60% and 80%, while for four provinces, including Heilongjiang, WFIs dropped below 60%.

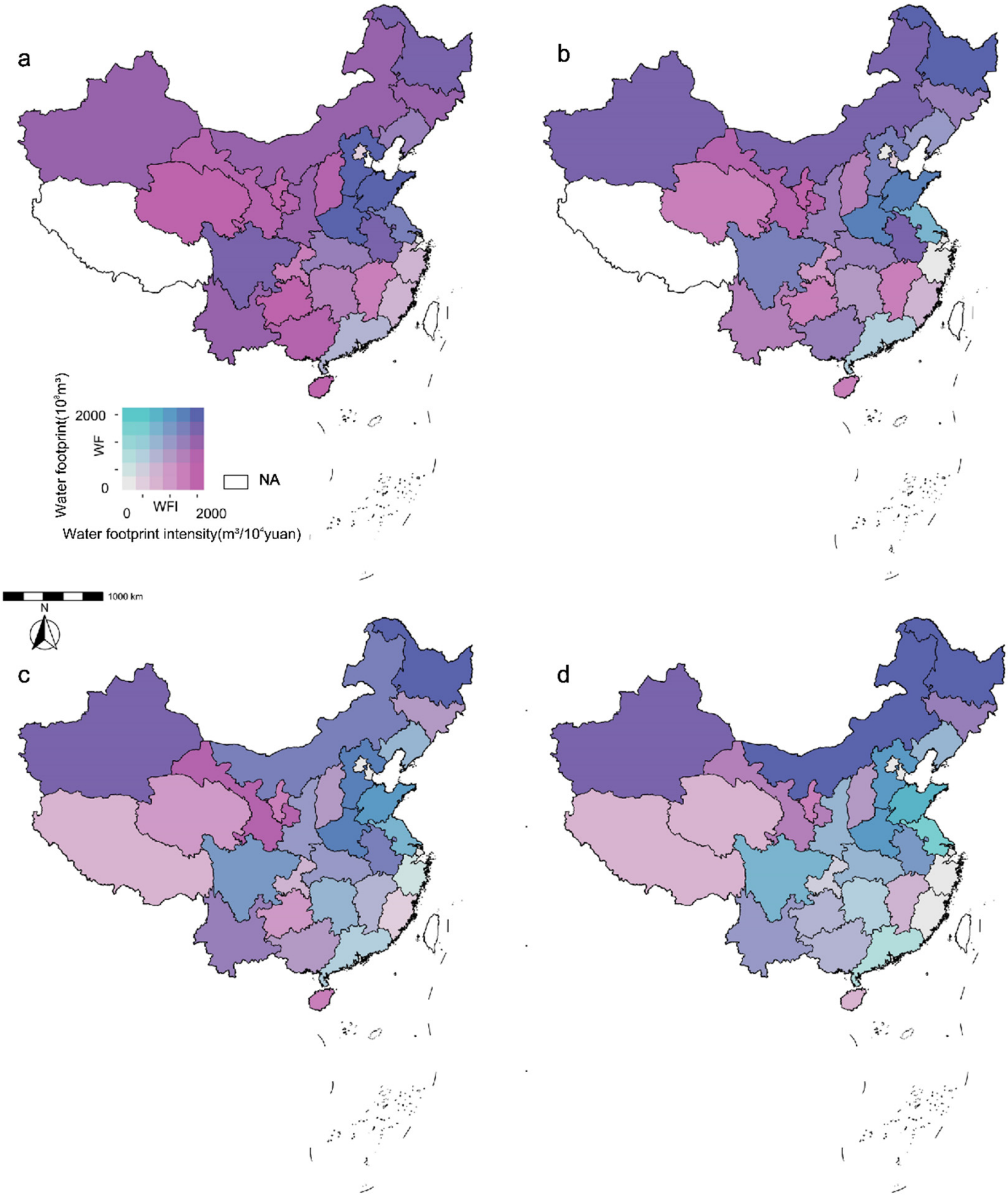

Figure 3. Water footprint and water footprint intensity on the provincial level from 2002–2017. (**a**–**d**) represents the situation of 2002, 2007, 2012 and 2017, respectively.

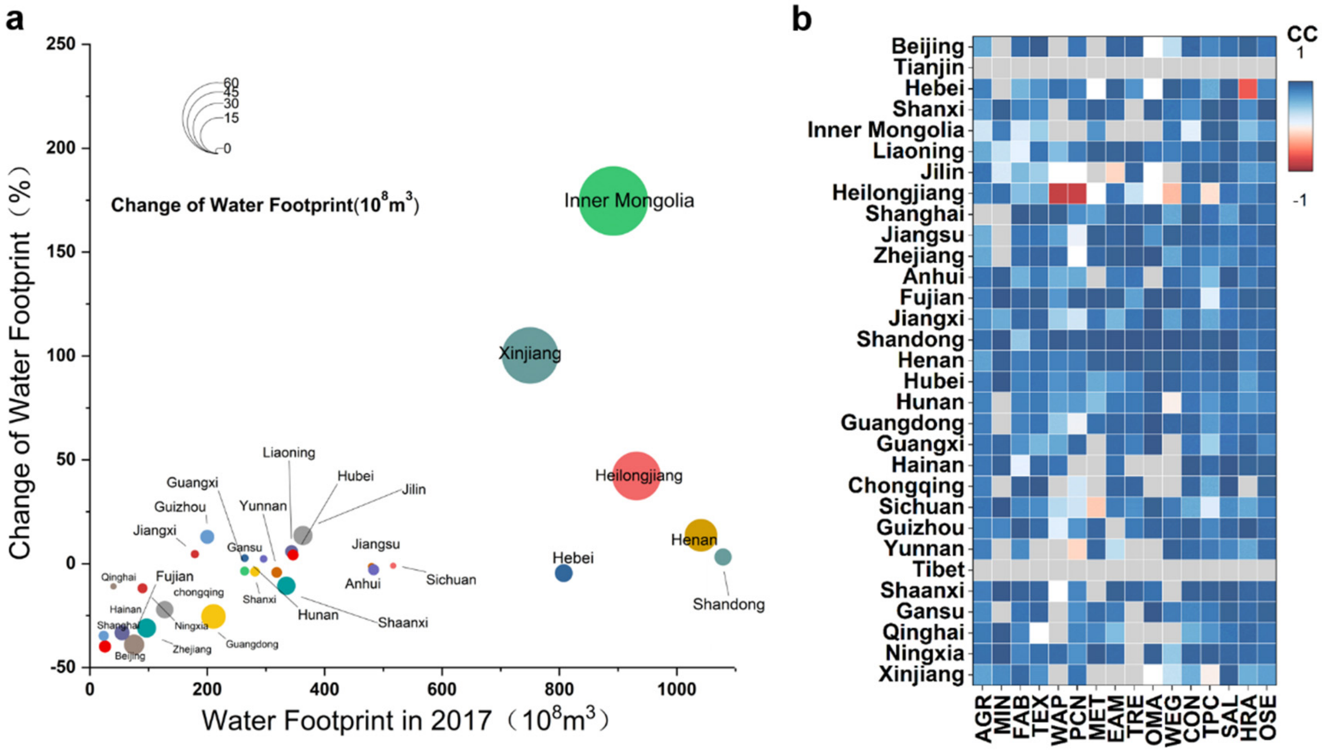

Figure 4. Evolvement on water footprint and changes in water footprint for 16 sectors from 2002 to 2017. In (**a**), the area of each circle represents the WF change, and (**b**) shows changes in water footprint for 16 the sectors. The depth of color represents the degree of change in WFI from 2002 to 2017, with Tibet and Tianjin in grey due to missing IO tables or no outputs of the corresponding sector in 2002.

3.4. Analysis of WF Driving Factors by Sector

As shown in Figure 5.The relationship between driving factors and sectoral WFI is reflected in the heat map (a), the red and blue represents positive and negative correlation respectively and the area of each circle represents the value of Spearman correlation coefficient. The relationship between driving factors and provincial WFI is reflected in the scatter plot (b to m). The "**" and "*" represent P value is less than 0.01 and 0.05, respectively. From the figure, we found that F10 (grain yield per capita) is significantly correlated with most sectors. There is a significant negative correlation between F5 (rural Engel's coefficient), F4 (urban Engel's coefficient), and most sectors. There are positive correlations between F1 (GDP per capita) and multiple sectors. We also found that AGR has a significant positive correlation with F12 (education level) and F10 (grain yield per capita). With FAB, F3 (groundwater supply ratio) has a significant positive correlation. For PCN, F11 (technical innovation index) is the factor with the most significant negative correlation, while F8 (output per capita) and F1 (GDP per capita) have positive correlations with CON and HRA, respectively.

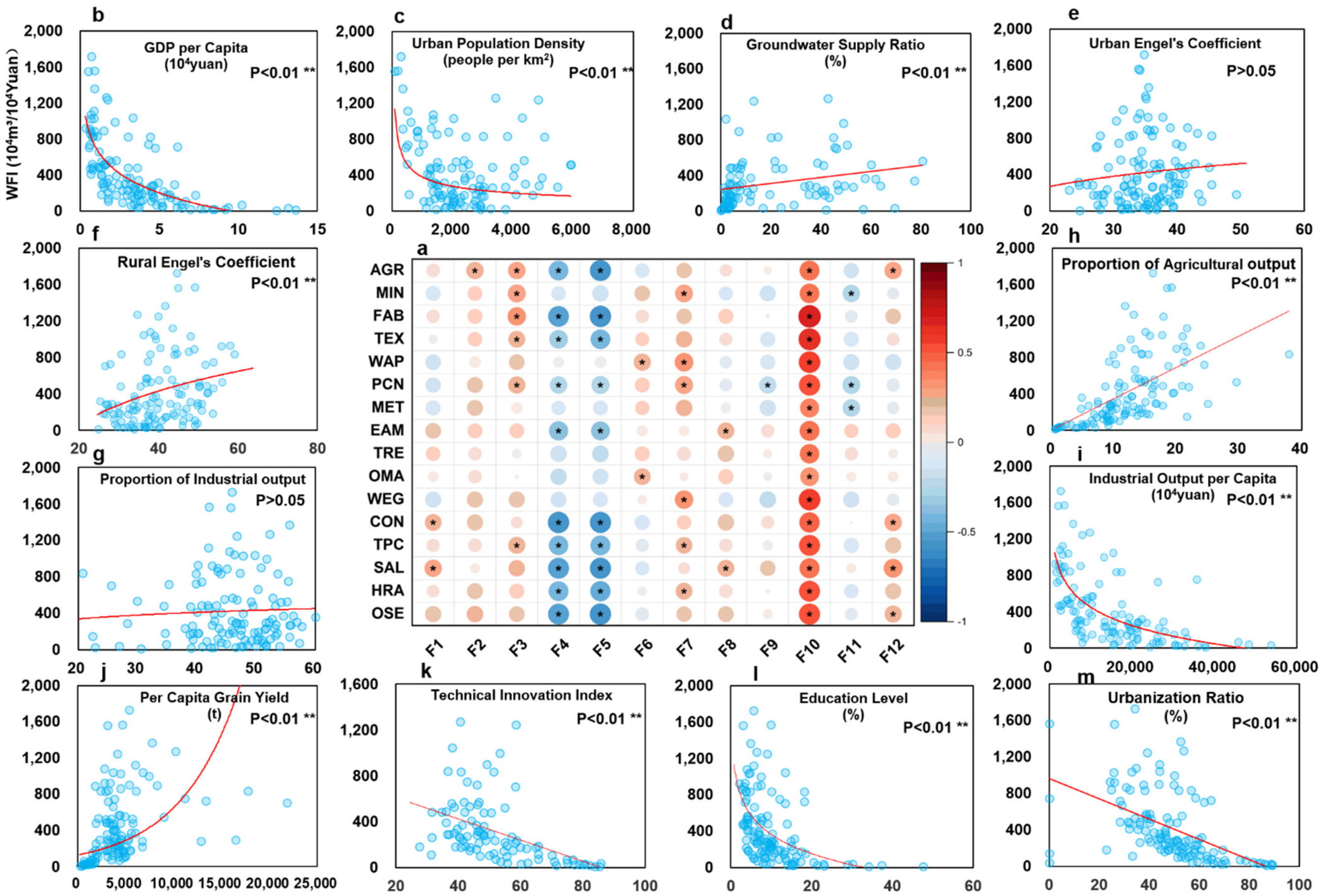

Figure 5. The relation between driving factors, WF, and WFI. Here, (**a**) represents the relationship between driving factors, while (**b**–**m**) reflect the relationship between driving factors and national WFI, on which P values are tagged. The "**" and "*" represent P value is less than 0.01 and 0.05, respectively.

4. Discussion

4.1. Differences in WF at the Provincial Level in China

By comparing the distribution of total WF, it can be seen that the regions with high WF are mainly located in Shandong, Henan, and Hebei, which are the main regions for water-intensive forms of production, and are regions with relatively high population densities [23]. The water consumption ratio of the grain production and metal product sectors, as well as the total population share of three provinces, reached 23.77%, 43.68%, and 19.94% of the national average, respectively, and the per capita WF are all approximately 135% of the national average (2017), making the WF of the three regions more prominent. In our study, the proportion of agricultural water consumption reached 51% in 2017, which is close to the 50% pointed out in Deng's research [26], but different from the 60% concluded in Xu's research [27]. Differing methods of agricultural and industrial water consumption can explain this discrepancy. The regions with larger variations in WF are Inner Mongolia, Xinjiang, and Heilongjiang, which may be due to the restructuring of local production and the development of water-saving irrigation agriculture, as the government pays more attention to water conservation and limits the development of high-water-consuming and inefficient industries. The WF of agricultural production obtained in this study is similar to the 624 billion m^3 [28] estimated by Hoekstra and Makonnen.

After comparing the distribution of WFI, it can be seen that the provinces with larger WFIs are mainly located in Heilongjiang, Inner Mongolia, and Xinjiang, which are also the bases of China's commercial grain and animal husbandry industries, and the proportion of high-water-consuming sectors shows a negative effect on industrial water efficiency improvement [29]. In contrast, some economically developed provinces like Shanghai and Beijing are not bases for water-intensive enterprises, but rather for industries such as service and maintenance [1], making these the regions with the smallest WFs in China. The difference in economic structure and sectoral water-consumption efficiency will likely be the primary cause of the difference in WFI [15]. Additionally, affected by severe water shortage, the share of high-water-consuming industries represented by agriculture is relatively small in the local area [30], which may be another reason for the difference.

4.2. Driving Factors Have Effects on WFI

National WF is rising in the face of a continuous decline in WFI, which, to some extent, reflects the rapid development of China's economy and the increased productive capacity of society [31]. The driving factors of WFI are ultimately determined by gross economic structure, social development, and technology, which accords with Wang's research [32]. The sectoral water efficiency of production is increasing in the context of technological innovation [33,34]. One of the most important factors influencing WFI is GDP per capita, probably because regions with a higher GDP per capita generally have higher economic security, more efficient water use, and stricter water management policies [23]. However, the relatively poorer areas are more inclined towards water-intensive enterprises [1] and lower standards for water resource management, which may lead to a more positive correlation between GDP per capita and WFI. Wang et al. [35] concluded that service and construction sectors consumed the largest portion of water in Beijing (2013), which is similar to our findings.

As for manufacturing sectors like petroleum and metal, production entails a degree of water pollution [36,37]. Technological innovation may have an impact on WFI in the following manner: water-saving technologies, techniques such as new water-saving processes, and development of unconventional water resources, such as salt and brackish water, require a model of integrated innovation across sector production. Additionally, undertaking advanced water-saving processes can offers producers an opportunity to enhance their wastewater-treatment capabilities. In regards to hotels and restaurants along with other services, population density and urbanization rates may be key factors that significantly influence WFI. It is widely believed that more-urbanized provinces tend to have a higher demand for products and services, which lessens WFI to some extent.

4.3. Policy Recommendations

The results show that the agricultural and food and beverage sectors account for over 70% of the WF. The WF of the agricultural sector results from the irrigation of farm crops, and the WFI of the food and beverage sector mainly stems from a large number of intermediate inputs of agricultural production. Given the large room for improvement in water-saving, measures including optimizing agricultural production structures, developing drought-resistant varieties, and promoting water-conserving food consumption should be taken. In 2006, China's government proposed "The National Outline for Medium and Long Term S&T Development", which encourages companies to introduce water-saving technologies for foreign countries. Adopting effective agricultural biotechnologies as well as promoting a healthy food-consumption structure [23], Long et al.'s research [38] indicated that the dietary restructuring would lead to a more than 50% reduction in WF. At the same time, the northern and northeastern China should adjust the current planting structure by introducing or developing water-saving crops [39,40]. As an example, Shandong increased the water-saving index to 1.348 by using new rice varieties in 2022.

Encouraging water-saving technological innovation in the production process is conducive to cutting sectoral WF at a reduced cost. In the hotel and restaurant sector, the level of local economic development and standard of living largely determine its water consumption and water-saving potential [41]. As fixed capital formation in the construction sector has high WFI [26,27], adjustments should be focused on architectural planning without affecting people's basic housing needs, as this will significantly reduce the water consumption simultaneously.

4.4. Limitations and Uncertainties

The uncertainties in our study come from consolidation of 16 sectors from IO tables. In calculation of agricultural water consumption, the crop coefficients referred are adopted from FAO-56 report, which may cause deviation in blue and green water calculation. At the same time, the water consumption data in the China Statistical Yearbook and Water Resources Bulletin is not divided by each sector. Therefore, we assume that water consumption intensity is the same in both manufacturing and service, which may result in bias results of their direct water consumption. However, this part of direct water consumption accounts for a small proportion of the total, having little influence on sectoral water footprint [28]. When calculating the direct water consumption of each province, we adopted the method of close-province substitution. In the end, gray WF was not included in this study as it is not a real water-consumption indicator [42].

5. Conclusions

This paper accounts for the spatial-temporal distribution of WF and WFI in China from 2002 to 2017 under the water-IOA model. This study utilizes the full life-cycle approach to account for water consumption in the agriculture sector and investigates the driving mechanisms of changes in WF and WFI through correlation analyses leading to the following conclusions:

(1) The average total WF in China from 2002 to 2017 was 1031.9 billion m^3, of which the production of agricultural and related products accounted for the majority, and its share has been decreasing since then.

(2) North China is the region with the largest WF and WFI, which is related to the local industrial structure and production efficiency. Inner Mongolia, Xinjiang, and Heilongjiang are the regions with the largest changes in China's WF, which are closely related to the improvement of agricultural water-use efficiency and restructuring of local production.

(3) The driving factors affecting China's WFI are mainly GDP per capita, urban and rural Engel's coefficients, and per capita grain production, as well as technical innovation index, etc. It will be possible to achieve a reduction in WFI by adjusting agricultural structure, optimizing the regional industrial layout, and improving the combined strength of science and technological innovation. For example, in Shandong, the water-saving index was increased to 1.348 by implementing new rice varieties in 2022.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w14152373/s1, Preconditioning methods of IO tables; Sectoral water consumption calculation methods; Comparison of WF and WFI in each province (the figure above contains the total WF and WFI both in 2002 and 2017 in each province, and the below figure contains the GDP of each province in 2017); Proportion of sectoral WF in each province from 2002 to 2017; Sectoral WF of typical provinces in China from 2002 to 2017; and Chinese geographical division.

Author Contributions: Conceptualization, R.H., Y.L. and X.C.; methodology, R.H., S.H., and X.C.; software, R.H., S.H., and T.Y.; validation, R.H. and S.H.; data curation, R.H., S.H., T.Y., R.L., and L.L.; writing-original draft preparation, R.H.; writing-review and editing, R.H., S.H., Y.L. and X.C.; visualization R.H. and S.H. All authors have read and agreed to the published version of the manuscript.

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