Quantification of the water-carbon nexus in food systems: A provincial-level perspective in China

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Abstract

Studying the water-carbon nexus is becoming crucial for the sustainability of agricultural economic systems. As the physical flows of water and carbon are hidden in trade, it makes sense to apply the concepts of “virtual water” and “embodied carbon” to explore the water and carbon flows in agricultural economic systems from a more holistic perspective. This study developed an agriculture-oriented multi-regional input-output (MRIO) model based on the IElab technology and the RAS method, which disaggregates the agricultural sector into 12 sub-sectors. The water consumption and carbon emissions generated by the food systems were allocated to the entire supply chain based on the input-output method, and then virtual water flow and embodied carbon emissions were calculated to identify the key nodes and routes of water-carbon nexus in China for 2017. This study has also calculated the carbon/water productivity of various agricultural products and analyzed their productivity levels and spatial distribution characteristics. Our results demonstrate that the China food sector is a high-intensive node of carbon-water nexus, with nearly 60% of embodied carbon and 75% of virtual water concentrated in downstream sectors of the production supply chain. The highest carbon-water productivity is found in Northeast and Central areas.

Keywords Water, Carbon, Nexus, Food system, Multi-regional input-output model, Provincial-level

JEL code D57 Input-Output Tables and Analysis, Q17 Agriculture in International Trade, Q51 Agriculture in International Trade see: www.aeaweb.org/jel/guide/jel.php?class=Q)

0. Introduction

As the global population continues to grow and urbanization accelerates, there is a parallel increase in global and per capita food demand, leading to considerable environmental stress. Limited availability of water resources, as well as carbon emission constraints, are major bottlenecks to developing a sustainable agricultural economy. The United Nations predicts that global water supply will exceed the Earth's water capacity in 2050. Consequently, approximately 4 billion people (or about 40% of world population) will suffer from severe water restrictions(Mountford 2011, Nations 2015). Almost 70% of global freshwater is consumed by agriculture(Nations 2018), but “Agricultural water use” as a statistical indicator cannot fully reflect water consumption. Furthermore, food systems are responsible for one third of global anthropogenic GHG emissions(Crippa, Solazzo et al. 2021). Therefore, agriculture is a significant sector for investigating climate change mitigation and reducing water usage.

Nexus is an interdisciplinary approach that acknowledges the inherent synergies and trade-offs involved in managing water, food and energy(Li, Zhao et al. 2020), for example, agricultural production consumes energy and water, and generates carbon emissions by material and equipment input (e.g., fertilizers, pesticides, irrigation activities). The investigation of water-carbon nexus is becoming crucial for the sustainability of agricultural economic systems. China is the largest food producer in the world(Wu and Zhu 2014). Therefore, exploring and clarifying the water-carbon nexus in China’s food system is necessary. The investigation of water-carbon nexus has also lately received attention from a policy perspective for the design of national strategies regarding the governance of natural resources of different economic sectors, including agriculture.

As the physical flows of water and carbon are hidden in trade, it makes sense to apply the concepts of “virtual water” and “embodied carbon” to explore the water and carbon flows in agricultural economic system from a holistic perspective(Fang and Chen 2017, Yang, Wang et al. 2018). There are two primary methodologies for calculating the virtual water and embodied carbon. One is the bottom-up approach using specific calculations of the resource’s consumption during each production period. For example, Yu, Liu et al. (2022) applied an energy-carbon-water nexus framework to assess the carbon emissions, water utilization, and energy flow, and their links with agricultural production on the Qinghai-Tibet Plateau, using Emergy analysis, footprint analysis and a coupling model. Their findings revealed imbalanced energy-carbon-water nexus of agricultural production and large spatial heterogeneity in the environmental footprint at county scale. However, this approach may not accurately trace the virtual water flows through the supply chain (Pfister, Bayer et al. 2011, Hoekstra, Arjen et al. 2012); The other methodology is the top-down approach, which is less precise than the bottom-up approach and uses input–output models to calculate resource consumption. The input-output analysis (IOA) was put forward by Leontief (1936), which can quantitatively analyze the resource consumption and environmental impact of the entire economic system based on economic structure matrix and resource consumption matrix. These models include both direct and indirect processes, and describe the supply chain effects to distinguish the responsibility of final users (Feng, Chapagain et al. 2011). Researchers such as White, Hubacek et al. (2018) have utilized inter-regional input-output approach to demonstrates the hidden virtual flows of water, energy, and food embodied in East Asia. Liang, Li et al. (2020) quantified the spatial interconnections of the FEW systems within China's economic supply chains at the provincial level from both demand-driven and supply-push perspectives. In addition, until recently, environmental factors such as carbon emissions and waste have not been the focus of nexus studies (Xu, Chen et al. 2020, Zhao and You 2021).

Despite the growing interest in analyzing the environmental impacts of food systems, current research is still relatively fragmented, and has largely neglected to examine these impacts at provincial scales. Limited data availability, model capability, and parameters have impeded the exploration of effective mitigation strategies and pathways for maintaining safe regional operating spaces. To address this knowledge gap, we developed an agriculture-oriented multi-regional input-output (MRIO) model based on the IElab technology and the RAS method. This model disaggregates the agricultural sector into 12 sub-sectors, enabling us to allocate water consumption and carbon emissions generated by the food systems to the entire supply chain based on the input-output method. Then, virtual water flow and embodied carbon emissions were calculated to identify the key nodes and routes of water-carbon nexus in China for 2017. National and subnational analyses of food systems would improve the understanding of China's water-carbon nexus and assist the government in developing region-specific strategies for reducing the environmental stress.

1. Methodology

1.1 Environmental inventor

1.1.1 Direct carbon emission inventory

The direct carbon emission inventory takes into account CO_2, CH_4, and N_2O. The detailed carbon emissions accounting approach and emissions factors are based on IPCC Guidelines for National Greenhouse Gas Inventories(IPCC guidelines)(IPCC 2006) and the Provincial Greenhouse Gas Inventory Guidelines (Pilot Version) in China (PGGIG), multiplying the activity data with emission factors (EF). The calculation method is as follows.

$$\mathrm{W}_{C} = \mathrm{EF} * \mathrm{Activity} \quad \cdots\cdots\cdots\cdots\cdots\cdots \quad (1.1)$$

Where, $\boldsymbol{W_C}$ is the carbon emission for each emission source; ***EF*** is a vector of emission factors and ***Activity*** is the consumption for each emission source, in the case of energy-related emission accounting, consumption refers to the combustion volume of fossil fuel. For non-energy related emission, the consumption refers to activity data in production activities, such as fertilizer application, rice production. The CO_2, CH_4, and N_2O are reported together as carbon dioxide equivalents (CO_2e) by global-warming potentials (GWPs) over a 100-year period, according to the IPCC Second Assessment Report (AR2), GWP_{100} for CH_4 is 21 and GWP_{100} for N_2O is 310.

(1) Carbon emission from food sectors

Carbon emissions from agriculture are divided into four parts: **plant food** (Cereal; Beans, oil and potatoes; Cotton, hemp, sugar, tobacco; Vegetables, edible fungi and horticultural crops; Fruit; Nuts, nectarines, species and beverage crops; others), **forestry**, **animal food** (Livestock Breeding; Poultry breeding; others), **aquatic products**. Detailed emission sources of each part are as follows:

- **Plant food:**
  - CO_2 emission from energy use (electricity, diesel, gasoline, coal);
  - CH_4 emission from rice cultivation;
  - N_2O emission from chemical fertilizer, manure and crop residues, and nitrogen deposition.
- **Forestry:**
  - CO_2 emission from energy use (electricity, diesel, gasoline, coal);
  - Assuming that carbon emissions from burning is countered by carbon uptake from the air during the growth of forests.
- **Animal food:**
  - CO_2 emission from energy use (electricity, diesel, gasoline, coal);
  - CH_4 emission from livestock enteric fermentation;
  - CH_4 and N_2O emission from livestock manure management.
- **Aquatic products:**
  - CO_2 emission from fuel consumption (fishing vessel);
  - CH_4 emission from carbon cycling process of the pond culture system
  - N_2O emission from fish feed input.

(2) Carbon emission from other 41 sectors

The calculation of carbon emission from the other 41 sectors is based on the IPCC method(IPCC 2006), with emission sources including **energy consumption** (i.e. energy-related emissions from fossil fuel) and **industrial production** (i.e. process-related emissions from industrial production).

1.2.2 Direct water consumption inventory

(1) Water consumption in food sectors

The direct water consumption inventory uses the ‘Water Footprint (WF)’ concept (Hoekstra, Chapagain et al. 2011). The WF of food production is obtained by multiplying the amount of food production and the virtual water content coefficient per unit of product. In the calculation, only **blue water** and **green water** are considered. The WF calculation equation is as follows:

$$W_w = \sum_n (VWC_i \times P_i) \quad \cdots\cdots\cdots\cdots\cdots\cdots \quad (1.2)$$

In the equation, $\boldsymbol{W_w}$ represents the food production WF (m^3/year); $\boldsymbol{VWC_i}$ represents the virtual water content per unit mass of each type of crop or animal product (m^3/kg); $\boldsymbol{P_i}$ represents the production of each category of crop or animal products (kg/year), and $\boldsymbol{i}$ refers to the different crop and livestock categories (i = 1,2,3,…).

(2) Water consumption in the other 41 sectors

There is no officially published water consumption for each industrial sector at the provincial scale. Thus, the detailed data process and source for water consumption need to be defined. In this study, the other 41 sectors are mainly divided into three categories: industrial sector(S2-S27), construction industry(S28) and service industry(S29-S42). **We first determine the total water consumption of the three sectors, and then allocate them proportionally to the sub-sectors.**

1.2 Input-output analysis

1.2.1 RAS-based method for updating the MRIO table

National IO models are built based on a vast amount of data from various economic surveys. Therefore, it usually takes a considerable amount of time to develop and balance the acquired data(Dalgaard and Gysting 2004, Nicolardi 2013, Serpell 2018). In China, they published IO tables in years whose unit digit is 2 or 7. The lack of timely IO tables poses a significant impediment for economic and environmental analyses in many areas that are critical for national policymaking. To improve the timeliness of IO models, many studies have used nonsurvey methods(Xing, Ye et al. 2011) to estimate future or missing IO models with the aim of avoiding the high costs and lengthy delays associated with constructing regional tables via traditional survey-based methods(Planting and Guo 2004), the RAS-based method is most well-known and widely used method(Saari, Hassan et al. 2014).

The standard RAS method is an iterative process that progressively updates the current IO table Z to approach the predefined constraints on the row-column balance (i.e., the gross output, intermediate output totals and intermediate input totals in the target year are known). Each iteration consists of biproportional adjustment on both input and output sides which are subject to two intertemporal effects (i.e., the fabrication effect and substitution effect). The iterative process ends when convergence is reached and the marginal totals of the updated IO table are as close to the target row-column constraints. Let t denote an iteration and $Z_0 = [Z_{ij}]$ denote the base year IO table. The fabrication effect represents the change of the ratio of intermediate inputs to the total input in industry j (interindustry substitution), while the substitution effect represents the extent to which the output of industry i has been replaced by (or used as a substitute for) the outputs of other industries (intercommodity substitution). The detailed procedure for this iteration can be written as(Parikh 1979):

t=0: $\mathrm{Z} = Z_0$
t=1
Step 1:

$$\hat{R}_1 = diag(\hat{u})\left(diag(Ze)\right)^{-1} = \begin{bmatrix} \frac{u_1}{\sum Z_{1j}} & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ \cdots & \cdots & \frac{u_n}{\sum Z_{nj}} \end{bmatrix}$$

$$\mathrm{Z} = \hat{R}_1 Z$$

Step 2:

$$\hat{S}_1 = diag(\hat{v})\left(diag(e^T Z)\right)^{-1} = \begin{bmatrix} \frac{v_1}{\sum Z_{i1}} & \cdots & \cdots \\ \cdots & \cdots & \cdots \\ \cdots & \cdots & \frac{v_n}{\sum Z_{in}} \end{bmatrix}$$

$$\mathrm{Z} = Z\hat{S}_1$$

…
t=k

$$\hat{R}_k \approx \hat{S}_k \approx \begin{bmatrix} 1 & \\ 1 & 1 \end{bmatrix} \text{stop} \cdots\cdots\cdots\cdots\cdots\cdots (1.3)$$

As a result of the fabrication effect and substitution effect, the new IO table can be written as:

$$Z^* = \hat{R}Z\hat{S}$$
$$\hat{R} = \hat{R}_1\hat{R}_2\hat{R}_3 \ldots \hat{R}_k$$
$$\hat{S} = \hat{S}_1\hat{S}_2\hat{S}_3 \ldots \hat{S}_k \cdots\cdots\cdots\cdots\cdots\cdots (1.4)$$

where $\hat{R}$ and $\hat{S}$ are diagonal matrices representing the overall fabrication and substitution effects, respectively; $\hat{u}$ is the column vector of the row sums of flow matrix in the target year; $\hat{v}$ is the row vector of its column totals; and e is the column vector with all its entries as 1.

1.2.2 Environmental impact accounting

Based on the MRIO table and the resource consumption intensity of total output per unit, the environmental impact caused by economic activities can be calculated using the following formulas:

$$\mathrm{Q} = \widehat{W}(I - A)^{-1}\mathrm{F} \cdots\cdots\cdots\cdots\cdots\cdots （1.5）$$

$$\omega_{ci}^{r} = \frac{w_{ci}^{r}}{x_{i}^{r}} \cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots\cdots \quad (1.6)$$

Where, Q defines environmental footprint; $(I\text{-}A)^{-1}$ is the Lentief inverse coefficient matrix; *I* is the identity matrix; *A* is the technology coefficient; W is a 1*(m*n) row vector that represents the direct resource consumption of total output per unit value of each sector in each region, $\widehat{W}$ represents its diagonal matrix whose diagonal element w is defined as equation (1.6); ω_{ci}^{r} represents the carbon emission produced or water uses by the production process of sector i in region r, and x_{i}^{r} represents the total output value of sector i in region r; F is the final consumption vector.

2. Data sources

2.1 Direct carbon emission inventory

The activity data and emission factors used in this research are shown in Table2.1 and table 2.2.

Table 2.1 Activity data and sources

Activity data	Description	Unit	Data sources
D1	sowing area of plants;	10^3 ha	China Statistical Yearbook 2018 (Chapter12, 12-8)
D2	total N or P fertilizer application	10^4 ton	China Rural Statistical Yearbook 2018 (Chapter3, 3-11)
D3	compound fertilizer	10^4 ton	China Rural Statistical Yearbook 2018(Chapter3, 3-11)
D4	food production	10^4 ton	China Statistical Yearbook 2018 (Chapter12, 12-10)
D5	rural population	10^4 person	China Statistical Yearbook 2018 (Chapter2, 2-6, 2-7)
D6	livestock and poultry on hand or output	10^4 ton	China Statistical Yearbook 2018 (Chapter12, 12-14)
D7	fishery fuel consumption	10^4 ton	China Fishery Statistical Yearbook 2018(Page 66,74)
D8	fishing vessel power	kw	China Fishery Statistical Yearbook 2018(Page 66,68,74)
D9	aquaculture area	ha	China Fishery Statistical Yearbook 2018(Page 30)
D10	aquaculture production	10^4 ton	China Fishery Statistical Yearbook 2018(Page 30-35)
D11	shellfish production	ton	China Fishery Statistical Yearbook 2018(Page 27)
D12	seaweed production	ton	China Fishery Statistical Yearbook 2018(Page 28)

Table 2.2 Parameters used in the research

Parameters	Description	Unit	Value	CV	Reference detail
R1	CH_4 emission factor from rice cultivation	kg N /ha	Table S2	Table S2	PGGIG
R2	chemical fertilizer application rate	-	$D1 \times R2 = D2 + D3/3$	-	Equivalent replacement
R3	direct N_2O emission factor of chemical fertilizer	kg N_2O-N/kg N input	Table S4	Table S4	PGGIG
R4	economic efficient of plant	-	Table S3	0	PGGIG
R5	shoot part of plant	-	Table S3	0	PGGIG
R6	ratio of reuse of straw	%	Table S3	0	(Cui, Shi et al. 2013)
R7	N content of straw and root	%	Table S3	0	(Cui, Shi et al. 2013)
R8	N_2O emission factors from straw reuse	kg N_2O-N/kg N input	Table S4	Table S4	PGGIG
R9	annual N content in excreta of people	kg N/cap per year	5.4	±10%	(Xing and Yan 1999)
R10	ratio of reuse of excreta of rural population	%	1980s: urban (30), rural (60); 1990s: urban (15), rural (53); 2000s:,urban (10), rural (30)	±5%	(Gao LW et al, 2009)

Parameters	Description	Unit	Value	CV	Reference detail
R11	N_2O emission factors from manure reuse	kg N_2O-N/kg N input	Table S4	Table S4	PGGIG
R12	annual N content in excreta of animal	kg N/head/yr	Table S5	±5%	PGGIG
R13	ratio of reuse of excreta of animal	%	~40	±20%	(Hongxiang, Shutian et al. 2006)
R14	N_2O emission factor from nitrogen deposition	-	0.01	±240%	IPCC Guidelines
R15	indirect N_2O emission factor from leach	-	0.0075	±163.33%	PGGIG
R16	energy input rate of crop production				
R17	N_2O emission factor	kg N_2O-N/kg N input	Table S4	Table S4	PGGIG
R18	CO_2 emission factor by types of energy				
R19	feed intake by animals	MJ/head/yr	Calculate	±5%	IPCC Guidelines and PGGIG
R20	CH_4 conversion factor from ruminant animals	%	Calculate	0	IPCC Guidelines
R21	CH_4 emission factor for enteric fermentation	kg N/head/yr	Table S7	±50%	PGGIG
R22	daily volatile excreta	kg dmVS/day	Calculate	0	IPCC Guidelines
R23	CH_4 producing rate	m^3/kg dmVS	See PGGIG	±5%	PGGIG

Parameters	Description	Unit	Value	CV	Reference detail
R24	manure management method	%	13 types	±5%	PGGIG
R25	CH_4 conversion factor at specific climate condition	%	See PGGIG	±10%	PGGIG
R26	CH_4 emission factor for manure management	kg/head/yr	Table S8	±50%	PGGIG
R27	N_2O emission factor for each of the manure management method	kg/head/yr	Table S9	±10%	PGGIG
R28	energy input rate of animal food production	%			
R29	standard coal conversion factor for fuel	-	1.4571	0	(Tang and Liu 2016)
R30	effective oxidation fraction	-	0.982	0	(Shao, Chu et al. 2018)
R31	standard coal carbon content	-	0.73257	0	(Shao, Chu et al. 2018)
R32	the ratio of CO_2 emissions from fuel to CO_2 emissions from coal combustion	-	0.813	0	(Shao, Chu et al. 2018)
R33	fuel usage factor	-	Table S10	0	Reference Standard for Calculation of Subsidy Oil Subsidy for Motor Fishing Vessels in China

Parameters	Description	Unit	Value	CV	Reference detail
R34	CH_4 emission factor per unit aquaculture area	kg/ha	51.6	±5%	(Ma, Sun et al. 2018)
R35	protein content of aquatic products	%	17.72 (Table S11)	±2.97%	(Hu, Lee et al. 2012)
R36	nitrogen content of proteins	%	16	0	(Ramseyer 2002)
R37	nitrogen consumed by aquatic products	%	23.22	±5.88%	(Hargreaves 1998)
R38	N_2O conversion ratio	%	1.80	±5%	(Hu, Lee et al. 2012)
R39	Wet and dry weight conversion factor	%	Table S12	0	(Yue and Wang 2012)
R40	soft tissue mass proportion	%	Table S12	0	(Yue and Wang 2012)
R41	soft tissue carbon content	%	Table S12	0	(Yue and Wang 2012)
R42	shell mass proportion	%	Table S13	0	(Zhang, Fang et al. 2005)
R43	shell carbon content	%	Table S13	±5%	(Zhang, Fang et al. 2005)
R44	seaweed carbon content	%	Table S13	±5%	(Zhang, Fang et al. 2005)

(2) Carbon emission from other 41 sectors

The carbon emission from other 41 sectors are based on the data provided by the **CEAD database(https://ceads.net/)**, which counts energy consumption and carbon emission data at the provincial scale by using IPCC method (Shan, Huang et al. 2020). It should be noted that the CEAD database only includes the total carbon emissions of the service industry. In this study, the service industry contains 14 sub-sectors, so we allocate the total carbon emissions to each sub-sector according to the proportion of the added value.

2.2 Direct water consumption inventory

(1) Water footprint in food sectors

In this study, we firstly obtained about 40 categories of agricultural production data from the official reports in China, and the corresponding virtual water content of the agricultural products were used by the study of Mekonnen(Mekonnen and Hoekstra 2011). For those food sectors that the virtual water content information was not available, we used the CropWat to calculate them. Then we calculate the water footprint of each product according to equation 1.4. Finally, we combine the food production water footprints into 12 categories(see Table 2.3), which correspond to the food sector in the MRIO table.

Table 2.3 Relationship comparison between food sectors and food products

Food sectors	**Food Scope in each sector**	**VWC sources**
Cereal	Rice, Wheat, Corn, Other	Mekonnen, 2011
Beans, oil and potatoes	Beans, Peanuts, Rapeseeds, Sesame and potatoes	Calculate with CropWat
Cotton, hemp, sugar, tobacco	Cotton, Fiber Crops, sugar, tobacco	Mekonnen, 2011
Vegetables, edible fungi and horticultural crops	Vegetables	Calculate with CropWat
Fruit	Apples, Citrus, Pears, Grapes, Bananas, Other	Calculate with CropWat
Nuts, nectarines, species and beverage crops	Nuts	Mekonnen, 2011
Other agriculture	Silkworm Cocoons, Tea	Mekonnen, 2011
Forestry	Rubber, Pine Resin, Lacquer, Tea-oil Seeds	Mekonnen, 2011
Livestock Breeding	Pork, Beef, Mutton	Mekonnen, 2011
Poultry breeding	Poultry Eggs	Mekonnen, 2011
Other animal husbandry	Sheep Wool, Cashmere, Honey	Mekonnen, 2011

Food sectors	Food Scope in each sector	VWC sources
Fisheries	Freshwater Aquatic Products	Mekonnen, 2011

Note: CropWat software is a decision support tool developed by the Land and Water Development Division of FAO; the meteorological data involved in the calculation process use the observation data in the Climwat software (FAO).

(2) Water consumption in the other 41 sectors

For industrial sector(S2-S27), the total water consumption of industrial sector is from the industrial water use data in the China Statistical Yearbook 2018, water consumption of each sub-sector is obtained based on the proportion of water used by each sector. In this study, the proportion of water withdrawal is used to replace the proportion of water use by each sector, and the water withdrawal of each sector is obtained by multiplying the water withdrawal per unit output value by the gross output value in 2017. The water withdrawal per unit output value is derived from the China Economic Census Yearbook, however, this statistical indicator was canceled after 2008. This study assumes that the water withdrawal per unit output value in 2017 is similar to that in 2008.

For construction industry(S28), the water consumption of construction industry is calculated based on the data in the Bulletin of the First Water Conservancy Census of 31 provinces. In the current industrial water consumption quotas announced by various provinces, the calculation basis for the construction industry is the construction area. This study assumes that the water consumption per unit construction area of each province in 2017 is the same as that in 2011, and the water consumption of the construction industry in 31 provinces is calculated. The construction area is from the "China Construction Industry Statistical Yearbook".

For service industry(S29-S42), similar to the construction industry, the total water consumption in the service industry is also calculated based on the data in the Bulletin of the First Water Conservancy Census of 31 provinces. The detailed water consumption in the service industry is calculated and allocated according to the water quota standards for the service industry in each province.

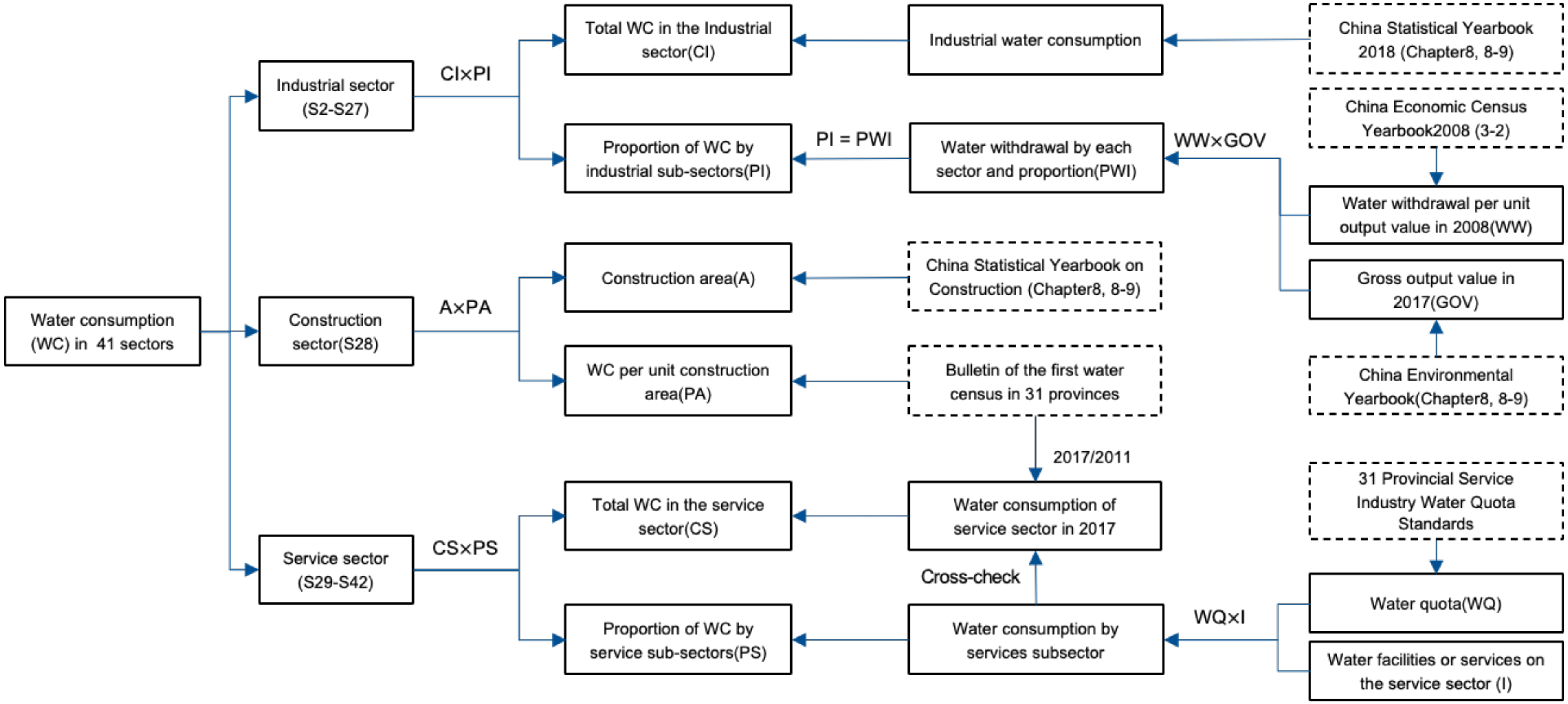

Figure 2.1 Water consumption in other 41 sectors

2.3 Data for updating MRIO table

2.3.1 Data processing for the target year

In our case, based on the agriculture-oriented multi-regional input-output table in 2011, we used the RAS method to update the table to 2017. According to Section 1.2.2, the RAS method generates an estimate from 3n pieces of information for 2017, these are total gross output(x), sum of intermediate demands(u), and sum of intermediate inputs(w). Data sources for these information include Provincial single region IO (SRIO) tables, Provincial/National statistical yearbooks and China Rural Statistical Yearbook. The contributions of different data sources to generate the 2017 MRIO table and their interrelationships are shown in Figure 2.2.

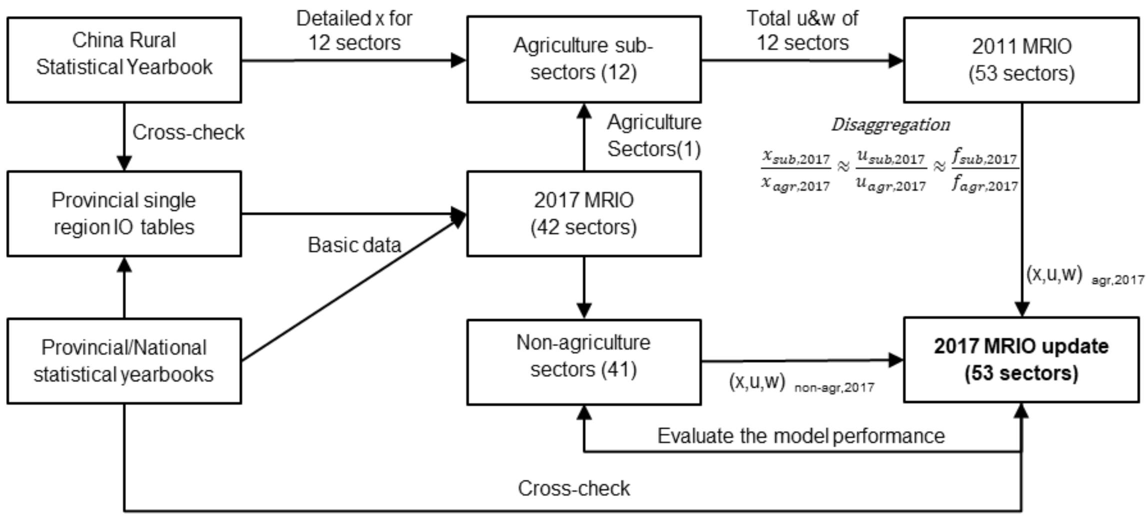

Figure 2.2 The contributions and interrelationships of different data sources to generate the 2017 MRIO table.

The SRIO tables are basic for the MRIO table construction, and they are normally published by provincial official agencies. From the SRIO table, we can get the total gross output xi for each sector in each province. Based on the SRIO table, some scholars have compiled the 2017 multi-regional input-output table of 42 sectors (only 1 agriculture sector) in China(Zheng, Zhang et al. 2020). Therefore, for the non-agricultural sector, x, u, and w can directly refer to the research results; for the agricultural sector, x, u, and w are calculated based on total agricultural output value, added value, and intermediate consumption of each agriculture sub-sectors. The variables and data sources are shown in table 2.4.

Table 2.4 List of variables and data sources.

Variables	Description	Sources
$x_{non\text{-}agr,2017}$	Total gross output of non-agricultural sectors	Provincial single region IO tables

$w_{non\text{-}agr,2017}$	Total intermediate input of non-agricultural sectors	2017 multi-regional input-output table
$u_{non\text{-}agr,2017}$	Total intermediate demand of non-agricultural sectors	2017 multi-regional input-output table
$x_{agr,2017}$	Total gross output of agricultural sectors	China Rural Statistical Yearbook 2018 (Table 6-3, 6-16,6-18)[a]
$f_{agr,2017}$	Total final demand of agricultural sectors	2017 multi-regional input-output table (Total)[a]
$v_{agr,2017}$	Value added of agricultural sectors	China Rural Statistical Yearbook 2018 (Total, Table 6-11)[a]
$w_{agr,2017}$	Total intermediate input of agricultural sectors	$w_{agr,2017} = x_{agr,2017} - v_{agr,2017}$
$u_{agr,2017}$	Total intermediate demand of agricultural sectors	$u_{agr,2017} = x_{agr,2017} - f_{agr,2017}$

a: The Rural Statistical Yearbooks only counts value-added(v) and final demand(f) at the level of agriculture, forestry, livestock and fisheries, for example, the agricultural includes 7 sub-sectors, we only have the sum of the data for 7 sectors. From the 2011 MRIO table we found that the proportion of value added(v) and final demand(f) of each sub-sector in the agricultural sector is equal to the proportion of total output/input(x) in the agricultural sector, Therefore, based on this feature, we obtained the added value(v) and final demand(f) of each sub-sector according to the proportion of the total output/input(x) of each sub-sector in 2017.

2.3.2 The 2017 agriculture-oriented MRIO table updating based on RAS method

With the targeted row and column sums (total gross output x, total intermediate demand u, total intermediate input w), RAS generated a new matrix Z for 2017 from the old matrix Z_0 (2011 MRIO table). The results are calculated by using R Studio based on the “ioanalysis” and “lpSolve” packages.

3. Results and discussions

3.1 The performance of RAS-based method

We evaluated the performance of the RAS method based on R^2, STEP, median APE and Theil's U. As shown in Table 3.1, the RAS method had great performance in estimating the 2017 MRIO table with R^2 over 0.992, STEP, median APE and Theil's U less than 8.7%, 8.1% and 8.7%.

Table 3.1 Model Performance Using RAS Method

Measures	RAS	RAS
R^2	$R^2 = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\lvert x_{ij} - x_{ij}^{*}\rvert}{\sum_{i=1}^{n}\sum_{j=1}^{n}\lvert x_{ij} - \overline{x_{ij}}\rvert}$	0.9921
Standardized Total Percentage Error (STPE)	$STEP = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\lvert x_{ij} - x_{ij}^{*}\rvert}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}}$	0.0870
Median absolute percentage error (Median APE)	$Median\ APE = median\left(\frac{\lvert x_{ij} - x_{ij}^{*}\rvert}{\lvert x_{ij}\rvert}\right)$	0.0801
Theil's U	$U = \sqrt{\left[\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(x_{ij} - x_{ij}^{*}\right)^2}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_{ij}^2}\right]}$	0.0870

Note: x_{ij} is the real total output, x_{ij}^{*} is the estimated total output. If the real value is zero and the predicted value is also zero, the APE is assigned as zero. If the true value is zero and the predicted value is non-zero, the APE is assigned as a very large value (100% in our study)(Zhao et al., 2022).

3.2 Inter-provincial water-carbon analysis

3.2.1 Production-side based water-carbon analysis

The water footprint and carbon footprint based on the production side refer to the direct water consumption and carbon emissions of a region in production activities. Figure 3.1 shows the water-carbon spatial distribution of food sectors. The carbon emissions and water footprints are concentrated in the main grain-producing areas, accounting for 63.5% and 63.9%, respectively.

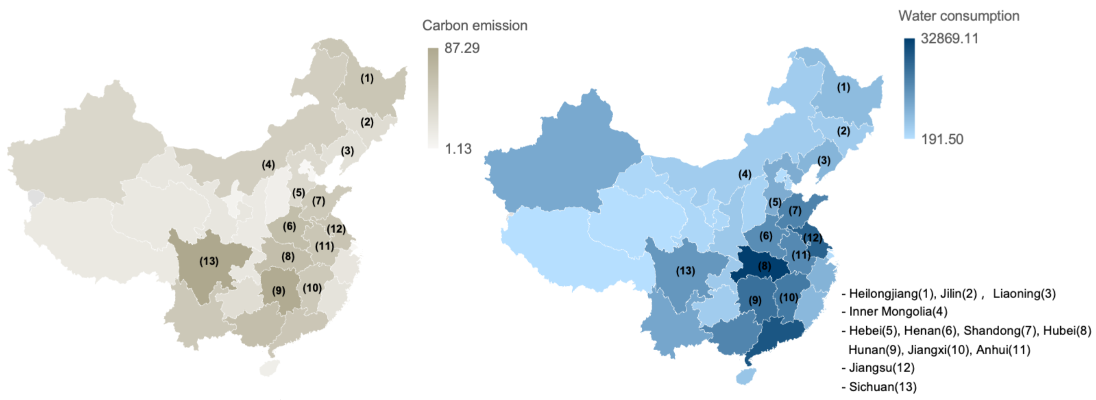

Figure 3.1 The spatial distribution of water-carbon

Figures 3.2 and 3.3 show the water and carbon footprints of the 12 sub-food sectors in each province in 2017, respectively. There are large differences between regions in terms of water use and carbon emissions. From the regional perspective, carbon emissions from food production are mainly concentrated in the central and coastal regions. The top five provinces are Sichuan (87.29Mt), Hunan (83.59Mt), Henan (63.57Mt), Guangxi (63.35Mt) and Hubei (62.84Mt), which together account for 32.7% of the national agricultural production carbon emissions. At the same time, the agricultural water consumption in these areas is higher than the national average, accounting for 29.4% of the national agricultural water consumption. From a sectoral perspective, carbon emissions from food production are mainly concentrated in the cereal and livestock breeding sectors. Hunan province has the highest carbon emissions from grain production, and Sichuan has the highest carbon emissions from livestock breeding. The water consumption of food production are mainly concentrated in areas that focus on agricultural development. The top five provinces are Henan ($157.59\times10^9 m^3$), Shandong ($123.26\times10^9 m^3$), Heilongjiang ($122.77\times10^9 m^3$), Anhui ($100.58\times10^9 m^3$) and Hubei ($98.87\times10^9 m^3$)

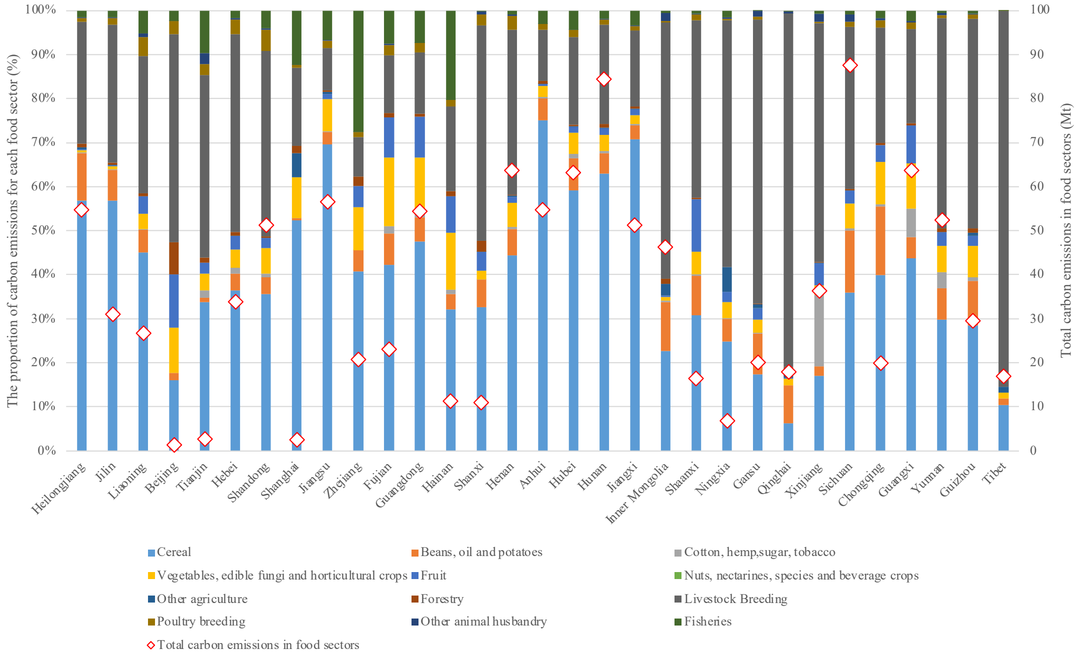

Figure 3.2 Direct carbon emissions from the production of 12 food sectors

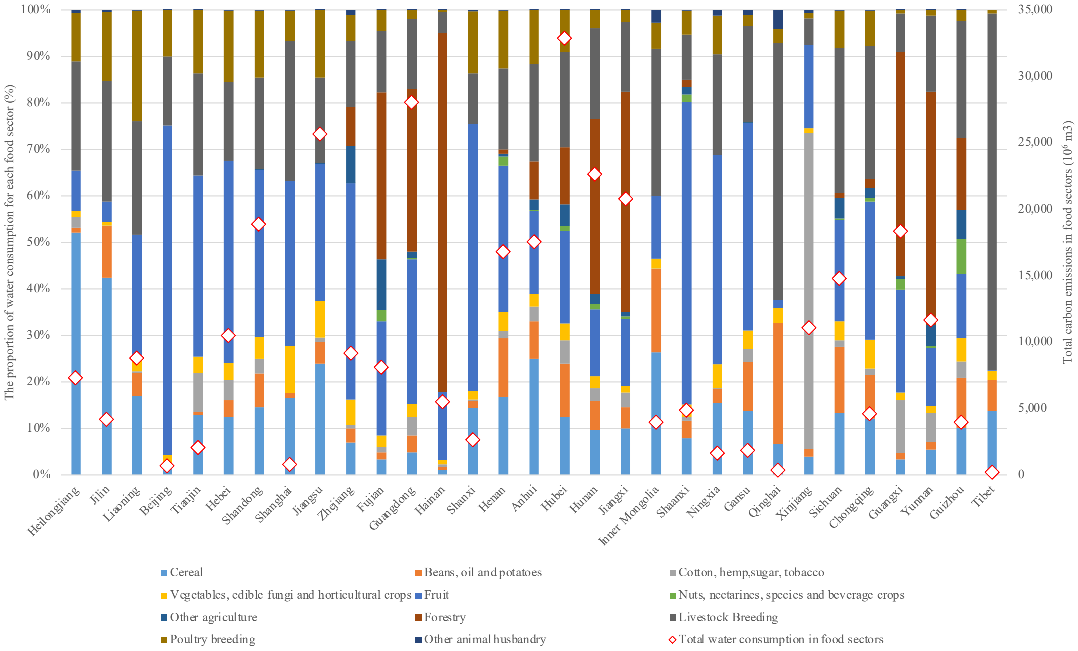

Figure 3.3 The water consumption from the production of 12 food sectors. Note: Fisheries sector is not included in this figure for its water footprints are typically excluded from consideration (i.e., equivalent to zero) when discussing global water footprints, and sensible dietary substitution of marine fish for livestock meat may efficiently reduce the potential consumption of water(Gjedrem, Robinson et al. 2012, Yuan, Song et al. 2017).

By merging 12 food sub-sectors into the agricultural sector, we can analyze the contribution of agriculture to the environmental impact in the entire national economic sectors. It can be seen from figure 3.4 that the contribution of the agricultural sector in carbon emissions is very low, and the carbon emissions of national agricultural sector account for the total 5% of emissions. “Construction” sector and “Production and supply of electricity, heat, gas and water(abbreviation: Electricity)” sector are the leading sectors of carbon emissions in China. From figures 3.5 and 3.6, it can be concluded that the food sectors have a small share of CEs (9.23%), however, they have a significant share of WFs, with the blue WFs accounting for 69% of the entire economic system and 90%, if the impact of precipitation (green WFs) is taken into account. As the major grain producing areas in China, Henan, Heilongjiang, Shandong, Hebei accounted for more than 95% of the water consumption in the agricultural sector.

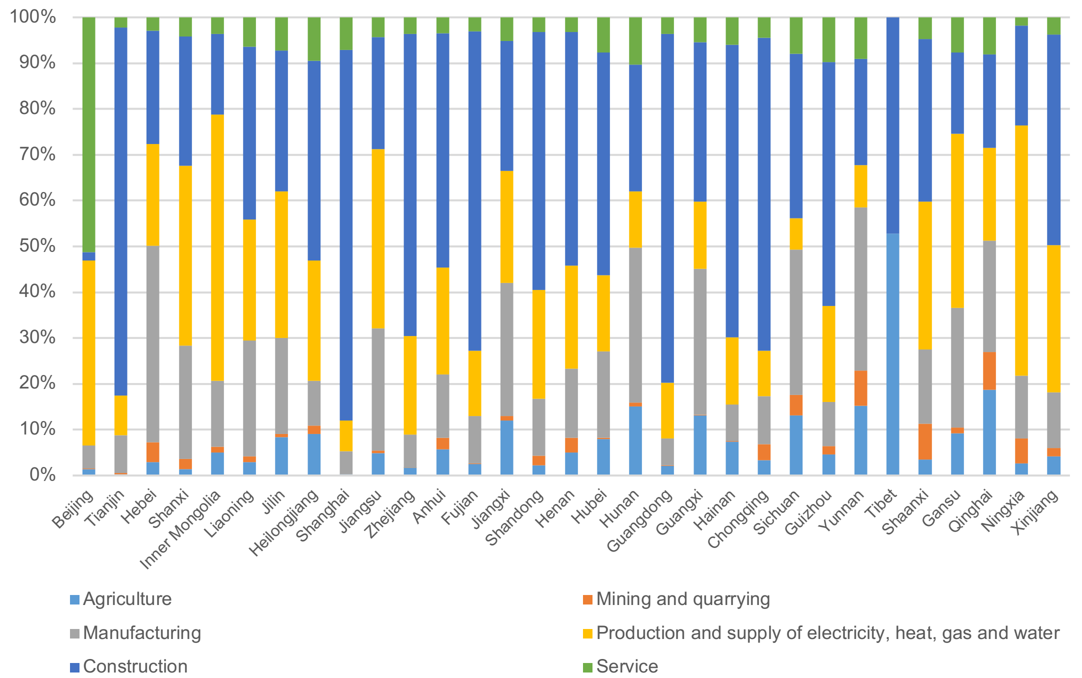

Figure 3.4 The contribution of each sector to the carbon emission

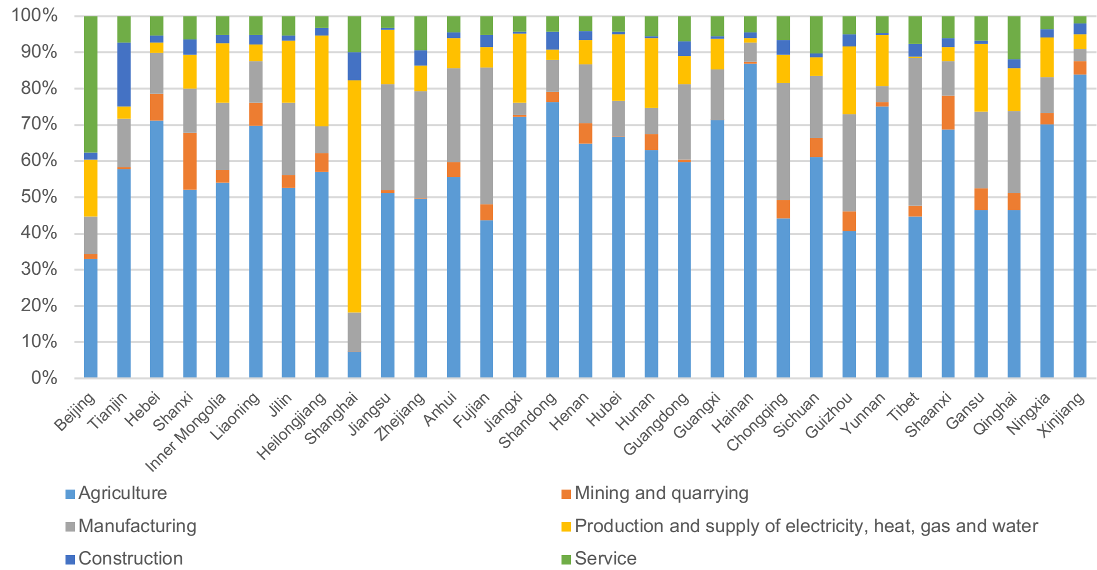

Figure 3.5 The contribution of each sector to the water consumption(Only blue)

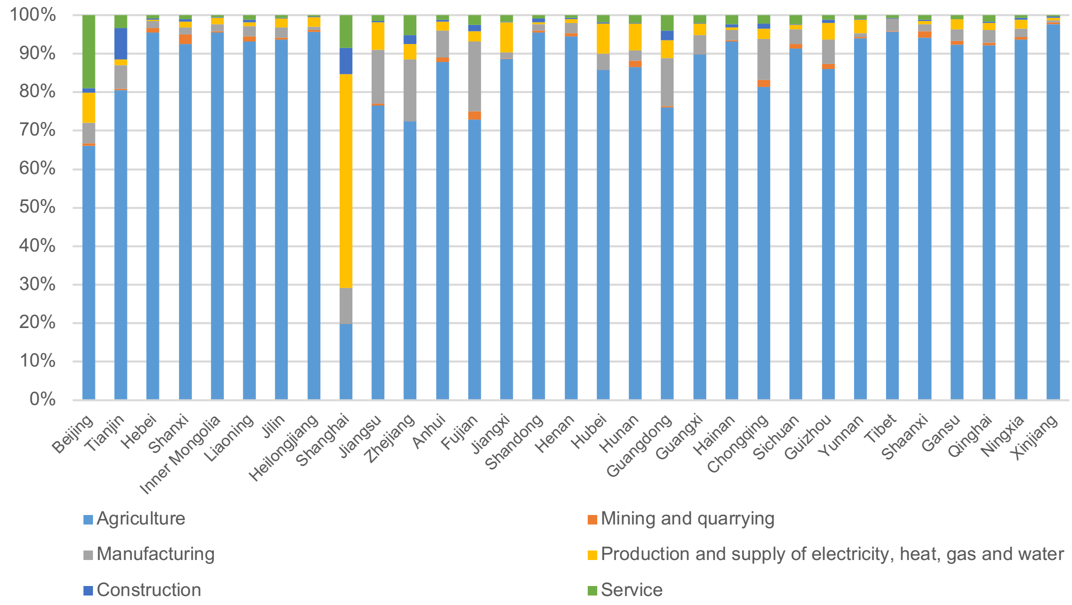

Figure 3.6 The contribution of each sector to the water consumption(blue+green)

3.2.2 Analysis of water-carbon transfer embodied in interregional trade

Figures 3.7 and 3.8 quantified the inputs and outputs of carbon emissions and water footprints in food sectors for 31 provinces, with negative output values and positive input values. It can be seen from figures that Beijing and Shanghai are the main carbon-water footprint net input regions, which meet local final demand through food imports; while for other regions, both carbon emissions and water consumption are negative in trade flows, which means that embodied carbon and virtual water are exported to other sectors or regions with food products. Furthermore, in terms of embodied carbon emission transfer, carbon emissions are outflow with the output of grains and livestock, and inflow with the input of vegetables and fruits. The net outflow regions are mainly distributed in the central, northeast and coastal areas. Hunan province has the largest outflow of -54.05Mt. In terms of virtual water transfer, the water footprint outflow with fruit and poultry output, mainly from central region, water footprint inflow with vegetables and livestock input, mainly from central and coastal region. Henan province has the most outflow of $-85.48\times10^9 m^3$. In addition, 60% of carbon and 75% of virtual water are net exported to other regions or sectors in the entire country, and the manufacturing and Electricity sectors are the main carbon-water input sectors.

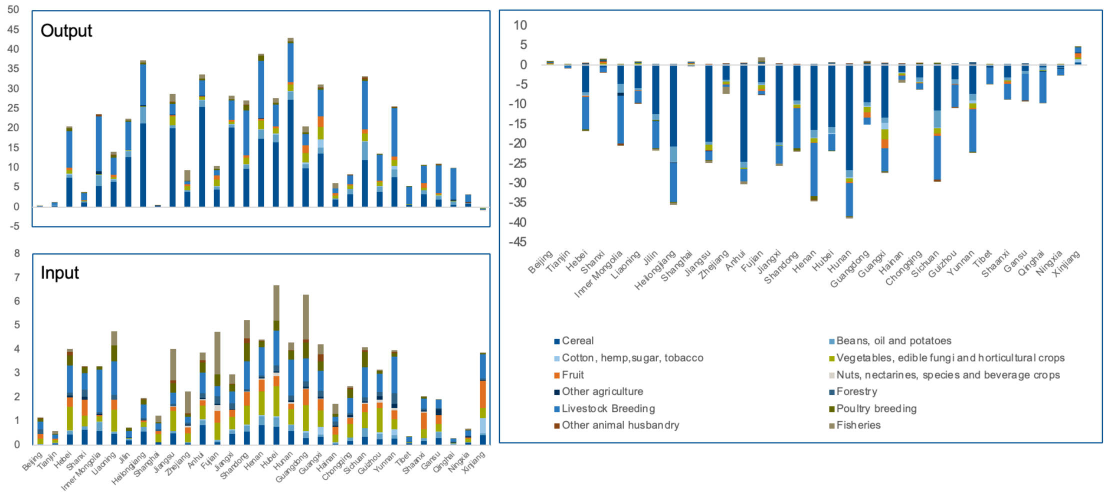

Figure 3.7 The carbon emissions of food sectors transfer in trade

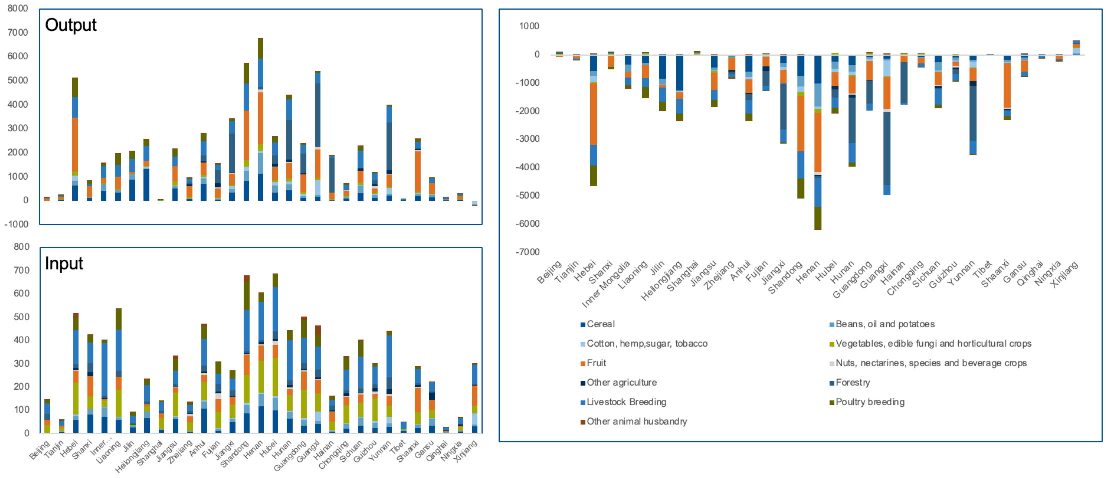

Figure 3.8 The virtual water of food sectors transfer in trade

3.2.3 Consumption-side based water-carbon analysis

The water footprint and carbon footprint based on the consumption side refer to both the direct and indirect water consumption and carbon emissions of a region in food production activities. As shown in Figures 3.9 and 3.10, after trade diversion, the differences in the spatial distribution of water-carbon footprints became relatively weaker.

From a regional perspective, coastal and central areas are characterized by high water-carbon footprints. The northwest area has a lower and water-carbon footprint. The Beijing-Tianjin area is limited by its population and area, and its water-carbon footprint is also relatively low. The southwest area has a low carbon footprint and a high water footprint except Sichuan, which has a high water-carbon footprint. From a sectoral perspective, the food sector has a high water-carbon footprint, and livestock breeding has a high carbon footprint and a low water footprint.

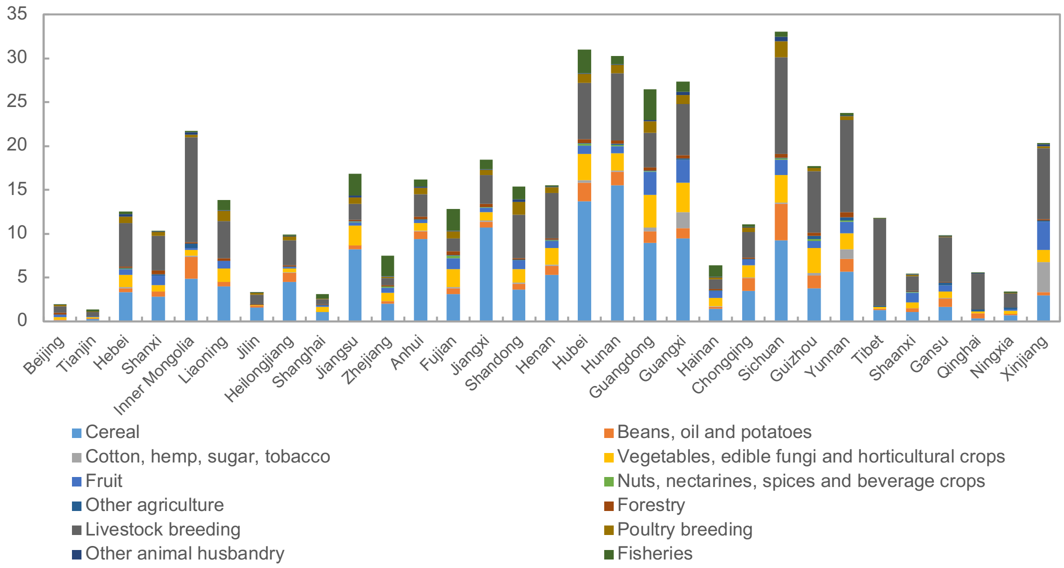

Figure 3.9 Carbon emissions in food sectors based on the consumption side

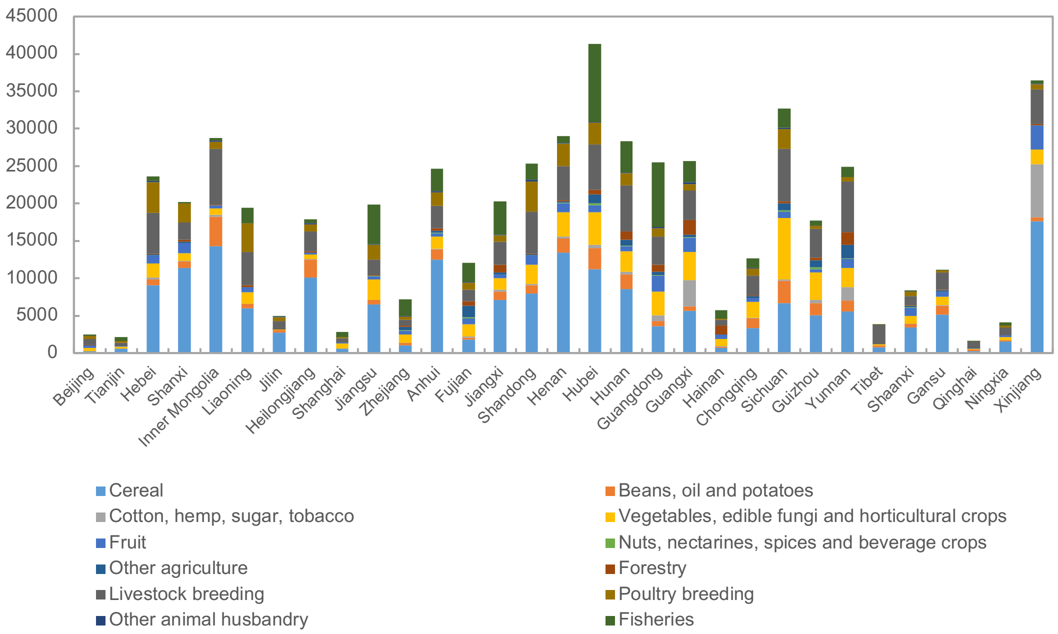

Figure 3.10 Water consumption in food sectors based on the consumption side

3.3 Water and carbon productivities from production side

We used "productivity" to evaluate the relationship between economic growth and resource utilization in the economic system. For the sake of comparison, we merged 53 sectors into four sectors of agriculture, industry, construction and services, and calculated the carbon and water productivity of the four major industries based on their gross output value and carbon-water footprint. It can be seen from the figure 3.11 that the construction sector has the lowest carbon productivity, while the agricultural sector has the lowest water productivity. The food sectors in the northeast and central regions have a higher carbon-water productivity than other regions, and the spatial distribution of carbon-water productivity in these two regions is positively correlated is positively correlated (R^2=0.60), meaning that regions with high carbon productivity also have high water productivity.

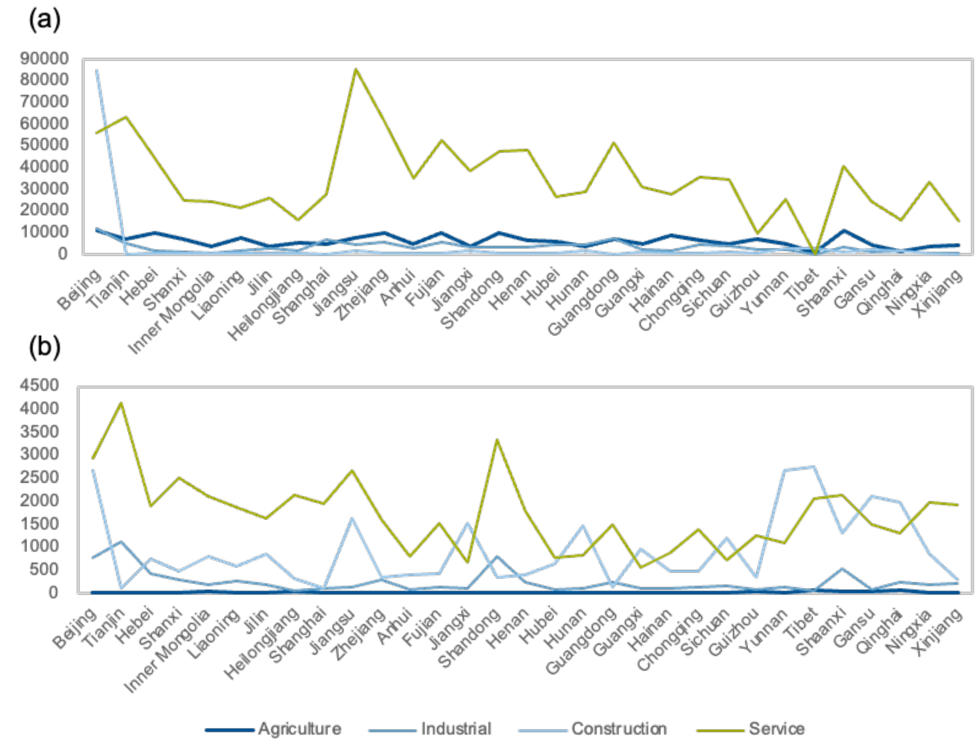

Figure 3.11 (a) the carbon productivities from production side; (b) the water productivities from production side

Furthermore, we calculated the water and carbon productivity of 12 food sub-sectors in 31 provinces, as shown in Figures 3.12 and 3.13. In terms of carbon productivity, from a sectoral perspective, the productivities of cereals, livestock farming and poultry farming are relatively high, while the productivities of fruits, vegetables and fisheries is low, which means that under the same carbon emission development scenario, the production of cereals and meat can create higher economic output; from a regional perspective, the carbon productivity of the cereals sector in northwest areas is higher than that of other regions, and the carbon productivity of animal husbandry in the southern coastal areas is the highest, although the output value of animal husbandry in northwest areas accounts for a large part of the country. However, affected by technical conditions, the carbon productivity of the western areas is lower than that of the economically developed central and eastern regions. The pattern of water productivity in terms of sectors is similar to that of carbon productivity, and the water productivity of cereal and livestock breeding is relatively high; but in terms of spatial distribution, the water productivity of the western region is higher than that of other regions, this is because the climate in the western region is dry and the values created by one unit water are higher, and it may also benefit from the application of water-saving technology.

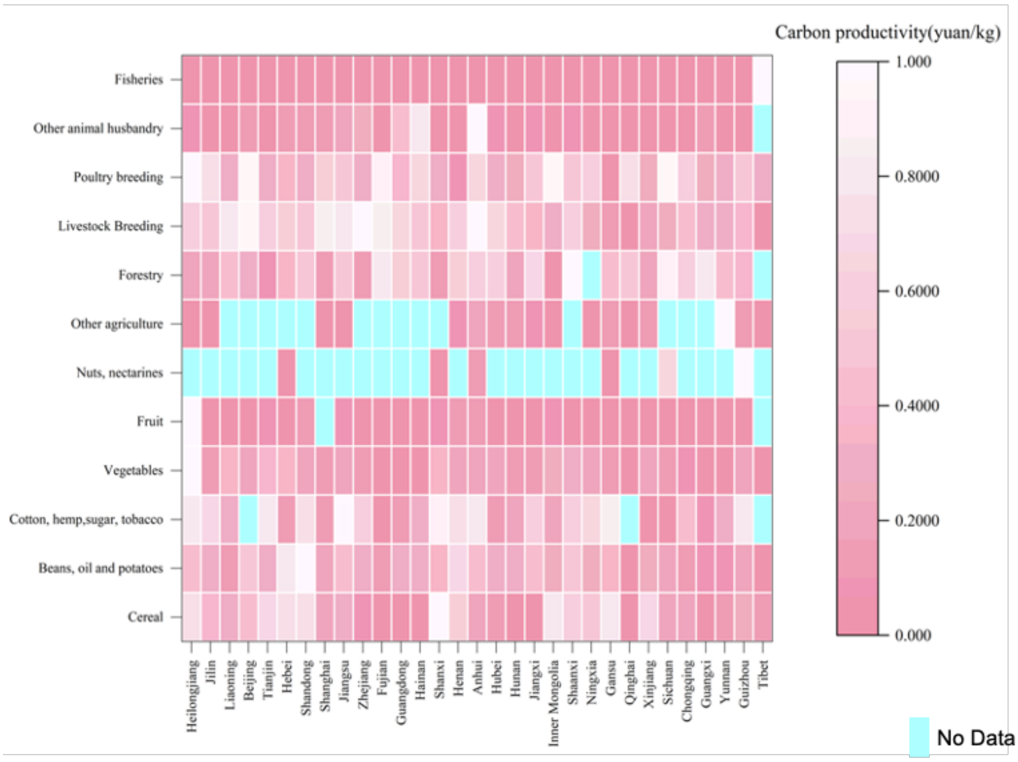

Figure 3.12 Carbon productivity distribution of 12 food sub-sectors in 31 provinces

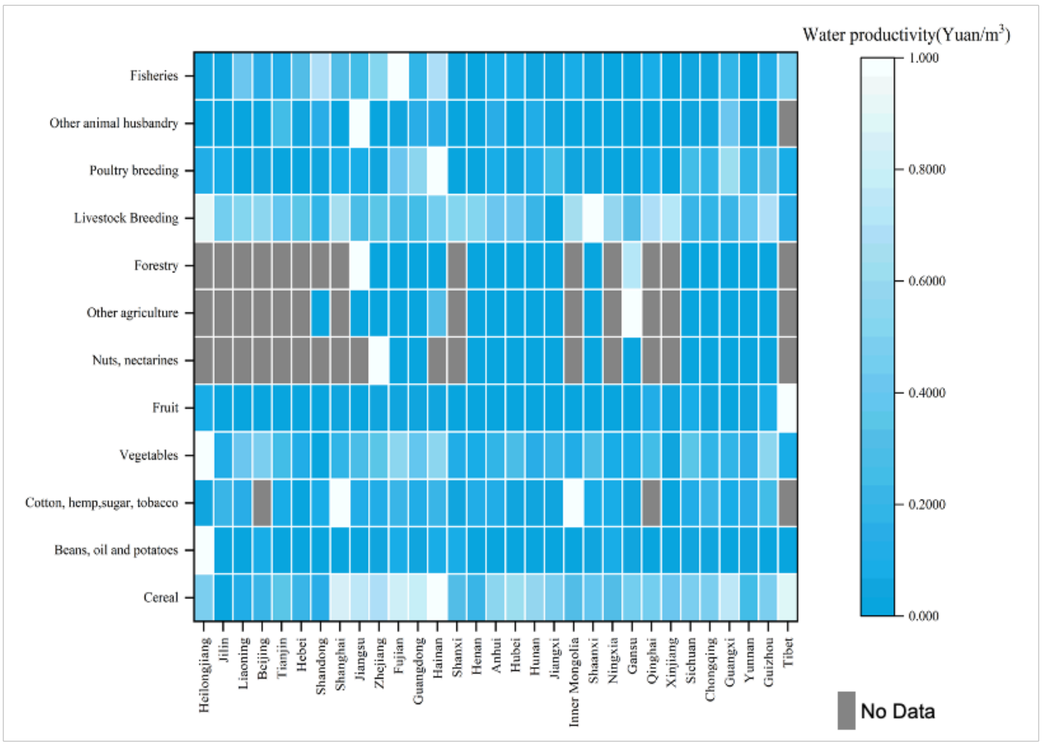

Figure 3.13 Water productivity distribution of 12 food sub-sectors in 31 provinces

4. Conclusion

This study developed a modified agriculture oriented carbon-water MRIO model based on the RAS method that disaggregates the agricultural sector into 12 subsectors and updates the MRIO table from 2011 to 2017. The CEs and WFs characteristics of 53 sectors in 31 provinces were analyzed from production side, inter-regional trade and consumption side by using the input-output method. Then, based on the production side, the carbon-water productivities were calculated, and the carbon-water nexus of 53 sectors in 31 provinces was initially explored.

(1) On the production side, there are obvious regional differences in provincial CEs and water resource utilization, due to natural conditions and the level of industrial technology. The electricity sector is the direct carbon-water nexus node, while the food sector has a weak carbon-water nexus.

(2) For carbon-water flow embodied in trade, economically developed or coastal areas, such as Beijing and Shanghai are the main importers of carbon-water footprints, transferring local environmental pressure through trade imports. For all these provinces, the food sector is a high-intensive embodied node of carbon-water nexus. Nearly 60% of embodied carbon and 75% of virtual water are focused in downstream sectors of the production supply chain.

(3) On the consumption side, the economically developed and densely populated coastal areas have the highest carbon-water footprint, followed by the central region, while the western region has a lower carbon-water footprint.

(4) In the economic system, the food sectors have the lowest water productivity. The northeast and coastal areas have the highest carbon-water productivity nexus. Owing to spatial differences in climatic and technological conditions, the carbon productivity of food sectors in the western region is lower than that of the central and eastern coastal regions, but its water productivity is higher than these regions.

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