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Research article

Sustainable water and emissions management in agriculture: The water-emissions-food nexus in China

Yang Liu [a,*], Maria Vrachioli [a], Huimei Li [b], Yafei Wang [c], Johannes Sauer [a]

[a] Chair of Agricultural Production and Resource Economics, Technical University of Munich (TUM), Freising 85354, Germany
[b] Faculty of Environment and Natural Resources, University of Freiburg, Freiburg 79106, Germany
[c] School of Statistics and Institute of National Accounts, Beijing Normal University, Beijing 100875, People's Republic of China

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ABSTRACT

Studying the water-emissions-food nexus (WEF Nexus) is crucial for the sustainability of agricultural economic systems. The multi-regional input–output (MRIO) model provides insights for water-emissions-food integrated collaborative management. This study develops a detailed agriculture-oriented MRIO model based on the RAS method, which disaggregates the agricultural sector into 12 sub-sectors. The water consumption and greenhouse gas (GHG) emissions are allocated to the entire supply chain to identify the key regions and routes of the WEF Nexus in China for 2017. Then the environmental output level of the agricultural sector and its sub-sectors is analyzed using productivity indicators. Results demonstrate that the agricultural sector exhibits a strongly connected WEF Nexus (coefficient of 0.87), particularly in Coastal and Southwest regions. The synergistic relationship between water and emissions suggests significant opportunities for implementing integrated management strategies. 73.3% of virtual water and 71.7% of embodied emissions are concentrated in downstream non-agricultural sectors of supply chains, highlighting the substantial impact of trade transmission on the environment. The water and emissions productivity in the agricultural sector are spatially aligned except in the Central and Southwest regions. As significant agricultural output regions, Northeast and Central regions have lower water or emissions productivity, making sustainable agricultural development more challenging. Therefore, practical measures should focus on promoting technological innovation and its adoption to enhance water use efficiency and reduce GHG emissions in agricultural production.

1. Introduction

As the global population continues to grow and urbanization accelerates, there is a parallel increase in global and per capita food demand (Chemeris et al., 2022). Water scarcity and greenhouse gas (GHG) emission constraints are major bottlenecks to developing a sustainable agricultural economy (Dalin et al., 2014). According to the forecast of the United Nations (2018), by 2050, nearly 60% of the world's population will suffer from severe water restrictions. Almost 70% of freshwater is consumed by agriculture (United Nations, 2022), highlighting the availability of blue water (Liu et al., 2017), which refers to surface and groundwater. In fact, green water derived from precipitation, is also used in agricultural production and contributes a considerable part (Rost et al., 2008). At the same time, carbon neutrality is a bold ambition for future global climate change governance (Wang et al., 2022). Non-CO_2 GHGs, such as methane (CH_4) and nitrous oxide (N_2O), play a vital role in efficient climate mitigation strategies (Liu et al., 2023). Agriculture contributes around one-third of non-CO_2 emissions (Crippa et al., 2021; Frank et al., 2019; Qiao et al., 2019), making its reduction essential for limiting global warming. As the world's largest food producer, China faces significant challenges, including limited water resources (FAO, 2020) and mounting internal pressure to reduce GHG emissions (Wu and Zhu, 2014). The agriculture sector holds considerable potential to contribute to climate change mitigation efforts while addressing water resource management challenges.

Nexus is an interdisciplinary approach aimed at describing the interlinkages between different environmental impacts (Li et al., 2020), such as climate change mitigation can be met through biofuel substitution that may require different levels of food, water, land, and other inputs. The application of biofuels may have different impacts across inputs — positive or negative. Understanding this interaction network provides essential information for assessing impacts (Castillo et al., 2019). The WEF Nexus refers to the interweaving within the

* Corresponding author.
E-mail addresses: yangitum.liu@tum.de (Y. Liu), maria.vrachioli@tum.de (M. Vrachioli), huimei.li@indecol.uni-freiburg.de (H. Li), ywang@bnu.edu.cn (Y. Wang), jo.sauer@tum.de (J. Sauer).

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socio-economic network of water and GHG emissions associated with agricultural production activities (Dodder et al., 2016). The escalating demand for food brings to the forefront of discussions the connection between agricultural production, water scarcity, and GHG emissions. Ignoring the interconnections of water, emissions, and food systems, and focusing on single-sector policy and technological solutions that address food production, water use, or low-carbon goals separately may lead to unintended consequences in other sectors, threatening food and environmental security at both regional and global scales (Li et al., 2024; Newell et al., 2019). Therefore, it is critical to sustain agricultural economic systems by exploring and untangling the inherent synergies and trade-offs in managing water and emissions in the agricultural sector.

Agricultural trade effectively addresses food distribution issues due to geographical constraints (Puma et al., 2015). However, interregional trade drives local-scale agriculture problems (Vorosmarty et al., 2015). Much of the water use and GHG emissions are from producing commodities for global and regional trade, which embody a large amount of virtual water and emissions flow and influence local natural resources and the environment (Fang and Chen, 2017; Yang et al., 2018). There are two primary approaches to calculating virtual water (refers to the amount of water resources required by products) and embodied emissions (refer to GHG emissions throughout the product life cycle). One is a bottom-up approach with detailed resource consumption calculations at various production stages. For example, Yu et al. (2022) applied the energy-carbon-water nexus framework, using energy analysis, footprint analysis, and coupled models, to assess the intrinsic linkages of carbon-water-energy-agricultural production. However, this approach may not accurately track virtual water flows throughout the supply chains (Hoekstra and Mekonnen, 2012; Pfister et al., 2011). The second approach is a top-down approach that uses an input–output model to calculate resource consumption (Leontief, 1936). According to the economic structure and resource consumption matrices, the resource consumption and environmental impact of the entire economic system can be quantitatively analyzed (Wei et al., 2020). The model includes both direct and indirect processes and describes supply chain effects to distinguish the responsibility of final users (Feng et al., 2011). Input–output analysis is an effective method for nexus analysis (Wiedmann, 2009; Zhang and Anadon, 2014). White et al. (2018) utilized an interregional input–output approach to demonstrate the hidden virtual flows of water, energy, and food embodied in East Asia. Liang et al. (2020) quantified the spatial interconnections of the Food-Energy-Water (FEW) systems within China's economic supply chains at the provincial level from both demand-driven and supply-push perspectives. Zhang et al. (2022b) revealed that China's agricultural sector had a strong water-energy relationship. Due to data limitations, most nexus analysis studies using top-down methods focus on earlier periods, mainly before 2012, and the research object includes all sectors in the economic system, however, until recently, little research has emphasized the water and emissions nexus in the agricultural sector (Xu et al., 2020; Zhao and You, 2021).

The traditional multi-regional input–output (MRIO) tables, including the latest for 2017 (Zheng et al., 2020) in China, only list the highly aggregated agricultural sector, namely "Crop, Forestry, Animal husbandry and Fishery Goods and Services" (Guan and Hubacek, 2007; Ye et al., 2022). Highly aggregated sectoral classifications hide production, trade and consumption characteristics in secondary sectors (such as the Crop sector), hindering the implementation of specific agricultural policies. A few studies have already improved the resolution of the agricultural sector in MRIO models. Hu et al. (2020) applied China's MRIO table including 12 agricultural sub-sectors in their research for the first time, describing production and trade relations in 53 sectors and 31 provinces in Mainland China (referred to hereafter as China) in 2011. They focused on quantifying current and future environmental impacts and mitigation strategies in China's food production within planetary boundaries. However, there is a lack of description of environmental productivity and nexus elements in the provincial agricultural sector. Zhao et al. (2022) and Ye et al. (2022) developed higher-resolution MRIO models, disaggregating the agricultural sector into 19 and 84 sub-sectors. Zhang et al. (2023) incorporated the traditional MRIO model with national survey data and calculated the water footprint of household consumption in different income groups. These models were applied to provincial water footprint accounting to validate performance and uncertainty. Although both results indicated significant water resource pressure in the agricultural sector, they did not consider the nexus with other environmental factors in the agricultural sector, such as GHG emissions. The above studies provide solutions for high-resolution MRIO models. It is worth noting that only highly aggregated sectoral data, such as water consumption data, can be obtained from statistical departments, which cannot be matched to each sector in the MRIO table. The finer the sectoral classification, the more detailed data estimation is required, which may introduce uncertainty into the results. Considering data availability and the research objectives, disaggregation into more sectors is not always better.

In summary, this study aims to address two research gaps: (i) developing a high-resolution MRIO model for the agricultural sector with robust performance under limited data, (ii) exploring the WEF Nexus to identify effective mitigation strategies and pathways for ensuring optimal allocation and sustainable management of water-emissions in agricultural systems. Therefore, this paper aims to make the following contributions. (i) the new 2017 agriculture-oriented multi-regional input–output (MRIO) model is developed, which generates 12 detailed agricultural product sectors based on Industrial Ecology Virtual Laboratory (IELab) technology (see Table S1) (Wang, 2017). Then the RAS method was applied to update the base MRIO table. (ii) Separate accounts were created for water consumption and GHG emissions in both agricultural and non-agricultural sectors. Water and emissions were then allocated across the entire supply chain based on the input–output method. (iii) The study introduced the concept of environmental productivity, defined as the ratio of agricultural production output to environmental input. It highlights the spatial differences in environmental resource utilization across sub-sectors. (iv) Virtual water flow and embodied GHG emissions were calculated to identify the key nodes and routes within the WEF Nexus in China for 2017. By analyzing both national and subnational agricultural sectors, this study enhances the understanding of China's WEF Nexus and offer valuable insights to support the development of region-specific strategies for mitigating environmental stress.

2. Methods and materials

2.1. Environmental inventory

2.1.1. Direct water consumption inventory

(1) Water consumption in the agricultural sector

The direct water consumption inventory uses the 'Water Footprint (WF)' concept (Hoekstra et al., 2011). The WF of food production is obtained by multiplying the food production and the virtual water content coefficient (Liu et al., 2021). In the calculation, only blue and green water are considered. The WF calculation equation is as follows:

$$W_w = \sum_n \left(VWC_i \times P_i \right) \tag{1}$$

where W_w represents agricultural production WF; VWC_i represents the virtual water content (VWC) per unit mass of each product; P_i represents the production of each category of crop or animal products; and i refers to the different agricultural products categories ($i = 1, 2, 3, \ldots$). About 40 categories of agricultural production data are obtained from the China Statistical Yearbook 2018 and the China Agricultural Statistical Yearbook 2018 (Department of Rural Socio-economic Surveys, 2018; National Bureau of Statistics, 2018), and Crop Water Requirements are obtained from CropWat (See Table S3 for details). For sub-sectors lacking the VWC information, the national-level VWC values provided by Mekonnen and Hoekstra (2011b) are used. Then, the WF of each product is calculated, and all WFs of 40 products are combined into 12 categories (see Table S3), which correspond to the agricultural sub-sectors in the MRIO table.

(2) Water consumption in the other 41 sectors

There is no officially published water consumption data for each industrial sector at the provincial scale. Thus, the detailed data for water consumption needs 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). Firstly, the total water consumption of each of the three sectors is determined based on the China Statistical Yearbook. Then, for each sector, the water consumption is allocated proportionally to its sub-sectors, for the detailed data on the sectoral workflow are provided in Fig. S2.

2.1.2. Direct GHG emission inventory

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

$$W_C = EF \times Activity \tag{2}$$

where, W_C is the GHG 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 and 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) (IPCC, 1996), with GWP_{100} for CH_4 being 21 and GWP_{100} for N_2O being 310.

(1) GHG emission from agricultural sector

GHG emissions from agriculture are divided into four parts: crop (7 sub-sectors), forestry, animal husbandry (3 sub-sectors) and fishery (see Table S6). The detailed calculation equations for each GHG emission are shown in Table S8. It is worth noting that GHG emissions from burning crop residues are not included due to limited data. In addition, the agricultural sector also contributes to a negative GHG emission, specifically through carbon sinks. Over time, land use changes (LUC) – such as afforestation – absorb emissions. Since the emissions only cover a single year, it is not possible to quantify the carbon sink from LUC. In order to maintain carbon cycle equilibrium, it is assumed that GHG emissions from burning are balanced by GHG uptake from LUC in 2017 (Liang et al., 2021). Only shellfish and seaweed carbon sinks are considered (Zhang et al., 2005). The activity data are mainly derived from the China Statistical Yearbook 2018 and China Fishery Statistical Yearbook 2018. The emission factors mainly refer to the IPCC and PGGIG guidelines, with some sourced from the literature. For further details, see Tables S9 and S10.

(2) GHG emissions from the other 41 sectors

The calculation of GHG emissions 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). The data is mainly provided by the CEAD database (CEADs, 2020), which counts energy consumption and carbon emission data at the provincial scale by using the IPCC method (Shan 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 the total carbon emissions are allocated to each sub-sector according to the proportion of the added value of each sub-sector.

2.2. Multi-regional input–output analysis

National IO models usually take considerable time to develop and balance the acquired data (Dalgaard and Gysting, 2004; Nicolardi, 2013; Serpell, 2018). The lack of timely IO tables poses a significant impediment for economic and environmental analyses. To improve the timeliness of IO models, many studies have used nonsurvey methods (Xing et al., 2011) to estimate future or missing IO models (Planting and Guo, 2004). The RAS-based method is the most well-known and widely used method for this purpose (Saari et al., 2014).

2.2.1. RAS-based method for updating the MRIO table

The standard RAS model iteratively adjusts the old IO matrix to generate the target year IO matrix, where the gross output (x), sum of intermediate demands (u) and the sum of intermediate inputs (w) in the target year are known. Each iteration consists of biproportional adjustment of rows (intermediate demand) and columns (intermediate inputs), which are subject to the effects of fabrication effect and substitution effect, respectively (Parikh, 1979). The iterative process ends when row-column sums of the updated IO table are as close to the target constraints. Detailed procedure for this iteration is provided in S4, and the new IO matrix can be written as:

$$\begin{aligned} Z^* &= \hat{R} Z_0 \hat{S} \\ \hat{R} &= \hat{R}_1 \hat{R}_2 \hat{R}_3 \ldots \hat{R}_k \\ \hat{S} &= \hat{S}_1 \hat{S}_2 \hat{S}_3 \ldots \hat{S}_k \end{aligned} \tag{3}$$

where Z^* and Z_0 are intermediate consumption matrix of target year and base year; $\hat{R}$ and $\hat{S}$ are diagonal matrices representing the overall fabrication and substitution effects.

In this study, based on the agriculture-oriented multi-regional input–output table in 2011, with the targeted three pieces of information: x, u, w, RAS generated a new matrix Z for 2017 from the old matrix Z_0 (2011 MRIO table) including 53 sub-sectors (Hu et al., 2020). Data sources for this information include the Provincial single region IO (SRIO) tables (National Bureau of Statistics, 2019), the Provincial/National statistical yearbooks, and the China Rural Statistical Yearbook. The contributions of the different data sources to generate the 2017 MRIO table and their interrelationships are shown in Fig. 1. Detailed data processing procedures are provided in Fig. S4. The results are calculated using R Studio based on the "ioanalysis" and "lpSolve" packages, and the method had a 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% (As shown in Table S12).

2.2.2. Environmental impact accounting

The production-side based environmental impacts of sector i in region r can be directly obtained from the inventory. While the consumption-side based environmental impacts can be calculated with the resource consumption intensity and the final consumption as follows:

$$\mathrm{Q} = \hat{W} (I - A)^{-1} \mathrm{F} \tag{4}$$

$$w_{ci}^r = \omega_{ci}^r / x_i^r \tag{5}$$

where Q defines the consumption-side based environmental impacts; $(I - A)^{-1}$ is the Leontief inverse coefficient matrix, which reflects the relationship between final demand and total output. The definition and derivation process is shown in equation (S10); I is the identity matrix; A is the technology coefficient; W is a $1*(m*n)$ row vector that represents the resource consumption intensity of each sector in each region; $\hat{W}$ represents its diagonal matrix whose diagonal element w is defined as Eq. (5); ω_{ci}^r represents the water used or GHG emissions produced by the production process of sector i in region r, as defined in Eqs. (1) and (2), and x_i^r represents the total output value of sector i in region r; F is the final consumption vector. For detailed environmental impact accounting based on the MRIO model

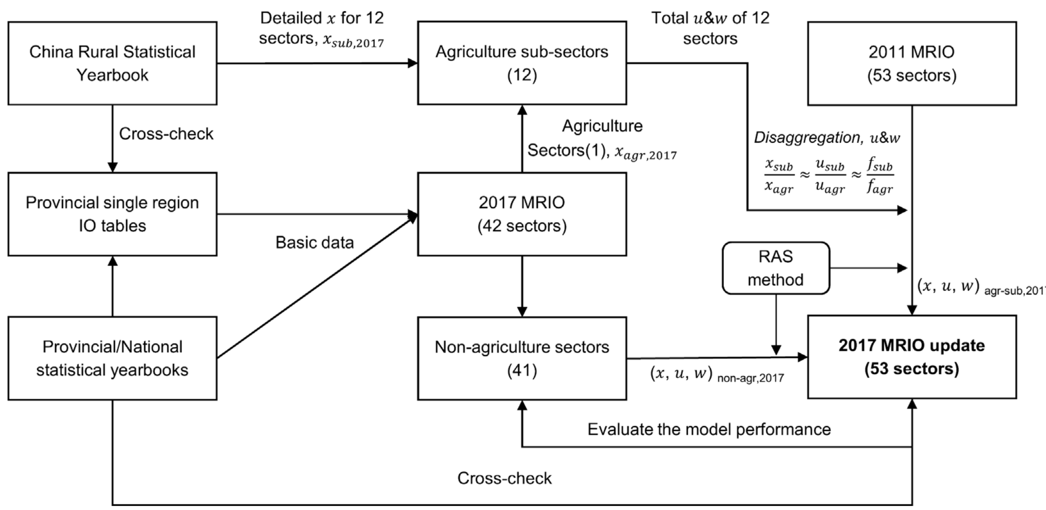


Fig. 1. The contributions and interrelationships of different data sources to generate the 2017 MRIO table.
Note: Although the 2017 MRIO was generated based on 2011 MRIO, the data source and economic structure are from 2017. For example, the intermediate output data are the actual values of 2017, only specific information on the decomposition of the agricultural sector is provided in 2011 MRIO. See 2.2 and Appendix.

is provided in Section S4.2. In addition, interregional trade serves the input and output process from the production-side to the consumption-side. Water-emissions transfer embodied in the trade. The input (or output) refers to the inflow (outflow) of virtual water and embodied emissions from products imported (or exported) to other regions or sectors. The difference between input minus output is used as the net flow, a positive value is a net input, and a negative value is a net output.

3. Results and discussion

3.1. Inter-provincial water-emissions analysis

3.1.1. Production-side based water-emissions analysis

The water and emissions of the production side refer to the direct water consumption and GHG emissions of a region in production activities. Fig. 2 shows the spatial distribution of direct water-emissions footprints and productivities in the agricultural sector and direct water-emissions in specific sub-sectors. For the water footprint, both blue water and green water footprints are calculated. The results can be detailed in Section S5.1. However, the water consumption mentioned in this section only focuses on the blue water footprint, which can better reflect the agricultural water use.

To enhance comparability and ease of presentation, this study organized the 31 provinces into eight regions based on their geographical location and economic conditions (Mi et al., 2017) (presented in Table S3). There are large differences between regions regarding water consumption and GHG emissions. Water consumption in agricultural production is mainly concentrated in the Central, Northern Coastal and Northeast regions. The top five water consumption provinces are Henan (55.4×10^9 m^3), Heilongjiang (41.2×10^9 m^3), Hubei (32.5×10^9 m^3), Shandong (31.5×10^9 m^3) and Guangdong (25.6×10^9 m^3), which together account for 39.8% of the national agricultural production water consumption. GHG emissions from agricultural production are mainly concentrated in the Central and Coastal regions (Fig. 2a). The top five GHG emissions provinces are Hunan (85.64Mt), Sichuan (69.3Mt), Hubei (64.4Mt), Jiangsu (64.2Mt) and Guangxi (59.7Mt), which together account for 32.7% of the national agricultural production emissions. From the sectoral perspective, water consumption mainly comes from crop and fishery (Fig. 2b). The water consumption of Central and Northwest regions is dominated by crop; the provinces along the Yangtze River Basin and Coastal regions are dominated by fishery. In some regions of Central and Southwest, including Jiangxi, Hunan, Guangxi, and Yunnan, the water consumption in forestry is significant, since these areas serve as or are close to major forest areas in China (Cheng et al., 2023), a considerable amount of agricultural water is contributed to forestry management or the production of forest products. GHG emissions mainly come from crop and animal husbandry (Fig. 2a). Furthermore, mainly concentrated in the cereal (S1-1) and livestock breeding (S1-9) sectors (Fig. 2c). Hunan province has the highest emissions in crop production, and Henan has the highest emissions in livestock breeding.

In general, regions with high water consumption tend to have high GHG emissions. The Crop sector is the main contributor to agricultural GHG emissions but is not necessarily a high water-consuming sector. The main reason is that the green water footprint meets the basic requirements for crop production and does not need to be supplemented with blue water for agricultural irrigation. This pattern is most typical in Southern and Coastal regions. The water-emissions footprint of the cereal sub-sector in Crop is prominent, individually, the Cotton (S1-3) sector in Xinjiang is prominent; the livestock breeding sub-sector in husbandry has a prominent water-emissions footprint. It is worth noting that in Main grain-producing (Zhang et al., 2021) areas in China (see Fig. S1 for the scope of MGP areas), the water and emissions footprints account for 63.5% and 63.9%, respectively. which are significantly more affected than other regions in China. Therefore, paying attention to the water-emissions nexus in the MGP regions is of significant importance for agricultural management, which aligns with the findings of Wang et al. (2020b).

The "productivity" is used to evaluate the relationship between economic growth and resource utilization in China's economic system (Liu and Feng, 2019). As an important indicator for evaluating food security, it measures the value derived per resource unit. In 2022, the global agricultural sector's water productivity (WP) and Emissions productivity (CP) were 4.77 Yuan/m^3 and 11.45×10^4 Yuan/t, respectively. China's WP and EP outperform the global average, at 17.83 yuan/m^3 and 19.72×10^4 yuan/t, respectively (Climate Watch Historical GHG Emissions, 2022; FAO, 2022). The WP in the agricultural sector is vertically higher in the Southern regions and lower in the Northern regions. Horizontally, the productivity is lower in the Central regions but higher in both the Eastern and Western regions. The Southwest region demonstrates the highest WP (Fig. 2a). Despite benefiting from water-saving technologies, for example, rainwater harvesting, mulching plus drip irrigation technologies and no-till farming, the WP in the Northwest region is limited due to naturally arid climate conditions. CP is vertically higher in the Central regions and lower values in the Southern and Northern regions (Fig. 2b). The Central, Northern and

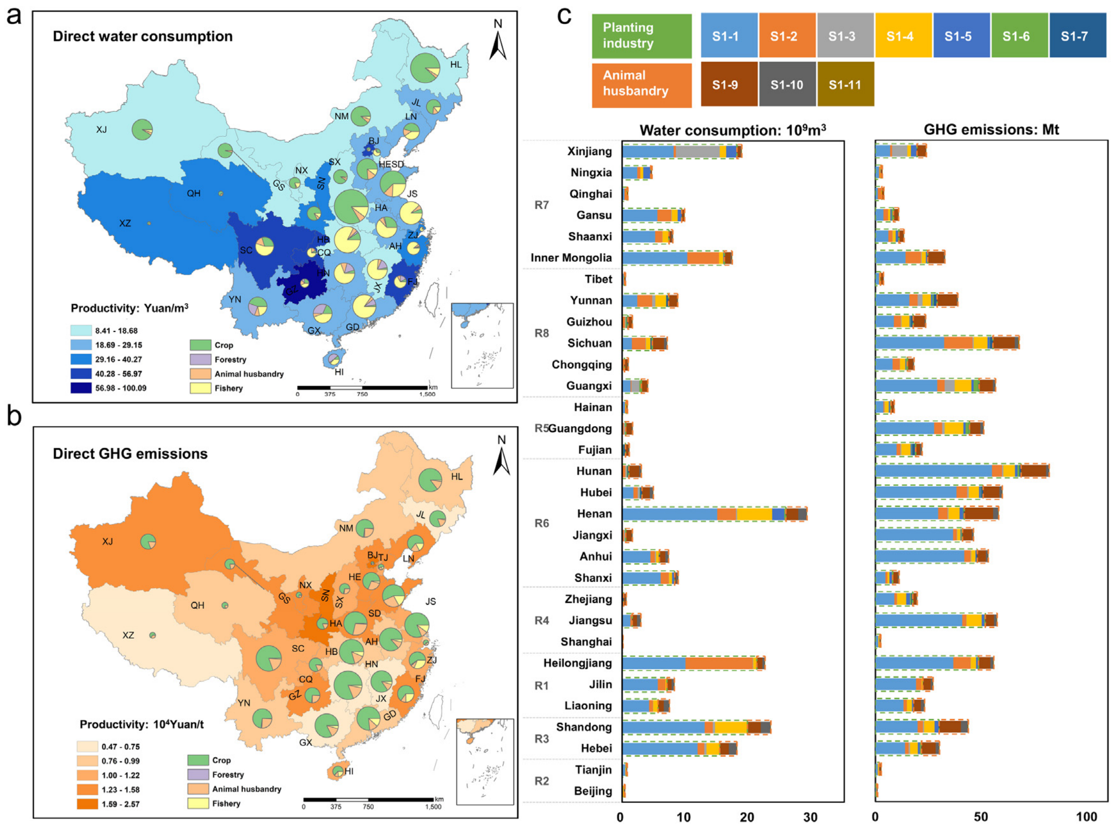


Fig. 2. Spatial distribution of direct water-emissions footprints and productivities in the agricultural sector. a. Direct water consumption and water productivity; b. Direct GHG emissions and emissions productivity; c. Direct water-emissions footprints of key sub-sectors.
Note: The actual values of the S1-1 in Henan and Heilongjiang are 46.2 × 10^9 m^3 and 25.1 × 10^9 m^3.

Eastern Coastal regions have a higher CP than others. However, the CP is lower in the Northeast and Southwest regions, despite agricultural green production technologies have been applied in these places to improve low-carbon efficiency (Nouri et al., 2020; Ward, 2022), they have not worked effectively (He et al., 2021). In the western region, the distribution characteristics of CP are opposite to WP, the CP in the northwest is higher than that in the southwest. In addition, the regions along the Hu Line have higher CP (Zhang et al., 2022a).

3.1.2. Consumption-side based water-emissions analysis

The water and emissions footprints based on the consumption side refer to both the direct and indirect water consumption and GHG emissions of a region regarding agricultural product consumption. As shown in Figs. 3a and 3b, the differences in the spatial distribution of water-emissions footprints became relatively weaker after the trade diversion. For all provinces, the water footprints decreased. Among them, Beijing and Shanghai decreased by 2.1% and 3.3%, respectively, basically the same as the production side, and the water footprint of the other regions decreased by an average of 62.7%. Compared with the production side, the GHG emissions of Beijing and Shanghai increased by 63.5% and 15.2%, respectively, while the rest of the provinces decreased by an average of 51.7%. From a regional perspective, Coastal and Central regions are characterized by high water-emissions footprints. The Northwest region has a lower water-emissions footprint, while the Jing-Jin area, which is limited by its population and coverage area, is relatively low. The Western region has a low emission but a high water footprint. From a sectoral perspective, the cereal and livestock sectors have a high water and emissions footprint.

The water intensity (WI) in the agricultural sector is higher in the Northern region and lower in the Southern region (Fig. 3a). Emissions intensity (CI) is higher in the Western region and lower in the Eastern region (Fig. 3b). Beijing and Shanghai have high water-emissions intensity, indicating that both high-water-consumption and high-emission sectors are in the upstream sectors.

3.1.3. Water-emissions transfer embodied in interregional trade

This section analyzes the input and output of water and GHG emissions in interregional trade transfers (International trade is not included). The importance of the interregional analysis lies in providing policy implications for domestic food security and environmental sustainability. The water-emissions conduction targets of the agricultural sector can be divided into self-demand (SD), local non-agricultural sector (LNAs), non-local agricultural sector (NLAs), and non-local non-agricultural sector (NLNAs) (see Table S17 and S18 for detailed water-emissions flows between provinces). Among the 31 provinces, Beijing and Shanghai are the main water-emissions footprint net input regions. As highly urbanized centers, they rely heavily on food imports from other regions due to limited local agricultural production. Their large populations and high demand for water-emissions-intensive goods contribute to significant virtual water and emissions inflows. Geographically, Limited water resources further drive the reliance on virtual water imports, reinforcing their status as net input regions for water-emissions footprints. For the other regions, both water and emissions are net outputs in trade flows, meaning virtual water and embodied emissions are exported to other sectors or regions through food products. Fig. 4 quantifies the interrelationships of embodied water and emissions flow within the agricultural sectors of the eight major regions (Hiplot, 2022; Li et al., 2022). Fig. 4a illustrates the flow of virtual water, and Fig. 4b depicts the flow of embodied emissions. Both figures exclude the SD water and emissions flows within the agricultural sector. Hence, lines on the graph that start and end in the same region represent water and emissions flows from the agricultural sector to LNAs. It can be seen that the virtual water flows from the

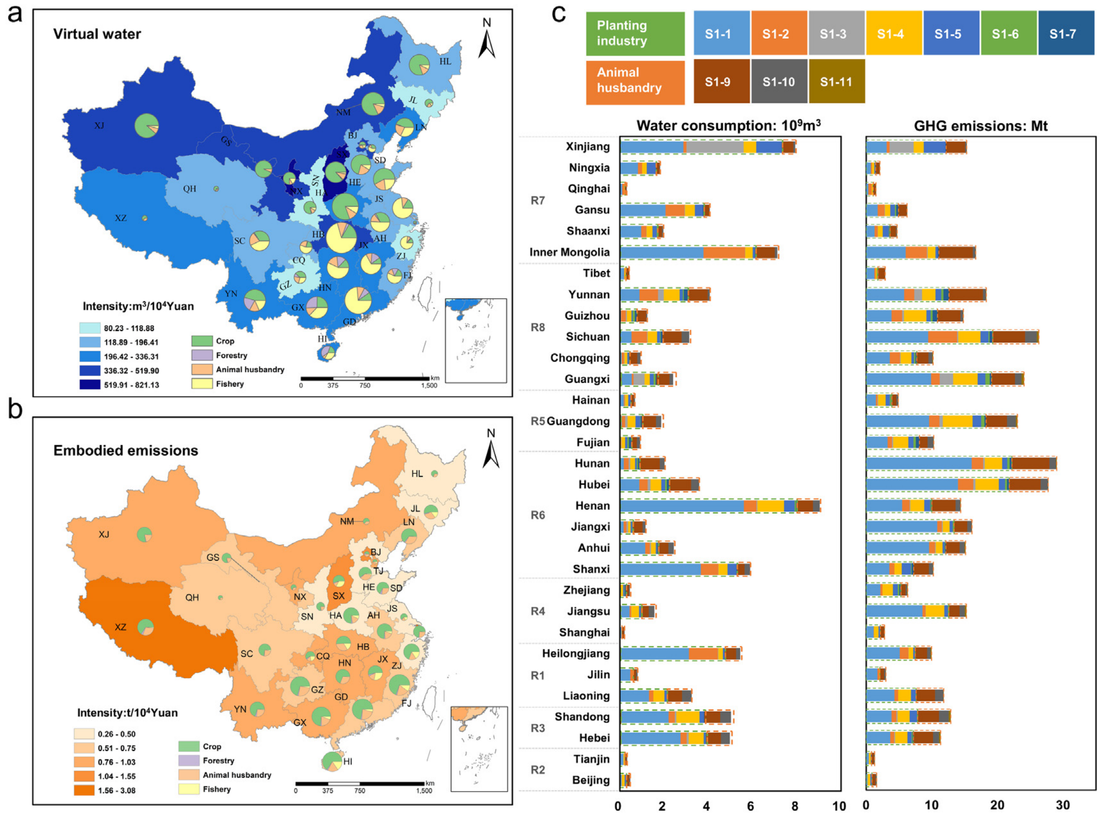
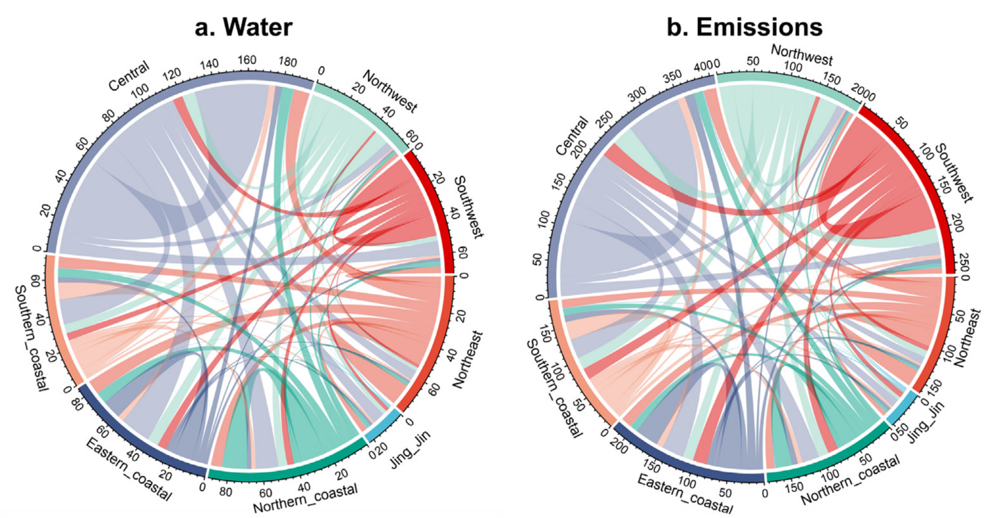


Fig. 3. Spatial distribution of embodied water-emissions footprints and intensities in the agricultural sector. a. Virtual water and water intensity; b. Embodied emissions and emissions intensity. c. Embodied water-emissions footprints of key sub-sectors.



Region	Embodied water flow ($10^{12}m^3$)				Embodied emissions flow (Mt)			
	LNAs	NLNAs	NLAs	Net Flow	LNAs	NLNAs	NLAs	Net Flow
Northeast	-10.8	-39.3	-1.5	-51.6	-18.1	-66.2	-2.4	-86.6
Jing-Jin	-0.5	-1.4	0.2	-1.6	-0.6	-1.1	0.5	-1.1
Northern Coastal	-12.2	-27.5	0.2	-39.5	-18.4	-40.6	1.0	-58.0
Eastern Coastal	-8.9	-15.3	0.3	-23.9	-25.0	-40.4	-0.3	-65.7
Southern Coastal	-8.2	-14.9	1.0	-22.2	-20.3	-32.4	1.3	-51.3
Central region	-27.8	-80.7	-0.8	-109.3	-42.7	-124.3	0.2	-166.8
Northwest	-7.0	-31.4	-0.5	-39. 0	-6.0	-37.9	0.3	-43.6
Southwest	-10.2	-24.1	1.2	-33.1	-35.8	-79.4	-0.6	-115.8

Fig. 4. Embodied emissions and virtual water flows among the eight regions in China.

Central, Eastern and Western regions mainly towards the Jing-Jin and Coastal regions. The Central region exhibits the most significant virtual water outflows, with a total of 1.1×10^{14} m^3, primarily driven by the cereal sector, which accounts for 33.0%. In contrast, the Coastal regions serve as the major recipients, with 1.6×10^{14} m^3. Additionally, the LNAs have the highest virtual water input in the Central region. Embedded emissions flows in the same direction as virtual water. Under the premise of the same agricultural product output, the Western region shows a more substantial emissions flow effect than virtual water flow. This is mainly influenced by the geographical location of the semi-arid climate, rainwater harvesting, mulching plus, drip irrigation technologies have improved agricultural water use efficiency (Li et al., 2023; Wang and Shangguan, 2015; Wang et al., 2018), and the output value of unit GHG emission is lower, that is, the emissions productivity is weaker. Moreover, the trade process involves higher embodied emissions inputs from non-agricultural sectors, such as transportation and manufacturing (Qaidi et al., 2021; Tayeh et al., 2022). In addition, 68.5% of virtual water and 57.1% of emissions are net exported to other regions or sectors. Non-agricultural sectors serve as water-emissions inflows from the agricultural sector, both LNAs and NLNAs, accounting for 73.3% and 71.7% of the embodied water and emissions in the downstream sector, respectively, with the manufacturing and electricity sectors being the main water-emissions inflows sectors. Therefore, policies that improve environmental productivity should prioritize interventions in these sectors. For instance, improving resource efficiency, and optimizing the transportation and processing stages of the supply chain could significantly reduce the overall environmental footprint. Regionally, improving the resource allocation and utilization efficiency in the trade process, the virtual water-emission flows from the Central and Northern Coastal regions with higher environmental productivity to the downstream areas such as Shanghai and Beijing, which can indirectly reduce environmental impacts. In addition, in the upstream agriculture sector, industry should be encouraged to adopt more water-saving and low-carbon materials and processes (Hong et al., 2022).

3.2. Water and emissions productivity estimates

The water (emissions) productivity of four aggregated sectors (agriculture, industry, construction and services) is calculated based on their gross output value and water (emissions) footprints. It can be seen from Fig. 5a that the agricultural sector has the lowest WP and lower CP. Moreover, the WP and CP in the agricultural sector are spatially aligned except in the Central and Southwest regions. Specifically, the Southwest and Coastal regions have a higher WP and CP than other regions (see Fig. 5b), and the WP and CP in these regions are positively correlated, meaning that regions with high WP also have high CP. However, WP and CP are generally lower in the Northeast and Northwest regions (Wang et al., 2020a).

As for water productivity of agricultural sub-sectors (Fig. 5c), the WP of livestock is relatively high, while the WPs of cereal, poultry, vegetables and fishery are low. The WP of cereal is significant only in MGP areas such as Jiangsu and Sichuan. Regarding spatial distribution, the WP of the Southwest region (especially in Guizhou and Sichuan) is higher than that of other regions. In contrast to WP, the characteristics of CP are not entirely the same, with cereal, vegetables and livestock being relatively higher. These results reveal that livestock production can create higher economic output under the same water and emissions development scenario. Besides, from the regional perspective, the CP of the cereals sector in the Northern Coast area (Shandong and Hebei) is higher than that of other regions, and the CP of animal husbandry in the Southwest areas (especially Sichuan) is the highest. The output value of animal husbandry in Northwest areas accounts for a large part of the country (Du et al., 2024). However, affected by technical conditions, the CP of the Northwest area is lower than that of the economically developed Central and Eastern regions (Sheng et al., 2020).

Table 1
WEF Nexus coefficients in different regions.

Description	Nexus coefficient	Region	Nexus coefficient
Irrelevant	≤0.3	Northeast region	0.21
Weak correlation	0.3–0.5	Northwest Region	0.50
Relevant	0.5–0.75	Jing-Jin & Northern Coastal area	0.66
		Central region	0.78
Strong correlation	0.75>	Eastern & Southern Coastal area	0.95
		Southwest region	0.95

3.3. The WEF Nexus of the agricultural sector

3.3.1. Nexus of production-related variables in the aggregated agriculture sector

This section investigates the relationship between water, emissions, and other agricultural-related variables. This set of variables includes: agricultural production, as part of the national gross domestic product (GDP); investment in environmental protection (PTI); fertilizer and pesticide use; energy (electricity, diesel) consumption; agricultural total output value (TOV); water footprint and GHG emissions (Fig. S14). Based on the agricultural sector data in 31 provinces, the correlation matrix of the agricultural-related variables was constructed, as shown in Fig. S14. The WEF Nexus is characterized by the water-carbon correlation coefficient. This coefficient measures the degree of interlinkage between water and emissions in the agricultural sector, indicating whether a region or sector's water use and emissions are tightly (strong coefficient) or more loosely connected (weak coefficient). A strong nexus coefficient suggests that changes in one variable will significantly impact the other, implying that integrated management strategies are necessary. In contrast, a weak coefficient indicates more flexibility in sector-specific policies (Sun et al., 2024). The WEF Nexus degree classification is shown in Table 1. The overall WEF Nexus is 0.87, indicating a strongly positive connection between water consumption and GHG emissions in agricultural production, i.e., the higher water consumption, the higher GHG emissions. Thus, confirming the existence of a WEF Nexus in the Chinese agricultural sector. Furthermore, there is a strong nexus in the Southwest and Southeast Coastal regions, while the nexus in the Northeast and Northwest regions gets relatively weak. The overall nexus coefficient in MGP is 0.69. Among these MGP areas, the Central region has the strongest nexus, while the Northeast region's WEF Nexus is insignificant. Therefore, in formulating policies for coordinated water-emissions management, measures should focus on guiding the Northeast and Northwest regions to improve their WEF Nexus in agricultural production (Yao et al., 2022).

3.3.2. WEF Nexus analysis by province

At the provincial level, the WEF Nexus in various agricultural subsectors are explored. Each province's WEF Nexus based on the nexus coefficient is divided, as shown in Table S17. Provinces with a low WEF Nexus magnitude are mainly concentrated in the Northeast and Northwest regions, and nearly half of the provinces have no nexus between water and emissions in their agricultural sector. This is because water usage and GHG emissions differ among different agricultural subsectors, such as the cereal sector and livestock breeding, which have completely different production processes. Therefore, the WEF Nexus is mainly influenced by local agricultural types and development scales for the entire agricultural sector (Smith et al., 2024). For example, diversifying corn and bean cropping practices can increase grain yields and reduce GHG emissions (Renard and Tilman, 2019), but also leads to increased competition for resource inputs, which is affected by the crop variety and scale (Sun et al., 2021). Crop diversification practice makes the water-emissions correlation unclear. The nexus magnitude is high for regions with a single production mode, such as Inner Mongolia, Xinjiang, and Tibet, which mainly focus on livestock breeding, and

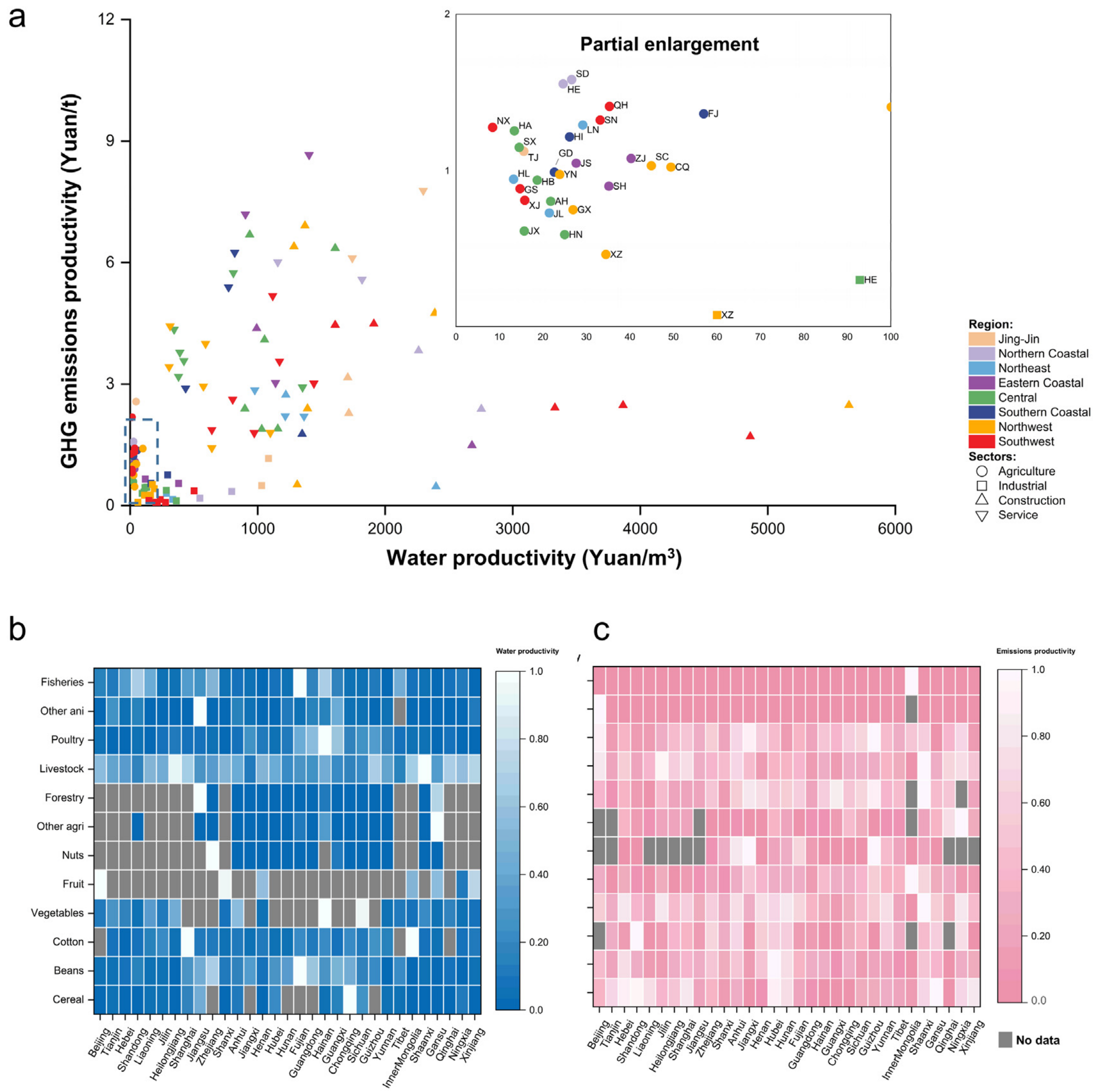


Fig. 5. Water and emissions productivity estimates. a. WP and CP in four highly aggregated sectors. b. WP (normalized value) distribution of 12 sub-sectors. c. CP (normalized value) distribution of 12 sub-sectors.

Jilin and Heilongjiang, which mainly produce grain. The WEF Nexus is weaker for regions with multiple integrated agricultural development modes, such as Hubei and Hunan, which simultaneously specialize in grain, vegetables, fruits, and livestock breeding. In addition, for MGP areas with large-scale grain development, there is a high water-emissions nexus to a certain extent (Zhang et al., 2020). Therefore, the diversity of agricultural structures reduces the water-emissions nexus of the agricultural sector and increases the complexity of agricultural management. This makes it difficult for policymakers to create one-size-fits-all policies for water use and emissions control (Ogunmoroti et al., 2022; Wang et al., 2021).

The synergy of water-emissions in the agricultural sector is generally performing well. Future policymaking should comprehensively consider regional differences and technological applicability in agricultural production, identify key regions and sectors with better synergistic relationships, and adopt adaptive measures that benefit the agricultural economy's development. Specifically, technological innovation and adoption should be implemented to improve agricultural production potential, such as optimizing the diversified crop rotations in the North China Plain (mainly the Central region) to reduce groundwater use and increase energy, and economic output (Nouri et al., 2020; Ward, 2022). Photovoltaic (PV) agriculture could be an ideal substitute energy resource with low GHG emissions. Moreover, PV can improve water-use efficiency by increasing soil health and moisture. Exploring and promoting the development model of photovoltaic agriculture in Central and Western regions will help address both water and emissions challenges (Xue, 2017). Attention should be paid to the role of emission reduction in MGP areas, as there are relatively sufficient raw materials for biomass, and biomass energy should be promoted. Priority should be given to the Northeast region to improve its emissions productivity. Optimizing the agricultural structure under the constraints of water resources and GHG emissions (Zhang et al., 2020), improving the water-emissions nexus and developing precision agriculture to minimize water inputs and GHG emissions (Feng et al., 2022). Also, water and carbon markets should be established to spur innovation across the agricultural sector.

3.4. Robustness analysis and technical validation

3.4.1. Robustness analysis of WEF Nexus results

This study involves a large number of parameters and methods. In order to ensure that the method and data are used correctly and robust results are obtained, it is necessary to conduct a robustness analysis to verify that the same nexus results can be obtained by using different water-emissions footprint accounting methods. The process analysis method is usually used in WF calculations, and determining the VWC of the product is the key to this method. For this, Mekonnen and Hoekstra (2011b) provided national-scale VWC averages for agricultural products, which means that VWC is the same for all provinces. In this study, the VWC of most crops at the provincial level adopts the crop water requirement method (CWR, based on CropWat), which can better reflect the actual situation of the regional WF. Here, the national-scale CWR can be used for robustness testing. For GHG emission accounting, this study is based on the PGGIG. Similarly, the IPCC method also provides accounting methods for various emission sources in the agricultural sector. However, since the formulation of the PGGIG is based on the IPCC method, and some parameters in this study are directly taken from the IPCC, it can be considered that GHG emission accounting combines the above two methods, and the IPCC method for robustness testing is weak. Therefore, this study focuses on the robustness test of the WF. A t-test is performed on the two groups of samples (case samples and samples used for robustness test), and the results show that the p-value is 0.779, which means there is no significant difference between the means of the two samples, the WF calculation is robust. In addition, the WEF Nexus coefficient is 0.83, which is similar to the results of this study (3.4% different). The results of this study are robust.

3.4.2. Uncertainties of environmental accounts

The uncertainty in the agriculture water consumption comes from the WF calculation due to the application of the national-scale VWC in some sub-sectors. The uncertainty comes from the sources of production data, which are within 10%–20% for different products (Mekonnen and Hoekstra, 2011a). The activity data and emission factors are the major quantifiable uncertainty sources in GHG emission accounts. The results show that the provincial average agricultural uncertainty for non-energy-related emissions is 32.44%, and the uncertainty of the crop sector is higher, at 52.96%, mainly from emission factors. The uncertainty of energy-related emissions is 30.3% (Shan et al., 2020).

3.4.3. Comparisons with existing MRIO in 2017

To validate the MRIO derived in this study, a comparison was made with the MRIO table compiled by Zheng et al. (2021). Following previous MRIO table comparisons, two indicators are employed, specifically, the Isard-Romanoff similarity index (DSIM) and the absolute entropy distance (AED) (Steen-Olsen et al., 2016). Here, we compare the intermediate demand matrices. It turns out the DSIM and AED are relatively small, 0.04 and 0.0065%, respectively, which means the estimated MRIO is similar to the latest MRIO table. The detailed mathematical formulas are shown in Table S15.

4. Conclusions

This study broadens the scope and methods of environmental impact assessments of production in the traditional agricultural sector, and aims to contribute novel insights for two key areas. Firstly, one significant contribution is developing a detailed MRIO model specifically for the agricultural sector, which establishes the supply chains of the agricultural sector from upstream to downstream. Empirically, this study reveals the nexus between water and emissions in the agricultural sector, and systematically analyzes the linkages among regions and sectors in the entire supply chain from agricultural production to final consumption, as well as the resulting environmental impact transfer between regions. At the same time, agriculture is a major water consumer and GHG emitter, in the face of growing food demand, regional trade, water scarcity, and carbon neutrality targets, such assessments are crucial to ensuring regional food security and environmental sustainability.

By assessing the water and GHG emissions impact of the agricultural sector's input and product supply chains, it can be concluded that the main grain-producing areas caused a relatively high environmental impact, accounting for about 63.5% of the water and 63.9% of the emissions for agricultural production. Meanwhile, the transfer of water and emissions footprint in the supply chains reaches as high as 73.3% and 71.7%, respectively, highlighting the substantial impact of trade transmission on the environment, which cannot be ignored. Current management of water resources and GHG emissions is isolated. However, the water-emissions nexus analysis in the agricultural sector reveals a strong positive correlation. Therefore, cross-sectoral collaboration needs to be strengthened. Cereal and livestock are key sub-sectors for integrated water and emissions management, particularly in the Northeast and Central regions. Beyond the agricultural sector, upstream sectors responsible for raw material and energy inputs are also responsible for improving their water efficiency and reducing GHG emissions during production.

Practical measures and suggestions should consider all roles within the supply chain network. Specifically, for agricultural production, widely recognized actions should be taken to enhance water use efficiency, reduce GHG emissions and increase carbon sinks, especially in the Central and Western regions. In the entire agricultural supply chain, optimizing the spatial configuration of products and the transmission path of embodied water-emissions to improve supply chain efficiency. For agricultural consumption, enhancing public information sharing and transparency by visualizing the environmental impacts of agricultural products, can promote the consumption of environmentally friendly agricultural products. In addition, throughout the entire food supply chain, attention should be paid to food loss and waste (FLW), and the linear model of FLW management (landfill or incineration) should be transformed into a circular economy model (reducing the amount of FLW and recycling food wastes), which will contribute to sustainable water-emissions-food Management.

Limitations and future work. From 2017 to 2020, the production efficiency of China's agricultural sector increased by 18.2%, and the annual growth rate of environmental total factor productivity (ETFP) is 2.8%. Technological progress is the driving force of ETFP growth. Despite technological improvements improved WP and CP, water scarcity and the second largest share of GHG emissions in the agricultural sector are remain consistent. Therefore, the general pattern of WEF Nexus is still relevant today, and the contribution of technological progress to WEF Nexus should be further quantified. In addition, climate change may affect water supply and emission intensity. For example, rising temperatures and changing climate conditions may increase water consumption and GHG emissions, affecting the overall water-emissions nexus in agriculture. Therefore, future policy interventions need to consider climate change adaptation strategies, and incorporating climate change scenarios into WEF Nexus's research will be a valuable perspective.

Abbreviations: (in alphabetical order)

CI: Emissions Intensity
CP: Emissions Productivity
CWR: Crop water requirement
EF: Emission Factors
GDP: Gross Domestic Product
LNAs: Local non-agricultural sector
LUC: land use changes
MRIO: Multi-regional input–output
MGP: Main Grain Producing
NLAs: Non-local agricultural sector
NLNAs: Non-local non-agricultural sector
PGGIG: Provincial Greenhouse Gas Inventory Guidelines (Pilot Version) in China
PTI: Investment in environmental protection
SD: Self-demand
TOV: Total output value
VWC: Virtual Water Content
WEF Nexus: Water-Emissions-Food Nexus
WF: Water Footprint
WI: Water Intensity
WP: Water Productivity

CRediT authorship contribution statement

Yang Liu: Writing – original draft, Formal analysis, Data curation, Conceptualization. **Maria Vrachioli:** Writing – review & editing, Visualization, Validation, Supervision. **Huimei Li:** Visualization, Methodology. **Yafei Wang:** Validation, Methodology, Data curation. **Johannes Sauer:** Writing – review & editing, Supervision.

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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Appendix A. Supplementary data

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