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A hybrid multi-regional input-output model of China: Integrating the physical agricultural biomass and food system into the monetary supply chain

Quanliang Ye^{a,*}, Martin Bruckner^b, Ranran Wang^c, Joep F Schyns^a, La Zhuo^{d,e}, Lan Yang^f, Han Su^a, Maarten S Krol^a

^a Multidisciplinary Water Management, Faculty of Engineering Technology, University of Twente, 7522 NB, Enschede, Netherlands

^b Institute for Ecological Economics, Vienna University of Economics and Business, Austria

^c Institute of Environmental Sciences (CML), Leiden University, 2333 CC Leiden, Netherlands

^d Institute of Soil and Water Conservation, Northwest A&F University, Yangling 712100, China

^e Institute of Soil and Water Conservation, Chinese Academy of Sciences and Ministry of Water Resources, Yangling 712100, China

^f Fudan Tyndall Center and Shanghai Key Laboratory of Atmospheric Particle Pollution and Prevention (LAP3), Department of Environmental Science & Engineering, Fudan University, 200438, Shanghai, China

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ABSTRACT

Lacking systematic supply-use information of agricultural biomass and food products within China makes the existing provincial environmental pressure assessments (e.g., water consumption) either not detailed enough (e.g., by the input-output table-based approach) or not comprehensive enough (e.g., by the process-based approach). This study develops a symmetric inter-provincial multi-regional input-output (MRIO) model that hybridizes the physical food and agricultural biomass system with the monetary supply chain of China. First, we construct the inter-provincial supply, use, and input-output tables in physical units of 84 agriculture, food and forestry products. These physical supply/use/MRIO tables systematically capture agri-food product flows, at an unprecedented level of product detail, along domestic supply chains within China. Then we integrate the physical MRIO table of agri-food products into the monetary all-sector MRIO table to construct a symmetric hybrid MRIO table of China. The application of our hybrid MRIO model to the case of provincial blue water footprint assessments reveals that the hybrid model enhances both the monetary MRIO table-based approach and the process-based approach from different aspects. For instance, the hybrid MRIO model can reduce the uncertainty of monetary MRIO modeling due to the aggregation of products with different environmental properties into homogeneous sectors. Lastly, uncertainty analysis is implemented to quantify the main sources of uncertainties, and understand the reliability of our new hybrid MRIO model for future sustainable development design.

1. Introduction

China has been one of the largest consumption countries of agricultural biomass and food products, because of its large population (The World Bank 2020), the meat-dominated (e.g., pork) diet of its inhabitants (Liang et al., 2020), and the significant food waste (Li et al., 2016). China is also one of the important global players in agricultural and food production and trade. In 2019, China produced around one-third of this planet's rice, 23% of this planet's maize, and 40% of this planet's pork (FAOSTAT 2020), most of which were supplied for

domestic consumption. Meanwhile, China also accounted for large shares, as an importer, of the global trade market for several agricultural and food products, e.g., 60% of soybean, 21% of sorghum, and 23% of pork (FAOSTAT 2020). Challenges to assure food security for the 1.4 billion people have been highlighted in China's 14th Five Year Plan (State Council of China 2020). On the other hand, domestic trade within China has grown rapidly (NBSC 2020). The growing domestic trade also led to new features of socioeconomic development patterns and environmental pressures because resource use and emissions during the production process of goods and services are virtually transferred along

* Corresponding author at: Multidisciplinary Water Management, Faculty of Engineering Technology, University of Twente, 7522 NB, Enschede, Netherlands.
E-mail address: q.ye@utwente.nl (Q. Ye).

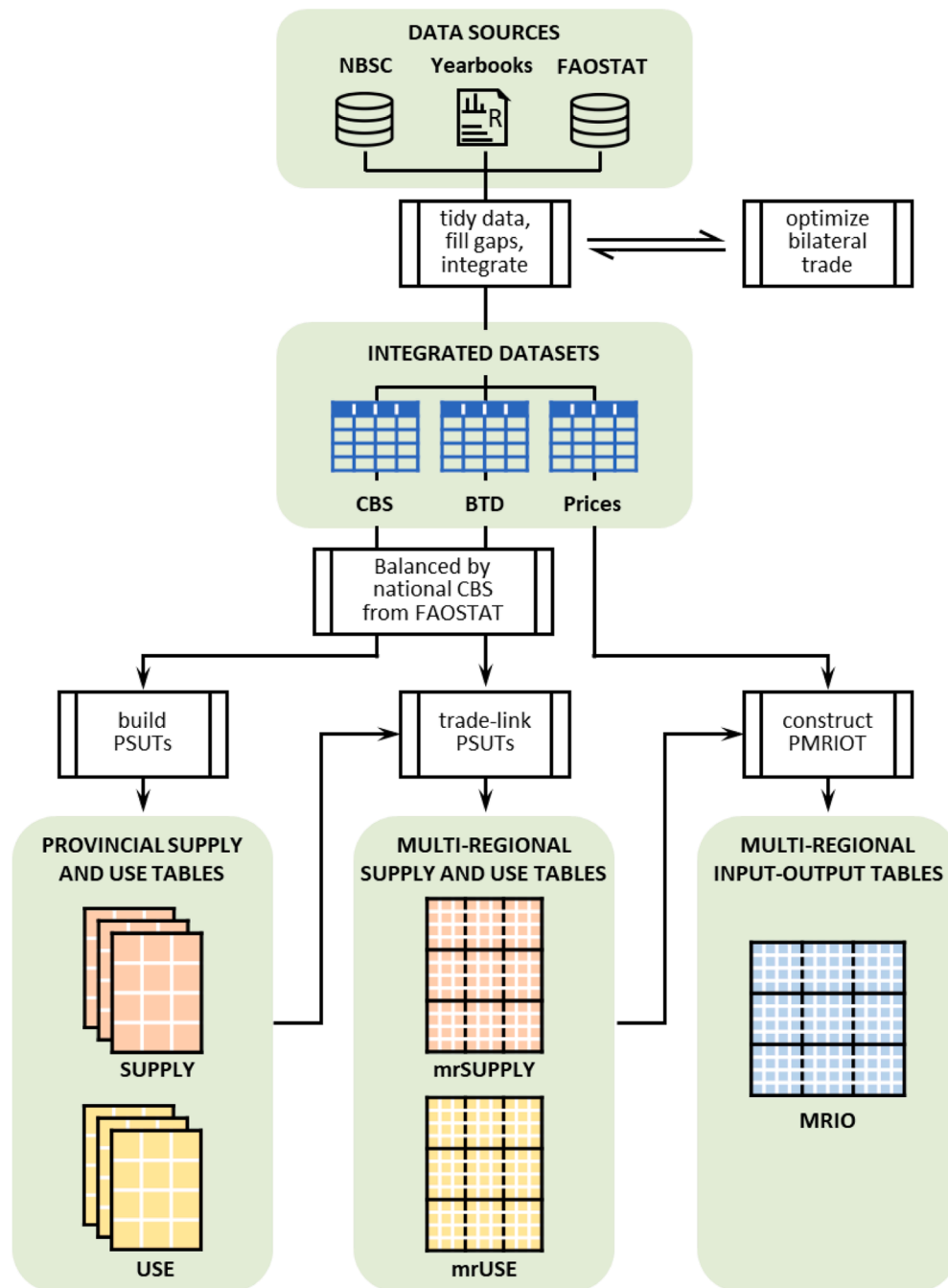


Fig. 1. Schematic for the procedures to build FABIO—CHN. Note, the PSUTs and PMRIOT in this chart only capture the transactions across 84 products and 75 processes specified in FABIO—CHN, which exclude other economic sectors such as electricity generation sectors or service sectors that will be further integrated at a latter step. The format of this chart is in accordance with Bruckner et al. (2019).

the trade. For example, virtual water flows embodied in the trade of those key food products such as maize and pork within China have increased by 40% and 23%, respectively, over the period of 2000–2013 (Zhuo et al., 2019); the carbon emissions embodied in China's exports have declined whereas the carbon transfer through inter-provincial trade in China has reversed since the global financial crisis (Mi et al., 2017); while the change in interprovincial trade structure has led to an increase of national average land use intensity during 1997–2012, with a result of 6.3 million hectares growth of land use (Chen et al., 2021). Given that the most significant driver for environmental pressures in China is economic activities (Guan et al., 2008; Zhou et al., 2020), gaining an accurate picture of the transactions across associated

sectors/products of the domestic economy is a prerequisite for achieving sustainable development goals. However, a comprehensive supply-use network of agricultural and food products that captures the production, trade, intermediate uses, conversion processes, and final consumption of associated products within China, to our best knowledge, has not been constructed yet.

To describe the supply-use chains, the monetary input-output (IO) model or multi-regional input-output (MRIO) model has been regarded as an appropriate tool, and widely applied in previous literature. Based on the IO/MRIO model, the carbon (Hertwich and Peters 2009), water (Wang and Zimmerman 2016), material (Wiedmann et al., 2015), and other environmental footprints (Cabernard and Pfister 2021) associated

with the annual human consumption of nations have been assessed. However, it argues in earlier publications (Bruckner et al., 2019; Ewing et al., 2012; Steen-Olsen et al., 2012) that current monetary-IO/MRIO-based environmental footprint assessments are often inadequate to account the specific environmental pressures related to a large range of agricultural products, as well as to capture the physical basis of the food system. It is because that the monetary structure of the economy does not always represent the physical product flows correctly, due to price variations of product flows between different customers (Bruckner et al., 2015). Moreover, mismatches also exist between agricultural and forestry statistics reported in physical units and macroeconomic production statistics in monetary units, for example due to different system boundaries (Schaffartzik et al., 2015). Lastly, from the perspective of macroeconomy, the monetary IO tables are constructed based on limited sectors, which have to aggregate products with different environmental properties into homogeneous sectors (Lenzen 2011).

A more comprehensive physical unit production, trade and consumption dataset, which could be further integrated into the monetary supply-use chains, has been suggested to reduce the uncertainties arising from the limitations of monetary IO models. As such, a hybrid approach that enriched the monetary IO/MRIO approach with detailed physical-unit production and trade data of agricultural products was developed (Ewing et al., 2012), and recently applied in studies on European consumption footprints (Steen-Olsen et al., 2012), Chinese exports (Weinzettel and Wood 2018), water consumption (Wang and Zimmerman 2016), and net primary production (Weinzettel et al., 2019). Yet, all these hybrid MRIO models rely on monetary input-output data to track biomass products from the first (or second) use stage to the final consumers. Thus, it was also suggested to describe the whole structure of material conversion and distribution networks in physical terms—by means of detailed physical supply (i.e., products supplied by sectors) and use (i.e., products used by sectors) tables (PSUT) (Heun et al., 2018; Kovanda 2018). To fill this data gap, systemic global PSUT and MRIO tables of food and agricultural biomass (FABIO) were constructed by Bruckner et al. (2019), describing the intermediate uses and conversion processes, thereby retaining flow information of associated global supply chains. One of the main limitations of FABIO is the exclusion of those highly food-related sectors (e.g., food manufacturing sectors) to capture the complete supply chain for input-output analysis and environmental pressure assessments. Besides, the existing PSUTs are mainly compiled at the national scale (i.e., describing the global economy). The economic

transactions as well as the associated resource transfers across fine-scale domestic regions are less understood, especially for some vast countries with great spatial variations in socioeconomic development patterns and resource endowments such as China.

This study tries to fill these gaps by developing a symmetric hybrid MRIO model that integrates the physical agricultural biomass and food supply-use system into the entire monetary supply chain across 22 provinces, 4 municipalities, and 5 autonomous regions (regarded as “province” from here, Table S1) of mainland China. Following the global FABIO model (Bruckner et al., 2019), this study develops the FABIO model for China (FABIO—CHN), i.e., a national set of inter-provincial trade-linked PSUTs and physical MRIO tables that capture specific supply chain information of agricultural and food products. We specify 84 raw and processed agricultural and food commodities (Table S2, generally designated as “agri-food” commodities) supplied and used by 75 processes (Table S3). The total 84 agri-food commodities cover the main grain crops (e.g., rice, maize, and wheat), cash crops (e.g., sugar beets, groundnuts, and cotton), fruits (e.g., apples, and citrus), vegetables (e.g., tomatoes), live animals (e.g., cattle, and sheep), livestock (e.g., bovine meat, mutton meat, and pork), fishery, and forestry products, which to our best knowledge formulates the most comprehensive classifications of agri-food commodities for sub-national supply chain analysis. After that, symmetric hybrid MRIO tables for China are further constructed by integrating the physical FABIO—CHN MRIO tables into the monetary MRIO tables obtained from Mi et al. (2017) for the year 2012. We apply the hybrid MRIO model to the case of blue water footprints (i.e., consumptive use of surface and groundwater resources) of provinces in China to examine the rationality of our model. We hypothesize that with a higher level of disaggregation of agri-food commodities in the MRIO modeling, the product-specific water footprints and associated virtual water trade networks can be understood more comprehensively, especially of key products for China’s food security. Lastly, uncertainty analysis is implemented to quantify the main sources of uncertainties, and understand the reliability of our new hybrid MRIO model.

2. Methods

The prerequisite of the hybrid MRIO model is the construction of inter-provincial PSUT and physical MRIO tables of agri-food commodities in physical terms (e.g., in tonnes, m³, or heads). Following the global FABIO model (Bruckner et al., 2019), the whole procedure of

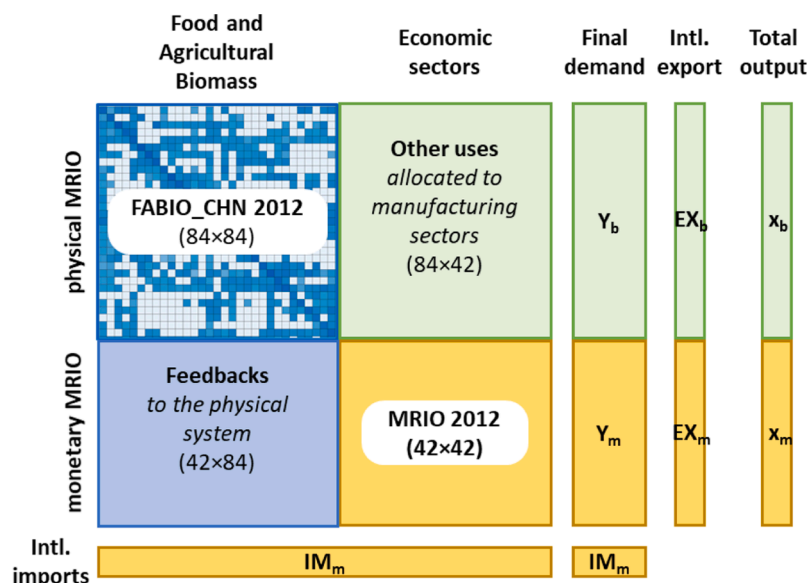


Fig. 2. Structure of a symmetric hybrid input-output (IO) table.

FAIBO—CHN also consists of four main steps—illustrated in Fig. 1:

- (1) quantify each commodity's supply from its primary production (e.g., maize from maize production) or processes (e.g., soybean oil and soybean cake from soybean oil extraction) for each province, and construct province-specific supply tables with 84 commodities from 75 processes in physical terms;
- (2) quantify each commodity's use, specifically for the purposes of seed, feed, waste, processing, food, and other uses, by associated primary production (e.g., maize used as seed by maize production), process (e.g., maize used as feed by cattle husbandry), and final demand (e.g., maize consumed as food by local population), and construct province-specific use tables with 84 commodities by 75 processes as well as 3 final demand categories in physical terms;
- (3) distribute each province's supply and use of 84 commodities across 31 provinces based on the inter-provincial trade information, thereby constructing multi-regional PSUTs;
- (4) construct the systemic physical MRIO table through industry technology assumption using the trade-linked supply and use tables of 31 provinces.

We describe the four steps in detail in the following sections. Before that, we first elaborate the data requirements and associated data sources as well as the main assumptions to fill the missing data, since the lack of data (e.g., inter-provincial trade data in physical terms) is one of the main challenges for FABIO—CHN compared to the global FABIO. The multi-regional PSUTs and MRIO tables are all available at the public repository Figshare (Ye 2021).

After constructing the physical MRIO tables of 84 agri-food commodities, symmetric hybrid MRIO tables for China are constructed by integrating the physical FABIO—CHN MRIO tables into the monetary MRIO tables. For this first trial, we use the monetary MRIO tables for the year 2012 compiled by Mi et al. (2017), which describe the production, inter-provincial and international trade, intermediate consumption, and final demand of China's economy by 42 sectors (listed in Table S4) and 31 provinces. Two highly-aggregated agri-food related sectors are included in the 42 sectors, i.e., sector "Agriculture, forestry, animal husbandry and fishery products and services" (AFF) and sector "Food and tobacco manufacturing" (FTM). Therefore, the integration procedures of physical and monetary MRIO tables are to disaggregate the transactions related to sectors AFF and FTM into 84 agri-food commodities in physical terms based on commodity-specific price information. Fig. 2 illustrates the framework of a symmetric hybrid input-output table. For each intra-provincial (from province m to province m) or inter-provincial (from province m to province n) intermediate input table, it consists of four blocks, with an overall dimension of 126×126 . The upper-left block records physical intermediate flows across 84 FABIO—CHN agri-food commodities. The lower-right block records the intermediate monetary flows across 42 economic sectors. The upper-right block records the physical intermediate inputs from the 84 agri-food commodities to manufacturing sectors for industrial use (e.g., oil for soap or fuels). The lower-left block records the monetary intermediate inputs from the 42 economic sectors to 84 agri-food commodities. The final demand table, international export table, and total output table have the same structure, i.e., with the upper agri-food demand/export/outputs in physical terms and the lower economic final demand/export/outputs in monetary values. The international imports of agri-food commodities as intermediate inputs or final demand are also in different physical units in our dataset. Here to give a clearer format of the hybrid IO table, we illustrate the international import table only in monetary terms.

2.1. Food and agricultural biomass input-output model for China (FABIO—CHN)

2.1.1. Data sources and missing data filling

The main data sources for building provincial supply and use tables are National Bureau of Statistics of China (NBSC 2020), statistical yearbooks including China Agriculture Yearbook 2013 (CAYEC 2013), China Light Industry Yearbook 2013 (CLIF 2013), and Almanac of China's Population 2013 (IPLE-CASS 2013). Table S5 summarizes the data requirements and associated data sources for FABIO—CHN. Besides, FAOSTAT also provides the national-level data of production, international trade, and use of agri-food commodities (FAOSTAT 2020), which will be used as benchmarks for the estimation of provincial missing data.

The construction of provincial Commodity Balance Sheets (CBS), in the same structure of national CBS from FAOSTAT, is the core of building FABIO—CHN PSUTs. The national CBS from FAOSTAT provide balanced supply (S^{dom}) and domestic use (U^{dom}) data for primary (e.g., wheat) and processed (e.g., soybean oil) commodities in terms of physical quantities. The national supply of each commodity equals to domestic production (P^{dom}) plus international import (im^{dom}) plus stock removals (Stk^{dom}) minus international export (ex^{dom}), while the domestic use categories include feed, seed, waste, processing, food, and other uses. We construct the provincial CBS by balancing the provincial supply and provincial use of each commodity in each province. The provincial supply of each commodity equals to provincial production (P^m) plus inter-provincial import ($\sum_{n,n \neq m} t^{mn}$) plus international import (im^m) plus provincial stock removals (Stk^m) minus inter-provincial export ($\sum_{n,n \neq m} t^{mn}$), and international export (ex^m), while the provincial use categories also include provincial feed (U_{fe}^m), seed (U_{s}^m), waste (U_{w}^m), processing (U_{p}^m), food (U_{fo}^m), and other uses (U_{oth}^m). The 31 provincial CBS of each commodity are also balanced into the national CBS of that commodity for each element (e.g., feed). The construction of provincial CBS by each element is described in detail below.

Feed. Provincial feed requirements of each crop are estimated by allocating the national feed requirement of each crop from FAOSTAT according to provincial hypothetical feed requirements for all live animals. We specify eight animal husbandry sectors in FABIO—CHN (Table S2). The hypothetical feed requirements are estimated based on the feeding periods of each animal and the daily feed requirements for that animal. The estimation approach is fully described in Supplementary Information A. We balance the hypothetical feed requirements of each crop in 31 provinces into the national feed use of that crop from the national CBS. It should be noted that the estimated feed requirements have high uncertainty due to key assumptions such as the same feed compositions, thus, we select feed requirements as one critical uncertainty factor of FABIO—CHN for uncertainty analysis (see section Uncertainty analysis).

Seed. Provincial seed requirements of crops for sowing, eggs for hatching, and fish for bait are estimated by the same method as FAO does. That is, the data of seed requirements have been estimated either by multiplying a seed rate with the sown area under the crop of the subsequent year, or as a percentage of supply like eggs for hatching. The associated data (e.g., a seed rate) are documented as technical conversion factors by FAO (FAO 1986, 2003).

Waste. Provincial wastes of commodities are also estimated by the same method proposed by FAO. Concretely, waste is estimated as a fixed percentage of availability (defined as production plus import plus stock variation). We set the ratio between the waste quantity and the availability in the national CBS from FAOSTAT as the fixed percentage of each commodity, i.e., $U_{w}^{dom}/(P^{dom}+im^{dom}+Stk^{dom})$. Consequently, the provincial stock removal can be derived according to the waste quantity and the fixed percentage, minus the production and import quantities.

Processing. Provincial processing data are estimated in three ways, which depend on the inputs and outputs of processes: 1) single-

processed commodities (e.g., oil crops), we estimate the processed quantities using a fixed percentage (equal to U_{p}^{dom}/U^{dom} given in the national CBS) of the overall provincial use quantity; 2) multiple crops for same output (e.g., sugar cane and sugar beet for refined sugar), we estimate the processed quantities by solving a constrained linear least-squares optimization problem; and 3) multipurpose crops (e.g., maize for maize germ oil and fermented beverages), we estimate the processed quantities as the input requirements to each process based on the national technical conversion factors. Details about the estimations could be found in **Supplementary Information B**.

Food. Provincial food requirements are estimated by multiplying the per-capita food requirement of each commodity with the provincial population. The per-capita food requirement of each commodity is calculated based on the U_{fo}^{dom} given in the national CBS and the national population. Totally, there are 54 agri-food commodities are used as food for local population.

Other Uses. Other uses refer to quantities of commodities used for non-food purposes, e.g., oil for soap (FAOSTAT 2020). Provincial other uses of commodities are estimated either as the rest of provincial use after feed, seed, waste, processing and food requirements (if all of these are already estimated), or as a fixed percentage of provincial use (equal to U_{oth}^{dom}/U^{dom} given in the national CBS from FAOSTAT).

Provincial total use. Provincial total use quantities of each commodity are estimated by the total quantities of feed, seed and food (plus processing if available) in each province divided the sharing of total quantities of feed, seed and food (plus processing if available) in the overall domestic use quantity as given in the national CBS from FAOSTAT.

Provincial production of vegetable oils, oil cakes, livestock offal, fats, and hides and skins are not recorded in China. We estimate the provincial production of these commodities based on the provincial processed quantities of primary oil crops or slaughtered animal and the national technical conversion factors. Provincial feed, seed, waste, processing, food and other use of vegetable oils, oil cakes, livestock offal, fats, and hides and skins are estimated by the same methods as described before.

Trade data, especially the inter-provincial trade data (t^{mn}), in the physical terms of 84 FABIO—CHN commodities are the main data gap for fine-scale domestic supply-use analysis of China. Here, we use a linear programming optimization model to estimate the bilateral trade quantities of FABIO—CHN commodities, which pursues a transport cost minimization for inter-provincial trade flows following Dalin et al. (2014) and Zhuo et al. (2019). The optimization model is fully described in **Supplementary Information C**. All estimated trade data, inter-provincial and international, of all 84 commodities are harmonized into one bilateral trade database.

2.1.2. Building provincial supply tables

Building the supply table is straightforward, as production quantity of commodities attributed to a specific process. First, we identify the processes that supply more than one output, i.e., joint products or byproducts. They are the crushing of oilseeds for oils and oil cakes, and livestock products, according to Bruckner et al. (2019). We insert the aggregated production data for each process-item combination into a supply table. Since five livestock commodities (milk from “Dairy cattle husbandry” and “Dairy sheep husbandry”, meat of other animals, and slaughtering byproducts such as edible offal, animal fats, and hides and skins) are supplied by multiple processes, the production quantities of those should be divided by the respective processes. Details could be found in Bruckner et al. (2019). We obtain one supply table S^m with 84 commodities from 75 processes for each province m in 2012.

2.1.3. Building provincial use tables

Provincial CBS contain the uses of each commodity as feed, seed, waste, processing, food, and other uses. Here, we invert the supply item *stock removals*, thereby converting it into the additional use item *stock*

additions. Besides, *food*, *stock additions*, and *other uses* are considered as final demand categories in FABIO—CHN, because these commodities are not further used as production inputs. We describe the allocation of feed, seed, waste, and processing quantities to associated processes as follows:

- Feed requirements of each commodity by eight animal husbandry sectors are allocated to the respective animal husbandry sectors in the use table.
- Seed requirement of a crop are considered an own use of the process which later harvests a crop. Seed requirement of eggs are considered an own use in poultry birds farming.
- Waste is allocated to the process where the waste occurs as the global FABIO did (Bruckner et al., 2019). This allows for the tracking of embodied flows, which is required for footprint accounting (Wiedmann and Lenzen 2018).
- Processing quantities are also allocated in three ways: (1) for single-process commodities, given processing quantities are directly allocated to the respective processes; (2) for processes with multiple input crops, we insert the optimal solutions from the linear least-squares optimization model that give the input requirements for these processes in each province; (3) for multipurpose crops, we allocate the estimated processed quantities of crops to each process.

We obtain one use table U^m with 84 commodities by 75 processes plus 3 final demand categories (Y^m) for each province m in 2012.

2.1.4. Trade-linking

Once the provincial supply and use tables are built, they are linked into multi-regional supply and use tables based on the trade data.

The multi-regional supply table S with the dimensions $\{m, c\} \times \{n, p\}$ contains zeros at the inter-provincial trade blocks (where $m \neq n$) and is filled with the domestic supply tables where $m = n$. c and p indicate commodity and process, respectively.

The provincial use tables are trade-linked by spreading the use of a commodity c in a process p in province n over the initial provinces m of that product: $u_{c,p}^{m,n} = u_{c,p}^n \cdot h_c^{m,n}$, where $h_c^{m,n} = t_c^{m,n} / (\sum_m t_c^{m,n} + im_c^n)$. Finally, we build a matrix U with the dimensions $\{m, c\} \times \{n, p\}$. Trade-linked final demand is spread by the same method for building provincial use tables. The use of international imported commodities in each process or final demand of each province are recorded in an extra matrix (IM) with the dimensions $c \times \{n, p+3\}$ (where the number 3 represents three categories of final demand), while the international exported commodities (EX) are compiled as an extra column with dimensions $\{m, c\} \times 1$.

2.1.5. Constructing a symmetric physical MRIO table

The transformation from rectangular commodity-by-process PSUTs into symmetric commodity-by-commodity MRIO tables are applied through the widely used industry technology assumption (Casler and Wilbur 1984; Miller and Blair 1985), i.e., process inputs are allocated to its respective outputs according to the supply shares documented in the supply table. We achieve this by first dividing the product mix matrix or transformation matrix $V = \widehat{S^T}^{-1} S^T$, where T is the transpose of a matrix, \mathbf{i} is a summation vector of appropriate length, “ $\widehat{\cdot}$ ” is the diagonalization of a vector; and then multiplying the use with the transformation matrix $Z = U \cdot V$. Part of the import matrix for processes only (IM^P in $c \times \{n, p\}$, excluding the import of final demand) is also transformed by $IM^P \cdot V$.

2.2. Integrating the physical MRIO into the monetary MRIO

Based on the physical and monetary MRIO tables, we construct a symmetric hybrid MRIO table for China, covering 126 commodities/sectors (i.e., 84 FABIO—CHN commodities and 42 economic sectors) in 31 provinces. As aforementioned, the main task is to disaggregate the transactions related to sector AFF and sector FTM in the monetary MRIO

Table 1

Comparison of provincial water footprints estimated in this study with those estimated by previous literature. “Blue water” refers to surface water and groundwater, while “green water” refers to rainwater in the unsaturated zone of the soil (and on top of vegetation).

	Literature						
	Zhang and Anadon (2014)	Xu et al. (2020)	Zhang et al. (2019)	Dalin et al. (2014)	Zhuo et al. (2016)	Zhuo et al. (2019)	This study
Year(s)	2007	2012	2012	2005	1978–2008	2000–2013	2012
Indicator(s)	Blue water consumption	Blue water consumption	Blue water withdrawal	Blue and green water consumption	Blue and green water consumption	Blue and green water consumption	Blue water withdrawal
Model (whether fully considering the supply chain-wide water consumption/withdrawal of final consumption)	Monetary MRIO modeling (√)	Monetary MRIO modeling (√)	Monetary MRIO modeling (√)	Process-based approach (×)	Process-based approach (×)	Process-based approach (×)	Hybrid MRIO modeling (√)
Number of sectors/products (number of agri-food sectors/products)	30 (2)	30 (2)	42 (2)	8 (8)	22 (22)	2 (2)	126 (84+2)
Degree of agri-food product disaggregation	Low	Low	Low	Low	Medium	Low	High
Water intensities of agri-food sectors/products	One value (m ³ /monetary unit) for all related products	One value (m ³ /monetary unit) for all related products	One value (m ³ /monetary unit) for all related products	Product-specific values (m ³ /physical unit)	Product-specific values (m ³ /physical unit)	Product-specific values (m ³ /physical unit)	Product- and sector-specific values (m ³ /physical unit and m ³ /monetary unit)
Reducing main limitations of applying monetary MRIO models for environmental footprint assessments	×	×	×				√

tables into 84 agri-food commodities in physical terms. We rely on the price allocation (Bruckner et al., 2015; Többen et al., 2018) to achieve this. The price information of agri-food commodities for the year 2012 is collected from FAOSTAT and China Price Statistical Yearbook 2013 (NBSC 2013). Besides, we keep the residual transactions of the two economic sectors after price allocation as “Rest of agriculture, forestry, animal husbandry and fishery products and services” and “Rest of food and tobacco manufacturing” in the monetary parts, to make sure the MRIO tables are well balanced before and after hybridization.

Since the physical and monetary MRIO tables are all constructed by 31 provinces, the hybridization processes are manipulated using the bilateral transactions between provinces, e.g., the physical intermediate input block (in 84 × 84) and the monetary intermediate input block (in 42 × 42) from province *m* to province *n*. The hybridization processes for the intermediation inputs from province *m* to province *n* (Fig. 2) are described below:

To obtain the upper-right block, we allocate the *other uses* (one category of final demand in the provincial use tables) to manufacturing and other economic sectors as intermediate inputs. The allocation relies on the shares of monetary inputs to the destination sectors from sector AFF for agricultural commodities (or from sector FTM for food commodities).

To obtain the lower-left block, we should first extract the transactions among 84 agri-food commodities (recorded in the upper-left block) and the transactions of 84 agri-food commodities for *other uses* (recorded in the upper-right block)—converted into monetary values based on the prices—from the monetary transactions from sector AFF and sector FTM to associated sectors. This step is to avoid double-counting. After that, the monetary intermediate inputs from the 42 economic sectors to sector AFF (or sector FTM) will be allocated to agricultural commodities (or food commodities) as intermediate inputs. This allocation relied on the shares of monetary value of agricultural commodities (or food commodities) in the total monetary values of all agricultural commodities (or food commodities).

The lower-right block is the residual transactions left in the monetary intermediate inputs. The changes in the lower-right block from the original 42 × 42 monetary intermediate input matrix only happen in the relevant transactions with sector AFF and sector FTM.

For hybridization process of final demand from province *m* to

province *n*, we first aggregate all the categories of final demand of province *m*, either in physical terms (omitting “Other uses”) or monetary terms. Then we extract the final demand of 84 agri-food commodities—converted into monetary values based on the prices—from the monetary final demand of sector AFF and sector FTM. The latter step is also applied to manipulate the international export and import. The total outputs of all 126 commodities/sectors then can be recalculated. Detailed features of our hybrid inter-provincial MRIO tables could be found in **Supplementary Information E**.

2.3. Provincial blue water footprint accounting

The direct blue water consumption data of FABIO—CHN crops are obtained from simulations with a crop water productivity model, following the accounting framework of Hoekstra et al. (2011). The direct blue water consumption of economic sectors is obtained from provincial Water Resource Bulletins (2012), and Chinese Economic Census Yearbook (2008). Details about the data sources could be found in **Supplementary Information D**.

The calculation of provincial blue water footprints based on our hybrid MRIO model equals the conventional monetary MRIO modeling. Eq. (1) calculates the supply chain-wide blue water footprints (WF_m^H , in million m³/yr) of province *m*’s final demand (Y_m^H):

$$WF_m^H = f^H L^H Y_m^H = S^H (I - A^H)^{-1} Y_m^H \tag{1}$$

f^H is a row vector of direct blue water consumption intensities of FABIO_CHN commodities or economic sectors (e.g., in million m³/tonne or million m³/Yuan). L^H is the Leontief inverse matrix (Leontief 1970), describing the supply chain-wide outputs associated with per unit finished goods and services. L^H is calculated from A^H with each element a_{ij}^H representing the amount of intermediate input *i* directly required per unit of output *j*, and an identity matrix *I*. It should be noted that the blue water footprint is a physical measure of supply chain-wide water consumption, which does not provide any information on the scarcity of blue water in provinces. To further assess how scarce the water is or the actual impact from blue water consumption, the water stress indicators should be integrated (Pfister and Hellweg 2009).

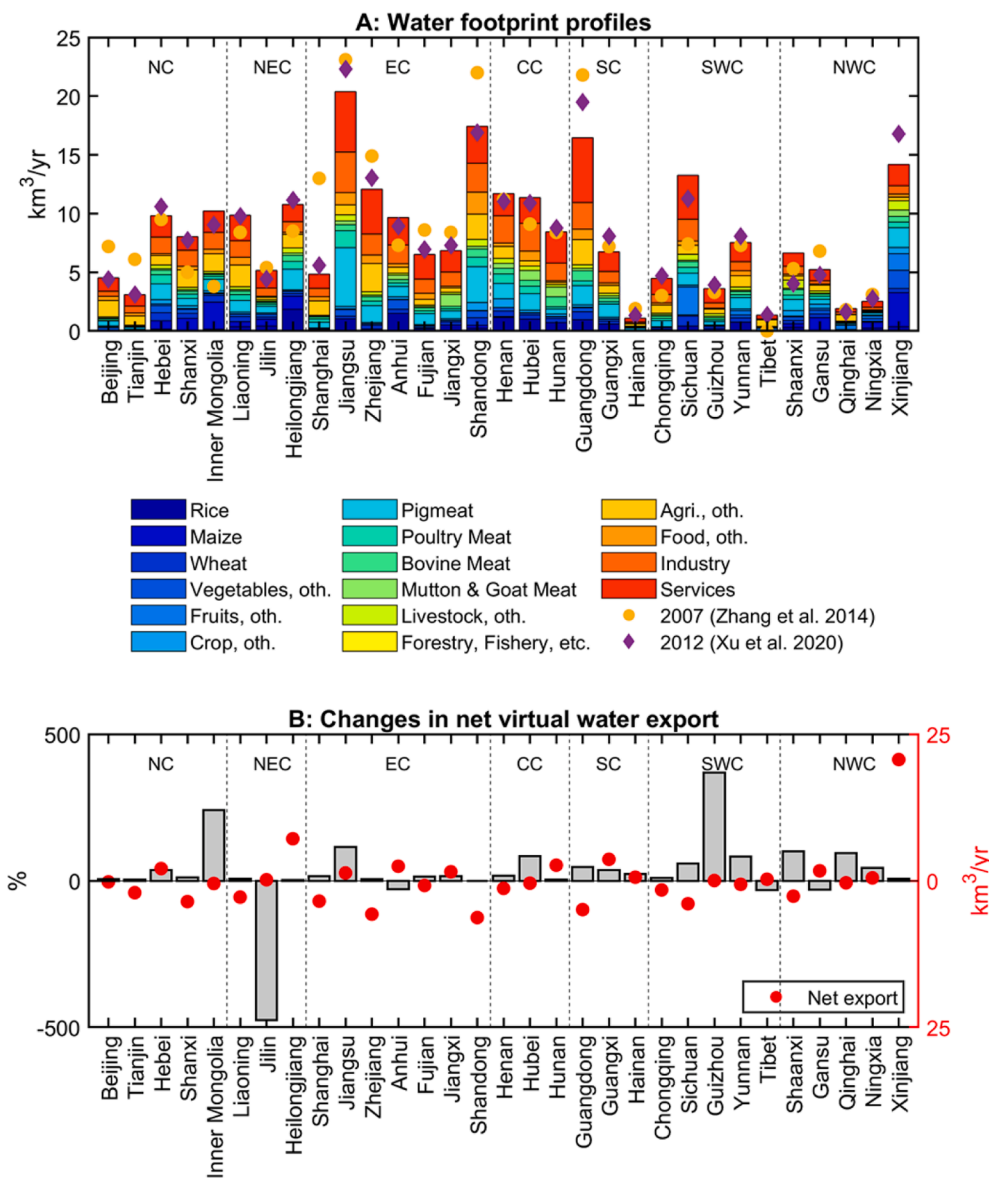


Fig. 3. Profile of blue water footprints (A), and the relative changes in net virtual water export (B) of 31 provinces in China. In A, we compare the blue water consumption footprints of year 2007 (Zhang and Anadon 2014) and 2012 (Xu et al., 2020) with our results. In B, relative changes in the net virtual water export (left y-axis) estimated by the hybrid MRIO model compared with those estimated by the monetary MRIO model are plotted. The red dots represent net virtual water export (right y-axis) estimated by the hybrid MRIO model. Full geographical names of regions: NC (North China), NEC (Northeast China), EC (East China), CC (Central China), SC (South China), SWC (Southwest China), and NWC (Northwest China).

3. Results and discussion

This section presents the results of applying our hybrid MRIO model in provincial water footprint assessment in China, and discusses uncertainties and limitations of the model. The demonstration of provincial water footprint assessment reveals that our hybrid MRIO model enhances both the traditional MRIO table-based approach and the process-based approach from different aspects (Table 1). Thus, the merits of our hybrid MRIO model are also justified from two perspectives. Compared with the traditional MRIO table-based approach, 1) the hybrid MRIO model provides specific information of agri-food products' water footprints and associated virtual water transfers within China; and 2) using product-specific water intensities also reduces the uncertainty of monetary MRIO modeling arising from the aggregation of products with different water intensities into homogeneous sectors. Compared with the traditional MRIO table-based approach, our hybrid MRIO model strengthens the process-based approach by capturing the whole supply chain-wide water consumption, which is the main limitation of the process-based approach (Feng et al., 2011). The total 84 commodities specified in our hybrid model covers the most categories of agri-food products compared with the literature of process-based water

footprint assessments in China. The results of uncertainty analysis show the reliability of this new hybrid MRIO model, and the confidence for future implication of the hybrid model in environmental and sustainable development research.

3.1. Provincial water footprints and virtual water trade in China

The comparison of provincial water footprints by our hybrid MRIO model with those estimated in previous studies, which is visualized in Fig. 3A and Table S7, highlights the role of product disaggregation within the supply chain for the water footprint assessment. The provincial water footprints estimated by our hybrid MRIO model are in line with those estimated by conventional monetary MRIO modeling (Xu et al., 2020; Zhang and Anadon 2014). Provinces, e.g., Xinjiang, Guangdong, and Jiangsu, have smaller water footprints in this study compared with Xu et al. (2020) which relied on the same monetary MRIO tables as we did. The main reduction is observed in crop-related water footprint. Using an identical water intensity ("drop per money") for all crops in monetary MRIO modeling could be regarded as the main reason. That is, using an identical water intensity results in the over-estimation of associated water footprints and virtual water flows of

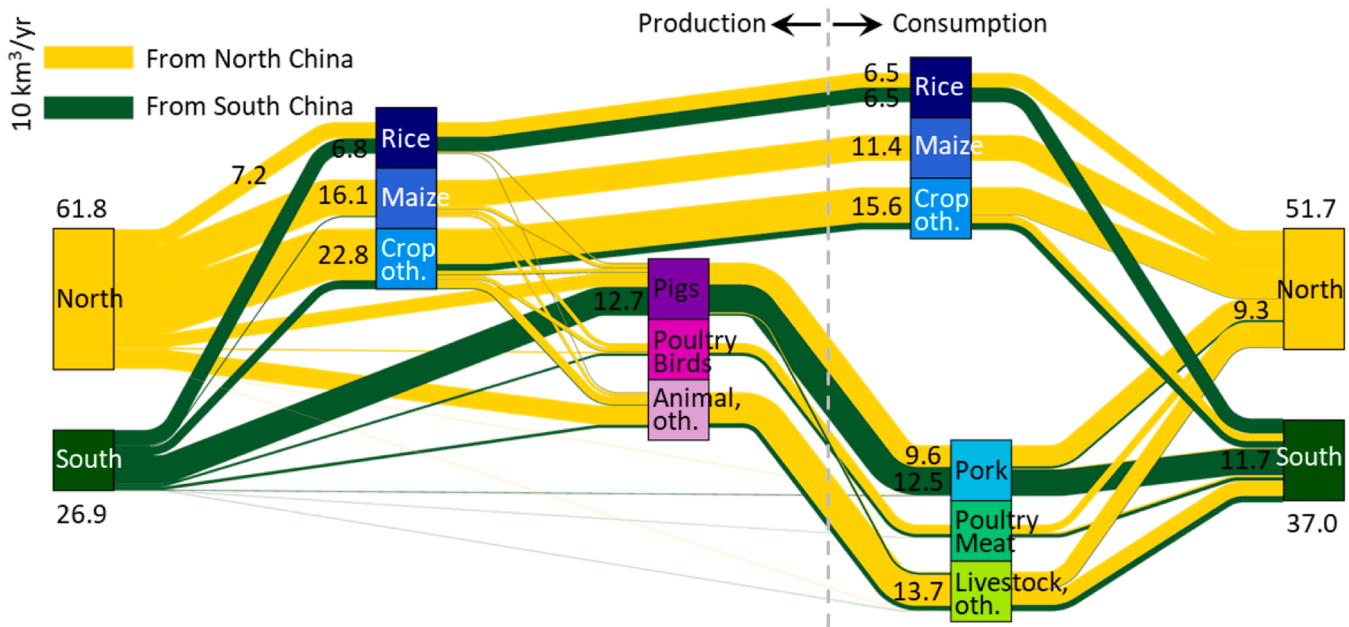


Fig. 4. Virtual water flows (km^3/yr) embodied in the transactions across crop production, animal husbandry, and animal slaughtering sectors. The top two commodities of each product categories that have the largest virtual water flows are shown in this plot.

those cash crops, e.g., sugarcane, sugar beet or fruits, which have relatively higher prices whereas lower blue water contents (“drop per ton”) compared with grain crops. Another reason is from the water flows embodied in crops that are used as *feed* for animal husbandry. The *feed*-related water flows share big parts in those crops’ total virtual water flows (shown in Fig. 4), and the final destinations of these *feed*-related water flows are animal slaughtering sectors (aggregated in sector FTM in the monetary MRIO tables used in this study). The monetary MRIO tables only record the transactions from animal husbandry sectors to animal slaughtering sectors, since crop production and animal husbandry are aggregated in sector AFF. Thus, this part of *feed*-related water footprints is accounted in the water footprint of sector AFF, and results in the overestimation of its water footprints. The lower water footprints observed in these provinces also imply that their net virtual water exports are underestimated by the monetary MRIO model (Fig. 3B), given that regional footprint (consumption-based) equals to the territorial pressure (production-based) minus the net export of the pressure. The relative changes in net export look significant for provinces Jilin, Guizhou, and Inner Mongolia, yet the significant changes only because their absolute export is too small and thus any little fluctuation of net export will raise significant relative changes.

From the profiles of provincial water footprints, we can find that the agri-food commodities (represented by cold color tones) share the main water footprints in all provinces, while service sectors also share big part in some provinces. The consumption of agri-food commodities accounts for more than 60% of the national water footprint, while in some provinces, mostly locating in North China like Heilongjiang, Gansu, and Xinjiang, the figure is around 80%. The water footprints of livestock commodities, especially pork, are obviously higher in Jiangsu, Shandong, and Hubei, compared with those in other provinces. Local population’s meat-dominate diet is one reason, while the relatively larger population is the other. Last but not least, the consumption from service sectors has relatively larger contribution in provinces locate in South China, such as Guangdong, Fujian, and Zhejiang, accounting for more than 30%. In comparison, the national average contribution of water footprint of service sectors is 23%. Water footprints of industrial sectors show relatively higher shares in provinces locate in Center China, e.g., Henan, Hunan, and Hubei, accounting for around 20% compared with 14% at the national average level. The associated results are similar with

those found in Xu et al. (2020) and Zhang and Anadon (2014).

Our hybrid MRIO model can also provide detailed information about the entire supply chain-wide water consumption and associated water flows of specific agri-food products. Fig. 4 illustrates the virtual water flows embodied in the transactions across crop production, animal husbandry, and animal slaughtering sectors. From the production-perspective, North China provides 70% of all blue water consumption ($61.8 \text{ km}^3/\text{yr}$) for the commodities and sectors analyzed here, mainly for the production of crops like maize and rice. Water from South China ($26.9 \text{ km}^3/\text{yr}$) is mainly used to raise animals, especially for pigs that account for 47% of the total water consumption from the South. Flows of crops to animal husbandry represent the consumed blue water embodied in the crops that are used as *feed*, 36% of which are attributable to maize. When switching from the production- to the consumption-perspective, the share of North China drops to 58%. Most of the blue water footprint of the North’s final demand ($51.7 \text{ km}^3/\text{yr}$) is from the North itself. In South China, the water footprint of local consumption of crops and livestock is $37 \text{ km}^3/\text{yr}$, of which 31% is imported from North China (mainly embodied in other livestock and crop commodities). It should be noted that the actual virtual water flows from South China to North China embodied in the livestock commodities may be larger than the results illustrated in Fig. 4, since the optimization model may underestimate trade flows. To achieve minimal cost of transportation, the model tends to trade commodities among adjacent provinces. The impact of uncertainties in the trade data on the water footprint results will be further discussed in the next section.

3.2. Uncertainty analysis

The hybrid MRIO model presented in this study relies on the data from multiple sources as well as a range of necessary assumptions, which introduce with uncertainties in the model. We expect that the main sources of uncertainties are: (1) the inter-provincial commodity trade in physical terms, which are estimated by an optimization model with the constraint of minimal costs of transportation following Dalin et al. (2014) and Zhuo et al. (2019); (2) commodity prices between trade partners, for which we rely on the national average prices to construct the symmetric hybrid MRIO model; (3) feed production and feed demand by animal husbandry sectors, which are estimated by fix amounts

of per-head feed demand by animal. To present uncertainty information of the hybrid model, we apply the typical Monte Carlo method and estimate the uncertainties arisen by these three factors, also with the blue water footprint case.

Overall, arisen by the same factor, the related uncertainty is more significant for commodity/sector-specific water footprints in term of standard deviation, compared with the province-specific ones (Fig. 5 and Table S9).

Uncertainty by inter-provincial trade. Lack of statistics data that cover the inter-provincial commodity trade in physical terms leads us to model the inter-provincial trade network. Main models that have been used to construct the inter-regional trade networks include computable general equilibrium (CGE) models (Partridge and Rickman 1998; West 1995), gravity models (Leontief and Strout 1963; Mi et al., 2018; Theil 1967), entropy-maximizing approaches (Roy and Thill 2004; Snickars and Weibull 1977; Többen et al., 2018; Wilson 2011), optimization models (Dalin et al., 2014; Zhuo et al., 2019), and others for example non-survey models (Sargento et al., 2012) or behavior-based models (Isard 1998; Lahr et al., 2020). However, these models strongly rely on the priori trade information while perform quite differently to a context of very limited trade information. Considering the data availability for agri-food commodities in China's provinces (e.g., production, demand, inter-provincial and international import and export), most of these models are not feasible for our analysis. For CGE models, the initial factor, capital, labor, and demand data of agri-food sectors are missing, while for gravity models the provincial gross inflows and outflows of agri-food commodities would be needed. Upholding the principle of hybridizing commodity-specific input-output information into the monetary supply chain as much as possible, we choose the optimization model in this study, which does not rely on the monetary trade data as the identical proxy to allocate the physical data. Besides, the optimization model, with relative lower robustness though, requires the least data to construct the trade networks, as long as the constraints and the boundary of each variable have adequate rationality and accuracy. It should also be noted that the optimization model cannot capture the whole bi- or multi-lateral trade activities of agri-food commodities. It is because that we assume only provinces with surplus (deficit) commodities are for the inter-provincial export (import) of the commodities. This assumption neglects the re-export of commodities, and the priority of commodity consumption (i.e., local consumption of local production is assumed as the priority compared to exports, yet exports can be prioritized compared to local consumption in one province driven by economic benefits). To apply the uncertainty analysis, we randomly generate ten thousand 31-by-31 matrices of uniformly distributed random numbers between 0 and 1 for each FABIO—CHN commodity, and allocate the total inter-provincial trade volume of that commodity into each element of the 31-by-31 matrices. For the water case in China, provinces with high trade-related activities in terms of virtual water trade (Fig. 3B), e.g., Shandong, Xinjiang, Guangdong, Jiangsu, and Shanghai, show higher impacts by the inter-provincial trade modeling, and vice versa. While at a sectoral level, the two rest of economic sectors, i.e., “Rest of agriculture, forestry, animal husbandry and fishery products and services” sector and “Rest of food manufacturing and tobacco” show the largest impact by the inter-provincial trade modeling, other commodities like poultry meat, bovine meat, and other meat show the relatively high impacts.

Uncertainty by commodity prices. The uncertainty of price variations of product flows between different customers is also a key issue in the monetary MRIO modeling, in which multiple commodities or sectors are aggregated into one or several sectors with same price systems. In this study, we only examine the uncertainty by commodity prices existing in the disaggregation of two monetary sectors AFF and FTM into the 84 FABIO—CHN commodities and the two rest of economic sectors. Although the hybrid model has significantly reduced the uncertainty by commodity prices compared with the monetary MRIO models, commodity prices still impact the final results of footprint accounting by big

margins. From the macroeconomic perspective, the changes in commodity prices, either for final expenditure or intermediate inputs, may not be too much. We apply -50%–100% uncertainty intervals of raw commodity prices from province m to province n , and run ten thousand times of the hybrid model. For the water case in China, provinces, e.g., Heilongjiang, Jiangsu, Guangdong, Shandong, and Hubei, show relative higher impacts by the price variations. While at a sectoral level, the two rest of economic sectors, i.e., “Rest of agriculture, forestry, animal husbandry and fishery products and services” sector and “Rest of food manufacturing and tobacco” are still with the largest impacts by the price variations, others like pig meat, poultry meat, and construction sector show relatively high impacts.

Uncertainty of feed requirements. Feed production and demand as an important part of crop use are always neglected in the existing monetary MRIO analysis, while the accurate estimation of feed demand is a big challenge. It not only depends on the farming system like industrial system or grazing system, but also differs among animal types (e.g., cattle vs. sheep), feed mix, and crops as fresh or dry matter. FABIO—CHN attempts to use the best available data and reconcile feed production and feed demand estimates into a mass-balance consistent model, but nevertheless it must be kept in mind that estimates of feed demand remain a source of uncertainty in the results. We select top five crops/oilcakes used for animal feed in China for uncertainty analysis, i. e., maize, soyabean cake, vegetables, roots, and wheat, which accounted for 76% of the total animal feed requirements in 2012. For the water case in China, provinces with higher farming of live animals or production of livestock, e.g., Hunan for pigs and pig meat, Shandong for poultry and poultry meat, and Xinjiang for mutton meat, show relative higher impacts by the feed requirements. While at a sectoral level, the most important livestock in the dietary of Chinese population, e.g., pig meat, poultry meat, and bovine meat, as well as the largest feed crop maize show the relatively high impacts by feed requirements.

Among the three key factors, the uncertainty of inter-provincial trade has the largest impacts on the blue water footprint estimation. Yet, the level of uncertainty arisen by the three factors may also vary among the environmental indicators for accounting. For instance, feed requirements would be a more significant factor for land footprint estimation, due to the high relevance with the animal farming sectors, while price variations would be a more significant factor for labor- or job-related indicator accounting. This study only demonstrates the uncertainty by the three factors with a water case. The indicator-specific uncertainty analysis is out of the scope of this study, but should be further addressed depending on the purposes of future application of the hybrid MRIO model.

3.3. Limitations

The hybrid MRIO model developed in this study overcomes the main limitation of the global FABIO model, i.e., integrating the physical agri-food system in China into the monetary MRIO model for year 2012. However, other uncertainties (e.g., the uncertainty by feed requirements) or limitations (e.g., linear dependency of feed inputs among monogastric and ruminant animals) also exist in FABIO—CHN. Meanwhile, FABIO—CHN has its own limitations, given the study area from a global scope into a provincial level of one nation. Besides the three key factors discussed before, the estimation of commodity production by technical conversion factors (e.g., crop oil, oil cake, or animal offal), and provincial use of seed, waste, and processing are also the potential limitations of our model. Although there are also other ways to estimate these missing data, such as the commodity balance model used in Kastner et al. (2012) or based on the value-to-weight relationships applied in Többen et al. (2018), we use the same approaches and parameters as FAOSTAT did because it will be easier to estimate associated data for multiple commodities. It should be noted that the actual “true” values must have differences from the estimated ones, and thus have potential uncertainties or limitations. As discussed in the uncertainty

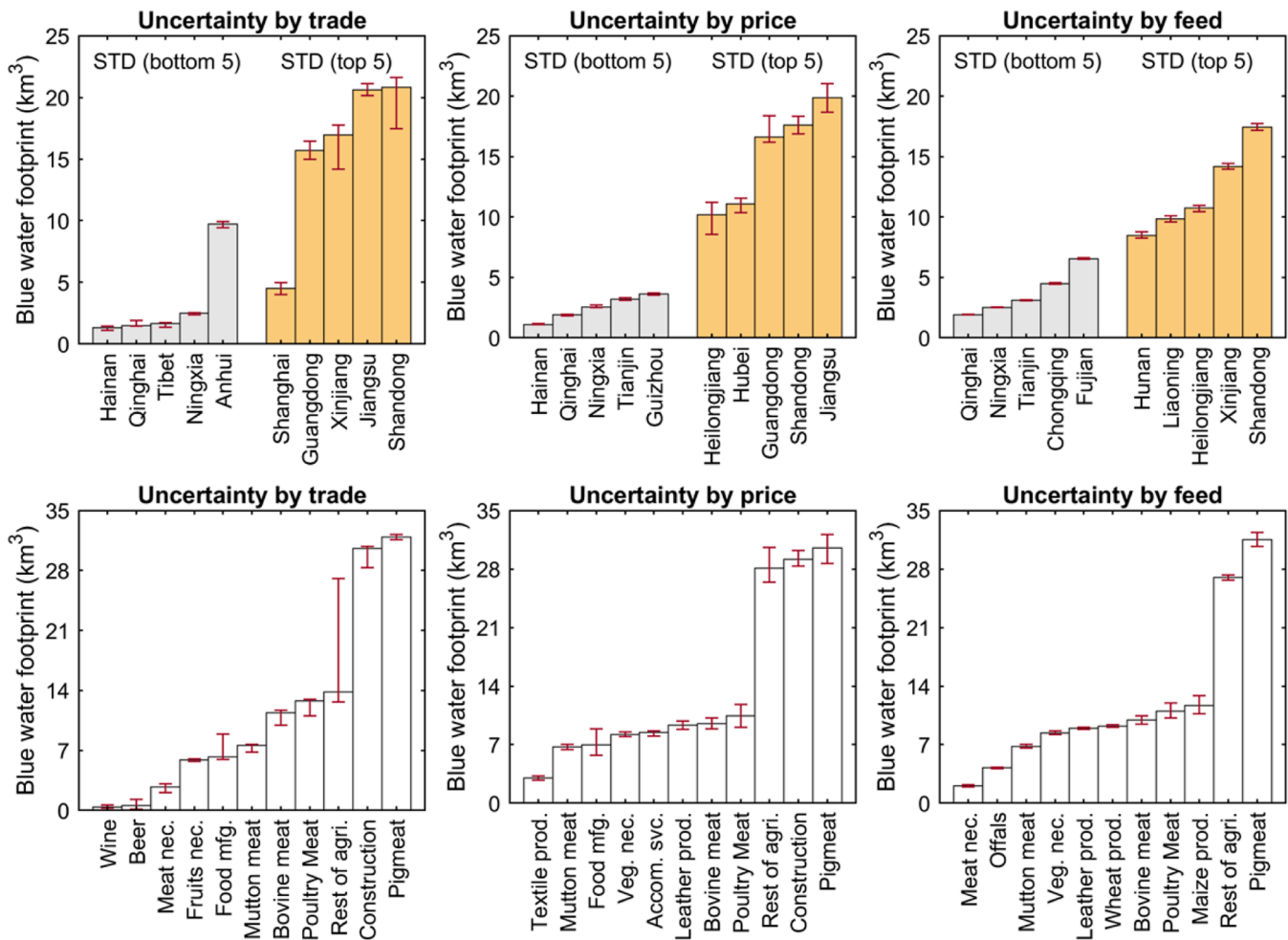


Fig. 5. Uncertainty analysis of provincial (upper plots) and sectoral (lower plots) blue water footprints by three key factors (i.e., inter-provincial trade, commodity prices, and feed requirements for animal husbandry). Five provinces with the smallest and largest, respectively, STD of blue water footprints are illustrated. While top eleven sectors with the largest STD of blue water footprints are illustrated. Results of uncertainty analysis, including the median, mean, and standard deviations of blue water footprints, in all 31 provinces could be found in Table. S8. The error bars indicate the deviation between each blue water footprint and the average blue water footprint of that province/sector. Full names of the abbreviations: mfg. = manufacturing, agri. = agriculture, prod. = products, and svc. = services.

analysis section, to reduce the uncertainty arising from the trade data, a systematic dataset recording adequate data that cover the production, consumption by purpose, inter-provincial trade of agri-food commodities is required. Even with only one-year specific data or trade data among big regions as estimated by the CHINAGRO economic model (Fischer et al., 2007), researchers can rely on that to estimate the associated data in near years, which would be more reliable compared with the data estimated without any actual data basis. When we collected the data of agri-food commodities from the statistics bureau, we also found that the boundaries or categories of crops, live animals, and other commodities varied or did not recorded in some years. For example, in early years around 2000, the slaughtered and end-of-year in-stock quantities of cattle and buffalo were recorded separately by the statistics bureau, but in recent years, they are aggregated together as “cattle”. In this context, a comprehensive system of commodity as well as industrial classifications should be formulated, like the international standard industrial classification, to guide the future statistics work with high spatiotemporal consistency.

Another limitation exists in the monetary MRIO tables for year 2012. To our knowledge, these monetary MRIO tables are also not officially constructed by the statistics bureau, but compiled by some research teams in China (Liu 2012; Liu et al., 2014; Mi et al., 2017; Zheng et al., 2020), based on the supply and use tables of each province.

FABIO—CHN also constructs the provincial PSUTs of agri-food commodities. Therefore, one of the potential approaches to reduce the uncertainty arising from the monetary MRIO model is integrating the provincial PSUTs of agri-food commodities into the provincial monetary SUTs in the first place, and then compiling the hybrid MRIO tables based on the hybrid SUTs. With this approach, the uncertainty by inter-provincial physical and monetary trade could be both reduced and the local economic structure in one province would also be captured more accurately. Considering that the product and sector classifications of these monetary SUTs differ among provinces and thus hard to be harmonized, this study directly integrates the PIOT into the monetary MRIO tables as the first trial for the symmetric hybrid MRIO model. The next step of our work is about to apply the province-based integrating approach to formulate the hybrid PSUTs and MRIO tables for multiple years and develop a time-series hybrid dataset.

4. Conclusions

This study develops a symmetric inter-provincial MRIO model that hybridizes the agri-food system with monetary supply chain within China. First of all, we construct the inter-provincial supply, use, and input-output tables in physical units of 84 agri-food products. Then we integrate the physical MRIO table of agri-food products into the

monetary all-sector MRIO table to construct a symmetric hybrid MRIO table of China. The application of our hybrid MRIO model to the case of provincial blue water footprint assessments reveals that the hybrid model enhances both the traditional monetary MRIO table-based approach and the process-based approach with different aspects. With the integration of 84 agri-food commodities specified in FABIO—CHN, the hybrid MRIO model could provide with specific information of agri-food products' water footprints and associated virtual water transfers. Besides, using product-specific water intensities also reduces the uncertainty of monetary MRIO modeling arising from the aggregation of products with different environmental properties into homogeneous sectors. Our hybrid MRIO model also strengthens the process-based approach by capturing the whole supply chain-wide water consumption, which is the main limitation of the process-based approach. The total 84 commodities specified in our hybrid model covers the most categories of agri-food products compared with the literature of process-based water footprint assessments in China.

With this hybrid MRIO model that specifies many different agri-food commodities with high granularity, we can determine those key commodities that have larger water consumption and are highly relevant for people's daily consumption habits. These key commodities will be crucial for future water management towards sustainability. For example, we suggest producers to further improve the water productivity in water scarce regions like Xinjiang to reduce their net water exports or replacing those water-intensive crops (e.g., maize) with less water-intensive oil cakes for feed use to reduce upstream water inputs. Consumers can diminish their water footprint by reducing the consumption of water-intensive foods like livestock products, identified in detail in our analysis. Information at this high level of regional and product detail, as provided by our hybrid MRIO model, is highly relevant to all actors along the supply chain interested in minimizing harmful impacts on the environment.

Beyond the water footprint assessment case demonstrated in this study, we also foresee a couple of research applications that can benefit from the capabilities of the presented hybrid MRIO model, including (1) re-assessing the key environmental footprints as well as the virtual flows embodied in the inter-provincial trade to reveal more complete stories

behind that, the water case of maize-pig-pork production and consumption for instance; (2) benchmarking setting of resource productivities (e.g., water) for agricultural, farming or industrial production to estimate the potential resource savings, which would provide efficient evidences for the management of key resources; (3) decomposition analysis to determine the main driving factors of resource consumption and pollution discharges, which would deliver an important empirical basis future trade-offs arising from the increased competition for biomass and for designing actions by business and policy makers to reduce competing demands. A prerequisite for such assessments is a comprehensive environmental inventory database has been constructed (Cabernard and Pfister 2021), including water stress, or land use and related biodiversity loss. Lastly, given that China is an important player in global agricultural and food production and trade, we can also link FABIO—CHN or the hybrid MRIO tables of China into the global MRIO database. After that, the roles of specific provinces played in the global market and the downstream environmental-social impacts can be further revealed, particularly for the provinces with high international exports or imports such as Liaoning, Guangdong and Zhejiang. Besides these potential applications, we believe the model can inspire and assist in other applications as well that need comprehensive information on physical and monetary flows in the Chinese economy.

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.

Acknowledgement

This work is dedicated to the memory of prof. Arjen Y. Hoekstra, who suddenly and unexpectedly passed away on 18th November 2019. Q. Ye is grateful for the scholarship he received from the China Scholarship Council (CSC), No. 201806710143. The time and comments from the editor and two anonymous referees are gratefully acknowledged.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.resconrec.2021.105981](https://doi.org/10.1016/j.resconrec.2021.105981).

Appendix

Nomenclature

A	technical coefficient matrix
AFF	sector "Agriculture, forestry, animal husbandry and fishery products and services"
Agri.	agriculture
b	food and agricultural biomass
BTD	bilateral trade database
<i>c</i>	agri-good commodity specified in FABIO—CHN
CBS	commodity balance sheets
CC	Central China
CGE	computable general equilibrium
<i>dom</i>	domestic
EC	East China
<i>ex</i>	international export volume of agri-food commodity
EX	international export table
<i>f</i>	a row vector of direct blue water consumption intensities
FABIO	food and agricultural biomass input-output model
FABIO—CHN	food and agricultural biomass input-output model for China
FAO	the Food and Agriculture Organization
FAOSTAT	the Food and Agriculture Organization Corporate Statistical Database
FTM	sector "Food and tobacco manufacturing"

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<i>h</i>	share of intermediate input product from each source
<i>H</i>	hybrid
<i>i</i>	a summation vector of appropriate length
<i>I</i>	the identity matrix
<i>im</i>	international import volume of commodity
IM	international import table
Intl.	international
IO	input-output
L	the Leontief inverse matrix
<i>m</i>	province in China
m	monetary
<i>mfg.</i>	manufacturing
MRIO	multi-regional input-output
<i>n</i>	province in China
NBSC	National Bureau of Statistics of China
NC	North China
NEC	Northeast China
NWC	Northwest China
<i>p</i>	primary production or process specified in FABIO—CHN
<i>P</i>	primary production volume of FABIO—CHN commodities
PMRIOT	physical multi-regional input–output table
PSUT	physical supply and use tables
<i>s</i>	economic sectors
<i>S</i>	the total supply volume of agri-food commodities
S	physical supply table
SC	South China
STD	standard deviations
<i>Stk</i>	stock removal volume
<i>svc.</i>	services
SWC	Southwest China
<i>t</i>	inter-provincially traded volume of commodity
T	the transpose of a matrix
<i>u</i>	use volume of commodity
U	physical use table
<i>U</i>	the total use volume of agri-food commodities
<i>U_{fe}</i>	the use volume of agri-food commodities for feed
<i>U_{fo}</i>	the use volume of agri-food commodities for food
<i>U_{oth}</i>	the use volume of agri-food commodities for other use
<i>U_p</i>	the use volume of agri-food commodities for processing
<i>U_s</i>	the use volume of agri-food commodities for seed
<i>U_w</i>	the use volume of agri-food commodities for waste
V	the product mix matrix or transformation matrix
WF	the supply chain-wide blue water footprint
x	total outputs
Y	final demand
Z	the intermediate input matrix

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