Enhanced Input-Output Modelling for Improved Assessment of Supply Chain-Wide Environmental Pressures in Space and Time: The Case of China

Quanliang Ye

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DISSERTATION

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by

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Table of Contents

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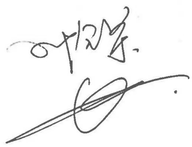

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20.07.2022

Aalborg, Denmark

Summary

In the context of the Paris Agreement, Sustainable Development Goals, and circular economy agendas, whoever is responsible for the resource extractions and pollution releases of final goods and services has been debated. The virtual displacement of environmental pressures (EPs) from final consumers to production sites is the prominent issue in these debates. To solve the virtual displacement (or outsourcing) issue of environmental pressures, the consumption-based accounting that relies on the environmental-extended multi-regional input-output (MRIO) model has been widely used to quantify supply chain-wide EPs of consumed goods and services. However, key limitations lie in the conventional MRIO model: 1) *the aggregation of products with different environmental properties into homogeneous sectors in the discipline of macroeconomics*, and 2) *the neglect of temporal dynamic feature of manufactured capital as primary production factors in economic activities*.

The goal of this thesis is to develop improved modelling techniques to better capture spatiotemporal virtual displacement of EPs along the entire supply and use chain of products. This thesis proposes two improved models based on the conventional environmentally extended MRIO model to address aforementioned limitations: the hybrid MRIO model and the capital-endogenized MRIO model. The two improved models are applied to answer four research questions, of which the former two are related to the spatial virtual displacement of EPs embodied in trade and the latter two are related to the temporal virtual displacement embodied in capital.

A hybrid multi-regional input-output model of China: integrating the physical agricultural biomass and food system into the monetary supply chain. This chapter develops a symmetric MRIO model that hybridizes the physical food and agricultural biomass system with the monetary supply chain of China. First, the inter-provincial supply, use, and input-output tables in physical units of 84 agriculture, food and forestry products are constructed. 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 the physical MRIO table of agri-food products are integrated 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 modelling 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.

Effects of production fragmentation and inter-provincial trade on spatial blue water consumption and scarcity patterns in China. This chapter formulates a comprehensive trade disaggregation approach to elaborate the virtual water networks of three trade patterns (i.e., direct final goods trade, intermediate goods trade for the last step of production, and value chain-related trade) within China, and further analyzes the impacts of trade on provincial blue water scarcity by comparing the actual water scarcity with that under a "no-trade" scenario (NTS). In 2012, there was 128 km^3 blue water virtually transferred across provinces because of inter-provincial trade. Direct final goods trade contributed the most to the virtual water trade (accounting for 47% of the total), whereas value chain-related trade induced the least (17%). Compared with the results under the NTS, current trade alleviated the water scarcity in provinces under extreme water scarcity, but worsened the water scarcity of this nation from a broader scope. It suggests policy makers fully considering specific trade patterns and their impacts on provincial or national water consumption to cope with water scarcity in China.

Linking the environmental pressures of China's capital development to global final consumption of the past decades and into the future. This chapter developed a new global model for assessing capital formation and use along the global supply chain. It is used to quantify the linkages between capital use and human need production and consumption over the past two decades between six EPs caused by China's capital formation and domestic as well as foreign consumption. Result show that only 35% of the assets acquired by China from 1995 to 2015, representing 32%-39% of the associated EPs (e.g., water consumption, GHG emissions, and metal ore extractions), have been depreciated, whilst the majority rest will serve future production and consumption. The outsourcing of capital services and the associated EPs are considerable, ranging from 14-25% of depending on the EP indicators. Without accounting for the capital-final consumption linkages across time and space, one would miscalculate China's environmental footprints related to the six EPs by big margins, from -61% to +114%.

Re-allocating CO_2 emissions of capital investment along capital's full lifespan. This chapter quantifies the temporal displacement of capital and associated carbon emissions within China for the period from 1995−2017. The results show that considering the temporal CO_2-emission displacement relieves the emission responsibilities of capital assets for the year of formation, with 25–46% declinations from conventional accounting methods. To understand this temporal displacement from the past to the future, three capital investment scenarios until 2030, based on different purposes of capital investments (e.g., for further economic growth or for low-carbon development), have been designed. Overall, the existing capital in 2017 will still contribute approximately 10% of China's carbon emissions in 2030, and account for more than 40% for

capital-intensive service sectors like real estate or transportation services. The virtual temporal displacement of carbon emissions associated with capital feeds into a discussion on the equity across generations due to historical and future 'commitments' of emissions.

Conclusion. The hybrid MRIO model and the capital-endogenized MRIO model developed and presented in this thesis solved key limitations in conventional IO modelling for environmental pressure assessments. In detail, the hybrid MRIO model combines advantages of both process- and IO table-based approaches, thus enabling to quantify the supply chain-wide environmental pressures of a specific agri-food product. The capital-endogenized MRIO model endogenizes capital investment and consumption into economic production over time, thus enabling to allocate environmental responsibilities of capital activities among different capital activities along capital's full lifespan. This thesis also has contributions related to datasets, such as a national dataset of inter-provincial trade-linked supply, use and input-output tables, and a capital investment dataset at the provincial level during the period of 1995-2017. Both of models can be used to better assign the environmental responsibilities of our production and consumption in space and time, and provide key information for policy makers, producers, and consumers to rethink their roles in global sustainable development and make their own contributions to deliver a sustainable future.

Samenvatting

In de context van de Overeenkomst van Parijs, de doelstellingen voor duurzame ontwikkeling en de agenda's voor de circulaire economie is er discussie geweest over wie verantwoordelijk is voor de winning van hulpbronnen en het vrijkomen van vervuiling door eindproducten en -diensten. De virtuele verplaatsing van milieudruk (MDs) van eindgebruikers naar productielocaties is het prominente onderwerp in deze debatten. Om het probleem van virtuele verplaatsing (of uitbesteding) van milieudruk op te lossen, is de op consumptie gebaseerde boekhouding die is gebaseerd op het milieu-uitgebreide multi-regionale input-output (MRIO) -model op grote schaal gebruikt om supply chain-brede MDs van verbruikte goederen te kwantificeren en diensten. De belangrijkste beperkingen liggen echter in het conventionele MRIO-model: 1) *de aggregatie van producten met verschillende milieu-eigenschappen in homogene sectoren in de discipline macro-economie*, en 2) *de verwaarlozing van het temporele dynamische kenmerk van gefabriceerd kapitaal als primaire productiefactoren in economische activiteiten.*

Het doel van dit proefschrift is het ontwikkelen van verbeterde modelleringstechnieken om de virtuele verplaatsing van MDs in de tijd in de ruimte beter vast te leggen in de gehele toeleverings- en gebruiksketen van producten. Dit proefschrift stelt twee verbeterde modellen voor die gebaseerd zijn op het conventionele, voor de omgeving uitgebreide MRIO-model om de bovengenoemde beperkingen aan te pakken: het hybride MRIO-model en het kapitaal-endogenized MRIO-model. De twee verbeterde modellen worden toegepast om vier onderzoeksvragen te beantwoorden, waarvan de eerste twee gerelateerd zijn aan de ruimtelijke virtuele verplaatsing van MD's belichaamd in handel en de laatste twee gerelateerd zijn aan de tijdelijke virtuele verplaatsing belichaamd in kapitaal.

Een hybride multiregionaal input-outputmodel van China: integratie van de fysieke landbouwbiomassa en het voedselsysteem in de monetaire toeleveringsketen. Dit hoofdstuk ontwikkelt een symmetrisch MRIO-model dat het fysieke voedsel- en landbouwbiomassasysteem hybridiseert met de monetaire toeleveringsketen van China. Eerst worden de interprovinciale aanbod-, gebruiks- en input-outputtabellen in fysieke eenheden van 84 landbouw-, voedsel- en bosbouwproducten geconstrueerd. Deze fysieke levering/gebruik/MRIO-tabellen leggen systematisch de productstromen van de agrovoeding vast, op een ongekend niveau van productdetails, langs binnenlandse toeleveringsketens in China. Vervolgens wordt de fysieke MRIO-tabel van agrovoedingsproducten geïntegreerd in de monetaire MRIO-tabel voor alle sectoren om een symmetrische hybride MRIO-tafel van China te construeren. De toepassing van ons hybride MRIO-model op provinciale beoordelingen van de blauwe watervoetafdruk laat zien

dat het hybride model zowel de monetaire MRIO-tabelgebaseerde benadering als de procesgebaseerde benadering vanuit verschillende aspecten verbetert. Het hybride MRIO-model kan bijvoorbeeld de onzekerheid van monetaire MRIO-modellering verminderen door de aggregatie van producten met verschillende milieu-eigenschappen in homogene sectoren. Ten slotte wordt onzekerheidsanalyse geïmplementeerd om de belangrijkste bronnen van onzekerheden te kwantificeren en de betrouwbaarheid van ons nieuwe hybride MRIO-model voor toekomstig ontwerp voor duurzame ontwikkeling te begrijpen.

Effecten van productiefragmentatie en interprovinciale handel op ruimtelijke blauwwaterconsumptie en schaarstepatronen in China. Dit hoofdstuk formuleert een alomvattende benadering om de handel uit te splitsen om de virtuele waternetwerken van drie handelspatronen (d.w.z. directe handel in finale goederen, handel in intermediaire goederen voor de laatste productiestap en handel in waardeketen) binnen China uit te werken, en analyseert verder de effecten van handel op provinciale blauwwaterschaarste door de werkelijke waterschaarste te vergelijken met die in een "no-trade"-scenario (NTS). In 2012 werd door interprovinciale handel 128 km3 blauw water nagenoeg over provincies getransporteerd. De directe handel in finale goederen droeg het meest bij aan de virtuele waterhandel (goed voor 47% van het totaal), terwijl de waardeketengerelateerde handel het minst leidde (17%). Vergeleken met de resultaten onder de NTS, verlichtte de huidige handel de waterschaarste in provincies met extreme waterschaarste, maar verergerde de waterschaarste van dit land vanuit een breder perspectief. Het stelt beleidsmakers voor om specifieke handelspatronen en hun impact op de provinciale of nationale waterconsumptie volledig in overweging te nemen om de waterschaarste in China het hoofd te bieden.

De milieudruk van de Chinese kapitaalontwikkeling koppelen aan de wereldwijde eindconsumptie van de afgelopen decennia en in de toekomst. In dit hoofdstuk is een nieuw mondiaal model ontwikkeld voor het beoordelen van kapitaalvorming en gebruik in de mondiale toeleveringsketen. Het wordt gebruikt om de verbanden te kwantificeren tussen kapitaalgebruik en menselijke behoefteproductie en -consumptie in de afgelopen twee decennia tussen zes MDs veroorzaakt door de Chinese kapitaalvorming en binnenlandse en buitenlandse consumptie. Uit de resultaten blijkt dat slechts 35% van de activa die China van 1995 tot 2015 heeft verworven, 32%-39% van de geassocieerde MDs vertegenwoordigen (bijv. het waterverbruik, de uitstoot van broeikasgassen en de winning van metaalerts), zijn afgeschreven, terwijl de rest voor de toekomstige productie en consumptie zal dienen. De uitbesteding van kapitaaldiensten en de bijbehorende MDs is aanzienlijk, variërend van 14-25% afhankelijk van de MD-indicatoren. Zonder rekening te houden met de verbanden tussen kapitaal en eindverbruik in tijd en ruimte, zou men de ecologische voetafdruk van China met betrekking tot de zes MDs met grote marges verkeerd inschatten, van -61% tot +114%.

Herallocatie van CO_2-emissies van kapitaalinvesteringen gedurende de volledige levensduur van kapitaal. Dit hoofdstuk kwantificeert de tijdelijke verplaatsing van kapitaal en de bijbehorende koolstofemissies binnen China voor de periode 1995-2017. De resultaten laten zien dat het beschouwen van de tijdelijke verplaatsing van CO_2-emissie de emissieverantwoordelijkheden van kapitaalgoederen voor het jaar van oprichting verlicht, met 25-46% declinaties ten opzichte van conventionele boekhoudmethoden. Om deze tijdelijke verplaatsing van het verleden naar de toekomst te begrijpen, zijn drie kapitaalinvesteringsscenario's tot 2030 ontworpen, gebaseerd op verschillende doeleinden van kapitaalinvesteringen (bijvoorbeeld voor verdere economische groei of voor koolstofarme ontwikkeling). Over het geheel genomen zal het bestaande kapitaal in 2017 nog steeds ongeveer 10% van de CO_2-uitstoot van China in 2030 bijdragen en meer dan 40% vertegenwoordigen voor kapitaalintensieve dienstensectoren zoals onroerend goed of transportdiensten. De virtuele tijdelijke verplaatsing van koolstofemissies in verband met kapitaal voedt een discussie over de gelijkheid tussen generaties als gevolg van historische en toekomstige 'verplichtingen' van emissies

Conclusie. Het hybride MRIO-model en het kapitaal-endogenized MRIO-model, ontwikkeld en gepresenteerd in dit proefschrift, losten belangrijke beperkingen op in conventionele IO-modellering voor milieudrukbeoordelingen. In detail combineert het hybride MRIO-model de voordelen van zowel proces- als IO-tabelgebaseerde benaderingen, waardoor het mogelijk wordt om de milieudruk in de toeleveringsketen van een specifiek agrovoedingsproduct te kwantificeren. Het kapitaal-endogenized MRIO-model endogeniseert kapitaalinvesteringen en -consumptie in economische productie in de loop van de tijd, waardoor milieuverantwoordelijkheden van kapitaalactiviteiten kunnen worden toegewezen aan verschillende kapitaalactiviteiten gedurende de volledige levensduur van kapitaal. Dit proefschrift heeft ook bijdragen met betrekking tot datasets, zoals een landelijke dataset van interprovinciale handelsgebonden aanbod-, gebruiks- en input-outputtabellen, en een kapitaalinvesteringsdataset op provinciaal niveau in de periode 1995-2017. Beide modellen kunnen worden gebruikt om de milieuverantwoordelijkheden van onze productie en consumptie in ruimte en tijd beter toe te wijzen, en om belangrijke informatie te verstrekken aan beleidsmakers, producenten en consumenten om hun rol in wereldwijde duurzame ontwikkeling te heroverwegen en hun eigen bijdragen te leveren om een duurzame toekomst.

1

Introduction

1.1. Concerns on Sustainability of Economic Development

Rapid growth in global population (doubled by 2017) and gross domestic product (GDP, more than fourfold by 2017) has been recorded since 1970 (The World Bank 2020). These trends have required large amounts of natural resources, such as water (Hoekstra and Mekonnen 2012), coals (IEA 2017), metals (Wiedmann et al. 2015), and land (Kastner et al. 2012), to fuel economic development and enhance human well-being. For example, global material extraction has grown from 27 billion tons (7 tons per capita) in 1970 to 92 billion tons (12 tons per capita) in 2017 (UNEP and IRP 2018). Significant environmental consequences (e.g., climate change or biodiversity loss) have been widely observed due to resource consumption. Natural resource extraction and processing make up approximately half of the global greenhouse gas (GHG) emissions (UNEP and IRP 2018). Global land use activities caused 11% loss of existing species (Lenzen et al. 2012b, Weinzettel et al. 2018). These phenomena have received a fair share of attention in the last decades with a series of environmental research and policies related to them. The international communities have widely committed, for instance, to combat climate change through the United Nations Framework Convention on Climate Change and the Paris Agreement (UNFCCC 2015), and biodiversity loss through the Convention on Biological Diversity (CBD 2006). These conventions are further incorporated in the Sustainable Development Goals (SDGs), which emphasize the key role they play in achieving global sustainability ambitions (United Nations 2017).

Literature has widely discussed the effectiveness of global or national policies of reducing anthropic environmental pressures (Eder and Narodoslawsky 1999, Lenzen et al. 2007, Rodrigues et al. 2006), and how to assign the environmental responsibilities across countries (Davis and Caldeira 2010, Hoekstra and Mekonnen 2012, Lenzen et al. 2012b, Wiedmann et al. 2015). Two perspectives on environmental pressures have been introduced, the production and consumption perspectives (Peters 2008, Peters and Hertwich 2007, Steininger et al. 2014). The production perspective focuses on the environmental pressures occurring at the production sites (IPCC 1996), i.e., producers being responsible for the pressures associated with the production of goods and services. Relevant policy suggestions to reduce environmental pressures mainly look at production sites, e.g., emphasizing optimizing production structures and technologies. The consumption perspective focuses on upstream pressures of final goods and services (Davis and Caldeira 2010, Hoekstra and Mekonnen 2012, Wiedmann et al. 2015), i.e., assigning the supply chain-wide environmental pressures to the end consumers. It drives policy makers to consider environmental problems more broadly—not only looking at local impacts, but from a broader system boundary such as a regional, national, or even global scope. Irrespective of the perspective on environmental pressures, the consensus is that if the rising trend in resource-intensive development pathway persists, the goals of the Paris Agreement will become difficult to meet and the achievement of the SDGs will be put at risk (Davis and Caldeira 2010, Hoekstra and Mekonnen 2012, Peters and Hertwich 2007, Steininger et al. 2014, Wiedmann et al. 2015).

1.2. Important Role of China in Global Sustainable Development

China has experienced one of the fastest economic growth in human history and increased its share in global GDP from 2% in 1995 to nearly 15% in 2015 (The World Bank 2020). This fast-economic growth was based on an export, capital and resource intensifying mode. China's annual share in global capital investment increased even faster than its share in global GDP, from 3% to 25% between 1995 and 2015 (The World Bank 2020). In addition, China exported two-fifths of the world's semiconductors, more than half of the world's mobile phones, and almost all of the world's printed circuit boards in 2016 (Allen 2018). As for resource use, from the production perspective, China consumed 2123 exajoules (EJ) of primary energy, and occupied 114 billion m^2 of land, and extracted 216 gigatons (Gt) of non-metallic mineral ores during 1995-2015, contributing 16%, 8%, and 39% of the global totals, respectively (Stadler et al. 2018). From the consumption perspective, researchers traced the environmental pressures embodied in China's exports along the global supply chain, and revealed a geographical shift of environmental pressures to China that were mostly from today's developed countries like the United States, Japan or Germany (Meng et al. 2018, Mi et al. 2017a). Thus, economic (e.g., capital development) and environmental performance (e.g., improving energy use efficiency) of China (in)directly influences both China itself and global social-economic-environmental development towards sustainability.

Efforts made by China such as technological improvement and resource conservation have been enhancing its sustainable development significantly (Liu and Diamond 2005, Mi et al. 2017b, Zhang et al. 2020). Back to 2004, the average carbon intensity of China's exports (2.18 kg of carbon dioxide per dollar) was four times of that of the United States' exports (0.49 kg of carbon dioxide per dollar) (Davis and Caldeira 2010). Main reasons include relatively inefficient energy use, coal-dominated energy structure, and export specialization of carbon-intensive products (Jakob and Marschinski 2012, Minx et al. 2011). Great efforts have been made by the Chinese government, companies, and individuals to reduce the environmental intensities of economic outputs, under the instructions of a series of policies and measures such as Five-Year Plans, carbon trade scheme, or the Intended Nationally Determined Contributions submitted to the Paris Agreement. By 2017, the average carbon intensity of China's exports have reduced to 0.74 kg of carbon dioxide per dollar (Shan et al. 2020a). China has entered an era of "new normal" economic growth mode, with rapid increase of domestic trade (NBSC 2020). The growing domestic trade also led to new features of environmental performance within China. For example, the growth in domestic trade have resulted in an expansion of 6.3 million hectares in national land use during 1997–2012 (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 to achieving China's sustainable development goals.

1.3. Spatio-Temporal Virtual Displacement of Environmental Pressures Making the Pressure Assessment Complicated

In the context of the Paris Agreement, SDGs, and circular economy agendas, whoever is responsible for the resource extractions and pollution releases of final goods and services has been debated. The virtual displacement of environmental pressures from primary production is the prominent issue in these debates. It hence transforms the consideration of environmental pressures from the production perspective into the consumption perspective. There are two dimensions of virtual displacement of environmental pressures, that is, spatially (**Section 1.3.1**) due to geospatial separations of producers and consumers via trade, and temporally (**Section 1.3.2**) because of using durable capital assets for economic production.

1.3.1. Spatial virtual displacement of environmental pressures via trade

Trade separates the locations of production and consumption of final products, and leads to a spatial virtual displacement of environmental pressures (Davis and Caldeira 2010, Feng et al. 2013, Hoekstra and Mekonnen 2012, Meng et al. 2018, Wiedmann and Lenzen 2018). Global exports of goods and services have tripled during the past two decades (1995-2015), from $8 trillion (2010 US dollars) to $23 trillion (2010 US dollars); and on average, exports accounted for 29% of a country's GDP in 2015 (The World Bank 2020). Along with the traded goods and services, the capital inputs, resource requirements, and pollution emissions during the production processes of (or "embodied in") these goods and services are also virtually displaced from the consumption sites to the producers.

Tracing environmental pressures along supply chains is challenging. Lacking systematic and supply chain-wide trade data in high resolutions of commodity categories made the spatial virtual displacement mainly assessed at the sectoral level (Davis and Caldeira 2010, Feng et al. 2013, Meng et al. 2018) or by few products such as palm oil (Meijaard et al. 2020) or livestock (Uwizeye et al. 2020). Moreover, traded goods and services can be directly consumed as final consumption of importers, directly re-exported to other regions, or further processed as intermediate inputs to produce other products (Arce González et al. 2012, López et al. 2013, Wang et al. 2017). These different using purposes of traded goods and services result in associated trade patterns across regions, and have different influences in regional economic structure and environmental profiles. For instance, primary production is generally resource-intensive while re-exporting products seems cost-efficient between resource consumption and economic benefits (Arce González et al. 2012, López et al. 2013, Wang et al. 2017). It indicates that both economic and environmental aspects are not homogeneous over supply-chains, making specification of trade patterns politically important.

1.3.2. Temporal virtual displacement of environmental pressures embodied in durable capital assets

Capital as one durable production factor links historical economic and resource inputs to current as well as future production and consumption. This capital is existing as diverse forms of fixed assets, from roads and railways to power plants, communication networks to cultivated machines, and factory warehouses to computer software.

Different from non-capital goods and services that are purchased to be consumed every year, capital assets have two unique features. First, capital assets are invested by economic sectors for their productive purposes, while the producers of capital assets are usually different from their investors and users. This feature raises arguments about how to allocate environmental pressures of capital activities (Chen et al. 2018, Lenzen and Treloar 2004, Sӧdersten et al. 2018a), to the producers or to the users or to the final consumers of goods and services that are produced by using associated assets. Second, capital assets can exist for several years or even decades, and serve economic production throughout their lifespans. This feature implies that future production and consumption will induce not only environmental pressures in the future, but also those that historically occurred and embodied in built-up capital as long as the capital is used in the future. It hence leads to the temporal displacement of environmental pressures of capital activities along capital's full lifespan. Such a temporal displacement is also important for assessing the sustainability and efficiency of national resource use especially in fast-developing countries which may have capital investment booms in short periods (Chen et al. 2018), and the equity of resource use across generations (Thacker et al. 2019).

To well understand this important temporal dimension of environmental responsibility displacement requests a full picture of capital flows across sectors and regions (according to the first feature) and throughout its lifespans from the past to the future (according to the second feature). It is challenged by both methodologies and data. First, conventional consumption-based accounting methods rely on input-output (IO) tables that are published on an annual basis which cannot represent capital use stretching over longer time periods. Second, data on capital investment and consumption at a sufficient resolution of both assets and sectors is lacking.

1.4. Consumption-Based Accounting of Environmental Pressures and Its Key Limitations

Scientific methods have been developed for environmental pressure assessments. These methods can be grouped in production-based and consumption-based accounting methods, which assess environmental pressures from the production and consumption perspective (see **Section 1.1**), respectively. The production-based accounting relies on the statistical data or survey data that record direct (or on-site) environmental pressures of entities belonging to a region (IPCC 1996, Peters 2008). The consumption-based accounting quantifies both direct and indirect (upstream pressures along the supply chains) environmental pressures during the production/trade/consumption of final goods and services of a region, yielding the environmental "footprints" of the region. By comparing consumption-based environmental pressures with production-based pressures—the net displacement of environmental pressures embodied in trade, regions can be categorized as either net exporters or net importers of associated environmental pressures. Such information is vital in the design of international policies (e.g., carbon abatement targets for each country) regarding environmentally sustainable development, but it also requires that approaches used for the consumption-based accounting are carefully devised to capture the indirect environmental pressures accurately and comprehensively.

The process-based and input-output table-based approaches are two main approaches for consumption-based accounting, but each has its (dis)advantages. The process-based approach is more detailed but has high data requirements regarding process and trade information—using raw physical data of production/trade for each product of interest multiplied by its environmental intensity. By far, it has been mainly applied for blue water consumption (Chapagain and Hoekstra 2003, Chapagain et al. 2005, Hoekstra and Mekonnen 2012), water stress (Boulay et al. 2017, Pfister et al. 2009) or land use (Ibarrola-Rivas and Nonhebel 2019, Kastner et al. 2014) of agricultural products with modestly complex production chains. *The IO table-based approach is based on economic IO or multi-regional IO (MRIO) tables that capture the entire supply chain-wide inputs in monetary terms, but at low resolutions of sectors which represent a range of products with different environmental properties yet aggregated into homogeneous sectors* (Lenzen 2011). In this context, it argues that the IO table-based approach would be inadequate to account for certain environmental pressures such as water consumption related to the production and consumption of a specific product like wheat or pork. To make use of the advantages of both consumption-based accounting approaches and limit the disadvantages, a hybrid approach has been developed (Ewing et al. 2012). The hybrid approach enriches the monetary IO/MRIO approach with detailed physical-unit production and trade data of agri-food products, and has recently been applied in studies on European consumption footprints (Steen-Olsen et al. 2012), Chinese exports (Weinzettel and Wood 2018), and analysis of global biodiversity (Weinzettel et al. 2018). Yet, *most literature just presented the spatial displacement of environmental pressures from the sources to the destinations with a total amount of virtual displacement, while few literature considered different trade patterns to conduct a systematic analysis of respective contributions of trade patterns to the total environmental pressure displacement.*

Neither the process-based nor IO table-based approach systematically captures capital's role in production and consumption, and hence fails to allocate the environmental responsibilities of capital activities throughout capital's full lifespan in footprint assessments. Neglecting capital's two important features, both consumption-based approaches treat the purchase of capital assets in the same way as the purchase of final consumption, and assign associated environmental pressures to the purchasing country and the purchasing year (Gao et al. 2020). Acknowledging the economic and environmental significance of capital (see **Section 1.3.2**), there have been a few endeavors to tackle the methodological and data challenges related to modeling capital assets as intermediate inputs used in production, also known as 'capital endogenization' in the IO table-based approach (Chen et al. 2018, Lenzen and Treloar 2004, Södersten et al. 2020, Södersten et al. 2018a, Södersten et al. 2018b). Consistently, they show that the inclusion of capital as intermediate inputs leads to substantial re-distribution of carbon and material footprints across industries and countries. *However, the inter-temporal features of environmental pressures embodied in capital assets remain unaddressed* since capital assets used for year *n*'s production and consumption are of different age cohorts that are produced based on the production recipe, trade networks, and environmental intensities of year *n*, *n-1*, *n-2*, *n-3*, ... Such temporal dynamics are inherent to the retrospective distribution of historically-generated resource use and emissions to current final consumption, and critical for understanding the temporal trends and thus the future needs of resources and emissions for capital formation particularly in rapid developing and transitioning economies.

1.5. Goal and Approach of this Research

The goal of this thesis is to develop improved modelling techniques to better capture spatiotemporal virtual displacement of environmental pressures along the entire supply and use chain of goods and services. To this end, an environmentally extended MRIO model is applied for the environmental pressure accounting throughout this thesis. This thesis proposes the following two improved models based on the conventional environmentally extended MRIO model to address aforementioned limitations (in italic font) that exist in previous analysis of environmental pressures: the hybrid MRIO model and the capital-endogenized MRIO model. The two improved models are applied to answer four research questions, of which the former two are related to the spatial virtual displacement of environmental pressures embodied in trade and the latter two are related to the temporal virtual displacement embodied in capital:

Q1. How to capture the supply chain-wide environmental pressures related to the production, trade, and consumption of a specific agri-food product?

Q2. What are the respective roles of different trade patterns in regional resource consumption and inter-regional virtual displacement of environmental pressures?

Q3. What is the role of capital system playing in satisfying human final consumption and associated environmental pressures?

Q4. How do the historically built-up capital assets—used in productive processes for years or decades—influence national environmental performances throughout their lifespans?

All the questions will be answered by using China as the main study area, because of its rapid economic transition and its important role in global sustainable development.

To answer Q1 and Q2, this thesis first develops a standard inter-provincial MRIO model that hybridizes the physical food and agricultural production system with the monetary supply chain of China. Secondly, this thesis disaggregates China's interprovincial trade into three patterns, i.e., direct final goods trade, intermediate goods trade for the last step of production, and value chain-related trade. After that, the hybrid MRIO model is applied to re-assess provincial blue water footprints and particularly quantify virtual water displacements of specific agri-food products across provinces (**Chapter 2**). Furthermore, this thesis elaborates on the virtual blue water networks of three trade patterns within China and their respective contributions to the virtual blue water networks (**Chapter 3**).

To answer Q3 and Q4, this thesis first develops a capital-endogenized MRIO method that addresses the temporality issue regarding dynamic formation and depreciation of capital assets as well as associated environmental pressure displacement. After that, the capital-endogenized MRIO model is applied to quantify the linkages between China's capital development and associated environmental pressures with the final consumption of China and other countries (**Chapter 4**). Secondly, this thesis narrates China's capital investment pathways by two capital-focused scenarios and a "business-as-usual" scenario into 2030. The two capital-focused investment pathways are developed on the principle of improving economic growth and social well-being, and the principle of low carbon development, respectively. Under each scenario, this thesis quantifies China's future CO_2 emissions that consider the temporal carbon transfers along capital's lifespan, to present a more comprehensive picture of carbon emissions for future production and consumption (**Chapter 5**).

1.6. Structure of the Research

The structure of this thesis is illustrated in **Figure 1-1.** Detailed conclusions of this thesis and outlook of future work are provided in **Chapter 6**.

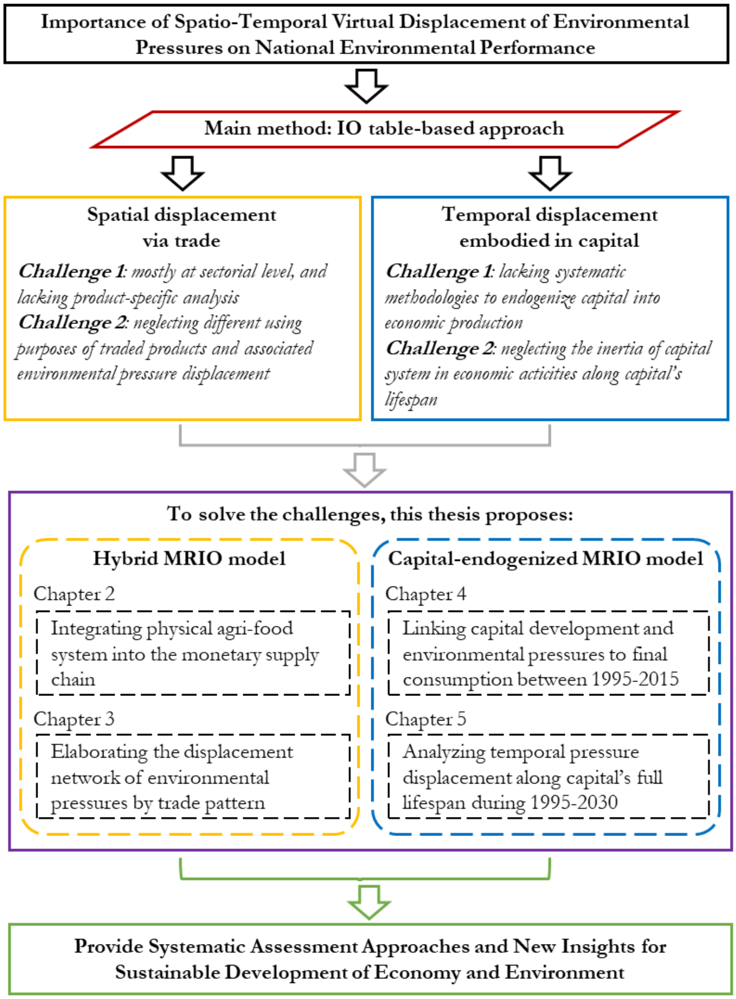

Figure 1-1. Conceptual diagram of the structure of this thesis.

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

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 modelling 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.

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2.1. 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 socio-economic development patterns and environmental pressures because resource use and emissions during the production process of goods and services are virtually transferred along 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. 2017a); while the change in interprovincial trade structure has led to an increase of national average land use intensity during 1997–2012, with a results 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), 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), 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. In addition, 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 socio-economic 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 A-1**, **Appendix A**) 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 A-2**, generally designated as "agri-food" commodities) supplied and used by 75 processes (**Table A-3**). 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. (2017a) 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.

2.2. 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, m^3, or heads). Following the global FABIO model (Bruckner et al. 2019), the whole procedure of FAIBO-CHN also consists of four main steps—illustrated in **Figure 2-1**:

(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;

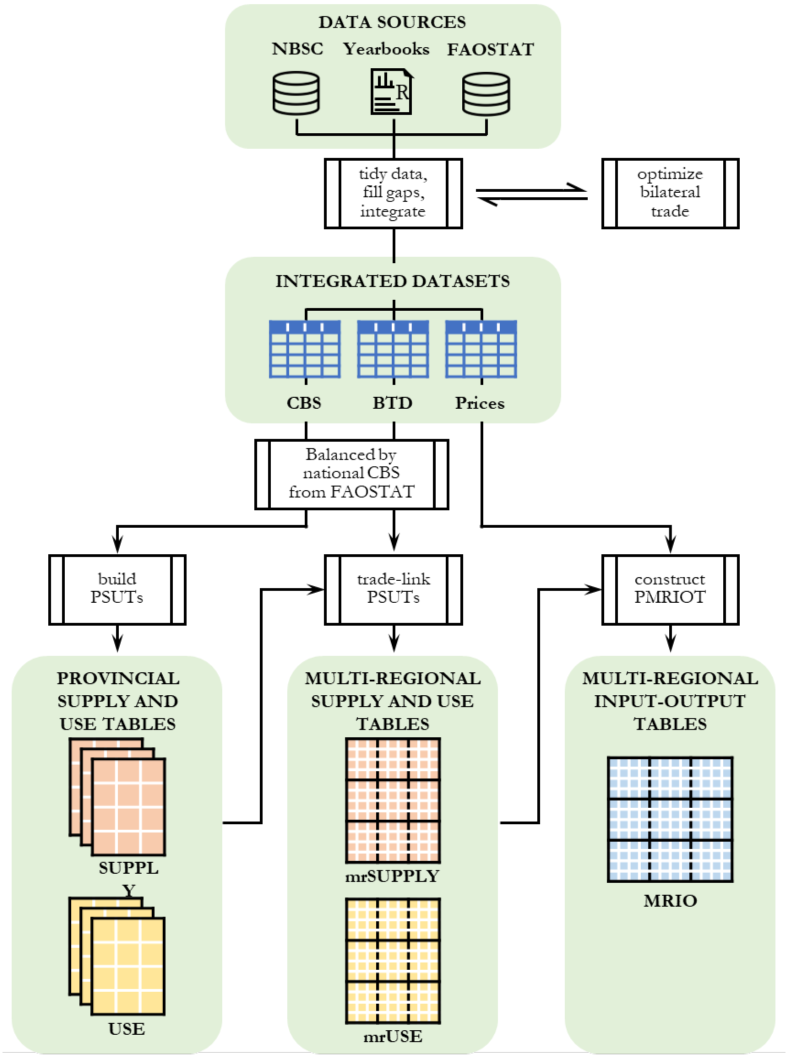

Figure 2-1. Schematic for the procedures to build FABIO-CHN. Note, the PSUTs and PMRIOT in this chart only capture the transactions across 84 products and 75 processes specified in FABIO-CHN, which exclude other economic sectors such as electricity generation sectors or service sectors that will be further integrated at a latter step. The format of this chart is in accordance with (Bruckner et al. 2019).

(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. (2017a), which describe the production, inter-provincial and international trade, intermediate consumption, and final demand of China's economy by 42 sectors (listed in **Table A-4**) 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. **Figure 2-2** 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.

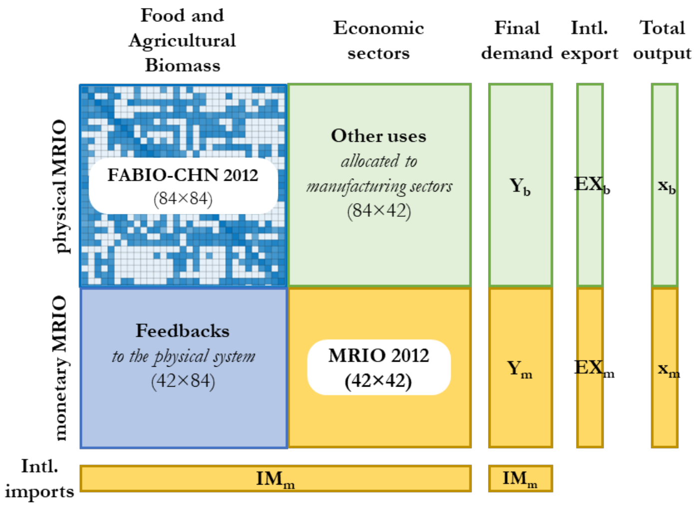

Figure 2-2. **Structure of a symmetric hybrid input-output (IO) table.**

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

2.2.1.1. 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 A-5** summarizes the data requirements and associated data sources for FABIO-CHN. In addition, 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 ($\sum_{n,\, n\neq m} t^{nm}$) 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 A-2**). 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 **Appendix A.2**. 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 2.3.2 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 **Appendix A.3**.

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 **Appendix A.4**. All estimated trade data, inter-provincial and international, of all 84 commodities are harmonized into one bilateral trade database.

2.2.1.2. 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 $\mathbf{S}^m$ with 84 commodities from 75 processes for each province m in 2012.

2.2.1.3. 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*. In addition, *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 $\mathbf{U}^m$ with 84 commodities by 75 processes plus 3 final demand categories ($\mathbf{Y}^m$) for each province m in 2012.

2.2.1.4. 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 $\{m, c\}\times 1$.

2.2.1.5. 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 $\mathbf{V}=\widehat{\mathbf{S}^{\mathrm{T}}\mathbf{i}}^{-1}\mathbf{S}^{\mathrm{T}}$, where T is the transpose of a matrix, **i** is a summation vector of appropriate length, "^" is the diagonalization of a vector; and then multiplying the use with the transformation matrix $\mathbf{Z}=\mathbf{U}\cdot\mathbf{V}$. Part of the import matrix for processes only ($\mathbf{IM}^p$ in $c\times\{n, p\}$, excluding the import of final demand) is also transformed by $\mathbf{IM}^p\cdot\mathbf{V}$.

2.2.2. 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 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). In addition, 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* (**Figure 2-2**) 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 **Appendix A.6**.

2.2.3. 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 **Appendix A.5**.

The calculation of provincial blue water footprints based on our hybrid MRIO model equals the conventional monetary MRIO modelling. **Eq. 2-1** calculates the supply chain-wide blue water footprints (WF_m^H, in million m^3/yr) of province *m*'s final demand ($\mathbf{Y}_m^H$):

$$WF_m^H=\mathbf{f}^H\mathbf{L}^H\mathbf{Y}_m^H=\mathbf{S}^H(\mathbf{I}\text{-}\mathbf{A}^H)^{-1}\mathbf{Y}_m^H \quad (2\text{-}1)$$

$\mathbf{f}^H$ is a row vector of direct blue water consumption intensities of FABIO_CHN commodities or economic sectors (e.g., in million m^3/tonne or million m^3/Yuan), calculated by the direct water consumption of FABIO_CHN commodities or economic sectors (**Appendix A.5**) divided by associated total outputs. $\mathbf{L}^H$ is the Leontief inverse matrix, describing the supply chain-wide outputs associated with per unit finished goods and services. $\mathbf{L}^H$ is calculated from $\mathbf{A}^H$ with each element $a_{i,j}^H$ 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).

2.3. 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 2-1**). 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

Table 2-1. Comparison of provincial water footprints estimated in this study with those estimated by previous literature.

	Literature						
	Zhang and Anadon (2014)	Xu et al. (2020a)	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 modelling (√)	Monetary MRIO modelling (√)	Monetary MRIO modelling (√)	Process-based approach (×)	Process-based approach (×)	Process-based approach (×)	Hybrid MRIO modelling (√)
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 monetary MRIO models for footprint assessments	×	×	×				√

monetary MRIO modelling 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.

2.3.1. 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 **Figure 2-3A** and **Table A-7**, 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 modelling (Xu et al. 2020a, Zhang and Anadon 2014). Provinces, e.g., Xinjiang, Guangdong, and Jiangsu, have smaller water footprints in this study compared with Xu et al. (2020a) 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 modelling could be regarded as the main reason. That is, using an identical water intensity results in the overestimation of associated water footprints and virtual water flows of 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 **Figure 2-4**), 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 (**Figure 2-3B**), 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.

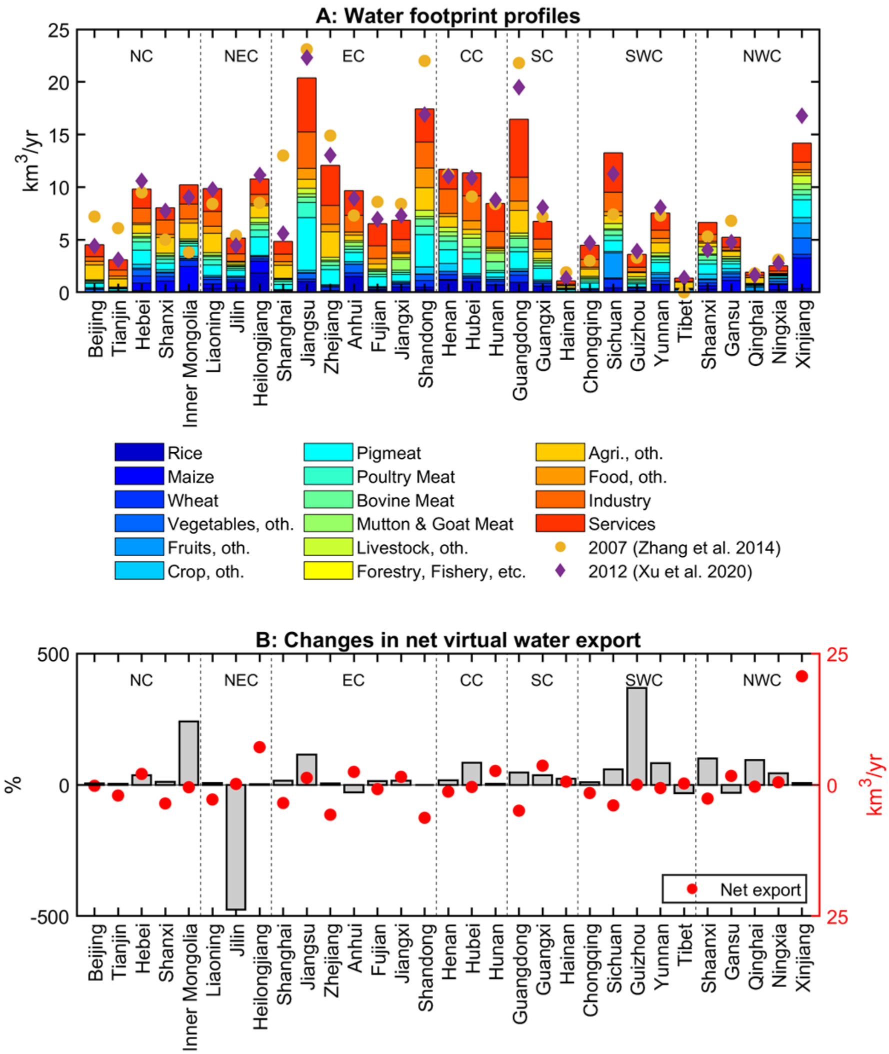

Figure 2-3. Profile of blue water footprints (A), and the relative changes in net virtual water export (B) of 31 provinces in China. In **A**, we compare the blue water consumption footprints of year 2007 (Zhang and Anadon 2014) and 2012 (Xu et al. 2020a) with our results. In **B**, relative changes 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).

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. (2020a) 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. **Figure 2-4** 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 km^3/yr) for the commodities and sectors analyzed here, mainly for the production of crops like maize and rice. Water from South China (26.9 km^3/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 km^3/yr) is from the North itself. In South China, the water footprint of local consumption of crops and livestock is 37 km^3/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 **Figure 2-4**, 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.

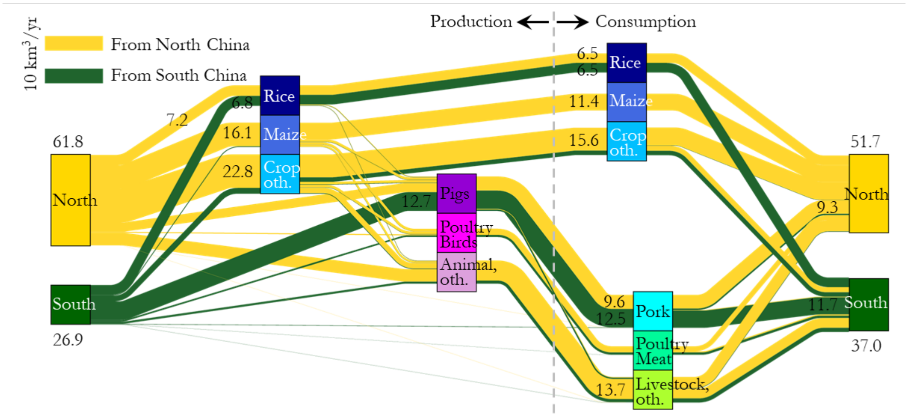

Figure 2-4. Virtual water flows (km³/yr) embodied in the transactions across crop production, animal husbandry, and animal slaughtering sectors. The top two commodities of each product categories that have the largest virtual water flows are shown in this plot.

2.3.2. 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 reply 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 (**Figure 2-5** and **Table A-8**).

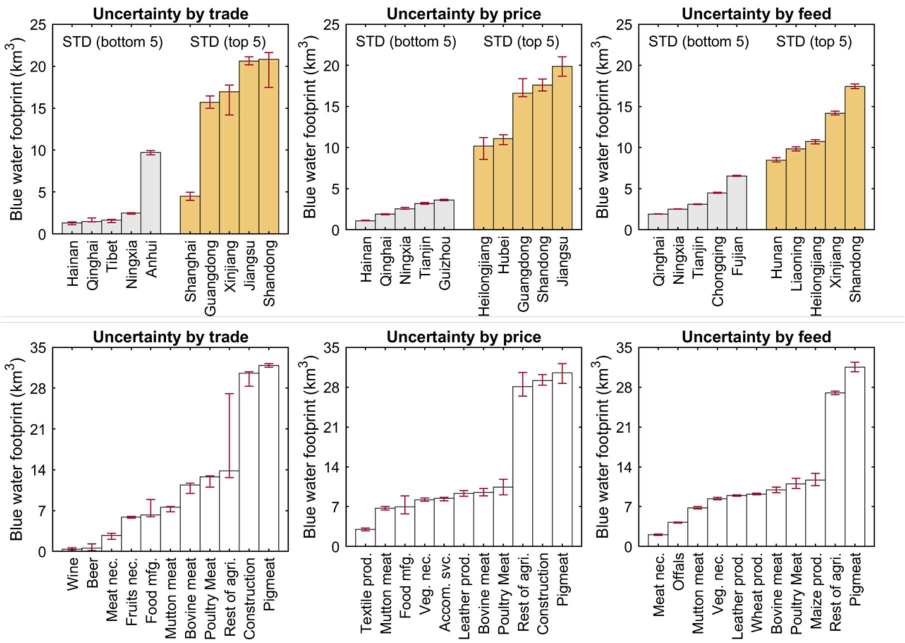

Figure 2-5. Uncertainty analysis of provincial (upper plots) and sectoral (lower plots) blue water footprints by three key factors (i.e., inter-provincial trade, commodity prices, and feed requirements for animal husbandry). Five provinces with the smallest and largest, respectively, STD of blue water 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. A-8**. 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.

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. In addition, 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 (**Figure 2-3B**), e.g., Shandong, Xinjiang, Guangdong, Jiangsu, and Shanghai, show higher impacts by the inter-provincial trade modelling, 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 modelling, 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 modelling, 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.

2.3.3. 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. In addition to 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 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 record 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. 2014a, Mi et al. 2017a, 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.

2.4. 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. In addition, using product-specific water intensities also reduces the uncertainty of monetary MRIO modelling 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. In addition to 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.

2.5. 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
c	agri-good commodity specified in FABIO-CHN
CBS	commodity balance sheets
CC	Central China
CGE	computable general equilibrium
dom	domestic
EC	East China
ex	international export volume of agri-food commodity
EX	international export table
f	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*"
h	share of intermediate input product from each source
H	hybrid
i	a summation vector of appropriate length
I	the identity matrix

im	international import volume of commodity
IM	international import table
Intl.	international
IO	input-output
L	the Leontief inverse matrix
m	province in China
m	monetary
mfg.	manufacturing
MRIO	multi-regional input-output
n	province in China
NBSC	National Bureau of Statistics of China
NC	North China
NEC	Northeast China
NWC	Northwest China
p	primary production or process specified in FABIO-CHN
P	primary production volume of FABIO-CHN commodities
PMRIOT	physical multi-regional input−output table
PSUT	physical supply and use tables
s	economic sectors
S	the total supply volume of agri-food commodities
S	physical supply table
SC	South China
STD	standard deviations
Stk	stock removal volume
svc.	services
SWC	Southwest China
t	inter-provincially traded volume of commodity
T	the transpose of a matrix
u	use volume of commodity
U	physical use table
U	the total use volume of agri-food commodities
U_fe	the use volume of agri-food commodities for feed
U_fo	the use volume of agri-food commodities for food
U_oth	the use volume of agri-food commodities for other use
U_p	the use volume of agri-food commodities for processing
U_s	the use volume of agri-food commodities for seed
U_w	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

Effects of production fragmentation and inter-provincial trade on spatial blue water consumption and scarcity patterns in China

Abstract

Freshwater resources are used to produce commodities that are traded and consumed elsewhere, which generate virtual water flows. The relation between regional blue water scarcity levels—the degree of competition over limited surface and groundwater flows—and inter-regional virtual water flows has been studied. However, the effects of production fragmentation on this relation are still not properly understood. Production fragmentation is the distribution of the production process across different regions, resulting in inter-regional trade of both intermediate and finished goods and services, which involve different virtual water networks. This study formulates a comprehensive trade disaggregation approach to elaborate the virtual water networks of three trade patterns (i.e., direct final goods trade, intermediate goods trade for the last step of production, and value chain-related trade) within China, and further analyzes the impacts of trade on provincial blue water scarcity by comparing the actual water scarcity with that under a "no-trade" scenario (NTS). In 2012, there was 128 km3 blue water virtually transferred across provinces because of inter-provincial trade. Direct final goods trade contributed the most to the virtual water trade (accounting for 47% of the total), whereas value chain-related trade induced the least (17%). Compared with the results under the NTS, we found that current trade alleviated the water scarcity in provinces under extreme water scarcity, but worsened the water scarcity of this nation from a broader scope. Our study suggests policy makers fully considering specific trade patterns and their impacts on provincial or national water consumption to cope with water scarcity in China.

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3.1. Introduction

China has entered an era of "new normal" economic growth recently, towards more sustainable and environmental-friendly development paths. Yet, the past decades' socioeconomic development has accompanied with significant resource and environmental consequences (Feng et al. 2013, Jiang et al. 2019), particularly for freshwater resources that are threatened by the stress of both quantity and quality (Guan et al. 2014, Ma et al. 2020). Over half of the population are affected by either quantity-related (0.9 billion) or quality-related water scarcity (1.2 billion) for at least one month of the year (Ma et al. 2020, Mekonnen and Hoekstra 2016). Thus, there is an urgent need to improve national or sub-national water resource management to cope with water scarcity in China. Moreover, domestic trade within China has grown rapidly (NBSC 2020), which presents new features of environmental pressures because resource use and emissions during the production process of goods and services are virtually transferred along the trade. For example, the intra-national virtual water trade has increased by 90% during the period of 2002-2012, mainly from the water-scarce Northwest and Northeast China to the water-rich South (Cai et al. 2019). As for product-specific environmental pressures, maize-related virtual water flow from the North to the South China has increased by 40%, while pork-related virtual water flow from South to North has increased by 23% over the period of 2000-2013 (Zhuo et al. 2019).

An important debate on virtual water transfers, bilateral or multi-lateral, is their ultimate role in reducing or increasing water consumption of such a system consisting of all related regions (Dalin et al. 2012, Hoekstra and Mekonnen 2012, Zhang et al. 2011). For instance, international trade of crops may help save water at the global scale by exchanging virtual water from highly productive countries to less productive locals, resulting in a smaller water consumption per unit of crop grown (Chapagain et al. 2005). The estimation of virtual water transfers, from the sources to the destinations, has been widely carried out (Chen and Chen 2013, Chen et al. 2012, Dalin et al. 2014, Han et al. 2017, Han et al. 2018, Hoekstra and Mekonnen 2012, Wu et al. 2019, Zhuo et al. 2019), and based on that, relevant research such as the drivers of virtual water flows or the potential water savings have been further addressed (Dalin et al. 2017, Tamea et al. 2014). However, the effects of production fragmentation on virtual water flows are still not properly understood. Production fragmentation is the distribution of production process across different regions, resulting in inter-regional trade by different trade patterns (e.g., the direct trade of final products or the trade of intermediate input products for production) which have different associated virtual water networks. The lack of data that provide sufficient information about the commodity trade and the supply chain-wide transactions among these commodities or economic sectors is the main reason (Feng et al. 2011).

Prior studies (Arce González et al. 2012, López et al. 2013, Wang et al. 2017) disaggregated the bilateral trade from the production perspective into three patterns, i.e., trade of final demand, trade of intermediate products for the last step of production, and trade of intermediate products for the remaining steps of inter-regional production. For the first two patterns of trade, products are absorbed by the trade partners, which also regarded as traditional Ricardian trade that represents the direct value added trade pattern (Borin and Mancini 2015). The last pattern of trade is regarded as supply chain-wide related trade, as the exported intermediate products are processed and re-exported as inputs for other regions' production (Wang et al. 2017, Zhang et al. 2017). Based on the disaggregation, the contributions of different trade patterns as well as the effects of different socioeconomic factors on the inter-regional virtual water flows could be addressed (Liu et al. 2019), as the cases of carbon transfers by Zhang et al. (2017) and Feng et al. (2020). Although previous studies presented a great framework for trade pattern disaggregation, there was still a calculation error in disaggregating the trade of intermediate products, i.e., neglecting the trade of intermediate products for the last step of final goods production that are further traded to trade partners. Without capturing this trade pattern, the actual inter-provincial trade values within China would be underestimated (a simple example demonstrating the underestimation could be found in **Appendix B.1**).

Apart from the research gap on the effects of production fragmentation on virtual water networks, the effects of trade (compared to a situation without trade) on national water consumption and provincial water scarcity are not sufficiently assessed either. With more attention on carbon emissions and carbon transfers, previous studies have made great contributions to reveal the effects of trade on global and regional carbon emissions, mainly using three methods—decomposition analysis (Arto and Dietzenbacher 2014, Hoekstra et al. 2016, Jakob and Marschinski 2012, Jiang and Guan 2017, Jiang et al. 2018, Zhu and Jiang 2019), the pollution haven hypothesis (López et al. 2018, Zhang et al. 2017), and the no-trade scenario (NTS). However, two totally opposite conclusions have been summarized from the studies relying on the first two methods. That is, a general net positive effect was found by decomposition analysis, whereas the current international trade generating global emission savings was revealed by the pollution haven hypothesis. This suggested that to comprehensively understand the effects of trade on global or national environmental performances (not only air pollution emissions but other environmental pressures like blue water consumption), the NTS method would be the most appropriate one compared with the other two methods. However, the existing NTSs, with the core of reallocating the supply chain-wide environmental pressures for product production into consuming region itself, had main limitations such as still using with-trade economic structures or neglecting the differences in commodity prices and production efficiencies among regions (Wu et al. 2021b). In addition, most of the previous NTSs were developed to re-construct the international (Duchin 2007, Wu et al. 2021b, Xu et al. 2020b) or bilateral trade (Liu et al. 2010, Shui and Harriss 2006, Tan et al. 2013) across countries. Little is known about the effects of domestic trade on sub-national environmental pressures, especially for vast countries with great spatial variations in socio-economic development patterns and resource endowments such as China.

In summary, although existing literature has addressed the changes in provincial water consumption and inter-provincial virtual water trade in China yielding novel insights and policy suggestions, the effects of product fragmentation and trade (compared to an NTS) on shaping the national water consumption and provincial water scarcity are not properly understood. Therefore, the objectives of this study are: 1) to formulate a comprehensive trade disaggregation approach to elaborate the virtual water networks of three trade patterns (i.e., direct final goods trade, intermediate products trade for the last production, and value chain-related trade) within China; and 2) to analyze the impacts of trade on provincial water scarcity by comparing the actual water scarcity with that under the NTS. In this analysis we include blue water consumption (BWC, the consumptive use of surface water and groundwater) as indicator for water-related pressures. Data availability at provincial level for BWC is better than for possible additional indicators such as the green water footprint (consumptive use of rainwater) or the grey water footprint (the volume of fresh water required for assimilation of pollutants Hoekstra et al. (2011)). Also BWC is relevant for both agricultural and other economic sectors, is less controversial and is more widely discussed in previous studies, allowing to compare our results to others. The remainder of this paper is organized as follows: **Section 3.2** elaborates the trade disaggregation approach and the NTS we formulate. **Section 3.3** presents the key results about the virtual water trade embodied in different trade patterns and the effects of trade on provincial water consumption as well as water scarcity. **Section 3.4** discusses our results and potential policy implementation. Conclusions will be summarized in **Section 3.5**.

3.2. Methods

The methodology improvements in this study include: 1) formulating a more accurate disaggregation approach to capture the three inter-provincial trade patterns in China, which addresses the underestimation issue of existing trade disaggregation approaches (Feng et al. 2020, Liu et al. 2019, Zhang et al. 2017); and 2) developing a novel NTS with the core of reallocating the supply chain-wide indirect inputs for the production of province *m*'s final demand into province *m* itself, whilst considering the distinctions of production structures and coefficients between provinces as well as the local production factor endowments (Duchin 2007, Wu et al. 2021b).

3.2.1. Disaggregation of trade patterns

Provinces are connected through the inter-provincial trade of intermediate and final products, and each province is connected with the global economy through international imports and exports. The exports from province m to province n ($\mathbf{T}^{mn}$) include the exports of final demands ($\mathbf{Y}^{mn}$) and intermediate inputs ($\mathbf{Z}^{mn}$), i.e., $\mathbf{T}^{mn}=\mathbf{Y}^{mn}+\mathbf{Z}^{mn}\mathbf{i}$, where $\mathbf{i}$ is a summation vector of appropriate length. The intermediate input ($\mathbf{Z}^{mn}$) can be calculated by $\mathbf{Z}^{mn}=\mathbf{A}^{mn}\widehat{\mathbf{x}^{n}}$, where $\mathbf{A}^{mn}$ is the input coefficient matrix that represents the direct economic requirements for one-unit output. The total output $\mathbf{x}^{n}$ equals to the sum of intermediate inputs, final demands and international exports ($\mathbf{EX}^{n}$), i.e., $\mathbf{x}^{n}=\sum_{r=1}^{g}\mathbf{Z}^{nr}\mathbf{i}+\sum_{r=1}^{g}\mathbf{Y}^{nr}+\mathbf{EX}^{n}=\sum_{r=1}^{g}\mathbf{A}^{nr}\mathbf{x}^{r}+\sum_{r=1}^{g}\mathbf{Y}^{nr}+\mathbf{EX}^{n}$, where g is the number of regions.

$$\begin{bmatrix}\mathbf{x}^{1}\\ \mathbf{x}^{2}\\ \cdots\\ \mathbf{x}^{g}\end{bmatrix}=\begin{bmatrix}\mathbf{A}^{11} & \mathbf{A}^{12} & \cdots & \mathbf{A}^{1g}\\ \mathbf{A}^{21} & \mathbf{A}^{22} & \cdots & \mathbf{A}^{2g}\\ \cdots & \cdots & \cdots & \cdots\\ \mathbf{A}^{g1} & \mathbf{A}^{g2} & \cdots & \mathbf{A}^{gg}\end{bmatrix}\begin{bmatrix}\mathbf{x}^{1}\\ \mathbf{x}^{2}\\ \cdots\\ \mathbf{x}^{g}\end{bmatrix}+\begin{bmatrix}\sum_{r=1}^{g}\mathbf{Y}^{1r}+\mathbf{EX}^{1}\\ \sum_{r=1}^{g}\mathbf{Y}^{2r}+\mathbf{EX}^{2}\\ \cdots\\ \sum_{r=1}^{g}\mathbf{Y}^{gr}+\mathbf{EX}^{g}\end{bmatrix}=\begin{bmatrix}\mathbf{B}^{11} & \mathbf{B}^{12} & \cdots & \mathbf{B}^{1g}\\ \mathbf{B}^{21} & \mathbf{B}^{22} & \cdots & \mathbf{B}^{2g}\\ \cdots & \cdots & \cdots & \cdots\\ \mathbf{B}^{g1} & \mathbf{B}^{g2} & \cdots & \mathbf{B}^{gg}\end{bmatrix}\begin{bmatrix}\sum_{r=1}^{g}\mathbf{Y}^{1r}+\mathbf{EX}^{1}\\ \sum_{r=1}^{g}\mathbf{Y}^{2r}+\mathbf{EX}^{2}\\ \cdots\\ \sum_{r=1}^{g}\mathbf{Y}^{gr}+\mathbf{EX}^{g}\end{bmatrix} \tag{3-1}$$

In a standard multi-regional input-output (MRIO) modelling, we have $\mathbf{x}=\mathbf{B}(\mathbf{Yi}+\mathbf{EX})$, where $\mathbf{B}=(\mathbf{I}-\mathbf{A})^{-1}$ is the Leontief inverse matrix, representing the supply chain-wide economic requirements to increase a one-unit monetary increase of final demand or exports. $\mathbf{I}$ is an identity matrix. Thus, the equation of total output $\mathbf{x}^{n}$ can be transformed into $\mathbf{x}^{n}=\sum_{r=1}^{g}\mathbf{B}^{nr}(\sum_{v=1}^{g}\mathbf{Y}^{rv}+\mathbf{EX}^{r})=\sum_{r=1}^{g}\mathbf{B}^{nr}\sum_{v=1}^{g}\mathbf{Y}^{rv}+\sum_{r=1}^{g}\mathbf{B}^{nr}\mathbf{EX}^{r}$, and then the exports $\mathbf{T}^{mn}$ can be calculated by:

$$\mathbf{T}^{mn}=\mathbf{Y}^{mn}+\mathbf{A}^{mn}\mathbf{x}^{n}=\underbrace{\mathbf{Y}^{mn}}_{\mathbf{T\_f}^{mn}}+\underbrace{\underbrace{\mathbf{A}^{mn}\mathbf{L}^{nn}\mathbf{Y}^{nn}}_{\mathbf{T\_i}_{n}^{mn}}+\underbrace{\mathbf{A}^{mn}\mathbf{L}^{nn}\sum_{v\neq n}^{g}\mathbf{Y}^{nv}}_{\mathbf{T\_i}_{non\_n}^{mn}}}_{\mathbf{T\_i}^{mn}}$$

$$+\underbrace{\underbrace{\mathbf{A}^{mn}\mathbf{L}^{nn}\sum_{r\neq n}^{g}\mathbf{A}^{nr}\mathbf{B}^{rn}\sum_{v=1}^{g}\mathbf{Y}^{nv}+\mathbf{A}^{mn}\sum_{r\neq n}^{g}\mathbf{B}^{nr}\sum_{v}^{g}\mathbf{Y}^{rv}}_{\mathbf{T\_d}^{mn}}+\underbrace{\mathbf{A}^{mn}\sum_{r=1}^{g}\mathbf{B}^{nr}\mathbf{EX}^{r}}_{\mathbf{T\_g}^{mn}}}_{\mathbf{T\_v}^{mn}} \tag{3-2}$$

where $\mathbf{L}$ is the local Leontief inverse matrix. $\mathbf{B}^{nn}$ in **Eq. 3-2** is decomposed into $\mathbf{B}^{nn}=\mathbf{L}^{nn}+\mathbf{L}^{nn}\sum_{r\neq n}^{g}\mathbf{A}^{nr}\mathbf{B}^{rn}$ according to Wang et al. (2017) and Zhang et al. (2020). We define: 1) $\mathbf{T\_f}^{mn}$ as the trade of final products—the trade partner n would directly absorb the exported products from m, and the exporter m is located in the last stage of production; 2) $\mathbf{T\_i}^{mn}$ as the trade of intermediate products for the last stage of production, which includes the last stage of final good production consumed by the trade partner ($\mathbf{T\_i}_{n}^{mn}$, with the traded products cross the border of region *m* once), as well as the trade partner's trade partners ($\mathbf{T\_i}_{non\_n}^{mn}$, with the traded products cross the border of regions *m* and *n* once) which has not been captured in previous studies (**Appendix B.1**); 3) $\mathbf{T\_v}^{mn}$ as the value chain-related trade of products—crossing the provincial or national borders more than once—finally absorbed by domestic provinces ($\mathbf{T\_d}^{mn}$) or further processed and exported to foreign counties ($\mathbf{T\_g}^{mn}$).

3.2.2. Supply chain-wide virtual water flows

The BWC coefficients of products and sectors in province *m* ($\mathbf{f}^{m}$) are calculated by $\mathbf{f}^{m}=\mathbf{F}^{m}\,\widehat{\mathbf{x}}^{n^{-1}}$, where $\mathbf{F}^{m}$ is a row vector of direct BWC of products and sectors in province *m*. The total BWC of province *m*, W^{m}, including the BWC for household purposes (W_hh^{m}) which accounts for a big part of BWC in some populous provinces but tends to be neglected in previous studies, can be calculated as:

$$W^{m}=\mathbf{f}^{m}\,\mathbf{x}^{m}+W\_hh^{m}=(\mathbf{f}^{m}\,\mathbf{L}^{mm}\mathbf{Y}^{mm}+W\_hh^{m})+\mathbf{f}^{m}\,\mathbf{L}^{mm}\mathbf{EX}^{m}$$
$$+\mathbf{f}^{m}\,\mathbf{L}^{mm}\sum\nolimits_{n\neq m}^{g}\mathbf{T\_f}^{mn}+\mathbf{f}^{m}\,\mathbf{L}^{mm}\sum\nolimits_{n\neq m}^{g}\mathbf{T\_i}^{mn}+\mathbf{f}^{m}\,\mathbf{L}^{mm}\sum\nolimits_{n\neq m}^{g}\mathbf{T\_v}^{mn} \tag{3-3}$$

The total BWC of province *m* is disaggregated into five terms. The first term represents the BWC assigned to the economic activities and household use within province *m*, which has no relation with the inter-provincial or international trade. The second term represents the BWC assigned to the direct exports of final products to foreign countries. The last three terms represent the BWC assigned to different trade patterns.

The local BWC embodied in the export, also known as virtual water outflow (Allan 1998), from province *m* to province *n* is:

$$W\_EX^{mn}=\mathbf{f}^{m}\mathbf{L}^{mm}\mathbf{T}^{mn}=\mathbf{f}^{m}\mathbf{L}^{mm}\mathbf{T\_f}^{mn}+\mathbf{f}^{m}\mathbf{L}^{mm}\mathbf{T\_i}^{mn}+\mathbf{f}^{m}\mathbf{L}^{mm}\mathbf{T\_v}^{mn} \tag{3-4}$$

The net virtual water flows (NVW) between provinces *m* and *n* are calculated by:

$$NVW^{mn}=W\_EX^{mn}\text{-}W\_EX^{nm}=\underbrace{\left(\mathbf{f}^{m}\,\mathbf{L}^{mm}\mathbf{T\_f}^{mn}\text{-}\mathbf{f}^{n}\,\mathbf{L}^{nn}\mathbf{T\_f}^{nm}\right)}_{NVW\text{-}1}+\underbrace{\left(\mathbf{f}^{m}\,\mathbf{L}^{mm}\mathbf{T\_i}_{n}^{mn}\text{-}\mathbf{f}^{n}\,\mathbf{L}^{nn}\mathbf{T\_i}_{n}^{nm}\right)}_{NVW\text{-}2}$$
$$+\underbrace{\left(\mathbf{f}^{m}\,\mathbf{L}^{mm}\mathbf{T\_i}_{non\text{-}n}^{mn}\text{-}\mathbf{f}^{n}\,\mathbf{L}^{nn}\mathbf{T\_i}_{non\text{-}n}^{nm}\right)}_{NVW\text{-}3}+\underbrace{\left(\mathbf{f}^{m}\,\mathbf{L}^{mm}\mathbf{T\_d}^{mn}\text{-}\mathbf{f}^{n}\,\mathbf{L}^{nn}\mathbf{T\_d}^{nm}\right)}_{NVW\text{-}4}$$
$$+\underbrace{\left(\mathbf{f}^{m}\,\mathbf{L}^{mm}\mathbf{T\_g}^{mn}\text{-}\mathbf{f}^{n}\,\mathbf{L}^{nn}\mathbf{T\_g}^{nm}\right)}_{NVW\text{-}5} \tag{3-5}$$

The right five terms *NVW-1*—*NVW-5* represent the net virtual water flows in different trade patterns. A positive value of NVW^{mn} indicates that the bilateral trade increases the BWC of province *m*, and vice versa for a negative value of NVW^{mn}.

3.2.3. Developing the no-trade scenario (NTS)

Before describing the development of the NTS, it should be clearly noted that the NTS is completely hypothetical, thus based on some key assumptions such as using production factors to constrain the hypothetical production capacities (Wu et al. 2021b). To reallocate the supply chain-wide indirect inputs for the production of province *m*'s final demand into province *m* itself, we first calculate the supply chain-wide indirect inputs (i.e., the intermediate inputs) for province *m*'s final demand, $\mathbf{Zm}=\mathbf{AB}\widehat{\mathbf{Y}^{m}}$ as:

$$\begin{bmatrix} \mathbf{Zm}^{11} & \ldots & \mathbf{Zm}^{1m} & \ldots & \mathbf{Zm}^{1g} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ \mathbf{Zm}^{m1} & \ldots & \mathbf{Zm}^{mm} & \ldots & \mathbf{Zm}^{mg} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ \mathbf{Zm}^{g1} & \ldots & \mathbf{Zm}^{gm} & \ldots & \mathbf{Zm}^{gg} \end{bmatrix} = \begin{bmatrix} \mathbf{A}^{11} & \ldots & \mathbf{A}^{1m} & \ldots & \mathbf{A}^{1g} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ \mathbf{A}^{m1} & \ldots & \mathbf{A}^{mm} & \ldots & \mathbf{A}^{mg} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ \mathbf{A}^{g1} & \ldots & \mathbf{A}^{gm} & \ldots & \mathbf{A}^{gg} \end{bmatrix} \times \begin{bmatrix} \mathbf{B}^{11} & \ldots & \mathbf{B}^{1m} & \ldots & \mathbf{B}^{1g} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ \mathbf{B}^{m1} & \ldots & \mathbf{B}^{mm} & \ldots & \mathbf{B}^{mg} \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ \mathbf{B}^{g1} & \ldots & \mathbf{B}^{gm} & \ldots & \mathbf{B}^{gg} \end{bmatrix} \times \begin{bmatrix} \mathbf{Y}^{1m} & \ldots & 0 & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & \ldots & \mathbf{Y}^{mm} & \ldots & 0 \\ \ldots & \ldots & \ldots & \ldots & \ldots \\ 0 & \ldots & 0 & \ldots & \mathbf{Y}^{gm} \end{bmatrix} \tag{3-6}$$

where $\mathbf{Zm}^{nm}$ is the indirect inputs for local production of province *m*'s final demand; $\mathbf{Zm}^{mn}$ ($n\neq m$) is the indirect inputs exported to other provinces for the external production of province *m*'s final demand; $\mathbf{Zm}^{nh}$ ($n\neq m$ and $h\neq m$) is the indirect inputs between other provinces for the external production of province *m*'s final demand.

Under the NTS, we assume the final demand of province *m* would not change, but all the outputs of its final demand (i.e., direct final demand $\mathbf{Y}^{m}$ plus indirect inputs $\mathbf{Zm}$) would be provided by province *m* itself. The reallocation of direct final demand is straightforward: we sum up the direct final demand by province, i.e., $\mathbf{Y}'^{m}=\sum_{n=1}^{g}\mathbf{Y}^{nm}$. The international import of final demand is allocated into each sector by the sectoral share in $\mathbf{Y}'^{m}$. To reallocate the indirect inputs for the production of province *m*'s final demand, we consider the distinctions of production structures and coefficients between provinces. The indirect inputs for province *h*'s production of province *m*'s final demand (i.e., $\sum_{n=1}^{g}\mathbf{Zm}^{nh}$) is proportionally reallocated into province *m* itself according to local technical coefficients, i.e., $\mathbf{D}^{m}\sum_{n=1}^{g}\mathbf{Zm}^{nh}/\mathbf{D}^{h}$, where $\mathbf{D}$ is the local technical coefficient matrix. Meanwhile, we also generate the national average technical coefficient of product *i* for one-unit output of product *j* to reallocate the indirect inputs to province *m* itself in any case that province *m* requires all the production requirements of product i from other provinces. The indirect inputs for the local production of province m's final demand under the NTS is:

$$\mathbf{Z'}^{m} = \sum_{h=1}^{g} \mathbf{D}^{m} \sum_{n=1}^{g} \mathbf{Zm}^{nh} / \mathbf{D}^{h} \tag{3-7}$$

The total outputs of province m under the NTS are:

$$\mathbf{x'}^{m} = \mathbf{Z'}^{m}\mathbf{i} + \mathbf{Y'}^{m} \tag{3-8}$$

We can see that under the NTS, not only the final use part of trade was removed, but also production upstream in the supply chain was shifted to the province of final use.

The next step is to apply the provincial constraints like resources or labour force in the NTS (Duchin 2007, Wu et al. 2021b). We consider three production factors as the main constraints in our NTS, i.e., land, blue water availability, and labour force. The hypothetical provincial economic production capacities under the NTS should be constrained by their territorial production factor endowments.

$$\mathbf{f}_{cs}^{m}\mathbf{x'}^{m} \leq F_{cs}^{m} \tag{3-9}$$

where $\mathbf{f}_{cs}^{m}$ is the vector of direct coefficient of constraint factor cs (e.g., km^2 per unit of the output for land) for each sector. F_{cs}^{m} is the provincial endowment of constraint factor cs. Provincial land endowment, blue water availability, and employment data are collected from the National Bureau of Statistics of China (NBSC 2020). If $\mathbf{f}_{cs}^{m}\mathbf{x'}^{m}$ exceed any provincial factor endowments, we use a scaling factor $F_{cs}^{m}/(\mathbf{f}_{cs}^{m}\mathbf{x'}^{m})$ to scale down $\mathbf{x'}^{m}$. $\mathbf{Z'}^{m}$ and $\mathbf{y'}^{m}$ are further balanced using RAS method (Günlük-Şenesen and Bates 1988).

The total BWC of province m under the NTS is:

$$W'^{m} = \mathbf{f'}^{m}(\mathbf{I} - \mathbf{Z'}^{m}\widehat{\mathbf{x'}^{m}}^{-1})^{-1}\mathbf{Y'}^{m} \tag{3-10}$$

The difference between W^{m} and W'^{m} represents the contribution of province m-related trade to the national blue water consumption (CNW). A positive value indicates that province m-related trade increases the national BWC, and vice versa for a negative value of CNW^{m} .

3.2.4. Blue water scarcity index

The blue water scarcity index of province m with and without trade (WSI^{m} and WSI'^{m}, respectively) are calculated as the ratio of BWC in province m with and without trade (W^{m} and W'^{m}, respectively) to the average annual blue water availability (WA^{m}), respectively (**Eq. 3-11** and **Eq. 3-12**):

$$WSI^m = \frac{W^m}{WA^m} \tag{3-11}$$

$$WSI'^m = \frac{W'^m}{WA^m} \tag{3-12}$$

The differences between the two water scarcity indices represent the effects of virtual water trade in terms of increasing (i.e., $WSI^m > WSI'^m$) or mitigating (i.e., $WSI^m < WSI'^m$) the water scarcity in province *m*. Low, moderate, severe, and extreme water scarcity levels are typically defined as previous studies did (Zhao et al. 2015). The details about water scarcity level of each province are illustrated in **Figure 3-1** and **Table B-1** in **Appendix B**.

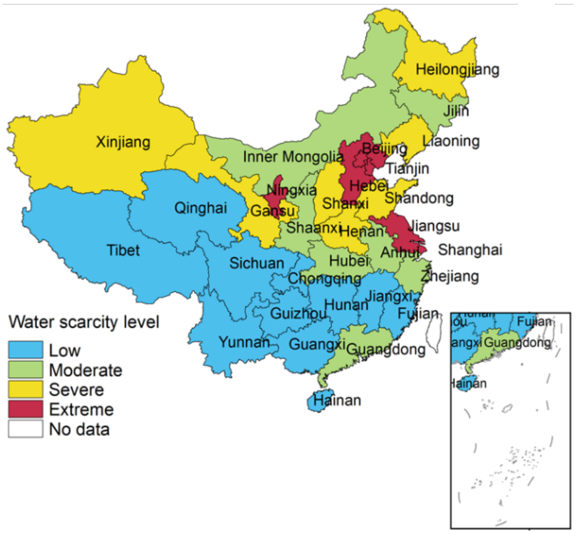

Figure 3-1. Geographical location of each province in China as well as local water scarcity level for the year 2012.

3.2.5. Data sources

The main data sources elaborated in this section include the data sources of multi-regional input-output tables, irrigational BWC of agricultural products, BWC of economic sectors, and annual blue water availability by province.

The hybrid MRIO model developed in **Chapter 2** is used in this study. It describes the Chinese economy by 84 agricultural biomass and food commodities and 42 monetary economic sectors in physical (such as tonnes, heads, or m^3) and monetary units at the provincial level for the year 2012. They particularly disaggregated the two highly-aggregated agri-food-related sectors included in the original 42 economic sectors (Mi et al. 2017a), i.e., sector "Agriculture, forestry, animal husbandry and fishery products and services" and sector "Food and tobacco manufacturing", into 84 individual agricultural biomass and food commodities in physical terms. 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.

The total irrigational BWC of each crop in each province is calculated by the provincial crop production multiplied by its average blue water content (in m^3 per ton). The average blue water content of crops are estimated at 5 × 5 arc-minute grid level following the accounting framework of Hoekstra et al. (2011), which are comprehensively described in **Appendix A.5**.

Provincial BWC of five main economic sectors, i.e., irrigation, animal husbandry, industry (including electricity generation), services (including construction), and household, are partially available in the provincial Water Resource Bulletin for the year 2012 (see **Table A-6**). To fill the data gaps of agricultural BWC in the provinces without available data, we use the national BWC coefficient to estimate local BWC of agriculture. For electricity generation sector, we calculate the average BWC coefficient of electricity generation sector in the provinces with available BWC data, and apply the average BWC coefficient in other provinces. For other industrial sectors, we rely on the national BWC data as well as the provincial water withdrawal data of each sector from Chinese Economic Census Yearbook (2008). We allocate the national BWC of each sector to provinces by the provincial water withdrawal. Here we assume that the more water withdrawn for sectoral production, the more water consumed by that sector. After that, we scale the adjusted industrial BWC into the actual industrial BWC in 2012. For construction sector, we calculate the average BWC coefficient of construction sector in the provinces with BWC data, and apply the average BWC coefficient in other provinces. For household BWC, we calculate the per-capita BWC by the provinces with available data and estimate the household BWC in provinces without available data based on the per-capita BWC and local population. The average annual blue water availability of province m is calculated from annual water availability data for the period 2007-2017 collected from the provincial Water Resource Bulletin (2012).

3.3. Results

3.3.1. Disaggregation of total blue water consumption

At the national scale, blue water is mainly consumed to produce goods and services for local final demands (i.e., without either inter-provincial or international trade) as well as for household use, which together account for 52% of the national BWC (the pie chart in **Figure 3-2**). This can be explained by the relative larger population in China and the higher domestic consumption of water-intensive food products such as rice, maize, and pork by local population (FAOSTAT 2020). Among all the trade activities, direct final goods trade makes the largest contribution to national BWC (19%), while the other three, intermediate goods trade for the last stage of local production, direct global export, and value chain-related trade, account for 15%, 7%, and 7%, respectively. At the provincial level, Xinjiang, Jiangsu and Heilongjiang are the top three provinces with the largest BWC in 2012, while Beijing, Tianjin and Qinghai have the lowest BWC. The BWC profile in each province has quite different features (the bar chart in **Figure 3-2** and **Table B-2**). The share of local activities in provincial BWC is only 23% in Hainan, in contrast, this figure in Shaanxi is 77%. Hainan has the largest share of both intermediate goods trade and value chain-related trade in its BWC, accounting for 35% and 17%, respectively, whereas Beijing has the lowest, for 7% and 2%, respectively. Direct final goods trade shows a high share in the BWC of provinces, e.g., Xinjiang (34%), Gansu (26%), and Heilongjiang (25%). From the production perspective, highly-developed provinces like Beijing or Shanghai mainly produce to satisfy local demand, and at the same time, import resource-intensive products either as intermediate inputs for local production or direct final products; these imports stem from less-developed provinces such as Xinjiang or Heilongjiang. As for global exports, coastal provinces like Zhejiang (24%), Guangdong (17%), Jiangsu (15%) and Fujian (15%) have relatively higher shares in their BWC compared with the national total.

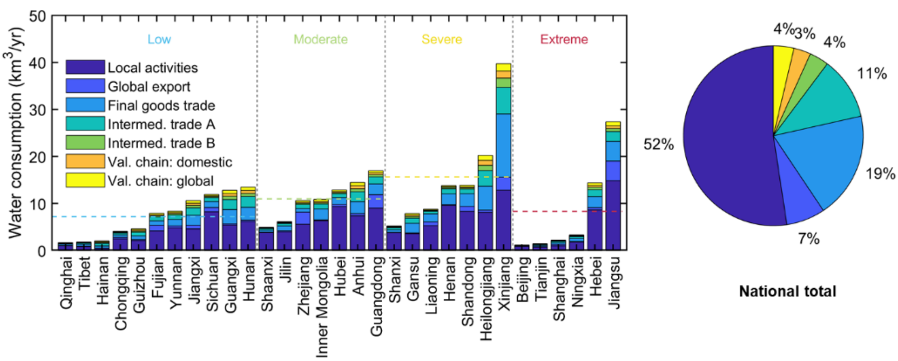

Figure 3-2. **Provincial (bar chart) and national (pie chart) blue water consumption (BWC) profile by economic activity in 2012.** The horizontal dashed lines in the **bar chart** represent the average BWC of provinces under the same water scarcity level. Local activities include the production of local final demand, and household activities. Global export indicates the direct final goods exported to foreign countries; final goods trade, intermediate goods trade for the last stage of production (Intermed. trade), and value chain-related trade (Val. chain) indicate different trade patterns of inter-provincial trade. Particularly, intermediate goods trade A and B represent the trade of intermediate products for the last stage of production for final demand of the trade partner and of the trade partner's trade partners, respectively.

Our results also reveal that local water scarcity level possibly plays a role in the provincial BWC profile. That is, provinces under moderate and extreme water scarcity have relatively higher share of local activities in their BWC (58% and 56% as averages, respectively) compared with the national total, whilst provinces under low water scarcity have relatively higher shares of trade-related activities in their BWC (particularly for intermediate goods trade, and value chain-related trade). This indicates that the economic structure of provinces could be influenced by the endowments of local resources such as water, and the marginal costs of economic production in water-scarce provinces would increase faster than those in water-abundant provinces, similar to the carbon emission reduction found in Feng et al. (2013). Provinces under severe water scarcity do not show similar profiles: for Xinjiang and Heilongjiang, they have higher shares of final goods trade and intermediate goods trade, together accounting for 51% of these two provinces' BWC; while for others (i.e., Shanxi, Gansu, Liaoning, Henan, and Shandong), a higher share of local activities is observed (62% on average). Last but not least, the average total BWC of provinces under severe and moderate water scarcity are higher than that of provinces under extreme and low water scarcity. In addition to the two agriculture-dominated provinces, i.e., Xinjiang and Heilongjiang, other provinces under severe and moderate water scarcity like Guangdong, Anhui, Hubei, and Zhejiang are all economically developed and populous provinces with high blue water requirements for their production of exports and finished goods, and for local household use.

3.3.2. Provincial balance of virtual water flows by trade pattern

Traditional debates on the displacement of environmental pressures (e.g., carbon emissions) from the consumption sites to the producers are also observed for this water case of China (**Figure 3-3A**). Provinces with high BWC, Xinjiang and Heilongjiang for instance, are those with large net water exports (i.e., $\sum_{n=1}^{g} NVW^{mn} > 0$), whereas consumption-oriented provinces, such as Zhejiang, Guangdong, Beijing, Tianjin and Shanghai, show net virtual water import (i.e., $\sum_{n=1}^{g} NVW^{mn} < 0$). The top three provinces with the largest net virtual water exports are Xinjiang (22.4 km^3/yr), Heilongjiang (8.3 km^3/yr), and Guangxi (4.3 km^3/yr), whereas the top three provinces with the largest net water imports are Shandong (10.5 km^3/yr), Zhejiang (6.5 km^3/yr), and Guangdong (5.3 km^3/yr). Among these six provinces, only Guangxi is under low water scarcity level. As for other provinces, generally, provinces under moderate and severe water scarcity have net virtual water imports, while provinces under low water scarcity have net virtual water exports. The number of provinces with net virtual water exports or imports under extreme water scarcity is equal in our analysis. Furthermore, provinces like Jiangsu (under extreme water scarcity), Hubei and Inner Mongolia (both under moderate water scarcity) have relatively high BWC yet low net virtual water flows. To explain this, a high share of local activities in their BWC (**Figure 3-2**) is one factor, the

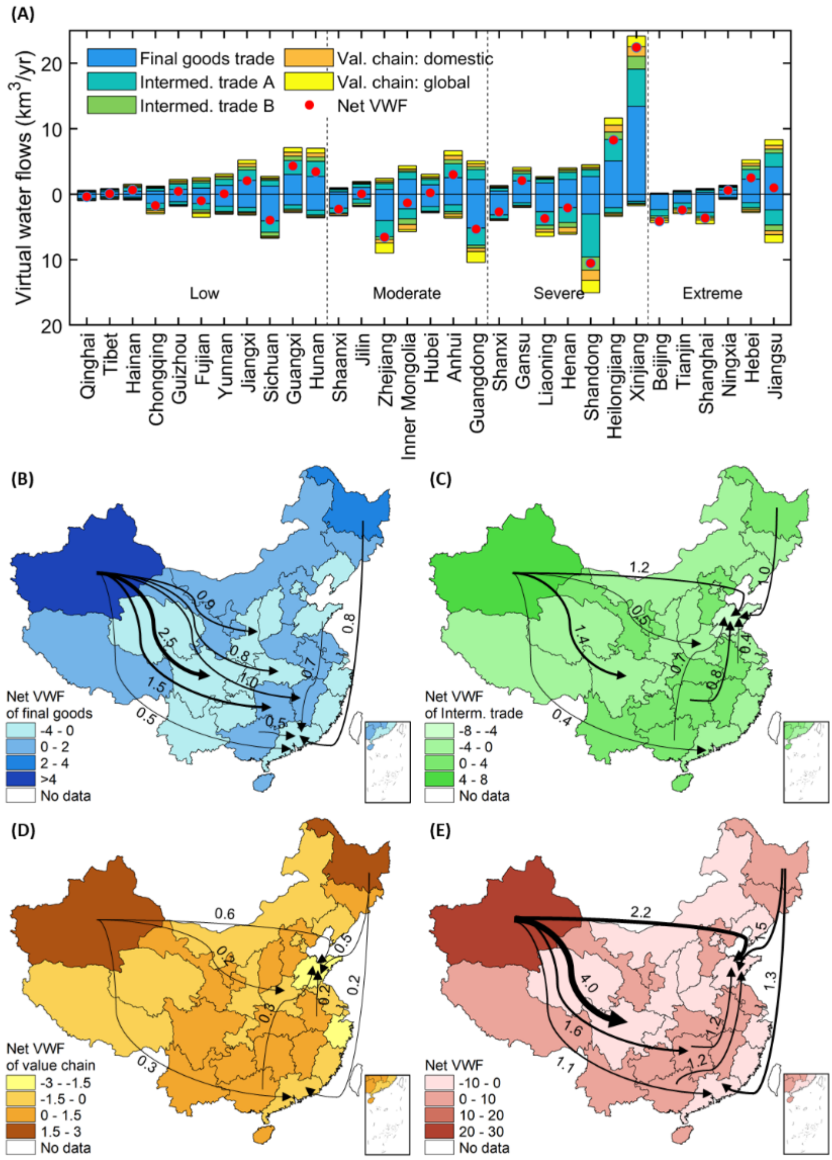

Figure 3-3. Virtual water flows related to the exports (above the abscissa in A) and imports (below the abscissa in A), as well as the largest net virtual water exports (red dots in A, and arrow lines in B-E) of 31 provinces in China for year 2012. Final goods trade, intermediate goods trade for the last stage of production (Intermed. trade), and value chain-related trade (Val. chain) indicate different trade patterns of inter-provincial trade. Particularly, intermediate goods trade A and B represent the trade of intermediate products for the last stage of production for final demand of the trade partner and of the trade partner's trade partners, respectively. The negative values in panels **B**-**E** indicate that the associated provinces have net virtual water imports. Unit in panels **B**-**E** is km³ per year.

almost even import and export of virtual water is another. It implies that these provinces also act actively in national commodity markets for more bilateral and multilateral collaboration with other provinces, and thus are also important in shaping the virtual water network within China.

The geographical distributions of net water flows related to intermediate goods trade (**Figure 3-3C**), value chain-related trade (**Figure 3-3D**) as well as the total net water flows of all trade patterns (**Figure 3-3E**) are similar within China, whilst that related to final goods trade (**Figure 3-3B**) shows some differences. Provinces with total net water exports are Xinjiang, Heilongjiang, and those located in the central and southwestern China, whereas provinces with total net water imports are Shandong, Sichuan and those located in southeastern and northern China. In similar distributions with that of the total net water flows, we further find that Xinjiang (7.2 km^3/yr and 2.8 km^3/yr, respectively), Heilongjiang (3.5 km^3/yr and 1.7 km^3/yr), and Hunan (2.1 km^3/yr and 1.1 km^3/yr) are the top three provinces with the largest virtual water exports related to intermediate goods trade and value chain-related trade, whereas Shandong (7.4 km^3/yr and 2.9 km^3/yr) and Zhejiang (1.8 km^3/yr and 1.5 km^3/yr) are the top two provinces with the largest virtual water imports related to these two trade patterns. The distribution of the net virtual water flows related to direct final goods trade is a little bit different from those related to other trade patterns. That is, provinces with large virtual water imports of direct final goods trade are those with high level of economic development like Zhejiang (3.3 km^3/yr), Guangdong (2.9 km^3/yr), and Shanghai (2.4 km^3/yr), or with large population like Sichuan (2.8 km^3/yr). From the export perspective, in addition to Xinjiang (12.4 km^3/yr) and Heilongjiang (3.0 km^3/yr), provinces like Jiangsu (1.8 km^3/yr), Guangxi (1.4 km^3/yr) and Hebei (1.1 km^3/yr) also show large net virtual water outflows of direct final goods trade within China.

Our results also find that direct final goods trade contribute the most to the net virtual water flows within China (accounting for 42% of the total), whereas value chain-related trade induces the least (19%), the rest are associated with the intermediate goods trade (39%). First, the total net water flows embodied in bilateral trade are mainly from Xinjiang to Sichuan and Shandong for fruits and cotton seeds while to Hunan for livestock, as well as from Heilongjiang to Shandong and Guangdong, and from Hunan and Guangxi to Shandong for agri-food products. Direct final goods trade is the major driver of the net virtual water flows. The net virtual water flows embodied in the direct final goods trade are largely from Xinjiang to Sichuan, Hunan, Jiangxi, Shaanxi and Hubei, as well as from Heilongjiang, Shandong, Guangxi and Xinjiang to Guangdong. The major traded commodities are also cotton seeds, fruits, and livestock from Xinjiang, while agri-food products to Guangdong. The net virtual water networks of intermediate goods trade and value chain-related trade look similar to that of the total net water flows. For the former trade pattern, the largest embodied water flow is from Xinjiang to Sichuan mainly for cottonseeds and live animals; moreover, Shandong is distinct for the net virtual water flows embodied in the intermediate goods trade (7.4 km^3), of which 76% is consumed for the last stage of Shandong's production to satisfy the final demand of local population while the rest is consumed for producing goods and services finished by Shandong's trade partners (**Figure 3-3A**). Although value chain-related trade induces the less virtual water flows within China, it is the most complicated trade pattern and hard to be captured. In our analysis, we find that provinces with high virtual water inflows or outflows, notably like Xinjiang and Heilongjiang (for outflows) as well as Shandong, Zhejiang and Guangdong (for inflows), are all with relatively large virtual water flows related to the value chain-related trade (**Figure 3-3A**). It indicates that these provinces are critical to link the intermediate production and product trade that cross borders many times through inter-provincial trade before final products are consumed by the end users, and thus play significant roles in shaping the virtual water network of value chain trade pattern. The associated virtual water flows are mainly from Xinjiang to Shandong and Guangdong for cotton lint and textile-related products, as well as from Heilongjiang to Shandong and Guangdong and from Guangxi to Shandong for agri-food products.

3.3.3. Effects of trade on provincial blue water consumption and water scarcity

As one of the main commodity-exporting countries, the current trade, both inter-provincial and international, benefits China's economic growth yet with more resource consumption. Under the NTS, China's total outputs would decrease \$4.3 trillion 2012 US dollars (accounting for 16% of the actual national outputs), as a consequence, the national total BWC would decrease 27.4 km^3/yr (accounting for 9% of the actual national BWC). This hypothetical deceleration of China's BWC would substantially mitigate the water scarcity in most provinces, particularly in the provinces under moderate and severe water scarcity (**Figure 3-4A**, and **Table B-3** for province-specific changes). Under the NTS, all provinces are self-sufficient for their finished goods and services, the water scarcity level would reduce (compared to the with-trade case) in seventeen provinces (mostly with net virtual water export like Xinjiang, Heilongjiang, Anhui, Hunan, and Guangxi), whereas it would increase in other fourteen provinces (mostly with net virtual water import like Zhejiang, Guangdong, Sichuan, and Beijing). Out of these fourteen, there are six provinces which are already under severe (Shanxi) or extreme water scarcity (Jiangsu, Ningxia, Beijing, Tianjin, and Shanghai) in reality, indicating that the current inter-regional trade only partially relieves water scarcity in these provinces, including Beijing and Tianjin which are the economic centers of North China meanwhile with limited available water resources.

Our results also reveal that the current trade has influenced the inequality of water scarcity among provinces within China, particularly for the inequality among provinces under low, moderate and

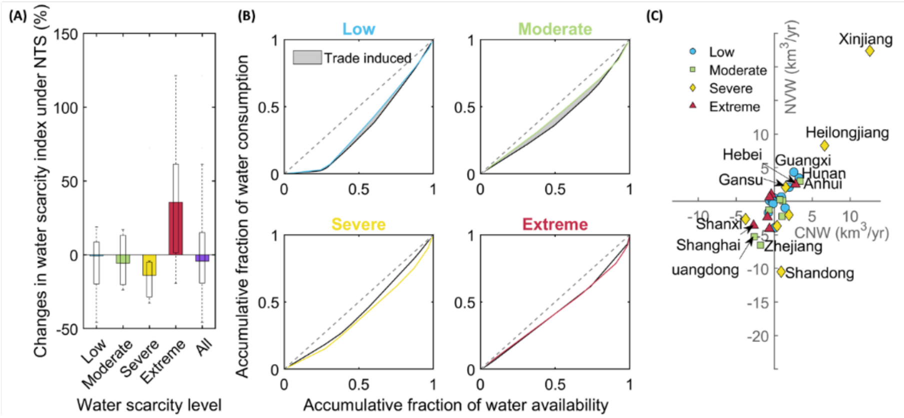

Figure 3-4. Effects of trade on the changes in provincial water scarcity index (A) and provincial inequality (B) by water scarcity level, and the trade-related environmental performance of each province on the national and provincial blue water consumption (C). Panel **B** illustrates the cumulative fraction of water availability against cumulative fraction of water consumption of provinces under the same water scarcity level, sorted by increasing magnitudes of water scarcity index. The deviation between the curved line (black for current with-trade situations while colorful for the NTS) and the diagonal dashed line (of perfect equality) indicates the provincial inequality of water scarcity. NVW and CNW in panel **C** are the net virtual water flows and the contribution to the national BWC, respectively.

severe water scarcity (**Figure 3-4B**). Specified previously, high inequality of spatial water scarcity among provinces exists in China (Ma et al. 2020, Zhao et al. 2015), which is also confirmed in this study (**Figure B-1**, **Appendix B**). As illustrated in **Figure 3-4B** and **Figure B-1**, the curves of cumulative fractions of water consumption and water availability (sorted in an ascending order of the provincial water scarcity indices) are far from the diagonal dashed line (representing perfect water consumption equality), which implies the high inequality in spatial water scarcity within China. Although effects of current trade on changing the inequality among all 31 provinces is slight, the associated effects on changing the inequality among provinces under low, moderate and severe water scarcity are visible. For the provinces under low and moderate water scarcity, the current trade has increased the water scarcity inequality among them, whereas for the provinces under severe water scarcity, current trade has decreased the water scarcity inequality among them. The reason is that provinces with relatively larger (smaller) water scarcity indices under low or moderate water scarcity are those with net virtual water exports (imports), such that under the NTS, their BWC would reduce (increase) and the associated water scarcity indices would reduce (increase). The situations among provinces under severe water scarcity are different, mainly because Henan and Liaoning are two provinces with relatively lower water scarcity which would further reduce their BWC under the NTS. The effects of current trade on the water scarcity inequality among provinces under extreme water scarcity is small.

We further examine the trade-induced environmental performances of each province on the provincial (by NVW) and national blue water consumption (by CNW). As illustrated in **Figure 3-4C**, by selecting CNW as the horizontal axis and NVW as the vertical axis, 31 provinces are sorted into four categories (or quadrants). Distinctly as the provinces located in the upper right quadrant, such as Xinjiang, Heilongjiang, Anhui, and Hunan, the trade related to these provinces increases both provincial and national BWC. Ideally as the provinces located in the lower left quadrant, mostly are affluent provinces like Shanghai, Zhejiang, Beijing and Tianjin, of which the related trade contributes to a reduction in both provincial and national BWC. Other provinces like Shandong, Jiangsu, and Henan have different environmental performances on the local provincial BWC and the national total. For the future water resource utilization and management towards sustainability, attention should be paid to the provinces in the upper right quadrant. It was already known that the virtual water exports of these provinces are mainly driven by final demand for some low-value-added but water-intensive agricultural (e.g., rice, wheat, cotton seeds, and fruits) and food products (e.g., livestock). Considering that future per-capita incomes in China could further increase and the diet of Chinese could be more westernized, the requirements of these agri-food products could be growing. Thus, it would be more critical for these provinces to sustainably use the limited water resources in the locals, meanwhile to contribute to the food security of China.

3.4. Discussion

We have assessed the effects of production fragmentation and trade on provincial blue water consumption and scarcity in China using an improved trade disaggregation approach and a novel "no-trade" scenario. In this section we first reflect on the potential implications of this study's finding for water management and policy making in China. Subsequently, we address the limitations of this study and provide recommendations for future research.

3.4.1. Potential policy implications

Although current trade alleviates the water scarcity in provinces under extreme water scarcity, it is worsening the water scarcity of this nation from a broader scope, i.e., the national water scarcity would be less if there is no trade. This finding is consistent with the previous analysis by Zhao et al. (2018), Zhao et al. (2015), and Zhuo et al. (2016). Given that future inter-provincial trade will further increase due to the development of multiple urban agglomerations (e.g., Jing-Jin-Ji, the Yangtze River Delta, and the Pearl River Delta) in China, the embodied virtual water flows will also be intensified. Previous policy suggestions for water saving and water scarcity alleviation mainly focused on supply-side measures, by putting caps to water consumption by river basin (Mekonnen and Hoekstra 2016), increasing water-use efficiencies of sectors (Zhou et al. 2020), and better sharing of the limited freshwater resources (Zhao et al. 2015). Based on our more accurate trade disaggregation, the purpose of traded commodities like for final consumption or as intermediate inputs for further production, and the effects on provincial water consumption and scarcity in China are now better understood. This knowledge can be used to consider re-organization of production sites and trade patterns among provinces to affect spatial water consumption and scarcity patterns. We have shown that the final demand-related trade contributes the largest part of China's virtual water flows (**Figure 3-2**), and is mainly related to agri-food products. The first suggested measure is to enhance local production of final commodities or decrease the final demand of water-intensive products like livestock, especially in provinces with high final goods-related virtual water import such as Guangdong, Jiangsu, and Sichuan. For provinces currently under extreme water scarcity like Beijing, Tianjin or Shanghai, their development under NTS would increase local water scarcity (as shown in **Figure 3-4A**); thus to enhance the trade with adjacent provinces or co-development with adjacent provinces will be the potential measures to improve their self-sufficient capacities as well as decrease the economic and resource cost for trading products. To optimize spatial cropping patterns with more production in rainfed areas for primary crops like rice, wheat and maize, or in places with higher irrigation efficiencies relying on more advanced irrigation technologies would also be potential options (Chouchane et al. 2020). A recent study showed that the massive investment on irrigation infrastructure in water-scarce regions of China during the period of 2002-2017 has driven a substantial reduction in the BWC of staple crops (Huang et al. 2021). Yet, how to formulate the cropping patterns should consider multiple social-economic-environmental factors to avoid the extra increasing in BWC due to the rebound effects arising from the improvement in water productivity and economic benefits by extending farming areas. This may be more important for less developed provinces located in the northwestern (with a relatively slow-growing economy and serious water shortages), central and northeastern China (major provinces for blue water export). The last is to promote better measures of water conservation, unconventional water resources (e.g., rainwater, seawater or reclaimed water), and industry productivity locally by all parties. This would help decrease national water use and enhance industrial commodity supplies in locals. For household BWC, which accounted for 9% of the national total in 2012, we suggest that formulating a rational water price system in urban areas as well as better managing the self-withdrawn groundwater in rural areas would be the options to reduce this part BWC.

Literature estimating water use and virtual water flows in different terms, such as "water withdrawal" (Liu et al. 2019, Zhao et al. 2015) or "water consumption" (Dalin et al. 2014, Zhuo et al. 2016), may come up with quite different policy suggestions. Estimating water use in "water withdrawal", Liu et al. (2019) found that electricity generation sector was another key sector in addition to agriculture sector with high water withdrawal in China, and then suggested future measures to reduce water withdrawal by shifting electricity generation system into air cooling systems. It is true that electricity generation sector abstracts a large quantity of water for cooling purpose. In Jiangsu for instance, water withdrawal by electricity generation sector (14 km^3/yr) was around three times of that by other industrial sectors (5 km^3/yr). Yet, the actual water consumption (i.e., loss of water from the available ground-surface water body in a catchment area) of this sector is relatively low in China (around 10% of its water withdrawal), and has been decreasing by adopting air-cooling or seawater-cooling technologies (Zhang et al. 2018). Other key sectors in addition to agriculture with high "water consumption", e.g., chemical industrial sector, metal smelting and rolling sector, and food manufacturing sector, should be paid more attention to for China's green-economic transition in future. Furthermore, other literature also weighted virtual water flows with the "water scarcity" concept and estimate as scarce virtual water flows (Feng et al. 2014, Liao et al. 2020, Zhao et al. 2018). The interdependence between "water scarcity index" and "water use" would make this indicator estimated based on a main assumption that "water scarcity index" is an independent and unchanged variable. Therefore, in some cases, the interpretation of scarce virtual water flows would be controversial, and hard for comparison with other studies.

3.4.2. Limitations and future work

The almost 10-year time lag of our analysis (for year 2012) should be noted when interpreting the main results. The most recent year for which inter-provincial MRIO tables of China are known is 2015 (Li et al. 2020, Zheng et al. 2020), but with high uncertainty arising from the main assumptions on provincial production structures and inter-provincial trading patterns in order to fill the data gap of actual inter-provincial transactions across industries. On the other hand, the hybrid MRIO model (**Chapter 2**) relies on food and agricultural biomass input-output model that is developed based on the production, trade and use data of crops, livestock, and foods from FAOSTAT, which only reported the associated data with high reliability by the year 2013. While other production and consumption data of crops, livestock and food products were also relatively comprehensively recorded for year 2012 by the Chinese National Bureau of Statistics. We also realized that where data on macro-economic structure in general do bear uncertainty and are experienced to undergo changes until far after the year of reference, the main results on virtual water trade networks are largely robust to such uncertainty. Therefore, we stick to use the best available MRIO tables of Mi et al. (2017a) and carry out this study in 2012. Lastly, the distribution of freshwater resources within the nation as well as the economic structures especially for main water-consuming provinces like Xinjiang, Jiangsu and Heilongjiang have not changed significantly in the past decades (NBSC 2020). The main water scarce regions are still located in the North (Beijing, Tianjin, and Hebei), Northeast

(Heilongjiang, Jilin and Liaoning) and Northwest (Ningxia, Xinjiang, and Gansu) China. Thus, the analysis of current virtual water networks associated different trade pattern may have small changes as 2012 did. Yet we still believe a more recent analysis of trade effects on national or provincial water consumption and water scarcity changes will be more reliable for future policy and decision making.

There exist other potential limitations in this study. To better simulate provincial economic structure and consumption patterns under the NTS, we need to analyze the changes in product-specific production, trade and consumption by one province. In this context, time-series MRIO tables should be constructed. Based on that, we could capture the key products that are increasingly imported to substitute associated products that are previously produced by the province itself. Yet, if we rely on the monetary MRIO table (in a relatively low resolution of sectors or product categories) to develop the no-trade scenario, although with high uncertainty, this misallocation issue (i.e., misallocating the products to the consumers that cannot produce them locally) may not influence the results by a big margin. When associated products, like crops, fruits and livestock, are aggregated into few product categories, the hypothetical inputs and outputs of these categories would be determined by the main crops that dominate local production. Future studies could focus on establishing such a database with time-series product-specific MRIO tables that give sufficient information about the development of provincial and national economy. Second, in this NTS analysis we selected three production factors as the main constraints on the provincial production capacities under the NTS. It should be noted that the hypothetical results of economic production, human consumption, and water consumption would highly depend on the constraint factors applied in the NTS. Future work needs to apply more resource and social constraints on the NTS, especially for key production factors and inputs such as materials or fuels, to simulate the production and environmental impacts under the NTS more comprehensively. Lastly, trade also impacts on economic structure, consumption patterns, and technology development (Jiborn et al. 2018), and therefore on provincial BWC. However, the economic structure, consumption patterns, and technology development cannot be simulated dynamically based on a static MRIO model. Insights from dynamic economic modelling could, to some extent, generate assumptions for altered MRIO model parameters in simulating scenarios with trade scenarios. Further integrating the static MRIO model with a dynamic economic model, to some extent, can reduce the uncertainty from these factors in the hypothetical BWC modelling. This line of research is beyond the scope of this analysis but worth future explorations.

3.5. Conclusions

Production fragmentation has been changing the traditional production and consumption models of commodities as well as the associated resources inputs and pollution emissions. In this study we formulated a comprehensive trade disaggregation approach to elaborate the virtual blue water networks of three trade patterns (i.e., final goods trade, the trade of intermediate products for the last stage of production, and value chain-related trade) within China, and further examined the impacts of trade on provincial blue water scarcity by comparing the actual water scarcity with the hypothetical results under the NTS. In 2012, there was 128 km^3 blue water that virtually transferred among provinces because of inter-provincial trade. Direct final goods trade contributed the most to the virtual water trade (accounting for 47% of the total), whereas value chain-related trade induced the least (17%), the rest are associated with the intermediate goods trade (36%). Compared with results under the NTS, we found that the current trade, both inter-provincial and international, benefits China's economic growth yet with more resource consumption. Furthermore, the current trade has influenced the inequality of water scarcity among provinces within China, particularly for the inequality among provinces under low, moderate and severe water scarcity. Our analysis enables the consideration of specific trade patterns and their impacts on provincial and national water consumption to cope with water scarcity in China, such as enhancing local production of final commodities or decreasing the final demand of water-intensive products like livestock, especially in provinces with high final goods-related virtual water import such as Guangdong, Jiangsu, and Sichuan, while promoting better measures of water conservation, unconventional water resources, and industry productivity locally by all parties.

3.6. Nomenclature

A	technical coefficient matrix
B	the Leontief inverse matrix
BAE	Balance of Avoided Emissions
BWC	blue water consumption
CNW	national blue water consumption
cs	constraint factor
D	local technical coefficients matrix
EX	a column vector representing international exports
f	a row vector representing blue water consumption coefficients of products and sectors
F	provincial endowments of constraint factors
F	a row vector representing direct blue water consumption of products and sectors
FAOSTAT	Food and Agriculture Organization Corporate Statistical Database
g	number of regions
h	a certain province in China
i	a certain product or sector
i	a summation vector of appropriate length
I	an identity matrix
L	local Leontief inverse matrix

m	a certain province in China
MRIO	multi-regional input-output
n	a certain province in China
non_n	other provinces in China except province *n*
NTS	no-trade scenario
NVW	net virtual water flows
T	a column vector representing exports from province
T_d	a column vector representing value chain-related trade of products finally absorbed by domestic provinces
T_f	a column vector representing trade of final products
T_g	a column vector representing value chain-related trade of products further processed and exported to foreign counties
T_i	a column vector representing trade of intermediate products for the last stage of production
T_v	a column vector representing value chain-related trade of products
W	total blue water consumption
W'	total blue water consumption under the no-trade scenario
W_EX	local blue water consumption embodied in the export
W_hh	blue water consumption for household purposes
WA	blue water availability
WSI	blue water scarcity index
WSI'	blue water scarcity index under the no-trade scenario
x	a column vector representing total outputs
x'	a column vector representing total outputs under the no-trade scenario
Y	a column vector representing final demands
Y'	a column vector representing final demand under the no-trade scenario
yr	year
Z	intermediate input matrix
Z'	intermediate input matrix under the no-trade scenario
Zm	a square matrix representing supply chain-wide indirect inputs for province *m*'s final demand

Linking Environmental Pressures of China's Capital Development to Global Final Consumption of the Past Decades and into the Future

Abstract

China's rapid growth was fueled by investments that grew more than ten folds since 1995. Little is known about how the capital assets acquired, while being used in productive processes for years or decades, satisfy global final consumption of goods and services, or how the resource use and emissions that occurred during capital formation are attributable to past or future consumption. Here, enabled by a new global model of capital formation and use, we quantify the linkages over the past two decades and into the future between six EPs caused by China's capital formation and domestic as well as foreign consumption. We show that only 35% of the assets acquired by China from 1995 to 2015, representing 32%-39% of the associated EPs (e.g., water consumption, GHG emissions, and metal ore extractions), have been depreciated, whilst the majority rest will serve future production and consumption. The outsourcing of capital services and the associated EPs are considerable, ranging from 14-25% of depending on the EP indicators. Without accounting for the capital-final consumption linkages across time and space, one would miscalculate China's environmental footprints related to the six EPs by big margins, from -61% to +114%..

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4.1 Introduction

In a period of unprecedented economic growth, China increased its share of world gross domestic product (GDP) from less than 2% in 1990 to nearly 15% in 2015 (The World Bank 2020). With investment accounting for 34-48% of the country's GDP since 1990, China produced or imported capital assets such as livestock for breeding, power plants, and communication networks, and computer software. The production of capital assets, however, typically requires more resources and generates more pollution than that of non-capital goods (Jiang et al. 2019, Tukker et al. 2016, Zheng et al. 2018). From 1995 to 2015, 22 million km^2 of land use, 630 km^3 of blue water consumption, 759 EJ (exajoules) of primary energy use, and 10 Gt (gigatonnes) of metal ore extractions were appropriated in China for its capital development, accounting for 15%, 21%, 41%, and 39% of the national totals, respectively; outside of China, another 16 million km^2 of land, 135 km^3 of blue water, 130 EJ of energy, and 7 Gt of metal ore extractions were associated with China's capital expansion (**Figures C-1** and **C-2**, **Appendix C**).

However, little is known about how significant environmental pressures (EPs) generated in capital assets production link to global final consumption, i.e., the satisfaction of human needs through the goods and services produced with the help of those assets. Conventionally, consumption-based accounting (CBA) is used to investigate the attribution of various EPs to the national final demand of products (i.e., goods and services), yielding the environmental footprints (EFs) of nations (Hertwich and Peters 2009, Wiedmann et al. 2015). The EFs of nations are thus the EPs occurring throughout the supply chain of goods and services allocated to the final consumption of those goods and services (Tukker et al. 2016, Wiedmann and Lenzen 2018). Historically, CBA was based on multi-regional input-output (MRIO) tables representing the production, trade, and consumption of products in a single year, so it could not represent the use of capital assets stretching over longer time periods. While CBA has become a crucial tool for assessing the sustainability, efficiency, and equity of resource use from the perspective of consumers and government (Tukker et al. 2016, Weinzettel et al. 2013), current CBA models fail to capture capital's role in production and consumption and hence misallocates the EPs embodied in capital assets (EP^K) in EF assessment. Unlike non-capital goods that are purchased for consumption, capital assets are bought to be used in productive processes. Therefore, intuitively, EP^K shall be allocated throughout the lifetime of the assets, i.e., over years or even decades, to those who consume the finished products made using the assets directly and indirectly, regardless of the geographical location of the assets or the final consumption. Neglecting capital's spatiotemporal features, conventional CBA models treat the purchase of capital assets in the same way as the purchase of non-capital goods, assigning EP^K to the purchasing country and the purchasing year (Gao et al. 2020).

Acknowledging the economic and environmental significance of capital, there have been a few endeavors to tackle the methodological and data challenges related to modeling capital assets as intermediate inputs used in production, also known as 'capital endogenization' in input-output analysis (Chen et al. 2018, Lenzen 1998, Södersten et al. 2020, Södersten and Lenzen 2020, Södersten et al. 2018a, Södersten et al. 2018b). Consistently, they show that the inclusion of capital as intermediate inputs leads to substantial re-distribution of carbon and material footprints across industries and countries. The implications are especially significant for countries featuring high capital investments and export, such as China, and the final consumption of services related to real estate, public administration, transport and storage, and education, which usually require a lot of material- and carbon-intensive capital assets, such as buildings and infrastructure (Södersten et al. 2020, Södersten et al. 2018a). However, the inter-temporal features of EP^K remain unaddressed since capital assets used for year *n*'s production and final consumption are of different age cohorts produced based on the production recipe, trade networks, and environmental intensities of year *n*, *n-1*, *n-2*, *n-3* …(Södersten et al. 2018a). Such temporal dynamics are inherent to the retrospective distribution of historically-generated resource use and emissions to current final consumption, and critical for understanding the temporal trends and thus the future needs of resources and emissions for capital formation.

By developing a new capital endogenization method that addresses the above temporality issue, we present a novel analysis on how China's capital development and the associated resource use and emissions over the past two decades (1995-2015) are linked to meeting the final consumption of China and other countries throughout this time period. Our analysis focuses on six indicators of environmental pressures: primary energy use, blue water consumption, land use, metal ore extractions, nonmetallic mineral mining, and greenhouse gas (GHG) emissions, because they represent priority resources and development goals in China and globally. With the linkages quantified, we then reassess China's environmental footprints. Our results indicate an urgent need to quantify and emphasize economic and environmental efficiency for the decision-making of capital use and investment.

4.2. Materials and methods

The new method for endogenizing capital in input-output analysis is achieved through three main steps:

(1) trace and allocate the contribution of year *t*'s capital investments to year *n*'s inter-industry production networks depicted by year *n*'s MRIO tables, obtaining $D^{K}_{t,n}$ ($t \leq n$);

(2) quantify the supply chain-wide EPs that were generated during the production of the capital inputs $D^{K}_{t,n}$ based on year *t*'s production structures and environmental intensities of production activities depicted by year *t*'s MRIO tables, obtaining ($F^{K}_{t,n}$);

(3) attribute $\sum_{t}^{n} F^{K}_{t,n}$ to year *n*'s final consumption based on year *n*'s production-consumption systems depicted by year *n*'s MRIO tables, obtaining $\sum_{t}^{n} EF^{K}_{t,n}$.

We describe the three steps in detail in the following sections. The MRIO tables are obtained from EXIOBASE 3 (Stadler et al. 2018), which offers a time series of MRIO tables and environmental intensity estimates ranging from 1995 to 2015 for 44 countries (28 EU member plus 16 major economies) and five rest of the world regions. EXIOBASE 3 offers MRIO tables with high level of consistent sectoral (200 products) and environmental (417 emission categories and 662 material and resources categories) detail.

4.2.1. Constructing the global capital consumption matrix $D^{K}_{t,n}$

The process to construct $D^{K}_{t,n}$ is composed of five segments. First, annual capital consumption from the capital investment times series is calculated. We modeled consumption in year *n* of asset *a* invested in year *t* by sector *s* in country *i* as capital depreciation ($D^{K}_{i,a,s,t,n}$) calculated using the geometric method (**Eq. 4-1**). The geometric method is a standard practice adopted by national and international statistical agencies and researchers for constructing capital consumption time series (O'Mahony and Timmer 2009). Geometric depreciation depicts each year the asset is depreciated by a constant percentage of the previous periods value. The capital consumption (depreciation) represents the gradual depreciation of assets via output generation, i.e., wearing out, getting lost or breaking down, or becoming obsolete through advances in technology or shifts in consumer demand.

$$D^{K}_{i,a,s,t,n} = \delta^{K}_{i,a,s}(1-\delta^{K}_{i,a,s})^{n-t} I^{K}_{i,a,s,t} \tag{4-1}$$

Capital investment values ($I^{K}_{i,a,s,t}$) and corresponding depreciation rates ($\delta^{K}_{i,a,s}$) are obtained from three macroeconomic datasets: EU KLEMS (2009 release and 2017 release) (EUKLEMS 2019), WORLDKLEMS (WORLDKLEMS 2019), and the Penn World Table (PWT) 9.1 (Feenstra et al. 2015). Details of the investment data and depreciation rates obtained from the three data sources, such as the classifications of the investing sectors and assets, are presented in **Appendix C.1**. For instance, Austria's annual capital investment data ($I^{K}_{Austria,t}$) are specified by 34 investing sectors and 10 assets, obtained from EU KLEMS (2017 release); the 34 sectors and 8 assets are further detailed in **Table C-3**, **Appendix C**. δ are constant throughout the years of our simulation (1995-2015), but vary by asset *a*, the capital investing sector *s*, and the capital investing country *i*. Note, we assume that the capital investing sectors are also the capital consuming sectors. Mathematically, $D^{K}_{i,t,n}$ is a two-dimension matrix variable with the same shape as $I^{K}_{i,t}$: sectors that invested and consumed assets are aligned by columns, assets are aligned by rows, while each element in $D^{K}_{i,t,n}$ is calculated through **Eq. 4-1**. All elements in the $I^{K}_{i,t}$ and $D^{K}_{i,t,n}$ are measured in million euros (€) of year *t*.

The second step is to link capital consuming sector *s* to capital producing sector *s** through capital asset *a*. Each element in the transformed $D^{K}_{i,t,n}$ matrix is $D^{K}_{i,s^*,s,t,n}$. Such a transformation is achieved through 'asset-capital producing sector' concordance tables created in a prior study (Södersten et al. 2018a). The capital producing sectors follow the 200-product sectoral classification adopted by EXIOBASE 3.

We then further distinguish the capital producing sectors to those located in country *i* and those outside of country *i*, i.e., capital assets that were imported. Such allocation is based on year *t*'s fixed capital formation matrix $Y^{K}_{i,t}$ available in EXIOBASE 3. $Y^{K}_{i,t}$ presents country *i*'s investment records in year *t*, specifying the expenditures across 200 sectors and 49 countries/regions. This step transforms the $D^{K}_{i,t,n}$ matrix again, expanding the number of rows (producing sectors) from 200 to 9800 (49×200). Throughout the second and third steps, the sum of all elements $D^{K}_{i,t,n}$ remains the same and the unit of each element is still million euros (€) of year *t*.

Next, we map the capital consuming sectors *s* that are defined in the macroeconomic datasets (e.g., 34 sectors in EU KLEMS 2017 release) to EXIOBASE 3's 200-product sectoral classification. Such transformation is based on the sector concordance tables created in a prior study (Södersten et al. 2018a). This step transforms $D^{K}_{i,t,n}$ to a matrix with 9800 rows specifying capital production across the world and 200 columns specifying capital consuming sectors in country *i*. The transformation does not change the sum of all elements in $D^{K}_{i,t,n}$ and the unit of each element is still million euros (€) of year *t*.

The final step in creating the global capital consumption matrix $D^{K}_{t,n}$ is to horizontally concatenate the aforementioned developed $D^{K}_{1,t,n}$, $D^{K}_{2,t,n}$, …, $D^{K}_{49,t,n}$ for each of the 49 countries/regions specified in EXIOBASE 3. $D^{K}_{t,n}$ is thus a 9800×9800 matrix with capital producing and capital consuming sectors along rows and columns, respectively; each element records the quantity of assets that were invested in year t and consumed (i.e., depreciated) in year n, measured in million euros (€) of year t.

4.2.2. Quantifying the supply chain-wide EPs attributable to the consumed capital assets

Eq. 4-2 calculates the supply chain-wide EPs that occurred in year t and is attributable to $D^K_{t,n}$:

$$F^K_{t,n}=\widehat{S}_t L_t D^K_{t,n}=\widehat{S}_t(I-A_t)^{-1} D^K_{t,n} \tag{4-2}$$

For any EP indicator (e.g., GHG emissions), S_t is a row vector of direct resource use or emissions intensities of economic activities (e.g., kg/million € of year t), specified by 200 sectors and 49 countries/regions (1×9800) and obtained from EXIOBASE 3. L_t is the Leontief inverse matrix (Leontief 1970), describing the supply chain-wide economic outputs associated with per unit finished goods and services in year t (9800×9800). L_t is calculated from A_t (9800×9800 in EXIOBASE 3) with each element $a_{i,j}$ representing the amount of intermediate input i directly required per unit of output j and a 9800×9800 identity matrix I.

$F^K_{t,n}$ is a 9800×9800 matrix. Aligned along the rows are the 9800 country-sector pairs that directly extracted resources or released emissions in year t while partaking in the supply chains of the capital assets produced in year t—the supply chain-wide connections are made through L_t. The 9800 columns specify the country-sector pairs that consumed the corresponding capital assets in year n, i.e., following the columns of $D^K_{t,n}$. Intuitively, $F^K_n=\sum_t^n \widehat{S}_t L_t D^K_{t,n}$ captures the supply chain-wide EPs that were generated from year t to year n when the capital inputs allocated to year n's production activities (i.e., $\sum_t^n D^K_{t,n}$) were produced. The unit of each element in $F^K_{t,n}$ and F^K_n, e.g., if the EP indicator is GHG emissions, is kg/year.

4.2.3. Re-assessing the environmental footprints (EFs)

From the consumption perspective, which is the key concept taken by environmental footprint accounting, F^K_n is ultimately attributable to final consumption in year n (Y^C_n). That is, the consumed capital ($\sum_t^n D^K_{t,n}$) and the associated EPs (F^K_n) are attributable to production activities in year n (x_n), and those production activities ultimately serve for final consumption in year n. Thus, we calculate the environmental intensities of year n's production activities owing to capital consumption as S^K_n (**Eq. 4-3**).

$$S^K_n=\varphi F^K_n \widehat{x}_n^{-1} \tag{4-3}$$

x_n is a 1×9800 column vector that records economic outputs of the 9800 country-sector pairs in year n, obtained from EXIOBASE 3 and measured in million euros (€) of year n. φ is a 1×9800 summation vector of ones. S_n^K is a row vector describing the resource use or emission intensities for the 9800 country-sector pairs that consumed $\sum_t^n D_{t,n}^K$ in year n. The unit of each element in S_n^K, e.g., if the EP indicator is GHG emissions, is kg/million € of year n.

We can then reassess the environmental footprints of countries (**Eqs. 4-4** and **4-5**):

$$EF_n^K = S_n^K L_n \; Y_n^C \tag{4-4}$$

$$EF_n = EF_n^C + EF_n^K + EF_n^{HH} = S_n \; L_n \; Y_n^C + EF_n^K + EF_n^{HH} \tag{4-5}$$

The final consumption matrix Y_n^C (9800x49) is obtained from EXIOBASE 3 and describes the finished goods and services, specified by the 9800 country-sector pairs, that are consumed by 49 countries/regions in year n. EF_n^K a 1x49 vector, captures the historical EPs that are attributable to Y_n^C owing to the capital consumption attributable to year n's production activities ($\sum_t^n D_{t,n}^K$). EF_n^C (1×49) captures the EPs that occurred in year n and are attributable to Y_n^C owing to the non-capital inputs used in year n's production activities, which can be calculated by the conventional CBA approach. EF_n^{HH} captures the EPs directly released by households in year n and is available in EXIOBASE 3.

4.3. Results

4.3.1. Annual profiles of China's capital consumption

Approximately one third of the $36.7 trillion (2015 US dollars) capital assets invested by China during 1995-2015 were consumed by 2015, whilst two thirds remain effective for future productive purposes. In most years, the assets acquired by non-industrial enterprises (i.e., agriculture, construction, and services), such as livestock for breeding, orchards, residential and office buildings, and intellectual property, dominated the capital consumption. In 2015, they accounted for 55% of the nation's total capital consumption, while the consumption of industrial equipment accounted for about another 40% (**Figure 4-1A**).

When examining annual profiles and trends, it is important to note that the consumption of capital goods invested before 1995 was not accounted for in our analysis, because data for earlier capital investments and production practices are sparse or not readily available for many countries. As a result, our estimates of capital consumption are conservative, especially for the early years in our modeling period (e.g., year 1995). For the later years, the impacts of neglecting pre-1995 capital

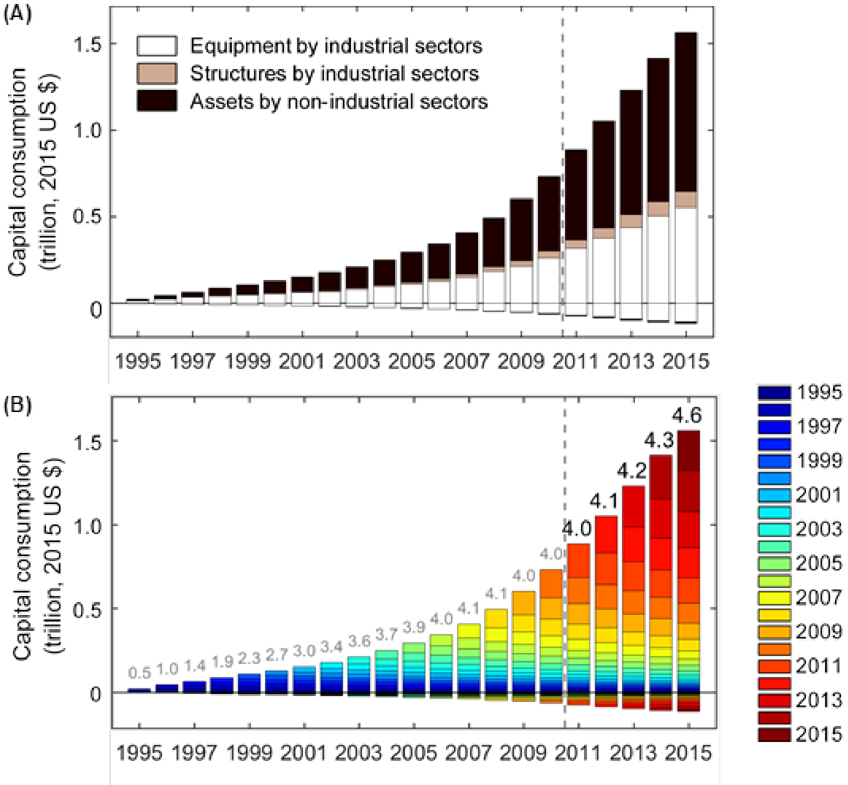

Figure 4-1. China's annual capital consumption (D^K_{China}) profile by the type of capital asset (A), and by year of investment (B). In both (**A**) and (**B**), capital assets purchased from China are plotted above the abscissa and those imported from other countries are plotted below the abscissa; all assets were invested during 1995-2015. The vertical dashed line illustrates that capital invested in 1995 accounted for less than 1% of annual capital consumption since 2011; further analysis indicates that pre-1995 investment likely accounts for a small fraction of the capital consumption profile since 2011 (**Appendix C.7** and **Figure C-3**, **Appendix C**). In **(A)**, 'Equipment by industrial sectors' covers computing, communication and transport equipment, other machinery and equipment, and computer software and databases; 'Structures by industrial sectors' includes non-dwelling buildings and structures; 'Assets by non-industrial sectors', invested by non-industrial enterprises (agriculture, construction, and service sectors), includes residential structures, cultivated assets, research and development, and other intellectual property products assets. In **(B)**, numbers on top of the bars show the weighted average age of capital assets consumed.

modeling period (e.g., year 1995). For the later years, the impacts of neglecting pre-1995 capital investments become much smaller (see additional analysis in **Appendix C.7** and **Figure C-3**). Starting with 2011, less than 1% of the capital consumption came from capital goods invested in 1995. Such a low presence of early investments is likely very unique to China, owing to the rapid growth of the capital stock in recent years (**Figure C-1)** as well as the relatively short life span of capital assets in China as compared to other countries (**Table C-9**). Based on the temporal results of 2011-2015, when the implications of neglecting pre-1995 investments are deemed low, our results show that the capital assets consumed in China averaged 4-4.6 years old (**Figure 4-1B**).

Our results also reveal that only 8% of the capital consumption originated from capital assets imported from outside of China, and this fraction decreased from 14% in 1995 to 7% in 2015 (**Figure 4-1B**). However, for industrial equipment and machinery, imported capital goods consistently accounted for a much larger share (16-21%) of the capital consumption throughout the 20 years (**Table C-10**). Japan, Germany and the United States have been the most important producers of capital assets consumed, accounting for half of the imported assets consumed in China's economic development. South Korea is playing an increasingly important role in China's capital investment and economic production. During 1995-2015, the industrial equipment and machinery imported from South Korea to China tripled; by 2015, capital assets imported from South Korea accounted for nearly 13% of China's consumption of imported capital goods, increased from 5% in 1995.

4.3.2. Attributing the EPs embodied in China's capital consumption to global final consumption

Significant resource use and emissions occurred during the production of the capital assets consumed in China between 1995-2015. This sums to 311 EJ primary energy used, 300 km^3 blue water consumed, 14.4 million km^2 land used, 5.4 Gt metal ore extracted, 42.7 Gt nonmetallic mineral mined, and 23.8 Gt GHG emitted (**Figure 4-2**). They account for 32% (metal ore extractions) to 39% (blue water consumption) of the six EPs embodied in the assets China acquired between 1995-2015, and 1% (land use) to 8% (nonmetallic mineral extractions) of the global resource use and emissions in the same period. The EPs are ultimately attributable to final consumption of goods and services, primarily in China. Across all six indicators, the final consumption of services in China dominates the EPs embodied in the capital consumption. Depending on the pressure indicators, 40% (metal) to 53% (mineral) of the EPs are attributable to real estate, public administration, education, and health services consumed in China (**Table 4-1**). This is not surprising given the real estate booms in China (Glaeser et al. 2017). The country's fast expansions of public services and medical services (Meng et al. 2005) also led to large purchases of capital goods, such as non-residential structures, machinery, and equipment.

Of all six indicators, more than half of the foreign-driven resource use and emissions are owing to the consumption in 22 OECD countries (country names are detailed in **Table C-1**) and nearly a quarter are attributed to the United States alone. The strong linkages between capital consumption in China and overseas final consumption are consistent with the crucial role that export activities

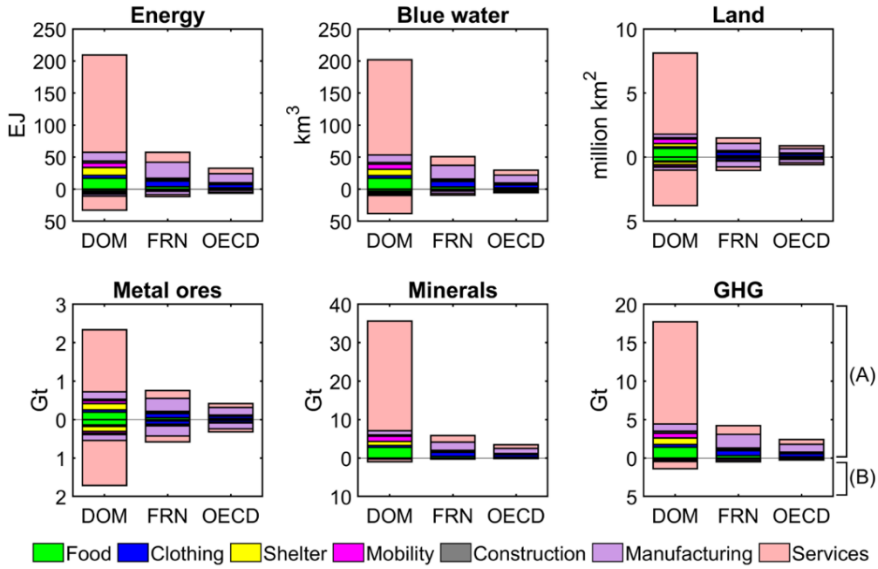

Figure 4-2. Attributing the resource use and emissions of China's capital consumption over 1995-2015 to the satisfaction of global consumption in the same period. Each subplot illustrates cumulative EP from 1995-2015, i.e., $\sum_{n=1995}^{2015}\sum_{t=1995}^{n} F_{China}^{K}$. In each subplot, the three bars correspond to the final consumption of Chinese domestic (DOM), foreign countries (FRN), and the Organization for Economic Co-operation and Development-1990 countries (OECD), respectively; the resource use or emissions that occurred in China and in other countries are plotted above and below the abscissa, respectively. To highlight the linkages between capital consumption and human needs satisfaction, here we categorized the finished goods and services defined by the 200-product categories in EXIOBASE 3 into 7 main categories of human needs (see **Table C-8**).

Table 4-1. Product categories of domestic (D) and foreign (F) final consumption that account for the highest EPs related to China's capital consumption from 1995-2015. All values are shown in percentages (%); blank indicates a value of less than <1%.

Footprint type	Energy		Water		Land		Metal		Minerals		GHG	
Product category	D	F	D	F	D	F	D	F	D	F	D	F
Radio, TV, communication equipment and apparatus		3		2		2		3		1		2
Motor vehicles, trailers and semi-trailers	2	1	1	1	1		2	2			1	1
Supporting transport and travel agency services	2		2		3		2		3		2	
Real estate services	17		18		20		15		24		19	
Computer and related services	2		2		2		2		2		2	
Public administration, defense, social security	14	2	14	2	16	2	13	2	17	1	15	2
Education services	6		7		7		6		7		7	
Health and social work services	6	1	5	1	5	1	6	2	5		5	1
Sum of the rest product categories	*29*	*14*	*29*	*13*	*28*	*11*	*29*	*15*	*27*	*10*	*28*	*13*
Total	**78**	**22**	**80**	**20**	**83**	**17**	**75**	**25**	**86**	**14**	**80**	**20**

have played in China's (accounting for 20% of China's GDP over 1995-2015) and the global economy. Different from China's domestic consumption, the foreign consumption of manufactured products dominates the capital-related EPs. Quite surprisingly, for the product category of '*Radio, TV, communication equipment and apparatuses*', foreign consumption even exceeded the domestic consumption in its attribution to all six environmental pressures (**Table 4-1**). China is known as the world's "manufacturing powerhouse." In 2016, two-fifths of the world's semiconductors were produced in China. Similarly, China was involved in the production of more than half of the world's mobile phones and produced almost all of the printed circuit boards (Allen 2018). A varying fraction of the EPs embodied in the consumed assets occurred outside of China, as the supply chains of the capital assets are distributed around the globe (**B** in **Figure 4-2**). The foreign implications are especially significant regarding metal and land, accounting for 43% of the metal ore extractions and 33% of the land use embodied in the consumed capital assets. Latin America is the most important region for the metal ore extractions underlying China's capital development, contributing 16% (38%) in the total (foreign) the metal ore extraction embodied in the consumed assets. As for the foreign land use embodied in China's capital consumption, it is mainly distributed in economies in transition, other Asian countries, and OECD countries, accounting for 28%, 25% and 22%, respectively. In contrast, only 3% of the nonmetallic mineral extractions and 8% GHG emissions embodied in the country's capital consumption occurred outside of China. Moreover, EPs associated with China's capital investment and depreciation as well as the domestic and foreign implications are contrasted and discussed in **Appendix C5** and **Figure C-2**.

4.3.3. EFs of China over 1995-2015 distinguishing between capital and non-capital goods

By linking the resource use and emissions associated with both capital and non-capital goods produced and consumed worldwide in 1995-2015 to China's final consumption in the same time period, we reassessed China's footprints in the six indicators (**b1** in **Figure 4-3**). We find that, depending on the pressure indicators, 8% (land)—46% (metal) of China's footprints are owing to capital consumption (gap between **b1** and **a2** in **Figure 4-3**). More than 40% of the metal ore extractions and land use and as little as 4% of the mineral mining and GHG emissions related to capital consumption occurred outside of China (gap between **b1** and **b2** in **Figure 4-3**). Note that the capital consumption attributable to China's final consumption include capital assets located in China as well as in other countries, as long as they were used to meet the final consumption of goods and services in China.

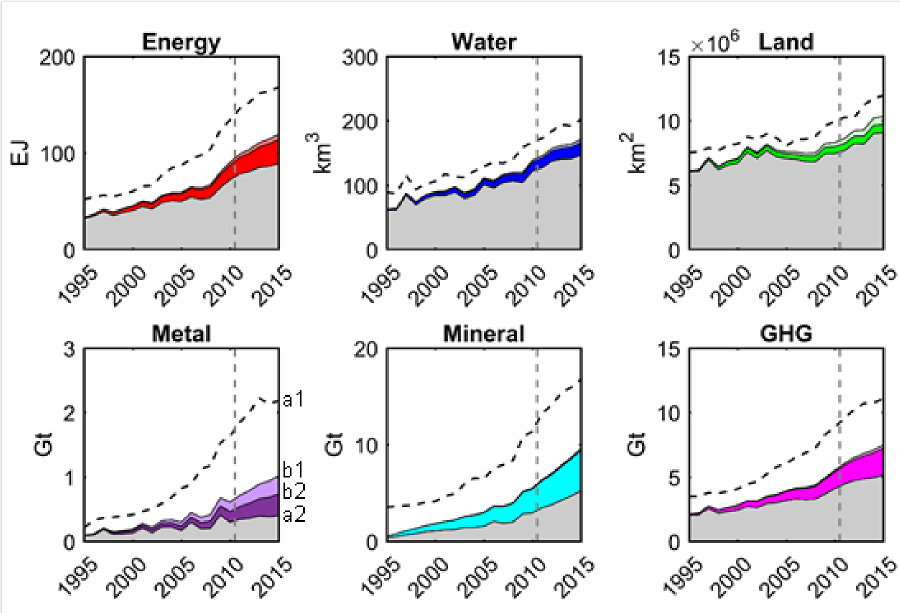

Figure 4-3. Environmental footprints of China's final consumption during 1995-2015 assessed by different consumption-based accounting (CBA) methods and scopes. Line **a1**, **a2**: The area between **a1** and **a2** represents EPs associated with China's capital investments since **a1** shows China's capital investments in year *n* and the related EPs included as part of China's EFs in year *n* using the existing CBA approach while **a2** shows the EF accounting with capital investments and related EPs omitted. Line **b1** shows the reassessed EFs of China using our capital endogenization method. The colored area between **b1** and **a2** indicates China's EFs related to capital consumption in year *n* (the consumed assets were produced in year *1995*, …, *n*, within China and abroad). The area between **a2** and **b2** indicates the resource use and emissions that occurred within China while the area between **b1** and **b2** indicates the resource use and emissions that occurred outside of China. For the EFs related to capital consumption, we further specified the years when EPs were generated in **Figure C-5**. The grey dashed line: additional analysis indicates that pre-1995 investments, which were neglected here due to data limitation, will likely have small impacts on the values of the reassessed EFs in recent years (e.g., 2011-2015 on the right side of the grey dashed line; see **Appendix C.7** and **Figure C-3**).

Our results demonstrate that, by treating capital investment the same as final consumption of non-capital goods or neglecting capital investment in footprint accounting, existing CBA methods grossly misrepresent China's EFs. For instance, in 2015, the energy, GHG, mineral, and metal footprints (**a1** in **Figure 4-3**) are 41%-114% higher than the values that results from allocating the EPs of investments to current and present, domestic and foreign, consumption (**b1** in **Figure 4-3**). Most of the overestimates come from failing to assign historical EPs to future consumption. Those assets will serve final consumption both in China and abroad, hence the embodied EPs need to be assigned accordingly. On the other hand, if the EPs associated with the production of capital assets are omitted from footprint accounting (**a2** in **Figure 4-3**), China's footprints in 2015 would be underestimated by 12% to 61% depending on the pressure indicators.

Table 4-2. Changes of China's *EF*^{K} in 2015 by varying the depreciate rates (i.e., effective life spans) of capital assets located in China. Notes: a smaller (larger) depreciation rate indicates a longer (shorter) life span; type of capital assets: a. equipment by industrial sectors, b. structures by industrial sectors, and c. assets by non-industrial sectors. Δ=0−0.1.

Changes in depreciation rate	Footprint type					
	Energy	Water	Land	Metal	Mineral	GHG
-10% (a)	-2.2%	-1.9%	-1.5%	-2.8%	-0.8%	-1.7%
-10% (b)	-Δ%	-Δ%	-Δ%	-Δ%	-Δ%	-Δ%
-10% (c)	-4.5%	-4.2%	-4.6%	-4.2%	-6.3%	-5.1%
-10% (a, b, c)	-6.7%	-6.1%	-6.1%	-7.0%	-7.0%	-6.8%
+10% (a)	2.0%	1.8%	1.4%	2.6%	0.7%	1.6%
+10% (b)	Δ%	Δ%	Δ%	Δ%	Δ%	Δ%
+10% (c)	4.2%	3.8%	4.2%	4.0%	5.9%	4.8%
+10% (a, b, c)	6.2%	5.6%	5.6%	6.6%	6.6%	6.3%

The EFs attributable to capital consumption (EF^K) can be effectively reduced by increasing the effective life spans of the capital assets (**Table 4-2**). When all capital assets are used for a longer time in China, with a -10% change of the depreciation rates, China's EF^K in 2015 would be reduced by 4.2-6.3% across the six indicators. In the case of buildings, due to different internal (e.g., inadequate architectural design, poor construction quality and non-effective operation and maintenance plans) and external (e.g., demolishing buildings to pursue commercial profits, poor planning) factors, the actual life span of buildings in China is about 30 years, much shorter than their designed life spans and the actual life spans of buildings in developed countries, which range from 44 to 132 years (Hertwich et al. 2019, Wang et al. 2018). For the purpose of using capital assets more efficiently and reducing the related EPs, several strategies could be considered in China, such as implementing more stringent quality standards for new capital projects, enhancing the maintenance of existing capital goods, as well as promoting circular economy strategies. Moreover, the EF^K appear to be the least sensitive to life span changes of industrial structures in China (e.g., warehouses, thermoelectricity plants) mainly due to these structures' already long lifespans.

4.4. Discussion

Capital development influences the attainment of all 17 of the sustainable development goals (SDGs) (Thacker et al. 2019). Our research, for the first time, reveals how China's vast capital development from 1995 to 2015 and the associated emissions and resource use are linked to the satisfaction of various human needs, both inside and outside of China. It also reveals that, from the consumption perspective, foreign countries especially the rich ones outsourced capital services to China, enabled by the country's capital development, and displaced the associated EPs to China and other places in the world. The capital-embodied EPs are mainly attributable to meeting final consumption of services, principally real estate, public administration, education and medical services in China, and the final consumption of manufactured products in other countries. The capital-final consumption linkages and the temporal cross-country interdependencies of the capital development are crucial yet neglected by the existing literature that use conventional CBA models.

Our results also shed light on future capital development. We show that 65% of the capital assets acquired by China from 1995 to 2015 remain effective for productive purposes after 2015, and 61% or more of the six EPs embodied in the acquired assets are attributable to final consumption beyond 2015. Based on the trend of 2011-2015, China's overall capital stock is still growing, measured in monetary values as well as by the amount of embodied resource use and emissions (**Figure C-6**). The compositions of the investing sectors are consistent, with the real estate, transportation and storage, public administration, and utility sectors dominating the capital stock and the embodied EPs. A recent study highlights that the level of residential floor area in China has surpassed that of the United Kingdom on a per capita basis and there is huge overcapacity of steel mills and power plants (Hertwich et al. 2019). Together the findings indicate an urgent need to emphasize economic and environmental efficiency in the decision-making of capital investment.

More broadly, our results demonstrate the importance of establishing long-term visions in assessing the resource and emission implications of achieving the SDGs through capital development. For instance, accounting for the temporal dynamics of GHGs emitted during current capital development and their attributions to future capital use can help make equitable carbon budgets at the national and global scales. On the other hand, due to the long life spans of capital assets, future generations are locked into operating and maintaining historically-developed capital stocks and the specific use patterns of assets, which may no longer meet future needs of resources efficiency and climate change mitigation (Hertwich et al. 2019). This line of research is beyond the scope of this analysis but worth future explorations.

Capital endogenization and its conceptual values are still quite new for both researchers and policy makers. Understanding and accounting for the temporal dynamics of capital goods in economic production and in allocating the associated EPs accordingly will benefit sustainability science and policy making, where inter-generational implications are considered to be important. In the dynamic framework, we further highlight the effects of asset lifespan and the roles of a global capital market for mitigating the considerable EPs associated with capital development and use. A few measures, such as implementing more stringent quality standards for new capital projects, enhancing the maintenance of existing capital goods, as well as promoting circular economy strategies, can effectively decrease the associated resource usage and emissions. Prior studies show that short-lived buildings in China have contributed to considerable environmental pressures that could have been avoided (Andrews 1993, Cai et al. 2015), consistent to what we found in the sensitivity analysis (**Table 4-2**). More specifically, prior studies indicate that if average building lifespan in China can be extended from 30 years to around 50 years, 5.8 km^3 water and 426 Mt CO_2 emissions would be avoided in one year (Cai et al. 2015). Future capital development in China needs to specify both "quantity" (more than $94 trillion US dollars predicted by 2040) (Thacker et al. 2019) and "quality" (resource-efficient, low-impact). Technology advancements, a major driver that historically reduced the consumption of key resources (e.g., water, or energy) and the emissions (Guan et al. 2008, Zhou et al. 2020), will also be a promising means for future sustainable capital development.

It is crucial to note that the magnitude of EPs we quantify here (e.g., 300 km^3 blue water consumption and 14.4 million km^2 land use) do not directly indicate the magnitude of environmental impacts (e.g., water stress and biodiversity loss) (Steffen et al. 2015). The latter are more complex to infer and depend upon many characteristics of the pressures, such as timing and location. For example, the environmental impacts of metal ore extraction, mineral mining, and GHG emissions importantly depend on temporal accumulations of the pressures. GHGs emitted in one year have limited implications on global climate change; resource depletion of metal and minerals are often a result of years' or decades' unsustainable extraction activities. For water use, the environmental impact in the form of water stress typically depends on temporary appropriations, unless the water is appropriated from non-renewable groundwater bodies. The impacts of land use are more complex, depending on temporal characteristics (i.e., short-term, permanent, or irreversible), the types of land-using capital (e.g., orchards and other plantations of trees, residential dwellings or industrial buildings), and land use change (e.g., from natural to human-dominated habitats). Moreover, some limitations of the method we use remain, primarily due to the limited availability of capital data in earlier years and developing countries. Future efforts are still needed, however, to develop a consistent dataset of capital investment and consumption, with a higher resolution of capital goods and economic sectors and longer time-series and involving more countries. Note that although this study focused on China, capital development accounts for a considerable fraction of resource use and emissions in many other countries and globally. The methodological improvement will become increasingly important as the global production networks linked by international trade continue to grow.

We also note that the new capital model we used in this analysis relies on various types of data—the MRIO data, capital time series, and resource use and emissions accounts, all of which come with uncertainty, as documented in *refs*. EUKLEMS (2019), Feenstra et al. (2015), and Stadler et al. (2018). Therefore, the estimates we present here are calculated results and need to be interpreted with caution. Crucially, our new model addressed the temporality issue left unresolved by prior capital endogenization efforts, e.g., *refs*. Chen et al. (2018), Lenzen (1998), Södersten et al. (2020), and Södersten et al. (2018a), which assume capital consumed today were produced using today's technology. As illustrated by **Figure C-7**, the EF estimates appear sensitive to this methodological improvement. However, such improvement comes with a trade-off. For each year from 1995 to 2015, the two key technology-related variables regarding production configuration and environmental intensity of production are described by matrix A and matrix S in EXIOBASE 3, respectively. As such, the temporal scope of our analysis is constrained to 1995-2015, the temporal coverage of EXIOBASE 3, although capital statistics in earlier years are available and earlier capital investments can have non-negligible implications to the EF estimates of 1995-2015. To the best of our knowledge, EXIOBASE 3 offers one of the longest times series of MRIO data and the corresponding environmental accounts among all global MRIO databases. Moreover, our model and the EP estimates are constrained by the aggregated capital asset classifications. In comparison to earlier capital endogenization studies, our work already benefited from the refined capital classifications enabled by recent capital data development efforts. Capital goods are classified into 8-10 asset categories in recent releases of KLEMS (EUKLEMS 2019), which cover most European Union countries, the United States, Japan, and Australia, 3-7 asset categories in WORLDKLEMS (WORLDKLEMS 2019) for China, South Korea, and Canada, and 4 asset categories in PWT 9.1 for the rest of countries/regions (see **Tables C-2** and **C-7**). Although such asset resolution suffices many economic studies, it remains rough for capturing the varying production inputs and environmental intensities associated with the production of different assets. Lastly, the temporal dynamics of the capital goods owned and used by final consumers (i.e., households, governments, and non-governmental organizations) are yet to be modeled and captured by future works. The consumption of those capital goods may follow different depreciation patterns than those used for economic production. Unlike the capital used in economic production, the beneficiaries of the capital goods owned by final consumers are more straightforward and will not change with time unless the capital goods enter the second-hand markets and get a new owner. However, all capital goods, whether owned by producers or final consumers, will eventually enter waste streams, either though disposal or through recycling and integration into further production. To the best of our knowledge, those flows are yet to be modeled and accounted for in future research.

4.5. Conclusions

Enabled by a new global model of capital formation and use, this study quantifies the linkages over the past two decades and into the future between six EPs caused by China's capital formation and domestic as well as foreign consumption. We show that only 35% of the assets acquired by China from 1995 to 2015, representing 32%-39% of the associated EPs (e.g., water consumption, GHG emissions, and metal ore extractions), have been depreciated, whilst the majority rest will serve future production and consumption. The capital-embodied EPs are mainly attributable to meeting final consumption of services, principally real estate, public administration, education and medical services in China, and the final consumption of manufactured products in other countries. The outsourcing of capital services and the associated EPs are considerable, ranging from 14-25% of depending on the EP indicators. Without accounting for the capital-final consumption linkages across time and space, one would miscalculate China's environmental footprints related to the six EPs by big margins, from -61% to +114%.

Re-allocating CO_2 emissions of capital investment along capital's full lifespan

Abstract

Future economic production depends on existing capital assets such as machinery, and buildings and hence induces embodied CO_2 that emitted in the past. The inertia of capital assets results in a temporal displacement of emission responsibilities along capital's lifespan. Neglecting this temporal displacement in conventional emission accountings misleads the allocation of capital-associated emission responsibilities to actual capital consumers in different time cohorts. Here we quantify the temporal displacement of capital and associated carbon emissions within China for the period from 1995−2017. The results show that considering the temporal CO_2-emission displacement relieves the emission responsibilities of capital assets for the year of formation, with 25–46% declinations from conventional accounting methods. To understand this temporal displacement from the past to the future, we further design three capital investment scenarios until 2030, based on different purposes of capital investments (e.g., for further economic growth or for low-carbon development). Overall, the existing capital in 2017 will still contribute approximately 10% of China's carbon emissions in 2030, and account for more than 40% for capital-intensive service sectors like real estate or transportation services. The virtual temporal displacement of carbon emissions associated with capital feeds into a discussion on the equity across generations due to historical and future 'commitments' of emissions.

5.1. Introduction

Considerable investments from government and economic sectors in capital assets such as power plants, machinery, and infrastructure have been acquired to enable global fast-growing production activities (GIH 2017, Thacker et al. 2019). Capital investments account for around one quarter of global gross domestic product (GDP) since 1970 (The World Bank 2020). In some developing countries, for instance China, capital investments could account for up to 47% of its national GDP, with an annual average growth rate of 12% since 1995 (The World Bank 2020). Building up capital assets requires considerable resource inputs and causes pollution (Jiang et al. 2019, Tukker et al. 2016). For instance, 156 gigatons (Gt) of carbon dioxide (CO_2) have been emitted globally to produce capital assets invested by China between 1995 and 2015, accounting for 32% of global total carbon emissions during the same period (Stadler et al. 2018).

Different from non-capital products that are purchased to be consumed every year, capital assets have two unique features. First, capital assets are invested and used by economic sectors for their productive purposes, while the producers of capital assets are usually different from their investors and users. This feature hence raises arguments about how to allocate environmental responsibilities of capital activities (Chen et al. 2018, Lenzen and Treloar 2004, Södersten et al. 2020, Södersten et al. 2018a), to the producers or to the users of the capital assets, or to the final consumers of goods and services that are produced by using these assets. Second, capital assets can exist for several years or even decades, and serve economic production throughout their lifespans. Taking China as an example, approximately one-third of the capital assets (in monetary terms) invested between 1995−2015 have been depreciated, while the rest remains effective for future production (**Chapter 4**). This feature implies that future production and consumption will induce not only direct economic inputs and environmental pressures in the future, but also those indirect inputs and pressures that historically occurred and embodied in capital. It hence leads to the temporal allocation of environmental responsibilities of capital activities along capital's full lifespan.

Little is known about the second feature of capital assets and its impacts on the allocation of environmental pressures along capital's lifespan. Literature has investigated the geospatial displacement of environmental pressures along supply chains, and allocated them from producers to final consumers, yielding consumption-based environmental pressures or environmental footprints (Hertwich and Peters 2009, Wiedmann and Lenzen 2018, Wiedmann et al. 2015). Due to aforementioned two features of capital, how to treat the purchase of capital assets and allocate associated environmental responsibilities is still debated. In a conventional way, literature treated capital assets in the same way as final consumption products, allocating environmental pressures that occurred during the production of capital assets to the purchasing sectors and countries in the year of purchasing (Davis and Caldeira 2010, Jiang et al. 2022, Wiedmann and Lenzen 2018, Wiedmann et al. 2015). Recently, studies treated capital as one production factor (i.e., as intermediate inputs for economic production), and allocated capital-related environmental pressures to final consumption across sectors and countries (Chen et al. 2018, Lenzen and Treloar 2004, Södersten et al. 2020, Södersten et al. 2018a). However, the intertemporal features of capital assets remain unaddressed since capital assets used in a specific year are from different age cohorts, and are produced using time-specific production characteristics, trade networks, and environmental intensities.

To properly understand this important temporal dimension of environmental responsibility displacement requests a full picture of capital flows across sectors and regions (according to the first feature) and throughout its lifespans from the past to the future (according to the second feature). This study presents a novel analysis of capital development and quantifies temporal CO_2 displacement along capital production, trade and consumption over the period of 1995−2017 as well as under three scenarios of capital investment for the near future until 2030. We take China as the study area because capital growth is the major driver of China's resource consumption and emissions (Jiang et al. 2022), and conduct this analysis at the provincial level since great spatial variations in socioeconomic development patterns and resource endowments exist across Chinese provinces (Feng et al. 2013, Jiang et al. 2019). We first develop an inter-provincial capital-endogenized multi-regional input-output (MRIO) model to link provincial capital depreciation to the production side of actual capital using sectors, and subsequently to the consumption side of final goods and services of each province. Second, to understand the temporal dimension of environmental responsibility displacement from the past to the future, we design China's future capital investment pathways by a 'business-as-usual' (BAU) scenario and two capital-oriented scenarios into 2030. The two capital-oriented investment pathways are developed on the principle of improving economic growth and social well-being (KES, here 'K' standing for capital), and the principle of low carbon development (KLC), respectively. We then quantify spatiotemporal CO_2 displacements embodied in capital flows across sectors and provinces, and over time. We show that temporally displaced CO_2 emissions along capital's full lifespan take a significant share in total emissions of China, and capital-intensive service sectors. This virtual temporal displacement, although virtual, is important for assessing the sustainability and efficiency of national resource use especially in developing countries which may have capital investment booms in short periods, and the equity of resource use across generations.

5.2. Methods

The procedures to endogenize capital investment and consumption into the economic supply chains of China are following (**Chapter 4**), which developed a capital-endogenized MRIO model for a global case. However, lacking systematic, complete, and consistent capital development data with high asset-by-sector resolutions and time-series MRIO tables makes this fine-scale capital-endogenized endeavor challenging. This section will start with the construction of time-series datasets of provincial capital investment (**Section 5.2.1**) and inter-provincial MRIO tables (**Section 5.2.2**), to fill the data gap of this sub-national capital endogenization model for China. After that, the main procedures of endogenizing capital investment and consumption into China's sub-national MRIO tables will be introduced (**Sections 5.2.3** and **5.2.4**). Lastly, the construction of three capital investment pathways until 2030 (i.e., BAU, KES, and KLC) and the key assumptions to support the three pathways will be elaborated (**Section 5.2.5**). All the data sources are summarized and described in **Appendix D.1**.

5.2.1. Constructing annual capital investment and depreciation flows

5.2.1.1. Annual capital investment by sector and by province

Official capital investment data from the National Bureau of Statistics of China (NBSC) are recorded by two main annual series, 'total investment in fixed assets (TIFA)' and 'newly increased fixed assets (NIFA)'. TIFA refers to the 'workload' of activities in construction and purchases of fixed assets in monetary terms (NBSC 2017b), which may not produce results that meet standards for fixed assets in the current period or may take many years to become qualified for fixed assets (Chow 1993). NIFA refers to the value of investment projects completed and put into production or meeting the standards for fixed assets in the current year (NBSC 2017b), hence reflecting the fixed assets formed in the current period as a result of those *effective* investment projects taking place in the current and previous periods. Given that the concept of 'capital investment' used in the perpetual inventory method (PIM), a standard geometric method that is adopted in this study to calculate capital consumption time series, are those *effective* capital assets that have been completed and put into production, this study relies on NIFA to construct the provincial capital investment time series. Official NIFA are distinguished as rural NIFA and urban NIFA by 19 major economic sectors (see **Table D-1**, **Appendix D**). Particularly, urban NIFA are also recorded by 40 specific industrial sectors (see **Table D-1**). More details about the differences between TIFA and NIFA and the problem of directly using TIFA in PIM are discussed in **Appendix D.2**.

Although NIFA (denoted as *N*) is more reasonable than TIFA to be used as capital investment (denoted as *I*) in PIM, an upward adjustment has to be made to transfer *N* to *I*. This upward adjustment is to include the projects less than half million yuan by non-state firms that are not reported in official investment statistics plus the value of likely underreported (Young 2000). The standard I by sector s of province m in year t could be estimated as:

$$I_{m,t,s} = \frac{N_{m,t,s}}{1-\lambda_{m,t,s}}, \ (\lambda<1) \tag{5-1}$$

where λ is to adjust N by the effects of missing and/or underreported investment, respectively. There is little information available on λ especially those at provincial level. We apply the national $\lambda_{t,s}$ from Wu (2015) to adjust $N_{m,t,s}$, and further scale $N_{m,t,s}$ into the national capital investment by sector s in year t from WORLDKLEMS (WORLDKLEMS 2019). Therefore, we also specify 37 sectors (**Table D-2**) in our provincial capital investment dataset, which are consistent with the sectoral classification in WORLDKLEMS.

5.2.1.2. Disaggregating capital investment by asset type

There are limited investment data by asset type, especially with specific investing sectors. In the official investment statistics, under the subcategories of TIFA 'capital construction' and 'technical update and transformation', there are data for 'equipment' and 'structures'. The 'structures' indicator also distinguishes 'housing' or 'non-productive' constructions. We rely on TIFA by these categories (although they are not directly relevant with NIFA), and industrial investment statistics in annual statistics bulletins (DITS multiple years) about industry and transportation economy, commune and brigade factories, and township and village enterprises to disaggregate the capital investment. According to Wu (2015), this study also disaggregates four categories of industry-specific fixed assets, namely, 'equipment', 'residential structures', 'non-residential structures' and 'others'. We re-allocate 'others' into 'equipment' and 'non-residential structures' by a ratio of 3:7 according to Wu (2015).

Without category-specific data on investments in non-industrial sectors (i.e., agriculture, construction, and all services), the estimation of capital investment by non-industrial sectors is largely based on assumptions. We assume that the non-industrial sector-specific I is equal to the official NIFA of that sector. Also due to the lack of necessary information, we use the share of productive structures given by the economic-wide TIFA to decompose the total investment into non-residential structures and equipment.

All the capital investment data by sector and asset will be scaled into the national capital investment from WORLDKLMES (WORLDKLEMS 2019).

5.2.1.3. Constructing capital consumption time series

The procedures to trace and allocate the contribution of year *t*'s capital investment to year *n*'s inter-industrial production networks are similar to the global capital endogenized MRIO model (**Chapter 4**). The key step to obtain the supply chain-wide capital consumption matrix $\mathbf{D}_{t,n}^{K}$ ($t \leq n$) within China is to re-create the concordance tables that are used to convert capital assets and capital consumption sectors into the sectoral classifications of MRIO tables. The classifications of capital consumption sectors (37 sectors from WORLDKLMES, **Table D-2**) are different from the 42 MRIO-sectors (see **section 5.2.2**, and **Table D-5**). The final capital consumption matrix $\mathbf{D}_{t,n}^{K}$ within China has capital producing and capital consuming sectors along rows and columns, respectively; and each element records the quantity of assets that were invested in year *t* and consumed (i.e., depreciated) in year *n*.

5.2.2. Constructing China's inter-provincial MRIO table series (1995−2017)

We rely on the current best available MRIO tables in 2007 (Liu et al. 2012), 2010 (Liu et al. 2014b), 2012 (Liu et al. 2018), 2015 and 2017 from CEADs (Zheng et al. 2020), 1995−2006 from Wang (2017) as the benchmarks to construct the inter-provincial MRIO table time series. Before that, we first adjust the final demand, exports, imports and value-added data in the benchmarking MRIO tables (see **Appendix D.3**), according to the available statistical data from the NBSC. This is because we found that some benchmarking MRIO tables have big data gaps from the available statistical data, especially for early years. We rebalance these benchmarking MRIO tables by the GRAS method (Günlük-Şenesen and Bates 1988), and use them to estimate the MRIO table in the missing years. The GRAS method can quantify the intermediate input matrix **Z**' in the target year based on the matrix **Z** in the reference year and gross intermediate inputs, gross intermediate outputs, and total outputs in the target year. Details about estimating final demand, exports, total outputs, and using the GRAS method to balance the MRIO tables in the target years could be found in **Appendix D.3**. In addition, the MRIO tables in 2007 and 2010 only have 30 regions (without Tibet) and 30 sectors, while others have 31 regions and 42 sectors. To ensure the consistency of MRIO table time series, we omit all the transactions relevant to Tibet in other MRIO tables, meanwhile disaggregate the 30 sectors into 42 sectors for further calculation.

5.2.3. Re-assigning capital-related carbon emissions

The supply chain-wide CO_2 emissions ($\mathbf{F}_{t,n}^{K}$) generated in year *t* when the capital inputs allocated to year *n*'s production activities (i.e., $\mathbf{D}_{t,n}^{K}$) can be estimated by IO modelling, $\mathbf{F}_{t,n}^{K}=\widehat{\mathbf{S}}_{t}\mathbf{L}_{t}\mathbf{D}_{t,n}^{K}$, where $\mathbf{S}_{t}$ is a row vector of direct carbon emission intensities of economic activities, collected from CEADs (Shan et al. 2018, Shan et al. 2020a, Shan et al. 2016); $\mathbf{L}_{t}$ is the Leontief inverse matrix (Leontief 1970), describing the supply chain-wide economic outputs associated with per unit final goods and services in year *t*. When allocating $\mathbf{F}^{K}_{t,n}$ to the actual capital using sectors in year *n*, we can obtain production-based emissions of capital depreciation in year *t* for year *n*'s production. When assigning $\mathbf{F}^{K}_{t,n}$ to final consumption ($\mathbf{Y}^{FC}_{n}$, including final expenditure of rural population, urban population, and government), GFCF ($\mathbf{Y}^{GFCF}_{n}$), and international exports ($\mathbf{Exp}_{n}$) in year *n*, we can obtain capital-related consumption-based emissions in year *t* for different economic activities in year *n* (**Eq. 2-4**).

$$\mathbf{S}^{K}_{t,n}\mathbf{L}_{n}\mathbf{Y}^{FC}_{n} \tag{5-2}$$

$$\mathbf{S}^{K}_{t,n}\mathbf{L}_{n}\mathbf{Y}^{GFCF}_{n} \tag{5-3}$$

$$\mathbf{S}^{K}_{t,n}\mathbf{L}_{n}\mathbf{Exp}_{n} \tag{5-4}$$

where $\boldsymbol{S}^{K}_{t,n}$ describes the one-unit carbon emissions of province-sector pairs in year *t* that consumed $\mathbf{D}^{K}_{t,n}$ in year *n*, calculated by $\mathbf{S}^{K}_{t,n}=\varphi\mathbf{F}^{K}_{t,n}\widehat{\mathbf{x}}_{n}^{-1}$, in which $\mathbf{x}_{n}$ is a column vector of total economic outputs of year *n*, and φ is a summation vector of ones.

5.2.4. Re-assessing carbon emissions of provinces

Different from conventional emission accounting of capital activities (represented by consumption-based carbon emissions of GFCF in one-year base, CBE^{GFCF}_{t}=$\mathbf{S}_{t}\mathbf{L}_{t}\mathbf{Y}^{GFCF}_{t}$), we re-allocate CBE^{GFCF}_{t} to the actual capital using sectors or further to the final demand throughout the assets' lifespans according to annual $\mathbf{F}^{K}_{t,t}$, $\mathbf{F}^{K}_{t,t+1}$, $\mathbf{F}^{K}_{t,t+1}$, … This re-allocation of F^{K} hence changes annual carbon emissions accounting of provinces from both production-based and consumption-based accounting (i.e., consumption-based carbon emissions of final demand, $\mathbf{S}_{n}\mathbf{L}_{n}(\mathbf{Y}^{FC}_{n}+\mathbf{Y}^{GFCF}_{n}+\mathbf{Exp}_{n}$)). Two steps are taken to re-assess provincial carbon emissions. One is omitting the conventional PBEs and CBEs that are related to GFCF of a center province. The other is adding back F^{K} re-allocated to capital using sectors generating PBEs after F^{K} re-allocation, or adding back F^{K} re-allocated to final demand generating CBEs after F^{K} re-allocation.

5.2.5. Developing scenarios of capital investment until 2030

We project China's capital investment pathways from reference year 2017 up to year 2030 by two capital-oriented scenarios, as variations of a 'business-as-usual' (BAU) scenario as the baseline scenario. The two capital investment pathways are developed on the principle of improving economic growth and social well-being (KES), and the principle of low carbon development (KLC), respectively. We select 2030 for a short-term analysis of capital investments because capital assets

Table 5-1. Summary of the 'business-as-usual' (BAU) scenario and the two capital investment scenarios. A is the direct coefficient matrix showing inputs per-unit total output. **vd** is the value-added matrix. $\mathbf{Y}^{FC}$ is the final consumption matrix. $\mathbf{Y}^{GFCF}$ is the gross fixed capital formation (GFCF) matrix. **F** is a row vector of direct carbon emissions of economic activities.

	Scenarios		
	BAU	KES	KLC
Explanation	Economic development (including capital investment) and carbon emissions following current paths and climate policies	A particular increase in infrastructure investment (i.e., transportation, power, water, and communication) to improve economic growth and social well-being*	A particular increase in capital investment in low-carbon technologies by the electricity generation sector, and end-use sectors such as transportation services**
Changes in **A**	General reductions in direct inputs due to the improvement in production efficiency, and particular changes in energy related sectors due to the changes in energy mix	Same as BAU	Adjusting **A** in BAU according to the energy mix changes under the low-carbon development
Changes in $\mathbf{Y}^{FC}$	Estimated by the predicted population, and per-capita final expenditure	Particular increase in $\mathbf{Y}^{FC}$ from the seven infrastructure-related sectors compared with BAU	Particular changes in $\mathbf{Y}^{FC}$ from the using sectors of low-carbon technologies compared with BAU
Changes in $\mathbf{Y}^{GFCF}$	Estimated by the capital investment of each investing sectors, and the capital production structure in the base year	Allocating specific investment in seven infrastructure categories to associated capital producing sectors, and further adjusted into the capital intensity of unit GDP in BAU	Allocating specific investment in low-carbon technologies by electricity generation sector and end-use sectors to associated capital producing sectors, and further adjusted into the capital intensity of unit GDP in BAU
Changes in **vd**	GDP growth rate set as 6.5% before 2020, and 5% after 2020	Changes according to $\mathbf{Y}^{FC}$ and $\mathbf{Y}^{GFCF}$	Changes according to $\mathbf{Y}^{FC}$ and $\mathbf{Y}^{GFCF}$
Changes in **F**	Consistent with the change in the intermediate inputs	Consistent with the change in the intermediate inputs	Adjusting **F** in BAU according to the carbon emissions of generation sector and end-use sectors under the low-carbon development

Notes: * associated capital investment in each infrastructure are collected from GIH (2017); ** associated capital investment in low-carbon technologies by electricity generation sector and end-use sectors are collected from World Energy Outlook (IEA 2017), and only relative changes in key parameters such as carbon intensity of one unit GDP are used.

currently in use in China are on average 4−4.6 years old, and the associated environmental pressures have on average occurred in the last 5-6 years (**Chapter 4**). Moreover, current policies in China such as peaking carbon emissions mostly set 2030 as the targeting year. All three scenarios are in constant prices of year 2017 and developed based on the economic activities and CO_2 emissions in 2017 as the base year. We assume that the national average capital intensity of one-unit GDP is the same for each scenario. All the scenarios will be implemented by manipulating the MRIO tables of the year 2017 to each projecting year, as summarized in **Table 5-1**. The narrative and implementation of each scenario are further described in the following sections and **Table 5-2**.

Table 5-2. The main parameters in the three capital investment scenarios and the base year.

	Base year (2017)*	BAU (2030)	KES (2030)	KLC (2030)
Economic-related				
GDP (in billion, 2017 Yuan)	83210	163725	165556	156905
Share of GFCF in GDP	42.7%	42.7%	42.4%	46.6%
Electricity price (annual change until 2030)		0.93%	0.93%	0.9%
Cumulative investment (in billion, 2017 Yuan)**				
Electricity/water		28656	31327	
Transportation		47402	51731	
Telecommunication		3543	3750	
Low-carbon technologies				13003
*Social-related****				
Population (billion)	1.39	1.46	1.46	1.45
Urbanization rate	59.0%	70.8%	70.8%	71.6%
*Energy-mix-related*****				
Total energy supply (million toe)	2490	3540	3578	2820
Coal	1819	2353	2379	1802
Oil	195	252	255	156
Natural gas	122	213	215	191
Nuclear	65	278	281	218
Renewable	289	442	447	453
Power generation (TWh)	6557	9321	9426	8771
Total energy use (million toe)				
Coal	1970	2549	2577	1873
Oil	578	822	831	711
Gas	198	393	397	374
Nuclear	65	164	166	218
Renewables	289	475	480	455

Note: * data for the base year were collected from the National Bureau of Statistics of China (NBSC 2020); ** the cumulative investment in the seven infrastructure under the KES, and on the low-carbon technology under the KLC are listed in this table, which do not show the total cumulative investment from all 42 economic sectors; *** future population and urbanization rate of China are collected from Chen et al. (2020); **** the associated energy mix data of China are collected from the New Policy Scenario developed in the World Energy Outlook 2017 (IEA 2017).

5.2.5.1. 'Business-as-usual' (BAU) scenario

The BAU scenario, referred to De Koning et al. (De Koning et al. 2015), is developed by continuing historical trends of population growth, efficiency improvements, and productivity growth until 2030 (summarized in **Table 5-2**). The trends in general efficiency improvement (influenced by current economic and climate policies) into 2030 are determined by actual trends in the last decade, looking in detail at sector- and province-specific development (recorded in **A**). If we assume total outputs in the projecting year would not change, efficiency improvements reduce intermediate inputs (including domestic inputs and imported inputs) for economic activities and further lead to substantial economic growth. We then make up the difference to meet overall GDP growth (recorded in **vd**) based on the autonomous economic growth accomplished by efficiency change. GDP growth rates are set as 6.5% per year before 2020, and 5% per year after 2020 (Guan et al. 2008, Yang et al. 2021). Final consumption of rural and urban population (recorded in $\mathbf{Y}^{FC}$) is estimated based on projected population, urbanization rates, and per-capita expenditures. Rural and urban population in each province until 2030 are estimated using total provincial population and national urbanization rate, obtained from Chen et al. (2020). Per-capita final expenditure of rural and urban population until 2030 are estimated by the same method used in previous studies (Hubacek and Sun 2001, Hubacek and Sun 2005). Final consumption of government is estimated according to the total changes in the final consumption of rural and urban population. Capital investment of sectors is estimated according to required future capital stock of each sector. We first predict the capital stock intensity of value-added of each sector in 2030, based on its capital stock intensity in the base year, elasticity parameter, and changes in capital price (Leimbach et al. 2017). Total capital stock of each sector in 2030 can be calculated by multiplying the capital stock intensity with its total value-added. Annual average capital investment until 2030 can be calculated by the PIM, given that the capital stock in year T equals to $\sum_t^T I(1\text{-}\delta)^{T\text{-}t+1}$, where δ is the depreciation rate of each asset. After that, we distribute the capital investment of each investing sector to capital producing sectors, based on the capital production structure in 2017, to obtain $\mathbf{Y}^{GFCF}$ in target year. International export is assumed to proportionally increase according to growth of GDP. Total outputs, intermediate inputs, and international imports for intermediate inputs in the target year can then be calculated by the basic equations of IO modelling. We balance total inputs and outputs through GRAS method. Furthermore, we adjust the balanced MRIO tables according to the changes in energy mix (**Figure D-2**, **Appendix D**). The total energy supply and use are consistent with the projections in IEA (2017). Changes in energy supply and use per source (i.e., coal, oil, natural gas, nuclear and renewable energy) lead to proportional changes in the transactions with associated sectors (e.g., coal mining). We also adjust the transactions from different energy sources to electricity generation sectors according to the changes in their shares in total power generation. The adjusted MRIO tables are balanced again using GRAS method. Direct carbon emissions from sectors are changed as well (recorded in **F**). It is assumed that the changed intermediate inputs in sectors brings changes in emissions accordingly.

5.2.5.2. Capital for economy and social well-being (KES) scenario

Under the KES scenario, China is increasingly focusing on the role of capital assets, especially infrastructure, to improve economic growth and social well-being (China 2020). We rely on the associated outlook of infrastructure development in China (summarized in **Table 5-2**) from GIH (2017), and integrate future infrastructure investment data into the MRIO model for carbon emission accounting. Seven infrastructure categories are covered in this scenario, i.e., roads, railways, airports, sea ports, electricity generation and supply, water generation and supply, and telecommunications. The KES scenario is developed on top of the BAU scenario. We first determine the sectors that invest in infrastructure. That is, we assume roads, railways, airports, and sea ports are mainly based on investments by the sector '*Transportation, storage and post services*', electricity/water generation and supply are invested by the sector '*Production and supply of electricity, heat, gas, and water*', and telecommunications are invested by the sector '*Information transfer, software and information technology services'*. According to statistical data recorded in NBSC (NBSC 2018b), investments in roads, railways, airports, and sea ports annually account for approximately 94% of total investment from '*Transportation, storage and post services*', investment in electricity/water generation and supply accounts for approximately 97% of total investment from '*Production and supply of electricity, heat, gas, and water*', and investment in telecommunications annually accounts for approximately 92% of total investment from '*Information transfer, software and information technology services*'. For each infrastructure category, we disaggregate its investment into three assets (see **section 5.2.1.2**). Asset-specific investment data will be allocated to capital producing sectors according to sectoral shares in GFCF, obtaining a GFCF matrix that represents the GFCF of producing sectors for building up the infrastructure. Furthermore, we scale the GFCF matrix of infrastructure according to the annual shares of investment in associated infrastructure in the total investment from the associated investing sector. Based on the scaled GFCF matrix, we further adjust the associated GFCF of infrastructure producing sectors under the BAU scenario (if there is any investment default) to get $\mathbf{Y}^{GFCF}$ under the KES scenario. Final consumption from seven infrastructure-related sectors will change proportionally according to their investment. We assume more investment in specific infrastructure will lead to more consumption (evidence to support this assumption can be found in **Figure D-3**). Value-added in this scenario would change due to changes in final demand, compared with the BAU scenario. Intermediate inputs would also change to meet economic production of final demand and exports. The adjusted MRIO tables are balanced again using GRAS method. Direct carbon emissions from sectors are changed as well. It is assumed that the changed intermediate inputs in sectors compared with those in the BAU scenario changes emissions accordingly.

5.2.5.3. Capital for low-carbon development (KLC) scenario

This scenario is designed to focus on China's future capital investment in low-carbon technologies by the electricity generation sector, and end-use sectors such as transportation services. The scenario assumes additional capital investments for relevant economic sectors (represented in $\mathbf{Y}^{\mathbf{GFCF}}$) which will yield a reduced carbon intensity (parameters leading to **F**). Data (**Table 5-2**) for energy supply and energy use by energy sources (i.e., coal, oil, natural gas, nuclear and renewable energy), capital investment requirements on low-carbon technologies (e.g., carbon capture and storage, or electric vehicles) by different using sectors (e.g., industry sectors, or transportation services), carbon emissions by economic sectors are collected from the World Energy Outlook 2017 (IEA 2017). The procedures to construct $\mathbf{Y}^{GFCF}$ matrix under the KLC scenario according to the capital investment in low-carbon technologies and further adjustments on $\mathbf{Y}^{FC}$ matrix are described in the development of the KES scenario. Changes in energy mix in the MRIO tables follows **Figure D-2**, which has been described in the development of the BAU scenario. International export would decline whereas international import would increase (O'Neill et al. 2017), since the objective of this capital investment pathway is to reduce China's territorial CO_2 emissions. The adjusted MRIO tables are balanced again using the GRAS method. Lastly, we further adjust the direct carbon emissions from sectors accordingly, based on emissions data from the World Energy Outlook. It should be noted that only relative changes in key parameters such as technology use in economy (**A**) and carbon intensity per unit of GDP are used in developing the KLC scenario, as more structural economic changes are not assumed to occur on the timescale at which the scenario is considered.

5.3. Results

5.3.1. Re-allocating monetary capital and associated carbon emissions

Distinguishing capital formation from capital investment and use is a prerequisite to understand the full lifespan of capital. Monetary capital flows and associated CO_2 flows across key sectors of capital investment (i.e., sectors undertaking the investment to build their capital stock), capital production (so-called 'capital formation' in national accounting), capital use (i.e., the original investing sectors), and final demand throughout the full lifespans of capital assets have been constructed in this study (**Figure 5-1**). Overall, the structures of the monetary capital flows and associated CO_2 flows look similar. In addition, CO_2 emissions from the primary production sectors such as electricity generation are not included in **Figure 5-1b**, considering that those sectors are not exclusively for capital-related production.

Monetary capital flows (**Figure 5-1a**) start from capital investing sectors to capital producing sectors, and end in capital using sectors for the production of final demand. Real estate services, transportation services, electricity generation, and residential services are the main capital investing sectors in China, which together accounted for half of total capital investment during the study period 1995−2017. Information of annual capital formation is recorded as gross fixed capital formation (GFCF) in the national accounts, which show that construction (contributing 58% of total GFCF), general equipment manufacturing (7%), and transportation equipment manufacturing (5%) dominated China's capital formation over 1995−2017. As such, main flows from capital investment to formation are observed among these key capital investing and producing sectors. Capital using sectors (i.e., the original investing sectors) will take over capital assets produced by capital formation sectors for their productive purposes over years. We find that approximately one-third of all the capital assets built-up during 1995–2017 have been depreciated to produce final consumption (14%), fixed capital (12%), and international exports (6%) by 2017. The remaining assets are still effective for future economic activities. Based on the three capital scenarios developed in this study, we show that another one-third (31%) of the capital assets built-up in 1995−2017 would be depreciated between 2018 to 2030. This depreciation in near thirteen years is almost equal to the depreciation during the past two decades. It can be explained by the rapid growth of capital investment in recent years in China (**Figure D-4**), such that the depreciation of capital assets built-up before 2017 in these two periods are mostly from recent years. As estimated in **Chapter 4**, the capital assets depreciated in China in 2015 were averagely invested in the proceeding five years.

Our study reveals that conventional estimations of supply chain-wide CO_2 emissions of 'capital investment' are, to some extent, misleading the allocation of capital-related emission responsibilities to capital producers instead of capital users. Sectors that mainly contribute capital-related CO_2 emission flows are same as those in the monetary flows (**Figure 5-1b**). the construction sector took the largest share in consumption-based CO_2 emissions of capital formation (CBE^{GFCF}), accounting for 68% of total CBE^{GFCF} during 1995–2017. This result is consistent with precious findings regarding CBEs of GFCF sectors (Davis and Caldeira 2010, Feng et al. 2013). As for consumption-based CO_2 emissions of capital use and depreciated capital (F^K), real estate service, transportation services, and residential services are observed as main contributors. CO_2 emissions

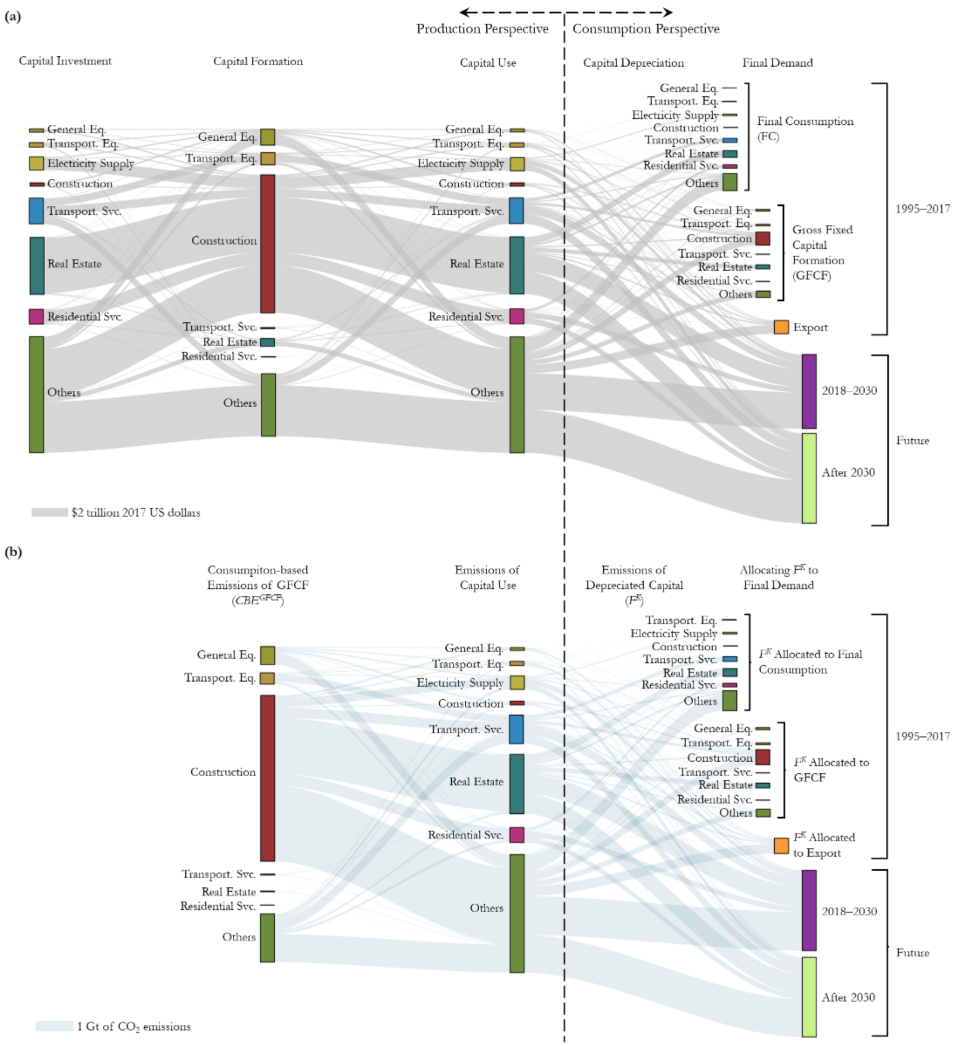

Figure 5-1. Monetary capital flows (a) and assocaited carbon transfers (b) among key sectors of China's capital development. The cumulative amounts of capital-related flows between 1995–2017 are shown in the plots. Only the *effective* capital investments from capital investment sectors to capital fromation sectors are shown in (**a**). Capital-related flows for the period 2018−2030 are shown as the average flows of all three sceanrios developed in this study. Seven key sectors highly relevant for China's capital development are selected in the plots. Full names of sectors could be found in **Table D-5**.

embodied in capital depreciation flows can also be allocated to final goods and services by 2017, between 2018 to 2030, and for long-term future production after 2030, which account for 35%, 33%, and 32%, respectively, of total CBE^{GFCF} during the study period. It is important to note that supply chain-wide CO_2 emissions embodied in capital investment and use have rarely been estimated for actual investing sectors. Previous supply chain-wide CO_2 emissions of 'capital investment' were calculated for capital formation sectors, i.e., CBE^{GFCF} (Davis and Caldeira 2010, Feng et al. 2013). As mentioned before, capital investing sectors—the final users of capital assets—are different from capital formation sectors. Therefore, a mis-allocation of capital-related emission responsibilities to capital producers instead of capital consumers is revealed in conventional input-output table-based estimates of supply chain-wide CO_2 emissions of 'capital investment'. Re-allocating this part of capital-related CO_2 emissions to the acutal capital consumers or further to final goods and services throughout the full lifespan of capital, substantially alters CO_2 emission accounting at both regional and sectoral levels.

5.3.2. Capital re-allocation altering regional carbon emission accounts

How we assign capital-related CO_2 emissions substantially influences regional CO_2 emission accounting from both production and consumption perspectives (**Figure 5-2**). Conventionally, scholars treat capital assets the same way as non-capital goods, and assign capital-related CO_2 emissions at annual basis to the producing region yielding PBEs of GFCF or to the purchasing region yielding CBEs of GFCF. In this study, we treat capital assets as production inputs by endogenizing capital investment and consumption into economic production over time and across provinces, and re-allocate supply chain-wide CO_2 emissions of annual capital depreciation (F^K) to capital using sectors for production-based accounting, or to final demand for consumption-based accounting.

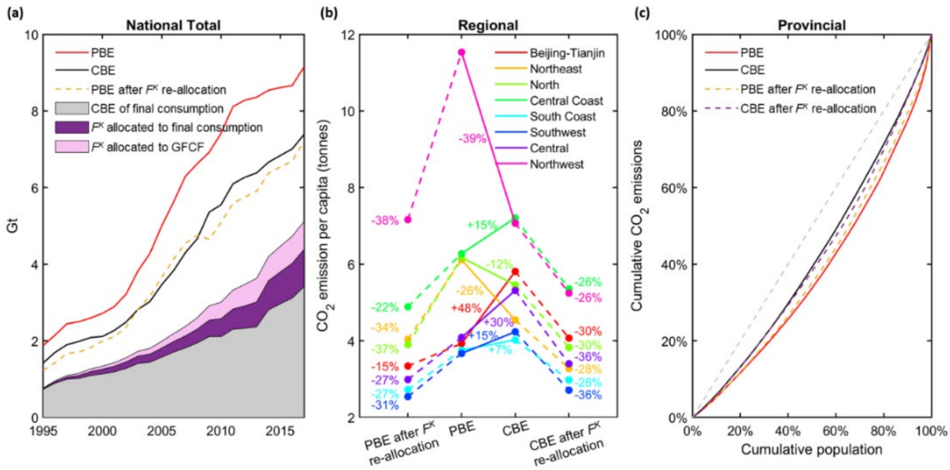

Figure 5-2. **Alteration to the production-based emissions (PBEs) and consumption-based emissions (CBEs) due to capital re-allocation at the (a) national, (b) regional, and (c) provincial levels.** In **(a)**, the national PBE and CBE with and without the re-allocation of capital-related carbon emissions (F^K) are shown. In (**b**), the changes in regional per-capita PBEs and CBEs

for the year 2017 with and without the re-allocation of F^K are plotted. The geographical partition of China can be found in **Table D-3**. In (**c**), the inter-provincial inequality of per-capita PBE and CBE in 2017 with and without the re-allocation of F^K are illustrated. The gray dashed line represents the perfect equality of per-capita carbon emissions.

National PBEs and CBEs after F^K re-allocation are lower than conventional PBEs and CBEs (**Figure 5-2a**). The reason is that only one third of the carbon emissions of GFCF occurring during 1995–2017 would be assigned to economic production over the same period (**Figure 5-1b**), and the rest hence will enable future production. From the production perspective, national PBEs after F^K re-allocation would decrease by 25–35% since 1995, compared with conventional PBEs. The decrease in national PBEs implies that conventional PBEs of GFCF in a certain year is still larger than cumulative F^K embodied in all capital depreciation from 1995 to that year for the production of capital using sectors. The changes would even be larger from a consumption perspective with 31–46% decrease from conventional CBEs. We also observe that the relative changes in recent years from conventional emission accounts to our capital-endogenized accounting method are generally smaller than those in the early years around 1995. Economic growth needing more capital inputs is one reason, whilst neglecting pre-1995 capital investment and their carbon emissions (due to lacking data) for current production is another. Our estimates of capital consumption and associated F^K are conservative, especially for the early years in our modeling period (e.g., year 1995). For the later years, the impacts of neglecting pre-1995 capital investments become much smaller. Starting with 2013, less than 1% of the F^K was allocated from the carbon emissions embodied in capital goods invested in 1995.

Changes in PBEs and CBEs drive associated changes in per-capita carbon emissions (**Figure 5-2b**). Similar to changes in national PBE and CBE, regional per-capita PBEs and CBEs after F^K re-allocation also decline compared with conventionally accounted emissions. Changes in per-capita carbon emissions vary significantly among regions for the year 2017, especially per-capita PBEs. The per-capita PBEs after F^K re-allocation are observed with a range of 15–38% reduction in 2017. The Northwest, the North, and the Northeast have relatively larger reductions in their regional per-capita PBEs, compared to regions such as Beijing-Tianjin and the Central Coast. Yet, these northern regions only invested around 28% of the total capital formation in 2017. We also observe that changes in per-capita PBEs with and without F^K re-allocation are consistent with regional changes from conventional per-capita PBEs to CBEs. Thus, to explain the relatively larger changes in per-capita PBEs in these northern regions, their net-exporting roles of capital assets and associated carbon emissions may be the main reason. In contrast, the relatively larger changes in per-capita CBEs are found in the regions having more capital investment, such as the Central (-36%) and the Southwest (-36%) which contributed 28% and 17%, respectively, of national total

GFCF in 2017. Lastly, our results also reveal that capital re-allocation would decrease the inter-provincial inequality of per-capita PBEs, but also to some extent increases the inequality of per-capita CBEs (**Figure 5-2c**). This is because the distinction among provinces of per-capita capital investment (with a standard deviation of 0.20) is more pronounced than that of per-capita CBEs (with a standard deviation of 0.17), whereas smaller than that of per-capita PBEs (with a standard deviation of 0.21).

5.3.3. Temporal displacement of carbon emissions is considerable

To reveal the full lifespans of capital assets from the past to the future, future production and use of capital in China are projected by a 'business-as-usual' (BAU) scenario and two capital-oriented pathways (i.e., KES and KLC scenarios) that focus on different purposes of capital investment. Conventional PBEs and CBEs of China substantially increase under the BAU and KES scenarios (**Figure 5-3a**), but show modest growth (less than 2%) under the KLC scenario, with potential decreases in some regions (e.g., the Beijing-Tianjin, and the Southwest, see **Figure D-5**). Uncertainty analysis (details see **Appendix D.9**) shows that national carbon emissions in 2030 would have the largest fluctuation of -4 to +6% under the KES scenario (**Figure 5-3a**). Moreover, compared with the BAU scenario, an extra 7% investments in low-carbon technology under the KLC scenario would gain a 9% reduction in national PBE, but would also result in a 4%-decrease in national GDP. Detailed analysis of future projections of conventional PBEs and CBEs of China and each region can be found in **Appendix D.7**.

When continuing allocating F^K occurring during 1995−2017 to economic production and consumption in the near future, our results show that approximately 10% of national carbon emissions (represented by PBE or CBE after F^K re-allocation) in 2030 would be allocated from the period of 1995−2017 (**Figure 5-3b**). This share of pre-2017 F^K in national carbon emissions would be even higher in 2018 and 2019, accounting for 23−30%, since the re-allocated F^K from a certain year decreases along the lifespans of assets (**Figure D-7**). The total share of F^K (including both pre-2017 emitted and future emissions between 2018 and 2030) in national PBE and CBE after F^K re-allocation would be respectively 32−34% and 37−39% in 2030, and both have ±2% fluctuations based on the uncertainty analysis.

In this study, we regard the part of capital-related emissions (i.e., re-allocated F^K) that occurred before year *n* but are finally allocated to economic production and consumption in year *n* as historically committed carbon emissions. The historically committed carbon emissions conceptually are different from *'commitment to future emissions'* (regarded as future committed carbon emissions from hereon) that were estimated by Davis et al. (2010) and Tong et al. (2019). The future committed carbon emissions look forward at expected carbon emissions after year n by operating existing fossil fuel-burning infrastructure by year n, extrapolating the implications of investments in capital assets up to the present. Our historically committed carbon emissions look backward at how much of the historically emitted CO_2 that was embodied in capital assets should be attributed to economic production and consumption in a year n, as production and consumption rely on these capital assets that were built up in the years preceding year n. Based on the three capital scenarios, this study extends the analysis of spatiotemporal downstream impacts of capital development on regional carbon emission accounting, and indeed quantify both historically and future committed carbon emissions of all economic sectors, while the previous future committed carbon emissions were only estimated for the power generation sector.

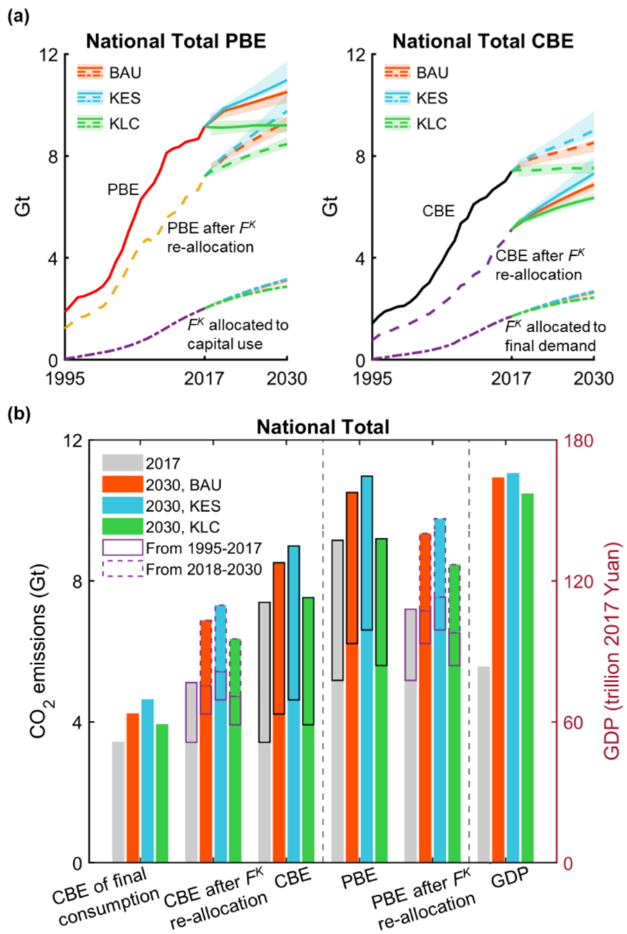

Figure 5-3. National carbon emissions with and without the re-allocation of capital-related carbon emissions under the three scenarios until 2030. In (**a**), the color-shaded areas represent

the 25th—75th percentile of uncertainty analysis results. In (**b**), the national carbon emissions and GDP for the year 2017, and year 2030 under the three capital scenarios are showed. The re-allocated carbon emissions of capital depreciation (F^K) are disaggregated into those occurred in the period of 1995−2017 (with solid purple edge line) and those would occur in the period of 2018−2030 (with dashed purple edge line).

Contributions of historically and future committed carbon emissions to sectoral carbon emission (represented by PBE or CBE after F^K re-allocation) vary widely in our analysis. **Table 5-3** summarizes historically and future committed carbon emissions of four capital-intensive production sectors in 2030 under each scenario. We find that most carbon emissions of the electricity generation and supply sector are future committed emissions, as highlighted in previous studies (Davis et al. 2010, Tong et al. 2019), whereas historically committed carbon emissions of its production and consumption are relatively small (only accounting for 4-6%). In contrast, historically committed carbon emissions of service-related sectors would occupy a significant share of their future carbon emissions. Particularly for real estate services and residential services, historically committed carbon emissions would dominate their future carbon emissions from both production and consumption perspectives, accounting for more than 83% of their carbon emissions. Transportation service sector would have less difference in its historically and future committed carbon emissions, compared with other sectors, and would have more future committed emissions (contributing more than 60%) in 2030. Furthermore, historically committed carbon emissions from 1995−2017 would take the largest share in carbon emissions of China and most sectors in 2030 under the KLC scenarios. This is because cleaner production under the KLC scenario would reduce associated carbon emissions of production and consumption in future, which hence enlarges the share of historical carbon emission of capital production that relied on lower-efficient production technologies. Our results suggest that the earlier development of efficient productive capital would bring less carbon emissions for future production, as did in today's developed countries like the United States and Japan (Feng et al. 2013, Wu et al. 2021a, Xiao et al. 2021).

Table 5-3. The sectoral carbon emissions for the year 2030 under the three capital investment scenarios.

	Electricity Supply			Construction			Transport. Svc.			Real Estate			Residential Svc.		
	BAU	KES	KLC	BAU	KES	KLC	BAU	KES	KLC	BAU	KES	KLC	BAU	KES	KLC
PBE	4443	4862	4038	78	79	77	717	725	901	15	15	15	11	11	10
PBE after F^K re-allocation	3105	3499	2808	32	32	30	763	769	867	595	598	546	398	401	359
From 1995–2017	42	43	40	13	13	13	97	97	97	227	227	227	103	103	103
	(1%)	*(1%)*	*(1%)*	*(42%)*	*(41%)*	*(45%)*	*(13%)*	*(13%)*	*(11%)*	*(38%)*	*(38%)*	*(42%)*	*(26%)*	*(26%)*	*(29%)*
From 2018–2030	110	114	96	17	17	14	188	189	162	358	361	310	286	289	247
	(4%)	*(3%)*	*(3%)*	*(51%)*	*(51%)*	*(48%)*	*(25%)*	*(25%)*	*(19%)*	*(60%)*	*(60%)*	*(57%)*	*(72%)*	*(72%)*	*(69%)*
CBE of final consumption	2381	2784	2158	11	11	9	514	519	606	22	21	20	43	43	39
CBE	2381	2784	2158	2576	2604	2112	544	549	639	31	31	29	45	44	40
CBE after F^K re-allocation	2505	2922	2274	421	425	379	725	731	801	492	493	451	266	263	239
From 1995–2017	35	38	35	122	122	119	69	69	70	181	181	181	60	59	60
	(1%)	*(1%)*	*(2%)*	*(29%)*	*(29%)*	*(31%)*	*(10%)*	*(9%)*	*(9%)*	*(37%)*	*(37%)*	*(40%)*	*(23%)*	*(22%)*	*(25%)*
From 2018–2030	89	100	82	289	292	251	141	142	125	290	291	250	163	161	141
	(4%)	*(3%)*	*(4%)*	*(69%)*	*(69%)*	*(66%)*	*(19%)*	*(19%)*	*(16%)*	*(59%)*	*(59%)*	*(55%)*	*(61%)*	*(61%)*	*(59%)*

Notes: We select four of the key sectors of capital development in China (see **Figure 5-1**). The percentages in commas represent the share of associated carbon emissions in the sectoral total emissions. Unit: Mt.

5.4. Discussion

5.4.1. The concept of historically committed CO_2 emissions

The two features of capital assets raise two important topics of analyzing capital activities and their environmental responsibilities. One is the allocation of environmental responsibilities across different capital activities such as capital formation or capital use, the other is temporal displacement of environmental responsibilities along capital's lifespan. The first topic has been explored by endogenizing capital into MRIO modelling (Chen et al. 2018, Lenzen and Treloar 2004, Södersten et al. 2020, Södersten et al. 2018a), while the second topic has not been well analyzed before in literature. This study explores the second topic, and demonstrates a new approach to quantify and allocate supply chain-wide capital inputs and associated CO_2 emissions among sectors, across regions, and over time. Historically committed CO_2 emissions are defined in this study, in contrast to future committed CO_2 emissions (Davis et al. 2010, Tong et al. 2019). Future committed carbon emissions limit the remaining carbon budgets for other economic and human activities. Historically committed carbon emissions have no influence on actual CO_2 emitted each year, but provide a new scheme to assign environmental responsibilities of capital activities. The new accounting scheme assigns environmental responsibilities of capital activities into capital users instead of capital producers as conventionally done, and allocates the environmental burden of capital formation from the year of emissions over capital's entire lifetime. Both historically and future committed CO_2 emissions start with the inertia of the capital system, and emphasize that any construction and plans of capital assets today will influence future resource use and emissions. This inertia of the capital system is especially important for environmental pressures such as CO_2 emissions which accumulate over time and have impacts on the earth system over long time spans. The concept of historically committed emissions complements the idea of future committed emissions. Both ideas suggest policy makers to consider the inertia of capital system when designing policies for future sustainable development, for instance by considering historically and future committed CO_2 emissions when setting per-capita emission caps for a distant future.

5.4.2. Implications for policy making

Capital systems influence the attainment of all of the Sustainable Development Goals (Thacker et al. 2019). Few studies systematically project future capital development at the global or national level, not to mention the analysis of supply chain-wide downstream impacts of capital development on regional environmental performance. This study fills this important research gap through developing the BAU, KES, and KLC scenarios to compare China's future capital development pathways and associated CO_2 emissions. China has promised to peak its CO_2 emissions by 2030.

To achieve this target, it is projected that China's energy and CO_2 intensity levels need to decline by 43% and 45%, respectively (Mi et al. 2017b). This indicates that a substantial amount of investments in high-efficient productive devices are expected in the near future, and associated carbon emissions possibly increase in the capital investment to achieve reduced use-phase emissions. The KLC scenario presents an alternative pathway for China, namely low-carbon development via efficiency improvement and energy transition. Results show that under the assumptions of the scenario, low-carbon technology investments designed in the KLC scenario would be cost-efficient at the national scale—an extra 7% low-carbon technology investments would gain a 9% decline in national CO_2 emissions compared with the BAU scenario—and in most provinces, especially in Hebei, Jiangxi, and Sichuan. In addition, we find that historically committed CO_2 emissions are mostly attributable to the production and consumption of capital-intensive service sectors (**Table 5-3**), which are not usually regarded as main CO_2-emitters because emissions for the supporting constructions are not accounted for. Failing to include this historically committed part of CO_2 emissions in the CO_2 emission accounting of service sectors hence strongly underestimates their impacts on the climate. Given that the post COVID-19 economy recovery needs further investments which are mostly assigned to service sectors (Hertwich 2021). The endogenization of capital is an additional necessary step to ensure that policy makers realize the synergies and trade-offs between intensive-capital-enabled economic development and the associated environmental burden, and pursue a cost-efficient pathway of economy recovery like the one demonstrated in the KLC scenario instead of the KES scenario.

China has launched its first national emissions-trading scheme on 16 July 2021, which is regarded as the world's biggest among countries having such carbon-pricing mechanisms (Nogrady 2021). The core of the emission-trading scheme is to provide incentives to more efficient generation or less carbon-intensive generation of energy, which requires considerable capital investments in associated high-efficient machinery and infrastructure. China's emission-trading scheme focuses on direct emissions of energy generation. This study draws attention to the indirect emissions that are not only embodied in the traded commodities at the annual basis, but also in the productive capital throughout their lifespans (i.e., historically committed carbon emissions). The choice for conventional emissions accounting or the consideration of such historically committed carbon emissions could considerably influence the emission accounting (section **5.3.2**), and finally determine the emission allowances of each plant in the emissions-trading market. The former influence will be more significant for the plants that were built-up earlier with relatively lower efficiencies of economic production and resource use, i.e., having more embodied emissions which would be allocated to future production as demonstrated in this study. The latter emission allowances cannot be specified based on the current study but could result from a similar dedicated scenario study. We also come up with some suggestions for policy makings to consider capital-related emissions in China's emissions-trading market, particularly for energy plants: 1) constructing a systematic database that covers the lifetime each device operating (the start date, retired or ceased operating date); 2) developing a standard accounting method to quantify capital inputs (either in physical terms or monetary terms) for economic production, better in high resolutions of capital assets and using sectors; and 3) formulating a rational and fair price mechanisms for both historical and current emissions for companies to trade their emission allowances.

5.4.3. Limitations

This study has several limitations. Our model relies on data from multiple sources with different levels of uncertainty, such that the calculated results need to be interpreted with caution. For instance, it is more reasonable to identify temporal changes of capital-related carbon emissions, relative importance of final consumption categories, or differences in results produced by different models. Second, evaluating the use of physical capital assets in production by capital consumption or capital services is highly debated (Södersten et al. 2018a). Data on capital consumption are more available than that of capital services, while capital services rely on the prices of capital assets which have higher uncertainty among provinces and in different years. Capital consumption data are mostly calculated using the PIM (O'Mahony and Timmer 2009), which has been widely accepted by national and international statistical agencies and researchers. Thus, we also conduct this analysis by relying on capital consumption to represent the use of the physical capital assets. The third limitation relates not to the general modelling framework, but rather to the actual implementation of the scenarios and how we design the scenarios. Compared with the KES scenarios based on investments in specific infrastructure, there is not sufficient data available for all the required low-carbon technology investments under the KLC scenario, e.g., increased storage capacity for electricity from renewables or electric vehicle charging stations, which are not explicitly considered in the scenario. This is also relevant to dynamically modeling the changes in economic and investment structure under different capital investment pathways, rather using a static input-output model. As shown by our main scenario results, using base year's investment structure results in relatively small differences between the scenarios. For the dynamical modeling, possible supply and production capacity constraints should be considered. Lastly, shifting the fossil-based economy to bio- or renewable-energy-based economy will also request significant capital investment. Furthermore, the post-COVID-19 economy recovery requires considerable capital investment in general and professional equipment or infrastructure on the one hand (Shan et al. 2020b), while has changed previous plans in capital investment on the other (IEA 2020). Other alternative pathways of capital development are also interesting for future exploration, yet need other methods and approaches to model the entire economic and energy structures for future capital development narratives.

5.5. Conclusions

Capital assets (e.g. machinery, and buildings) underpin economic production throughout their full lifespans, but associated carbon emissions from the production of the capital assets themselves are concentrated in the period of their production. The durable feature of capital assets poses serious challenges in allocating the emissions related to capital assets over their full life span. This study provides a conceptual and operational approach for consistently allocating emissions related to capital assets to final uses including the consideration of temporal displacement.

Different from a conventional way that treated capital as one category of final demand and assigning associated carbon emissions to the capital producers (i.e., capital formation sectors) at annual basis, this study treats capital assets as production inputs and re-allocates carbon emissions of annual capital production to actual capital using sectors, and further to final goods and services over time. Capital formation is clearly distinguished from capital investment and use. Based on this, we found that conventional estimations of supply chain-wide CO_2 emissions of 'capital investment' are misleading the allocation of capital-related emission responsibilities to capital producers instead of capital users. For instance, CO_2 emitted during the construction phase of airports are assigned to construction sectors from conventional consumption-based accounting, instead of to the actual users of airports such as transportation services.

We also show that conceptual and methodological choices in the way we treat capital purchase and associated carbon emissions considerably influences China's emission accounts. Similar conclusions have also been summarized by previous studies (Chen et al. 2018, Lenzen and Treloar 2004, Södersten et al. 2020, Södersten et al. 2018a), but neglecting the temporal feature of capital assets led previous conclusions heavily skewed to the spatial displacement of emissions, and hence made the conclusions not comprehensive enough. Considering the temporal CO_2-emission displacement relieves the emission responsibilities of capital assets for the year of formation but also takes associated responsibilities from the past. Consequently, the consideration of temporal CO_2-emission displacements in national CO_2 accounts results in 25–35% and 31–46% net decrease compared to conventional accounting methods from the production and consumption perspective since 1995, respectively.

To understand this temporal displacement from the past to the future, we further design three capital-investment scenarios until 2030 (i.e., the BAU, KES, and KLC scenarios), based on different purposes of capital investments. Conventional PBEs and CBEs of China substantially increase under the BAU and KES scenarios, but show modest growth (less than 2%) under the KLC scenario, with potential decreases in some regions (e.g., the Beijing-Tianjin, and the Southwest). Considering the temporal CO_2-emission displacement in future CO_2 emission accounting, the pre-2017 capital-associated CO_2 emissions will contribute 10 (under the BAU scenario) –13% (under the KLC scenario) of China's CO_2 emissions in 2030, and could reach more than 40% for capital-intensive service sectors (e.g., real estate services or transportation services) under all the three scenarios.

This study provides a new scheme to assign environmental responsibilities of capital activities based on the concept of historically committed CO_2 emissions, which improves our understanding of the role of the capital system played in economic production and associated spatiotemporal displacement along capital's lifespan. The temporal displacement that is highlighted in this study, although virtual, is also important for assessing the sustainability and efficiency of emissions across regions, and the equity of emissions across generations due to historical and future 'commitments' of CO_2 emissions.

6

Conclusions

The goal of this thesis is to develop improved modelling techniques to better capture spatiotemporal virtual displacement of environmental pressures along the supply chain of goods and services. The hybrid MRIO model and the capital-endogenized MRIO model developed and presented in the previous chapters intend to solve key limitations in conventional IO modelling for environmental pressure assessments. In detail, the hybrid MRIO model combines advantages of both process- and IO table-based approaches, thus enabling to quantify the supply chain-wide environmental pressures of a specific agri-food product. The capital-endogenized MRIO model endogenizes capital investment and consumption into economic production over time, thus enabling to allocate environmental responsibilities of capital activities among different capital activities along capital's full lifespan. Scientific contributions of this thesis and possible implications for policy making are summarized in **Sections 6.1** and **6.2**. In **Section 6.3**, some future research directions that promisingly strengthen the consumption-based accounting of environmental pressures are introduced.

6.1. Scientific contributions of this thesis

6.1.1. Improvements in MRIO models to better capture *spatial* virtual displacement of environmental pressures

The hybrid MRIO model (**Chapters 2** and **3**) enables to capture product-specific environmental pressure displacement along its entire supply chain. The hybrid MRIO model integrates the physical supply and use systems of total eighty-four agri-food products into the monetary MRIO tables of China. Before the integration, the physical multi-regional supply, use, and IO tables of the specified agri-food products for China during the period of 1990-2013 are also compiled. Compared with existing hybrid IO models that rely on monetary IO data to track biomass products from the first (or second) use stage to the final consumers (Ewing et al. 2012, Steen-Olsen et al. 2012), the proposed hybrid MRIO model describes the whole structure of material conversion and distribution networks by means of detailed physical supply and use tables. Compared with the global FABIO model that only includes agri-food products (Bruckner et al. 2019), the proposed hybrid MRIO model integrates the physical agri-food supply-use system into the monetary all-sector supply chain. The two applications of the hybrid MRIO model show:

- The first application to the case of provincial blue water footprint assessments in China (**Chapter 2**) illustrates that the hybrid model enhances both the traditional monetary IO table-based approach and the process-based approach. Compared with the traditional monetary IO table-based approach, the hybrid model reduces the uncertainty arising from the aggregation of different products into homogeneous sectors, by using product-and sector-specific environmental intensities rather using one value for all related agri-food products. Compared with the process-based approach, the hybrid model captures the whole supply chain-wide environmental pressures, and allows to quantify upstream environmental pressures occurring along the supply chain for final consumed agri-food products.

- The second application combines the hybrid MRIO model with a trade disaggregation approach and a novel no-trade scenario, to analyze effects of production fragmentation and inter-provincial trade on blue water consumption and scarcity patterns in China (**Chapter 3**). It shows that the hybrid model is applicable to be jointly used with other approaches for broader research studies. The combination demonstrated in this thesis reveals the opposite roles of current trade in alleviating water scarcity in provinces under extreme water scarcity and in China from the national scope. It hence sheds light on the consideration of specific trade patterns and their impacts on provincial and national water consumption to cope with water scarcity in China, such as enhancing local production of direct final consumption commodities.

6.1.2. Improvements in MRIO models to capture *temporal* virtual displacement of environmental pressures

The capital-endogenized MRIO model (**Chapters 4** and **5**) enables to capture the temporal virtual displacement of environmental responsibilities embodied in dynamic capital development over time. The improved capital-endogenized MRIO model quantifies the linkages between temporal capital development, the economic production as enabled by capital assets, and human final consumption throughout the full lifespan of capital. Compared with existing capital-endogenized MRIO models (Chen et al. 2018, Lenzen and Treloar 2004, Södersten et al. 2020, Södersten et al. 2018a), the capital-endogenized MRIO model developed in this thesis considers both inter- and intra-annual dynamic features of capital production (using different technologies during different age cohorts) and consumption (with an intra-annual production-depreciation-reproduction cycle). The two applications of the capital-endogenized MRIO model in this thesis allow to extend the traditional debate of spatially environmental displacement with a temporal dimension. In detail:

- The first application to China's capital development and the re-assessment of its environmental footprints (**Chapter 4**) results in a new accounting scheme of regional environmental pressures. In the chapter, China's capital development during 1995-2015 is linked to current human consumption around the world. The results show that without accounting for the capital−final consumption linkages across time and space, one would miscalculate environmental footprints by big margins.

- The second application to the projections of China's future capital development and associated carbon emissions (**Chapter 5**) extends the linkages from past and present into the future. The capital-endogenized MRIO model is used to quantify the '*historically committed*' carbon emissions that occurred in the historical time when producing the used capital assets but will serve future economic production and consumption. The results highlight the important role of historically built-up capital assets in future economic production and sustainable environmental development, especially when focusing on specific sectors such as transportation services. This historically committed environmental pressure concept allows the conventional debates of inter-regional virtual displacement of resource and pollution to consider inter-annual responsibility displacement according to capital investment, trade, and consumption.

6.1.3. Contributions related to datasets

This thesis also has contributions related to datasets. First, a national dataset was constructed with inter-provincial trade-linked supply, use and input-output tables that capture specific supply chains of agri-food products in physical units (e.g., tonnes, heads) during the period of 1990-2012 in China (**Chapter 2**). Eighty-four raw and processed agri-food commodities supplied and used by seventy-five processes are specified in the dataset. The dataset covers 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 encompasses the most comprehensive classification of agri-food commodities for sub-national supply chain analysis. Second, this thesis also developed a capital investment dataset at the provincial level during the period of 1995-2017 for China (**Chapter 5**). The provincial capital investment dataset recorded annual *effective* capital investment, i.e., the newly increased fixed assets, for each province at the resolution of three asset types and thirty-seven investing sectors, following WORLDKLEMS. The recorded *effective* capital investment is more appropriate for environmental pressure-related studies of capital investment, compared with the annual initiated capital investments which always result in an overestimation issue. The two datasets have been made publicly available in the open data repository Figshare.

6.2. Possible implications for policy making

The virtual displacement of environmental pressures from primary production to the final consumers is a prominent issue in current international debates regarding the assignment of environmental responsibilities (COP26 2021, IPCC 2014). In this context, traceability tools are needed to support both stakeholders and policy makers in monitoring and governing spatiotemporal flows of products, capital requirements, and the embodied environmental pressures.

6.2.1. Production- or consumption-based?

Production and consumption perspectives present different scopes of regional environmental responsibilities.

The production-based accounting focuses on territorial factors that drive environmental pressures such as economic production, technology levels, and resource endowments, but tends to overlook the interdependence among regions via trade. The trade disaggregation approach (**Chapter 3**) provides relevant information about different use-purposes of traded commodities like for final consumption or as intermediate inputs for further production, and reveals their respective contributions to regional resource consumption. This knowledge can help policy makers fully consider specific trade patterns and their pressures on local environment to further optimize trade patterns among regions. For instance, given that direct final goods trade contributed the most to the virtual water trade within China and the main exporting provinces of virtual water are those water-deficient provinces (e.g., Xinjiang or Heilongjiang), associated water importing provinces are suggested to change their trade partners of direct final commodities from water-deficient provinces to water-adequate provinces if these water-adequate provinces can also supply same or substitute final commodities. In addition, long-distance trade will lead to more resource consumption for the transportation, which can be reduced by trade with adjacent regions. The idea of co-development among adjacent regions and urban agglomerations (such as Jing-Jin-Ji) has been widely suggested in China. The co-development among adjacent regions, to some extent, can increase the self-sufficient capacities of a single region in the agglomeration if the region is limited in resources and products, which hence costs less resource consumption for importing goods from outside of the agglomeration especially from long-distance regions.

The consumption-based accounting shows the virtual spatial displacement (or outsourcing) of environmental pressures from the commodity importers to the exporters, and reveals the spatial inequality of environmental pressures of human consumption. Yet, the inter-generational inequality of environmental responsibilities is not assessed. The capital-endogenized MRIO model (**Chapters 4** and **5**) fills this research gap and quantifies the temporal virtual displacement of environmental pressures embodied in capital production and consumption. Using the capital-endogenized MRIO model, researchers or policy makers can achieve a better estimate of expected benefits from current capital investment instead of perpetuating a lock-in through investment-heavy consumption. As for private capital investment or individual asset purchasing, the in-use stock levels differ widely among population with different income levels—spatially across countries and temporally across generations. The durable feature of in-use capital stocks implies that putting more investments in less-resource-intensive assets or capital assets with high efficiencies of resource consumption are important for current and future resource consumption to produce and operate these assets. This inertia of the capital system is especially important for environmental pressures such as CO_2 emissions which accumulate over time and have impacts on the earth system over long time spans. When designing policies for future sustainable development, policy can take into account this inertia of the capital system, for instance by considering historically and future committed carbon emissions when setting per-capita emission caps for a distant future.

6.2.2. Choice of system boundaries and environmental indicators

Environmental pressure assessments at which scale (e.g., national or provincial) or of which object (e.g., a certain product or sector) influence sustainability-oriented suggestions for policy making. The choice of system boundaries shows its importance. Usually, a systematic all-sector analysis of resource consumption and emissions would miss detailed information regarding a certain product, which is regarded as the main trade-off between process-based and IO table-based approaches for environmental pressure assessments. The proposed hybrid MRIO model well balances the product-level details and the sector-level comprehensiveness, and captures the transactions among not only main agri-food products but also with other manufacturing and service sectors. Information derived from using the hybrid model can help policy makers determine key agri-food products with large environmental pressures and highly relevant to people's daily consumption habits for future resource management towards sustainability. According to the Chinese case analyzed in **Chapter 2**, key agri-food products consuming most water include maize and rice in the North China whilst pigs in the South China. This implies that measures to reduce water consumption can mainly direct to maize and rice in the North China (e.g., constructing irrigation infrastructure), whilst to pig farming in the South China (e.g., applying industrial farming systems or concentrated farming systems).

For the same environmental problem, choosing different indicators, e.g., to estimate pressures on freshwater in the terms of water withdrawals or water consumption, may also result in quite different policy suggestions. The capital-endogenized MRIO model re-assigns the capital-related environmental pressures first to the capital using sectors and further to the final goods and services that are produced by the assets along capital's lifespan. Previous assessment of environmental pressures of capital investment always stopped at the capital production phase, and neglected the downstream use of capital assets. When extending the system boundaries by including the downstream operation of capital assets, it can lead to a totally different conclusion of environmental responsibilities of capital activities, that is, switching from the producers of capital assets to the actual users. Based on the capital-endogenized MRIO model, we also point out two new environmental indicators from production and consumption perspectives (i.e., production- and consumption-based emissions after capital allocation) and a new concept '*historically committed*' environmental pressures. The newly proposed indicators and concept theoretically distributes the environmental burden of capital formation from the year of emissions over capital's entire lifetime, and offers the decision makers new insights into the construction plans of capital-intensive projects. For instance, when current huge environmental pressures are the main concern to launch a capital-intensive project, the idea of mortgages of environmental burden, which are complemented by environmental pressure neutrality measures during the pay-back period, can be applied on the project.

6.2.3. Synergies and trade-offs for sustainable development.

Understanding the synergies and trade-offs among inter-regional trade, capital investment, economic structure and environmental pressures is vital to achieve the SDGs (Thacker et al. 2019, Wang et al. 2022, Xu et al. 2020b). Although this thesis does not directly identify synergies or trade-offs between different components of the earth system, the proposed hybrid and capital-endogenized models can be used to analyze them.

According to the Chinese case in **Chapter 3**, under the no-trade scenario, China's total outputs would decrease $4.3 trillion 2012 US dollars, and the national total water consumption would also decrease 27.4 km^3/yr. This shows that there is a synergy between inter-regional trade and economic growth, and a trade-off between inter-regional trade and water consumption. Enabled by the hybrid MRIO model developed in this thesis, this synergy between inter-regional trade and economic growth and the trade-off between inter-regional trade and broader environmental pressures can be conducted at the agri-food-product level, if policies and decisions are related to associated products. For example, whether a relative or absolute decoupling can be achieved between water consumption and economic benefits of crop production.

As for capital system, the synergy and trade-offs will be even clearer. That is, the manufactured capital system enables sectors to produce essential goods, services, and shelter for human beings, while consumes resources and induces environmental pollutions when using the assets. This, in turn, necessitates changes in human, nature, and capital and their interactions, such as the rapid growth in low-carbon technology of energy supply and use to cope with climate changes. The proposed capital-endogenized MRIO model reveals the full lifespans of capital assets from their original investment to the formation, and the depreciation processes by the using sectors to produce different goods and services. It presents not only the upstream economic and resource inputs for capital cycle, but also the downstream impacts on economic production, commodity consumption, and associated spatiotemporal environmental displacement. Information generated by the capital model can be used to better understand the synergies and trade-offs among capital, economy and environment, and support future policy making of capital development for a long-term planning.

6.3. Future Research Directions

The proposed hybrid MRIO model and capital-endogenized MRIO model have well solved the selected key limitations in conventional IO modelling for environmental pressure assessments. Yet, there still are relevant research challenges ahead that need following-up research to strengthen these two models.

Key factors with high uncertainty that are revealed in the implementations of two proposed models trigger a first main challenge for future research. For the hybrid model, key uncertain factors include inter-regional trade amounts of various products and feed requirements for animal farming, whilst for the capital-endogenized model, key uncertain factors are limited categories of capital assets and less information of capital consumption by time cohorts. A promising research strategy on these themes would be to develop systematic and comprehensive databases regarding inter-regional trade of various products in different units and in high resolutions of resources, pollutions, capital assets, capital investing sectors, and lifespans.

Second, the integration of multiple industrial products will also be a potential research interest to strengthen the hybrid MRIO model. This research line can be further combined with circular economy agendas, analyzing the challenges and solutions for countries to achieve resource recycling and reusing in industrial sectors like cement manufacturing. To hybridize industrial products will depend on the development of associated databases described for the first challenge, which states the importance of developing such databases in the future. Overall, the hybrid MRIO model can benefit future research relevant to product-specific environmental pressure assessments, spatiotemporal displacement, and benchmarking of resource productivities, but the prerequisite is to extend with comprehensive environmental inventories such as water stress, land use, and related biodiversity loss.

Capital investments serve fundamentally different purposes. Capital theorists often differentiate between the replacement capital, which constitutes the investments done to maintain and upgrade the existing capital, and the net capital formation, which entails new investments. Incorporating the dynamics of capital would hence constitute a potential direction for future versions of the capital-endogenized model, not only based on input-output modelling but also in other accounting approach such as life cycle assessments. Particularly for the input-output model, the relatively static feature of the model is the main challenge to conduct this research line. Hence, the construction of a capital coefficients matrix that represents the dynamic changes in capital investment and consumption and further to be endogenized into the standard dynamic Leontief models will be a potential solution. Future research can also focus on practical uses of the historically committed concept of capital and associated environmental pressures pointed out in this thesis, for instance, in the assessment of environmental pressures as conducted in **Chapter 5**, or in the trading schemes of carbon emissions or other resources. This research line depends largely on specific questions researchers are looking at.

Lastly, the idea of integrating the two proposed models is also on the table for future exploration. The key point of this integration will focus on the linkages between agricultural production and its investment on different capital terms, i.e., natural capital like land, manufactured capital like irrigation machinery, and human capital like labor force. Fully understanding the interactions between natural, manufactured, and human capital will be helpful to build up a more interdependent and sustainable capital system for our planet.

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Appendix

Appendix A: An Appendix to Chapter 2

A.1. Supplementary Tables for Chapters 2 and 3

Table A-1. Lists of 31 provinces of mainland China covered in FABIO_CHN.

Province Code	Name	Region
r1	Beijing	North China
r2	Tianjin	North China
r3	Hebei	North China
r4	Shanxi	North China
r5	Inner Mongolia	North China
r6	Liaoning	Northeast China
r7	Jilin	Northeast China
r8	Heilongjiang	Northeast China
r9	Shanghai	East China
r10	Jiangsu	East China
r11	Zhejiang	East China
r12	Anhui	East China
r13	Fujian	East China
r14	Jiangxi	East China
r15	Shandong	East China
r16	Henan	Central China
r17	Hubei	Central China
r18	Hunan	Central China
r19	Guangdong	South China
r20	Guangxi	South China
r21	Hainan	South China
r22	Chongqing	Southwest China
r23	Sichuan	Southwest China
r24	Guizhou	Southwest China
r25	Yunnan	Southwest China
r26	Tibet	Southwest China
r27	Shaanxi	Northwest China
r28	Gansu	Northwest China
r29	Qinghai	Northwest China
r30	Ningxia	Northwest China
r31	Xinjiang	Northwest China

Table A-2. Lists of commodities covered in FABIO_CHN.

Commodity Code	FAO Name	FAO Group	Notes
c1	Rice (Paddy Equivalent)	Cereals	
c2	Wheat and products	Cereals	
c3	Barley and products	Cereals	
c4	Maize and products	Cereals	

c5	Millet and products	Cereals	
c6	Sorghum and products	Cereals	
c7	Cereals, Other	Cereals	Including rye and oats
c8	Potatoes and products	Roots and tubers	
c9	Roots, Other	Roots and tubers	Including cassava, and sweet potatoes
c10	Sugar cane	Sugar crops	
c11	Sugar beet	Sugar crops	
c12	Beans	Vegetables, fruit, pulses	Excluding soyabeans
c13	Soyabeans	Oil crops	
c14	Groundnuts (Shelled Eq)	Oil crops	
c15	Sunflower seed	Oil crops	
c16	Rape and Mustardseed	Oil crops	
c17	Coconuts - Incl Copra	Oil crops	
c18	Sesame seed	Oil crops	
c19	Oilcrops, Other	Oil crops	Including olives
c20	Tomatoes and products	Vegetables, fruit, pulses	
c21	Vegetables, Other	Vegetables, fruit, pulses	
c22	Oranges, Mandarines	Vegetables, fruit, pulses	
c23	Grapefruit and products	Vegetables, fruit, pulses	
c24	Citrus, Other	Vegetables, fruit, pulses	
c25	Bananas	Vegetables, fruit, pulses	
c26	Apples and products	Vegetables, fruit, pulses	
c27	Pineapples and products	Vegetables, fruit, pulses	
c28	Dates	Vegetables, fruit, pulses	
c29	Grapes and products (excl wine)	Vegetables, fruit, pulses	
c30	Fruits, Other	Vegetables, fruit, pulses	
c31	Coffee and products	Coffee, tea, cocoa	
c32	Tea (including mate)	Coffee, tea, cocoa	
c33	Jute	Fibre crops	
c34	Sisal	Fibre crops	

c35	Tobacco	Tobacco, rubber	
c36	Rubber	Tobacco, rubber	
c37	Cottonseed	Oil crops	Estimated by TCF of China based on the data of cotton lint
c38	Sugar, Refined Equiv	Sugar, sweeteners	
c39	Soyabean Oil	Vegetable oils	Estimated by TCF of China
c40	Groundnut Oil	Vegetable oils	Estimated by TCF of China
c41	Sunflowerseed Oil	Vegetable oils	Estimated by TCF of China
c42	Rape and Mustard Oil	Vegetable oils	Estimated by TCF of China
c43	Cottonseed Oil	Vegetable oils	Estimated by TCF of China
c44	Coconut Oil	Vegetable oils	Estimated by TCF of China
c45	Sesameseed Oil	Vegetable oils	Estimated by TCF of China
c46	Ricebran Oil	Vegetable oils	Estimated by TCF of China
c47	Maize Germ Oil	Vegetable oils	Estimated by TCF of China
c48	Oilcrops Oil, Other	Vegetable oils	Estimated by TCF of China
c49	Soyabean Cake	Oil cakes	Estimated by TCF of China
c50	Groundnut Cake	Oil cakes	Estimated by TCF of China
c51	Sunflowerseed Cake	Oil cakes	Estimated by TCF of China
c52	Rape and Mustard Cake	Oil cakes	Estimated by TCF of China
c53	Cottonseed Cake	Oil cakes	Estimated by TCF of China
c54	Copra Cake	Oil cakes	Estimated by TCF of China
c55	Sesameseed Cake	Oil cakes	Estimated by TCF of China
c56	Oilseed Cakes, Other	Oil cakes	Estimated by TCF of China
c57	Wine	Alcohol	
c58	Beer	Alcohol	Including beer of barley, maize, millet, and sorghum
c59	Beverages, Fermented	Alcohol	Including beverages by fermented rice, wheat, and apple
c60	Alcohol, Non-Food	Ethanol	
c61	Cotton lint	Fibre crops	
c62	Cattle	Live animals	Including buffalo
c63	Sheep	Live animals	Including goat
c64	Pigs	Live animals	
c65	Poultry Birds	Live animals	
c66	Horses	Live animals	
c67	Asses	Live animals	
c68	Mules	Live animals	
c69	Camels	Live animals	
c70	Milk - Excluding Butter	Milk	
c71	Eggs	Eggs	

c72	Wool (Clean Eq.)	Hides, skins, wool	
c73	Bovine Meat	Meat	Including meat of cattle and buffalo
c74	Mutton & Goat Meat	Meat	Including meat of sheep and goat
c75	Pigmeat	Meat	
c76	Poultry Meat	Meat	
c77	Meat, Other	Meat	
c78	Offals, Edible	Meat	Including offal from cattle, buffalo, sheep, goat, pig, horse, and camel; Estimated by TCF of China
c79	Fats, Animals, Raw	Animal fats	Including fats from cattle, buffalo, sheep, goat, pig, and camel; Estimated by TCF of China
c80	Hides and skins	Hides, skins, wool	Including hides and skins from cattle, buffalo, sheep, and goat; Estimated by TCF of China
c81	Honey	Honey	
c82	Silk	Hides, skins, wool	
c83	Fish, Seafood	Fish	
c84	Wood fuel	Wood	

Note: TCF represents the technical conversion factor from the giving the conversion efficiencies for food processing.

Table A-3. Lists of processes covered in FABIO_CHN.

Processing Code	Process	Processing Type
p1	Rice production	Primary production
p2	Wheat production	Primary production
p3	Barley production	Primary production
p4	Maize production	Primary production
p5	Millet production	Primary production
p6	Sorghum production	Primary production
p7	Cereals production, Other	Primary production
p8	Potatoes production	Primary production
p9	Roots production, Other	Primary production
p10	Suga cane production	Primary production
p11	Sugar beet production	Primary production
p12	Beans production	Primary production
p13	Soyabeans production	Primary production
p14	Groundnuts (Shelled Eq) production	Primary production
p15	Sunflower seed production	Primary production
p16	Rape and Mustardseed production	Primary production
p17	Seed cotton production	Primary production
p18	Coconuts production	Primary production
p19	Sesame seed production	Primary production
p20	Oilcrops production, Other	Primary production
p21	Tomatoes production	Primary production

p22	Vegetables production, Other	Primary production
p23	Oranges, Mandarines production	Primary production
p24	Grapefruit production	Primary production
p25	Citrus production, Other	Primary production
p26	Bananas production	Primary production
p27	Apples production	Primary production
p28	Pineapples production	Primary production
p29	Dates production	Primary production
p30	Grapes production	Primary production
p31	Fruits production, Other	Primary production
p32	Coffee production	Primary production
p33	Tea production	Primary production
p34	Jute production	Primary production
p35	Sisal production	Primary production
p36	Tobacco production	Primary production
p37	Rubber production	Primary production
p38	Cotton production	Primary production
p39	Sugar production	Processing
p40	Soyabean Oil extraction	Processing
p41	Groundnut Oil extraction	Processing
p42	Sunflowerseed Oil extraction	Processing
p43	Rape and Mustard Oil extraction	Processing
p44	Cottonseed Oil extraction	Processing
p45	Coconut Oil extraction	Processing
p46	Sesameseed Oil extraction	Processing
p47	Ricebran Oil extraction	Processing
p48	Maize Germ Oil extraction	Processing
p49	Oilcrops Oil extraction, Other	Processing
p50	Wine production	Processing
p51	Beer production	Processing
p52	Beverages production, Fermented	Processing
p53	Alcohol production, Non-Food	Processing
p54	Cattle husbandry	Primary production
p55	Sheep husbandry	Primary production
p56	Pigs farming	Primary production
p57	Poultry Birds farming	Primary production
p58	Horses husbandry	Primary production
p59	Asses husbandry	Primary production
p60	Mules husbandry	Primary production
p61	Camels husbandry	Primary production
p62	Dairy cattle husbandry	Primary production
p63	Dairy sheep husbandry	Primary production
p64	Cattle slaughtering	Processing
p65	Sheep slaughtering	Processing
p66	Pigs slaughtering	Processing
p67	Poultry slaughtering	Processing
p68	Horses slaughtering	Processing
p69	Asses slaughtering	Processing
p70	Mules slaughtering	Processing
p71	Camels slaughtering	Processing

p72	Beekeeping	Primary production
p73	Silkworm breeding	Primary production
p74	Fishing	Primary production
p75	Forestry	Primary production

Table A-4. **List of the 42 sectors covered in the monetary MRIO table of 2012 (Mi et al. 2017).**

Sector_code	Name	Abbreviations
1	Agriculture, forestry, animal husbandry and fishery products and services	AFF
2	Coal Mining Products	CMP
3	Oil and natural gas extraction products	OGE
4	Metal ore mining and products	MOM
5	Non-metallic minerals and other mining products	NMM
6	Food and tobacco manufacturing	FTM
7	Textile and products	TTP
8	Leather and down of textiles, clothing, shoes, hats and articles thereof	LCS
9	Wood products and furniture	WPF
10	Paper printing, culture, education, and sporting goods	PCE
11	Petroleum, coking products and nuclear fuel processed products	PCN
12	Chemical product	CHP
13	Non-metallic mineral product manufacturing	NPM
14	Metal smelting and rolling product manufacturing	MSR
15	Metal product manufacturing	MPM
16	General Equipment	GEQ
17	Professional equipment	PEQ
18	Transportation equipment	TEQ
19	Electrical machinery and equipment	EEQ
20	Communication equipment, computers and other electronic equipment	CEQ
21	Instrumentation	IST
22	Other manufactured products	OMP
23	Waste of materials	WTM
24	Repair of metal products, machinery and equipment	RME
25	Production and supply of electricity and heat	EPS
26	Gas production and supply	GPS
27	Water production and supply	WPS
28	Construction	CON
29	Wholesale and retail	WSR
30	Transportation, storage and post services	TSP
31	Accommodation and restruant	AHR
32	Information transfer, software and information technology services	ISI
33	Financial services	FIS
34	Real estate services	RES
35	Leasing and business services	LBS
36	Scientific research and technical services	STS

37	Public services, hydrology, environment and public facilities management	PES
38	Resident services, repairs and other services	RRS
39	Education	EDU
40	Health and social work	HSS
41	Culture, sports and entertainment	CSS
42	Public administration, social security and social organization	PSS

Table A-5. Summary of data requirements and associated data sources for FABIO_CHN.

Data types	**Data sources**	**Notes**
Production quantity		
crops, live animals, livestock products, fish, forestry	National Bureau of Statistics of China (NBSC 2020)	Data for live animals include the slaughtered quantity and the end-of-2012 in-stock quantity which will be used to estimate feed requirements
	China Agriculture Yearbook 2013 (CAYEC 2013)	
food manufacturing products (excluding vegetable oils, oil cakes, offal, fats, and hides and skins)	China Light Industry Yearbook 2013 (CLIF 2013)	
International import/export	China Agriculture Yearbook 2013 (CAYEC 2013)	
Sown areas of crops	National Bureau of Statistics of China (NBSC 2020)	The sown areas of crops are for the year 2013
	China Agriculture Yearbook 2014 (CAYEC 2014)	
Population	Almanac of China's Population 2013 (IPLE-CASS 2013)	
Price of commodities	FAOSTAT (FAOSTAT 2020)	
	China Price Statistical Yearbook 2013 (NBSC 2013)	

Note: CAYEC (2013) China Agricultural Yearbook (2013), China Agricultural Yearbook Editorial Committee; CLIF (2013) China Light Industry Yearbook (2013). Federation, C.L.I. (ed); FAOSTAT (2020) FAOSTAT Statistics Database (accessed on April 06, 2020). Nations, F.a.A.O.o.t.U. (ed); IPLE-CASS (2013) Almanac of China's Population (2013), The Institute of Population and Labor Economics, Chinese Academy of Social Sciences; NBSC (2013) China Price Statistical Yearbook (2013). Statistics, D.o.U.S.a.E. (ed), China Statistics Press; NBSC (2020) Annual Statistics Data by Province (accessed on April 06, 2020). China, N.B.o.S.o. (ed).

Table A-6. An overview of the availability of water consumption data in 31 provinces.

Provinces	Water consumption purposes							
	Agriculture	Irrigation	Livestock	Industry	Electricity	Construction	Services	Household
Beijing								
Tianjin	√	√	√	√		√	√	√
Hebei	√	√	√	√				√
Shanxi	√	√	√	√			√	√
Inner Mongolia	√	√	√	√			√	√
Liaoning	√	√	√	√			√	√
Jilin	√	√	√	√			√	√
Heilongjiang								
Shanghai								
Jiangsu	√	√	√	√				√
Zhejiang	√	√	√	√			√	√
Anhui	√	√	√	√			√	√
Fujian								
Jiangxi	√	√	√	√			√	√
Shandong	√	√	√	√	√	√	√	√
Henan	√	√	√	√				√
Hubei	√			√			√	√
Hunan	√			√			√	√
Guangdong	√			√	√		√	√
Guangxi	√	√	√	√			√	√
Hainan	√			√			√	√
Chongqing	√			√		√	√	√
Sichuan	√	√	√	√		√	√	√
Guizhou	√	√	√	√			√	√
Yunnan	√			√		√	√	√
Tibet								
Shaanxi	√	√	√	√			√	√
Gansu	√	√	√	√	√	√	√	√
Qinghai	√	√	√	√			√	√
Ningxia	√			√				√
Xinjiang	√	√	√	√		√	√	√

Table A-7. **Blue water footprints (km^3 per year) of provinces in China estimated in previous studies and this study.**

Province.Code	**Name**	2007 (Zhang et al. 2014)	2012 (Xu et al. 2020)	2012 (Zhang et al. 2019)	2012 (This study, hybrid)
r1	Beijing	7.2	7.1	14.0	5.4
r2	Tianjin	6.1	5.5	7.5	4.0
r3	Hebei	9.5	22.0	15.9	11.8
r4	Shanxi	5.0	7.6	7.3	8.9

r5	Inner Mongolia	3.8	11.1	9.5	10.7
r6	Liaoning	8.4	13.0	17.1	11.4
r7	Jilin	5.4	5.3	10.8	6.1
r8	Heilongjiang	8.5	14.8	18.1	12.7
r9	Shanghai	13.0	11.3	27.6	8.3
r10	Jiangsu	23.1	27.5	53.9	28.1
r11	Zhejiang	14.9	16.5	40.7	14.2
r12	Anhui	7.3	14.3	19.0	10.7
r13	Fujian	8.6	9.4	18.1	8.0
r14	Jiangxi	8.4	11.5	14.5	8.1
r15	Shandong	22.0	20.7	35.0	20.6
r16	Henan	11.2	16.0	20.8	13.2
r17	Hubei	9.1	16.6	20.5	12.7
r18	Hunan	8.4	16.2	22.0	11.3
r19	Guangdong	21.8	24.2	79.8	20.4
r20	Guangxi	7.2	10.5	17.1	7.9
r21	Hainan	1.9	2.2	2.5	1.4
r22	Chongqing	3.0	8.0	10.0	5.4
r23	Sichuan	7.4	16.8	21.7	14.0
r24	Guizhou	3.3	6.1	8.7	3.9
r25	Yunnan	7.3	11.3	12.5	8.7
r26	Tibet			2.2	1.4
r27	Shaanxi	5.3	7.6	7.9	7.4
r28	Gansu	6.8	6.3	7.6	5.9
r29	Qinghai	1.8	2.1	2.6	2.1
r30	Ningxia	3.1	3.3	3.1	3.0
r31	Xinjiang	87.3	19.5	14.0	13.7
National total		**336.1**	**364.27**	**562.2**	**301.7**

Notes: Zhang, C. & Anadon, L. D. A multi-regional input–output analysis of domestic virtual water trade and provincial water footprint in China. Ecological Economics 100, 159-172, doi:10.1016/j.ecolecon.2014.02.006 (2014); Xu, X., Zhang, Y. & Chen, Y. Projecting China's future water footprint under the shared socio-economic pathways. J Environ Manage 260, 110102, doi:10.1016/j.jenvman.2020.110102 (2020); Zhang, S. et al. Regional water footprints and interregional virtual water transfers in China. J Clean Prod 228, 1401-1412, doi:10.1016/j.jclepro.2019.04.298 (2019).

Table A-8. Uncertainty analysis of the provincial blue water footprints by three key factors (i.e., inter-provincial trade, commodity prices, and feed requirements for animal husbandry).

		By trade			By price			By feed		
Province .Code	**Name**	**Mean**	**Median**	**Standard deviation**	**Mean**	**Median**	**Standard deviation**	**Mean**	**Median**	**Standard deviation**
r1	Beijing	3708	3708	107	4665	4665	47	4532	4532	21
r2	Tianjin	2993	2993	86	3197	3196	33	3102	3102	11

r3	Hebei	9878	9875	86	9736	9729	150	9825	9827	78
r4	Shanxi	6714	6714	154	8105	8103	60	8031	8031	43
r5	Inner Mongolia	10041	10041	118	10359	10351	89	10217	10219	39
r6	Liaoning	10632	10634	126	9843	9848	144	9853	9853	94
r7	Jilin	5348	5345	82	5187	5190	34	5177	5172	60
r8	Heilongjiang	10549	10547	127	10199	10281	468	10746	10753	98
r9	Shanghai	4528	4530	176	4866	4866	63	4832	4833	23
r10	Jiangsu	20602	20604	159	19893	19962	560	20398	20395	38
r11	Zhejiang	11609	11605	143	12356	12351	97	12050	12063	51
r12	Anhui	9720	9721	77	9675	9642	105	9656	9664	74
r13	Fujian	6701	6700	91	6432	6439	150	6532	6530	16
r14	Jiangxi	6701	6699	111	6872	6873	50	6850	6851	25
r15	Shandong	20837	20843	212	17602	17598	258	17441	17433	116
r16	Henan	12704	12703	152	11803	11801	91	11721	11713	71
r17	Hubei	10858	10859	99	11072	11117	297	11361	11361	31
r18	Hunan	8305	8306	120	8378	8361	114	8465	8460	106
r19	Guangdong	15699	15696	248	16610	16592	192	16443	16442	54
r20	Guangxi	6873	6873	90	6805	6803	56	6750	6750	26
r21	Hainan	1315	1315	37	1114	1113	10	1110	1105	19
r22	Chongqing	4241	4239	95	4529	4525	48	4485	4484	16
r23	Sichuan	10306	10301	149	13294	13284	74	13277	13274	61
r24	Guizhou	3696	3694	104	3614	3612	31	3626	3625	21
r25	Yunnan	7045	7045	130	7336	7271	176	7537	7537	31
r26	Tibet	1671	1673	29	1197	1216	142	1352	1357	24
r27	Shaanxi	5117	5114	97	6677	6676	44	6650	6649	36

r28	Gansu	4737	4735	78	5289	5287	35	5194	5198	48
r29	Qinghai	1510	1509	29	1902	1906	24	1915	1914	10
r30	Ningxia	2480	2480	26	2545	2542	16	2528	2528	9
r31	Xinjiang	16973	16968	300	14120	14138	112	14183	14182	82

A.2. Estimation of provincial feed requirements

We specify eight animal husbandry sectors in FABIO-CHN, i.e., cattle (including buffaloes), sheep (including goats), pigs, poultry birds, horses, asses, mules, and camels. We obtain feed requirements (in ton per year) of cattle, sheep, goats, pigs, poultry birds, horses, asses, and mules from (Chapagain and Hoekstra 2003). The composition of animal feeds in industrial systems and grazing systems are distinguished into wheat, barley, maize, oats, other cereals, peas, soyabeans, rapeseed, and other feeds (e.g., oil cakes). See below:

Unit: ton/(head·yr)	**Feed compositions**								
Animals	Wheat and products	Barley and products	Maize and products	Oats	Cereals, Other	Peas	Soybeans	Rape and Mustardseed	Other feeds
Industrial systems									
Cattle	0.054	0.533	0.792	0.069	0.034	0.005	0.151	0.058	4.020
Sheep	0.002	0.032	0.004	0.005	0.001	0.001	0.002	0.001	0.703
Goats		0.013	0.006	0.004	0.001		0.002	0.001	0.163
Pigs	0.069	0.39	0.220	0.039	0.004	0.018	0.053	0.048	0.133
Poultry Birds	0.011		0.010				0.003	0.002	0.008
Horses	0.001	0.078	0.025	0.200	0.012	0.002	0.026	0.003	3.341
Donkey	0.001	0.078	0.025	0.200	0.012	0.002	0.026	0.003	3.341
Mules	0.001	0.078	0.025	0.200	0.012	0.002	0.026	0.003	3.341
Grazing systems									
Cattle	0.012	0.129	0.162	0.025	0.007	0.002	0.032	0.013	5.393
Sheep	0.001	0.013	0.003	0.003	0.001	0.001	0.001	0.001	0.416

Goats		0.007	0.003	0.002	0.001		0.001	0.001	0.254
Pigs		0.047			0.140		0.024		0.379
Poultry Birds	0.011		0.010				0.003	0.002	0.008
Horses	0.001	0.031	0.010	0.078	0.005	0.001	0.010	0.001	4.061
Donkey	0.001	0.031	0.010	0.078	0.005	0.001	0.010	0.001	4.062
Mules	0.001	0.031	0.010	0.078	0.005	0.001	0.010	0.001	4.062

We assume that grazing systems are applied in Inner Mongolia, Tibet, Gansu, Qinghai, Ningxia, and Xinjiang, while industrial systems applied in the rest provinces. Given that some animals are fed for only a few weeks or months before slaughtering while others for several years, we classify two categories of animals according to their average farming periods (Chapagain and Hoekstra 2003), one as animals raised and slaughtered within a year (including sheep, pigs, poultry birds, and other live animals), the other as animals raised for years (including cattle, horses, asses, mules, and camels). For each animal of the former category, we first convert the annual quantity of each crop used as feed into daily basis, and multiply the daily feed requirement with the average lifespan of that animal, and lastly multiply with the end-of-2012 in-stock quantity (regarded as 0.5 head) as well as the slaughtered quantity of that animal. For each animal of the later category, we calculate the quantity of each crop used as feed by multiplying the end-of-2012 in-stock quantity as well as the slaughtered quantity (regarded as 0.5 head) of that animals with its annual feed requirements. The last step is balancing the provincial animal feed requirement of each crop to match the national feed use from the national CBS.

Feed requirements of each commodity by 8 animal husbandry sectors are aggregated in provincial CBS, but it will be allocated to specific animal husbandry sectors when we build provincial use tables (see **Section 2.2.1.3 Building provincial use tables**).

A.3. Estimation of provincial use of commodities for processing

Provincial processing data are estimated in different ways, which depend on the inputs and outputs of processes:

- *single-process commodities*. They are oil crops (processed in the respective oil extraction processes into oil and oil cake), cotton (processed in the cotton production process), and live animals (processed by the respective slaughtering sectors). We estimate the processed quantities of oil crops and cotton as a fixed percentage (equal to the share of processing in all domestic uses in the national CBS from FAOSTAT) of the overall **provincial use** quantity; while the processed quantities of live animals as the slaughtered quantities.

- *multiple crops for same output*. They are sugar cane and sugar beet for refined sugar; barley, maize, millet and sorghum for beer; rice, wheat, apple for fermented beverages. We estimate the processed quantities of crops by solving an optimization problem. With sugar cane and sugar beet used in sugar production as an example, we have the provincial production of sugar crops d_c^m and refined sugar b_s^m, the national technical conversion factors $\varphi_{c,s}$[4], and the national processed quantity of sugar crops U_P_c. With these inputs, we solve the constrained linear least-squares problem, $\min_{u\_p} \frac{1}{2} \| \boldsymbol{\varphi} \cdot \boldsymbol{u\_p} - \mathbf{b} \|_2^2$ such that $0 \leq u\_p_c^m \leq d_c^m$, and $\sum_i u\_p_c^m = U\_P_c$, to estimate the provincial processing requirements of sugar crops $u\_p_c^m$. We can obtain an optimal solution representing the processed sugar crop requirements for sugar production in each province.

- *multipurpose crops*. They are rice for ricebran oil and fermented beverages, maize for maize germ oil and fermented beverages, and grape for wine and juice (juice excluded in FABIO-CHN). We estimate the processed quantities of crops as the input requirements to each process based on the national technical conversion factors. The processed quantities of rice (same with maize and grape) for different purposes are aggregated in provincial CBS, but it will be allocated to the detailed processes when we build the provincial use tables (see details in the **Section 2.2.1.3 Building the Provincial Use Tables** in the main text).

for all other commodities. We estimate the processed quantities as a fixed percentage of **provincial use** (equal to the national rate of processing in the overall domestic use quantity as given in the national CBS from FAOSTAT).

A.4. Estimation of inter-provincial trade quantities

Trade data, especially the inter-provincial trade data, in the physical terms of 84 FABIO-CHN commodities are the main data gap for fine-scale domestic supply-use analysis of China, thus, we use a linear programming optimization model to estimate the bilateral trade quantities of FABIO-CHN commodities. We pursue a transport cost minimization for inter-provincial trade flows following Dalin et al. (2014) and Zhuo et al. (2019). We demonstrate the optimization model in a case that the inter-provincial and international trade data of one specific commodities (e.g., millet)

[4] Technical conversion factors represent the conversion efficiencies of food processing (e.g., 66% of soybean is converted into soybean oil, while the rest 33% is converted into soybean oil cake), and differs from countries, products, and processing technologies.

are missing for each province, and assume that inter-provincial and international export (import) occur in provinces where **provincial supply** is larger (smaller) than **provincial use**. We consider four harbor provinces (Tianjin, Liaoning, Shandong and Guangdong) for shipping export and distributing foreign import.

$$min\ TC_c = \underbrace{\textstyle\sum_{m,n,m\neq n} t_c^{m,n} \cdot tc^{m,n}}_{inter\text{-}provincial} + \underbrace{\textstyle\sum_{m,h} t_c^{m,h} \cdot tc^{m,h}}_{export} + \underbrace{\textstyle\sum_{h,n} t_c^{h,n} \cdot tc^{h,n}}_{import} \quad \text{(A-1)}$$

subject to:

- $\forall m \in [1:31]$:

$$\underbrace{P_c^m + \textstyle\sum_{n,m\neq n} (t_c^{n,m} - t_c^{m,n}) + \sum_h (t_c^{h,m} - t_c^{m,h}) + Stock_c^m}_{Supply} = \underbrace{U_c^m}_{Use} \quad \text{(A-2)}$$

- $\sum_{m,h} t_c^{m,h} = Exp_c$ (A-3)
- $\sum_{h,n} t_c^{h,n} = Imp_c$ (A-4)
- $t_c^{m,n} \geq 0,\ t_c^{m,h} \geq 0,\ t_c^{h,n} \geq 0$ (A-5)

where TC_c is the total transport cost for the trade of commodity c; $t_c^{m,n}$ is inter-provincial trade quantity of commodity c from initial province m to destination province n; $t_c^{m,h}$ is the international export of commodity c from initial province m to harbor province h; $t_c^{h,n}$ is the international import of commodity c from harbor province h to destination province n; P_c^m is the production quantity of commodity c in province m; $Stock_c^m$ is the stock removal of commodity c in province m; U_c^m is the total **provincial use** of commodity c in province m; Exp_c is the national export of commodity c from FAOSTAT; Imp_c is the national import of commodity c from FAOSTAT. The inter-provincial transport cost ($tc^{m,n}$, in Yuan per ton) is obtained through a GIS based dataset of different transportation modes (rail, river, and road) between the provinces' capital city (Gao et al. 2014).

A.5. Data of product- and sector-specific blue water consumption

The blue water consumption of FABIO-CHN crops, i.e., water footprints (WFs), are obtained from simulations with a crop water productivity model. The direct blue water consumption of economic sectors is obtained from provincial Water Resource Bulletins (2012), and Chinese Economic Census Yearbook (2008).

For the FABIO-CHN crops specified in this study, the average WFs (in m^3 per ton of harvested crop) of crop production per province for year 2012 are estimated following the accounting framework of Hoekstra et al. (2011). The WF of a crop is calculated as the actual crop water use (CWU, in m^3 per ha) divided by the crop yield (Y, in ton per ha). CWU is the sum of actual evapotranspiration (ET, in mm) from the crop field over the crop's growing period. We use the computational framework described in (Hogeboom 2019), which applies the FAO's crop water productivity model AquaCrop (Raes et al. 2009) to estimate ET and Y at 5 × 5 arc-minute grid level by simulating the soil water balance and crop growth (in growing degree days mode) with a time step of one day. The model distinguished between ET of green water (precipitation water in the unsaturated zone) and the ET of blue water from irrigation or from water entering the root zone via capillary rise in areas where a shallow groundwater table is present using the approach described by Hoekstra (2019). The model was run for a sequence of years (1996-2015) with a continues soil water balance accounting. Afterwards estimated ET of blue water and Y for the year 2012 have been extracted. Details on input datasets for daily climate, crop growing areas, irrigated areas, soil parameters and, groundwater are described in (Hogeboom et al. 2021). The model does not account for non-optimal management which may occur in practice. To correct for this, we scale the simulated Y of each crop in all grid cells such that they match provincial production statistics (P_c^m) when aggregated to the provincial level, by using a scaling factor (f_c^m) for each crop c in province m:

$$f_c^m = \frac{P_c^m}{\sum_g Y_c^{m,g} HA_c^{m,g}} \tag{A-6}$$

where $Y_c^{m,g}$ and $HA_c^{m,g}$ are the estimated yield and harvest areas of crop c in grid cell g of province m. The average WF of crop c in province m is then calculated as:

$$WF_c^m = \frac{10 \times \overline{ET}_c^{m,g}}{f_c^m \sum_g Y_c^{m,g}} \tag{A-7}$$

where $\overline{ET}_c^{m,g}$ is the average evapotranspiration of blue water over the growing period of crop c in each grid cell of province m; the factor 10 is to convert mm to m^3/ha. The total blue WF of crop c in province m (in m^3/y) is the provincial production (t/y) multiplied by the average WF (m^3/t).

Provincial water consumption of five main purposes, i.e., crop irrigation (including the irrigation water for FABIO-CHN included and excluded crops), animal husbandry, industry (including electricity generation), services (including construction), and household, are partially available in the provincial Water Resource Bulletin 2012 (see **Table A-6**). For agricultural water consumption in those provinces without available data, we use the national water consumption coefficient to estimate local water consumption of agriculture. For electricity generation sector, we calculate the average water coefficient of electricity generation sector in those provinces with available water consumption data, and apply the average water coefficient in other provinces. For other industrial sectors, we rely on the national water consumption data as well as the provincial water withdrawal data of each sector from Chinese Economic Census Yearbook (2008). We allocate the national water consumption of each sector to provinces by the provincial water withdrawal. Here we assume that the more water withdrawn for sectoral production, the more water consumption of that sector. After that, we scale the adjusted industrial water consumption into the actual industrial water consumption in 2012. For services sector, we calculate the average water coefficient of construction sector in those provinces with available water consumption data, and apply the average water coefficient in other provinces. For household water consumption, we calculate the per-capita water consumption by those provinces with available data and estimate the household water consumption in provinces without data based on the per-capita water consumption and local population. The direct blue water consumption of "*Rest of* a*griculture, forestry, animal husbandry and fishery products and services*" sector and "*Rest of food manufacturing and tobacco*" sector is the blue water consumption of agriculture, forestry, animal husbandry and fishery products and services and food manufacturing and tobacco omitting the blue water consumption of associated commodities included in FABIO-CHN.

A.6. Features of the hybrid MRIO model

Figure A-1 illustrates the heatmap of the constructed physical MRIO table of 84 FABIO-CHN commodities in China for the year 2012. We aggregate the transaction matrix **Z** over all provinces and receive a matrix with commodity-by-commodity format. The largest flows are found within commodities, i.e., on the main diagonal elements. The great number of blank elements in the commodity-by-commodity **Z** matrix implies that the physical MRIO table of FABIO-CHN is a highly sparse matrix with flows mainly on the main diagonal, in addition to some important processing activities. These processing activities include the feed use in the livestock sector, oil crops processed into oils and cakes, as well as live animals converted into animal products, which are consistent with the flows documented in the global FABIO database (Bruckner et al. 2019). Although the international trade is not illustrated in **Figure A-1**, the role of the international trade is relatively more important for some specific commodities, like international imports in the domestic consumption of barley, soybean, and coffee, whereas international exports of tea.

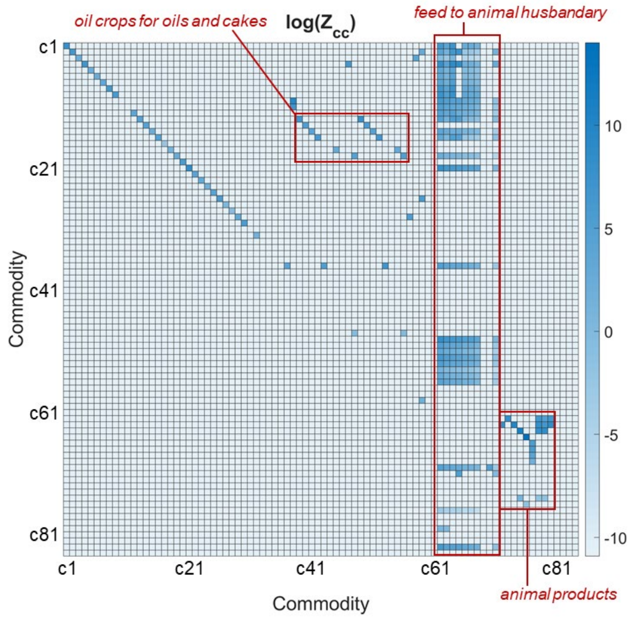

Figure A-1. Transactions of food and agricultural biomass commodities for the year 2012, with the format of commodity-by-commodity. The logarithm of the contained values is illustrated. The unit of each element depends on the commodity, e.g., wheat in 10^4 tonnes, cattle in 10^4 heads, or wood fuel in 10^4 cubic meters. Full names of c1-c84 are listed in **Table A-2**.

Our hybrid model offers inter-provincial MRIO tables in China for the year 2012 with relative high level of details for products and sectors. Products/sectors represented in the national IO tables of countries like the United States, Australia, Japan, and Canada have used less-aggregated categories (see **Table A-9**), yet none of them have a higher resolution in agri-food products compared to our hybrid MRIO model. We note that Japan specifics 81 agriculture and food products in its IO tables, almost as many categories as those in our hybrid model, yet it only provides supply and use information at the national scale which excludes the intra-national transactions. The MRIO database Eora captures totally 83 agri-food products for global economy. However, the limitations of using monetary MRIO model for environmental footprint assessments cannot be avoided when using Eora. Lastly, our hybrid MRIO model documents product flows in physical as well as monetary units. In that way, it reduces the impacts of price variations among different customers on supply chain analysis and environmental footprint assessments.

Table A-9. Summary of national input-output (IO) and multi-regional input-output (MRIO) tables. The number of products or sectors are the maximum of all the available IO tables by country.

	Products/Sectors			Spatial resolution	Unit
	Agri-food	Forestry	Other sectors & services		
IO tables				National	
United States (BEA 2020)	41	2	350		USD
Australia (ABS 2020)	18	2	95		AUD
Japan (JGS 2020)	78	3	429		JPY
Canada (SC 2020)	55	6	361		CAD
United Kingdom (ONSUK 2020)	3	1	60		GBP
China (NBSC 2020)	19	2	129		CNY
India (MSPI 2020)	33	1	96		INR
MRIO tables					
China (Mi et al. 2017a)	2	0	40	Provincial	CNY
GTAP (Aguiar et al. 2016)	21	1	35	National	USD
EXIOBASE (Stadler et al. 2018)	27	1	172	National	EURO
Eora (Lenzen et al. 2012a)	80	3	936	National	USD
WIOD (Timmer et al. 2015)	2	1	53	National	USD
Hybrid MRIO tables in this study	83	1	42	Provincial	tonnes, heads, m^3, CNY

Appendix B: An Appendix to Chapter 3

B.1. A simple Example to demonstrate the disaggregation of inter-provincial trade

We apply a simple 2-region with 2-sector case to demonstrate the disaggregation of the inter-regional trade. The main disaggregation of the inter-regional trade is following previous studies Feng et al. (2020), Liu et al. (2019), and Zhang et al. (2017). Although previous studies have provided a helpful and powerful approach to disaggregate the inter-regional trade, we still find that there is another trade pattern that was ignored before, i.e., the intermediate goods trade for the last production in province *m* for the final demand consumed in province *m*'s trade partners.

We use the MRIO table listed as:

Intermediate inoputs (**Z**)					
		r1		r2	
		s1	s2	s1	s2
r1	s1	5	4	3	2
	s2	7	8	9	3
r2	s1	4	3	7	6
	s2	2	1	8	9

Final demand (**Y**)	
r1	r2
23	6
17	7
10	30
5	26

Export (**EX**)
7
8
9
10

Output (**x**)
50
59
69
61

We have $\mathbf{A}=\mathbf{Z}\hat{\mathbf{x}}^{-1}=\left(\begin{array}{cc|cc} 0.1000 & 0.0678 & 0.0435 & 0.0328 \\ 0.1400 & 0.1356 & 0.1304 & 0.0492 \\ 0.0800 & 0.0508 & 0.1014 & 0.0984 \\ 0.0400 & 0.0169 & 0.1159 & 0.1475 \end{array}\right)$,

$$\mathbf{B}=(\mathbf{I}\text{-}\mathbf{A})^{-1}=\left(\begin{array}{cc|cc} 1.1352 & 0.0946 & 0.0761 & 0.0579 \\ 0.2063 & 1.1864 & 0.1950 & 0.0989 \\ 0.1208 & 0.0798 & 1.1486 & 0.1418 \\ 0.0738 & 0.0389 & 0.1637 & 1.1970 \end{array}\right),$$

$$\mathbf{L}^{11}=(\mathbf{I}\text{-}\mathbf{A}^{11})^{-1}=\begin{pmatrix} 1.1248 & 0.0882 \\ 0.1822 & 1.1712 \end{pmatrix}.$$

The trade from region 2 to region 1 is:

$$\mathbf{T}^{21}=\mathbf{Y}^{21}+\mathbf{Z}^{21}=\mathbf{Y}^{21}+\mathbf{A}^{21}\mathbf{x}^{1}=\begin{pmatrix} 10 \\ 5 \end{pmatrix}+\begin{pmatrix} 0.1000 & 0.0678 \\ 0.1400 & 0.1356 \end{pmatrix}\times\begin{pmatrix} 50 \\ 59 \end{pmatrix}=\begin{pmatrix} 17 \\ 8 \end{pmatrix}.$$

According to the disaggregation formation in previous studies:

$$\mathbf{T}^{sr}=\mathbf{Y}^{sr}+\mathbf{A}^{sr}\mathbf{L}^{rr}\mathbf{Y}^{rr}+\mathbf{A}^{sr}\mathbf{L}^{rr}\sum_{t\neq r}^{g}\mathbf{A}^{rt}\mathbf{B}^{tr}\mathbf{Y}^{rr}+\mathbf{A}^{sr}\sum_{t\neq r}^{g}\mathbf{B}^{rt}\mathbf{Y}^{tr}+\mathbf{A}^{sr}\sum_{t\neq r}^{g}\mathbf{B}^{rt}\sum_{u}^{g}\mathbf{Y}^{tu}+\mathbf{A}^{sr}\sum_{t}^{g}\mathbf{B}^{rt}\mathbf{E}\mathbf{X}^{t}$$

where g is the number of regions. For $\mathbf{T}^{21}$, We have s=2 and r=1. Thus, the trade from region 2 to region 1 is:

$$\mathbf{T}^{21}=\mathbf{Y}^{21}+\mathbf{A}^{21}\mathbf{L}^{11}\mathbf{Y}^{11}+\mathbf{A}^{21}\mathbf{L}^{11}(\mathbf{A}^{12}\mathbf{B}^{21}\mathbf{Y}^{11})+\mathbf{A}^{21}\left(\mathbf{B}^{12}\mathbf{Y}^{21}\right)+\mathbf{A}^{21}\mathbf{B}^{12}\left(\mathbf{Y}^{21}+\mathbf{Y}^{22}\right)+\mathbf{A}^{21}(\mathbf{B}^{11}\mathbf{EX}^{1}+\mathbf{B}^{12}\mathbf{EX}^{2})$$

$$=\begin{pmatrix}10\\5\end{pmatrix}+\begin{pmatrix}0.0800 & 0.0508\\0.0400 & 0.0169\end{pmatrix}\times\begin{pmatrix}1.1248 & 0.0882\\0.1822 & 1.1712\end{pmatrix}\times\begin{pmatrix}23\\17\end{pmatrix}$$

$$+\begin{pmatrix}0.0800 & 0.0508\\0.0400 & 0.0169\end{pmatrix}\times\begin{pmatrix}1.1248 & 0.0882\\0.1822 & 1.1712\end{pmatrix}\times\begin{pmatrix}0.0435 & 0.0328\\0.1304 & 0.0492\end{pmatrix}\times\begin{pmatrix}0.1208 & 0.0798\\0.0738 & 0.0389\end{pmatrix}\times\begin{pmatrix}23\\17\end{pmatrix}$$

$$+\begin{pmatrix}0.0800 & 0.0508\\0.0400 & 0.0169\end{pmatrix}\times\begin{pmatrix}0.0761 & 0.0579\\0.1950 & 0.0989\end{pmatrix}\times\begin{pmatrix}10\\5\end{pmatrix}$$

$$+\begin{pmatrix}0.0800 & 0.0508\\0.0400 & 0.0169\end{pmatrix}\times\begin{pmatrix}0.0761 & 0.0579\\0.1950 & 0.0989\end{pmatrix}\times\left[\begin{pmatrix}10\\5\end{pmatrix}+\begin{pmatrix}30\\26\end{pmatrix}\right]$$

$$+\begin{pmatrix}0.0800 & 0.0508\\0.0400 & 0.0169\end{pmatrix}\times\left[\begin{pmatrix}1.1352 & 0.0946\\0.2063 & 1.1864\end{pmatrix}\times\begin{pmatrix}7\\8\end{pmatrix}+\begin{pmatrix}0.0761 & 0.0579\\0.1950 & 0.0989\end{pmatrix}\times\begin{pmatrix}9\\10\end{pmatrix}\right]=\begin{pmatrix}\mathbf{16.1252}\\\mathbf{7.6228}\end{pmatrix}$$

According to the disaggregation formation in this study:

$$\mathbf{T}^{sr}=\mathbf{Y}^{sr}+\mathbf{A}^{sr}\mathbf{L}^{rr}\mathbf{Y}^{rr}+\mathbf{A}^{sr}\mathbf{L}^{rr}\sum_{u\neq r}\mathbf{Y}^{ru}+\mathbf{A}^{sr}\mathbf{L}^{rr}\sum_{t\neq r}\mathbf{A}^{rt}\mathbf{B}^{tr}\sum_{u}\mathbf{Y}^{ru}+\mathbf{A}^{sr}\sum_{t\neq r}\mathbf{B}^{rt}\sum_{u}\mathbf{Y}^{tu}+\mathbf{A}^{sr}\sum_{t}\mathbf{B}^{rt}\mathbf{EX}^{t}$$

We have:

$$\mathbf{T}^{21}=\mathbf{Y}^{21}+\mathbf{A}^{21}\mathbf{L}^{11}\mathbf{Y}^{11}+\mathbf{A}^{21}\mathbf{L}^{11}\mathbf{Y}^{12}+\mathbf{A}^{21}\mathbf{L}^{11}\mathbf{A}^{12}\mathbf{B}^{21}(\mathbf{Y}^{11}+\mathbf{Y}^{12})+\mathbf{A}^{21}\mathbf{B}^{12}\left(\mathbf{Y}^{21}+\mathbf{Y}^{22}\right)+\mathbf{A}^{21}(\mathbf{B}^{11}\mathbf{EX}^{1}+\mathbf{B}^{12}\mathbf{EX}^{2})$$

$$=\begin{pmatrix}10\\5\end{pmatrix}+\begin{pmatrix}0.0800 & 0.0508\\0.0400 & 0.0169\end{pmatrix}\times\begin{pmatrix}1.1248 & 0.0882\\0.1822 & 1.1712\end{pmatrix}\times\begin{pmatrix}23\\17\end{pmatrix}$$

$$+\begin{pmatrix}0.0800 & 0.0508\\0.0400 & 0.0169\end{pmatrix}\times\begin{pmatrix}1.1248 & 0.0882\\0.1822 & 1.1712\end{pmatrix}\times\begin{pmatrix}6\\7\end{pmatrix}$$

$$+\begin{pmatrix}0.0800 & 0.0508\\0.0400 & 0.0169\end{pmatrix}\times\begin{pmatrix}1.1248 & 0.0882\\0.1822 & 1.1712\end{pmatrix}\times\begin{pmatrix}0.0435 & 0.0328\\0.1304 & 0.0492\end{pmatrix}\times\begin{pmatrix}0.1208 & 0.0798\\0.0738 & 0.0389\end{pmatrix}\times\left[\begin{pmatrix}23\\17\end{pmatrix}+\begin{pmatrix}6\\7\end{pmatrix}\right]$$

$$+\begin{pmatrix}0.0800 & 0.0508\\0.0400 & 0.0169\end{pmatrix}\times\begin{pmatrix}0.0761 & 0.0579\\0.1950 & 0.0989\end{pmatrix}\times\left[\begin{pmatrix}10\\5\end{pmatrix}+\begin{pmatrix}30\\26\end{pmatrix}\right]$$

$$+\begin{pmatrix}0.0800 & 0.0508\\0.0400 & 0.0169\end{pmatrix}\times\left[\begin{pmatrix}1.1352 & 0.0946\\0.2063 & 1.1864\end{pmatrix}\times\begin{pmatrix}7\\8\end{pmatrix}+\begin{pmatrix}0.0761 & 0.0579\\0.1950 & 0.0989\end{pmatrix}\times\begin{pmatrix}9\\10\end{pmatrix}\right]=\begin{pmatrix}\mathbf{17.0000}\\\mathbf{8.0000}\end{pmatrix}$$

The part highlighted in red color is the trade pattern not captured in previous studies. We further find that without capturing this pattern of trade, the actual inter-provincial trade would be underestimated by 7% within China for year 2012, more than the total economic outputs of Xinjiang province that year.

B.2. 31 provinces in mainland China

Table B-1. List of 31 provinces in mainland China.

Name	Region	Water scarcity level
Beijing	North China	Extreme
Tianjin	North China	Extreme
Hebei	North China	Extreme
Shanxi	North China	Severe
Inner Mongolia	North China	Moderate
Liaoning	Northeast China	Severe
Jilin	Northeast China	Moderate
Heilongjiang	Northeast China	Severe
Shanghai	East China	Extreme
Jiangsu	East China	Extreme
Zhejiang	East China	Moderate
Anhui	East China	Moderate
Fujian	East China	Low
Jiangxi	East China	Low
Shandong	East China	Severe
Henan	Central China	Severe
Hubei	Central China	Moderate
Hunan	Central China	Low
Guangdong	South China	Moderate
Guangxi	South China	Low
Hainan	South China	Low
Chongqing	Southwest China	Low
Sichuan	Southwest China	Low
Guizhou	Southwest China	Low
Yunnan	Southwest China	Low
Tibet	Southwest China	Low
Shaanxi	Northwest China	Moderate
Gansu	Northwest China	Severe
Qinghai	Northwest China	Low
Ningxia	Northwest China	Extreme
Xinjiang	Northwest China	Severe

B.3. Provincial blue water consumption

Table B-2. Blue water consumption (km^3/yr) in each province for year 2012.

Province	Local activities	Global Export	Final goods trade	Interm. trade A	Interm. trade B	Val. chain: domestic	Val. chain: global	Total
Beijing	0.89	0.10	0.11	0.06	0.02	0.02	0.01	1.20
Tianjin	0.73	0.13	0.22	0.19	0.06	0.06	0.06	1.45

Hebei	8.64	0.48	2.33	1.46	0.56	0.35	0.57	14.40
Shanxi	3.81	0.08	0.50	0.44	0.11	0.15	0.15	5.24
Inner Mongolia	6.35	0.16	2.31	1.08	0.23	0.28	0.47	10.89
Liaoning	5.30	0.77	1.75	0.53	0.13	0.13	0.18	8.79
Jilin	3.99	0.20	1.04	0.51	0.14	0.13	0.15	6.16
Heilongjiang	8.13	0.47	5.07	3.31	1.13	1.04	1.08	20.24
Shanghai	1.03	0.32	0.32	0.30	0.09	0.09	0.09	2.24
Jiangsu	14.86	4.16	4.17	2.11	0.61	0.58	0.88	27.37
Zhejiang	5.59	2.59	0.76	0.87	0.24	0.24	0.34	10.62
Anhui	7.36	0.48	2.54	2.11	0.63	0.65	0.70	14.48
Fujian	4.18	1.20	0.95	0.82	0.26	0.24	0.26	7.91
Jiangxi	4.61	0.77	2.12	1.59	0.51	0.47	0.55	10.61
Shandong	8.31	1.07	2.71	1.00	0.24	0.22	0.34	13.89
Henan	9.60	0.17	2.28	1.08	0.27	0.17	0.23	13.81
Hubei	9.38	0.44	1.45	0.81	0.23	0.23	0.34	12.87
Hunan	6.17	0.29	2.73	2.30	0.66	0.62	0.73	13.49
Guangdong	9.03	2.84	2.28	1.50	0.45	0.43	0.44	16.97
Guangxi	5.44	0.25	3.02	2.13	0.68	0.59	0.69	12.81
Hainan	0.48	0.03	0.48	0.54	0.18	0.17	0.18	2.05
Chongqing	2.48	0.34	0.51	0.42	0.10	0.12	0.14	4.10
Sichuan	8.25	0.90	1.27	0.84	0.21	0.18	0.27	11.91
Guizhou	2.12	0.21	0.78	0.79	0.24	0.24	0.25	4.62
Yunnan	4.87	0.37	1.37	0.93	0.29	0.25	0.28	8.36
Tibet	0.85	0.09	0.42	0.22	0.09	0.07	0.08	1.83
Shaanxi	3.83	0.11	0.39	0.33	0.09	0.09	0.12	4.96
Gansu	3.58	0.17	2.05	1.10	0.37	0.27	0.32	7.86
Qinghai	1.05	0.03	0.32	0.15	0.08	0.04	0.05	1.71
Ningxia	1.85	0.08	0.67	0.37	0.12	0.11	0.12	3.31
Xinjiang	12.83	2.75	13.44	5.66	1.96	1.48	1.60	39.72

B.4. Changes in water scarcity index under the no-trade scenario

Table B-3. **Changes in water scarcity index under the no-trade scenario from the current with-trade situations.**

Province	Water scarcity level	Change in water scarcity index

Beijing	Extreme	53%
Tianjin	Extreme	61%
Hebei	Extreme	-19%
Shanxi	Severe	72%
Inner Mongolia	Moderate	6%
Liaoning	Severe	-4%
Jilin	Moderate	-18%
Heilongjiang	Severe	-33%
Shanghai	Extreme	121%
Jiangsu	Extreme	1%
Zhejiang	Moderate	17%
Anhui	Moderate	-24%
Fujian	Low	-18%
Jiangxi	Low	-19%
Shandong	Severe	-7%
Henan	Severe	-14%
Hubei	Moderate	-6%
Hunan	Low	-24%
Guangdong	Moderate	15%
Guangxi	Low	-20%
Hainan	Low	-46%
Chongqing	Low	19%
Sichuan	Low	0%
Guizhou	Low	-1%
Yunnan	Low	7%
Tibet	Low	14%
Shaanxi	Moderate	-21%
Gansu	Severe	-19%
Qinghai	Low	9%
Ningxia	Extreme	19%
Xinjiang	Severe	-32%

B.5. Provincial inequality of water scarcity

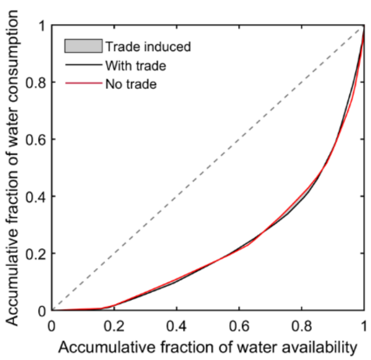

Figure B-1. Inequality of water scarcity among all 31 provinces of China. Cumulative probability of water availability against cumulative portability of water consumption of provinces in China, sorted by increasing magnitudes of water scarcity indices.

Appendix C: An Appendix to Chapter 4

C.1. Data sources

EXIOBASE

EXIOBASE 3.6 provides detailed environmental extended MRIO tables, trade-linked in order to follow global supply and use chains (Stadler et al. 2018). The MRIO tables describe the world economy in terms of the annual production, trade, intermediate consumption and final consumption of 200 products between and within 44 countries (**Table C-1**) and 5 continental groups of countries (i.e., the rest of world (RoW) Asia and Pacific, RoW America, RoW Europe, RoW Africa, RoW Middle East) for the period 1995 to 2015 in current prices. They distinguish final demands into: the final consumption expenditures by households, nonprofit organizations serving households, and government; gross fixed capital formation (GFCF); changes in inventories, and valuables.

EU KLMES, World KLEMS and Penn World Table

The capital investment data and depreciation rates of assets by sector are obtained from different sources according to the availability of data (see **Table C-1** for an overview). The EU KLEMS Growth and Productivity Accounts (EU KLEMS) are a set of detailed accounts on capital expenditure and use covering 25 European as well as 5 non-European countries (i.e., Australia, Canada, Japan, South Korea, and the United States) (EUKLEMS 2019). Capital investment, capital stocks, capital consumption accounts, and depreciation rates in an asset-by-sector resolution until 2007 are available for 13 countries from the EU KLEMS 2009 release. Capital investment, capital stock, and depreciation rates are available for 23 countries from the EU KLEMS 2017 release. Details about the categories of assets and sectors could be found in **Tables C-2** and **C-3**.

The World KLEMS initiative is a global collaborative project derived from the EU KLEMS project (WORLDKLEMS 2019), also aims at facilitating the analysis of growth and productivity patterns around the world. Although it is less harmonized and standardized than the EU KLEMS, the database provides capital accounts and depreciation rates that are more detailed than traditional national account tables. We relied on the World KLEMS to obtain capital investment data of China, Canada, and South Korea (see **Table C-1**). Details about the categories of assets and sectors could be found in **Tables C-4**, **C-5**, and **C-6**.

Penn World Table (PWT) version 9.1 provides capital information on capital investment, capital stock, and capital consumption data by four assets, covering 182 countries between 1950 and 2017 (Feenstra et al. 2015). We rely on the PWT database for those countries not covered neither in EU

KLEMS nor World KLEMS (see **Table C-1**). Moreover, a year-specific disaggregated proxy is used to disaggregate the total investment of each asset to KLEMS sectors. The disaggregated proxy is built on as an average formation pattern of countries with complete data from EU KLEMS 2017 release. Details about the categories of assets could be found in **Table C-7**.

When capital investment in several years are not available, the nearest available capital data scaled up by the missing year's GFCF from EXIOBASE is used.

Table C-1. An overview of countries (country names and affiliated regions) in our model and data sources of their capital investments. OECD1990, the Organization for Economic Co-operation and Development in the1990s; EIT, economies in transition; ASIA, Asia; LAM, Latin America; MAF, Middle East and Africa. RoW = rest of the world.

Country	Assets	Investing sectors	Sources
Austria (OECD1990)	10	34	EU KLEMS 2017 Release
Belgium (OECD1990)	4		PWT 9.1
Bulgaria (EIT)	10	34	EU KLEMS 2017 Release
Cyprus (EIT)	10	34	EU KLEMS 2017 Release
Czech Republic (EIT)	10	34	EU KLEMS 2017 Release
Germany (OECD1990)	10	34	EU KLEMS 2017 Release
Denmark (OECD1990)	10	34	EU KLEMS 2017 Release
Estonia (EIT)	10	34	EU KLEMS 2017 Release
Spain (OECD1990)	10	34	EU KLEMS 2017 Release
Finland (OECD1990)	10	34	EU KLEMS 2017 Release
France (OECD1990)	10	34	EU KLEMS 2017 Release
Greece (OECD1990)	10	34	EU KLEMS 2017 Release
Croatia (EIT)	4		PWT 9.1
Hungary (EIT)	10	34	EU KLEMS 2017 Release
Ireland (OECD1990)	10	34	EU KLEMS 2017 Release
Italy (OECD1990)	10	34	EU KLEMS 2017 Release
Lithuania (EIT)	10	34	EU KLEMS 2017 Release
Luxembourg (OECD1990)	10	34	EU KLEMS 2017 Release
Latvia (EIT)	10	34	EU KLEMS 2017 Release
Malta (EIT)	10	34	EU KLEMS 2017 Release
Netherlands (OECD1990)	10	34	EU KLEMS 2017 Release

Poland (EIT)	10	34	EU KLEMS 2017 Release
Portugal (OECD1990)	10	34	EU KLEMS 2017 Release
Romania (EIT)	10	34	EU KLEMS 2017 Release
Sweden (OECD1990)	10	34	EU KLEMS 2017 Release
Slovenia (EIT)	10	34	EU KLEMS 2017 Release
Slovakia (EIT)	10	34	EU KLEMS 2017 Release
United Kingdom (OECD1990)	8	32	EU KLEMS 2009 Release
	10	34	EU KLEMS 2017 Release
United States (OECD1990)	9	34	EU KLEMS 2017 Release
Japan (OECD1990)	8	32	EU KLEMS 2009 Release
China (ASIA)	3	37	World KLEMS
Canada (OECD1990)	4	31	World KLEMS
South Korea (ASIA)	11	62	World KLEMS
Brazil (LAM)	4		PWT 9.1
India (ASIA)	4		PWT 9.1
Mexico (LAM)	4		PWT 9.1
Russia (EIT)	4		PWT 9.1
Australia (OECD1990)	8	32	EU KLEMS 2009 Release
Switzerland (OECD1990)	4		PWT 9.1
Turkey (OECD1990)	4		PWT 9.1
Taiwan (ASIA)	4		PWT 9.1
Norway (OECD1990)	4		PWT 9.1
Indonesia (ASIA)	4		PWT 9.1
South Africa (MAF)	4		PWT 9.1
RoW Asia and Pacific (ASIA)	4		PWT 9.1
RoW America (LAM)	4		PWT 9.1
RoW Europe (EIT)	4		PWT 9.1
RoW Africa (MAF)	4		PWT 9.1
RoW Middle East (MAF)	4		PWT 9.1

Table C-2. Categories of assets and sectors of capital investment data and depreciation rates from EU KLEMS 2009 Release.

Assets	Sectors
Computing equipment	Agriculture, hunting, forestry and fishing
Communications equipment	Mining and quarrying
Software	Food, beverages and tobacco
Transport Equipment	Textiles, textile, leather and footwear
Other Machinery and Equipment	Wood and of wood and cork
Total Non-residential investment	Pulp, paper, paper, printing and publishing
Residential structures	Coke, refined petroleum and nuclear fuel
Other assets	Chemicals and chemical
	Rubber and plastics
	Other non-metallic mineral
	Basic metals and fabricated metal
	Machinery, nec
	Electrical and optical equipment
	Transport equipment
	Manufacturing nec; recycling
	Electricity, gas and water supply
	Construction
	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
	Wholesale trade and commission trade, except of motor vehicles and motorcycles
	Retail trade, except of motor vehicles and motorcycles; repair of household goods
	Hotels and restaurants
	Transport and storage
	Post and telecommunications
	Financial intermediation
	Real estate activities
	Renting of m&eq and other business activities
	Public admin and defence; compulsory social security
	Education
	Health and social work
	Other community, social and personal services
	Private households with employed persons
	Extra-territorial organizations and bodies

Table C-3. Categories of assets and sectors of capital investment data and depreciation rates from EU KLEMS 2017 Release.

Assets	Sectors
Computing equipment	Agriculture, forestry and fishing
Communication equipment	Mining and quarrying
Software	Food products, beverages and tobacco
Transport Equipment	Textiles, wearing apparel, leather and related products

Other Machinery and Equipment	Wood and paper products; printing and reproduction of recorded media
Total Non-residential investment	Coke and refined petroleum products
Residential structures	Chemicals and chemical products
Cultivated assets	Rubber and plastics products, and other non-metallic mineral products
Research and development	Basic metals and fabricated metal products, except machinery and equipment
Other Intellectual Property Products	Electrical and optical equipment
	Machinery and equipment n.e.c.
	Transport equipment
	Other manufacturing; repair and installation of machinery and equipment
	Electricity, gas and water supply
	Construction
	Wholesale and retail trade and repair of motor vehicles and motorcycles
	Wholesale trade, except of motor vehicles and motorcycles
	Retail trade, except of motor vehicles and motorcycles
	Transport and storage
	Postal and courier activities
	Accommodation and food service activities
	Publishing, audiovisual and broadcasting activities
	Telecommunications
	IT and other information services
	Financial and insurance activities
	Real estate activities
	Professional, scientific, technical, administrative and support service activities
	Public administration and defence; compulsory social security
	Education
	Health and social work
	Arts, entertainment and recreation
	Other service activities
	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
	Activities of extraterritorial organizations and bodies

Table C-4. Categories of assets and sectors of capital investment data and depreciation rates in China

Assets	**Sectors**
Equipment by industrial enterprises	Agriculture, forestry, animal husbandry & fishery
Non-residential structures by industrial enterprises	Coal mining

Investment by non-industrial enterprises (agriculture, construction, and all services)	Oil & gas excavation
	Metal mining
	Non-metallic minerals mining
	Food and kindred products
	Tobacco products
	Textile mill products
	Apparel and other textile products
	Leather and leather products
	Saw mill products, furniture, fixtures
	Paper products, printing & publishing
	Petroleum and coal products
	Chemicals and allied products
	Rubber and plastics products
	Stone, clay, and glass products
	Primary & fabricated metal industries
	Metal products (excluding rolling products)
	Industrial machinery and equipment
	Electric equipment
	Electronic and telecommunication equipment
	Instruments and office equipment
	Motor vehicles & other transportation equipment
	Miscellaneous manufacturing industries
	Power, steam, gas and tap water supply
	Construction
	Wholesale and retail trades
	Hotels and restaurants
	Transport, storage & post services
	Information & computer services
	Financial Intermediations
	Real estate services
	Leasing, technical, science & business services
	Government, public administration, and political and social organizations, etc.
	Education
	Healthcare and social security services
	Cultural, sports, entertainment services; residential and other services

Table C-5. Categories of assets and sectors of capital investment data and depreciation rates in Canada.

Assets	**Sectors**
Total Non-residential investment	Agriculture, hunting, forestry and fishing
Residential structures	Mining and quarrying
ICT assets	Food products, beverages and tobacco
Non-ICT assets	Textiles, textile products, leather and footwear
	Wood and products of wood and cork

	Pulp, paper, paper products, printing and publishing
	Coke, refined petroleum products and nuclear fuel
	Chemicals and chemical products
	Rubber and plastics products
	Other non-metallic mineral products
	Basic metals and fabricated metal products
	Machinery, nec
	Electrical and optical equipment
	Transport equipment
	Manufacturing nec; recycling
	Electricity, gas and water supply
	Construction
	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel
	Wholesale trade and commission trade, except of motor vehicles and motorcycles
	Retail trade, except of motor vehicles and motorcycles; repair of household goods
	Hotels and restaurants
	Transport and storage
	Post and telecommunications
	Financial intermediation
	Real estate activities
	Renting of m&eq and other business activities
	Public admin and defence; compulsory social security
	Education
	Health and social work
	Other community, social and personal services
	Private households with employed persons

Table C-6. Categories of assets and sectors of capital investment data and depreciation rates in South Korea.

Assets	Sectors	Sectors (continued)
Residential structures	Agriculture	Railroad equipment and transport equipment nec
Total Non-residential investment	Forestry	Manufacturing nec
Transport equipment	Fishing	Recycling
Computing equipment	Mining of coal and lignite; extraction of peat	Electricity supply
Communications equipment	Extraction of crude petroleum and natural gas and services	Gas supply
Other Machinery and Equipment	Mining of uranium and thorium ores	Water supply
Computer software and databases	Mining of metal ores	Construction
	Other mining and quarrying	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel

	Food products and beverages	Wholesale trade and commission trade, except of motor vehicles and motorcycles
	Tobacco products	Retail trade, except of motor vehicles and motorcycles; repair of household goods
	Textiles	Hotels and restaurants
	Wearing apparel, dressing and dying of fur	Inland transport
	Leather, leather products and footwear	Water transport
	Wood and products of wood and cork	Air transport
	Pulp, paper and paper products	Supporting and auxiliary transport activities; activities of travel agencies
	Publishing	Ost and telecommunications
	Printing and reproduction	Financial intermediation, except insurance and pension funding
	Coke, refined petroleum products and nuclear fuel	Insurance and pension funding, except compulsory social security
	Pharmaceuticals	Activities related to financial intermediation
	Chemicals excluding pharmaceuticals	Imputation of owner occupied rents
	Rubber and plastics products	Other real estate activities
	Other non-metallic mineral products	Renting of machinery and equipment
	Basic metals	Computer and related activities
	Fabricated metal products	Research and development
	Machinery, nec	Legal, technical and advertising
	Office, accounting and computing machinery	Other business activities, nec
	Insulated wire	Public admin and defence; compulsory social security
	Other electrical machinery and apparatus nec	Education
	Electronic valves and tubes	Health and social work
	Telecommunication equipment	Sewage and refuse disposal, sanitation and similar activities
	Radio and television receivers	Activities of membership organizations nec
	Scientific instruments	Media activities
	Other instruments	Other recreational activities
	Motor vehicles, trailers and semi-trailers	Other service activities
	Building and repairing of ships and boats	Private households with employed persons
	Aircraft and spacecraft	Extra-territorial organizations and bodies

Table C-7. Categories of assets of Penn World Table version 9.1

Assets
Structure
Machinery
Transport equipment
Other

C.2. Sector classifications

Table C-8. 200 EXIOBASE product categories to 7 human needs categories. Details about the 200 product categories are available in Stadler et al. (2018).

Human Needs	Product Codes from EXIOBASE
Clothing	15, 55, 56, 57
Construction	33, 34, 35, 36, 37, 38, 39, 40, 41, 97, 98, 99, 100, 101, 102, 103, 150, 151
Food	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 16, 17, 19, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 88, 89
Manufacturing	60, 61, 62, 63, 86, 87, 90, 96, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127
Mobility	67, 68, 69, 70, 71, 72, 73, 92, 93, 94, 95, 157, 158, 159, 160, 161, 162
Services	152, 153, 154, 155, 156, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 173, 174, 175, 196, 197, 198, 200
Shelter	18, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 58, 59, 64, 65, 66, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 91, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 176, 177, 178, 179, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195, 199

C.3. Building life spans in various countries

Table C-9. Statistics data of building lifespans in China and other countries. Data sources: *refs.* Aktas and Bilec (2011), CABR (2014), Cai et al. (2015), Erik Bradley and Kohler (2007), Huang et al. (2017), Huang et al. (2013), Komatsu (2008), Moura et al. (2015), Müller (2006), Reyna and Chester (2015), Sandberg et al. (2016), Song (2004), Tanikawa and Hashimoto (2010).

Country	Lifespan (years)
China	25-30
Japan	30-40
United States	50-60
Germany	64
Spain	77
Switzerland	71
Austria	80
France	102
United Kingdom	132.6
Belgium	90

Netherlands	71.5

C.4. Capital investment time trends

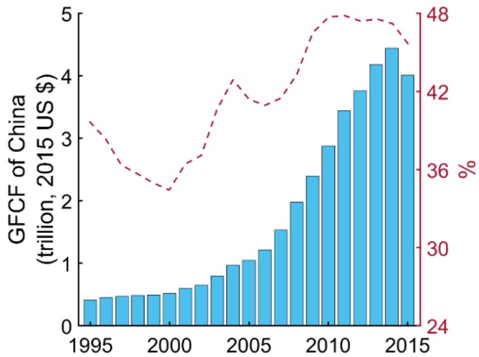

Figure C-1. China's gross fixed capital formation (GFCF) and share in GDP, 1995-2015. Red line represents the share of capital investments in national gross domestic product (GDP). Results in the figure are calculated based on EXIOBASE 3.6. (Stadler et al. 2018).

C.5. EPs embodied in China's capital investment and depreciation

The EPs embodied in China's gross fixed capital formation (GFCF) and capital depreciation (F_n^K) are contrasted in **Figure C-2**. We also distinguish between the EPs that occurred in China from those that occurred in foreign countries. Over the period of 1995-2015, 759 EJ (exajoules) of energy, 630 km^3 of blue water, 22 million km^2 of land, 10 Gt (gigatonnes) of metal ores, 124 Gt of non-metallic mineral ores, and 63 Gt greenhouse gas (GHG) emissions were appropriated in China for its capital investment. Outside of China, another 130 EJ of energy, 135 km^3 of blue water, 16 million km^2 of land, 7 Gt of metal ores, 4 Gt of non-metallic mineral ores, and 6 Gt GHG emissions were associated with China's capital expansion. The shares of foreign EPs embodied in China's capital investment vary greatly among the six environmental indicators we analyzed, with the most significant in land use (66% in 2015) and metal ore extractions (42%) and the least significant in non-metallic mineral extractions (5%) and GHG emissions (10%).

EPs embodied in China's capital depreciation were much smaller than those embodied in its capital investment, accounting for 267 EJ of energy, 253 km^3 of blue water, 10 million km^2 of land, 3 Gt of metal ores, 41 Gt of non-metallic mineral ores, and 22 Gt GHG in China, while 44 EJ of energy, 48 km^3 of blue water, 5 million km^2 of land, 2 Gt of metal ores, 1 Gt of non-metallic mineral ores, and 2 Gt GHG emissions outside of China.

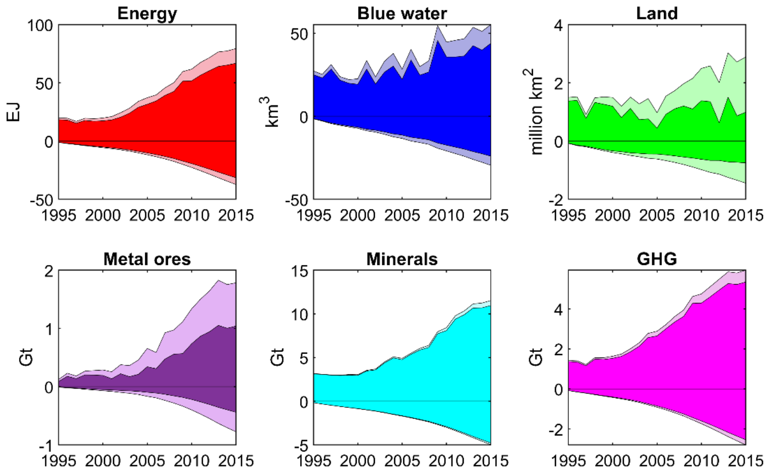

Figure C-2. EPs embodied in China's gross fixed capital formation (above the abscissa) and capital depreciation (below the abscissa), 1995-2015. Darker and lighter color tones indicate EPs occurred in China and overseas, respectively.

C.6. Sources of the capital assets consumed in China

Table C-10. Capital consumed in China: domestic and imported capital assets over 1995-2015. The cumulative capital consumption (in million 2015 US dollars) of the capital assets imported from the top 20 countries are listed. "Equipment by industrial sectors" covers computing, communication and transport equipment, other machinery and equipment, and computer software and databases; "Structures by industrial sectors" includes non-dwelling buildings and structures; "Assets by non-industrial sectors", encompasses those assets by non-industrial enterprises (agriculture, construction, and service sectors), and includes residential structures, cultivated assets, research and development, and other intellectual property products assets. RoW = rest of the world.

	Equipment by industrial sectors	Structures by industrial sectors	Assets by non-industrial sectors
China	917288	2745021	6415067
Japan	46201	147364	5585
Germany	31090	91026	5424
USA	27889	89277	4075
South Korea	25230	74804	3571
RoW Asia and Pacific	18809	60821	7768
France	5446	17173	2790
Italy	5468	17714	1373
United Kingdom	5198	15592	3096
Sweden	2264	7464	956
Switzerland	2307	6986	1236
RoW Middle East	1868	5485	2115
Finland	1703	5993	653
Russia	1289	4790	1482
Netherlands	1303	4144	2024
Belgium	1500	4848	1089
Austria	1635	5024	643

Canada	1393	4546	1185
Spain	1069	3324	1872
Australia	957	2977	1010
Indonesia	985	3073	269
Others	9080	26717	7114

C.7. Hypothetical contributions of pre-1995 capital investments and EPs

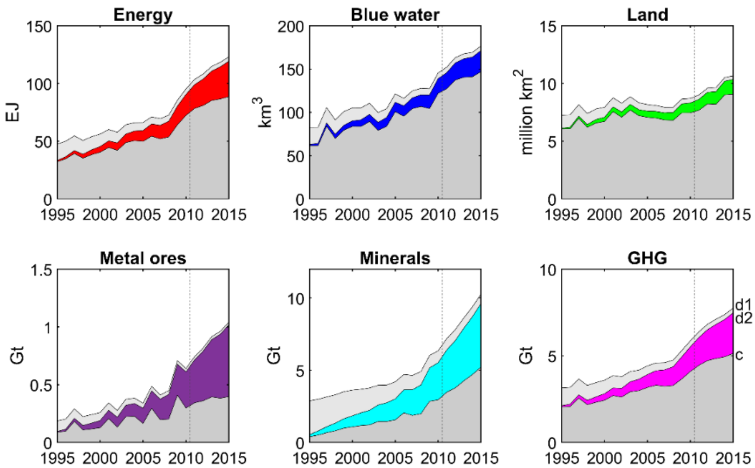

Figure C-3. Environmental footprints of China's final consumption during 1995-2015 accounting for capital invested from 1975-2015. Line **c**: EFs calculated by conventional CBA. Lines **d1**-**d2**: reassessed EFs accounting for capital consumption and the associated EPs. Line **d2** accounts for capital assets produced from 1995 to 2015, whilst Line **d1** accounts for capital assets produced since 1975.

Since capital investment data for pre-1995 capital investments and production practices (MRIO tables) are sparse or not readily available for many countries, we assume that the capital investment each year before 1995 equals to the investment in 1995, which was actually less than the values in 1995; thus, the associated EPs in year *t* (the gap between **d1** and **d2**) would be overestimated in **Figure C-3**. We found that the pre-1995 capital investment and the associated EPs would contribute for a great proportion in early years (e.g., 1995), especially of minerals ore extractions. In 2015, the EPs related with the pre-1995 capital investment would share 2%-6% percentage of that year total EPs. Yet, the actual contribution of pre-1995 investment would be less as **Figure C-3** illustrates.

C.8. Linking capital consumption to final consumption

Figure C-4 below are extended results related to **Figure 4-2** in the main manuscript.

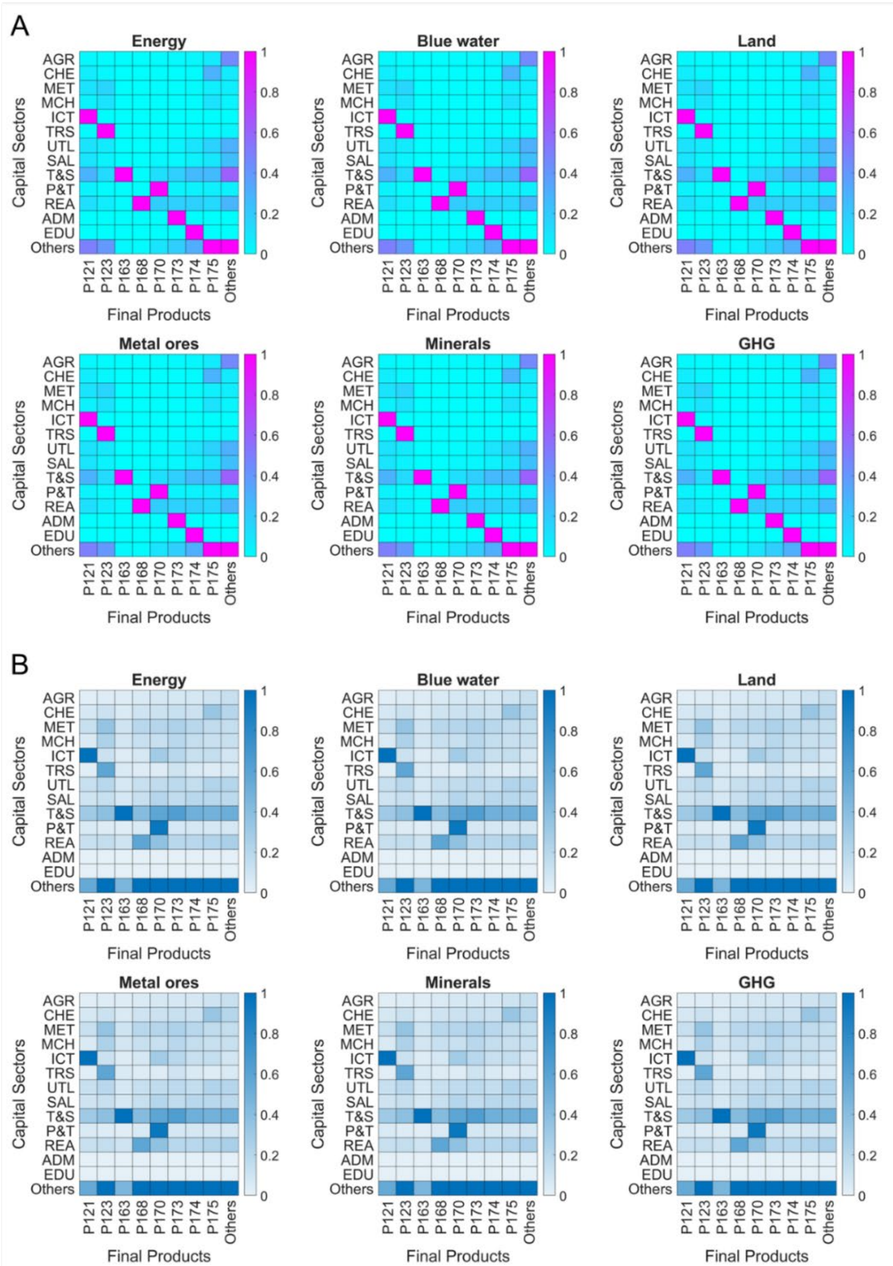

Figure C-4. Heat maps linking top capital investing (using) sectors (rows) with the top sectors of final consumption in China (A) and in foreign countries (B).

The final consumption sectors shown in this figure made at least a 2% contribution to the total environmental pressures embodied in China's capital consumption. For the abbreviated sector names: "AGR" (Agriculture, forestry, animal husbandry & fishery), "CHE" (Chemicals and allied products), "MET" (Primary & fabricated metal industries), "MCH" (Industrial machinery and equipment), "ICT" (Electronic and telecommunication equipment), "TRS" (Motor vehicles & other transportation equipment), "UTL" (Power, steam, gas and tap water supply), "SAL" (Wholesale and retail trades), "T&S" (Transport, storage & post services), "P&T" (Information & computer services), "REA" (Real estate services), "ADM" (Government, public administration, and political and social organizations, etc.), "EDU" (Education); P121 (Radio, TV, communication equipment and apparatus), P123 (Motor vehicles, trailers and semi-trailers), P163 (Supporting transport and travel agency services), P168 (Real estate services), P170 (Computer and related services), P173 (Public administration, defense, social security), P174 (Education services), and P175 (Health and social work services).

C.9. Capital-related EP of China's final consumption (EF^K)

The annual profiles and trends of the capital-related EFs of China's final consumption (EF^K) are presented in **Figure C-5**. These extended results are related to **Figure 4-3** in the main manuscript. We also note that capital consumption attributable to China's final consumption include capital assets located both in and outside of China.

Depending on the year of final consumption and the EP indicators, the share of the foreign-occurred EP in EFK varies substantially. During 1995-2015, the foreign shares range from 10-17% for the energy footprint, 10-21% of the blue water footprint, 12-50% of the land footprint, 30%-48% for the metal footprint, 1%-5% for the mineral footprint, and 6%-10% for the GHG footprint. Notably, foreign land use related to capital consumption has become increasingly important in supporting China's final consumption. Capital consumption has increased from 12% to 50% of the capital-related land footprint from 1995 to 2015. Over the years, a large fraction (30%-48%) of the metal footprint related to capital consumption occurred outside of China. Among the six EP indicators, mineral extractions related to capital consumption had the lowest foreign requirements, ranging from 1%-5%.

The average ages of capital-related EP attributable to China's final consumption i.e., average time EP occurred, can be revealed based on the temporal results of 2011-2015. The average age for energy use, blue water consumption, land use, metal ore extractions, mineral extractions, and GHG emissions is 6, 7, 7, 5, 6, and 6 years, respectively.

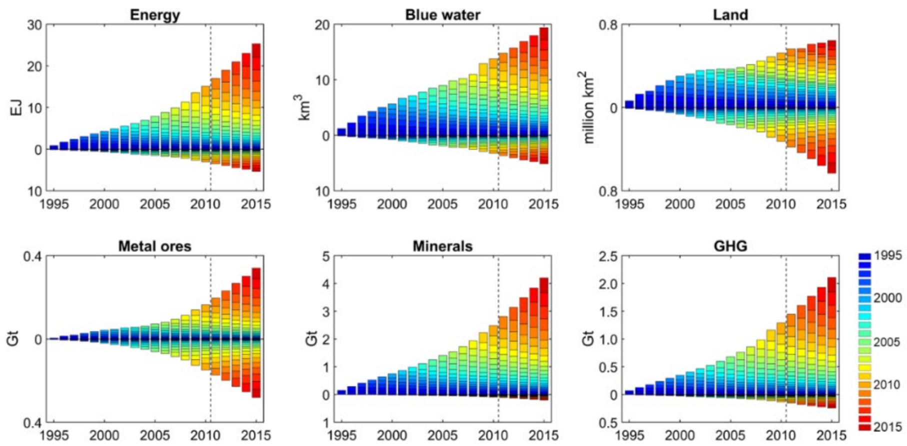

Figure C-5. Annual profiles of capital-related EPs of China's final consumption (*EF^K*) by the year when the EP occurred. *EF^K* occurred in China and in other countries are plotted above and below the abscissa, respectively.

C.10. Capital stocks and EP embodied in capital stocks

Results in **Figure C-6** support the discussion section. In the figure, we present the capital stock results from 2011-2015. The choice of 2011-2015 is because these years were not significantly affected by the fact that our model did not include pre-1995 capital investments. Capital invested in 1995 accounted for less than 1% of annual capital stocks after 2011 and therefore pre-1995 capital investments are considered negligible.

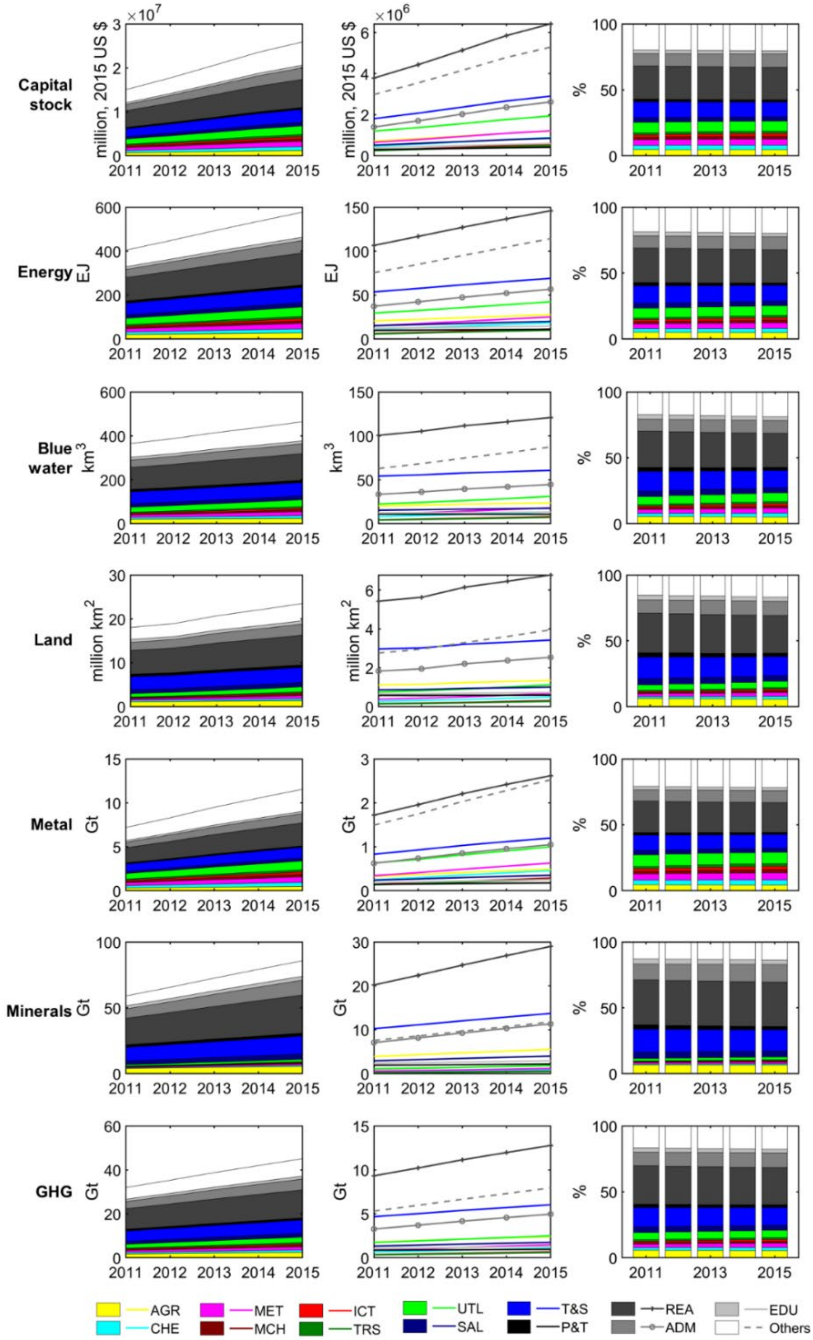

Figure C-6. Capital stocks and the embodied EP of main capital investing (i.e., using) sectors in China, 2011-2015. For the abbreviated sector names: "AGR" (Agriculture, forestry, animal husbandry & fishery), "CHE" (Chemicals and allied products), "MET" (Primary & fabricated metal industries), "MCH" (Industrial machinery and equipment), "ICT" (Electronic and telecommunication equipment), "TRS" (Motor vehicles & other transportation equipment), "UTL" (Power, steam, gas and tap water supply), "SAL" (Wholesale and retail trades), "T&S" (Transport, storage & post services), "P&T" (Information & computer services), "REA" (Real estate services), "ADM" (Government, public administration, and political and social organizations, etc.), "EDU" (Education).

C.11. Implications of technology change in assessing the capital-related EFs.

Inherent to the retrospective distribution of historical resource extractions and emissions, the capital goods used in current year come from different age cohorts, produced using different technologies, i.e., with different environmental intensities. In general, productivity and technology improvement make production processes increasingly cleaner, such as indicated by decreasing resource and emissions intensity of the same production sector along time. Assuming capital assets produced previously were produced using current technologies, as current capital-endogenized CBA models did (Chen et al. 2018, Lenzen 2001, Södersten et al. 2018a), the EPs associated with capital use for current final consumption would be underestimated in general. As shown in **Figure C-7**, such underestimates are particularly high for blue water consumption and land use, for they experienced a relatively large reduction of the intensities. As for GHG emissions, the yearly underestimates have the median (25th-75th percentile) of 16% (5-27%), which explains the difference between our results and those in *ref.* [8]. However, for metal ore extractions, the 'current technology assumption' led to overestimates of the capital-related EF during the period of 2002-2008, possibly due to decreasing ore grades.

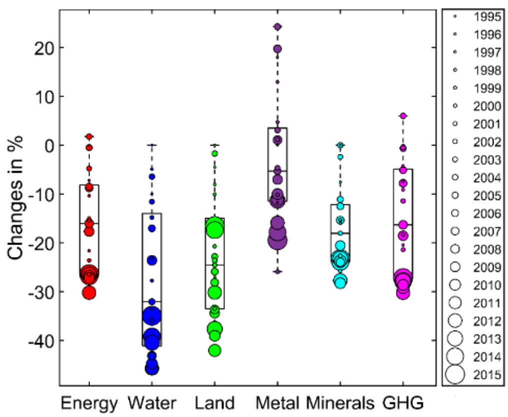

Figure C-7. Difference in China's EF^{KC} estimates when assuming all consumed capital assets of different age cohorts were produced with current production systems and resource and environmental intensities. The median and 25th–75th percentiles (box), and maximum and minimal values (whiskers) are shown.

C.12. EFs of China over 2011-2015 distinguishing between capital and non-capital goods

Table C-11 below is extended results related to **Figure 4-3** in the main manuscript.

Table C-11. Environmental footprints of China's final consumption during 2011-2015 assessed by different consumption-based accounting (CBA) methods and scopes. a1, a2, b1, and **b2** indicate Lines **a1, a2, b1**, and **b2** in **Figure 4-3** in the main manuscript, respectively.

	2011	2012	2013	2014	2015
Energy (EJ)					
a1	145.9	152.5	161.8	164.0	168.0
a2	78.4	80.9	85.3	86.6	88.6
b1	98.9	103.8	110.7	114.4	119.3
b2	95.4	99.9	106.2	109.6	114.0
BWC (km^3)					
a1	173.0	184.0	194.1	192.2	202.1
a2	127.2	137.2	140.5	141.0	146.8
b1	145.7	157.0	161.8	163.7	171.3
b2	142.0	152.9	157.4	158.9	166.2
Land (million m^2)					
a1	10.3	10.2	11.2	11.7	12.0
a2	7.7	8.2	8.2	9.0	9.1
b1	8.6	9.2	9.3	10.2	10.3
b2	8.2	8.8	8.8	9.6	9.7
Metal (Gt)					
a1	1.8	2.0	2.2	2.1	2.2
a2	0.3	0.4	0.4	0.4	0.4
b1	0.7	0.8	0.9	0.9	1.0
b2	0.5	0.6	0.7	0.7	0.7
Minerals (Gt)					
a1	13.3	14.1	15.4	15.9	16.7
a2	3.5	3.8	4.3	4.7	5.2
b1	6.4	7.1	7.9	8.7	9.6
b2	6.3	6.9	7.8	8.5	9.4
GHG (Gt)					
a1	9.6	10.2	10.7	10.8	11.1
a2	4.5	4.7	4.8	4.9	5.1
b1	6.1	6.5	6.8	7.1	7.5
b2	5.9	6.3	6.6	6.9	7.2

Appendix D: An Appendix to Chapter 5

D.1. Data Sources

D.1.1 Capital data

The major capital data we use in this study include total investment in fixed assets (TIFA) by sector and by province, newly increased fixed assets (NIFA) by sector and by province, and depreciation rates by asset and by capital consuming sectors. TIFA and NIFA are mainly collected from the statistical database of the National Bureau of Statistics of China (NBSC) (NBSC 2020) and the Statistical Yearbook of the Chinese Investment in Fixed Assets (NBSC 2018b). Official NIFA are distinguished as rural NIFA and urban NIFA by 19 major economic sectors (e.g., "Agriculture, Forestry, Animal Husbandry and Fishery" or "Construction", see **Table D-1**). Particularly, urban NIFA are also recorded by 40 specific industrial sectors (e.g., "Food Manufacturing" or "Electricity, Heat Production and Supply", see **Table D-1**). However, the industrial classifications of the official data are inconsistent overt time. That is, before 2002, sector "*Hotels and Catering Services*" was aggregated into sector "*Wholesale and Retail Trades*"; sector "*Education*" was aggregated into sector "*Cultural, Sports, and Entertainment Services*"; while sectors "*Information Transmission, Computer Services and Software*", "*Leasing and Business Services*", "*Services to Households and Other Services*" and "*Public Administration and Social Organization Services*" were aggregated as "*Public Services*". To ensure the consistency of sectoral classification during the study period, we re-allocate these aggregated sectors' capital investment into each sector based on their shares in the capital investment in the year 2003. Furthermore, rural NIFA of major industry sectors, i.e., "*Mining and Quarrying Industry*", "*Manufacturing Industry*", and "*Production and Supply of Electricity, Gas and Water*", are disaggregated into 40 specific industrial sectors based on their shares in urban NIFA in each province.

Table D-1. Categories of sectors of newly increased fixed assets (NIFA) recorded by the National Bureau of Statistics of China.

Rural NIFA	Urban NIFA
Agriculture, Forestry, Animal Husbandry and Fishery	Agriculture, Forestry, Animal Husbandry and Fishery
Mining and Quarrying Industry	Mining and Quarrying Industry
Manufacturing Industry	Mining and Washing of Coal
Production and Supply of Electricity, Gas and Water	Petroleum and Natural Gas
Construction	Mining and Processing of Ferrous Metal Ores
Wholesale and Retail Trades	Mining and Processing of Non-Ferrous Metal Ores
Transport, Storage and Post	Minging and Processing of Nonmetal Ores
Hotels and Catering Services	Mining Supportive Activities
Information Transmission, Computer Services and Software	Minging of Other Ores

Financial Intermediation	Manufacturing Industry
Real Estate Services	Processing of Food from Agricultural Products
Leasing and Business Services	Manufacture of Foods
Scientific Research, Technical Service and Geologic Prospecting	Manufacture of Beverages
Management of Water Conservancy, Environment and Public Facilities	Manufacture of Tobacco
Services to Households and Other Services	Manufacture of Textile
Education	Manufacture of Textile Wearing Apparel, Footware and caps
Healthy Services	Manufacture of Leather, Fur, Feather and Related Products
Cultural, Sports, and Entertainment Services	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm and Straw Products
Public Administration and Social Organization Services	Manufacture of Furniture
	Manufacture of Paper and Paper Products
	Printing, Reproduction of Recording Media
	Manufacture of Articles For Culture, Education and Sports Activities
	Processing of Petroleum, Coking, Processing of Nuclear Fuel
	Manufacture of Raw Chemical Materials and Chemical Products
	Manufacture of Medicines
	Manufacture of Chemical Fibers
	Manufacture of Rubber and Plastics Products
	Manufacture of Non-metallic Mineral Products
	Smelting and Pressing of Ferrous Metals
	Smelting and Pressing of Non-ferrous Metals
	Manufacture of Metal Products
	Manufacture of General Purpose Machinery
	Manufacture of Special Purpose Machinery
	Manufacture of Transport Equipment
	Manufacture of Electrical Machinery and Equipment
	Manufacture of Communication Equipment, Computers and Other Electronic Equipment
	Manufacture of Measuring Instruments and Machinery for Cultural Activity and Office Work
	Manufacture of Artwork and Other Manufacturing
	Recycling and Disposal of Waste
	Metal Product Machinery and Equipment Repair Industry
	Production and Supply of Electricity, Gas and Water
	Production and Supply of Electric Power and Heat Power
	Production and Supply of Gas
	Production and Supply of water

	Construction
	Wholesale and Retail Trades
	Transport, Storage and Post
	Hotels and Catering Services
	Information Transmission, Computer Services and Software
	Financial Intermediation
	Real Estate Services
	Leasing and Business Services
	Scientific Research, Technical Service and Geologic Prospecting
	Management of Water Conservancy, Environment and Public Facilities
	Services to Households and Other Services
	Education
	Healthy Services
	Cultural, Sports, and Entertainment Services
	Public Administration and Social Organization Services

Table D-2. Categories of 37 capital investing sectors recorded in the WorldKLEMS (WORLDKLEMS 2019).

Sector Number	**Full Name**
1	Agriculture, forestry, animal husbandry & fishery
2	Coal mining
3	Oil & gas excavation
4	Metal mining
5	Non-metallic minerals mining
6	Food and kindred products
7	Tobacco products
8	Textile mill products
9	Apparel and other textile products
10	Leather and leather products
11	Saw mill products, furniture, fixtures
12	Paper products, printing & publishing
13	Petroleum and coal products
14	Chemicals and allied products
15	Rubber and plastics products
16	Stone, clay, and glass products
17	Primary & fabricated metal industries
18	Metal products (excluding rolling products)
19	Industrial machinery and equipment
20	Electric equipment
21	Electronic and telecommunication equipment
22	Instruments and office equipment
23	Motor vehicles & other transportation equipment
24	Miscellaneous manufacturing industries
25	Power, steam, gas and tap water supply

26	Construction
27	Wholesale and retail trades
28	Hotels and restaurants
29	Transport, storage & post services
30	Information & computer services
31	Financial Intermediations
32	Real estate services
33	Leasing, technical, science & business services
34	Government, public administration, and political and social organizations, etc.
35	Education
36	Healthcare and social security services
37	Cultural, sports, entertainment services; residential and other services

D.1.2 MRIO-related data

According to the data needed to construct China's inter-provincial MRIO table series, the associated data sources include: the current best available MRIO tables collected for the year 2007 (Liu et al. 2012), 2010 (Liu et al. 2014b), 2012 (Liu et al. 2018), 2015 and 2017 from CEADs (Zheng et al. 2020), and 1995-2016 from Wang (2017); product-specific per-capita expenditures of rural and urban population in each province from China Statistical Yearbooks (NBSC 2017b); rural and urban population of each province from China Statistical Yearbook , and 1995-2016 from Wang (2017); product-specific per-capita expenditures of rural and urban population in each province from China Statistical Yearbooks (NBSC 2017b), and China Rural Statistical Yearbook (NBSC 2018a); gross final expenditures, GFCF, and stock changes of each province from China Statistical Yearbook (NBSC 2017b), see **Table D-3** for associated data in 2017; product-specific export data from China Statistical Yearbook (NBSC 2017b), China Trade And External Economic Statistical Yearbook (NBSC 2017a), and Market Statistical Yearbook Of China (NBSC 1997).

Table D-3. Gross regional product by expenditure approach for the year 2017. Unit: 10^8 Yuan.

Region	Province	Final expenditure			GFCF	Stock changes
		Rural population	Urban population	Government		
Beijing-Tianjin	Beijing	768	10724	5351	10375	768
Beijing-Tianjin	Tianjin	638	5441	2346	10138	638
North	Hebei	3486	8425	4144	19035	3486
Northwest	Shanxi	1801	4894	2062	6700	1801
Northwest	Inner Mongolia	1375	4661	2428	10392	1375
Northeast	Liaoning	1927	8948	2903	9639	1927
Northeast	Jilin	1089	3010	1701	10014	1089
Northeast	Heilongjiang	1753	5402	2967	9651	1753

Central Coast	Shanghai	756	12214	4581	11507	756
Central Coast	Jiangsu	6810	25083	11128	36417	6810
Central Coast	Zhejiang	4334	14702	6443	21862	4334
Central	Anhui	2827	7843	2829	13569	2827
South Coast	Fujian	2491	7617	3043	17638	2491
Central	Jiangxi	2553	5413	2258	9738	2553
North	Shandong	7431	20854	6901	34704	7431
Central	Henan	4978	12052	6100	30415	4978
Central	Hubei	3026	9729	4417	20587	3026
Central	Hunan	3645	9639	4792	17160	3645
South Coast	Guangdong	5385	28712	11032	38391	5385
Southwest	Guangxi	2325	5522	2658	9035	2325
South Coast	Hainan	465	1465	852	2809	465
Southwest	Chongqing	1181	5838	2271	9907	1181
Southwest	Sichuan	5323	9518	4525	17689	5323
Southwest	Guizhou	1935	3897	1674	9086	1935
Southwest	Yunnan	2335	5265	2906	14826	2335
Southwest	Shaanxi	1650	5419	2607	14144	1650
Central	Gansu	1054	2664	1430	3557	1054
Northwest	Qinghai	337	737	742	3918	337
Northwest	Ningxia	348	1081	685	3836	348
Northwest	Xinjiang	1185	2867	3220	10695	1185

D.1.3 Carbon emission inventory

Carbon emissions by sector of 30 regions during the period of 1997-2017 are collected from emission inventories complied by CEADs (Shan et al. 2018, Shan et al. 2020a, Shan et al. 2016). The CEADs' carbon emission inventories are constructed in a resolution of 45 sectors, as well as household emissions of rural and urban population. We aggregate the 45-sectorial emission data into the resolution of 42 MRIO-sectors. Moreover, there are still two-year carbon emission data missing. We assume the sectorial carbon emission intensities of sectors in 1995 and 1996 are equal to those in 1997.

D.2. Total investment in fixed assets (TIFA) V.S. newly increased fixed assets (NIFA)

Official capital investment data from the National Bureau of Statistics of China (NBSC) are recorded by two main annual series, "total investment in fixed assets (TIFA)" (*"quanshehui guding zichan touzi"* in Chinese) and "newly increased fixed assets (NIFA)" ("*xinzeng guding zichan*" in Chinese). TIFA and/or NIFA are supposed to be the basis for the gross fixed capital formation

(GFCF) item in the Chinese national accounts. However, these indicators do not appear to be consistent (**Figure D-1**), hence causing confusions to their users.

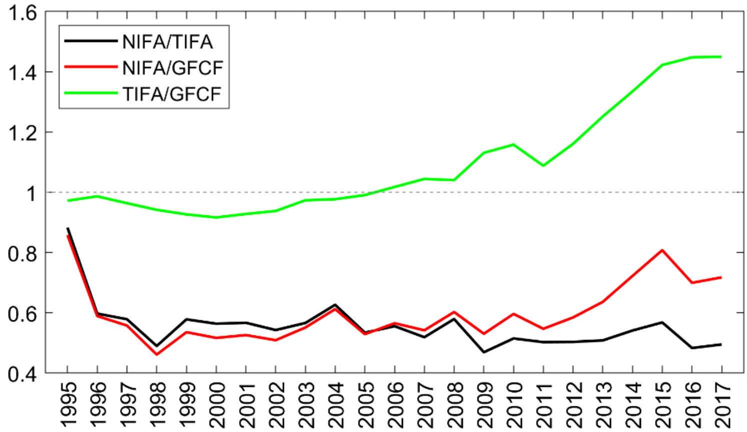

Figure D-1. Relationship between Chinese statistical capital data. TIFA=total investment in fixed assets; NIFA=newly increased fixed assets; GFCF=gross fixed capital formation. Data source: National Bureau of Statistics of China.

An often made, significant mistake is the direct use of TIFA as the investment variable in estimating capital stock or capital depreciation with the perpetual inventory method (PIM) (Hu and Khan 1997, Huang et al. 2002, Li 1992) which is conceptually inappropriate. By official definition, TIFA refers to the "workload" of activities in construction and purchases of fixed assets in money terms (NBSC 2017b), which may not produce results that meet standards for fixed assets in the current period or may take many years to become qualified for fixed assets and some may never meet the standards, hence be completely wasted, which is a typical phenomenon in all centrally planned economies (Chow 1993). The problem is aggravated in the case of a large project because its investment "workload" is counted by stage of construction, but it cannot be used for production (hence should be counted as the increase in inventory) before all stages are completed and the operation actually commences. It can be sure that the official TIFA indicator and hence GFCF exaggerates the real level of fixed asset investment.

Compared with TIFA, the series of NIFA is much more compatible with the concept of "fixed asset investment" used in PIM because it refers to the value of investment projects completed and put into production or meeting the standards for fixed assets in the current year (NBSC 2017b), hence reflecting the fixed assets formed in the current period as a results of those *effective* investment projects taking place in the current and previous periods. They are *effective* because they have been (or will be) turned into new fixed assets for production services rather than wasted.

If denote NIFA as N and TIFA as M (or the "workload" of investment projects), assuming no coverage problem and double counting, then N in period t is the sum of M's in $\tau+1$ periods (i=0, 1, 2, …, τ) multiplied by their respective ratios θ ($\theta<1$), defined as, in value terms, the proportion of actually completed investment in period t in the total "workload" of the investment projects taking place in period t-i, that is,

$$N_t=\sum_{i=0}^{\tau}\theta_{t-i}M_{t-i}\,,\ (i=0,\ 1,\ 2,\ldots\tau)$$

It should be mentioned that there is little information available on θ and τ. An officially often used ratio, namely "rate of fixed assets put into use" ("*guding zichan jiaofu shiyonglv*" in Chinese) defined as $N_t/M_t=\sum_{i=0}^{\tau}\theta_{t-i}M_{t-i}/M_t$, is misleading because it compares two concepts that are virtually incompatible (see Table 10-17 in China Statistical Yearbook 2017 (NBSC 2017b).

Although NIFA is more reasonable than TIFA to be used as capital investment (denoted as I) in PIM, two adjustments have to be made to transfer N to I. One is a downward adjustment to remove the investment in residential buildings, a prerequisite for conducting any production function analysis. The other is an upward adjustment to include the projects less than half million yuan by non-state firms that are not reported in official investment statistics plus the value of likely underreporting (Young 2000). The standard I by sector s of province m could be estimated as:

$$I_{m,t,s}=N_{m,t,s}\frac{1-\eta_{m,t,s}}{1-\lambda_{m,t,s}},\ (\eta<1;\ \lambda<1)$$

where η and λ are two parameters to adjust N by the effects of residential structures and missing and/or underreported investment, respectively.

D.3. Constructing China's inter-provincial MRIO table series (1995-2017)

The basic framework to construct China's inter-provincial MRIO table series (1995-2017) follows previous studies by Guan et al. (2008), Hubacek and Sun (2001), Hubacek and Sun (2005), and Zhao et al. (2015), and uses the GRAS method (Günlük-Şenesen and Bates 1988). The GRAS method is a branch of the RAS method, which is a procedure that is widely used for updating IO information over time. Here we present a brief introduction. We denote the column sum of the intermediate input matrix **Z** as **U**, while denote the row sum of **Z** as **V**. The RAS method is used to quantify the intermediate input matrix **Z'** in the target year, given the matrix **Z** in the reference year and **U'**, **V'** and **x'** in the target year. The quantification procedure is to give iterative trial and adjustment of **U'** and **V'** to obtain a balanced matrix **Z'**.

The current best available MRIO tables in 2007 (Liu et al. 2012), 2010 (Liu et al. 2014b), 2012 (Liu et al. 2018), 2015 and 2017 from CEADs (Zheng et al. 2020), 1995-2006 from Wang (2017) are relied on as MRIO tables in the reference years. Although Wang (2017) construct the time series of MRIO tables since 1978, the features of these MRIO tables are quite different from the statistical data recorded in the National Bureau of Statistics of China (NBSC). An example of provincial value added in 2012 recorded in the NBSC, and from MRIO tables from Liu et al. (2018) and Wang (2017), respectively, are listed in **Table D-4**. Because of the big differences of data in the MRIO tables complied by Wang (2017) from those in the NBSC, we only use the MRIO tables of the period 1995-2006 from Wang (2017) for our analysis. In addition, before we construct the MRIO tables in the missing years, we first adjust the final demand, exports, imports and value-added data in the existing MRIO tables, to make sure all the data compiled in MRIO tables are well balanced with the statistical data from the National Bureau of Statistics of China. The intermediate input table is then adjusted using the GRAS method to make sure the balances between total outputs and total inputs.

Table D-4. Provincial value added in 2012 recorded in the National Bureau of Statistics of China (NBSC), MRIO tables from Liu et al. (2018) and Wang (2017), respectively. Unit in 10^8 Yuan.

Provinces	NBSC	Liu et al. (2018)	Wang (2017)
Beijing	19025	17879	6151
Tianjin	9043	12894	2226
Hebei	23077	26575	14924
Shanxi	11683	12113	6152
Inner Mongolia	10470	16372	4346
Liaoning	17849	24898	9108
Jilin	8678	11939	4213
Heilongjiang	11016	13733	6173
Shanghai	21306	20184	7326
Jiangsu	53702	59972	21799
Zhejiang	34382	35911	19614
Anhui	18342	17214	9694
Fujian	20191	19702	8377
Jiangxi	12808	12949	7774
Shandong	42957	50028	20624
Henan	28962	29599	15031
Hubei	22591	22415	9650
Hunan	21207	22154	10855
Guangdong	57008	55463	29217
Guangxi	11304	13035	5469
Hainan	2789	2856	1067
Chongqing	11595	11410	4450
Sichuan	23922	23873	13848
Guizhou	6742	6852	3960
Yunnan	11097	10371	6125
Tibet	710	701	221

Shaanxi	14142	14454	6518
Gansu	5393	5658	3149
Qinghai	1528	1894	813
Ningxia	2131	2347	1050
Xinjiang	7412	7509	3489

It should also be noted that the MRIO tables in 2007 and 2010 only have 30 regions (without Tibet) and 30 sectors, while the MRIO tables in 1995-2006, 2012, 2015 and 2017 have 31 regions and 42 sectors. To ensure the consistency of MRIO table time series, we omit all the transactions relevant to Tibet in the MRIO tables in 2012, 2015 and 2017, and disaggregate the 30 sectors into 42 sectors (**Table D-5**) for further calculation. We also specify five final demand categories, i.e., final expenditures of rural population, final expenditures of urban population, final expenditures of government, gross fixed capital formation (GFCF), and stock changes, according to the best available MRIO tables.

Table D-5. **List of the 42 sectors in China's inter-provincial MRIO table time series.**

Sector Number	Full Name	Short Name
1	Agriculture, forestry, animal husbandry and fishery products and services	Agri. sect.
2	Coal mining products	Coal mining
3	Oil and natural gas extraction products	Oil and nat. gas
4	Metal ore mining and products	Metal ore mining
5	Non-metallic minerals and other mining products	Mineral mining
6	Food manufacturing and tobacco	Food & tobacco
7	Textile and products	Textile
8	Leather and down of textiles, clothing, shoes, hats and articles thereof	Leather n.e.c
9	Wood products and furniture	Wood mfg.
10	Paper printing, culture, education, and sporting goods	Paper n.e.c
11	Petroleum, coking products and nuclear fuel processed products	Petroleum n.e.c
12	Chemical product	Chemical prod.
13	Non-metallic mineral product manufacturing	Mineral prod.
14	Metal smelting and rolling product manufacturing	Metal smelting
15	Metal product manufacturing	Metal prod.
16	General equipment	General eq.
17	Professional equipment	Professional eq.
18	Transportation equipment	Transportation eq.
19	Electrical machinery and equipment	Electricity eq.
20	Communication equipment, computers and other electronic equipment	Electronic eq.
21	Instrumentation	Instrumentation
22	Other manufactured products	Other mfg.
23	Waste of materials	Waste of materials
24	Repair of metal products, machinery and equipment	Repair mfg

25	Production and supply of electricity and heat	Electricity supply
26	Gas production and supply	Gas supply
27	Water production and supply	Water supply
28	Construction	Construction
29	Wholesale and retail	Wholesale etc.
30	Transportation, storage and post services	Transport. sev.
31	Accommodation and restruant	Accommodation
32	Information transfer, software and information technology services	Info. sev.
33	Financial services	Financial sev.
34	Real estate services	Real estate
35	Leasing and business services	Business sev.
36	Scientific research and technical services	Sci. res. tech.
37	Public services, hydrology, environment and public facilities management	Public sev.
38	Resident services, repairs and other services	Resident sev.
39	Education	Education
40	Health and social work	Health sev.
41	Culture, sports and entertainment	Culture sev.
42	Public administration, social security and social organization	Public admin. sev.

To estimate **U**', **V**' and **x**' in the target year, we first estimate final demand **y**' and the export **EX**' in the target year, and then we assume **U**', **V**' and **x**' will all change proportionally with total changes in **y**' and **EX**'. Final expenditures of rural population ($\mathbf{y\_r}'_m$) and final expenditures of urban population ($\mathbf{y\_u}'_m$) in the target year of province *m* are estimated in this way: we first determine the changes in product-specific expenditures of rural population (also for urban population) in the target year of province *m* from that in the reference year, which are calculated using the statistical data of product-specific per-capita expenditures of rural population (also for urban population) of province *m*, the number of rural population (also for urban population) of province *m*, and the inflation rates of associated years of province *m*; then we apply the product-specific changes to the final expenditures of associated producing sectors in $\mathbf{y\_r}_m$ (also for $\mathbf{y\_u}_m$); finally we balance $\mathbf{y\_r}'_m$ (also for $\mathbf{y\_u}'_m$) into the statistical data of gross final expenditures of rural population (also for urban population) in the target year of province *m*. Since there is no detailed per-capital expenditure data of government expenditures (**y_g**), we rely on the changes in final expenditures of rural and urban population in the target year from that in the reference year to estimate $\mathbf{y\_g}'_m$ in the target year, and also balance it into the statistical data of gross final expenditures of government in the target year of province *m*. GFCF ($\mathbf{y\_gfcf}'_m$) and stock changes ($\mathbf{y\_s}'_m$) in the target year of province *m* are estimated in the similar way of $\mathbf{y\_r}'_m$ or $\mathbf{y\_u}'_m$, but both rely on the changes in newly constructed capital investment time series, and finally balance them into the statistical data of gross

GFCF and gross stock changes in the target year of province *m*, respectively. It should be noted that the statistical data of gross final expenditures of rural population, urban population, and government, GFCF, and stock changes of each province include the imported part. Therefore, when we estimate **y**' in the target year, we distinguish **y**' into domestic and imported ones. Since we only have nationally product-specific export data, we first determine product-specific export changes in the target year from the reference year, and proportionally adjust the export of each province based on the national changes in associated producing sectors, and lastly balance **EX**' into the nationally product-specific export data in the target year. We believe relying on more actual statistical data will reduce the uncertainty in estimating **y**' and **EX**' as much as possible.

D.4. Applying energy mix changes in MRIO tables

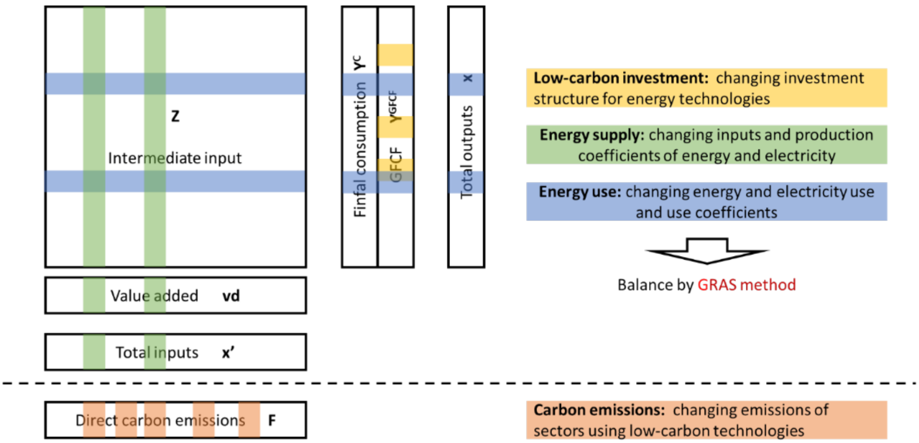

Figure D-2. Diagram to apply energy mix changes in MRIO tables. The diagram is referred to Wiebe et al. (2018).

D.5. Relationships between sectorial capital investment and final consumption

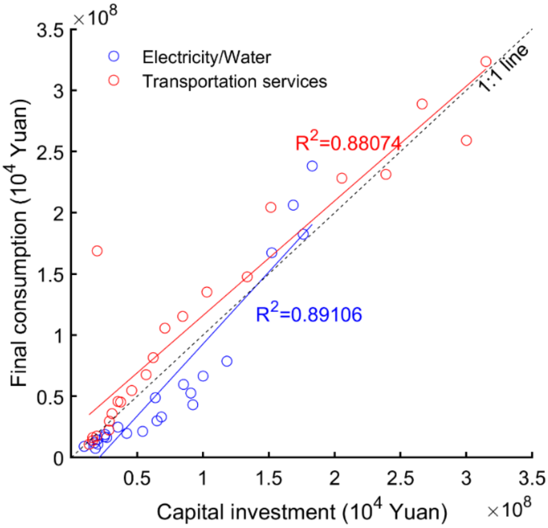

Figure D-3. Trends in capital investment by, and final consumption of electricity/water production and supply sector as well as transportation service sector. Each scatter in this plot represents the pair of capital investment and final consumption of associated sector in one year. The data sources of capital investment and final consumption could be found in **Appendix D.1**.

D.6. Capital investment in China

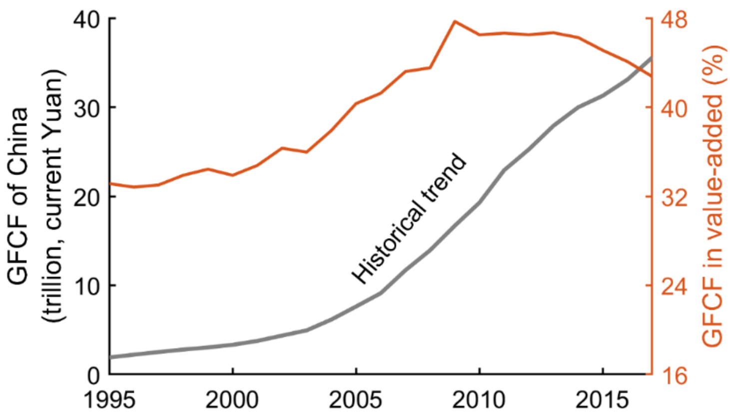

Figure D-4. Capital investment (left y-axis) and the share of gross fixed capital formation (GFCF) in national value-added (right y-axis) of China during the period 1995-2017.

D.7. Carbon emissions under capital scenarios

National PBEs and CBEs would substantially increase under the BAU and KES scenarios compared with those in 2017 (**Figure 5-3a** in **Chapter 5**), while under the KLC scenario, only a slight growth (less than 2%) is observed for them and potential decreases could also be expected in some certain regions (e.g., the Beijing-Tianjin, and the Southwest, see **Figure D-5**).

From a production perspective, the national PBE in 2030 (**Figure 5-3b** in **Chapter 5**) would increase by 15% under the BAU scenario from the base-year level, and by 20% under the KES scenario because more investment will be made in infrastructure for economic growth and social well-being improvement. The main growth in national PBEs under the BAU and KLC would be observed in transportation services due to the increase of its final consumption, whereas offset by carbon emissions from electricity generation given the efficiency improvement of production and energy use (**Figure D-6**). From the consumption perspective, similar growth rates would also be found in national consumption-based carbon emissions of final consumption and final demand, showing the largest changes under the KES scenario (by 35% and 22%, respectively) whereas least changes under the KLC scenario (by 15% and 1.8%, respectively). Moreover, at the regional level, the relative changes in regional consumption-based carbon emissions of final demand are larger in less developed regions such as the Northeast and the Northwest (+9–34%), mainly due to the growth of electricity generation, construction, and transportation services. In comparison, the changes in consumption-based carbon emissions of final demand in highly developed regions like Beijing-Tianjin, the Central Coast, and the South Coast would be in the range of -4–+20%.

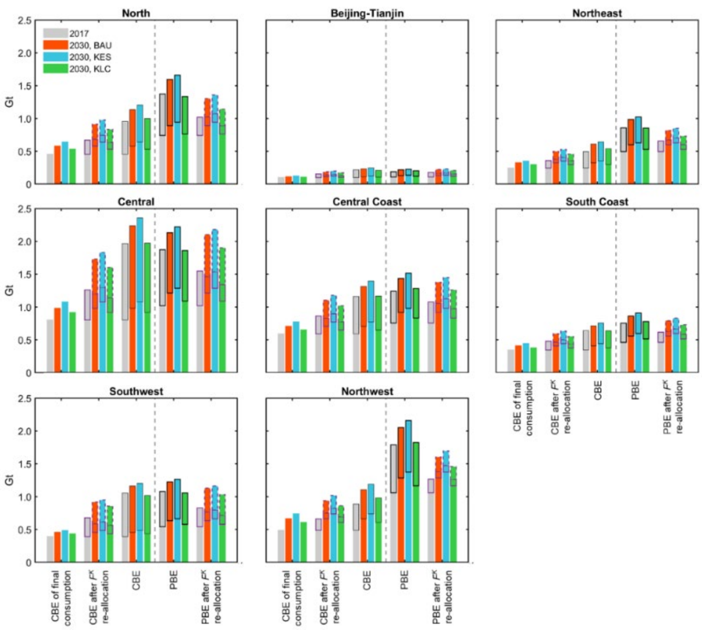

Figure D-5. Regional carbon emissions for the year 2017, and year 2030 under the three capital investment scenarios. In each panel, capital-related carbon emissions (F^K) are disaggregated into those occurred in the period of 1995−2017 (with solid edge line) and those would occur in the period of 2018−2030 (with dashed edge line).

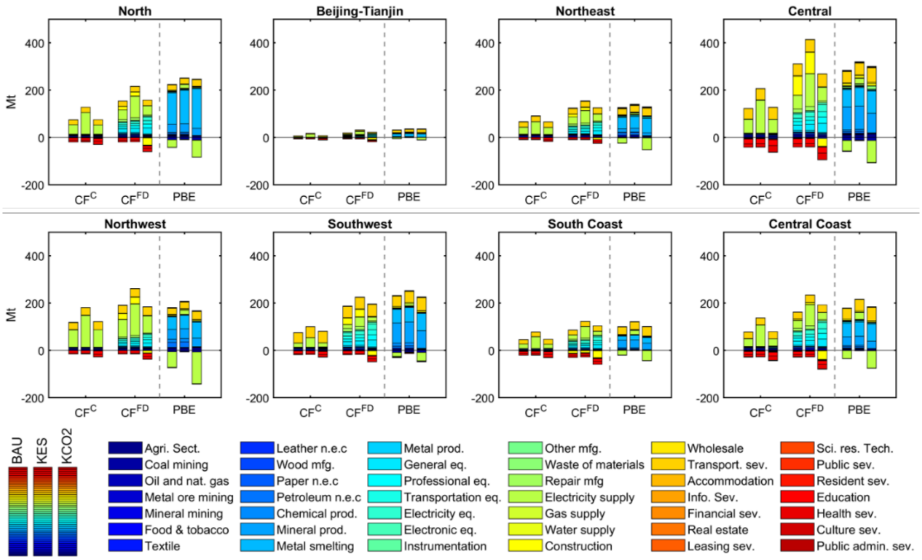

Figure D-6. Sectoral contributions to the regional carbon emission changes in 2030 under the three capital investment scenarios. CF^C and CF^{FD} represent the carbon footprint of final consumption and final demand, respectively, by conventional consumption-base accounting. PBE represents the production-based carbon emissions, excluding the carbon emissions embodied in international exports.

D.8. Annual profile of capital-considered carbon footprints

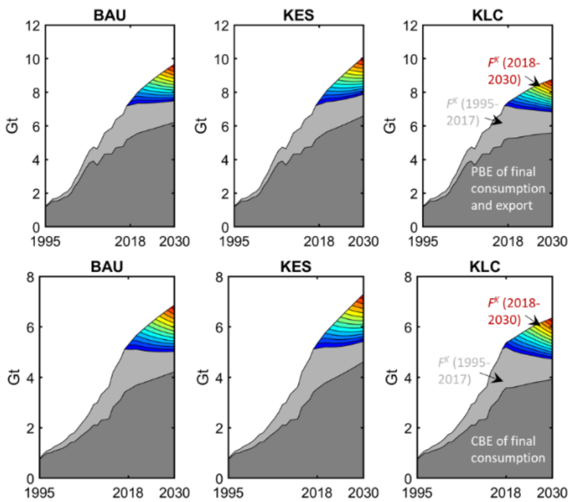

Figure D-7. Annual profiles of national carbon emissions with the re-allocation of capital-related emissions (F^K) during the period of 2018-2050. The re-allocated F^K is further disaggregated into those occurred in the period of 1995-2017 (in grey color tone) and those would occur in the period of 2018-2050 (in bright color tones).

D.9. Uncertainty analysis

To further improve the confidence in our main findings about future carbon emission assessments, we examine the uncertainties arising from key assumptions applied in scenario narratives. That is, we rely on the Monte Carlo method to rerun (10,000 times) the capital endogenized MRIO model using the randomly generated parameters for each scenario, which include the annual growth rates of GDP under the BAU scenario, the annual investment on each infrastructure under the KES scenario, and the annual investment in low-carbon technologies under the KLC scenario. We realize that there are other uncertain factors that influence the robustness of emission results. Multi-factor uncertainty analysis is out of the scope of this study, but should be further addressed depending on the purposes of future application of the capital-endogenized MRIO model and associated scenarios.

List of Publications

Peer-Reviewed Journal Articles

Ye, Q., Hubacek, K., Shan, Y., Berger, M., and Krol, M.S. Spatiotemporal carbon emissions embodied in the full lifespan of capital for China's production and consumption from 1995 to 2030. *Under Review*

Ye, Q.*, Wang, R., Schyns, J.F., Zhuo, L., Yang, L. and Krol, M.S. (2022) Effects of production fragmentation and inter-provincial trade on spatial blue water consumption and scarcity patterns in China. *Journal of Cleaner Production* 334

Ye, Q.*, Bruckner, M., Wang, R., Schyns, J.F., Zhuo, L., Yang, L., Su, H. and Krol, M.S. (2022) A hybrid multi-regional input-output model of China: Integrating the physical agricultural biomass and food system into the monetary supply chain. *Resources, Conservation and Recycling* 177

Ye, Q., Hertwich, E.G., Krol, M.S., Font Vivanco, D., Lounsbury, A.W., Zheng, X., Hoekstra, A.Y., Wang, Y. and Wang, R.* (2021). Linking the Environmental Pressures of China's Capital Development to Global Final Consumption of the Past Decades and into the Future. *Environmental Science & Technology* 55(9), 6421-6429

Wu, Z., Wang, M. and **Ye, Q.*** (2021) Integrating the inter- and intra-annual dynamic features of capital into environmental footprint assessment: Revisiting China's greenhouse gas footprints, 1995-2015. *Science of the Total Environment* 801, 149629

Wu, Z., Yang, L., Chen, Q. and **Ye, Q.*** (2021) The impacts of international trade on global greenhouse gas emissions: A thought experiment based on a novel no-trade analysis. *Journal of Environmental Management* 300

Wu, Z. and **Ye, Q.*** (2020). Water pollution loads and shifting within China's inter-province trade. *Journal of Cleaner Production* 259

Wu, Z., **Ye, Q.*** and Tian, Z. (2020). Effects of the Policy and Human Intervention on the Infrastructure-Environment Nexus in China. *Sustainability* 12(18)

Ye, Q., Li, Y.*, Zhang, W. and Cai, W. (2019). Influential factors on water footprint: A focus on wheat production and consumption in virtual water import and export regions. *Ecological Indicators* 102, 309-315

Ye, Q., Li, Y.*, Zhuo, L., Zhang, W., et al. (2018). Optimal allocation of physical water resources integrated with virtual water trade in water scarce regions: A case study for Beijing, China. *Water Research* 129, 264-276

Li, Y., Huang, Y., **Ye, Q.***, Zhang, W., et al. (2018). Multi-objective optimization integrated with life cycle assessment for rainwater harvesting systems. *Journal of Hydrology* 558, 659-666

Xiong, W., Li, Y.*, Zhang, W., **Ye, Q.** (2018). Integrated multi-objective optimization framework for urban water supply systems under alternative climates and future policy. *Journal of Cleaner Production* 195, 640-650

Li, Y.*, **Ye, Q.**, Liu, A., Meng, F., Zhang, W., Xiong, W., Wang, P. and Wang, C. (2017). Seeking urbanization security and sustainability: Multi-objective optimization of rainwater harvesting systems in China. *Journal of Hydrology* 550, 42-53

*Note: Authors marked with * is the first corresponding authors of associated articles*

About the Author

Quanliang Ye (叶全梁) was born on 6th of April 1993 in Shaoxing, Zhejiang Province, China. He loves his four-people family, with a warm-heart mom, an always-optimistic dad, and a beautiful sister. He also loves his hometown which has more than 2,500-year history since ancient China's Spring and Autumn period. In Shaoxing, Quanliang was taken good care of in his sweet family and completed his pre-university education at Luxun High School in 2011.

Education-wise: Quanliang's background mainly focuses on environmental science, but not in the first place of his education. He obtained a BSc degree of Applied Mathematics at Hohai Univeristy in 2015. After that, he changed his major into environmental science, and finally obtained his MSc degree of Environmental Science and Engineering also at Hohai University in 2018. Thereafter, in September 2018, Quanliang started his oversea studies at University of Twente, the Netherlands, and now is approaching the end of his PhD at Multidisplinary Water Management group.

Research-wise: Quanliang's research aims to better understand and reveal the human effects on natural environments in the context of climate change, globalization and sustainable development. This is built upon cross-disciplinary academic training in mathematics and environmental science, and research experiences with systems modeling like multi-objective optimization, multi-regional input-output analysis, and statistics analysis. At this moment, Quanliang is pretty interested in environmental footprint assessments and sustainable development pathway design.

Life-wise: Quanliang has been living in the Netherlands for three and half years. He really likes the cozy life in Enschede——a quite and lovely city locating in the eastern border of the country. After his graduation, he will continue his life in Denmark. He likes cooking a lot, and really good at it. He is also a sport guy. He plays several sports every week, including but not limited to badminton, tennis, basketball, and swim (mostly in the summer time).

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