UNIVERSITY OF LEEDS

This is a repository copy of *Disaggregating the electricity sector of china's input-output table for improved environmental life-cycle assessment*.

White Rose Research Online URL for this paper:
http://eprints.whiterose.ac.uk/80153/

Version: Accepted Version

Article:

Lindner, S, Legault, J and Guan, D (2013) Disaggregating the electricity sector of china's input-output table for improved environmental life-cycle assessment. Economic Systems Research, 25 (3). 300 - 320. ISSN 0953-5314

https://doi.org/10.1080/09535314.2012.746646

Reuse
Unless indicated otherwise, fulltext items are protected by copyright with all rights reserved. The copyright exception in section 29 of the Copyright, Designs and Patents Act 1988 allows the making of a single copy solely for the purpose of non-commercial research or private study within the limits of fair dealing. The publisher or other rights-holder may allow further reproduction and re-use of this version - refer to the White Rose Research Online record for this item. Where records identify the publisher as the copyright holder, users can verify any specific terms of use on the publisher's website.

Takedown
If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.

White Rose
university consortium
Universities of Leeds, Sheffield & York

eprints@whiterose.ac.uk
https://eprints.whiterose.ac.uk/

This article was downloaded by: [University of Cambridge]
On: 12 August 2014, At: 11:36
Publisher: Routledge
Informa Ltd Registered in England and Wales Registered Number: 1072954 Registered office: Mortimer House, 37-41 Mortimer Street, London W1T 3JH, UK

Economic Systems Research
Publication details, including instructions for authors and subscription information:
http://www.tandfonline.com/loi/cesr20

DISAGGREGATING THE ELECTRICITY SECTOR OF CHINA'S INPUT–OUTPUT TABLE FOR IMPROVED ENVIRONMENTAL LIFE-CYCLE ASSESSMENT

S. Lindner [a], J. Legault [b] & D. Guan [c]
[a] Department of Land Economy, University of Cambridge, Cambridge, UK
[b] Department of Engineering, University of Cambridge, Cambridge, UK
[c] School of Earth and Environment, University of Leeds, Leeds, UK

Published online: 20 Feb 2013.

To cite this article: S. Lindner, J. Legault & D. Guan (2013) DISAGGREGATING THE ELECTRICITY SECTOR OF CHINA'S INPUT–OUTPUT TABLE FOR IMPROVED ENVIRONMENTAL LIFE-CYCLE ASSESSMENT, Economic Systems Research, 25:3, 300-320, DOI: 10.1080/09535314.2012.746646

To link to this article: http://dx.doi.org/10.1080/09535314.2012.746646

PLEASE SCROLL DOWN FOR ARTICLE

Taylor & Francis makes every effort to ensure the accuracy of all the information (the "Content") contained in the publications on our platform. However, Taylor & Francis, our agents, and our licensors make no representations or warranties whatsoever as to the accuracy, completeness, or suitability for any purpose of the Content. Any opinions and views expressed in this publication are the opinions and views of the authors, and are not the views of or endorsed by Taylor & Francis. The accuracy of the Content should not be relied upon and should be independently verified with primary sources of information. Taylor and Francis shall not be liable for any losses, actions, claims, proceedings, demands, costs, expenses, damages, and other liabilities whatsoever or howsoever caused arising directly or indirectly in connection with, in relation to or arising out of the use of the Content.

This article may be used for research, teaching, and private study purposes. Any substantial or systematic reproduction, redistribution, reselling, loan, sub-licensing, systematic supply, or distribution in any form to anyone is expressly forbidden. Terms &

Economic Systems Research, 2013
Vol. 25, No. 3, 300–320, http://dx.doi.org/10.1080/09535314.2012.746646

Routledge
Taylor & Francis Group

DISAGGREGATING THE ELECTRICITY SECTOR OF CHINA'S INPUT–OUTPUT TABLE FOR IMPROVED ENVIRONMENTAL LIFE-CYCLE ASSESSMENT

S. LINDNER[a]*, J. LEGAULT[b] and D. GUAN[c]

[a]*Department of Land Economy, University of Cambridge, Cambridge, UK;* [b]*Department of Engineering, University of Cambridge, Cambridge, UK;* [c]*School of Earth and Environment, University of Leeds, Leeds, UK*

(*Received 4 August 2012; In final form 1 November 2012*)

Missing process detail of sectors in Input–Output (I–O) tables has been pointed out as a limitation of I–O analysis in environmental-economic life cycle assessment. Aggregation of resource-intensive sectors decreases the accuracy of the results. Often, economic sectors are compiled in a more aggregated form than environmental satellite accounts, and as [Lenzen, M. (2011) Aggregation Versus Disaggregation in Input–Output Analysis of the Environment. *Economic Systems Research*, 23, 73–89] asserts, it is superior for environmental analysis to disaggregate the I–O table, even if only partial information exists for the disaggregation. In this paper we present a methodology to disaggregate the electricity sector of the Chinese national I–O table by using regional information and cost data for operation and maintenance of power plants. The electricity sector is disaggregated into a transmission and distribution sector as well as eight sub-sectors representing different types of technology in power plants (subcritical coal, hydro, etc.). The electricity consumption mix of each industry is determined by using regional industry presence and regional electricity power mixes. The disaggregated I–O table offers refined results for calculating emissions embodied in international exports from China, a valuable contribution for estimating national greenhouse gases emissions inventories under the consumption-based approach for countries that rely heavily on imports of goods from China.

Keywords: Disaggregation; Environmental-economic life-cycle assessment; Electricity sector

1. INTRODUCTION

1.1. Background

During the construction of national Input–Output (I–O) tables, sectors with a similar production structure are often aggregated into one sector. This is because sector entries in I–O tables rely on comprehensive surveying of sales and purchase patterns of industries which is a time consuming and a difficult process since most of the required information is often considered confidential. The loss of detailed information about the aggregated subsectors leads to the so called aggregation bias problem (Morimoto, 1970; Fisher, 1986; Kymn, 1990). The aggregation bias is often disregarded by I–O practitioners since its consequences are a lesser problem than the additional time and resources that need to be spent on detailed industry surveys to produce a highly disaggregated table.

---

*Corresponding author. E-mail: sml51@cam.ac.uk

However, for environmental-economic analysis, sector aggregation can have a significant influence on the results (Su et al., 2010; Majeau-Bettez et al., 2011). Often data on environmental factors (e.g. CO_2 emissions or water use) are either available for a larger number of sectors, or are in a different sector classification altogether. Lenzen (2011) concludes in his paper that even when based on partial information, the disaggregation of economic I–O data to match the size of environmental satellite accounts leads to a smaller relative error than aggregating the environmental satellite accounts to the size of the I–O table. He thus recommends disaggregating I–O tables whenever possible to do so. In a previous paper, we picked up on this conclusion and extended Wolsky's approach (Wolsky, 1984) by showing how a sector can be disaggregated into an arbitrary number of new sectors when the total outputs of the new sectors is the only available information (Lindner et al., 2012). In Wolsky's approach (Wolsky, 1984), output weights are formed using the output ratio of the new sectors in relation to the aggregated sector they originate from. The methodology was illustrated by disaggregating the electricity sector of China into three electricity generation sectors, and we showed how the output weights are used to form an initial guess for the disaggregation. This initial guess assumes that the input from new sectors to all the other sectors is split in proportion to the relative weight of their *national* total output. Since this initial guess is only *one* of the many possible solutions for the disaggregated I–O table, we showed how to explore the full range of possible solutions. We then compared the CO_2 emissions intensities of each sector obtained with the initial guess against the full range of possible emissions intensities. It was shown that for a given sector, the maximal possible emission intensity can be much larger than the one obtained with the initial guess (up to two times). Therefore, we concluded that as much information should be used in the disaggregation so that the range of possible results on the emission intensities can be narrowed down to the disaggregation solution that corresponds to the real economy.

The aim of this paper is to disaggregate the electricity sector of the Chinese 2007 I–O table into nine new sectors: a transmission and distribution (T&D) sector and eight different power generation sectors. The other sectors of the economy, i.e. the 'common' sectors, are not disaggregated further. Regional data on electricity generation mixes and spatial distribution of industry is used to obtain a regionally weighted estimate of the supply of each electricity generation sector into the common sectors while information on operation and maintenance (O&M) costs of power plants is used to estimate the supply of the common sectors into the new sectors. The use of this additional information leads to a refined estimate of the disaggregated I–O table and is what distinguishes this paper from our previous study (Lindner et al., 2012) where the national output of the different electricity generation sectors was considered to be the only available information. In the results section, we compare the emission intensities obtained from this refined estimate with the emission intensities obtained with the cruder initial guess based on the national total outputs.

1.2. Motivation

In the context of mitigating climate change, the greenhouse gases (GHG) emissions from China's electricity sector play a key role. The electric power industry was responsible for 3.5 Mt CO_2 of emissions in 2010, more than twice the total emissions of Japan (IEA, 2011). A large body of studies use environmentally extended multi-regional I–O analysis to calculate emissions embodied in trade (EET) from China to other countries (Wiedmann et al., 2007 provide an overview). EET are important for allocating emissions reduction responsibilities to countries based on the producer- or consumer of goods and services, two principles currently discussed in post-Kyoto climate policy-making (Peters and Hertwich, 2008). Several authors of MRIO studies note that missing technology detail of the aggregated electricity sector leads to uncertainty in results on EET, and recommend disaggregating that sector (Wiedmann et al., 2011a). Using an aggregated entry for the electricity sector assumes that each electricity generation technology is an average of that sector, which is not correct. For example, the embedded emissions of CO_2 in a unit of electricity produced with hydro-power are significantly less than a unit of electricity produced with coal. Also, Hondo (2005), Dones et al. (2004) and Weisser (2007) note that the upstream[1] emissions of power plants are very different. Coal and gas power plants have up to 25% of total emissions embodied in upstream emissions because they require extraction and transport of resources before combustion, whereas upstream emissions of nuclear power and renewable energy technologies are lower than 10%. These differences need to be included in a global MRIO framework, as opposed to just using an average, because they impact the results on consumption-based CO_2 emissions inventories of a country. Since 20% of Chinese domestic CO_2 emissions are due to exports, it is important to use Chinese I–O tables with a high disaggregated electricity sector.

A comprehensive literature review on disaggregation in general, and on disaggregation of the electricity sector in particular, revealed that the data required for alternative methods to Wolsky's weight factor disaggregation is either difficult to access in China, or requires time-consuming preparation. For example, Heijungs and Suh (2002) present a methodology in which process-based life cycle assessment (LCA) data is tiered with I–O tables to express some sectors in more detail. This hybrid LCA approach overcomes truncation errors of process LCA and enhances sector detail of the environmental-economic input–output framework (Ferrao and Nhambiu, 2009), and is widely used. Wiedmann et al. (2011b) follow this approach and use the Ecoinvent database to disaggregate the wind power subsector from the electricity sector in the UK. For China, a process-based LCA database on electricity generation power plants is, to our knowledge, not available so the I–O practitioner cannot conduct a typical hybrid-LCA study and must look for alternative approaches instead. Gillen and Guccione (1990) showed how the disaggregated I–O table can be estimated with information on commodity prices. Turner et al. (2007) use confidential electricity sales and price data to disaggregate the Scottish power sector. Unfortunately, confidentiality prohibits access to exact price data for individual sales between regional power companies and industries in China, so this disaggregation method cannot be used. A third approach to disaggregation, the hybrid-unit approach as proposed originally by Bullard et al. (1978), requires data use on primary energy consumption by industries. Emissions intensities are calculated using the IPPC reference approach. This disaggregation method has been recently applied to the Taiwanese electricity sector (Liu et al., 2012) and is also followed in Cruz (2002, 2004) as well as Limmeechokchai and Suksuntornsiri (2007). For China a hybrid unit- approach has been undertaken by Lindner et al. (2011) to analyse differences in emissions intensities of sectors. It offers a valid alternative to the disaggregation presented in this

---

[1] Except for direct operation, all processes and associated emissions in power plant operations are categorized in *upstream* (e.g. fuel exploration, mining, fuel transport) and *downstream* (e.g. decommissioning, waste management and disposal) emissions. Emissions resulting from the direct operation (e.g. CO_2 released by the combustion) are referred to as *direct* emissions, or point source emissions (Weisser, 2007).

study. The drawback here is that constructing the bottom-up energy and emissions inventory by fuel type is very time consuming. For I–O-practitioners who disaggregate merely as an intermediate step to modify the I–O table for further use in a larger project, hybrid unit-I–O tables may not be the right approach, especially if I–O tables of all other countries are only in monetary units. A further disadvantage is that the official national data on energy consumption may be prone to under-estimation as the sum of each provincial data exceeds national data by a large fraction. Thus, even results on CO_2 emissions using the hybrid-unit approach may contain large uncertainty (Guan et al., 2012). In the light of this discussion, a disaggregation based on weight factors as presented in this study appears to be a good alternative.

1.3. Paper structure

The paper is structured as follows. First, the structure of the disaggregation of the electricity sector is described, followed by the methodology showing how to carry each step of that disaggregation. We also describe Wolsky's (1984) disaggregation based on the national output weight factors (i.e. disaggregation without regional weighting), and then explain our technique for deriving the regionally weighted disaggregated I–O table, and for modelling the disaggregated upstream emissions of power plants. The emissions intensities obtained with the disaggregation techniques are compared and conclusions are drawn.

2. DISAGGREGATION STRUCTURE, ASSUMPTIONS AND DATA REQUIREMENT

2.1. Disaggregation structure

The goal is to disaggregate sector 23 of the Chinese national I–O table (electricity production, heat and water distribution and supply) into nine new sectors. The aggregated I–O table is of size 42 × 42. Thus, the disaggregated I–O table will be of size 50 × 50. The electricity production and distribution is first disaggregated into two separate sub-sectors, the T&D sector and the electricity production sector. The latter is further disaggregated into eight types of electricity generation: pulverized coal fired power (PCFP) stations with sub critical boiler type (sub-c), PCFP with super-critical boiler type (super-crit), PCFP with ultra-super critical boiler type (USC), wind power plants, solar power plants, nuclear power plants, hydroelectric power and natural gas power plants (NG plants). The disaggregation scheme is shown in Table 1, with the last column representing all the new sectors in the disaggregated I–O table.

This level of disaggregation captures the major electricity production options with different CO_2 emissions per unit output. We include the range of coal fired power stations with different boiler efficiency currently used in China because their emissions output and requirement for upstream processes varies as well. The new generation of coal-fired power stations with highly efficient boilers, such as USC boilers, are increasingly installed in the Eastern coastal provinces (Ma, 2008). We use the boiler efficiency for coal-fired power plants in China outlined in Ma (2008): sub-critical power stations have 35% efficiency, super-critical boilers 42%, and ultra-supercritical 47%. Although natural gas and solar power currently only represent a fraction of the total electricity produced in China, we also

TABLE 1. Disaggregation of the electricity production and distribution entry.

Sector entry 23 in 42 × 42 I–O table of China		
Electricity production, transmission and distribution, heat and water supply	Electricity production transmission and distribution (T&D)	Pulverized coal plants (sub-c)
		PC coal plants (super-crit)
		PC coal plants (ultra-super critical)
		Wind power plants
		Solar
		Nuclear power
		Hydro power
		Natural gas power plants
		T&D

include these two plant types because all necessary data for disaggregation was available and because they will likely play a more dominant role in China's future generation mix (Wang and Chen, 2010).

We refer to as 'common sectors' the 41 sectors in the I–O table that remain aggregated. 'New sectors' or 'disaggregated sectors' are the sectors that result from the disaggregation of the electricity sector.

2.2. Assumptions

We assume that in each region, sectors consume electricity in proportion to the power generation mix of the grid system the region belongs to. This assumption allows building sector-specific electricity consumption mixes where each sector in the I–O table consumes electricity from a specific power mix with a generic emission intensity. In China, it is important to consider these regional differences because the power mix of the six grid systems is not equal. Instead it differs from the national average. Table 2 shows power generated by different technologies in each of the six independent electricity grids of China as a percentile fraction, and compares it with the national average. The information is taken from the Chinese Electricity Yearbook (NBS, 2008). We do not consider electricity trade among grid systems, except for the case of Inner Mongolia. Here, we assume that Inner Mongolia is part of the North China grid which also contains Beijing and Tianjin, because the majority of their electricity is exported into this grid system. The allocation of provinces according to their grid system is given in Table A1.

For the analysis, we also account for the fact that the economic production structure in China is not homogenous in all six grid systems. Indeed, the production of many sectors is not distributed uniformly across China; it is concentrated in a few specific regions. Several authors point out that regional specialization in production activities has resulted in industry clusters (Batisse and Poncet, 2004; Li and Xu, 2010). A combination of decentralization, inter-provincial competition, international trade and foreign direct investment has encouraged industry agglomeration and specialization of production activities among Chinese provinces (Gao, 2004). For instance, the coastal regions have a well-developed manufacturing and service-oriented industry, whereas inland provinces are specialized in either agriculture or primary resource extraction (northwest), and provinces in the north are dominated by heavy industries (Meng et al., 2011; Zhang et al., 2011).

TABLE 2. Power generation in each grid expressed in percentile fractions (2007).

	Electricity generation in six operating power transmission and distribution networks in China							
%	Hydro	Coal Sub-c	Coal SC	Coal USC	NG	Nuclear	Wind	Solar Pv
North China	0.03	0.83	0.08	0.01	0.00	0.01	0.04	0.00
Central China	0.40	0.50	0.05	0.01	0.00	0.00	0.04	0.00
East	0.12	0.63	0.02	0.19	0.00	0.03	0.01	0.00
North East	0.09	0.81	0.07	0.00	0.01	0.00	0.02	0.00
South	0.47	0.41	0.07	0.00	0.01	0.04	0.00	0.00
Northwest	0.29	0.56	0.06	0.03	0.04	0.00	0.02	0.01
National average	0.22	0.64	0.06	0.03	0.01	0.01	0.02	0.01

Notes: Coal sub-c, coal power plants with sub critical boiler type; Coal super critical, power plants with super critical boiler type; Coal USC, coal ultra super critical boiler type; NG, natural gas power plants; Other, contains wind power and solar PV.
Source: NBS (2008).

Although these assumptions are sensible, they could be relaxed in future studies. For instance, Marriot (2007) developed a logistic model which accounts for proximity of industries to individual power plants in each state of the USA. He also distinguishes between electricity production mixes of states and consumption mixes, of which the latter includes net interstate trade of electricity. For China, data showing the electricity production mix in each province is available. Therefore, instead of using the grid systems, we could have chosen provinces as the boundary for determining sector-specific electricity consumption mixes. Yet, when evaluating the interprovincial trade data in the Chinese Electricity Yearbook, we noticed that a considerable amount of electricity is traded among provinces within each grid system. Therefore, we concluded that the generation mix in each province likely to approach the grid mix it belongs to. In comparison, the amount of trade between different grid systems is less important (with the exception of Inner Mongolia), and using the grid systems is thus a better option.

2.3. Data Requirement

To build the disaggregated I–O model for China, we use the following data:

- I–O tables of 30 Chinese provinces of the year 2007 (NBS, 2010b). The tables are in 42 × 42 sector format and are used to estimate regional industry location.
- Chinese national I–O table of 2007(NBS, 2010a). The table is in 42 × 42 sector format.
- Power generation plant mix for all six power networks in China. These data are obtained from the Chinese Electricity Yearbook (NBS, 2008) and is in GigaWatt. The data are used in combination with provincial I–O tables to estimate sector-specific consumption profiles.
- Operation and management cost data (RMB/kWh) of power generation plants in China. These data are taken from the book ‘Projected Costs of Generating Electricity’ issued by the International Energy Agency (IEA, 2010). The cost data are used to estimate proportional weight factors for the input of all sectors in the I–O table into new technology sectors. This is shown in Table 3.

TABLE 3. Range of O&M costs by power plant.

Electricity O&M prices by generation type (RMB/kWh)			
Technology	Median	Low	High
Coal (SC)	11.2	9.5	12.9
Coal (USC)	12.3	10.3	14.3
Coal (sub-c)	8.5	7.5	9.5
Natural gas	20.3	12.6	28.1
Nuclear	9.4	7.9	10.9
Hydroelectricty	13.4	12.0	14.8
Wind power	14.7	13.9	15.5
Solar PV	15.3	14.7	16.0

Source: IEA (2010).

TABLE 4. CO_2 intensity of power plants.

Technology	CO_2 intensity (gCO_2/kwh)
Hydroelectricity	18
Coal sub-c	1,000
Coal super-c	900
Coal USC	750
Natural gas	400
Nuclear	45
Wind power	10
Solar PV	30

- Estimates of electricity costs. The numbers are taken from the Electricity Yearbook of China. A homogeneous price across all regions and sectors is assumed
- Emissions factors. Numbers are obtained from the literature as shown in Table 4 (Nsakala and Marion, 2001).

3. METHODOLOGY

In this section, we describe how to derive the technical coefficient of the disaggregated I–O table based on the assumptions made in the previous section. First, we outline the I–O Leontief framework (Section 3.1) and describe the disaggregation based on Wolsky's method (Section 3.2). We then describe the regionally weighted disaggregation (Sections 3.3–3.6).

3.1. The Leontief Framework

Consider an economy with $N + 1$ sectors where each sector i produces a unique good. The total output of good i from the ith sector is noted x_i and the amount of good i that sector j consumes from sector i is noted z_{ij}. The total output x_i corresponds to the sum of the intermediate consumption by the economy and the final demand f_i

$$x_i = \sum_{j=1}^{N} z_{ij} + f_i, \quad \text{for } i = 1 \text{ to } N + 1. \tag{1}$$

In the I–O Leontief framework, it is assumed that the industry flow from sector i to sector j depends linearly on the total output of sector j. If sector j needs a_{ij} units of good i to produce 1 unit of good j, Equation 1 can be rewritten as

$$x_i = \sum_{j=1}^{N} a_{ij} x_{ij} + f_i, \quad \text{for } i = 1 \text{ to } N + 1. \tag{2}$$

Writing Equation 2 in matrix form and inverting the system leads to

$$\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f} = \mathbf{L}\mathbf{f}, \tag{3}$$

where $\mathbf{A}$ is the technical coefficient matrix, $\mathbf{I}$ is the identity matrix of size $(N + 1) \times (N + 1)$ and $\mathbf{L}$ the Leontief inverse matrix. The ijth coefficient in the inverse Leontief matrix $\mathbf{L}$ represents the total requirement of goods from sector i to meet the final demand of sector j. This framework can be extended to include environmental satellite accounts. Let e be a row vector of size $N + n$ with the first N components equal to zero and the last n components of specific CO_2 emissions per kwh of electricity output by the power plant type (gCO_2/kwh). In order to determine the emissions (gCO_2) per unit of RMB final demand ε, we multiply e with the total requirements matrix:

$$\boldsymbol{\varepsilon} = \mathbf{e}(\mathbf{I} - \mathbf{A})^{-1}. \tag{4}$$

3.2. Disaggregation Based on Wolsky's Method

Let the technical coefficient matrix $\mathbf{A}^*$ describe the same economy as $\mathbf{A}$ with the only difference that the last sector of the economy (sector $N + 1$) has been disaggregated into n distinct new sectors. Matrix $\mathbf{A}^*$ is thus of size $(N + n) \times (N + n)$. In the 42×42 Chinese I–O table, the electricity sector corresponds to sector 23 of the table. The table is thus reordered so that the electricity corresponds to the last sector. The total output of sector i in the disaggregated economy is noted x_i^* and the final demand f_i^*. The weight factors formed in Wolsky's approach describe the conservation of the amount of goods consumed by the common sectors from the new sectors, by the new sectors from the common sectors and by the new sectors from themselves. A set of constraints relate the unknown technical coefficients of the disaggregated matrix to the coefficients of the aggregated matrix. In total, there are $2Nn + n^2$ unknown technical coefficients and n unknown final demand ratios describing the disaggregated economy (see Lindner et al., 2012). An initial estimate is constructed for the unknown technical coefficients of matrix $\mathbf{A}^*$ and the final demand ratios of the new sectors. This estimate assumes that the new sectors have identical technologies and that they supply the other sectors proportionally to their *national* output weights w_k, where $w_k = x_{N+k}^*/x_{N+1}$ is the output weight associated with the kth new sector. The final demand and the supply from the other sectors are also in proportion to these weights. Under these assumptions, formulas for the unknown technical coefficients of the disaggregated

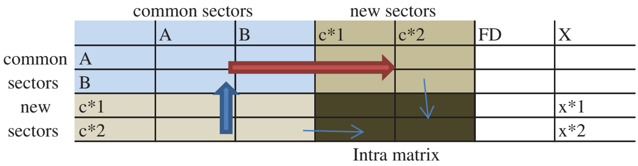

FIGURE 1. Schematic example of disaggregation an I–O table.

TABLE 5. Investment in the power sector.

Investment in Chinese power sector (bill. RMB)	
Total	549.29
Power generation	304.15
T&D	245.14

technical coefficient matrix are obtained. These formulas are given by Lindner et al. (2012) and are not reproduced here.

Figure 1 shows an arbitrary example of a disaggregation, where the last sector, C is disaggregated into c*1 and c*2. The blue arrow marks all possible output weights of new sectors into common sectors ($2n^2$ possibilities, where n = number of new sectors). Input weight factors need to be built to show the input from common sector A into c*1 and c*2, as well as B into c*1 and c*2. This is indicated by the red arrow. Both sets of weight factors also determine the allocation of intra-industry sales between sector C, marked by the dark shaded quadrant in the lower right hand side of the table.

3.3. Disaggregating the Electricity Sector into Production and Supply

The first level of disaggregation in our work consists in splitting the aggregated sector into the production part and the T&D part. This step can be understood as an adjustment to the inter-industry (**Z**) matrix before a more detailed disaggregation of the electricity production sector is made. We found no data detailing the input proportion of common sectors to T&D and production of electricity, or the proportion of monetary supply from T&D and production sector to other sectors in the economy. Hence, an assumption needs to be made. The Chinese electricity yearbook (NBS, 2008) lists the investment made into both sectors separately for the year 2007. These data are shown in Table 5.

We see that about 45% of investment spending went to the supply and distribution of electricity. Since this is the only reliable number distinguishing the two sub-sectors, we have to assume that industry input from all economic sectors into the two electricity subsectors is made according to the proportion of investment costs. Moreover, the output from both sectors into all other sectors is also split into this proportion, and the same is done with the final demand. The result is a 43 × 43 sector I–O table where the electricity generation row and column entry contains 55% of monetary value of the previously aggregated sector.

3.4. Disaggregating the Electricity Generation Sector

We derive two sets of weight factors. One set splits all inputs into the new electricity production sectors from the common sectors. These factors are called the input weight factors. The other splits the output of the new electricity production sectors into all the other sectors, according to the regionally weighted industry consumption mixes. These factors are called the output weight factors.

3.4.1. Deriving Values for the Input Weight Factors

In this section, we determine in what proportion the common sectors supply the new electricity generation sectors. In the real economy, it is not true that all the common sectors supply the electricity generation sectors in proportion to their output weights. In reality, the supply mix of products needed to operate and maintain a wind power plant will be different from that of a nuclear power plant or a coal fired power plant. Thus, the allocation of industry input to the new power generation sectors should not be based solely on the electricity output of the new sectors, but rather on how the money is spent during a year to generate the said output (Marriot, 2007). For example, fuel is required to operate a coal power plant whereas it is not for a wind power plant. Moreover, there are other costs (materials, maintenance, waste disposal, etc.) that occur throughout a year and their relative magnitude varies among plant types. Here, we use these differences to build the input weight factors. However, it should be noted that the construction costs of power plants which are reflected in capital costs of power plants are not considered. Construction is an economic activity within the construction sector of the I–O table and so it is preferable to avoid including it in the electricity sector (Marriot, 2007). If we were to consider construction of power plants, we would have to disaggregate the construction sector as well.

We introduce the input weight factor $\rho_{i,k}$ which describe the proportion of input from the ith common sector into each new sector k ($\rho_{i,k} = z^*_{i,N+k}/z_{i,N+1}$). By definition $\sum_{k=1}^{n} \rho_{i,k} = 1$. Moreover, the input from each common sector into the new sectors must be equal to the input of into the aggregated sector. This leads to the following set of constraints for the technical coefficients of the disaggregated I–O table:

$$\rho_k a^*_{i,N+n} = a_{i,N+1}, \quad \text{for } k = 1 \text{ to } n, \text{ and } i = 1 \text{ to } N. \qquad (5)$$

The input weight factors for each common sector are derived by taking the weighted sum of the power plants O&M costs and annual electricity generation output. This is done according to the method described by Marriot (2007). O&M costs of power plants in China are taken from the IEA book (2010). For each power-generating technology, the book gives a range of O&M costs in USD/kWh. These include fuel costs. We convert the costs into RMB/kWh, using a currency conversion rate of 6.5 (as stated by the IEA).

For disaggregating the upstream inputs to power plants some exceptions need to be considered. For instance, all purchases from the common sector coal mining and processing (sector entry 2) are most likely entirely made by the three coal-fired power generation sectors. Likewise, output from gas production and supply is allocated entirely to the natural gas power plant sector. The allocation of the inputs of the petroleum processing and coking and crude petroleum sector and of the natural gas sector into the new sectors was made according to Marriot (2007).

3.5. Construction of the Intra Matrix

The intra matrix corresponds to the bottom right part of the disaggregated I–O table, i.e. to the part associated with the input of the new sectors into themselves. The Chinese 2007 national I–O table reveals that the electricity sector purchased 11.3 billion RMB from itself. This could be power purchased by utility companies utilities to cover supply shortfalls. We disaggregate this value to power purchases among the nine new sectors, including T&D. We use the assumption made by Marriot (2007) as well as Wolsky (1984): the intra-industry value is split among each entry in the new intra-matrix by multiplication with the row and column weight factor.

3.6. Deriving Output Weight Factors

In this section, we determine in what proportion common sectors purchase electricity from the newly formed power generation sectors. We explain how to derive the unknown technical coefficients of the bottom left part of matrix $\mathbf{A}^*$ by considering regional electricity generation mixes and industry clusters. We use a regionally weighted industry coefficient method that is analogous to the simple location quotient (SLQ) method (Miller and Blair, 2009). The SLQ method is a non-survey technique for regionalization of national coefficients, made through adjustments based on regional employment, income or output by industry. In this study, we extract information from regional tables which detail the electricity purchased by the common sectors and relate it to the national table. In the generalized form, the location quotient, LQ, for region r and sector i is defined by

$$\mathrm{LQ}_i^r = \frac{x_i^r/x^r}{x_i^n/x^n}. \tag{6}$$

Where x_i^r is the gross output of sector i in region r and x^r is the total output of all sectors i in region r. The denominator denotes these totals, but at the national level. A step-by-step description of our weighted coefficient method is given below:

(1) We group the I–O tables of the 30 provinces in aggregated 42 × 42 format according to the electricity grid system they belong to. There are six grid systems in China and the grouping of provinces to each grid system is shown in Table A1. These grid systems will henceforth be called the 'regions'.
(2) For each region, we extract the aggregated electricity sector row from the provincial I–O tables and add them together. Hence, we obtain six vectors of size 1 × 42 describing the monetary input from the electricity sector to all the common sectors.
(3) We compare the sum of the six regional electricity vectors with the value of the electricity sector entry in the national I–O table of China. There are some differences and the deviation is between 4 and 10% of the national I–O table, but can be as high as 35% for some sectors. We normalize each regional electricity vector so that the sum of the six regional electricity vectors is equal to the row vector in the national table.
(4) From the Chinese electricity yearbook, we calculate the electricity generation mix for each grid system containing the eight electricity generation types.
(5) We disaggregate the regional electricity vector according to a Wolsky type disaggregation. We multiply each regional electricity vector with the fraction of power plants making up the grid-specific generation mix. Results are grouped into eight matrices

of the size 6 × 41. Each matrix shows the monetary value of electricity input to the common sectors for each grid according to the power plant type.

(6) The row sum of each matrix is divided by the total input of the aggregated electricity sector in the national table I–O. As a result, we obtain the 8 × 41 output weight factors which define the sector-specific consumption mix of the common sectors.

To describe the method with equations, the following notation is adopted: $w_{k,(j)}$ is the regional output weight factor, i.e. the percentage of total output of electricity generation sector of type k in region j, $P_{i,(j)}$ is the percentage of total output of common sector i produced in the jth region, N_{r} is the number of regions (six in total).

We introduce two additional constraints: the fraction of industry output from the common sectors produced in each region needs to sum up to 1 (to equal the output of the national table) and the fraction of regional electricity generation mix of power plant type k needs to sum up to 1 as well:

$$\sum_{j=1}^{N_{\mathrm{r}}} P_{i,(j)} = 1, \tag{7}$$

$$\sum_{j=1}^{N_{\mathrm{r}}} w_{k,(j)} = 1. \tag{8}$$

We express the technical coefficients of the aggregated matrix (left-hand side of the equation) as the sum of inter-industry transfer z divided by total output in each of the six regions:

$$a_{N+1,i} = \frac{z_{N+1,i}}{x_{N+1}} = \frac{1}{x_{N+1}} \sum_{j=1}^{N_{\mathrm{r}}} z_{N+1,(j)}. \tag{9}$$

Moreover, since the output x_i (j) of a common sector i in region j is expressed as the sum of fraction P_i of national output x, we write:

$$z_{N+1,i(j)} = a_{N+1,i,(j)} x_{i,(j)} = a_{N+1,i,(j)} P_{i,(j)} x_i. \tag{10}$$

Therefore, Equation 10 is rewritten as:

$$a_{N+1,i} = \frac{1}{x_{N+1}} \sum_{j=1}^{N_{\mathrm{r}}} a_{N+1,i,(j)} x_{N+1,i,(j)} = \frac{1}{x_{N+1}} \sum_{j=1}^{N_{\mathrm{r}}} a_{N+1,i,(j)} P_{i,(j)} x_i = \sum_{j=1}^{N_{\mathrm{r}}} a_{N+1,i,(j)} P_{i,(j)} \tag{11}$$

and the technical coefficient associated with the k electricity generation will be given by

$$a^*_{N+k,i} = \frac{z^*_{N+k,i}}{x^*_i} = \frac{1}{x^*_i} \sum_{j=1}^{N_{\mathrm{r}}} z^*_{N+k,i,(j)} \approx \frac{1}{x_i} \sum_{j=1}^{N_{\mathrm{r}}} z_{N+1,i.,(j)} w_{k,(j)}. \tag{12}$$

The quantities $z_{N+1,i,(j)}$ and $w_{k(j)}$ can be determined for each region. Since we know the total national output x_{N+1}, we can write

$$a^*_{N+k,i} \approx \frac{1}{x_i} \sum_{j=1}^{N_{\mathrm{r}}} z_{N+1,i} w_{k,(j)} = \sum_{j=1}^{N_{\mathrm{r}}} a_{N+1,i,(j)} P_{i,(j)} w_{k(j)}. \tag{13}$$

From the last equation, we can see that the departure of the coefficients $a^*_{N+k,i}$ from the national average of electricity generation input can be attributed to two factors: the combined presence of regional industry clusters with regional electricity mix clusters and the difference in the regional industry efficiency from the national industry efficiency, i.e. the difference between the regional coefficients $a_{N+k,i,(j)}$ and the national coefficient $a_{N+1.i}$.

4. RESULTS

4.1. Input and Output Weight Factors

In this sub-section, we present the calculated input weight factors, ρ, and output weight factors wk. Results for the input weight factors are shown in Table 6. Input weight factors were calculated using the low-end and high-end results the O&M data provided by the IEA (2010). The difference between low and high end values depends on the variance in fuel costs, which were calculated using a range for costs. We also calculated a median value and used the weight factors obtained with this value for the actual disaggregation.

The input weight factors offer a first estimate on how to allocate supply from the common sectors to the disaggregated sectors. We notice that the factors differ from the fractions of electricity generation for power plants in the national mix. For instance, the input weight factor for hydroelectricity's is 0.3 instead of 0.23 for the national mix, and the coal fired power plants with the sub-critical boiler has an input weight factor of 0.54. In general, coal-fired power stations with sub-critical boiler have lower O&M costs than hydroelectricity power plants and this effect is weighted into the input factors.

The results for the manual allocation of supply from common sectors to newly disaggregated sectors are shown in Table 7. All the output of the coal mining and processing sector is consumed by the three coal-based production sectors according to a ratio based on their boiler type efficiency. The same is done for the water production and supply sector and the transport and warehousing sector.

The full table of the calculated output weights is given in Table A2. The calculation revealed that the pattern of electricity consumption by each industry can be quite different from the national average. For example, the national output weight factor for hydropower is 23%. Using sector-specific consumption mixes, results for the sector-specific output weight

TABLE 6. Input weight factors from common sectors to power-generating sectors.

	Input weight factors (%)		
Technology	Median	Low	High
Coal (SC)	0.07	0.06	0.06
Coal (USC)	0.05	0.04	0.04
Coal (sub-c)	0.54	0.48	0.44
Natural gas	0.02	0.01	0.02
Nuclear	0.01	0.01	0.01
Hydroelectricty	0.30	0.28	0.23
Wind power	0.01	0.01	0.01
Solar PV	0.01	0.01	0.01

TABLE 7. Manual allocation of common sector's input to new sectors.

	Allocation across generation types							
Common sector	Coal SC	Coal USC	Coal sub-c	NG plant	Nuclear	Hydroelectricity	Wind power	Solar pv
Coal mining and processing	0.11	0.08	0.81	0	0	0	0	0
Petroleum processing and coking	0.02	0.03	0.05	0.9	0	0	0	0
Transport and warehousing	0.11	0.08	0.81	0	0	0	0	0
Crude petroleum and natural gas products	0.02	0.03	0.05	0.9	0	0	0	0
Water production and supply	0.11	0.08	0.81	0	0	0	0	0
Gas production and supply	0	0	0	1	0	0	0	0

factors associated with hydropower fluctuate between 13% (coal mining and processing) to 28% (construction sector). Similar variations are observed for coal-fired power generation with sub-critical boiler technologies. The national average is 64%, but the consumption of electricity for the coal mining and processing sector from this technology sector is 74%, whereas it is only 58% for the construction sector. Service sectors, like education, real estate and finance sectors consume 2% of electricity from nuclear power plants, whereas the national average is below 1%. This is not surprising since service sectors are primarily located in Eastern coastal and South-eastern, provinces where the majority of nuclear power plants are located. Coal mining and processing takes place in North- and North Central China, the regions with the highest fraction coal fired power stations.

We finally construct the intra-matrix, distributing the value of intra-industry sales from the electricity to each new sector in the economy according to Marriot (2007). Results of the monetary **Z**-matrix, after disaggregation, are shown in Table 8 where the unit monetary value is 10.000 RMB.

Only a few parts of the disaggregated Chinese I–O table are displayed in this paper, mainly due to the fact that a 50 × 50 sector matrix would be difficult to present in this paper. In the appendix, however, we show the nine row and nine column matrices of the disaggregated electricity sector in the Chinese I–O table, including the final demand and total output of the new sectors.

4.2. CO_2 Emission Intensity

One objective of this work is to determine the effect of choosing different weight factors for the disaggregation on the results of the CO_2 emission intensities of each sector. Using the final demand of the 2007 Chinese I–O table, we compare the emissions embodied in one unit of final demand for two disaggregation methods presented in this paper. The first method (method L1) uses the new set of weight factors which were determined as described in the previous section to disaggregate the row and column entry of the electricity sector. The second method (method L2) corresponds to Wolsky's method (see Section 3.2). It uses the national electricity total output as weight factors. For each method, we build the Leontief inverse coefficient matrix of the disaggregated I–O table and multiply with a CO_2 satellite account as described in Equation 4. Results for both methods are shown in Figure 2. With

TABLE 8. Intra-matrix of Chinese disaggregated I–O table.

Unit: RMB	0.45 T&D	0.167 Hydro	0.29 Coal Sub-C	0.037 Coal SC	0.027 Coal USC	0.012 NG power	0.006 Nuclear	0.006 Wind power	0.005 Solar PV
T&D	22882500	8491950	14746500	1881450	1372950	610200	305100	305100	254250
Hydro	8491950	3151457	5472590	698227	509517	226452	113226	113226	94355
Coal Sub-c	14746500	5472590	9503300	1212490	884790	393240	196620	196620	163850
Coal SC	1881450	698227	1212490	154697	112887	50172	25086	25086	20905
Coal USC	1372950	509517	884790	112887	82377	36612	18306	18306	15255
NG power plant	610200	226452	393240	50172	36612	16272	8136	8136	6780
Nuclear	305100	113226	196620	25086	18306	8136	4068	4068	3390
Wind power	305100	113226	196620	25086	18306	8136	4068	4068	3390
Solar PV	254250	94355	163850	20905	15255	6780	3390	3390	2825

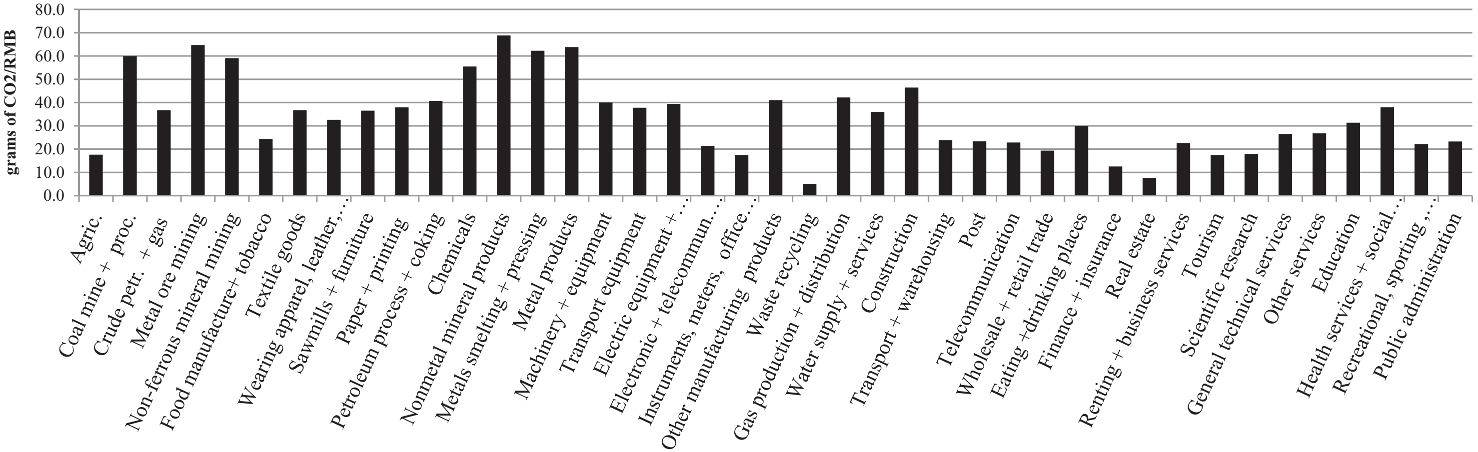

FIGURE 2. CO_2 emissions intensity of 41 common sectors in the Chinese I–O table.

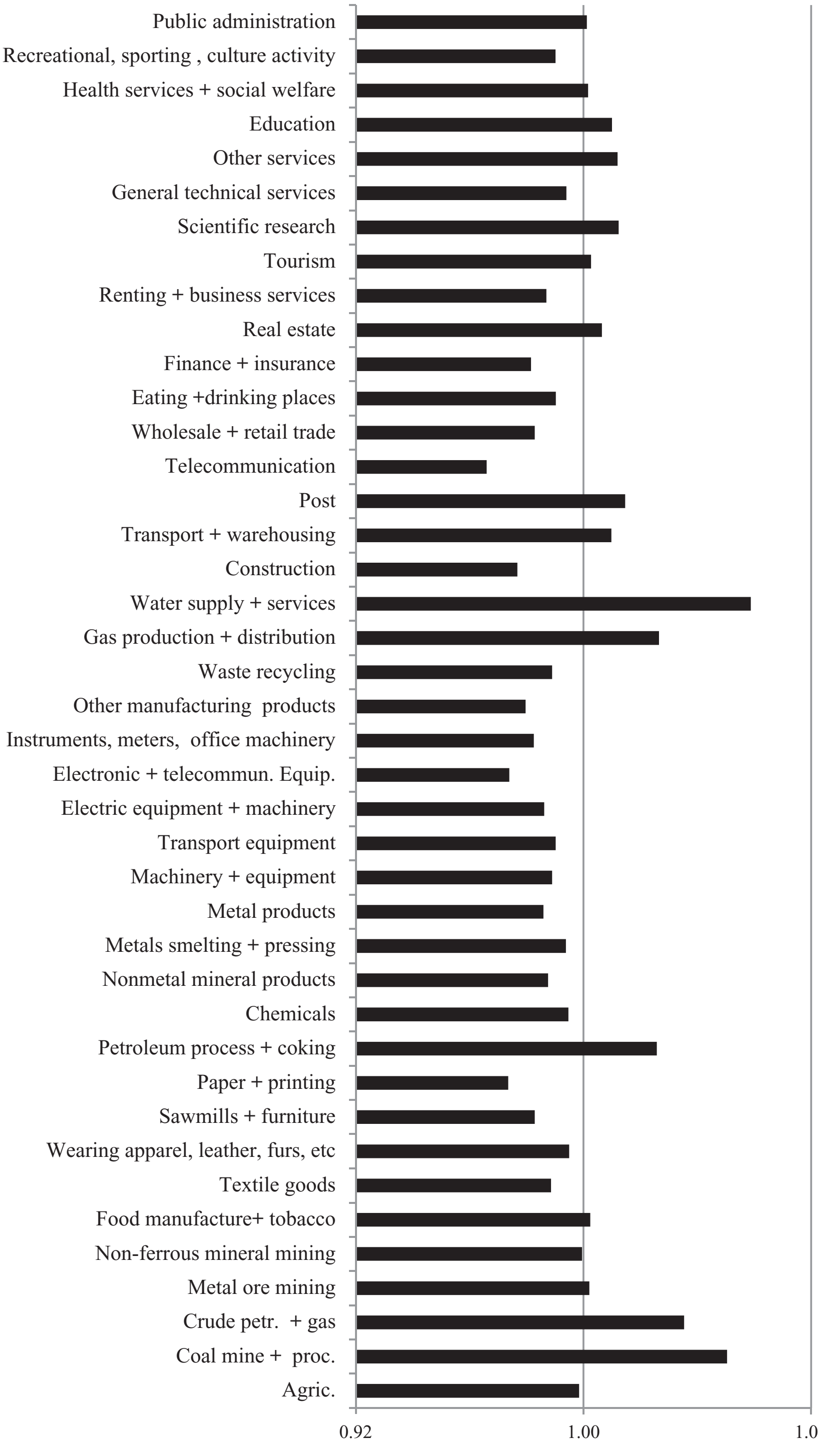

FIGURE 3. Difference in CO_2 emissions intensity between two disaggregation model runs. 1, no difference; <1, the emissions intensity of L2 is lower; >1, emissions intensity of L2 is higher than L1.

the first method, we see that primary industry sectors like resource extraction and mining sectors or metallurgy sectors have the highest emissions intensity, whereas service sectors (real estate, finance and insurance) have the lowest intensity.

In Figure 3, we compare results of method 1 with method 2 by looking at the percentage of deviation of method 1 from method 2. The relative difference between the two methods oscillates between −6% and 6% depending on the sector. In other words, using regionally weighted sector-specific consumption mixes has an effect on the emissions intensities of individual sectors, but the deviation is rather small. This is the main finding of this paper.

5. DISCUSSION AND CONCLUSION

The aim of this paper was to show how to use publicly available information to disaggregate the electricity sector of the Chinese I–O table. Because of the absence of process-based life-cycle data and accurate prices of electricity sales to industries, we used regional data to disaggregate the electricity sector and thus to construct a regionally weighted estimate of the disaggregated I–O table. We compared the CO_2 emissions intensities obtained with this refined estimate against the CO_2 emissions intensities obtained with a cruder estimate of the disaggregated I–O table based on national data only. Non-negligible differences were found between the two estimates, but these differences remained small on average (less than 5%).

We conclude that using regional information to build industry-specific electricity consumption mixes appears to be a valid approach for improving estimates on embedded emission in international trade between China and other countries. Most exports out of China are actually products from secondary industries such as textile goods, wearing apparel, leather and furs. These industries are concentrated along the east coast in provinces like Guangdong, Zhejiang and Jiangsu. Our results showed a change in the composition of electricity consumption of these sectors when using the regionally weighted estimate instead of the cruder national estimate. Therefore, more accurate results on electricity consumption mixes can be obtained using this method.

However, for the environmental analysis, i.e. for the CO_2 emission intensities, we expected to see a higher variation than the 5% variations we observed between both estimates. Since the supply of electricity to industries from one individual electricity generation technology differs often more than 5% when compared to the national average, we expected that the effect of industry-specific electricity consumption mixes would be reflected more strongly in the actual emission intensities. The low variation is likely due to the fact that we present the total embodied emissions which include the indirect emissions along the supply chain of sectors. Since each sector has a generic electricity consumption mix, accounting for emissions along the supply chain will necessarily result in the emissions intensity to approach the intensity of the national average. The effect of individual sector mixes on emissions intensity should be most visible when direct emissions are calculated, and decrease further down the supply chain. The results can be improved if a logistic model is used which detects the closest proximity of each industry's enterprise or manufacturing site to a power station nearby. We conclude that using regionally weighted sector-specific electricity consumption mixes is good to detect industry-specific direct emissions, but it might not be necessary for analysing total emissions (direct and indirect) because the emissions will approach the value based on the national average.

Disaggregating sectors in I–O tables is done for different reasons. Some I–O practitioners may disaggregate as an intermediate step to bring I–O tables of different country origin to the same size, or to magnify in more detail one particular sector of interest. The disaggregated matrix is often used for a more complex project goal, for example in constructing a multi-regional I–O model. Given that I–O practitioners will likely weigh off the time invested in disaggregation and the benefit gained they have to choose the method of disaggregation carefully. We have discussed in this paper that the method of disaggregation depends primarily on data availability, and note that access may vary from country to country. In the case of China useful price data for the electricity sector is not publicly available. Estimating the disaggregated matrix based only on output weights offers a good alternative, especially if the time spent on disaggregation is limited because the method is straightforward. Using the methodology presented here, it is possible to estimate upstream emissions. However, throughout the process of disaggregation with the use of additional information one of the main goals of disaggregation, which is to decrease uncertainty of embodied emissions (for example in trade of goods and products), may actually be missed. This is due to the nature of data we used to refine our weight factor estimate, which in itself is based on estimates.

Acknowledgments

The authors thank two anonymous reviewers for their valuable comments.

References

Batisse, C. and S. Poncet. (2004) Protectionism and Industry Location in Chinese Provinces. *Journal of Chinese Economic and Business Studies*, 2, 133–154.

Bullard, C., P. Penner and D. Pilati (1978) Net Energy Analysis. Handbook for Combining Process and Input–Output Analysis. *Resources and Energy* 1, 276–313.

Cruz, L. (2002) Energy–Environment–Economy Interactions: An Input–Output Approach Applied to the Portuguese Case (Paper for the 7th Biennial Conference of the International Society for Ecological Economics, ‘Environment and Development: Globalisation & the Challenges for Local & International Governance’, Sousse (Tunisia), 6–9 March 2002).

Cruz, L.M. (2004) Energy Use and CO_2 Emissions in Portugal (Paper for the Conference on Input–Output and General Equilibrium ‘Data, Modelling and Policy Analysis’, Brussels).

Dones, R., C. Bauer, R. Bolliger, B. Burger, T. Heck, A. Röder, M.F. Emmenegger, R. Frischknecht and N. Jungbluth (2004) *Life Cycle Inventories of Energy Systems: Results for Current Systems in Switzerland and Other UCTE Countries*. Dübendorf, Switzerland: PSI and ESU-Services.

Ferrao, P. and J.A. Nhambiu (2009) Comparison Between Conventional LCA and Hybrid EIO-LCA: Analyzing Crystal Giftware Contribution to Global Warming Potential. In: S. Suh (ed.) *Handbook of Input–Output Economics in Industrial Ecology*. Netherlands, Springer, 219–230.

Fisher, W.D. (1986) Criteria for Aggregation in Input Output Analysis: Implications for Industrial Ecology. In: I. Sohn (ed.) *Readings in Input–Output Analysis*. New York, Oxford University Press, 210–225.

Gao, T. (2004) Regional Industrial Growth: Evidence from Chinese Industries. *Regional Science and Urban Economics*, 34, 101–124.

Gillen, W.J. and A. Guccione (1990) Disaggregating Input–Output Models: An Alternative to Wolsky’s Method. *Economic Systems Research*, 2, 39–42.

Guan, D., Z. Liu, Y. Geng, S. Lindner, and K. Hubacek (2012) The Gigatonne Gap in China’s Carbon Dioxide Inventories. *Nature Climate Change*, 2, 672–675.

Heijungs, R. and S. Suh (2002) *The Computational Structure of Life Cycle Assessment*. Dordrecht, Kluwer Academic Publishers.

Hondo, H. (2005) Life Cycle GHG Emission Analysis of Power Generation Systems. *Japanese case Energy*, 30, 2042–2056.

IEA. (2010) International Energy Agency, Projected Costs of Generating Electricity. France, IEA/OECD.

IEA. (2011) International Energy Agency, Integration of Renewables Status and Challenges in China (IEA Working Paper). France, IEA/OECD.

Kymn, K.O. (1990) Aggregation in Input–Output Models: A Comprehensive Review, 1946–1971. *Economic Systems Research*, 2, 65–93.

Lenzen, M. (2011) Aggregation Versus Disaggregation in Input–Output Analysis of the Environment. *Economic Systems Research*, 23, 73–89.

Li, S. and Z. Xu (2010) Estimating the China Inter-Regional Trade Based on 2002 IO Tables (Conference Paper for the International Input–Output Conference, Alexandria 2011).

Limmeechokchai, B. and P. Suksuntornsiri (2007) Assessment of Cleaner Electricity Generation Technologies for Net CO_2 Mitigation in Thailand. *Renewable and Sustainable Energy Reviews*, 11, 315–330.

Lindner, S., J. Legault, and D. Guan (2012) Disaggregating Input–Output Models with Incomplete Information. *Economic Systems Research*, 24, 329–347.

Lindner, S., X. Li, D. Guan and K. Hubacek (2011) Embodied Energy of Chinese Provinces (Conference Paper at the 19th IIOA Conference, Alexandria).

Liu, C., M. Lenzen and J. Murray (2012) A Disaggregated Emissions Inventory for Taiwan with Uses in Hybrid Input–Output Life-Cycle Assessment (IO-LCA). *Natural Resources Forum*, 36, 123–141.

Ma, L. (2008) Future Energy Technology Perspectives. Coal Technology Assessment (NZEC Report on Future Coal Policies). Beijing, Tsinghua University.

Majeau-Bettez, G., A. Stromman and E. Hertwich. (2011) Evaluation of Process-and Input–Output based life cycle Inventory Data with Regard to Truncation and Aggregation Issues. *Environmental Science and Technology*, 45, 10170–10177.

Marriot, J. (2007) An Electricity-Focused Economic Input–Output Model: Life-Cycle Assessment and Policy Implications of Future Electricity Generation Scenarios (PhD Thesis Dissertation, Carnegie Mellon University, Pittsburgh).

Meng, L., J.E. Guo, J. Chai and Z. Zhang (2011) China's Regional CO_2 Emissions: Characteristics, Inter-Regional Transfer and Emission Reduction Policies. *Energy Policy*, 39, 6136–6144.

Miller, R.E. and P.D. Blair (2009) *Input–Output Analysis – Foundations and Extensions*, 2nd edn. Cambridge, Cambridge University Press.

Morimoto, Y. (1970) On Aggregation Problems in Input–Output Analysis. *Review of Economic and Statistics*, 37, 369–383.

NBS. (2008) *Chinese Electricity Yearbook (CEY) for 2007*. Beijing, National Bureau of Statistics, Energy Bureau, National Development Reform Comission, China Statistics Press.

NBS. (2010a) *National Bureau of Statistic, 2007 Input Output Table of China*. Beijing, China Statistics Press.

NBS. (2010b) *National Bureau of Statistics, 2007 Input Output Table of Chinese Provinces*. Beijing, China Statistics Press.

Nsakala, N. and J. Marion. (2001) Controlling Power Plant CO_2 Emissions. A Long Range View (Alstom Power Technology Centre, Baden-Daettwill, Working Paper). Available at http://www.netl.doe.gov/publications/proceedings/01/carbon_seq/1b2.pdf

Peters, G.P. and E.G. Hertwich. (2008) CO_2 Embodied in International Trade With Implications for Global Climate Policy. *Environmental Science and Technology*, 42, 1401–1407.

Su, B., H.C. Huang, B.W. Ang and P. Zhou (2010) Input–Output Analysis of CO_2 Emissions Embodied in Trade: The Effects of Sector Aggregation. *Energy Economics*, 32, 166–175.

Turner, K., J.K. Swales, P.G. McGregor and G. Allan (2007) Impact of Alternative Electricity Generation Technologies on the Scottish Economy: An Illustrative Input–Output Analysis. *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy*, 221, 243–254.

Wang, Q. and Y. Chen (2010) Status and Outlook of China's Free-Carbon Electricity. *Renewable and Sustainable Energy Reviews* 14, 1014–1025. http://dx.doi.org/10.1016/j.rser.2009.10.012

Weisser, D. (2007) A Guide to Life-Cycle Greenhouse Gas Emissions from Electric Supply Technologies. *Energy*, 32, 1543–1559.

Wiedmann, T., M. Lenzen, K. Turner and J. Barrett (2007) Examining the Global Environmental Impact of Regional Consumption Activities – Part 2: Review of Input–Output Models for the Assessment of Environmental Impacts Embodied in Trade. *Ecological Economics*, 61, 15–26.

Wiedmann, T., H.C. Wilting, M. Lenzen, S. Lutter and V. Palm (2011a) Quo Vadis MRIO? Methodological, Data and Institutional Requirements for Multi-region Input–Output Analysis. *Ecological Economics*, 70, 1937–1945. doi: 10.1016/j.ecolecon.2011.06.014.

Wiedmann, T.O., S. Suh, K. Feng, M. Lenzen, A. Acquaye, K. Scott and J.R. Barrett (2011b) Application of Hybrid Life Cycle Approaches to Emerging Energy Technologies – The Case of Wind Power in the UK. *Environmental Science & Technology*, 45, 5900–5907.

Wolsky, A. (1984) Disaggregating Input–Output Models. *The Review of Economics and Statistics*, 66, 283–291.

Zhang, Y., J. Zhang, Z. Yang and S. Li. (2011) Regional Differences in the Factors that Influence China's Energy-Related Carbon Emissions, and Potential Mitigation Strategies. *Energy Policy*, 39, 7712–7718.

APPENDIX A

TABLE A1. Province allocation to six electricity generation grids.

Region	Provinces with more than 90% of power generation by fossil fuels			Provinces between 50% and 80% of power generation by fossil fuels			Provinces with less than 50% of power generation by fossil fuels	
Central China				Henan, Chongqing	Hunan	Jiangxi	Hubei	Sichuan
Eastern China	Shanghai	Jiangsu	Anhui	Fujian	Zhejiang			
North East	Jilin	Heilongjiang	Lianoning					
North West	Ningxia,	Shaanxi		Gansu,	Xinjiang		Qinghai	
South China				Guizhou	Guangdong		Yunnan	Guangxi
North China Grid	Shanxi Inner Mongolia	Shandong Tianjing	Beijing Hebei					

TABLE A2. Sector-specific electricity consumption mixes by technology type, compared to national average.

	Hydro	Sub-c	Super crit	USC	NG	Nuclear	wind	solar pv
National average	0.23	0.64	0.06	0.04	0.01	0.01	0.01	0.00
Agriculture	0.19	0.67	0.06	0.03	0.01	0.01	0.02	0.00
Coal mining and processing	0.13	0.74	0.07	0.02	0.01	0.00	0.03	0.00
Crude petroleum and natural gas products	0.15	0.72	0.07	0.01	0.02	0.00	0.02	0.00
Metal ore mining	0.19	0.67	0.07	0.02	0.01	0.00	0.03	0.00
Non-ferrous mineral mining	0.19	0.66	0.05	0.05	0.00	0.01	0.03	0.00
Manufacture of food products and tobacco processing	0.18	0.68	0.06	0.03	0.01	0.01	0.03	0.00
Textile goods	0.20	0.63	0.05	0.08	0.01	0.02	0.02	0.00
Wearing apparel, leather, furs, down and related products	0.19	0.65	0.05	0.07	0.00	0.02	0.02	0.00
Sawmills and furniture	0.24	0.63	0.06	0.03	0.01	0.01	0.02	0.00
Paper and products, printing and record medium reproduction	0.24	0.61	0.06	0.05	0.01	0.01	0.02	0.00
Petroleum processing and coking	0.18	0.68	0.06	0.03	0.02	0.00	0.02	0.00
Chemicals	0.19	0.64	0.05	0.06	0.01	0.01	0.02	0.00
Non-metal mineral products	0.21	0.64	0.06	0.04	0.01	0.01	0.02	0.00
Metals smelting and pressing	0.20	0.65	0.06	0.04	0.01	0.01	0.03	0.00
Metal products	0.20	0.62	0.05	0.08	0.00	0.02	0.02	0.00
Machinery and equipment	0.20	0.63	0.05	0.06	0.02	0.01	0.02	0.00
Transport equipment	0.20	0.65	0.06	0.05	0.01	0.01	0.02	0.00
Electric equipment and machinery	0.22	0.61	0.05	0.07	0.01	0.02	0.02	0.00
Electronic and telecommunication equipment	0.24	0.59	0.05	0.08	0.01	0.02	0.01	0.00
Instruments, metres, cultural and office machinery	0.22	0.61	0.05	0.07	0.01	0.02	0.02	0.00
Other manufacturing products	0.23	0.59	0.05	0.09	0.00	0.02	0.01	0.00
Waste recycling	0.20	0.63	0.05	0.09	0.00	0.02	0.02	0.00
Gas production and distribution	0.18	0.69	0.06	0.03	0.01	0.01	0.03	0.00
Water supply and services	0.18	0.69	0.06	0.03	0.01	0.01	0.02	0.00
Construction	0.28	0.58	0.06	0.04	0.01	0.02	0.02	0.00
Transport and warehousing	0.18	0.68	0.06	0.04	0.01	0.00	0.03	0.00
Post	0.15	0.72	0.07	0.02	0.01	0.00	0.02	0.00
Telecommunication	0.23	0.61	0.06	0.04	0.02	0.00	0.02	0.01
Wholesale and retail trade	0.22	0.64	0.06	0.04	0.01	0.01	0.03	0.00
Eating and drinking places	0.21	0.65	0.06	0.03	0.01	0.01	0.02	0.00
Finance and insurance	0.22	0.64	0.06	0.04	0.02	0.01	0.02	0.00
Real estate	0.16	0.70	0.06	0.04	0.01	0.01	0.02	0.00
Renting and business services	0.20	0.64	0.06	0.05	0.01	0.01	0.02	0.00
Tourism	0.08	0.79	0.07	0.02	0.00	0.00	0.03	0.00
Scientific research	0.13	0.73	0.06	0.04	0.01	0.01	0.02	0.00
General technical services	0.20	0.65	0.06	0.03	0.02	0.01	0.02	0.00
Other services	0.15	0.72	0.06	0.02	0.01	0.00	0.02	0.00
Education	0.17	0.69	0.06	0.03	0.01	0.00	0.02	0.00
Health services and social welfare	0.17	0.69	0.06	0.04	0.01	0.01	0.02	0.00
Recreational, sporting and cultural activities	0.20	0.66	0.06	0.05	0.01	0.01	0.02	0.00
Public administration and other sectors	0.18	0.68	0.06	0.03	0.01	0.01	0.02	0.00
T&D	0.21	0.64	0.06	0.05	0.01	0.01	0.02	0.00