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A Hybrid-Unit Energy Input-Output Model to Evaluate Embodied Energy and Life Cycle Emissions for China's Economy

Sören Lindner and Dabo Guan

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Summary

We develop a hybrid-unit energy input-output (I/O) model with a disaggregated electricity sector for China. The model replaces primary energy rows in monetary value, namely, coal, gas, crude oil, and renewable energy, with physical flow units in order to overcome errors associated with the proportionality assumption in environmental I/O analysis models. Model development and data use are explained and compared with other approaches in the field of environmental life cycle assessment. The model is applied to evaluate the primary energy embodied in economic output to meet Chinese final consumption for the year 2007. Direct and indirect carbon dioxide emissions intensities are determined. We find that different final demand categories pose distinctive requirements on the primary energy mix. Also, a considerable amount of energy is embodied in the supply chain of secondary industries. Embodied energy and emissions are crucial to consider for policy development in China based on consumption, rather than production. Consumption-based policies will likely play a more important role in China when per capita income levels have reached those of western countries.

Introduction

Life cycle assessment (LCA) tools are rather complex models with the goal to assess direct and indirect environmental impacts of goods and services that are produced or consumed in the economy (Majeau-Bettez et al. 2011). This can be achieved with process analysis (PA) or environmentally extended input-output analysis (EIOA). Both are useful policy instruments to inform businesses, consumers, and government entities of their material and resource use along global supply chains. A wide range of applications for LCA tools exist, from evaluating economic impacts on energy consumption of countries, impacts on water, ecosystems, as well as carbon dioxide (CO_2) footprint analysis (Bullard and Herendeen 1975; Feng et al. 2011; Hubacek and Sun 2001; Minx et al. 2009).

However, PA and EIOA each suffer from errors, and the related uncertainty requires attention so that policy makers gain full confidence in the modeling results (Hawkins et al. 2007; Lenzen 2000; Williams et al. 2009). As a solution to mitigate errors of each individual model, several researchers have suggested combining both approaches in a hybrid LCA model (Lenzen 2002b; Suh et al. 2004). In this article, we develop such a hybrid model for China. It combines primary energy processes with input-output (I/O) data in which, additionally, the electricity sector is disaggregated into generation technologies. The model attempts to overcome two of the commonly known errors of EIOA, namely, aggregation uncertainty and error resulting from the proportionality assumption. It is then used to evaluate the amount of direct and indirect primary energy embodied in Chinese final consumption of goods and services as well as looking at embodied CO_2 emissions.

Address correspondence to: Dr. Soeren Lindner, IPTS, Joint Research Center of the EC, Calle Inca Garcilaso s/n, 41002 Seville, España. *Email:* Soeren.Lindner@ec.europa.eu

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Literature Review

Life Cycle Assessment Methods

The two methods typically used to evaluate direct and indirect environmental impacts, PA and EIOA, have both been discussed extensively in the literature in regard to their strengths and weaknesses (Hendrickson et al. 1998; Majeau-Bettez et al. 2011; Suh 2004; Suh et al. 2004; Williams et al. 2009). PA is the preferred method when the life cycle of individual products is evaluated, but is less suitable to analyze economy-wide effects because this would require modeling environmental impacts of all interindustry linkages in the economy individually, which is a tedious task. As a result, LCA practitioners typically define an arbitrary cut-off line beyond the first- or second-order linkage of a process and assume an average energy or emissions intensity for all higher orders when determining the life cycle inventory. This is known as truncation error.

EIOA is suitable to assess direct and indirect impacts of an economy, including all industry sectors producing commodities. Its system boundary therefore exceeds that of PA. But, EIOA-based LCA suffers from aggregation uncertainty as well as error related to the proportionality assumption (Lenzen 2002a).[1] In regard to the latter, proportionality uncertainty in EIOA arises as a result of the assumption that, in the I/O tables (IOTs), physical unit flows of resource commodities between industries are represented one to one by monetary values (Hawkins et al. 2007; Joshi 1999; Williams et al. 2009). To illustrate, under this assumption, the amount of physical quantity in 1 renminbi (RMB) worth of electricity supplied to the Chinese steel industry is the same as 1 RMB worth of electricity supplied to any other sector. This is not always true: Despite tight regulation of the electricity price by Chinese authorities, prices differ between industries, factories, and end users (NBS 2010b). The same can be said about primary energy carriers, such as coal, crude oil, and gas. Their sales price to industries differs, depending on the region and province, and is often determined through private contracting with mines and refineries. Thus, expressing primary energy production sectors in physical units in Chinese IOTs, as opposed to monetary units, will likely provide more-accurate results when these tables are used for environmental-economic LCA. Chapman (1974) and Wright (1974) both state that a hybrid-unit expression of IOTs can overcome the proportionality assumption (Chapman 1974; Wright 1974).

In regard to aggregation uncertainty in I/O, this issue has been addressed by several researchers (Gillen and Guccione 1990; Joshi 1999; Wolsky 1984), and aggregation of sectors with high resource requirement was pointed out to be a particular problem when IOTs are used for environmental-economic LCA (Lenzen 2011). As a result, some of our past work has been related to disaggregating the electricity sector of China's IOT into individual generation components to improve its use for evaluating life cycle emissions of Chinese industry sectors (Lindner et al. 2012).

Suh (2004), along with several other researchers, recommends combining PA with EIOA into hybrid models. The purpose of this is to extend the system boundary of process-based LCA to an entire economy. Hybrid-LCA models combine the strengths of both models: PA-LCA offers detail at the product level, whereas I/O-based LCA covers the interindustry linkages of the entire economy (Majeau-Bettez et al. 2011; Suh et al. 2004). As Suh and colleagues (2004) describe, PA can be either added to IOTs as a process flow, in matrix form, or by disaggregating a sector in the IOT. The former was first introduced by Bullard and Herendeen (1975) as hybrid-energy analysis. They showed a method to replace energy rows in the IOT, expressed in monetary data, with energy flows in physical data. The model was used to analyze energy as a production factor and evaluate direct and indirect energy requirements of producing goods and services in the U.S. economy. This method of extending the system boundary of process flow to an entire economy, as shown originally by Bullard and Herendeen, is applied in this article for the case of China. In addition to that, our IOT has added process detail in the electricity sector because we disaggregated the energy transformation sector into technology detail.

Hybrid-Energy Modeling

Hybrid-energy modeling is referred to as hybrid-unit energy analysis whenever a mixed-unit IOT is deployed. But, technically, hybrid-unit analysis can be done for different process flows, such as water, zinc, or lead. Early work on hybrid-unit analysis started in the late 1960s when some specialists brought I/O analysis (IOA) to the fields of ecology, energy, and environment (Daly 1968; Isard 1969). These early models combined physical-unit models with IOTs in monetary units. In the 1970s, hybrid-unit energy IOA was then heavily applied after economies experienced acute energy shortages stemming from the international energy crisis. Research was primarily driven by a need for a robust framework for energy policy analysis. Hannon (1973) introduced the concept of hybrid-unit energy analysis to U.S. I/O accounts. His work was followed by several other researchers analyzing energy use of production activities with U.S. national accounts: Wright (1974) used hybrid energy analysis to trace back several industry inputs to their requirements of primary energy.

More recently, hybrid-unit analysis, in combination with the IO framework, has gained renewed attention to evaluate energy as well as CO_2 emissions embodied in products and trade. Casler and Blair (1996) apply the hybrid method to a number of emission pollutants embodied in products using 1985 I/O data of the U.S. economy. Treloar (1997) uses hybrid energy analysis to model direct and indirect energy requirement in the Australian residential sector. Machado and colleagues (2001) use a hybrid-unit energy model for Brazil to evaluate embodied energy and carbon in international trade with Brazil. Frequently, hybrid-unit energy analysis is also combined with material flow analysis and structural decomposition analysis (Hawkins et al. 2007). This enables tracing energy flows induced for production of single products through the economy. Hybrid-unit energy analysis shall not be confused with an alternative approach for calculating embodied energy in IOA. Technically, the monetary I/O model can be multiplied by a vector showing energy intensities for each sector. This type of EIOA model has been applied in many cases, but it does not overcome the proportionality assumption (Lin and Polenske 1995; Liu et al. 2012; Yuan et al. 2010).

Environmental Input-Output Modeling for China

It is important to have accurate data to work with in environmental LCA so that policy makers gain confidence in modeling results. At the same time, energy- and emissions-based LCA studies in China are eminent. For one, China is already the number one emitter of absolute CO_2 emissions in the world and also requires more energy to fuel its economy than any other country. On the other hand, once China levels out socioeconomic disparities and completes the transition into a developed country, its consumption patterns will likely resemble those of current Western countries (Guan et al. 2008; Minx et al. 2011). As a result, China's energy and CO_2 emissions footprint will increase as well (Feng et al. 2009; Hubacek et al. 2007). Research on domestic carbon footprints in regional China has shown that well-developed provinces along the eastern coast have already increased their consumption-based emissions at a much faster rate than production-based emissions and also quicker than less-developed provinces (Guo et al. 2012). Other literature generally supports the idea that with growing wealth of citizens and related lifestyle changes, goods and services are consumed that have higher life cycle energy requirements and thus CO_2 emissions (Stern et al. 1996).

Given the growing importance of consumption volume as a driver of energy and emissions, policy makers may decide to develop regulations for energy and emissions reduction based on the consumer, rather than the producer. For this policy directive, energy- and emissions-related LCA research at a national level is becoming essential as an analysis tool. For example, Liu and colleagues (2012) found that a considerable amount of energy is embodied indirectly in industry supply chains of China. As a result, policy makers should not only target those sectors that are traditionally energy intensive from a production perspective, but also consider supplier industries and conduct emissions inventories from the consumption side (Liu et al. 2012). One aspect this article did not touch on is about what kind of primary energy different industries consume. Obviously, there is a stark difference in environmental impact between primary energy from renewable generation, as compared to coal. The differentiation of what kind of energy is actually consumed does matter in China because of two reasons: (1) A spatial disparity exists in resource extraction with the majority of coal extracted in the North and Northwest of China, whereas hydropower is predominant in the South and Southwest. Although resources are transported over long distances, it is likely true that regional industrial parks primarily consume energy according to the regional energy mix. (2) As a new policy, the Chinese government plans to diversify its fuel mix and expand the fraction of renewable energy technologies in the energy mix to 15% by 2020. In order to assess the functionality of such a policy, models must be capable of showing the direct and indirect energy requirements by fuel type for each industry sector.

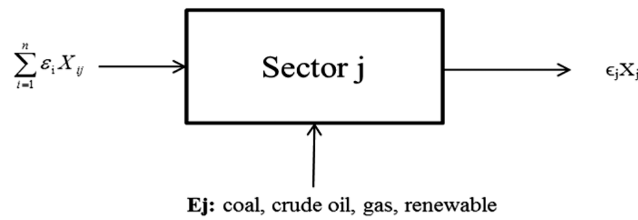

Figure 1 Conservation of embodied energy (after Bullard and Herendeen 1975).

Aim of the Study and Article Structure

To summarize, both from a modeling development as well as an energy policy perspective, there exists a need to build a hybrid model for China in which the primary energy requirement of industries is expressed in physical units. In this article, we explain data use and construction of such a hybrid-unit model. Several research questions can be answered with such a model. Given that consumption volume and production in the power sector have been identified in the literature as primary driving forces for the increase in energy use and CO_2 emissions in China, we focus on two questions. (1) What are direct and indirect energy requirements for Chinese production to satisfy different final demand categories in 2007? What are the related direct and indirect emissions? (2) For the electricity sector, what are direct and indirect requirements for primary energy for different power generation technologies?

The article is structured as follows: In the next section, data requirements and methodology are explained. In the *Results* section, we provide the direct and indirect energy embodied in final demand of Chinese industry sectors as well as emissions intensities. This is followed by a discussion and conclusion.

Methodology

Input-Output Methodology

The concept described in this article is based on the idea of "conservation of embodied energy" (Bullard and Herendeen 1975). Each sector in the economy uses primary energy as direct energy input into their production process, and the energy eventually gravitates toward final demand. Thus, every sector takes direct energy through extraction from the earth and indirectly through the embodied energy intensity in inputs from another sector. This is illustrated in figure 1. Below, we briefly review the I/O methodology, followed by the basic concepts of hybrid-unit analysis. These were originally outlined previously (Bullard et al. 1978; Gay and Proops 1993).

We let y be a vector $(n \times 1)$ of final demand from industry sectors $i = 1, \ldots, n$. X_{ij} describes elements of a matrix $(n \times n)$ of intermediate demand of industries $j = 1, \ldots, n$ from industries $i = 1, \ldots, n$. We can then write the total (intermediate plus final) demand x_i from industry$_i$ as shown in equation (1):

$$x_i = \sum_{j=1}^{n} x_{ij} + y_i \tag{1}$$

A is a matrix ($n \times n$) of technological coefficients a_{ij}. They relate the output x_j of industry j to its inputs from industries i by equation (2):

$$X_{ij} = a_{ij} x_j \tag{2}$$

In matrix notation, equation (1) can be written as equation (3):

$$x = \mathbf{A}x + y \tag{3}$$

When equation (3) is solved for x, we obtain equation (4):

$$X = (1 - \mathbf{A})^{-1} y \tag{4}$$

Here, the expression $(1 - \mathbf{A})^{-1}$ is called the Leontief inverse and 1 denotes a unity matrix of size $n \times n$.

Extension to Hybrid-Unit Energy Analysis

E_I is a matrix ($e \times n$) of the industrial energy consumption, expressed in physical units (PJ) of e types of primary energy per unit of total output of n industries. $\in_j$ is the embodied energy per unit of X_j. E_I, in our case, considers crude oil, raw coal, natural gas, and renewable energy. The latter is a sum of all wind power, hydropower, solar power, as well as nuclear energy harnessed in China.

The matrixes A, Z, and X defined in equations (1) through (3) are replaced with a hybrid unit notation, *. For example, $Z^* = z^*_{ij}$ contains z_{ij} where sector i is a nonenergy sector as well as e_{qj} where k is an energy sector. It follows, in equations (5) and (6), that

$$A^* = Z^*(X^*)^{-1} \text{ and} \tag{5}$$

$$L^* = (I - A^*)^{-1} \tag{6}$$

In this article, we assume that imports have the same energy intensity as their domestic counterpart. Although this is not accurate, we need to work with this assumption because we simply do not know the import structure and emissions intensities from the countries of origin. Therefore, we first remove imports, then calculate the domestic emission intensity of sectors in China, and reintroduce them. Assuming that each sector is in energy balance, we write equation (7):

$$\sum_{i=1}^{n} \varepsilon_i x_{ij} + E_{Ij} = \varepsilon_j (X_j^* - P_j) \tag{7}$$

In matrix notation, equation (5) becomes equation (8):

$$\varepsilon = E_I(\hat{X}^* - \hat{P} - X^*)^{-1} \tag{8}$$

where $\hat{X}$ is a diagonal with gross outputs and $\hat{P}$ is a diagonal with transferred imports P_j on the diagonal. By defining A, the matrix of domestic technological coefficients is shown as equation (9):

$$A^* = X^*(\hat{X}^* - \hat{P})^{-1} \tag{9}$$

$\in$ becomes equation (10):

$$\in = e(I - A^*)^{-1} \tag{10}$$

The expression in equation (8) gives the total energy requirement matrix. e in this case is a vector whose elements are zero except for the energy sector.

Carbon Dioxide Emissions

The total CO_2 emissions, C, resulting from fossil fuel combustion can be simply calculated by introducing a vector c of size $f \times 1$, which contains the CO_2 contents per energy unit of primary energy combusted, as shown in equation (11).

$$C = c(I - A^*)^{-1} \tag{11}$$

Data Requirement and Preparation

The following data were used:

- Chinese national IOT of 2007 (NBS 2010a). The table is originally in a 135×135 sector format when published by the NBS, but we obtained and worked with a table that was in the 42×42 sector format. This table was then disaggregated by us to 47×47 sectors.
- Chinese Energy Statistics Yearbook (CESYB) (NBS 2010b). It contains data in energy balance tables (EBTs) and final energy consumption data showing final energy consumption of 44 sectors plus urban and rural households for 19 fuel types, including heat and electricity.
- CO_2 emissions and conversion factors provided by the Intergovernmental Panel on Climate Change (IPCC 2007). These emissions factors allow the conversion from energy use per unit sector output to obtain emissions intensities. They are fuel and sector specific.

Preparing the Input-Output Table

This section explains the modifications that had to be made with the IO table in order to allow for a hybrid unit expression.

1. We disaggregated the electricity production sector entry (23 in the table) into four new sectors: renewable energy generation; coal-fired power generation with subcritical boiler; coal-fired power generation with supercritical boiler-type efficiency; and coal-fired power generation with ultra-super-critical boiler type. We used a weight-factor disaggregation method, and the method plus motivation and rationale behind disaggregating this sector is described in detail in Lindner and colleagues (2012).
2. Two more sectors in the IOT need to be disaggregated: sector entry 2: coal mining and processing, as well as sector entry 3: crude oil and natural gas extraction. Sector entry 2 contains, in monetary units, the primary sector (raw coal extraction) as well as all processed coal products combined, such as washed coal, briquettes, and coke. We disaggregated raw coal from processed coal products using

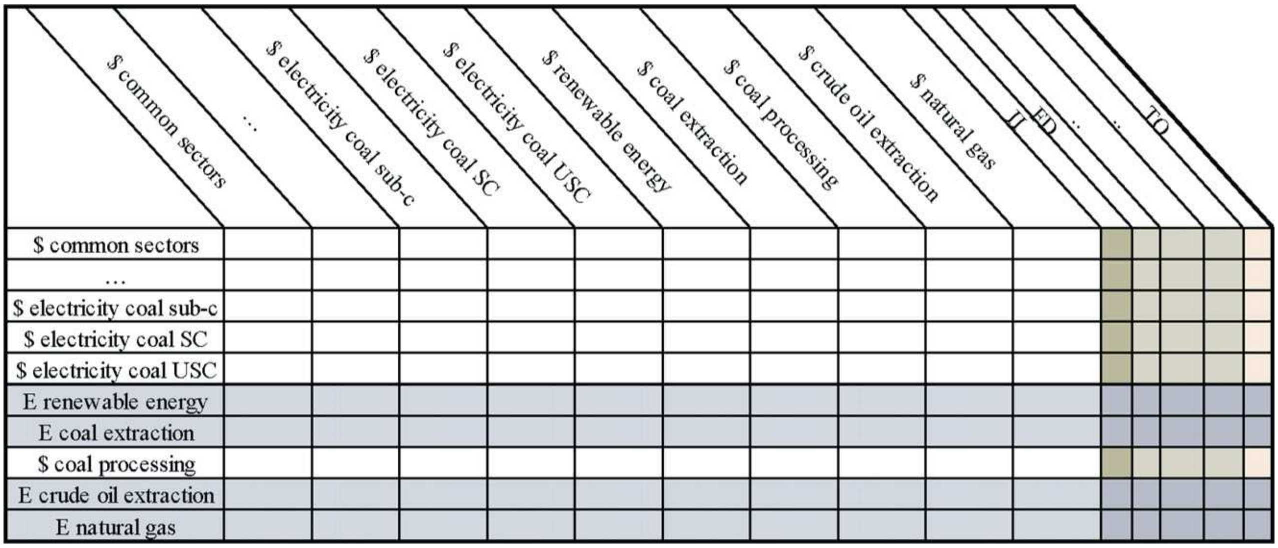

Figure 2 Schematic expression of hybrid-unit input-output table. *Note*: "$" simply expresses rows and columns in monetary terms; the actual currency used is renminbi. sub-c = subcritical boiler; SC = supercritical boiler type; USC = ultra-super-critical boiler type; II = intermediate demand; FD = final demand; TO = total output. The grey shaded rows indicate that monetary values have been replaced with physical units. The dark shaded last 5 columns show final consumption. The ellipses in the columns, "…", indicate that in the real hybrid table contains more "common sectors" and final demand categories.

a weight-factor disaggregation. This was done because we only replace the primary energy sector with physical units in the hybrid-unit model, but not any processing sectors. Sector 3 needed to be disaggregated in order to express crude oil and natural gas extraction in physical units separately from each other.

An illustration of the modified IOT is given in figure 2.

Preparing the Energy Data

The data in the EBT of China's statistics data need to be modified in several ways:

1. Following the exact outline in Peters and colleagues (2006), we prepared the data so that all energy is allocated to the sector that combusts the fuel (Peters et al. 2006). Typically, energy data show the distribution of secondary energy to its final users. For use of energy data in an EIOA framework, however, it is important to allocate (-back) all energy to the primary carrier. An example, given by Peters and colleagues (2006), is the electricity sector: In our case, the energy-combusted (and -related) emissions are allocated to the electricity production sector, and not to the (end) user of electricity.
2. The energy data contain 19 different energy carriers (fuel types). These are either primary energy carriers (raw coal, natural gas, crude oil, or renewable energy carriers) or processed energy carriers, such as washed coal, liquefied petroleum gas, petroleum products, or briquettes. The energy of these processed carriers was added to the four primary energy carriers: raw coal; crude oil; gas; and renewable energy.
3. The number of sectors in the energy consumption data is 44 and in a slightly different format than in the IOT. For example, the sector "others" in the energy consumption data contains 16 tertiary sectors that are disaggregated in the IOT. Using concordance matrixes, we first matched the energy data to a 42-sector size comparably with the original IOT. We then disaggregated the energy data to 47 sectors to match the new size.

Results

Primary Energy Embodied in Chinese Final Demand

Table 1 shows the primary energy mix as input to final consumption for different categories. We see that, in all cases, raw coal makes up the largest fraction, varying between 74.5% and 86.3% of total energy requirement. The energy mix composition also slightly varies among all final demand categories. Different final demand sections drive production for a different set of goods and services. For example, the goods produced to meet export demand are different from the type of goods produced to meet demand for gross capital formation or households. Each set has different primary energy requirements. Products destined for international export are mainly manufacturing goods, such as textile goods, wearing apparel, leather, and electronics. In contrast, gross capital formation drives production primarily in the construction sector, heavy machinery, as well as electric products.

We notice that the primary energy mix behind the production to satisfy a unit of final demand depends, on the one hand, on the kind of industries producing for final demand. This, in return, may likely depend on where production entities are located geographically and what energy mix is prevalent. For

Table 1 Total requirement of energy carriers to meet final demand in China

	Renewable energy (%)	*Raw coal (%)*	*Crude oil (%)*	*Natural gas (%)*
Total final demand: total requirement	3.1	79.3	15.6	2.0
Urban household final demand: total requirement	2.5	74.5	17.6	5.4
Rural household final demand: total requirement	4.1	71.6	16.8	7.5
Gross capital formation: total requirement	1.3	86.3	11.2	1.2
Export: total requirement	0.8	83.5	14.3	1.4
Government expenditure: total requirement	1.8	85.8	8.3	4.1

instance, the manufacturing industry, which is largely driven by international export, is located in the Southeast, where a larger fraction of energy is supplied by hydropower, as opposed to other regions in China, such as the Northwest. On the other hand, the primary energy input into the supply chain of products for final demand also determines the total energy mix composition. For example, a final good that requires a large amount of electricity as an input at stages in its supply chain will likely have a high proportion of raw coal as a total requirement—in particular, if these intermediate goods are produced in regions where most of the electricity is generated with coal-fired power stations.

Direct and Indirect Energy Embodied in Sectoral Production

In table 2, we show, broken down by primary energy input, direct and indirect requirements per unit output for Chinese sectors. We see that, in almost all cases, the indirect or embodied energy in a production process is higher than direct energy. As an example, embodied coal in the construction sector exceeds 95% of total raw coal consumption from this sector (i.e., less than 5% of total energy required in a unit of production stems from direct input of coal). Most secondary industry sectors, such as machinery and equipment manufacturing, electronics and telecommunication equipment, as well as tertiary service sectors, require low direct input of coal. The fraction of direct input increases in resource-intensive sectors, (energy) transformation sectors, as well as waste recycling.

Embodied Carbon Dioxide Emissions

In figure 3, we show the CO_2 emissions associated with total energy requirement of 41 sectors in China disaggregated by primary energy type. Raw coal contributes, in all sectors, the most to CO_2 emissions. The magnitude, however, differs: It is generally highest in the secondary sectors, such as nonmetal mineral products, chemicals, smelting, and pressing. This has been shown by other researchers as well (Meng et al. 2011; Guo et al. 2012; Liu et al. 2012). In the tertiary sectors, such as service sectors, and sectors with transport and logistics (post, transport, and warehousing), emissions from crude oil and natural gas are proportionally higher. Overall, we note that service sectors generally have lower overall CO_2 emissions, in total as well as from raw coal. Instead, the fraction of crude oil and natural gas is higher than in secondary and primary sectors.

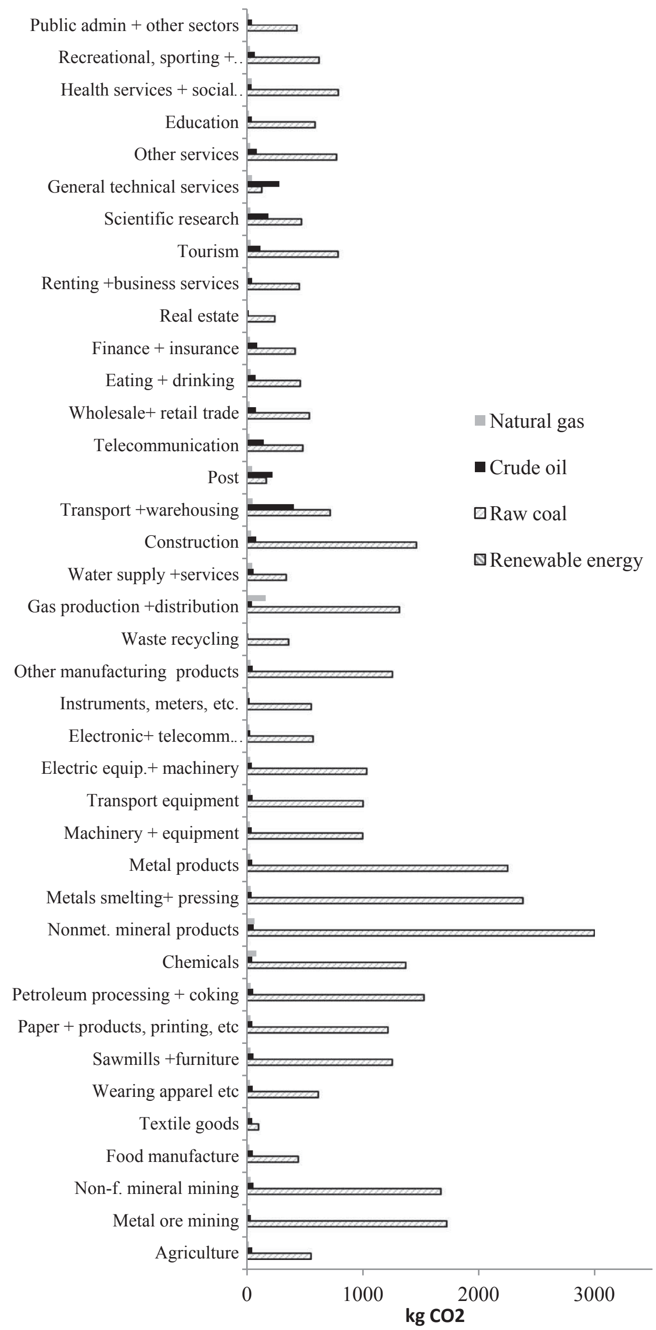

Figure 3 Total CO_2 emissions by energy type for Chinese sectors. kg = kilograms; CO_2 = carbon dioxide.

Table 2 Direct and indirect requirement of sectors in China

	Raw coal (MJ)		*Renewable energy (MJ)*		*Crude oil (MJ)*		*Natural gas (MJ)*	
	Direct	*Indirect*	*Direct*	*Indirect*	*Direct*	*Indirect*	*Direct*	*Indirect*
Agriculture	1,403.2	5,348.3	147.9	247.5	220.1	433.4	0.0	266.0
Metal ore mining	934.1	15,015.8	371.5	273.0	50.7	433.1	2.2	358.5
Nonferrous mineral mining	2030.5	11,976.2	204.1	403.7	55.4	742.2	3.8	513.8
Food products and tobacco	1,219.2	8,222.5	111.7	373.8	39.1	686.5	27.8	317.8
Textile goods	936.3	8,732.2	123.8	361.2	27.5	627.6	7.9	483.0
Wearing apparel, leather, furs, etc.	391.1	8,995.7	102.9	250.5	56.0	661.0	3.9	436.1
Sawmills and furniture	1,276.1	10,830.9	290.6	537.7	102.5	697.1	19.1	470.5
Paper and products, printing + record	1,700.2	11,352.4	258.4	555.9	66.5	594.9	25.5	518.0
Petroleum processing and coking	1,022.1	15,011.8	230.9	815.8	429.8	318.1	345.1	202.3
Chemicals	1,563.7	15,479.2	402.3	753.6	43.4	614.2	684.4	866.0
Nonmetal mineral products	1,172.1	19,370.6	581.9	605.3	98.5	740.8	522.1	700.1
Metals smelting and pressing	2,126.2	18,140.0	569.6	745.6	26.3	566.4	117.8	488.0
Metal products	282.5	18,559.4	266.7	807.1	64.5	596.9	21.6	526.6
Machinery and equipment	306.6	11,849.9	107.0	577.1	60.8	530.9	58.9	398.2
Transport equipment	317.8	11,709.3	89.9	621.8	65.9	636.0	80.6	494.6
Electric equipment and machinery	92.8	12,477.1	82.4	705.3	37.7	568.2	23.1	485.4
Electronic + telecommunications	32.5	6,755.0	62.7	336.3	12.0	391.4	46.3	322.7
Instruments, meters, cultural machine	46.0	5,632.5	51.4	281.0	29.6	307.3	5.7	267.6
Other manufacturing products	918.2	9,458.3	366.2	252.6	50.2	660.3	3.8	520.7
Waste recycling	1,004.2	2,506.9	200.4	140.0	54.9	93.2	4.1	86.2
Gas production and distribution	2,544.9	11,656.1	316.4	194.5	130.5	410.8	2357.3	556.7
Water supply and services	511.5	9,229.5	257.5	257.0	127.9	647.4	26.6	669.9
Construction	189.7	17,170.3	36.4	732.2	137.9	1,020.2	13.3	620.6
Transport and warehousing	414.4	7,771.2	48.9	202.8	4,626.7	1,227.5	119.3	430.7
Post	105.4	7,301.1	34.2	215.7	1,906.0	1,157.3	24.5	314.0
Telecommunications	71.9	7,155.3	87.0	231.9	1,530.0	564.9	21.0	245.8
Wholesale and retail trade	304.6	6,074.7	109.4	224.7	284.8	841.0	125.7	247.9
Eating and drinking places	403.3	9,077.4	57.4	311.7	485.4	588.9	214.2	313.7
Finance and insurance	322.7	4,805.0	83.0	199.9	774.8	506.0	208.5	211.3
Real estate	28.8	2,195.3	5.8	96.1	41.5	170.1	9.9	95.5
Renting and business services	97.8	4,004.7	54.3	245.7	124.3	503.3	37.3	311.8
Tourism	28.9	5,516.3	10.5	259.1	33.2	1,588.0	8.8	327.4
Scientific research	283.7	2,475.3	128.4	290.7	1,956.8	728.1	48.0	305.1
General technical services	1,084.2	5,866.1	103.2	341.0	3,068.2	954.1	39.3	388.8
Other services	297.8	4,270.7	143.2	266.5	654.3	580.3	51.3	394.9
Education	55.6	3,290.5	6.4	239.5	53.1	537.8	6.9	262.1
Health services and social welfare	89.1	6,097.7	29.0	502.9	54.6	514.5	48.8	700.7
Recreational, sporting + cultural activities	125.0	4,314.0	122.5	322.9	362.8	589.2	72.7	316.0
Public administration and other sectors	4.5	4,561.3	1.7	236.4	25.5	590.6	0.7	247.5

Note: MJ = megajoules.

Energy Requirements of the Disaggregated Electricity Sector

In terms of energy and CO_2 emissions, the Chinese electricity sector is arguably the most important. Energy requirement and emissions intensity of individual power plants are highly diverse. Direct, as well as upstream and downstream, requirements between technologies are very different. This is confirmed by our results summarized in table 3. The range of power plants provided here is limited; for example, we did not disaggregate renewable energy technologies (RETs) into wind power, hydropower, solar power, and nuclear energy. The main focus is put on the coal-fired power stations with different boiler types installed in China (table 3).

In 2007, coal-fired power stations with subcritical boiler types (average efficiency of approximately 34%) made up 64% of the electricity generation mix. Our results show that all coal-fired power stations consume between 69% and 71% of their coal directly at the station, and hence approximately 30% of coal is consumed indirectly along the supply chain. For crude oil, approximately 41% to 50% are consumed directly. RETs have a different energy profile. For example, all raw coal in the total energy requirement from RETs stems from the supply chain and there is no direct consumption of coal. Total raw coal

Table 3 Energy requirement of different electricity generation plants

	Coal sub-c (MJ)	*Coal SC (MJ)*	*Coal USC (MJ)*	*Renewables (MJ)*
Total energy requirement				
Renewable energy	552	444	408	45,322
Raw coal	214,838	172,804	158,793	9,057
Crude oil	2,927	2,355	2,164	493
Natural gas	894	719	661	180
Direct energy requirement				
Renewable energy	0	0	0	45,156
Raw coal	150,147	123,770	111,978	0
Crude oil	1,721	1,394	269	0
Natural gas	73	49	54	12
Indirect energy requirement				
Renewable energy	552	444	408	166
Raw coal	64,691	49,034	46,815	9,057
Crude oil	1,207	961	1,895	493
Natural gas	821	670	607	168

Note: MJ = megajoules; sub-c = subcritical boiler; SC = supercritical boiler type; USC = ultra-super-critical boiler type.

consumption throughout the entire life cycle is relatively low: it is only 5% of that from coal-fired power stations. The prevalent differences between direct and indirect energy requirement from different power stations indicate how important it is to disaggregate the electricity sector in EIOA studies into its power generation components.

Discussion

Discussion of the Model

In this article, we presented an internally consistent hybrid-unit I/O model that preserves those fuel sources ultimately responsible for CO_2 emissions. We showed that such a model can be used to answer a wide range of policy questions in the field of energy and CO_2 emissions. In particular, our model is applicable to the evaluation of energy and emission requirements along the entire life cycle of industry sectors. Results of such a model are useful to support policies aiming to regulate fuel requiremements—as well as its composition—to meet final consumption of goods and services in an economy.

The mixed-unit model has the advantage to overcome the proportionality assumption and uncertainty associated with aggregation of important, resource-intensive sectors.

On the downside, our hybrid model contains other sources of uncertainty. For one, the quality of energy data must be improved during collection and initial construction of EBTs and energy consumption data by the Chinese Bureau of Statistics. It is likely that the national energy data are under-reported; at least it does not match the sum of data from each province (Guan et al. 2012). Guan and colleagues (2012) have found 18% to be the discrepancy between provincial and national energy statistics in 2010. The error margin is the largest for processed coal. Despite this issue, we have to rely on the most updated data from the regional statistical agencies because it is the most consistent, comprehensive data set and published annually.

Second, our model does not contain biomass as an input. This may affect the energy and emissions balance of rural households that use biomass.

The third point concerns the match of energy data with Chinese I/O data. In order to build the hybrid model, the sectoral energy consumption data were subjected to a number of aggregation and disaggregation steps during data preparation. In particular, during the disaggregation of the sector "others" (in the energy classification) into 11 service sectors with the concordance matrix, we had to assume that their energy consumption is the same ratio as their individual monetary output. This may not be true, but we have no accurate data showing energy consumption of tertiary sectors in the Chinese economy. It would be beneficial for studies in the field of energy and CO_2 emissions for China if the sector classification in the energy statistics would match more closely those of the I/O data.

A fourth weakness of this model, as presented in its current form, is the "import assumption." Future work must focus on quantifying international imports and their related production coefficients, especially of primary energy, by China. For example, a considerable amount of coal is imported from Australia. Natural gas and, particularly, crude oil is now increasingly transported from East Asia, Saudi Arabia, and also Mongolia (natural gas).

I/O practitioners who wish to conduct an economy-wide LCA study ultimately have a number of model options to choose from. This option, however, depends on the country and the related quality of data. For China, we have observed that data for conducting EIOA studies with a high quality of data turn out to be difficult. First, Chinese IOTs still lack sector detail. To compare, the U.S. I/O data are published in a 500-sector resolution. Second, process databases for LCA that can be used to build hybrid models by either disaggregation or tiered hybrid analysis (Suh et al. 2004) are not publicly available. For example, the large ecoinvent database contains detailed information on resource input and use for each commodity sector in several countries (Frischknecht 2009). For China, these data are currently being collected by a team from the ecoinvent institute for the new version of the database and thus are not yet available. Third, disaggregation of sectors, or processes in the monetary IOT with the help of prices, also turns out to be difficult. For example, if exact prices of primary energy and quantities sold to industries and households had been known, the energy and emissions analysis could have been performed without using a hybrid-unit approach. Some information on commodity prices could be obtained from the Chinese Price Yearbook, but it is quite time-consuming to extract the information and conduct such a sector disaggregation.

Thus, to conclude, the choices for EIOA-based LCA models to work with in China are generally hampered by data availability. We strongly encourage Chinese officials to spend time and resources on data collection suitable for LCA.

Policy Discussion

Economy-wide environmental LCA models allow one to trace direct, as well as indirect, impacts along the supply chain of products and are therefore suitable as a supporting tool for consumption-based policy making. Our results imply that when energy as an input to production in the economy is viewed from the perspective of the final consumer of goods and services, then embodied energy plays a more significant role, as opposed to direct energy inputs. Compared to the production-based approaches currently applied to determine energy-intensity reduction targets in China, viewing energy and emissions from the perspective of the final consumer reveals otherwise "hidden" energy-intensive industries. Sectors, such as the construction sector and many service sectors, actually become energy intensive because of their requirements of energy-intensive intermediate products from heavy industries. Liu and colleagues (2012) give the example of cement and steel production to supply the construction industry, which, in return, is driven by the government's large capital investment into construction to maintain China's gross domestic product (GDP) growth throughout the economic crisis. Our results support findings by Liu and colleagues (2012) and go beyond those by showing what type of energy is actually embodied in final consumption categories. In this regard, our results support a stronger focus of policy on diversifying the primary energy mix in China to increase the fraction of renewable energy in the mix. China has implemented a policy to increase the fraction of renewable energy in the electricity generation mix to 15%, but such efforts must be accompanied by making sure that RETs, such as wind and solar power, become competitive with coal and gas and actually have guaranteed access to the grid system. This could be achieved with feed-in tariffs in the electricity sector, but also requires additional investment into transmission and distribution lines. Because our results also showed that capital investment, export, and government expenditure place a proportionally higher requirement on raw coal, then other final demand categories, as well as efforts to increase energy and emissions efficiency, must be focused on the sectors whose production is driven by these final demand categories.

Results from the electricity sector imply that the supply-chain energy and emissions requirements of power generation technologies need to be taken more strongly into consideration when decisions are made over which type of power plant to invest in and install. Although highly efficient boilers in coal-fired power stations improve direct energy requirements and decrease emissions at the power plant itself, these plants still have very high requirements further up the supply chain that cannot be neglected. The issue of supply-chain requirements will become particularly important when China starts to build carbon capture and storage power plants because they reduce the efficiency of the power plant itself and therefore require more raw coal to meet the electricity demand. This will ultimately result in even more energy and emissions further up the supply chain of the power plant and this CO_2 is not captured, but instead emitted.

To encourage overall reduction of energy and emissions in China's power sector, a more integrated policy approach, which captures and weighs all impacts along the supply chain of individual power plants, is therefore encouraged. This can be achieved by implementing reduction targets in this sector that are measured based on the life cycle energy and emissions requirements of power plants. Such a policy can also be implemented first in provinces along the East coast, whose demand for electricity exceeds their supply. Because most of the mining activity for raw coal, crude oil, and gas actually takes place in economically less-developed provinces, this approach to energy and emissions inventory in the electricity sector would capture the associated energy and emissions increase of mining and transport activities in provinces such as Shanxi, Inner Mongolia, and Henan. It would naturally encourage energy and grid companies in the East of China to invest into energy efficiency improvements in North and Northwestern China.

Conclusion

The aim of this article is to show and discuss the construction of a hybrid-unit energy model for China that combines process analysis with I/O data. With this hybrid model, the system boundary of process-based LCA for energy carriers can be extended to cover all industry sectors in the Chinese economy to analyze direct and indirect energy requirements. Given that the energy consumption data in the CESYB is the only publicly available data set for conducting such an LCA analysis, and these data are difficult to make compatible with Chinese I/O data, we conclude that further time and resources should be spent on building extensive life cycle databases, specifically for China. The need for that is justified by the great potential for a shift in Chinese policy making toward a focus on energy (and emissions) consumption.

Note

1. There are other sources of uncertainty inherent in EIOA models, which are summarized in Lenzen (2000), or Joshi (1999). They are not further discussed here.

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About the Authors

Sören Lindner was a Ph.D. student at the University of Cambridge (Cambridge, UK), Cambridge Centre for Climate Change Mitigation Research (4CMR), at the time this article was written. He is currently a postdoctoral researcher at the Joint Research Center, Institute for Prospective Technological Studies (IPTS), of the European Commission in Sevilla, Spain. **Dabo Guan** is a senior lecturer at the School of Earth and Environment at the University of Leeds, in Leeds, UK.