Evaluating European imports of Asian aquaculture products using statistically supported life cycle assessments

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Chapter 4

Updated unit process data for coal-based energy in China including parameters for overall dispersions

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Abstract

Purpose: Chinese coal power generation is part of the life cycle of most products and the largest single source for many emissions. Reducing these emissions has been a priority for the Chinese government over the last decade, with improvements made by replacing older power plants, improving thermal efficiency and installing air pollution control devices. In the present research, we aim to acknowledge these improvements and present updated unit process data for Chinese coal power. In the course of doing so, we also explore the implementation and interpretation of overall dispersions related to a generically averaged process, such as Chinese coal power.

Methods: In order to capture geographical and temporal dispersions, updated unit process data were calculated for Chinese coal power at both a national and a provincial level. The updated unit process dataset was also propagated into life cycle inventory (LCI) ranges using Monte Carlo simulations, allowing for discrepancies to be evaluated against the most commonly used inventory database (ecoinvent) and overall dispersions to be shown for some selected provinces.

Results and discussion: Compared to ecoinvent, the updated dataset resulted in reductions with between 8 and 67% for all evaluated inventory flows except for dinitrogen monoxide (N_2O). However, interprovincial differences in emissions diverged with up to 250%. A random outcome in a few Monte Carlo runs was inverted operators, where positive values became negative or the other way around. This is a known possible outcome of matrix calculations that needs to be better evaluated when interpreting propagated outcomes.

Conclusions: The present manuscript provides recommendations on how to implement and interpret dispersions propagated into LCI results. In addition, updated and easily accessible unit process data for coal power plants averaged across China and for individual provinces are presented, with clear distinctions of inherent uncertainties, spread (variance) and unrepresentativeness. Recommendations are also provided for future research and software developments.

4.1 Introduction

Chinese coal power is the world's largest single source for anthropogenic greenhouse gases (GHGs) and air pollutants (Guan *et al.* 2012; Lin *et al.* 2014). China produces 47% of the world's coal and is also the world's largest importer of coal, thereby accounting for more than half of global coal consumption (BP 2013; Wang and Ducruet 2014). The country also holds coal reserves large enough to maintain current domestic consumption rates for over 60 years (BP 2013), reserves not yet fully utilised due to infrastructure limitations between the mines in the northwest and the consumption centres along the coast (Wang and Ducruet 2014). In 2010, coal provided 76% (3.2 billion GWh) of the electricity consumed in China and 94% of the thermal power production (NBS 2011), of which roughly a third was used for the production of goods aimed for export (Su and Ang 2013). The life cycle emissions from coal power in China therefore influence many life cycle assessments (LCAs), both in and outside of China.

Reducing the emissions from the coal power sector has been a priority for the Chinese government over the last decade (Xu *et al.* 2013). Improvements have also been made by altering the load factor of the power plant (capacity of plant in use), boiler types, the use of scrubbers and the size of power plants. Larger thermal power plants with a capacity to produce over 300 MW have to a great extent replaced older smaller power plants, with their contribution to the overall thermal power capacity increasing from 48 to 73% between 2005 and 2010 (NBS 2011; Xu *et al.* 2013). The majority (over 90%) of the power plants today are also installed with pulverised-coal burners, instead of the fluidised-bed furnaces and stoker-fired boilers used in some of the remaining smaller power plants (Tian *et al.* 2012). This has resulted in a thermal efficiency amongst Chinese coal power plants that actually surpasses that found amongst US power plants (Xu *et al.* 2013), a claim that to a great extent can be verified by the shutting down of small inefficient power plants, reductions in power plants' own use of electricity and improved technology (Xu *et al.* 2013). China's Electricity Council (CEC 2013a) also reports that the ratio of Chinese coal power plants equipped with flue-gas desulphurisation (FGD) units today is 90% and that 98% of all newly built power plants are installed with low-NO_x burners (LNBs). Pollution control measures for particulate matter (PM), including dust collectors, wet FGD units, wet scrubbers and electrostatic precipitators (ESPs), are also being installed at an impressive rate (Zhao *et al.* 2010; Cai *et al.* 2013), resulting in a rapid overall improvement of the Chinese coal sector.

In order to quantify resource extractions and emissions resulting from the provision from coal power, LCA is often used. An LCA quantifies the environmental and economic flows entering and exiting different unit processes in a product's lifecycle. The unit processes are then scaled to a functional unit and aggregated into life cycle inventory (LCI) results. The LCI results can, in turn, be classified and characterised into different impact categories (e.g. global warming, eutrophication and acidification) in the life cycle impact assessment (LCIA) phase. As LCIs often involve a wide range of processes (including e.g. transportation, infrastructure, water, etc.), databases are often consulted, the most extensive and commonly used being the ecoinvent LCI database (www.ecoinvent.org).

The ecoinvent LCI database includes unit processes for Chinese coal power, with data deriving mainly from Dones *et al.* (2004) and Dones *et al.* (2007), describing coal power plants in the

Shandong province just south of Beijing. The structure of these unit processes in version 2.2 of the database is illustrated in **Fig. 4.1** (process IDs referred to in hard brackets). In the latest version of the database (v3), the related unit processes remain largely dependent upon the same unit process dataset, as is also clearly stated: "This is a dataset that was already contained in ecoinvent database version 2 that was not extensively or individually updated during the transfer to ecoinvent version 3". The only two changes to the dataset were the merging of burning [11094] and electricity production [11089] into one unit process (Treyer and Bauer 2013) and a reduction of losses in the transportation of coal from 3% in ecoinvent v2.2 [11094] to 0.2% in ecoinvent v3. In the meantime, a loss of 0.21 kg coal per kg coal mined remained indifferent between the two versions of the database. This loss is related to coal seam fires, started by natural causes or human error, which latently consume large amounts of China's coal reserves annually (Kuenzer *et al.* 2007). The coal then enters the coal supply mix before reaching the power plants with small losses, as mentioned

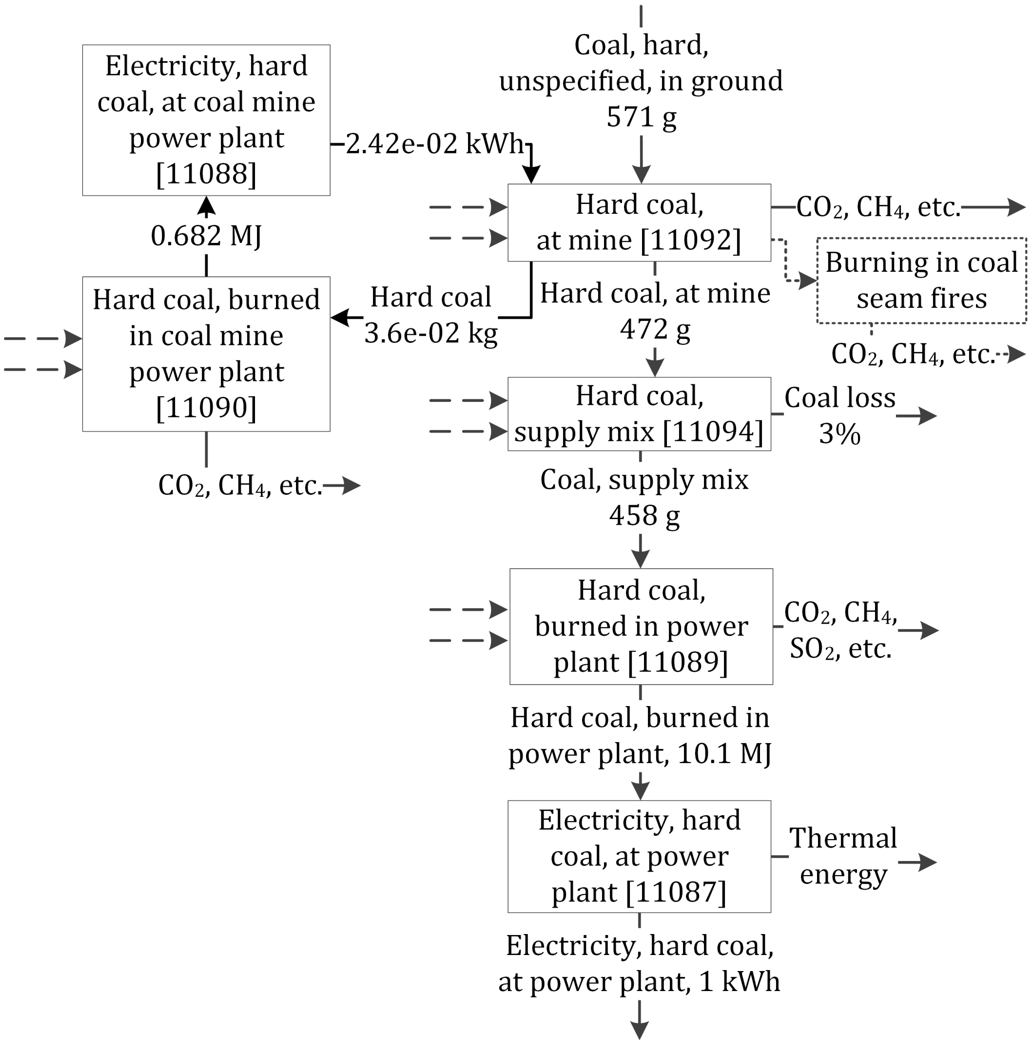

Fig. 4.1: Simplified process tree of Chinese electricity generation from coal in ecoinvent v2.2. Boxes indicate processes, solid lines product/environmental flows, dashed lines additional products not addressed in the present study, and dotted lines/boxes suggested flows/processes.

above. Finally, the coal is burned with an assumed thermal efficiency of 35.6%, indifferent of database version. The ecoinvent data for coal- based electricity generation in China thus represents electricity generation from coal in one province of China in 1998–1999 and assumes no use of FGD units. The limitations of this dataset and its generic nature are also clearly stated in the accompanying report (Dones *et al.* 2007).

A more recent LCI on Chinese electricity generation was presented by Di *et al.* (2007), but again, a lack of FGD units is reported (only 2% of capacity), as well as no control of NO_x in place. Cui *et al.* (2012), in the meantime, reported that 80% of the coal-fired power plants had FGDs and 14% denitrisation systems, but the study only evaluates three types of coal-based electricity generation scenarios. Similarly, Liang *et al.* (2013) acknowledged the extensive use of FGDs and other improvements but only explored possible clean coal power technologies and not the present scenario. The same study, in the meantime, presents data on fuel consumed in the mining process and for rail transportation (Liang *et al.* 2013). Ou *et al.* (2011) present LCA results for Chinese coal power but refer inventory data to a reference untraceable to us. Other studies have also used LCA to evaluate coal-to-liquid pathways (Ou *et al.* 2012; Yang and Jackson 2013).

China is almost the size of Europe and is a very diverse country. The performance of coal power plants, consequently, differs greatly amongst different provinces (NBS 2011). Coal characteristics also differ depending upon which mine they originate from, with e.g. sulphur contents ranging from 0 to 4.6% (Su *et al.* 2011). Scrubbing technologies, in the mean- time, tend to be more advanced around metropolitan areas in attempts to limit harmful particulate emissions (Tian *et al.* 2012; Cai *et al.* 2013). The life cycle emissions per kilowatt hour (kWh) can therefore differ greatly amongst provinces and individual power plants. Despite these discrepancies, most LCAs of Chinese coal energy to date only provide point value estimates. A study of French coal power, however, estimated the uncertainties around life cycle emissions, using generic uncertainty estimates, and highlighted extensive time demands, difficulty to quantify all types of uncertainties and the choice of a representative probability distribution as major challenges for many unit process parameters (Maurice *et al.* 2000). In two later LCAs of US coal, Burnham *et al.* (2012) and Steinmann *et al.* (2014) both present detailed lists of distributions for key parameters, but it remains unclear how these distributions were defined (e.g. goodness-of-fit tests or simply intuition). Meanwhile, Venkatesh (2012) specifies the use of the Akaike information criterion (AIC) goodness-of-fit test in his LCA study but also encounters data that do not fit any of the common probability distributions. In ecoSpold v1, the file format used in ecoinvent v2.2, distributions are defined by two moments (a mean and a variance) fit to one out of four distributions (normal, lognormal, uniform and triangular). In the second version of ecoSpold, the file format used in ecoinvent v3, three additional distributions were added (BetaPERT, gamma and binomial) together with an undefined range estimate (Weidema *et al.* 2012). Meanwhile, lognormal is used as a default distribution for many parameters in both versions of the database, in order to avoid negative values and better represent large variances (Henriksson *et al.* 2013; Henriksson *et al.* 2014a). Distributions in LCIs are consequently often chosen based upon desired characteristics, rather than goodness-of-fit. Moreover, only a few studies acknowledge the existence of covariance (correlated variables), with no LCA to our knowledge accounting for it.

The study will initially detail the different methodological choices made in the goal scope definition in Section 2 (ISO 14044 2006). This is followed by updated unit process data for hard coal at mine [11092] and hard coal burned in power plant [11094], as defined in **Fig. 4.1**. In addition to these two processes, a waste process for coal seam fires is introduced and connected to coal mining [11092], in order to allow for the propagation of overall dispersions for both the amount of coal latently burned and emissions due to the burning of that coal. Subsequently, the results are propagated into inventory results that are presented as overall dispersions around LCI results in Section 3. Finally, conclusions are drawn and future research needs are suggested in Section 4.

4.2 Goal and scope

The aim of the present study was to present updated unit process data for Chinese coal power including estimates for overall dispersions. In the processes of doing so, many inevitable challenges related to calculating and interpreting data needed to be addressed. Therefore, throughout the averaging process, methodological choices and assumptions will be reflected upon and discussed. The main focus will be on pulverised-coal power plants burning bituminous coal in China, given it is the dominant source of Chinese coal energy.

The study adopts an attributional LCA approach, with changes only to the unit processes outlined in **Fig. 4.1**, as these had the strongest influence on LCI results. Thus, all choices related to background unit process data, allocation and system boundaries are those defined in ecoinvent v2.2 (Dones *et al.* 2007). The functional unit is 1 kWh of net electricity at power plant. Infrastructure was not updated in the present study, as it was presumed to have negligible effects on overall emissions (Liang *et al.* 2013). The scope of the study was limited to six environmental flows (CO_2, CH_4, N_2O, NO_x, SO_2 and particulate matter) as they are common contributors to many impact categories (e.g. global warming, eutrophication, acidification and human health). Many of the updated parameters also act as scaling factors and therefore result in improvements for all life cycle flows. Studies adopting the present dataset should, however, consider updating emissions and resource extractions specific to the impact categories under evaluation.

The protocol presented in Henriksson *et al.* (2013) was used to define parameters. According to this protocol, overall dispersions (σ_o) are quantified as the sum of inherent uncertainties (σ_u; inaccuracies in measurements and models), spread (σ_s; variability in horizontally averaged data) and unrepresentativeness (σ_r; mismatch between data sources and their application). Unrepresentativeness was evaluated according to the pedigree scores and uncertainty factors presented by Frischknecht *et al.* (2007b) and reported as indicator scores within brackets. The characteristics evaluated in this pedigree include reliability, completeness, temporal correlation, geographical correlation, further technical correlation and sample size (Frischknecht *et al.* 2007b). The protocol further promotes central values that correspond with those assumed by the software used, which is the arithmetic mean for Chain Management by Life Cycle Assessment (CMLCA), with weighted means based upon the inherent uncertainty and unrepresentativeness representing secondary data (Henriksson *et al.* 2013; Henriksson *et al.* 2014a). The presented unit process dataset was also propagated into LCI results using Monte Carlo simulations. This allowed for the accuracy of results and spread amongst Chinese provinces to be evaluated.

Ranges are presented as coefficients of variation (CVs), as these can be easily converted to either Phi, the input parameter for lognormal distributions in the CMLCA v5.2 software (cmlca.eu), or "SD95" the uncertainty parameter used in ecoSpold (Heijungs and Frischknecht 2005). Ranges of more than eight data points were transposed to a distribution using Anderson-Darling tests in the EasyFit software v5.5 (mathwave.com). The Anderson-Darling test is a modification of the Kolmogorov-Smirnov test that gives more weight to the tail of the distribution and has been argued as more robust when evaluating independent outcomes, as e.g. Monte Carlo outcomes (Noceti *et al.* 2003). When less than eight data points were available, a lognormal distribution was assumed. In cases where confidence intervals (CIs) were presented around central values, as e.g. in the Intergovernmental Panel on Climate Change (IPCC) guidelines, the distribution was assumed from the upper and lower 95% CI's relation to the central value. The CV was thus estimated assuming Eq. (4.1) for normal distributions and Eq. (4.2) for lognormal distributions:

$$CI95\pm = \bar{x}_a \pm 1.96\sigma_a \qquad \textbf{Eq 4.1}$$

$$CI95\pm = \bar{x}_g \sigma_g^{1.96}; \bar{x}_g / \sigma_g^{1.96} \qquad \textbf{Eq. 4.2}$$

where $\bar{x}_a$ is the arithmetic mean, σ_a the arithmetic standard deviation, $\bar{x}_g$ the geometric mean and σ_g the geometric standard deviation. Additional equations used to derive and combine CVs were taken from Henriksson *et al.* (2013). For the economic flows where inherent uncertainties were not available, a default CV of 0.05 was assumed. We acknowledge the crudeness of some of these estimates and that the presented central value sometimes had to be assumed as a geometric mean, but find the small discrepancies resulting from the current approach are negligible in proportion to the scale of the overall dispersions. Covariance was not accounted for in the current models. Once parameters were defined, data modelling and propagation were conducted in the CMLCA software by running 1000 randomly sampled Monte Carlo simulations.

4.3 Life cycle inventory

4.3.1 Unit process data

4.3.1.1 Hard coal, at mine [11092]

Coal production in China has increased with 36% since the release of Dones *et al.* (2007) to almost 2700 Mt year^{-1} (BP 2013). Meanwhile, the current amount of coal being passively burnt in seam fires has been reported to amount to between 5 and 200 Mt (0.2 and 7.4% of the coal mined) (Rosema *et al.* 1993; Kuenzer *et al.* 2007; van Dijk *et al.* 2011). The weighted mean amongst these reported values calculated according to Henriksson *et al.* (2013) equalled 26 g coal per kg coal mined (2.6%). The overall dispersion around this value, assuming an inherent uncertainty of σ_u = 0.31 according to the estimates of van Dijk *et al.* (2011), added up to an overall dispersion of σ_o = 1.39. As the two dispersion parameters are consequent to each other (amount of coal burned and resulting emissions from burning that coal) and another methane flow from coal mining needed to be defined for coal mine methane (CMM, see below), the best way to include coal seam fires was to create a waste flow and a separate process for burning in coal seam fires.

A flow of 0.026 kg (σ_o = 1.39) "hard coal, burned in coal seam fires" should therefore be connected per kilogram coal mined [11092], and the flows defined in **Table 4.1** disconnected. In place of methane, a flow of CMM needs to be connected. In China, CMM emissions have been estimated to 13.8 Mt year^{-1} with a release of 4.5–7.2 kg CH_4 per tonne of mined coal (estimated σ_u = 0.3) (Zhang and Chen 2010; Cheng *et al.* 2011). The environmental outflow of methane from the process "hard coal, at mine [11092]" should therefore be reduced from 1.69e^{-2} to 6.05e^{-3} kg CH_4 per kg of hard coal mined with a CV of σ_o = 0.385. The environmental input of "coal, hard, unspecified, in ground" also needs to be adjusted to 1 kg.

Mining and the supply mix of coal also consume electricity, which need to be corrected for in the unit process data. One of the electricity-generating processes involved, "hard coal, at coal mine power plant" [11088], describes highly inefficient power generation (15% thermal efficiency) at the mine site, thus resulting in a large coal consumption ((3.6 MJ/0.15)/ 27.1 MJ kg^{-1} coal = 886 grams of coal equivalent (gce) per 3.6 MJ^{-1} or kWh^{-1}) (Dones *et al.* 2007). Emissions from this power-generating process were modelled neglecting air pollution control devices, as described below. Moreover, noteworthy is that only one train line in China remains serviced by coal steam engines; transportations by rail were therefore adjusted to 71% diesel locomotives and 29% by electric locomotives (Liu *et al.* 2013).

4.3.1.2 Hard coal, burned in coal seam fires

Emissions of carbon dioxide (CO_2), methane (CH_4) and dinitrogen monoxide (N_2O) from burning of coal were calculated according to IPCC (Gómez *et al.* 2006), and sulphur dioxide (SO_2), nitrogen oxides (NO_x) and particulate emissions according to (Zhao *et al.* 2010) and Su *et al.* (2011) (see below), assuming uncontrolled burning as a proxy for coal seam fires. Also, 1 kg of hard coal extracted from the ground needs to be connected (**Table 4.1**).

Table 4.1: Unit process data for the process "Burning in coal seam fires", resource extraction and emissions resulting from coal seam fires per kg of coal mined in China

Unit process flow	Unit	Value, kg	σ^r	σ^o	Distribution
Waste input					
Hard coal, burned in coal seam fires	kg	1	-	-	-
Environmental input					
Coal, hard unspecified	kg	1	-	-	-
Environmental output					
Carbon dioxide, to air	kg	2.55	2,1,1,2,1,3	0.047	N
Methane, fossil, to air	kg	2.70e-05	2,1,1,2,1,3	0.652	LN
Dinitrogen monoxide, to air	kg	4.05e-05	2,1,1,2,1,3	0.652	LN
Sulphur dioxide, to air	kg	1.84e-02	3,1,2,1,1,3	0.331	LN
Nitrogen oxides, to air	kg	8.37e-03	3,1,2,1,1,3	0.323	LN
PM >10, to air	kg	1.16e-01	2,1,2,2,1,3	0.531	LN
PM 2.5-10, to air	kg	2.40e-02	2,1,2,2,1,3	0.837	LN
PM <2.5, to air		9.33e-03	2,1,2,2,1,3	0.857	LN

4.3.1.3 Burning at power plant [11089]

Coal comes in many kinds and qualities, which influence both energy content and emissions (Zhao *et al.* 2008; Steinmann *et al.* 2014). Anthracite (black coal) is considered of highest quality, followed by bituminous coal, and finally lignite, which is also related to the largest GHG emissions (Steinmann *et al.* 2014). In 2008, roughly 77% of all coal consumed in China was bituminous, 16% anthracite and 7% lignite (CCI 2010). Apart from the type of coal burned, emissions from coal power plants are influenced by the sulphur and ash content of the fuel, the sulphur retention in ash, the emission control technologies adopted and the coal consumption per kilowatt hour produced (Zhao *et al.* 2008).

Higher heating values (1.07 times the lower heating value) for bituminous coal in China have been reported ranging from 23.7 to 30.5 MJ kg^{-1}, while for anthracite, these values range from 31.4 to 31.8 MJ kg^{-1} (Patzek and Croft 2010). Thermal power generation efficiency in Chinese coal power plants has increased from 392 gce kWh^{-1} or 33.9% in 2000 to 370 gce kWh^{-1} in 2005, 333 gce kWh^{-1} in 2010 and 321 gce kWh^{-1} or 41.4% in Jan–Aug 2013 (CEC 2011; CEC 2013b). The thermal efficiency, however, differed greatly amongst provinces, from 282 gce kWh^{-1} in Beijing to 409 gce kWh^{-1} in Xinjiang (NBS 2011). As data on individual power plants were limited, the spread for thermal efficiency amongst power plants within provinces was estimated to σ_u = 0.035 based upon Xu *et al.* (2011).

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Table 4.2: Important parameters for calculating the emissions from Chinese power plants.

Flow	Unit	Value,	CV	Distribution
Coal	g kWh^{-1}	333	0.062	Lognormal
Higher heating value	MJ kg^{-1}	27.1	0.064	Normal
Sulphur content	%	1.02%	0.44	Lognormal
Sulphur retention in ash	%	10%	0.22	Lognormal
FGD efficiency	%	59%	0.174	Normal

The carbon dioxide emissions presented by the IPCC from burning of bituminous coal are 94.6 g MJ^{-1} (σ_u=0.03) (Gómez *et al.* 2006). The CIs around this value also suggest a symmetric distribution, with the normal distribution being the most logical choice given the central limit theorem. However, since the tails of a normal distribution exceed the amount of CO_2 that theoretically can be emitted by burning coal, a triangular distribution was used for carbon dioxide emissions. IPCC also reports methane emissions from coal power plants of 1e−03 g MJ^{-1} (σ_u = 0.65) and emissions of N_2O of 1.5e−03 g MJ^{-1} (σ_u = 0.65) (Gómez *et al.* 2006). Meanwhile, sulphur contents of coal vary from low in the northeastern parts of the country to relatively high in the southern parts (Su *et al.* 2011). The national average is 1.02% (σ_s = 0.326), with provincial sulphur contents available in the Electronic supplementary material of this article (Su *et al.* 2011). Reports on sulphur retention in ash range from 5 to 15%, with an estimated average of 10% (σ_u = 0.255) (Zhao *et al.* 2008; Zhao *et al.* 2010). Wet FGD units are most common and have a potential sulphur removal efficiency of 95%, while dry and simple scrubbers have removal efficiencies of 80 and 17%, respectively (Zhao *et al.* 2010). However, poor performance and limited operating rates

Table 4.3: Updated unit process data flows for average Chinese coal-based electricity production in 2010. For ecoinvent v2.2 structure, please divide the values with the MJ per kWh provided on the second row and adjust accordingly. LN = Lognormal; T = Triangular.

	Unit	Dones et al. 2007	China, whole		Beijing		Xinjiang		Coal mine power plant		
MJ kWh^{-1}		10.1 MJ	9.02 MJ		7.64 MJ		11.08 MJ		24.0 MJ		
		$\overline{x}$	$\overline{x}$	CV	$\overline{x}$	CV	$\overline{x}$	CV	$\overline{x}$	CV	Dist.
Updated economic inflows											
Hard coal supply mix	kg	4.58e-01	3.33e-01	0.080	2.82e-01	0.052	4.09e-01	0.052	8.86e-01	0.052	LN
SOx retained, in hard coal flue gas desulphurisation	kg	0	3.63e-03	0.453	3.18E-03	0.273	2.28E-03	0.120	0	-	LN
NOx retained, in LNBs	kg	0	1.07e-03	0.380	1.44E-03	0.339	1.03E-03	0.339	0	-	LN
Electricity, high voltage, at grid	kWh	0	0.121	0.775	0.121	0.775	0.121	0.775	0	-	LN
Economic outflows											
Electricity, hard coal, at power plant	kWh	1E00	1E00	-	1E00	-	1	-	1	-	-
Environmental outflows											
Carbon dioxide, fossil	kg	9.60e-01	8.54e-01	0.076	7.23E-01	0.047	1.049	0.046	2.271	0.046	T
Methane, fossil	kg	1.01e-05	9.02e-06	0.655	7.64E-06	0.652	1.11E-05	0.652	2.40E-05	0.652	LN
Dinitrogen monoxide	kg	5.05e-06	1.35e-05	0.655	1.15E-05	0.652	1.66E-05	0.652	3.60E-05	0.652	LN
Sulphur dioxide	kg	7.81e-03	2.58e-03	0.432	3.18E-03	0.447	2.48E-03	0.447	1.63E-02	0.331	LN
Nitrogen oxides	kg	4.12e-03	1.72e-03	0.367	9.16E-04	0.334	2.40E-03	0.323	7.42E-03	0.315	LN
Particulates, <2.5 μm, to air	kg	4.27e-04	2.57E-04	1.046	2.67E-04	1.042	3.87e-04	1.042	8.27E-03	1.042	LN
Particulates, >2.5 um, and < 10um, to air	kg	5.02e-05	4.35E-04	0.840	4.46E-04	0.837	6.47E-04	0.837	2.13E-02	0.837	LN
Particulates, > 10 um, to air	kg	1.07e-04	1.82E-03	0.552	1.72E-03	0.531	2.49e-03	0.531	1.03E-01	0.531	LN

due to high running costs have resulted in practical removal efficiencies of between 66 and 75% (average 70.5%, σ_u = 0.136) (Zhao *et al.* 2011; CEC 2013c).

Emissions of NO_x are controlled by the temperature and degree of oxygen enrichment, which in turn depend upon the type of coal, unit capacity, burner and air pollution control devices. Measures to limit NO_x emissions include LNBs and selective catalytic reduction (SCR) units, with removal efficiencies of 27 and 43%, respectively (Zhao *et al.* 2008). China's Electricity Council (CEC 2013a) reports that generators equipped with LNB facilities generated 28% of the thermal power in 2012. Meanwhile, SCRs are only incipient in China at this point (Zhao *et al.* 2010). From these data, parameters for unit process data could be calculated according to the formulas provided by Zhao *et al.* (2010) (**Table 4.2**). A full list of province-specific parameters is provided in the Electronic supplementary material of this article.

PM is one of the most prominent risks to human health associated with coal power generation in China (Zhang *et al.* 2010). The amount of particles emitted depends upon the ash content of the fuel, the ratio of bottom ash to total ash, the particulate mass fraction by size, the particulate size and again the pollution control devices adopted. The removal efficiencies of installed ESPs are 98.1–99.5% of total PM, while when combined with wet FGD units, up to 99.8% of the particulates can be removed (Zhao *et al.* 2010). Assuming an average ash content in fuels of 22.0% (σ_s = 0.24), the emissions could be calculated adopting equations provided by Zhao *et al.* (2010). As for NO_x emissions, a pollutant concentration in the flue gas of 900 mg Nm^{-3} (σ_u=0.31) was assumed together with a flue gas volume of 9.3 m3 kg^{-1} (σ_u = 0.065, based upon an excess air coefficient of 1.25, ranging from 1.1 to 1.4). In order to be consistent with other ecoinvent processes, the processes "NO_x retained, in SCR" [882] and "SO_x retained, in hard coal flue gas desulphurisation" [883] also need to be connected.

Electricity is also used in the power plant itself for its operation, maintenance and repairs. According to the International Energy Agency (IEA; iea.org accessed October 3, 2014), the energy industries' own use in China across all kinds of electricity plants amounts to 12.1%. However, with regard to US electricity production, the IEA reports an own use of 7.8% across power sectors, while a more detailed account from the US Energy Information Administration (eia.gov accessed October 3, 2014) reports an electricity own use of 11.5±10.4% for coal power plants. The own use of 12.1% reported by the IEA for China was therefore used in the present study, with an assumed spread of σ_s = 0.904 based upon the US example.

Averaged updated unit process data flows for the whole of China are presented in **Table 4.3**, alongside Beijing, Xinjiang and coal mine power plants (CPP). Beijing was selected for having the best thermal efficiency and Xinjiang for having the worst. Naturally, features such as coal quality and flue gas treatment also influence emissions, resulting in each province exhibiting its own unique set of emissions. However, for the purpose of the present research, we will only explore two provinces. Emissions from coal mine power plants were included as a rough proxy for unregulated coal combustion, a still common practice throughout China (e.g. in small boilers and power generators). Data at provincial level were calculated with regard to thermal efficiency, sulphur content and pollutant removal technologies (NBS 2011; Su *et al.* 2011; Cai *et al.* 2013). For a detailed description of all provinces, see the Electronic supplementary material of this article.

4.3.2 Life cycle inventory results

The propagated LCI results for the production of 1 kWh net electricity at power plant using ecoinvent (ecoi) data and the updated unit process datasets for China (CN), Beijing (BJ), Xinjiang (XJ) and coal mine power plants (MPP) are presented as box-and-whisker plots in **Figs. 4.2, 4.3, 4.4, 4.5, 4.6** and **4.7**. The central line represents the median, the edges of the box the 25th and 75th percentiles and the whiskers the first and last deciles (10th and 90th percentiles) (see **Fig. 4.2**), in line with Bowley's seven-figure summary (excluding the min and max values in order to maintain better scaling). Overall, the emissions from the updated unit process dataset averaged across China resulted in lower emissions than the ecoinvent estimates, with the exception of dinitrogen monoxide. For ecoinvent, Dones *et al.* (2007) assumed 0.5 kg N_2O TJ^{-1} coal burned based upon a number of publications from 1988 to 1996, while the current study adopted the IPCC estimate of 1.5 kg N_2O TJ^{-1} (Gómez *et al.* 2006). Carbon dioxide emissions were only slightly lower for the updated processes as they are largely based upon the amount of fuel used and the carbon content of that fuel. Sulphur dioxide, nitrogen oxides, methane and particulate emissions, however, were between 49 and 67% lower in this study compared to those in ecoinvent. Coal power plant emissions amongst provinces also indicated a large spread, especially for nitrogen oxides (2.5 higher in Xinjiang compared to Beijing). Coal mine power plants (uncontrolled) unsurprisingly had the largest emissions, where particulate emissions stood out as especially worrying.

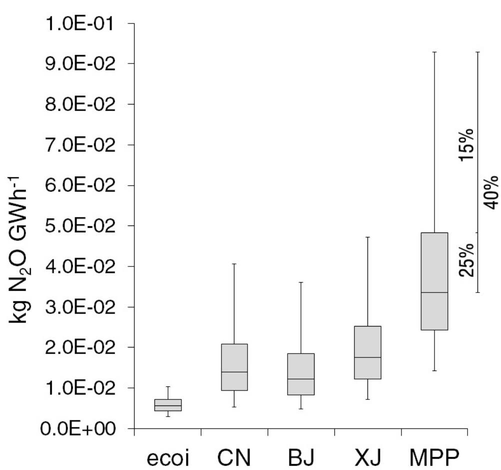

Fig 4.2: Box-and-whisker plot of the life cycle dinitrogen monoxide emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

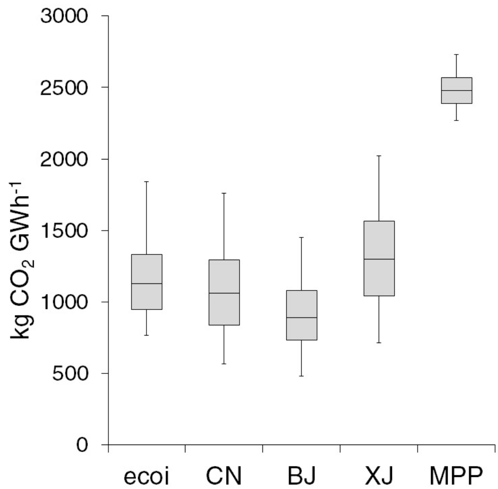

Fig 4.3: Box-and-whisker plot of the life cycle carbon dioxide emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

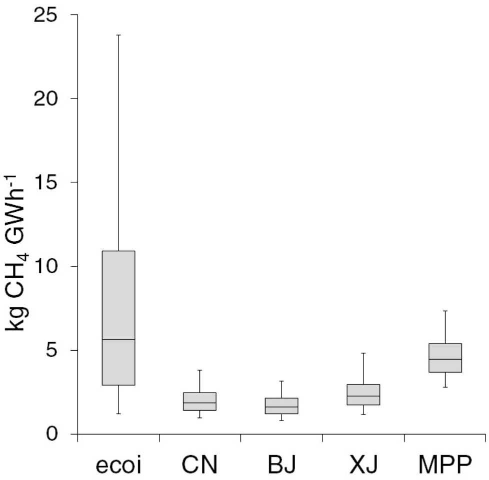

Fig 4.4: Box-and-whisker plot of the life cycle methane emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

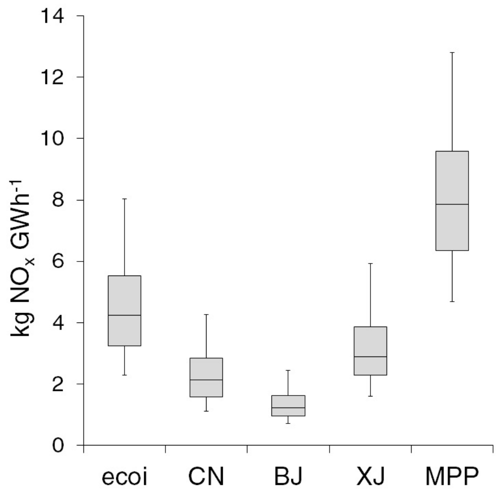

Fig 4.5: Box-and-whisker plot of the life cycle nitrogen oxides emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

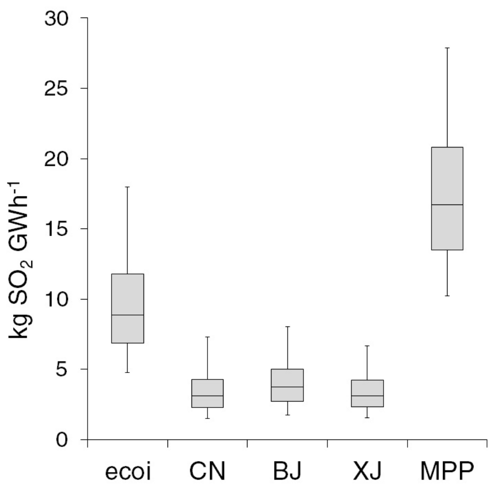

Fig 4.6: Box-and-whisker plot of the life cycle sulphur dioxide emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

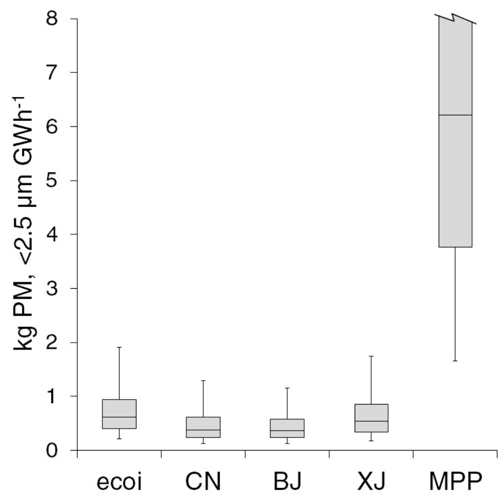

Fig 4.7: Box-and-whisker plot of the life cycle particulate emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

Spread had a much stronger influence on economic flows (41–63% of the overall dispersions) than unrepresentative- ness (only 4–7% of the overall dispersions). Meanwhile, the default inherent uncertainties used by ecoinvent often exceeded the calculated overall dispersions for environmental emissions. This was the result of ecoinvent using large generic basic uncertainty factors to capture inherent uncertainty and spread, a simplified practice that resulted in some strange outcomes. For example, an environmental inflow of 1.21 kg of hard coal per kg hard coal produced was assumed by ecoinvent in the mining process [11092], with an accompanying lognormal uncertainty estimate of SD95 = 1.5, resulting in a 95% CI of 0.81–1.8 kg of coal extracted per kg delivered, which is an "impossible" range in terms of mass balance.

4.4 Discussion and conclusions

Over the last decade, China has cleaned up its coal power sector quite effectively. As a consequence, the unit process data on coal-based electricity production in China available in the ecoinvent database have become outdated and overestimate most emissions from the Chinese coal sector. For example, the methane and carbon dioxide emissions from coal mining per kWh generated in the present study were only 32 and 17% of those estimated by Dones *et al.* (2007). This was largely due to increases in the quantity of coal mined (with the number of coal seam fires and amount of CMM seeming to have remained similar) and energy efficiency improvements within the power plants. A rapid implementation of air pollution control devices has also greatly reduced the sulphur dioxide, nitrogen oxides and particulate emissions from the Chinese power sector over the last decade. While generally disregarded in previous inventories, reductions of up to 99% of the emissions are documented in the present research. However, uncontrolled coal combustion, such as those at the coal mine power plant, remains a very dirty source of energy and is better replaced by grid electricity.

The scale of the overall dispersions estimated in this study was quite similar to that concluded by Steinmann *et al.* (2014) in their study of the US coal power sector. Steinmann *et al.* (2014) additionally concluded that spread (variability) is more prominent than inherent uncertainty, a conclusion that could not be reconfirmed in the present study. The reason for this could be that Chinese power generation is more uniform than American. Another more likely explanation is that the level of horizontal averaging and the modelling assumptions differ between the two studies.

Populations are difficult to typify and rarely distributed exactly as their mathematical ideals (Serlin 2000). In the present research, many of the data ranges could neither be statistically argued to fit any of the distributions commonly available in LCA software and databases (uniform, triangular, normal or lognormal). Other ranges were fit to distributions that resulted in physically impossible MC outcomes (e.g. unrealistic physical balances). This is one of many inevitable consequences of fitting natural processes into quantitative models and one of many arguments often used to unsettle environmental model predictions (Pilkey and Pilkey-Jarvis 2007). Simply discounting unrealistic values as outliers is not recommended, as it will shift the central value. Instead, there are several steps that should be taken to limit the number of counter-intuitive outcomes. For example, in the present study, we disaggregated the emissions from coal seam fires from the mining process to make sure that the amount of coal leaving the mine would not exceed the amount extracted from the ground. Also, by adopting a triangular distribution for carbon dioxide emissions, the upper bound could not exceed the physical limit set by the amount of carbon burned. Ultimately, however, we encourage practitioners to acknowledge that all distributions have their limitations and to communicate these alongside their quantitative dispersion estimates. We also encourage the option to enable practitioners to better define and evaluate data in software and databases, e.g. by allowing for the implementation of the third and fourth moments (skewness and kurtosis). Another desired improvement would be to allow for covariance correlations in LCI models, where e.g. low SO_2 emissions could be correlated with the amounts of SO_x retained in the flue gas desulphurisation unit.

Since propagated LCI results rarely are normally distributed, the use of the arithmetic means as the central values should also be questioned. This is due to the strong influence of outliers (which sometimes are produced in random Monte Carlo sampling) on arithmetic means. Box-and-whisker plots were therefore deemed useful as they provide a rough indication of the distribution of these non-parameterised data. The computational matrix of LCIs can also result in inverted operators (pluses become minuses or the other way around) as a result of random sampling of normal distributions (which theoretically can yield both negative and positive operators) or circular product flows (e.g. if by chance the coal used by the coal mine power plant exceeds that produced in coal mining in one Monte Carlo run) (Heijungs and Suh 2002). This phenomenon was observed in the Monte Carlo outcomes of the present model (at roughly 3‰ of the iterations) but only noticed because the raw data were critically evaluated and negative inverted values removed. Identifying inverted operators would, however, be much more difficult in more complex models where only partial emissions are inverted and the final outcome ends up with the expected operator (e.g. positive values for emissions). As a result of the above-mentioned features, the mean and the "baseline" (the point values commonly calculated in LCIs) easily deviate from each other, which consequently puts point value results into question. As no clear definition of the baseline exists to our knowledge, and today most likely is a mix of means, medians and expert judgments, we promote a more robust nomenclature for statistical parameters in the field of LCA.

In a recent editorial commentary in the present journal, the limitations of case studies largely relying on modern LCA software and LCI databases were addressed (Klöpffer and Curran 2013). The large differences observed in the present research reconfirm these concerns, bringing us to some suggestions on how the situation could be improved. Firstly, databases should be updated regularly to reflect the contemporary state of technologies as appropriately as possible, for which sufficient resources should be made available. Secondly, LCA practitioners need to comply with the ISO 14044 (2006) requirement of checking the validity of LCI data, especially for processes that heavily contribute to important inventory results, using generic unit process data only to fill gaps which otherwise would be excluded. In response, presenting unit process data in a way similar to the present study allows practitioners to more easily amend and update their inventories. It is also encouraged to share raw data, as limited reporting on data has proven to be a major hurdle in the implementation of dispersions in the field of LCA (Henriksson *et al.* 2012c; Henriksson *et al.* 2014b).

In the present study, we focused only on a limited number of provinces and emissions for practical reasons. While these emissions are related to some of the most commonly used impact categories, other emissions from the above-mentioned processes will most likely also be influenced by the improvements in the Chinese coal power sector (e.g. heavy metals, carbon monoxide, etc.). We therefore encourage further efforts towards updating the inventory for the world's single largest energy-producing sector. Another improvement would be to evaluate the spread amongst individual power plants, data that were unavailable for the present study. This could also help to critically evaluate some of the questionable data provided by the Chinese government (Guan *et al.* 2012). We also encourage more research into the handling of dispersions in the field of LCA, as calculations, modelling choices and interpretation all influence outcomes.

Acknowledgments

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