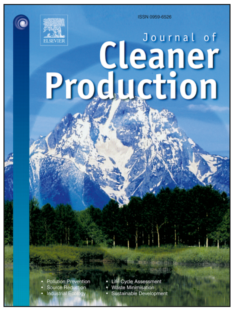

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C. Kennelly, M. Berners-Lee, C.N. Hewitt

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Hybrid life-cycle assessment for robust, best-practice carbon accounting

C. Kennelly[1], M. Berners-Lee[2,3*] and C.N. Hewitt[1]

1. Lancaster Environment Centre, Lancaster University, Lancaster LA1 4YQ UK

2. Small World Consulting Ltd, Lancaster Environment Centre, Lancaster University, Lancaster LA1 4YQ UK

3. Institute of Social Futures, Lancaster University, Lancaster LA1 4YQ UK.

* corresponding author

Email addresses:

cara.kennelly@gmail.com

m.berners-lee@lancaster.ac.uk

n.hewitt@lancaster.ac.uk

Abstract

In order to meet internationally agreed targets for avoiding dangerous anthropogenic climate change, an absolute priority for global society is to rapidly stabilise and then reduce carbon dioxide emissions into the atmosphere. Any entity, be it individual, company, or nation state, is more able to reduce its carbon dioxide (and other greenhouse gas) emissions if these can be quantified and attributed and the effects of interventions estimated. The current state of product and supply chain carbon accounting methods does not consistently meet the standards required to tackle this global challenge. This study therefore aims to identify key methodological practices affecting the accuracy of carbon accounting models and in particular to assess the effects of the system boundaries they employ. Models currently available for estimating carbon emissions are either input-output based (using macro-economic analysis), process-based (using specific carbon emissions attributes through the life-cycle of a product, service or event), or a hybrid of the two. Here, a detailed comparison has been made between various input-output and process-based models and the results compared with those from a hybrid model that was taken to represent 'best practice' in carbon accounting. Key factors affecting accuracy were found to lie in: the detail of methodological decisions for input-output models, the economic region or regions upon which the model is based, and the quality, disaggregation and, especially for price-volatile products, the temporal alignment of the data. The relative significance of these factors is explored. For copper wire, a system boundary gap analysis was conducted on an industry-leading process-based model (GREET.net) compared with a complete system as described by the best performing input-output model. GREET.net was found to suffer a 60% truncation error. The copper wire example demonstrates the practicality of substituting process-based analysis into input-output based supply chain emissions assessments.

Key words

Carbon accounting; embodied carbon; input-output models; life cycle analysis; process-based analysis

1. Introduction

Climate change is arguably the most important global environmental issue faced by humanity (IPCC, 2014). A key part of addressing climate change is reducing the emissions of greenhouse gases associated with specific goods and services, often called the 'carbon footprint' of a product or activity. The goods and services that businesses provide are key sources of carbon dioxide and other greenhouse gases (collectively expressed in units of carbon dioxide equivalents: CO_2e). Estimating the magnitude of emissions allows mitigation efforts to be directed more strategically, which is particularly important following ratification of the Paris Climate Agreement (2016) and anticipated zero-carbon policies. Despite the complexities and uncertainties, company supply chain carbon accounting is gaining popularity as businesses increasingly seek to become 'Paris compliant'. For example, the Science Based Targets Initiative (http://sciencebasedtargets.org/), to which over 400 companies have committed, requires an element of supply chain carbon reduction and has recently started pressing for science-based scope 3 targets alongside the more traditional emphasis on scope 1 and 2 emissions.

Currently, two different types of models are available for estimating embodied or supply chain carbon emissions: input-output (IO) based models that use macro-economic analysis (e.g. Bullard et al., 1978; Brizga et al., 2017), and process-based (PB) models that use specific carbon emission attributes through the life-cycle of a product or activity (e.g. Samaras and Meisterling, 2008), and hence are sometimes known as life-cycle assessments. Hybrid methods that contain elements of the two are also used (e.g. Pomponi and Lenzen, 2018). This study compares a PB model, four IO models (see Table 1) and a constructed 'best-practice' hybrid model with the aim of identifying what effects different methodological choices have on the accuracy and precision of a carbon accounting model. We use the production of copper wire as a case study.

The debate between PB and IO carbon accounting methods is still on-going (e.g. Yang et al., 2017; Pomponi & Lenzen, 2018) and additions to the evidence base for this debate will bring us closer to its conclusion. Hybrid carbon accounting models and the system boundary identification methods used within them are research areas in relative infancy. Thus additional research on best-practice maintains and advances the scientific conversation on improvement of the methods.

2. Carbon accounting methods

2.1 Input-output carbon accounting models

IO analysis is a ‘top-down’ technique that uses financial transaction data to account for the complexities of modern production and consumption systems (Lenzen, 2000). By applying known environmental data to this method it can be “environmentally extended”, creating an ‘EEIO’ (environmentally extended IO) model. IO is well described, consistent, and can be applied at various scales to a wide variety of products and services. It is standardised and, despite limitations at the micro level (Wiedmann, 2009), has economy-wide completeness and an unambiguous consumption-production link. Due to the versatility of the method, IO analysis can be used to evaluate trade-offs in decision-making scenarios between carbon, financial and social objectives (Weber et al., 2009). Despite the relative complexity of creating IO models, their operation, once established, is relatively simple, and the necessary data is often readily available (Wiedmann, 2009).

At the heart of IO models are matrices which map the trade between economic sectors. In carbon accounting, the system under investigation is usually an economy at regional, national or international scales. The relationships are mathematically described using the Leontief inverse which follows the equation: $L = (I-A)^{-1}$where I represents the identity matrix and A represents the technical coefficient matrix. A detailed description of the theory behind this equation and how to build an IO model can be found, for example, in Miller and Blair (2009).

Until recently, IO models described only a single-region of production and trade, but latterly some have been redesigned to represent multiple regions, in an attempt to better represent the globalised nature of modern economies (for summaries of these multi-regional IO databases and trends see: Murray and Lenzen, 2013; Inomata and Owen, 2014). However, this has substantially increased the data requirement of IO models (Andrew et al., 2009). IO analysis has inherent limitations and uncertainties, including but not limited to: aggregation error; atypical expenditure; economic category changes; data update requirements; and method inaccessibility. An in-depth analysis of IO model limitations can be found in Andrew et al. (2009).

2.2 Process-based life-cycle assessments

PB analysis is a ‘bottom-up’ approach to carbon accounting that involves itemised estimation of the carbon burden of each step in a product’s life-cycle. PB analysis is often high cost, labour-intensive, inflexible and always has subjective boundary definition (Joshi, 1999) which leads to truncation errors (Lenzen, 2000) as the diminishing contribution of infinite terms creates limits where it is too costly or labour intensive to extend the system boundary further. The truncation error is the numeric gap between the reported figure and the actual figure caused by the exclusion of supply chain pathways, meaning that not all of the carbon emissions are accounted for (Ward et al., 2017). The carbon cost of processes beyond the system boundary can be very substantial (up to 87% in one analysis; Crawford, 2008).

Although there have been many previous publications of PB life-cycle analyses, these have often been either so specific as to be irrelevant to most carbon intensity analyses (for example: Pearce et al., 2013; Hu, 2012; Stylos and Koroneos, 2014) and/or funded by businesses and hence open to bias (for example: Kumar et al., 2014, funded by HP and Ayushmaan Technologies; Zhang et al., 2015, funded by the Kunming Engineering Corporation Ltd). Even the methods used in life-cycle assessments (LCAs) can be subject to possible biases (e.g. Steinmann et al., 2014, funded by ExxonMobil). Hence a robust, transparent and standardised approach is needed to enable widespread use and understanding of carbon footprints and life-cycle analyses.

Because of truncation errors, the amount of carbon embodied in a product estimated by PB analysis is generally lower than that estimated by IO analysis (Lenzen and Dey, 2000; Lenzen and Treloar, 2002; Crawford, 2008). However, there are exceptions which may be caused by better quality and/or quantity of process data than is usually available (Crawford, 2008) but these exceptions can be based on unusual circumstances or unrealistic settings for tests (e.g. Pomponi and Lenzen, 2018). Despite the different PB analysis approaches, truncation error is always significant and usually unquantified (Suh et al., 2004).

2.3 Hybrid carbon accounting methods

A hybrid carbon model uses both PB and IO data and the application of a system boundary selection process to describe where to use each model in order to utilise the best of each methodology and to count all emissions only once. A hybrid model stands to combine the system-completeness and cost-effectiveness of a top-down model (Wiedmann, 2009) with the specificity that a bottom-up approach can make possible (Bullard et al., 1978). These improvements are widely thought to give hybrid approaches the potential for greater accuracy than purely PB or IO models (Crawford, 2008) and thus have been recommended as being superior to either of the two “base” model types (Minx et al., 2008; Lenzen, 2002).

There are three main methods of hybridisation: tiered, integrated, and path-exchange. Tiered methods use IO data to fill the gaps left by process-based data, but can result in double counting if system boundaries are not fully and consistently defined (Strømman et al., 2009). The integrated method is based on make-use level process and economic data disaggregation and requires large data input and high complexity (Heijungs and Suh, 2002; Suh, 2004; 2006). Path-exchange hybrid methods begin with a structural path analysis after which relevant average IO factors can be replaced with specific process-based factors (Treloar, 1997; Lenzen and Crawford, 2009). All three of these methods require thoroughly understood and defined system boundaries to function optimally.

2.4 Consumption-based accounting

Consumption-based accounting, based on IO theory, has dominated carbon accounting methods recently due to its methodological grounding in economics, ease of data gathering and its system completeness. While production-based accounting methods show only a limited part of the carbon emission embodied in a product, an IO model can describe the entire supply chain. This is an increasingly important dimension of the environmental impact of products as markets and society become more complex. Analyses of supply chains through consumption-based accounting can help identify and address risks that are intrinsically tied to procurement, such as resource taxation, price volatility and availability shocks (Owen et al., 2017). It is crucial for a regulatory body, at any spatial or political scale, to have an understanding of the causes, drivers and mitigation strategies for these risks. This method can and has been used to inform and influence national policy as countries respond to these risks (Barrett et al., 2013), and in the UK this function of consumption-based accounting has proved invaluable, providing information that would otherwise not be available to decision-makers (Wiedmann and Barrett, 2013) at both national and local levels (e.g. Energy and Climate Change Committee, 2012; Small World Consulting Ltd., 2011; 2017). Accuracy and consistency in these analyses encourages stability in emissions reduction programmes and supply chains that can be destabilised by economic, political or environmental factors.

2.5 System boundary selection

All models require the setting up of system boundaries, beyond which the model does not venture. In the case of carbon accounting models these boundaries may be selected on the basis of physical allocation, economic allocation, or system expansion (BSI, 2006). The results of studies that employ different system boundary identification methods cannot be compared to each other (Lenzen, 2000) as there is different methodological treatment of data falling on either side of the system boundary (e.g. Chau et al., 2015). It is therefore important not only to identify the most appropriate system boundary selection method, but also that this isuniversally adopted to ensure comparable carbon accounts across platforms. For example, business reports and academic reports could be used in tandem if the methodologies were comparable.

One of the challenges in combining IO and PB into hybrid models is that of mapping the system boundaries in order to eliminate both truncation error and double counting. Gap analysis can isolate system boundaries within carbon accounting methods and enable the identification of excluded emissions in a PB framework, which can then be compensated for using IO, such as occurs in the Path Exchange Method (Lenzen and Crawford, 2009; Baboulet and Lenzen, 2010). While IO analysis achieves completeness, on its own it provides only a generic, economy-averaged estimate of the carbon embodied in a product. PB analysis on the other hand sacrifices completeness for greater specificity. Gap analysis has previously been widely used to help assess environmental impacts, from the powering of China's construction industry (Shen et al., 2016) to analysis of the ecological burden of the Finnish economy (Mattila, 2011).

Commercially, system boundary selection has been critical to the development of GHG reporting standards such as PAS2050/60 and the GHG Protocol which many global corporations use to build their CO2e emissions inventories and to make decisions about corporate operations (e.g. procurement). IO methods enable a better understanding of environment and other trade-offs in corporate situations (Weber et al., 2009), and hybrid approaches to calculating emissions under these standards can lead to results that are less expensive, in both time and money, and more complete (Murray and Lenzen, 2010). With the wide uptake of these systems and corporate dependence on them in emissions reduction plans it is important that business has access to the most appropriate and effective tools.

In this study we compare different IO models for precision and accuracy (as defined below). Using gap analysis, we analyse the role of system boundaries in causing uncertainties in hybrid carbon accounting methods used for environmental impact assessments, and identify the potential to make any part of this process more generic in order to make it more accessible and transparent to a wider audience.

3. Methodology

3.1 IO model comparison

Four different carbon accounting IO models were sourced (see Table 1) along with their supporting methodological documents and these were analysed to isolate influential methodological practices. These were run using 2012 data and according to the published versions of the models and in deconstructed ways (as far as methodological transparency would allow). Deconstruction describes the manipulation of each model to remove specific methodological practices (such as differences in the treatment of high altitude emissions and capital expenditure), allowing for more like-for-like comparisons. The results from the four IO models were then compared with each other and with the process-based estimates provided by Defra (Defra, 2012) for ‘electricity’, ‘coal mining’ and ‘coke and refined petroleum products’. These industries were chosen for comparison as they were considered simple enough that a process-based analysis method would represent them relatively accurately and because their supply chain documentation was sufficiently complete that any findings could be relatively easily contextualised. A gap analysis was carried out on Defra’s PB estimates for these three products, and these were accordingly ‘topped up’ using the Small World Consulting Ltd (SWC) single regional IO model (Berners-Lee et al., 2011), chosen as it provided the greatest methodological deconstruction opportunity and therefore the most detailed gap analysis, to eliminate truncation errors. These hybrid results were taken to be the most accurate estimates, against which each IO model was compared.

The results of this IO comparison were the basis of more detailed comparison, building from sector-wide to a specific product in order to identify methodological issues at each scale of consumption-based accounting. This enabled system-boundary findings relating to potential hybrid methods to be contextulaised in a wider, pre-assessed IO methods.

Model/Database	SWC SRIO	SWC MRIO	Defra MRIO	CMU SRIO
Reference year	2012	2012	2012	2002
Year released	2015	TBC	2013	2008
Number of sectors	106	106	106	458
Number of regions	1	4	4	1
Original Currency	GBP	GBP	GBP	USD
Economic data source	Office of National Statistics Supply and Use Tables	Office of National Statistics Supply and Use Tables	Office of National Statistics Supply and Use Tables	Bureau of Economic Analysis
Environmental data source	Office of National	The Eora MRIO Database	UK GHG Inventory; JEC	US Census Bureau; US

	Statistics Environmental Accounts		Well-to-Wheels; DECC Quarterly Energy Statistics for Renewables;	Energy Information Administration; US Department of Energy;
Includes high altitude factor	Yes	No	Partial	Unknown (assumed no)
Includes gross fixed capital formation	Yes	Yes	Yes	Unknown (assumed no)
Link	2011 SWC SRIO: http://media.ontheplatform.org.uk/sites/default/files/gm_footprint_final_110817.pdf	N/A	https://www.gov.uk/government/statistics/uks-carbon-footprint	http://www.eiolca.net/cgi-bin/dft/use.pl?newmatrix=US428PURCH2002

Table 1. Overview of IO models compared in this study

Notes: SWC SRIO: Small World Consulting Ltd single-region input-output model; SWC MRIO: Small World Consulting Ltd multi-region input-output model; Defra MRIO: UK Department of Environment, Food and Rural Affairs multi-region input-output model; CMU SRIO: Carnegie Mellon University single-region input-output model. The economic basis of the Carnegie Mellon University model is the United States, and therefore not directly comparable to the other models, which are UK-economy based. This was addressed through year-specific currency correction.

3.2. Aligning data for comparison of IO and PB models using copper wire production as a case study

The production of 1 kg of uncoated drawn copper wire was used as a more detailed case study. Copper wire was studied because it is a common product frequently used across multiple industrial sectors around the world and, as with the industries compared in the IO assessment, it is a product with mid-range complexity it neither benefits the PB or IO methodologies. The system boundaries of the PB Argonne Laboratory GREET.net model (2012 model now dismantled, 2017 model available at: https://greet.es.anl.gov/net) were assessed using structural path decomposition analysis. The GREET.net model estimate was compared to the result from the SWC single regional IO model (Berners-Lee et al., 2010), since this had performed closest to the Defra-SWC hybrid model.

The data used in the PB model was made as compatible as possible with the IO model by temporally aligning the data using the 2012 version of the GREET.net model, rather than the more recent 2017 iteration. The main changes between these versions are additional pathways included for fuels and updates to datasets (for more information see: https://greet.es.anl.gov/).

As the 2012 version of the GREET.net model was being dismantled by the Argonne National Laboratory at the time of this study, detailed descriptive methodology papers do not exist (Dieffenthaler, 2016). An in-depth understanding of the processes is therefore not possible; however copper wire supply chain data was supplied by personal correspondence from the Argonne National Laboratory and the following system boundary analysis was based on that.

3.3. Gap Analysis

To understand the extent of truncation errors, a gap analysis was undertaken by comparing IO sectors of the SWC single-region model with those in the GREET.net model database and methodology papers. IO sectors were identified, using supporting literature and methodological documents, as either included or excluded from the PB assessment, and where IO sectors were not wholly included or excluded in the PB analysis an effort was made to understand what fraction of the data included in the GREET.net analysis covered the full sector data of the IO analysis (see S.I.). The percentage difference between the complete IO model and the truncated PB model was calculated and this ratio was substituted into the gap analysis to calculate the amount of the associated data 'gap'. This gap analysis method is similar to the path exchange method as mentioned in section 2.3.

3.3.1 'Best practice' model calculation

The theoretical 'best practice' has been taken to be a hybrid of a detailed process-based life-cycle analysis ('PBLCA'), the GREET.net model, augmented with a gap analysis to calculate the proportionate truncation error, and a multiplier used to adjust accordingly ('PBLCA + gap analysis'). This process is described in the following equation: 'PBCLA + gap analysis' = 'PBLCA' * (1 + % truncation error). This calculation is similar, though not the same as, the Path Exchange method described by Treloar (1997) and Lenzen and Crawford (2002).

The GREET.net model draws data primarily from the US economy, but the IO model it is hybridised with is based on the UK economy. This spatial difference is not critical in the context of this present study as the intent here is to study the relative rather than absolute results. For the production of copper wire, the GREET.net model includes the following commodities: virgin copper, petroleum as manufactured from crude oil by industrial boilers, coal (average US mix), and electricity (average US mix). Embodied within the model methodology is the energy requirement at Chilean and American manufacturing locations, though at a significantly aggregated level.

4. Results

4.1. Accuracy and gap analysis

As noted above, although PB methods in the absence of resource limitation have the theoretical potential for high accuracy, defined as closeness to the true carbon emissions value, in reality finite resources always result in truncation error, and this is usually serious. The inclusion of gap analysis enables system completeness. The theoretical 'best practice' has been taken to be a hybrid of a detailed process-based life-cycle analysis (PBLCA) augmented with a gap analysis to calculate the proportionate truncation error, and a multiplier used to adjust accordingly (PBLCA + gap analysis).

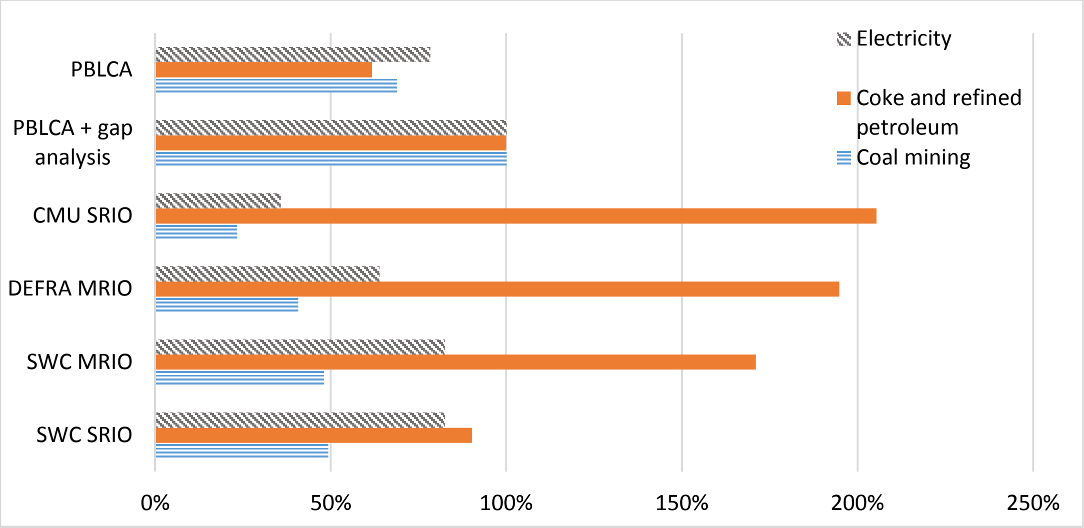

Figure 1. The carbon emission factor for three industrial sectors calculated by each of the different IO models and a process-based assessment, expressed as a percentage of the 'best practice' value found by PB life cycle assessment with gap analysis. Model acronyms are: PBLCA: process-based life cycle analysis; PBLCA + gap analysis: PBLCA supplemented with gap analysis; others as for Table 1.

Figure 1 shows the carbon emission factors for three industrial sectors calculated by each of the different IO models as a percentage of the PBLCA (using the 2012 Argonne GREET.net model) with gap analysis. The sectors studied were: the mining of coal and lignite ("Coal Mining"); the manufacture of coke and refined petroleum products ("Coke and refined petroleum"); and electricity production, transmission, and distribution ("Electricity"). The SWC SRIO model produced the most consistent and accurate model estimates (49% to 90% of the 'best practice' estimates, see Figure 1). The Carnegie Mellon University model had the widest range of estimates (53% to 205%) suggesting lower model accuracy. Production of coke and refined petroleum products was the most variable industry sector across models, with estimates covering 62% to 205% of the PB analysis (Figure 1).

4.1.1. The mining of coal and lignite

The benefits of accurate data can offset inaccurate methodologies. The three UK-based IO models broadly agree with each other at 48-52% compared with the 'best practice' estimate. One reason that the PB estimate was significantly higher than the IO estimates may have been the difference in the source of coal used in each analysis. The IO models used coal supplied from the countries they describe, i.e. UK or US, whereas the PB models used a globally weighted average. In the PB model only 52% of the coal is assumed to be European, and only 18% to be from the UK (Edwards et al., 2011). The rest is from South Africa (16%), Australia (12%), the US (10%), Columbia (7%) and the Commonwealth of Independent States (3%).

4.1.2. The manufacture of coke and refined petroleum products

The two SWC models provided the closest estimates to the 'best practice' values in the manufacture of coke and refined petroleum products sector by a significant margin. The Carnegie Mellon University model estimated a value of 205% of the 'best practice' value and thus performed most poorly, though the Defra and SWC MRIO models also substantially overestimated embodied carbon compared to the PB value. In the case of the Defra model this may be due to a specific methodological problem associated with the derivation of the carbon intensity of petroleum products, as described in the associated methodological report (Defra, 2012).

4.1.3. Electricity production, transmission and distribution

The four IO models under-estimated the emissions associated with 'Electricity production, transmission and distribution' compared to the 'best practice' analysis. The two SWC models came closest, each at 82%, followed by the Defra MRIO at 64% and the CMU SRIO model at 36%. Fluctuations in price are significant in the electricity industry, which may account for the difference in carbon emissions intensities estimated by the models. However, the IO models marginally out-performed the unadjusted PB analysis.

4.2. Precision analysis

Precision (agreement between models) can vary between models and industry sectors; therefore, each sector was analysed independently. The emissions factor calculated by each model for each sector was compared with the mean emissions factor for that sector, calculated by the four IO models. Where models broadly agreed, the model ensemble for that sector was deemed to have high precision. Where variation was higher, model ensemble precision was lower. However, it should be noted that a high degree of precision does not necessarily equate to high accuracy (i.e. closeness of the model estimates to the true value, here taken to be the ‘best practice’ estimate).

Out of 106 industry sectors, the five with greatest relative precision were all services sectors with complex supply chains, including real estate services and accounting services, implying that supply chain complexity does not always lead to IO model disagreement, as conventional wisdom suggests. Perhaps, instead of increased supply chain complexity leading to different methodological practices, it leads to similar assumptions being made in all model methodologies to allow the economic theory of IO models to apply with relative ease to the industry sector. Hence models may be in close agreement (high precision) but not correctly represent real-world emissions (low accuracy).

Across the 106 IO sectors, influencing factors for precision vary depending on industry. In some cases, the regions covered by the model seemed to be the most influential factor. For a few sectors, the inclusion or exclusion of gross fixed capital formation was important. The availability of methodological details varied considerably between the four IO models. For example, gross fixed capital formation was not always explicitly included or excluded in the methodological descriptions, whereas regional coverage was more consistently documented.

4.3. Comparison of IO and process-based model estimates using copper wire production as a case study

As no methodological documents directly relating to the GREET.net 2012 model construction were available, the understanding of the system boundary of this PB model was based on articles from which the Argonne Laboratory collected data. The system boundary identification made in the current study therefore required estimations based on what was included in published documents, personal correspondence with the Argonne Laboratory, and reasonable assumptions made based on available information.

All copper in the GREET.net methodology was assumed to be Chilean or American primary copper, as the bulk of the copper used in the United States is sourced from these two locations (Kelly, 2016; Kelly et al., 2015). The energy used in the production of copper wire is separated into electricity and other fuel types for the first three supply chain tiers. Data on the Chilean use of fuels was aggregated and nonspecific and therefore cannot be said to accurately reflect all of that aspect of the supply chain.

Inclusion or exclusion of any supply chain path is often not explicitly stated in PB methodologies, confusing system boundary identification for anyone attempting to understand the analysis provided by carbon accounting. For example, there is no mention in any associated literature of the in/exclusion of overheads. Although not explicitly stated, it is highly unlikely that these processes were included in the GREET.net assessment of copper wire as they are beyond the scope of almost all PB analyses due to the complexity of supply chain pathways.

4.3.1. Gap analysis

The potential impact of truncation error is significant (up to 95% of the supply chain for the product, Table 2). When production processes up to and including the second supply chain tier are included in PB analysis, the truncation error reduces to 55% (Table 2), yet over half of the true carbon burden remains unaccounted for. The initial GREET.net model allocated a carbon burden of 3.08 kg CO_2e /kg to the production of copper wire.

Table 2 Estimation of truncation error for copper wire with system boundary cut-offs at different supply chain tiers and as estimated through structural path decomposition. The resultant emissions factors when the GREET.net estimate is adjusted accordingly are shown in the right-hand column.

Supply chain tier	Supply chain carbon embodied up to and including this tier	Truncation error with system boundary at this tier	Estimation of carbon footprint of copper wire based on gap analysis findings ($kgCO_2e/kg$)
Direct	5%	95%	57.49
1	24%	76%	12.70
2	45%	55%	6.80
3	62%	38%	4.99
4	73%	27%	4.19
Initial GREET.net assessment (ignoring truncation error)	100%	0%	3.08
GREET.net assessment following structural path decomposition and gap analysis	40%	60%	7.64

Gap analysis showed a true carbon burden more than double the GREET.net estimate (Table 2). The largest single contributor to the gap between the 'best estimate' carbon footprint of copper wire and the initial GREET.net model estimated figure was exclusion of 'Electricity production, transmission and distribution' beyond the third supply chain tier (11% of the total carbon footprint omitted). The majority of this occurs in tiers five and higher. A further 10% was lost through exclusion of the supply chain remainders of the 'Basic iron & steel', 'Crude petroleum & natural gas', 'Industrial gases', and 'Petrochemicals' sectors in approximately equal parts.

Overall the copper wire supply chain is diffuse and complex; more than might be expected of this comparatively simple product. 27% of the supply chain emissions are a result of processes beyond the fourth supply chain tier. This is a substantial burden, significantly far removed from the final product and therefore extremely difficult to include in PBLCA. The more complex the supply chain, the harder it is to identify the system boundary, upon which the 'best practice' hybrid carbon accounting method used here relies. This difficulty applies to all industry sectors and all economic areas.

5. Discussion

5.1. Factors affecting model precision

5.1.1. Economic region on which models are based

Different regions have different supply chains and their industries have different carbon intensities. This may partially explain why the Carnegie Mellon University model is an outlier compared to models based on the UK and global economies. However, there was evidence for some industries, (such as 'Coke and refined petroleum industry') that the greater disaggregation used in the Carnegie Mellon University model was of some value.

5.1.2. Differences in model construction and underlying data

Differences in the detailed construction of the IO models, and the underlying assumptions used, can have a significant effect on the results. For example, the low agreement within the 'Coke and refined petroleum products' sector was significantly influenced by price volatility and the different ways in which this was adjusted for. To give another example, there is a degree of subjectivity in the selection of input data in the construction of the underlying tables that feed into each model.

5.1.3. Other influential issues

The ‘Mining of coal and lignite’ and the ‘Manufacture of iron and steel’ sectors are highly regulated and well researched, as well as containing comparatively simple processes. This allows the creation of detailed supply chain maps with relatively up-to-date data enabling the creation of models that are consistently representative of these sectors. However, simple supply chains do not always enable precise emissions calculations, as defined within the context of this study, nor do complex supply chains prohibit them. For example, the complexity of the ‘Legal services’ sector should theoretically have resulted in low agreement between models; however high precision was found between models for this sector. This implies that other methodological factors may be more important to the precision of a carbon emissions model than supply chain complexity, such as data quality. A similar effect was found by Owen et al. (2017).

5.2. Accuracy of model estimates

5.2.1. Inclusion of multi-regional data

Although IO tables often describe only one region, trade in almost all commodities occurs in a global market, and the effects of spatial aggregation in IO carbon modelling can be significant (Su and Ang, 2010). One of the most prominent issues this can cause with single-region carbon models is incorrect substitution of carbon emissions from domestically produced goods to imported goods. For example, in 2012 the UK imported £25,415,000,000 into the ‘Coke and refined petroleum products’ sector from across the world (ONS, 2015), all of which, in a single-region model, would have been assumed to have the same carbon intensity as UK-produced coke and refined petroleum products. However, the carbon intensity of production of all commodities varies globally (Andrew et al., 2009). For example, China has a significantly more carbon intensive manufacturing sector than the UK, yet the single-region models apply the same carbon intensity to goods produced in China as in the UK, or anywhere else.

While both the multi-regional IO models studied (SWC MRIO and Defra MRIO) use the UK as one of their regions of the world, they divide up the rest of the world in different ways. The Defra model uses Organisation for Economic Co-operation and Development (OECD) regions, based on economic development indicators, whereas Small World Consulting Ltd. uses geographical regions (UK, EU, China, and the ‘Rest of the World’). As this changes the details and aggregations of the models, this could significantly affect carbon intensity calculations.

5.2.2. Economic differences

The use of different sources for commodity prices, especially electricity which is particularly volatile, different rounding or averaging methods or using prices for a single month to represent price over a year can all cause significant variation in IO analysis and final carbon emissions intensity.

For only a few sectors, the addition of gross fixed capital formation into the supply and use tables has a significant impact on the carbon emissions factor calculated by a model. In this study, the 'Coke and refined petroleum' sector was found to be one such example.

5.3. System boundary analysis findings

In most cases, it can be assumed without controversy that PBLCAs would not cover supply chain pathways at or beyond the fifth supply chain tier. This was the case for copper wire production in the GREET.net model. This allows a potentially simple mechanism for utilising the system boundary to improve model performance across all products and services, since it is relatively easy, using structural path analysis, to identify the proportion of embodied carbon that lies in the fifth tier and beyond and adjust accordingly. More complicated, as demonstrated here, yet still feasible, is the detailed structural path decomposition analysis of the higher supply chain tiers, to establish the full system boundary and thereby adjust to eliminate truncation error altogether.

The ambiguity of system boundary identification in most carbon accounting estimates is of serious concern. It is impossible with almost all PB analyses to know, with precision and confidence, exactly where the system ends. While this study has identified some difficulties with isolating system boundaries in carbon accounting, we have also shown that it is possible.

One issue with the reliability of carbon accounting has been the trade-off between system completeness and precision regarding system boundary selection. The significantly large gap between the complete system as assessed by IO models and the truncated system as assessed by PB methods suggests that any purported precision gained from PB does not result in greater accuracy in real or comparative terms. The implications are far reaching: thorough PBLCAs such as those presented in the GREET.net model are widely considered to have high accuracy, but this analysis suggests otherwise (see: Lenzen and Dey, 2000; Lenzen, 2000; Crawford, 2008). Even in the case of a simple product such as copper wire, the PB model under-reports the carbon burden of the product dramatically, with a truncation error of 60% (Table 2).

5.4. Implications

This study has implications for public and corporate understanding and practise of carbon accounting as it demonstrates the necessity of having clearly defined and coherent system boundaries, with process-based accounting methods likely to suffer from very significant truncation errors, relative to input-output or hybrid methods. It is likely that governance or operational decisions made on the basis of process-based accounting methods may in fact be flawed by under representation of supply chain impacts. For companies looking to manage supply chain carbon, the quantification of truncation error in their product PBLCAs enables the relative importance of upstream, downstream and operational emissions to be understood and priorities estabilished accordingy. This will be essential, for example, if companies are to set and the SBTi is to meaningly assess progress toward scope 3 science-based targets. To give one very specific example, the impact of a company no longer needing to purchase a particular product can be assessed as the carbon embodied in the product as determined by PBLCA scaled up by a truncation error factor. In the case of a network provider requiring less copper wire, this scaling would more than double the modelled emissions impact of such a change compared to a purely PBLCA-based analysis.

The relatively similar performance of the single region compared to multi-region IO models is encouraging from the practical perspective of model construction, since the data requirements are so much more manageable.

Regarding consumption-based accounting practice, a key result is the need for greater transparency in published accounts which would greatly increase the available data on which to improve methods and understand the complexities of these processes. More evidence has been provided in favour of non-PB methods for carbon accounting, particularly hybrid methods, supporting existing literature and continuing the necessary debate to improve these methods.

Greater transparency and more effective models better inform a policy maker, leading to the opportunity for more effective policy. This could be particularly influential in governmental departments such as Business, Energy & Industrial Strategy due to the link between financial and environmental data.

For sustainability or environmental managers within corporations, these models could become tools to target and manage effective carbon emissions mitigation strategies. Following the corporate trope that ‘what gets measured gets managed’ giving managers the ability to monitor their carbon emissions will better enable them to manage, and reduce, their carbon emissions. This could have a direct impact on the severity of resultant anthropogenic climate change.

5.5. Limitations of the study

5.5.1. Input-output model comparisons

While largely accurate, there are specific issues with the PB data. The coal and lignite mining result from Defra is based on a percentage calculation of direct emissions from the burning of coal and lignite, with a ratio calculated from the automotive industry applied to estimate the mining figure (Defra, 2012). Not only is this figure calculated from data of an unrelated industry, it is based on the average composition of coal as used across Europe (Edwards et al., 2011) rather than national average composition, as IO models would assume. This disparity of methods may be the main reason why, despite truncation error, the PB carbon intensity figure is larger than all of the IO estimates.

5.5.2. Process-based life-cycle assessments

The Defra PB carbon emissions intensity for petroleum coke, a significant portion of the ‘Coke and refined petroleum products’ sector, were calculated indirectly using liquefied petroleum gas emissions and adjusting them artificially to represent petroleum coke emissions, introducing inaccuracy to the model.

5.5.3. System-boundary analysis

Understanding system boundaries was not aided by the variable quality of supporting documents for the models used. For example, different mining methods have different carbon impacts, and these were not considered in the Defra analysis. The inclusion of international coal sources in the PB figures more accurately reflects the real-world nature of supply chains. Thus these could be considered more accurate than the single-region models or simplified region representations of the multi-region IO models, however these data were still over a decade out of date.

For the copper wire analysis, comparing an IO model based on the UK economy with a PB model developed in the US was in some ways not ideal. It was seen as the best option because the GREET.net model is one of the most comprehensive PB models publicly available, and is therefore likely to have lower truncation error than other PBLCA datasets. The SWC IO model was chosen as it was the best performing and although the differences in supply chains between economies may be influential, there are reasonable similarities in trade patterns in the UK and the US (UN Comtrade, DESA/UNSD, ND).

6. Conclusions

Inclusion of multi-regional data in IO models can potentially increase the accuracy of carbon emissions estimates by allowing greater expression of the complexity of the global supply chains. However, we have shown that a well-constructed single region IO model can perform as well as or better than a multi-regional model, when compared with a ‘best practice’ hybrid model. Regardless of which model is used, the quality of underlying data is critical. This is particularly the case for IO models, which are susceptible to temporal variations in economic parameters. The benefits of detailed methodological choices and high quality data in model construction to improve the realism of system descriptions can outweigh the potential benefits of a multi-regional approach which may lack critical details and/or be susceptible to data uncertainties or errors .

The seriousness of truncation errors suffered by even detailed PB analysis, as already documented elsewhere, is further demonstrated here using copper wire as a case study. The embodied carbon of even this simple product suffered truncation errors of 60% when modelled using the PB approach. However we have shown that it is possible to correct for this. We demonstrate a method for eliminating truncation error whilst keeping the specificity of PB analysis to create a description of embodied carbon that is system complete, transparent, impartial, practical and is capable of tracking supply chain carbon changes over time. This approach should allow company supply chain carbon estimates, for example, to be both system complete and to reflect specific supply chain processes and mitigation efforts over time. Although the accuracy of embodied carbon modelling (i.e. knowing how near the modelled value is to the true value) is difficult or impossible to quantify the best models should allow the relative changes in embodied carbon in a product or service to be tracked over time. This will become increasingly important as global society acts on its carbon reduction commitments.

7. Further Research

Research into refining the process of identifying system boundaries in hybrid carbon emissions models without losing accuracy is evidently key to the improvement of hybrid carbon accounting techniques. Progress could be made by developing the techniques currently available and expanding their applications. Of particular note from this study is structural path analysis. As this technique has only been commonly applied in the carbon accounting field for the last decade there is likely to be significant progress to be made into new and innovative uses.

The creation of a system boundary identification method that is broadly applicable over a given industry sector would greatly simplify the system boundary reporting process. Manufacturing may be the best sector to start with as it contains the theoretically simplest supply chains. These macro industry identification methods could then be refined for sub-categories. It would be crucial for this identification method to be openly and freely available to enable consistent understanding of carbon accounting reports.

Although there are papers published frequently on carbon accounts of various products and services, there is a significant lack of clarity in academic publications of carbon accounting methods. This has the potential to lead to a significant knowledge gap and/or dissemination of erroneous information in the future. With the current lack of detailed reporting in the carbon accounting industry and increasing demand for this throughout the world it is imperative that the methods of carbon accounting are rigorously examined and improved to keep up with the need.

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Highlights

- Detailed process-based life cycle analysis of embodied emissions in copper wire was found to suffer 60% truncation error.
- System boundary identification was possible and practical through structural path decomposition to enable insertion of the process based study into a system-complete input-output model, thus eliminating systematic truncation error and double counting
- Comparison of input output models reveals methodological details, data quality and capacity to adjust for price fluctuation can influence accuracy more than the construction of a multi-regional model.