Author: Henriksson, Patrik John Gustav
Title: Evaluating European imports of Asian aquaculture products using statistically supported life cycle assessments
Issue Date: 2015-11-12

Evaluating European Imports of Asian Aquaculture Products using Statistically Supported Life Cycle Assessments

Patrik JG Henriksson

Evaluating European imports of Asian aquaculture products using statistically supported Life Cycle Assessments

Proefschrift

ter verkrijging van
de graad van Doctor aan de Universiteit Leiden,
op gezag van Rector Magnificus prof.mr. C.J.J.M. Stolker,
volgens besluit van het College voor Promoties
te verdedigen op donderdag 12 November 2015
klokke 13.45 uur

door

Patrik John Gustav Henriksson

geboren te Lidingö, Zweden,
in 1979

Promotiecommissie
Promotor: Prof. dr. GR de Snoo (Leiden Universiteit)
Co-promotor: Dr. ir. JB Guinée (Leiden Universiteit)
Co-promotor: Dr. R Heijungs (Leiden Universiteit & Vrije Universiteit Amsterdam)

Overige leden:
Prof. dr. A Tukker (Leiden University)
Prof. dr. ir. PJ van den Brink (Alterra & Wageningen University)
Prof. dr. ir. J Dewulf (Universiteit Gent)
Prof. dr. E Worrell (Universiteit Utrecht)

This research was conducted under the auspices of the Graduate School for Socio-Economic and Natural Sciences of the Environment (SENSE), and financed by the European Commission, within the Seventh Framework Programme—Sustainable Development Global Change and Ecosystem, as part of the Sustaining Ethical Aquaculture Trade (SEAT) project

To John and the two Gustavs, whom I never knew

SV

"Man har långt mera nytta av en instängd jord till damm än av den vackraste åker"

EN

"Soil used to make a pond, thus yields far more than the loveliest cultivated field"

Carl Linnæus 1749

Evaluating European Imports of Asian Aquaculture Products using Statistically Supported Life Cycle Assessments

ISBN: 978-94-6203-952-0

Doctoral Thesis Leiden University, Netherlands

Cover design: Mikael Printz

Thesis layout: Annick Lang

Proofreading and translation: Nathalie Bax

Printing: CPI – KONINKLIJKE WÖHRMANN

Chapter 2: Reprinted from International Journal of Life Cycle Assessment. 17:304-313. Patrik JG Henriksson, Jeroen B Guinée, René Kleijn & Geert R de Snoo.
Life cycle assessment of aquaculture systems—a review of methodologies©
(2012) doi:10.1007/s11367-011-0369-4. Supplementary material available online.

Chapter 3: Reprinted from International Journal of Life Cycle Assessment. 19(2):429-436. Patrik JG Henriksson, Jeroen B Guinée, Reinout Heijungs, Arjan de Koning & Darren M Green.
A protocol for horizontal averaging of unit process data—including estimates for uncertainty©
(2013) doi:10.1007/s11367-013-0647-4. Supplementary material available online.

Chapter 4: Reprinted from International Journal of Life Cycle Assessment. 20(2):185-195. Patrik JG Henriksson, Wenbo Zhang & Jeroen B Guinée.
Updated unit process data for coal-based energy in China including parameters for overall dispersions© (2014) doi:10.1007/s11367-014-0816-0. Supplementary material available online.

Chapter 5: Reprinted from PLOS ONE: Patrik JG Henriksson, Reinout Heijungs, Hai M Dao, Lam T Phan, Geert R de Snoo and Jeroen B Guinée. Product Carbon Footprints and Their Uncertainties in Comparative Decision Contexts© (2015) doi: 10.1371/journal.pone.0121221. Supplementary material available online.

Chapter 6: Reprinted from Environmental Science & Technology: Patrik JG Henriksson, Andreu Rico, Wenbo Zhang, Sk Ahmad-Al-Nahid, Richard Newton, Lam T Phan, Zongfeng Zhang, Jintana Jaithiang, Hai M Dao, Tran M Phu, David C Little, Francis J Murray, Kriengkrai Satapornvanit, Liping Liu, Qigen Liu, M Mahfujul Haque, Froukje Kruijssen, Geert R de Snoo, Reinout Heijungs, Peter M van Bodegom, and Jeroen Guinée. A comparison of Asian aquaculture products using statistically supported LCA© (2015) doi: 10.1021/acs.est.5b04634. Supplementary material available online.

Table of Contents

Chapter 1

General Introduction

1.1 Aquaculture and food

Many of the anthropogenic pressures currently pushing the planet's ecosystems to their limits are a direct result to food and feed production (Steffen *et al.* 2015): forests have to give way to agricultural fields, pastures and aquaculture ponds (Galford *et al.* 2010; Donato *et al.* 2011; Smith *et al.* 2013), large quantities of pesticides and herbicides are dispersed into nature (González-Rodríguez *et al.* 2011), enteric and other anoxic degradation of biomass result in large methane emissions (Pelletier and Tyedmers 2010a; Lindquist *et al.* 2012), soils are being eroded (Stoate *et al.* 2001; Wiloso *et al.* 2014), and extensive external energy inputs are needed to maintain production (Pelletier *et al.* 2011). As a result, biodiversity is being lost at record rates (Hooper *et al.* 2012; Steffen *et al.* 2015), natural cycles of nitrogen and phosphorus are being distorted (Bouwman *et al.* 2013), and the regenerative capacity of many biotic resources are being undermined by overexploitation (Foley *et al.* 2007; Burgess *et al.* 2013). Meanwhile, the planet's human population continues to grow, as is the per capita demand for animal proteins with increasing standards of living (FAO 2006; Godfray *et al.* 2010).

Livestock dominates animal production by mass, but is also commonly identified as the environmentally worst food group (FAO 2006; Duarte *et al.* 2009; Röös *et al.* 2015). 'Fish' (see glossary), in the meantime, supplied roughly 17% of the animal proteins consumed globally in 2010 (FAO 2014a). Per capita consumption of fish has, however, doubled over the last fifty years, thanks to improved logistics, production practices and processing techniques (Muir 2005). In some parts of the world, fish are even the primary source of proteins and/or the major source of income (FAO 2014a). Capture fisheries' catches, historically the dominating source of fish, supplied most of the increases in production until the early 1990s when landings peaked and have since stagnated, or even declined, as a result of overexploitation (FAO 2014a). Increases in demand for aquatic food products have therefore instead been met by aquaculture, the currently fastest growing animal food sector (Duarte *et al.* 2009). Exhibiting a rough doubling in production every decade (Duarte *et al.* 2009) and today providing half of all finfish consumed globally (FAO 2014a), the aquaculture industry has grown to become a cornerstone for feeding future generations.

Aquaculture holds many advantages over capture fisheries and other food production systems by avoiding undersized catches and bycatch, stabilising market prices, allowing for live fish transports and genetic improvements, and improving resilience by accommodating more diverse production practices (Muir 2005; Belton and Thilsted 2014; Troell *et al.* 2014). The diversity in the number of species farmed exceeds both that of agriculture (30 species make up 90% of production) and livestock production (5 species make up 90% of production), with around 35 species making up 90% of production (Duarte *et al.* 2009; Troell *et al.* 2014). Aquaculture also has the advantage of being able to shift production to meet demand and has therefore often thrived upon markets where overharvested wild fish-stocks have left shortages in supply and soaring prices (Diana 2009). The salmon industry is maybe the most notable such market, where landings of wild salmon started declining in 1990 only to be replaced by farmed salmon (Diana 2009). Similar situations exist throughout Asia, where aquaculture has maintained prices for many species at affordable levels (Belton and Thilsted 2014).

Over the more recent decades, increases in demand have shifted aquaculture production towards more intensive monoculture practices that source feed resources from globally diverse origins (Muir 2005; Tacon and Metian 2008; FAO 2014a). It is, for example, not unusual that fish today are grown on feeds containing both wild fish, agriculture products and livestock byproducts (**Fig 1.1**). These resources are generally opportunistically sourced from global markets, where fish may be fed raw materials originating from more than three continents, processed in another country, only to be consumed in a seafood restaurant on the opposite side of the globe.

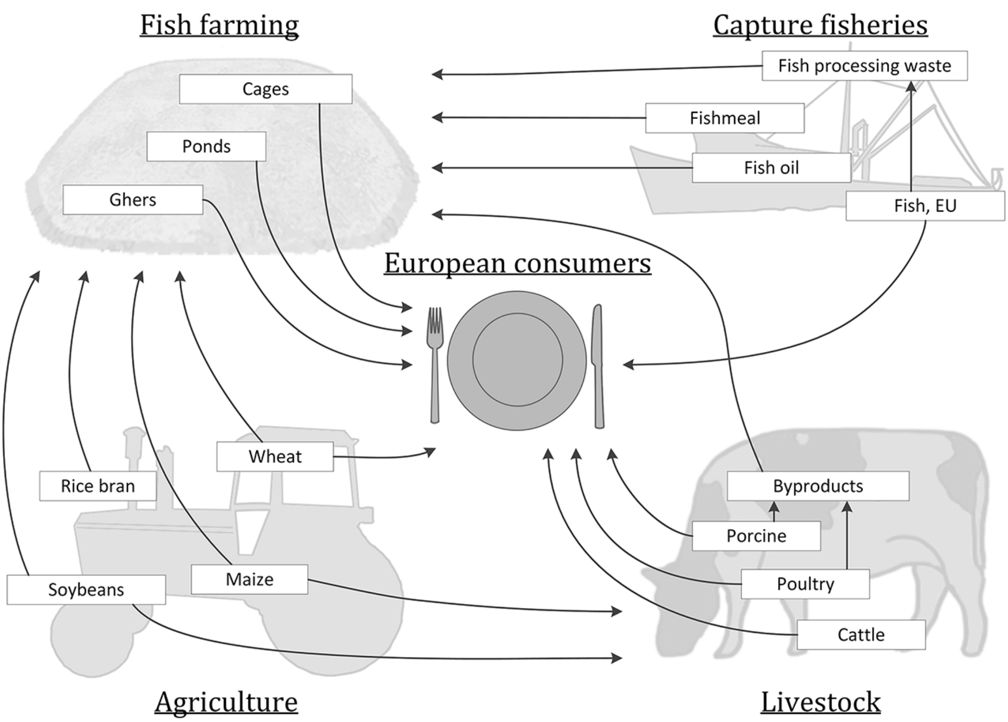

Fig. 1.1: Modern aquaculture is a globalised industry, relying upon fisheries, agriculture and livestock products from around the world, with roughly 40% of the seafood produced entering global markets.

Intensification of production has also brought with it concerns about negative environmental consequences, including the release of nutrients and chemicals, introduction of non-indigenous species, habitat destruction, reliance on wild fish stocks, energy usage, spread/amplification of diseases and parasites, mangrove deforestation and appropriation of ecological goods and services (Beveridge *et al.* 1997; Pelletier and Tyedmers 2008; Henriksson *et al.* 2011). The increasingly diverse selection of resources used to support modern aquaculture production is also related to environmental concerns of its own. To date, most of these concerns have been related to feeds, including the provision of fishmeal, soybeans, wheat, maize, meat and bone meal, and various other resources. Other environmental concerns are related to the supply of juveniles (which still are collected in the wild for many farmed species) (Ahamed *et al.* 2012), provision of energy (Ayer and Tyedmers 2009), cooling/freezing (Winther *et al.* 2009), etc. While practices have been greatly improved over the last decade with regards to some of these concerns (Vanhonacker *et al.* 2011; Rico *et al.* 2013; Noor Uddin *et al.* 2013), a wide range of issues remain. Many of these issues are, however, associated to specific farming systems (e.g. eutrophication to cages systems or aquaculture ponds to deforestation). In order to identify best farming practices, one therefore needs to consider the diverse set of environmental impacts caused by fish farming, capture fisheries, agriculture, livestock farming and other supporting processes.

1.2 Aquaculture production systems

Aquaculture production can be divided into many different categories, with one of the crudest being that into farming in fresh-, brackish- or marine-water (mariculture). By weight, mariculture is dominated by aquatic plants, but by value molluscs and finfish are the main commodity groups (**Table 1.1**) (FAO 2014b). In freshwater, finfish makes up roughly half of aquaculture production by volume, mainly by different carp species. Representing 67% of all finfish farmed, the most common carp species include: common (*Cyprinus carpio*), grass (*Ctenopharyngodon idella*), silver (*Hypophthalmichthys molitrix*), bighead (*Hypophthalmichthys nobilis*), catla (*Catla catla*) and crucian (*Carassius carassius*) carps. Most carp species are, however, consumed locally, where they yield relatively low market prices, thus shifting the focus in monetary terms towards species like Chinese mitten crabs (*Eriocheir sinensis*) (6.3% by value), Nile tilapia (*Oreochromis niloticus*) (5.1%), whiteleg shrimps (*Litopenaeus vannamei*) (4.4%) and pangasius (*Pangasianodon hypophthalmus*) (3.3%) (**Table 1.2**) (FAO 2014b). While the Chinese mitten crab is a species almost solely grown and consumed in China, the other three are globally traded commodities. Frozen shrimps and finfish fillets are actually the two most frequently traded aquatic products by value, followed by fishmeal (FAO 2014b).

Table 1.1: Global production volume of aquaculture commodities in 2012 (million tonnes). From: FAO (2014b).

	Brackish	Freshwater	Marine	% of total
Aquatic plants	0.8	0.1	22.9	26%
Crustaceans	3.2	2.5	0.7	7%
Finfish	2.1	37.7	4.4	49%
Molluscs	0.1	0.3	14.8	17%
Others	0.0	0.5	0.4	1%
% of total	7%	46%	48%	

Table 1.2: Global value of aquaculture commodities in 2012 (million USD). From: FAO (2014b).

	Brackish	Freshwater	Marine	% of total
Aquatic plants	125	42	6202	4%
Crustaceans	13929	13962	2972	21%
Finfish	4671	62270	20558	61%
Molluscs	297	248	15312	11%
Others	1	2540	1194	3%
% of total	13%	55%	32%	

Another crude division that can be made is that into fed and non-fed aquaculture. Non-fed aquaculture refers to photosynthesisers, extensively farmed animals and filter-feeders. Filter-feeders, in turn, are mainly made up of bivalves, but also by filter-feeding finfish such as the bighead carp that are commonly found in Chinese aquaculture ponds. Extensive farming relates to systems that are large enough to maintain enough primary production to sustain the organisms farmed (**Table 1.3**). Fed aquaculture, on the other hand, include many of the most valued organisms and is also responsible for most of the recent increases in production. These systems can be semi-intensive, intensive or hyper-intensive, depending upon how densely they are stocked. The definitions for these different systems, however, often differ amongst publications, with the definitions used in the present research presented alongside FAO's definitions presented in **Table 1.3**.

Table 1.3: Definitions for different farming intensities as presented by FAO (Crespi and Coche 2008) and in this thesis (Murray *et al.* 2014).

	FAO definition	Definition in this thesis
Extensive	Exclusion of predators and control of competitors yielding no more than 500 kg ha^{-1} yr^{-1}	Passive stocking of seed, no added feeds, fertilisers, 1-3 fish m^{-2}
Improved extensive	n/a	Passive/active stocking of seed, no feeds, fertilisers, <10 fish m^{-2}
Semi-intensive	Semi-intensive – supplementary feed and fry, yielding 0.5 to 20 tonnes ha^{-1} yr^{-1}	Active stocking of seed, feed, fertilisation, <30 fish m^{-2}
Intensive	Intensive systems – provision of all nutritional requirements, yielding up to 200 tonnes ha^{-1} yr^{-1}	Active stocking of seed, feed, fertilisation, >30 fish m^{-2}
Hyper-intensive	Hyper intensive – Usually pumped or gravity supplied water or cage-based, yielding more than 200 tonnes ha^{-1} yr^{-1}	n/a

1.3 Problem identification

Like the production of most commodities in today's globalised society, modern aquaculture subjects stress on ecosystems around the world. For example, half of the fishmeal currently used in fed aquaculture practices originates from the Peruvian anchoveta (*Engraulis ringens*) fishery, a fishery that already has experienced a collapse due to overfishing (Sandweiss *et al.* 2004). Soybean is another resource commonly used in aquaculture feeds that is related to its own controversies, with marginal demands subjecting the Amazon forest to constant encroachments by agricultural farmers seeking new fertile agricultural soils (Dalgaard 2008; Galford *et al.* 2010). Similar problems apply to cattle and other livestock production systems that displace large land areas either as pastures or for feed provision (Cederberg *et al.* 2011; Middelaar *et al.* 2013). More global concerns involve the great dependence on inorganic fertilisers in agricultural practices that threatens to unbalance global nutrient cycles and exhaust finite resource deposits, while consuming vast quantities of energy (Rockström *et al.* 2009; Cordell *et al.* 2009; Pelletier and Leip 2013). Food production actually accounts for 20% to 25% of the energy use in developed countries, with an average of about five kcal of anthropogenic energy (mainly fossil fuels) going into each kcal of food produced (Carlsson-Kanyama 2003). In addition to this, it is estimated that about 30% to 40% of global food supplies never are consumed, but end up as waste (Godfray *et al.* 2010); a fraction that might be higher for fresh fish as it is a highly perishable commodity.

Apart from reducing food waste, the most efficient way of shrinking the environmental footprint of food provision is to promote more sustainable food products, while trying to displace any detrimental hot-spots in the production chain. In order to identify these hot-spots, the whole value chain needs to be evaluated. Life cycle assessment (LCA) is a quantitative tool developed to perform such evaluations. The tool has a history running back more than forty years and has over the last decades become commonplace in environmental standards, labelling schemes, policy and even legislation (Guinée *et al.* 2011). Supported by its own ISO standard (ISO 14044 2006), LCA is often said to capture a product's environmental impacts from "cradle to grave". Thus referring to emissions resulting from the extraction of raw materials, to the end of life of those materials. The most common goal when applying LCAs, however, is to determine if product A is environmentally more sound than product B (Guinée *et al.* 2011).

Comparisons of LCA results have, to date, mainly been done on a point-value basis. In the meantime, there are many discrepancies influencing outcomes, originating from methodological choices and sourcing of data (de Koning *et al.* 2009). In response, several initiatives have tried to standardise methodological choices (e.g. JRC's ILCD handbook or UNEP-SETAC's Life Cycle Initiative) and a number of LCA studies have quantified the uncertainties around LCA results. Limited consensus has, however, been reached with regards to methodological choices, as the goals of studies differ, as does the mindsets of practitioners. Quantified uncertainty estimates have also had limited success as they generally have been too data intensive or complex, restraining practitioners to only consider some sources of uncertainty or regress to conjectural estimates. Most LCA studies also lack a predefined hypothesis, indicating a rare use of significance tests in the field of LCA. Little is therefore known about the level of confidence behind LCA conclusions (Huijbregts *et al.* 2004).

1.4 Research questions

The objective of the present research was to evaluate European imports of Asian aquaculture products using LCA. The main research question was accordingly:

Are there significant differences among the environmental impacts resulting from the production of Asian aquaculture commodities, and if so, what are the main causes?

In order to address this question, four sub-question arose and were addressed:

1. Are there shortcomings in methods, data or coverage in existing aquaculture LCAs?
2. Can variance parameters be defined for unit process data in aquaculture LCAs?
3. Can these variance parameters be processed into ranges of results?
4. How can we determine if the LCA results of two systems fulfilling the same functional unit are significantly different?

In order to address the main research question, a total of 21 LCAs were conducted for four major aquaculture commodities commonly found in European freezers, namely frozen Pangasius fillets, tilapia fillets, peeled tail-on (PTO) shrimp and headless shell-on (HLSO) prawn from Bangladesh, China, Thailand and Vietnam.

1.5 The species and countries under study

Asia has always been dominating when it comes to aquaculture production and still accounts for (88%) of global production by weight (FAO 2014a). China is the main producing country, but also a major consumer, of aquaculture products. Europe, in turn, is struggling with declining fisheries landings, while being the origin of only 4% of global aquaculture production (FAO 2014b). Europe is, in the meantime, home to some of the world's largest fish consuming nations, including Spain, Portugal and Norway, all which have an annual per capita consumption of over 40 kg. This has resulted in Europe becoming the largest single market for international trade of aquatic products, responsible for 36% of total world imports by value (FAO 2014a).

The selection of the cultured species investigated in the current research was based upon their long export history, large trade or rapid growth. The two shrimp species are often farmed under similar circumstances in brackish water (**Fig. 1.2**), with the indigenous Asian tiger shrimp (*Panaeus monodon*) being replaced by the whiteleg shrimp (*Litopenaeus vannamei*) from the Eastern Pacific due to persisting disease problems (Lebel *et al.* 2010). In contrast to these two crustaceans, the indigenous giant river prawn (*Macrobrachium rosenbergii*) was selected as a crustacean representative produced in freshwater systems, where production practices have evolved in response to local opportunities and resource constraints, rather than to global demands (**Fig. 1.3**). Two freshwater finfish were also evaluated, namely Pangasius catfish (**Fig. 1.4**) and tilapia (**Fig. 1.5**). Tilapia is the common name for a wide range of cichlids originating from Africa that have become extremely popular in Asian aquaculture, with the Nile tilapia (*Oreochromis niloticus*) being the most commonly farmed species (71% of Asian tilapia production by weight) (FAO 2014b). However, many other species of tilapia are prevalent in Asian aquaculture, including countless strains of hybrids (Thodesen *et al.* 2013). Pangasius catfish (*Pangasius* spp.), in the meantime, constitute a more closely related group of freshwater finfish indigenous to South East Asia. The striped catfish (*Pangasius hypophthalmus*) is the most commonly farmed species and the Mekong delta the dominating producing region.

Fig. 1.2: Different countries contribution to the production of whiteleg (*Litopenaeus vannamei*) and Asian tiger shrimp (*Penaeus monodon*).

Fig. 1.3: Different countries contribution to the production of giant river prawn (*Macrobrachium rosenbergii*)

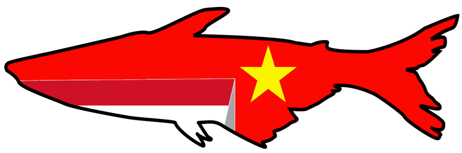

Fig. 1.4: Different countries contribution to the production of Pangasius catfish (*Pangasianodon hypophthalmus*)

Fig. 1.5: Different countries contribution to the production of tilapia (*Oreochromis niloticus*)

Unlike salmon that is a carnivorous species, all of the species here under study are omnivorous, allowing for lower inclusions of fishmeal and fish oil in diets, and therefore potentially greater net gains of fish protein. In the meantime, many Asian countries lack regulations on farming practices, chemical use, employment conditions, water treatment, etc., that are often expected by European consumers. In addition to this, many aquaculture systems in Asia are reliant on local resources that are related to their own sets of environmental interactions. For example, fish are often fed rice derived products (rice bran, rice husks, boiled rice, etc.), a crop that is responsible for a large share of anthropogenic methane emissions (Yan *et al.* 2009). There is also a flow of regionally caught low-value fish (also referred to as trash fish) into Asian aquaculture production, with social and environmental consequences (Edwards *et al.* 2004; Cao *et al.* 2015). Nutrient run-off from aquaculture cages and ponds have also resulted in regional algae blooms and anoxic aquatic conditions (Verdegem 2013). This in addition to the many concerns raised above highlights the broad range of both proximal and global environmental impacts related to Asian aquaculture production.

In order to evaluate the environmental impacts throughout production chains in a systematic way, the present research applied LCA to different Asian aquaculture production systems. Given the diversity of producing countries and production systems, a selection limited the scope of the study to four countries, five species and 21 production systems. The environmental impacts evaluated were also limited to those supported by rigorous impact assessment methods, deemed relevant to aquaculture production and relevant to the inventory data.

1.6 Life Cycle Assessment (LCA) and associated uncertainties

The ISO standard (ISO 14040 2006) define four phases of an LCA: goal and scope definition, life cycle inventory analysis (LCI), life cycle impact assessment (LCIA) and interpretation. The goal and scope is a qualitative description of the methodological choices and assumptions made throughout the LCA. These choices are important as they greatly influence outcomes, which is why several guidelines have been produced to harmonise results (ISO 14044 2006; BSI 2008; JRC 2010a; JRC 2010b). The second phase, the LCI, is the most data intensive part of most LCAs, detailing all the connections among economic and environmental flows entering or exiting the product's lifecycle. Several software and databases have in response been established to make LCIs more easily attainable and complete, ecoinvent being the most extensive. In the LCIA phase, the environmental flows from the LCI are classified and characterised towards the impact categories detailed in the goal and scope. Each impact category is generally supported by one or more impact assessment methods that can be either midpoint-oriented (characterising elementary flows to a common indicator close to the elementary flows, e.g. radiative forcing for greenhouse gas emissions) or endpoint-oriented (characterising elementary flows to a common indicator close to the areas of protection, e.g. temperature increase for the same greenhouse gases). Finally the outcomes are evaluated and conclusions are drawn in the interpretation phase.

LCA results have, to date, generally been presented as point-values that are often compared to each other without any indication of the confidence behind the estimates. In the meantime, methodological choices and assumptions made in the goal and scope can have huge influence on outcomes (de Koning *et al.* 2009). For studies following the same standard these discrepancies can, at least in theory, be greatly reduced. This is, however, more difficult in the LCI phase, as each of the diverse production systems supporting aquaculture farming are subject to their own sets of uncertainties and variability (from here on jointly referred to as dispersions). Ranging from natural fluctuations in fish stocks (Sandweiss *et al.* 2004), to variations in agricultural yields (Naylor *et al.* 1997), to uncertainty around the emissions from manure management (De Vries *et al.* 2013), to simply different energy efficiencies in machinery, these variables are next to impossible to normalise across studies.

Also in the LCIA phase are there uncertainties related to the classification and characterisation of environmental emissions. All these different sources of dispersions have, up until recently, mainly been addressed by performing sensitivity analyses (Lloyd and Ries 2007). While sensitivity analyses are useful for increasing the understanding of the relationships between input parameters/choices and results (Middelaar *et al.* 2013; van der Harst and Potting 2014), they fail to account for the cumulative effect from all dispersions influencing aggregated LCA results and therefore greatly limit available post-hoc analyses. A more holistic indicator of the accuracy of LCA results can instead be generated by quantifying and aggregating the dispersions related to input parameters and choices.

The importance of providing quantified dispersions around LCA results have since long been recognised (Hanssen and Asbjørnsen 1996; Finnveden 1998) and repeatedly upturned (Björklund 2002; Ross *et al.* 2002). Ross *et al.* (2002), for example, state: "If practitioners of LCA continue to neglect the problem of uncertainty in their work, they run the risk of generating conclusions that cannot be justified by the indicator results". In response, early estimates of inherent uncertainties were also quantified as early as in the 1990s for a number of emission parameters (Hanssen and Asbjørnsen 1996; Finnveden 1998). Around the same time, there were also several new methodologies suggested for how to include quantitative uncertainties in LCIs (Heijungs 1996; Weidema and Wesnaes 1996; Huijbregts 1998a; Huijbregts 1998b; Huijbregts *et al.* 2001). Weidema and Wesnaes (1996), for example, presented a pedigree approach for addressing data quality issues in LCIs, while Heijungs (1996) suggested a more empirical approach. These and other efforts were followed up by Huijbregts (2001), who also developed the ideas surrounding uncertainties related to characterisation factors. Despite these initiatives, only a few LCA studies had quantified uncertainties around results at the beginning of the present research (Lloyd and Ries 2007), none of which focused on aquaculture production. Most of the studies that did quantify uncertainties, moreover, only evaluated specific sources of uncertainty and/or only used conjectural dispersion estimates. In other cases, the drivers behind the presented ranges simply remained unclear (Steinmann *et al.* 2014). Concerns were even raised that if all dispersion sources were accounted for, LCA results might be rendered meaningless (Huijbregts *et al.* 2004).

Only in the past few years have some LCA studies moved closer towards a complete inclusion of dispersions derived from empirical data (Mattila *et al.* 2011; Steinmann *et al.* 2014; Hauck *et al.* 2014). The reasons for why quantitative uncertainties have not been more extensively implemented before are many, including lack of data, no uncertainty estimates in databases, many unquantifiable sources of dispersions, an absence of propagation methods in LCA software, insufficient computing power, time limitations, or simply the lack of a comprehensive methodology (Björklund 2002; Ross *et al.* 2002; Lloyd and Ries 2007). For example, data limitations forced ecoinvent (v2) to only rely upon generic uncertainties and a pedigree approach when they finally included uncertainty estimates in their LCI database (Frischknecht *et al.* 2007b). This sudden widespread availability of uncertainty parameters, however, initiated many software developers to allow for the inclusion of uncertainties. In the meantime, computing power and software algorithms improved substantially, providing the standard personal laptop with more than sufficient processing power for normal dispersion calculations. Remaining unresolved, however, was a method that allowed for the inclusion of quantified dispersions based upon empirical data together with a standardised nomenclature. While some attempts had been made to meet this need, their outcomes were often too complex to be attainable to LCA modellers, which, in their defence, already need to be experts in two topics apart from statistical theory (those of LCA and the production system under study).

By developing a method for identifying and quantifying the dispersions around LCA results, the quantification of dispersions around results could become commonplace. This would also allow for the implementation of significance tests, which, in turn, would allow for statistically supported conclusions to be made. This would further open questions about the type of significance tests to be used, with regards to the characteristics of the data. Applying the wrong test might result in Type I statistical error, where a null-hypothesis is falsely rejected (false positive), or a Type II statistical error, where the null-hypothesis is falsely retained (false negative). In addition, being transparent about eventual shortcomings of analyses made is of utter importance, especially with regards to LCA that is an applied science where many values are 'soft' and underpinned by subjective judgement (Ravetz 1999).

1.7 Thesis outline

In order to provide a platform to extend this research from, **Chapter 2** of this thesis presents a review of existing aquaculture LCAs (Henriksson *et al.* 2012c). At the time of the review, twelve peer-reviewed LCAs of aquaculture systems were found in the literature, two of which were PhD theses. The LCA studies were evaluated on the systems evaluated, methodological choices made, data sourcing, interpretation techniques and conclusions drawn.

From the review, data sourcing and data quality stood out as important topics for improving aquaculture LCAs. This is also the topic of **Chapter 3** of the present thesis — A protocol for horizontal averaging of unit process data—including estimates for uncertainty (Henriksson *et al.* 2013). Building upon earlier efforts by Funtowicz and Ravetz (1990), Heijungs (1996), Weidema and Wesnaes (1996), Huijbregts (2001), Sonnemann *et al.* (2011) and others, this article tries to identify the major sources of dispersions in unit process data and present a workable method for quantifying these (Henriksson *et al.* 2013).

In order to evaluate the protocol and to identify the best method for propagating unit processes into LCI results, an updated unit process dataset for coal-based energy in China was used as an example. Chinese coal power was selected as it presents a much more limited model than the generally diverse aquaculture production chains, and since it was surprisingly poorly represented in LCA literature and inventory databases. **Chapter 4** consequently explores different levels for averaging unit process data and methods for propagating these into results (Henriksson *et al.* 2014c).

Once ranges could be produced as results, the question of which conclusions could be drawn from these arose. In **Chapter 5**, entitled "Product carbon footprints and their uncertainties in comparative decision contexts", an approach for propagating and interpreting LCA results using significance tests was therefore developed (Henriksson *et al.* 2015a). This chapter also highlighted the importance of defining a hypothesis to work towards.

In **Chapter 6**, the methodological advancements developed were finally used to test the main research question. Using significance tests, the hypothesis "different production systems providing the same aquaculture commodity to European consumers are associated with different environmental impacts" was tested (Henriksson *et al.* 2015b). Three impact categories (global warming, eutrophication and freshwater ecotoxicity) were evaluated. Alongside identifying production systems associated with significantly lower environmental impacts, best practices are promoted.

Chapter 2

Life cycle assessment of aquaculture systems—a review of methodologies

Patrik JG Henriksson, Jeroen B Guinée, René Kleijn & Geert R de Snoo

Accepted: 9 December 2011. International Journal of Life Cycle Assessment. Vol. 17, pp. 304-313. DOI: 10.1007/s11367-011-0369-4

Chapter 2

Abstract

Purpose: As capture fishery production has reached its limits and global demand for aquatic products is still increasing, aquaculture has become the world's fastest growing animal production sector. In attempts to evaluate the environmental consequences of this rapid expansion, life cycle assessment (LCA) has become a frequently used method. The present review of current peer-reviewed literature focusing on LCA of aquaculture systems is intended to clarify the methodological choices made, identify possible data gaps, and provide recommendations for future development within this field of research. The results of this review will also serve as a start-up activity of the EU FP7 SEAT (Sustaining Ethical Aquaculture Trade) project, which aims to perform several LCA studies on aquaculture systems in Asia over the next few years.

Methods: From a full analysis of methodology in LCA, six phases were identified to differ the most amongst ten peer-reviewed articles and two PhD theses (functional unit, system boundaries, data and data quality, allocation, impact assessment methods, interpretation methods). Each phase is discussed with regards to differences amongst the studies, current LCA literature followed by recommendations where appropriate. The conclusions and recommendations section reflects on aquaculture-specific scenarios as well as on some more general issues in LCA.

Results: Aquaculture LCAs often require large system boundaries, including fisheries, agriculture, and livestock production systems from around the globe. The reviewed studies offered limited coverage of production in developing countries, low-intensity farming practices, and non-finfish species, although most farmed aquatic products originate from a wide range of farming practices in Asia. Apart from different choices of functional unit, system boundaries and impact assessment methods, the studies also differed in their choice of allocation factors and data sourcing. Interpretation of results also differed amongst the studies, and a number of methodological choices were identified influencing the outcomes.

Conclusions and recommendations: Efforts should be made to increase transparency to allow the results to be reproduced, and to construct aquaculture related database(s). More extensive data reporting, including environmental flows, within the greater field of LCA could be achieved, without compromising the focus of studies, by providing supporting information to articles and/or reporting only ID numbers from background databases. More research is needed into aquaculture in Asia based on the latest progress made by the LCA community.

2.1 Introduction

Historical increases of yields from capture fisheries have been achieved by increasing fishing efforts and exploring new fishing grounds. Around 1990, however, global fish landings levelled off, followed by increases in fuel consumption as fishing boats had to cover larger distances to reach productive fishing grounds and greater efforts were required to maintain catches (Tlusty and Lagueux 2009; FAO 2010a). As a result of this development, aquaculture has become increasingly important in meeting the rising global demand for aquatic food products, with annual per capita supply from aquaculture growing from 0.7 to 7.8 kg globally since the 1970s (FAO 2010a). Farming methods for aquatic organisms are highly diverse, and 91% of global production is based in Asia (FAO 2010b). Global aquaculture production is dominated by finfish (49% by weight), followed by aquatic plants (23%), bivalves (19%), and crustaceans (7%) (FAO 2010b). Small-scale production of freshwater fish from ponds in Asia is the most common production system, with a general global trend towards intensification (Naylor *et al.* 2000; Muir 2005; FAO 2010a).

The rapid expansion of the aquaculture sector has been associated with many sustainability concerns, such as emissions leading to climate change, eutrophication, toxic and ecotoxic impacts, use of antibiotics, use of land and water needed for feed production, loss of biodiversity, introduction of non-indigenous species, spread/amplification of parasites and disease, genetic pollution, dependence on capture fisheries, and socio-economic concerns (Naylor *et al.* 2000; Pelletier *et al.* 2007; Pelletier and Tyedmers 2008; Ayer and Tyedmers 2009; Naylor *et al.* 2009). In the process of better understanding the environmental impacts of aquaculture, life cycle assessment (LCA) has become more frequently used to identify best practices and to assess overall environmental performance (Pelletier and Tyedmers 2008). As part of the EU FP7 SEAT project (Sustaining Ethical Aquaculture Trade, www.seatglobal.eu), LCA studies of shrimp, freshwater prawn, tilapia, and catfish will be performed in Bangladesh, Thailand, Vietnam, and China during the upcoming years. To provide a starting point for these studies, we have reviewed ten articles found in ISI Web of Knowledge (accessed on 30-Nov-2010) and two PhD theses focusing on LCA of aquaculture systems. Although several other studies are available, this review only focuses on peer-reviewed literature. The present review aims to clarify the methodological choices made, identify possible data gaps, and provide recommendations for future developments in this field of research, as well as for the upcoming SEAT LCA studies.

2.2 Materials and methods

Originally developed for industrial production and processes, LCA was later applied to food products with the first LCA studies of food production being published in the early 1990s (Roy *et al.* 2009). These allowed for the first aquaculture LCAs, where agricultural and livestock systems provide resources for fish-feed production. The first published aquaculture-related LCA was done by Papatryphon *et al.* (2004) in order to evaluate salmon feed. This was followed by a number of publications on aquaculture production in the second half of that decade (**Table 2.1**). The most productive institutes in this field of research have been the French INRA-IFREMER and Dalhousie University, Canada. Ten of the LCAs focused on finfish production, while Mungkung (2005) studied shrimp farming and Iribarren *et al.* (2010) examined mussel production. Of the ten finfish studies, nine focused on intensive production, and one (Phong 2010; Phong *et al.* 2011) described integrated semi-intensive farming systems. Six studies examined production systems based in Europe, three in Asia, and two in North America, while one study described global production.

Below, we discuss the LCA methodology that exhibited the greatest difference amongst the LCA studies listed in **Table 2.1** (Guinée *et al.* 2002):

- Functional unit
- System boundaries
- Data and data quality
- Allocation
- Impact assessment methods
- Interpretation methods

The selection of these six phases is based on an analysis of all methodological assumptions and choices made and data sources adopted for the different steps of Goal and Scope definition, Inventory Analysis, Impact Assessment, and Interpretation. An analysis of other methodological phases and a detailed discussion of the impact categories are published as online resource to this article. Each of the six phases listed above is analyzed below in terms of differences amongst the studies, followed by a summary of the current LCA literature and, where appropriate, recommendations for research or harmonization.

2.3 Results

2.3.1 Functional unit

The functional unit is the reference unit used to quantify the performance of a production system (ISO 14044 2006). The most commonly used functional unit in the twelve studies reviewed here is 1 ton of live fish at the farm gate (six studies; see **Table 2.1**). Two other studies also limit themselves to the farm gate, with Grönroos *et al.* (2006) adopting dead weight and Phong (2010) adopting 1 kcal alongside 1 kg as his two functional units. Four studies defined their functional unit in terms of edible yield, defined as the main part of the organism that was marketed (fillets, flesh or tails).

The functional unit is the basis of comparison in comparative LCAs. The functional unit follows the goal of the study, since different goals may require different functional units. The goal of the study and the associated functional unit partially defines the system boundary of the inventory. For example, if frozen fillets in supermarkets are chosen as a functional unit, the system boundary needs to be defined so as to include processing, transportation, and distribution. The functional unit may, moreover, significantly influence comparative LCAs involving different species, since the edible portions and nutritional values of products can differ by an order of magnitude (Roy *et al.* 2009). Mussels and shrimp, for example, provide respectively, 13.6 and 140 kg of protein per ton of whole animals harvested (Mungkung 2005; Iribarren *et al.* 2010; www.nutraqua.com accessed 23-June-2010).

The choice of the functional unit is important for comparisons between species as well as across cultures, as the definition of edible will depend on cultural influenced consumer preferences. The choice of functional unit will also influence allocation decisions at the farm gate where more descriptive functional units, such as kilocalorie, may be more appropriate for comparisons between multi-output systems (Phong 2010). We therefore recommended to carefully choose a functional unit tailored to the goal and scope of the study.

Table 2.1: The ten articles and two PhD theses under review with general methodological choices highlighted.

General				Functional unit	System boundary	Allocation method	Data and data quality		Institute
Reference	Species	System	Country				Software	Database	
Aubin et al. 2006	Turbot	Re-circulating	France	1 tonne live weight	Farm-gate	Economic value	SimaPro v.6.0	Buwal B250, Ecoinvent[a]	INRA/ IFREMER
Aubin et al. 2009	Rainbow trout, sea-bass and turbot	Various	France	1 tonne live weight	Farm-gate	Economic value	SimaPro v.6.0	Buwal B250, Ecoinvent[a]	
d'Orbcastel et al. 2009	Trout	Various	(Model)	1 tonne live weight	Farm-gate	Economic value	SimaPro v.6.0	EDF 2004; etc	
Pelletier and Tyedmers 2007	Atlantic salmon	Salmon feeds	Canada	1 tonne live weight	Farm-gate	Gross nutritional energy	SimaPro v.7.0	Ecoinvent v.2; Franklin[a]	
Ayer and Tyedmers 2009	Atlantic salmon & char	Various	Canada	1 tonne live weight	Farm-gate	Gross nutritional energy	SimaPro v.7.0	Ecoinvent 1.2; Franklin; IDEMAT 2001; LCA Food 2005	Dalhousie
Pelletier et al. 2009	Atlantic salmon	Cage	Global	1 tonne live weight	Farm-gate	Gross nutritional energy	Simapro v.7.1.8	Ecoinvent v.2	

Pelletier and Tyedmers 2010	Tilapia	Net cage & ponds	Indonesia	1 tonne fillets	Market	Gross nutritional energy	SimaPro v.7.0	Ecoinvent v.2	
Mungkung 2005	Shrimps	Ponds	Thailand	1.8 kg shrimp tails	Waste	Economic value	SimaPro v.5.1	Buwal B250; etc[a]	
Grönroos et al. 2006	Rainbow trout	Net cage	Finland	1 tonne dead weight	Farm-gate	Mass	KCL-ECO 2003	Silvenius & Grönroos 2003	Other
Ellingsen and Aanondsen 2006	Atlantic salmon	Net cage	Norway	200 gram fillet	Market	Mass/ Economic value	SimaPro v.6.0	ETH-ESU 96; Buwal 250	
Iribarren et al. 2010	Blue mussels	Rafts	Spain	1 kg of dry mussel flesh	Consumer	System expansion	SimaPro v.6.0	Ecoinvent v.2	
Phong 2010	Various[b]	Ponds, integrated	Vietnam	1 kg of live fish/ 1 kcal	Farm-gate	Economic value	Excel[a]	Ecoinvent[a]	

2.3.2 System boundaries

The system boundary determines which unit processes will be included within an LCA study and which ones are to be excluded. With respect to the diverse goals of the reviewed studies, few have considered supply chain impacts beyond the farm gate (Pelletier and Tyedmers 2010b). Iribarren *et al.* (2010), however, did include the whole production chain and found that a significant part of the emissions from mussel production is related to processing and marketing, with dispatch centers contributing significantly to the overall emissions from live mussel production. Infrastructure is also often excluded, due to the large amount of time that has to be invested in calculating the total input in relation to the small impact that is considered (Ayer and Tyedmers 2009). Where included and distinguished (Aubin *et al.* 2006; Aubin *et al.* 2009; Ayer and Tyedmers 2009; d'Orbcastel *et al.* 2009), however, infrastructure was found to contribute between 0% and 19.0% to the overall impacts in terms of global warming, eutrophication, and acidification indicators. Common cut-offs were based on the outcomes of previous studies, selection of impact categories, available data, and resource constraints (Mungkung 2005; Ellingsen and Aanondsen 2006; Grönroos *et al.* 2006; Pelletier *et al.* 2009; Pelletier and Tyedmers 2010b).

The selection of the system boundary should be consistent with the goal of the study, and the criteria used to establish the system boundary should be identified and explained (ISO 14044 2006). In aquaculture systems, the length of the full production chain is largely dependent on the type of system (**Fig. 2.1**). For example, external inputs of feed and hatchery-reared juveniles may not be needed in extensive systems and if the product is sold fresh on the market it needs no processing (e.g., carp in China). Fish and seafood are also the most perishable of food products, and the level of processing will influence the longevity of the product, as well as the amounts wasted, hence the environmental impacts (Sonesson *et al.* 2005).

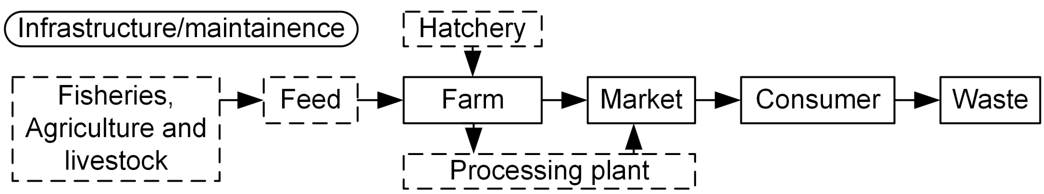

Fig. 2.1: Simplified flow chart of aquaculture production. The inclusion of some processes (dashed lines) are dependent upon the system in focus.

The problem in defining cut-offs for the quantification of inventories is a lack of readily accessible data, implying disproportionate expenditure of funds and efforts on data collection. Limitations of time, funds, or data access will inevitably lead to the exclusion of processes and to less complete and accurate results. Nowadays, it is, however, possible to handle the cut-off problem better, by estimating the environmental interventions associated with flows for which no readily accessible data is available using environ- mentally extended input–output analysis (EIOA) (Suh *et al.* 2004). For the purpose of consumer guidance, we recommend a more extensive system boundary at or beyond the market, as impacts may otherwise be underestimated (Iribarren *et al.* 2010). Further efforts should also be directed towards expanding current knowledge about the contributions from infrastructure, as this has been reported to have a larger influence on agriculture than on most other industrial processes (Frischknecht *et al.* 2007a).

2.3.3 Data and data quality

Although all of the studies reviewed here model relevant agriculture, fisheries and other related processes—to different extents—most of the inventory details of these modeling efforts remain unpublished. Articles that do extensively report the data mainly specify economic flows, with environmental flows often limited to nutrient balances. This may be due to the aquaculture-based background of most of the researchers for whom eutrophication has historically been a major concern. In various articles, it remains unclear whether background databases were used or whether real foreground data (site-samples) had been collected (ILCD 2010); neither is it always clear which processes that were included in the study. Consequently, reproducing their results is difficult or impossible. For example, Ellingsen and Aanondsen (2006) reported: "Data are generally collected from various sources by both literature surveys, a study of available data sources, telephone conversations, and meetings". This, unfortunately, provides no clue as to which processes, data, or data sources were included in the study.

Background data used in the studies were derived from a wide range of databases, including some which were quite outdated (ETH 1996 and BUWAL 250) (see **Table 2.1**). Some authors used combinations of different databases or did not clearly specify the precise database(s) consulted. Several studies, for example, reported that they had used SimaPro software, with all of the databases included in it. As SimaPro includes many different databases (e.g., Ecoinvent, US LCI database, US IO dbase, Danish IO dbase, Dutch IO dbase, LCA food dbase, Industry data, Japanese IO dbase, IVAM dbase; see http://www.pre.nl/ simapro/inventory_databases.htm), the actual data sources used in these studies remain unclear. All studies, moreover, rely on European databases (commonly different versions of Ecoinvent), even though various studies dealt with aqua- culture in non-European countries. Although the authors of several studies did invest much effort in adapting inventories to regional conditions, there remains a real need for databases representing technologies of developing countries.

The focus of the studies ranged from single farms (Aubin *et al.* 2009; Ayer and Tyedmers 2009) to small samples of each farming system (Phong 2010), to aggregated industry averages representing significant parts of national outputs (Pelletier *et al.* 2009; Pelletier and Tyedmers 2010b). However, the quality of foreground data available for aquaculture systems often depends on the intensity of the system and the region of data collection. Highly intensive systems, such as land-based salmon systems, often keep more complete records of all inputs and outputs, while only general estimations are available for most extensive pond systems in rural areas. Accessibility to feed inventories may, moreover, be subject to the scale and nature of the feed mill, as exact mixtures of ingredients often are held confidential. Site-specific measurements are, moreover, dependent on the resources available. The articles offer limited reporting on other environmental flows beyond nutrient budgets (including methane, nitrous oxide emissions, copper-based anti-fouling agents, antibiotics, etc.).

The International Organization for Standardization (ISO 14044 2006) states that data quality requirements should be specified to enable the goal and scope of the LCA to be met, and also that the treatment of missing data should be documented, and that data sources as well as an assessment of the reproducibility of the study results by independent practitioners should be addressed as part of the data quality requirements. ISO does not, however, demand publication of all data used.

Transparency in the reporting of data and reproducibility of results are important for proper peer-reviewing and interpretation of background data, at least to the extent that this is possible with regards to sensitive industry inventory data. A good example of the way data can be published without compromising the focus of the article was given by Grönroos *et al.* (2006) and Pelletier *et al.* (2009), who both published supporting documents describing inventories (although with different coverage of environmental data; see above), core processes, assumptions, and calculations. Another solution to fitting large inventories to the often restricted format of scientific journals is to report which processes derived from a background database (e.g., ecoinvent) were included in the study without actually including the data of that process. Such processes could simply be reported using the process ID numbers, rather than the full process names. This kind of more open reporting of data is critical for developing specific LCA data sets for aquaculture-related processes, as much primary data currently are lost by aggregating results and by only presenting impacts, rather than inventories. It should, however, be pointed out that the data sourcing and reporting issues discussed here are not unique to aquaculture LCAs, but rather apply to the majority of LCA studies published, whether peer-reviewed or not.

2.3.4 Allocation

Some of the main differences amongst the studies reviewed here are related to allocation. While all of the most commonly applied procedures for allocation (including mass, economic value, gross energetic content, and system expansion) have been applied to aquaculture LCAs, economic value and gross nutritional energy content have more frequently been used in the more recent publications (see **Table 2.1**). This is also the main methodological difference between the two main publishing institutions, with INRA-IFREMER applying economic allocation, while researchers at Dalhousie University commonly prefer gross energy content as the basis for allocation (see **Table 2.1**).

Four publications applied system expansion to certain allocation situations (Ayer and Tyedmers 2009; Pelletier *et al.* 2009; Iribarren *et al.* 2010; Pelletier and Tyedmers 2010b). Iribarren *et al.* (2010), for example, used system expansion for Spanish mussel production (with mussel as the main product and shells as a co-product) with the assumption that mussel shells could be used to replace conventional calcium carbonate production. Grönroos *et al.* (2006) restricted their analysis to whole fish at the farm gate to avoid allocation in the processing phase, while mass allocation was used for feed inputs. Some authors did not report their allocation decisions in their articles.

Most industrial processes yield more than one product, and some recycle expanded products as raw materials. As a result, the materials and energy flows, as well as the associated environmental releases, have to be allocated to the different products according to clearly stated and justified procedures. In aquaculture, many of the feed inputs are co-produced in other production systems (e.g., rice bran, fisheries by-catch, and co-products from livestock processing), and co-products also occur in the processing phase.

It is our belief that the multi-functionality problem is an artefact of the desire to isolate one function out of many and as artefacts can only be resolved in an artificial way, there will always be more than one way of solving the multi- functionality problem. This is illustrated by the debate on methods to deal with the multi-functionality problem over the last two to three decades which still has not provided a generally accepted method. Depending on the application (e.g., policy or scientific publications), using alternative allocation methods could be seen as an opportunity to produce more realistic ranges of results and provide stronger conclusions. There are, however, certain requirements that need to be addressed when dealing with allocation issues, such as that the solution should be consistent, well justified and in-line with main methodological principles (Guinée *et al.* 2004; ILCD 2010). It is also important to always report on the allocation method(s) applied and perform a sensitivity analysis, as allocation plays a pivotal role in the performance of a production system (ISO 14044 2006).

2.3.5 Life cycle impact assessment methods

All reviewed studies applied one or more life-cycle impact assessment methods. The major impact assessment method- ology used for characterization was the midpoint CML baseline method (Guinée *et al.* 2002) with only Ellingsen and Aanondsen (2006) applying an endpoint approach (eco-indicator 99 method; Goedkoop and Spriensma 1999). Grönroos *et al.* (2006) choose to use region-specific characterization factors for eutrophication and acidification, while making a distinction between aquatic and terrestrial emissions. Only climate change, acidification, and eutrophication were adopted as impact categories by all studies. In addition, a few novel methods were introduced for biotic resource use, water dependency, and land (surface) use (**Table 2.2**).

As regards climate change, the characterization factors suggested by the international panel on climate change (IPCC; Houghton *et al.* 2001) were the basis for all reviewed studies. This therefore enables for valid conclusions to be drawn amongst the studies, e.g., the great importance of feed inputs for aquaculture systems.

As regards acidification, all but three studies adopted the approach developed by Huijbregts (1999). Apart from Ellingsen and Aanondsen (2006) and Grönroos *et al.* (2006), Phong (2010) chose alternative characterization factors, in this case, the older Heijungs *et al.* (1992) acidification method.

As regards eutrophication, similar differences are found as for acidification, while Grönroos *et al.* (2006) chose to separate terrestrial and aquatic emissions due to their distinct association to feed production and feed application, respectively. Phong (2010), again, refers to an older alternative publication, Weidema *et al.* (1996).

Cumulative primary fossil energy demand was the fourth most commonly included impact category amongst the studies and showed a large overlap with abiotic resource depletion (Ayer and Tyedmers 2009). Strikingly, six studies adopted and quantified a novel impact category, biotic resource use. Its use aims to capture the ultimate carbon-based energy stemming from biological systems that support fed aquaculture production, although a standardized protocol for this impact category still remains to be developed (Pelletier *et al.* 2007). Marine exotoxicity, an impact category for which the existing characterization methods have been widely debated within the LCA community (Gloria *et al.* 2006; Pettersen and Hertwich 2008), was adopted and quantified in four studies. A range of other toxicity related impact categories were less frequently adopted, along with abiotic resource depletion and ozone depletion. Water dependency and land use were represented in only two studies each, using own methodology. Little consideration was, however, given to the type of water use (e.g., marine or freshwater, degradative or consumptive; Bayart *et al.* 2010) on either the input or the output side, nor were emissions relating to land use and transformation considered (ILCD 2010). Other concerns not covered by the LCA methodologies reported in our review include impacts on the seafloor from capture fisheries, the introduction of invasive species, the spread of diseases, genetic pollution, and socio-economic concerns (Pelletier *et al.* 2007).

Table 2.2: Frequency of applying different impact categories in LCA studies on aquaculture, and the impact assessment method used. Global warming, acidification and eutrophication were the only impact categories applied by all authors. References: [1]Mungkung 2005; [2]Aubin *et al.* 2006; [3]Ellingsen and Aanondsen 2006; [4]Grönroos *et al.* 2006; [5]Pelletier and Tyedmers 2007; [6]Aubin *et al.* 2009; [7]Ayer and Tyedmers 2009; [8]d'Orbcastel *et al.* 2009; [9]Pelletier *et al.* 2009; [10]Iribarren *et al.* 2010; [11]Pelletier and Tyedmers 2010; [12]Phong 2010. For full references on the impact assessment methods, please refer to the Online Resources online.

Impact category	Σ	Impact Assessment method
Global warming	12	Houghton et al. 2001[1,2,3,4,5,6,7,8,9,10,11,12]
Acidification	12	Huijbregts 1999a[1,2,5,6,7,8.9,10,11]; Goedkoop and Spriensma 1999[3]; Seppälä et al. 2006[4]; Heijungs et al. 1992[12]
Eutrophication	12	Heijungs et al. 1992[1,2,5,6,7,8,9,10]; Goedkoop and Spriensma 1999[3]; Weidema et al. 1996[12], Seppälä et al. 2004[4a]; Seppälä et al. 2006[4a]
Energy use	8	VDI 1997[2,5,6,7,8,9,11]; Goedkoop and Spriensma 1999[3]; Article specific[12]
Biotic resource use	6	Papatryphon et al.2004[2,6,8]; Pelletier and Tyedmers 2007[5,9,11]
Marine aquatic ecotoxicity	4	Huijbregts 1999b[5,7,10]; Meent and Klepper 1997[3b]
Abiotic depletion potential	3	Guinée and Heijungs 1995[1,7,10]
Ozone depletion potential	3	WMO1999[1,10]; Goedkoop and Spriensma 1999[3]
Human toxicity	3	Huijbregts 1999b[1,7,10]
Water dependence	2	Own methodology[6,8]
Photochemical oxidant formation	2	Derwent et al. 1998/Jenkin and Hayman 1999[1,10]
Freshwater aquatic ecotoxicity	2	Meent and Klepper 1997[3b]; Huijbregts 1999b[10]
Terrestrial ecotoxicity	2	Meent and Klepper 1997[3b]; Huijbregts 1999b[10]
Surface use	2	Own methodology[8, 12]
Respiratory impacts from inorganics	1	Goedkoop and Spriensma 1999[3]
Cancinogenic effects on humans	1	Goedkoop and Spriensma 1999[3]

[a]Aquatic and terrestrial eutrophication was reported separately
[b]Ecotoxicity is summarized under one category

In summary, the current review of aquaculture LCAs shows that impact assessment methodologies have been applied to all studies reviewed. The range of impact categories covered is, however, limited, and the methods adopted for the various categories differ, hampering comparisons of study results. Some authors used old characterization factors, while others developed their own quantification methods. Future harmonization with the developments within the LCA community is therefore advised, focusing on the standardization efforts promoted by ILCD (the European Commission's Join Research Centre) and UNEP- SETAC (the United Nations Environment Programme and the Society of Environmental Toxicology and Chemistry) including the ILCD handbook (lct.jrc.ec.europa.eu), USEtox™ (www.usetox.org), land-use (lcinitiative.unep.fr, accessed: 17-Oct-2010) and freshwater use (Bayart *et al.* 2010) (for a complete overview of the life cycle impact assessment methods adopted by the different studies reviewed here, please see the Online Resource to this paper).

2.3.6 Interpretation methods

Although all studies performed a dominance or contribution analysis, many did not perform a complete set of sensitivity analyses, as is required by the current ISO standards. Ayer and Tyedmers (2009), however, conducted an extensive set of sensitivity analyses, one of which highlighted the importance of electricity sourcing. Another study by Pelletier and Tyedmers (2007) concluded that allocation factors strongly influence the impact of different feed inputs. Both d'Orbcastel *et al.* (2009) and Pelletier *et al.* (2009) drew a parallel between food conversion ratios (FCRs, defined as kilogram dry feed/kilogram live fish) and GHG (greenhouse gas) emissions, while Mungkung (2005) supported her conclusions by performing a sensitivity analysis on data assumptions for fishing practices as well as for different impact assessment methods. Ellingsen and Aanondsen (2006) also used two alternative impact assessment methods to strengthen their conclusions. Pelletier *et al.* (2009) evaluated the range of nitrous oxide emissions from nitrogen fertilizers, compared to the default value indicated by the IPCC. Only Phong (2010) applied statistical tools to different farming practices, in the form of one-way ANOVA (analysis of variance).

According to ISO (2006), the life cycle interpretation phase of an LCA comprises the identification of the significant issues based on the results of the LCI (life cycle inventory) and LCIA stages, an evaluation involving completeness, sensitivity, and consistency checks, and finally the formulation of conclusions, limitations, and recommendations. It is an important phase of any LCA study, where any weaknesses should be highlighted and results critically tested.

Irregularities at temporal and spatial scales give rise to deviations in inventories of aquaculture production. Underlying models, moreover, rely on assumptions and methodological choices influence the results. Statistical tools and sensitivity analyses are therefore important to strengthen the arguments and conclusions in aquaculture LCAs. Treating farms individually, rather than as averages, would here allow for more extensive statistical comparisons to be made between farms. Known pivotal factors identified in the articles reviewed here include various inventory choices (feeds, raw materials, infrastructure, etc.), GHG emissions from agricultural fields and aquatic systems, nitrogen and phosphorus emissions, allocation factors, and characterization factors. Further efforts are therefore needed to account for the many degrees of freedom, using more extensive sensitivity analyses and implementing, e.g., Monte Carlo analysis.

2.4 Discussion

Aquaculture is currently the fastest growing animal production sector, and ever-larger amounts of farmed aquatic products are being traded on international markets. Increasing concerns about the sustainability of production have, however, been raised, and the standards and requirements imposed on the aquaculture sector are becoming ever stricter. In the search for best practice, LCA has proved to be a valuable tool to identify environmental hot spots and compare different production systems. To date, however, there has been limited LCA coverage of the various farming systems worldwide, especially in Asia from where the bulk of farmed aquatic products originate. The present review has identified a range of methodological and data sourcing approaches reported in existing publications, where methodological choices often govern the outcomes.

Nine of the twelve peer-reviewed publications included in this review focused on intensive finfish production, which represents a small share of the global aquaculture output. Eight of the studies were, moreover, limited to whole fish at the farm gate, which may give misleading results if consumer guidance is the objective. Distribution of fish and seafood to markets may, for example, contribute disproportionately to the overall impacts as these are highly perishable commodities with high value attached to their freshness (Tlusty and Lagueux 2009). More LCA-based research is therefore needed to guide this still expanding sector towards best practice. With the widespread of aquaculture in Asia, these studies should focus on Asian aquaculture and alternative farming practices, using a functional unit relevant to the aim of the study.

The greatest single methodological difference amongst the studies was in allocation, with monetary value and gross energy content being the most commonly applied allocation factors. However, the level of reasoning and consistency regarding choices made varied greatly amongst studies. As consensus, let alone scientific clarity, is not likely to be achieved soon, allocation choices should be clearly defined and justified. Inventory results with regard to the allocation method adopted should also be supported by thorough sensitivity analysis, as advocated by ISO. Databases and software should, moreover, simplify the application of alternative allocation decisions to enable more extensive sensitivity analyses.

All studies had adopted the IPCC recommendations for global warming, as it represents a highly resourceful centralized scientific body. Similar developments should be encouraged for other impact categories, following initiatives by ILCD and UNEP-SETAC. However, inventories of the characterized environmental flows need to be made available to allow alternative characterization factors to be implemented. Toxicological implications should also be given more attention as they have historical importance in the aquaculture sector (e.g., Malachite green). New characterization factors and standardized protocols need to be developed to address more aquaculture-specific concerns (e.g., seafloor disturbance and biotic resource use). A distinction between terrestrial and aquatic eutrophication may also have to be made, as these emissions usually have distinctly different origins.

2.5 Conclusions and recommendations

There is a need for more detailed LCA studies of non-finfish species, as well as of integrated, extensive, and semi- intensive production of finfish in developing countries (especially in Asia), in order to guide the industry towards best practice, highlight hot spots, and guide consumers. These studies should conform to up-to-date guidelines from, e.g., ISO, ILCD, and SETAC-UNEP in order to move towards a more harmonized methodology. The characterization factors and background databases selected should also be the latest available versions. There is also a need to develop impact categories more specifically related to aquaculture, such as seafloor disturbance, biotic resource depletion, and loss of biodiversity. Moreover, the reporting of methodological choices and data should be improved to allow for comprehensive critical analysis and the joint development of extensive inventories.

Sourcing of background data should be consistent and give consideration to the underlying methodological and geographical characteristics of the database used. More extensive reporting of inventory data as online resource and by defining process numbers is also recommended, as well as efforts to extend the coverage of environmental flows. This would assist the development of specific data (and databases) for aquaculture practices and feeds, which would further promote the quantity and quality of aquaculture LCAs. Finally, the contribution of infrastructure seems to be strongly influenced by the methodology and impact categories used, while applying EIOA to aquaculture systems would allow the importance of missing data in aquaculture LCAs to be estimated. Many of the improvement options mentioned here can be implemented by increasing knowledge exchange between the aquaculture community, from which most of the reviewed studies originate, and the LCA community.

In the ongoing SEAT project, the ambition over the coming years is to describe four major aquaculture exports farmed in Asia. Detailed LCAs will be conducted of a representative sample of each major farming system, supported by a larger scoping survey collecting basic data for 1,600 grow-out farmers in the region. Foreground data will also be collected on other actors in the value chain, including feed producers, processing plants, hatcheries, nurseries, and fishmeal factories in each country. The results of this research are to be presented in inventory and impact assessment reports over the upcoming years, with the ambition to adopt the recommendations suggested above. These efforts together with several other LCA studies published after this review (e.g. Cao *et al.* 2011; Bosma *et al.* 2011) will hopefully improve our current knowledge of the impacts of the aquaculture sector and promote best practice.

Acknowledgements

This work is part of the Sustaining Ethical Aquaculture Trade (SEAT) project, which is co-funded by the European Commission within the Seventh Framework Programme—Sustainable Development Global Change and Ecosystem (project no. 222889). www.seatglobal.eu.

Chapter 3

A protocol for horizontal averaging of unit process data—including estimates for uncertainty

Patrik JG Henriksson, Jeroen B Guinée, Reinout Heijungs, Arjan de Koning & Darren M Green

Accepted: 15 August 2013. International Journal of Life Cycle Assessment. Volume 19, Issue 2, pp. 429-436. DOI 10.1007/s11367-013-0647-4

Abstract

Purpose: Quantitative uncertainties are a direct consequence of averaging, a common procedure when building life cycle inventories (LCIs). This averaging can be amongst locations, times, products, scales or production technologies. To date, however, quantified uncertainties at the unit process level have largely been generated using a Numerical Unit Spread Assessment Pedigree (NUSAP) approach and often disregard inherent uncertainties (inaccurate measurements) and spread (variability around means).

Methods: A decision tree for primary and secondary data at the unit process level was initially created. Around this decision tree, a protocol was developed with the recognition that dispersions can be either results of inherent uncertainty, spread amongst data points or products of unrepresentative data. In order to estimate the characteristics of uncertainties for secondary data, a method for weighting means amongst studies is proposed. As for unrepresentativeness, the origin and adaptation of NUSAP to the field of life cycle assessment are discussed, and recommendations are given.

Results and discussion: By using the proposed protocol, cross- referencing of outdated data is avoided, and user influence on results is reduced. In the meantime, more accurate estimates can be made for horizontally averaged data with accompanying spread and inherent uncertainties, as these deviations often contribute substantially towards the overall dispersion.

Conclusions: In this article, we highlight the importance of including inherent uncertainties and spread alongside the NUSAP pedigree. As uncertainty data often are missing in LCI literature, we here describe a method for evaluating these by taking several reported values into account. While this protocol presents a practical way towards estimating overall dispersion, better reporting in literature is promoted in order to determine real uncertainty parameters.

3.1 Introduction

Life cycle assessment (LCA) results are commonly presented as point values without even giving a qualitative indication of the underlying uncertainties (Björklund 2002; Ross *et al.* 2002). Results of LCAs are also strongly influenced by the LCA practitioner, and even ISO 14044 (ISO 14044 2006) compliant studies describing identical systems may experience an order of magnitude difference in assessed impacts (de Koning *et al.* 2009; Williams *et al.* 2009; da Silva *et al.* 2010). This practice easily results in unstable conclusions, which subsequently attract criticism and may put public trust in LCA results at risk (Williams *et al.* 2009; Lazarevic *et al.* 2012). Desired advancements in the field of LCA are therefore to reduce practitioner influence and to produce uncertainty ranges around life cycle inventory (LCI) results.

Part of the divergence in LCA outcomes relates to different methodological choices made by practitioners. These may include different views on system boundary setting, inclusion of capital goods, allocation, biogenic carbon handling and storage, end of life of products, land use change and characterisation factors (Finkbeiner 2009; Henriksson *et al.* 2011). In theory, however, all of the above can be resolved by a common set of product category rules (de Koning *et al.* 2009). Collecting representative LCI data, on the contrary, is like hunting a moving target as processes constantly change or experience natural variance. Available data for individual unit process flows therefore often remain outdated or of otherwise limited quality. The sourcing of representative unit process data is, moreover, influenced by value judgements, epistemological perspectives and ethics, which may further influence results (Lazarevic *et al.* 2012). Additional dispersion around averages, in the form of spread, is also introduced by the process of horizontal averaging. In the field of LCA, horizontal averaging is commonly performed when multiple unit processes, or aggregated datasets, are combined to represent a more general process (UNEP 2011). This may, e.g. be the averaging of thermal efficiencies amongst coal power plants in a country towards a countrywide average.

Producing uncertainty estimates around results requires input parameters and a propagation method (**Fig. 3.1**). Many methods for propagating statistical uncertainties around LCI results were proposed already at an early stage of LCA development, including Monte Carlo analysis, analytical error propagation and fuzzy logic (Heijungs 1996; Huijbregts *et al.* 2001; Lloyd and Ries 2007). Meanwhile, their application has so far been sporadic due to limitations in quality and quantity of input parameters, time, computing, etc. Most of these hurdles can, however, today be overcome; uncertainty information is becoming more and more available in background data, software allow for the adoption of ranges and computing power has improved. Still limited, however, are clear definitions of how the input parameters should be de- fined and what they need to enclose.

Uncertainty is dynamic, and it is of importance to identify all of its origins. Already in 1996, Heijungs made a distinction between uncertainties (lack of knowledge) and variability (likely to change often) at the unit process data level. Huijbregts (1998a) later classified these into parameter uncertainty, model uncertainty, spatial variability, temporal variability and variability between objects or sources. Variables are, moreover, subject to covariance (e.g. the causal relationship between amount of fertilizer applied and total yield), directional over time (e.g. efficiency improvements) and influenced by their own previous predictions (e.g. climate predictions can influence climate negotiations, which in turn influence climate).

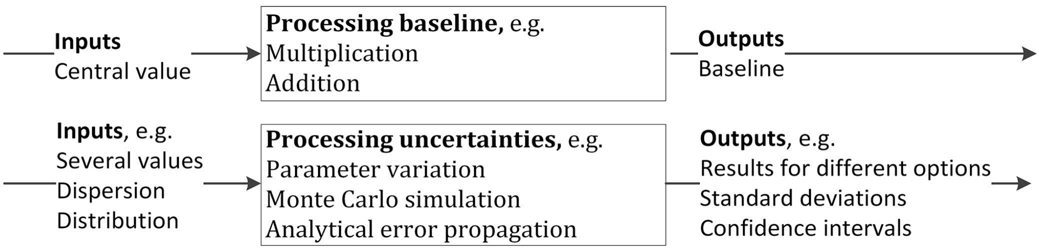

Fig. 3.1: Types of input parameters required to process point values or range outputs.

Applied and interdisciplinary sciences, including the field of LCA, are goal-oriented disciplines, in which social values, ethics, policies, managers, funders, competition and personal beliefs become unavoidable forces that may influence scientific results (Funtowicz and Ravetz 1990; Ravetz 1999; Lazarevic *et al.* 2012). These underlying forces have motivated the concept of post -normal science, where uncertainty is endorsed to be managed, and values are made explicit (**Table 3.1**) (Funtowicz and Ravetz 1990). In the field of LCA, this can be related to, e.g. the user influence on results or the often more available access to inventories describing improved or alternative production methods (e.g. organic farmers are often more keen to share their production practices than non-organic farmers). In order to acknowledge these inferences, Funtowicz and Ravetz (1990) introduced the Numeral Unit Spread Assessment Pedigree (NUSAP) approach. The NUSAP approach supplements traditional quantitative uncertainty parameters (numeral, unit and spread) with qualitative judgements about the information used and its scientific status (assessment and pedigree) (van der Sluijs *et al.* 2005). In this article, we will refer to this as unrepresentativeness.

Table 3.1: Definitions and examples of uncertainties originating from normal and post-normal science (Funtowicz and Ravetz 1990; Weidema and Wesnaes 1996; Huijbregts 1998a; Huijbregts 1998b; Ravetz 1999; van der Sluijs *et al.* 2005).

Normal science (NUS)	Post-normal science (AP)
Inherent deviations and spread of data	Unrepresentativeness of data
Source: Uncertainty and variability	Source: Systems uncertainty and decision stakes
Including: Parameter uncertainty, model uncertainty, spatial variability, temporal variability, variability between objects/sources	Including: Qualitative judgements, reliability, completeness, temporal correlation, geographical correlation and further technological correlation

NUSAP's pedigree approach was first introduced to the field of LCA by Weidema and Wesnaes (1996), the pedigree serving as a data quality indicator for LCIs. Later, it was also practically applied as a quantitative tool within the ecoinvent database, in order to produce estimates of uncertainty by attributing a set of uncertainty factors, based on expert judgement, to the pedigree quality indicators (Frischknecht *et al.* 2007b). Uncertainty factors were first introduced by Huijbregts (1998b) as minimum and maximum estimates and later reinterpreted as geometric standard deviations, as almost all data were assumed to be lognormally distributed (Frischknecht *et al.* 2007b). This quantitative use of the pedigree part of the NUSAP scheme, however, may be questioned with regard to its original intent and appropriateness, and it only ever estimates the unrepresentativeness of a dataset to its proposed use, thus excluding any inherent uncertainty or spread.

The work presented here is conducted as part of the on-going Sustaining Ethical Aquaculture Trade project (SEAT; www.seatglobal.eu), an EU FP7-funded collaboration project that aims to evaluate European imports of aquatic products from Asia. As an initial step of the project, an integrated survey was conducted to collect an extensive sample (n = 1600 farms) of primary data (as defined in **Table 3.2**) for aquaculture farms in Bangladesh, China, Thailand and Vietnam. Additional primary data have also been collected for related processes, including feed mills, hatcheries, nurseries, processing plants, fishmeal factories and reduction fisheries (n =10–40). With limited representation of Asian processes in available LCI databases, most supporting processes need to be modelled using secondary data (e.g. electricity production in Vietnam). Many secondary data sources, however, report inconsistent values and often lack information on inherent uncertainty ranges. In response to this—and in order to support SEAT's extensive primary dataset—we here propose a new, more consistent method for approaching and averaging data horizontally.

The purpose of this manuscript is to propose a methodology for horizontal averaging of data where dispersion from inherent uncertainty, spread and unrepresentativeness is incorporated in the input parameters. The methodology was developed to allow for subjective unit processes to be produced, which can support the LCIs produced within the SEAT project.

Table 3.2: Glossary of terms used throughout this study.

Primary data	Data collected specifically for the intended study and representing relevant suppliers. (UNEP 2011)
Secondary data	Previously published data describing processes for the intended study at different levels of aggregation and representativeness. (UNEP 2011)
Unit process	Smallest element considered in the life cycle inventory analysis for which input and output data are quantified (ISO 2006).
Dispersion	Any form of range around a variable, resulting from inherent uncertainty, spread or unrepresentativeness
Inherent uncertainty	Uncertainties related to the inaccuracies of measurements or model at no level of horizontal averaging
Spread	Variability around an average resulting from horizontal averaging

3.2 Methods

Horizontal averaging of data is driven by many motives and goals, e.g. to comply with the goal of a study, ensure confidentiality, increase ease of use or provide computation efficiency (UNEP 2011). Given that each sample ideally should be handled as a unique unit process, the level of averaging should be kept to a minimum (UNEP 2011). However, out of practical reasons, both primary and secondary data almost always need to be averaged to some extent to make them manageable in the inventory phase. While averaging most often is discussed on a geographical level, as in **Fig. 3.2**, it also applies to technologies, seasons, scales of production, products (e.g. different varieties of crops), etc. As a direct result of averaging, the level of overall dispersion will generally increase, partially by spread and partially from unrepresentativeness. As processes often are presented on a global level (734 processes in ecoinvent v2.2), using average technology, or from different time periods, the importance of including dispersion is again highlighted.

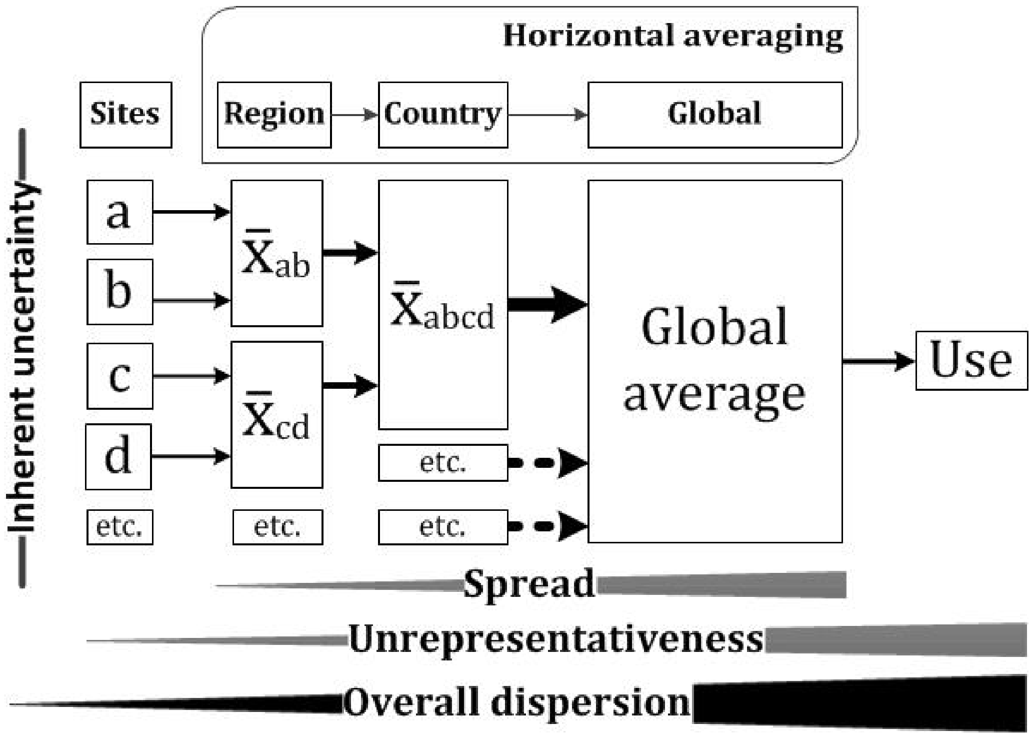

Fig. 3.2: The process of horizontal averaging displaying the cumulative effect on dispersion, originating from inherent uncertainty, spread and unrepresentativeness, using spatial averaging as a reference.

Every sample of values can be described by a large number of moments, of which the first four (a central value, a variance, a coefficient of skewness and a coefficient of kurtosis) typically suffice to capture the main characteristics of the distribution. The estimates of these moments should be consistent, unbiased, efficient, sufficient, robust and practical (Morgan and Henrion 1990). With focus on the practical, unit process data are often described by the two first moments fit to one of a limited number of distributions (e.g. normal, uniform, triangular and log-normal). While the central limit theorem states that the mean values of independent random variables are approximately normally distributed, multiplicative independent random variables tend to be log-normally distributed (Limpert *et al.* 2001). This, in addition to the desire to avoid negative numbers and to better represent large variances, explains the preference for lognormal distributions in LCI datasets. However, where sufficient data are avail- able, the best fit distribution should be determined using a goodness-of-fit test for each dataset, as distributions based upon value choices may increase the data uncertainty it aims to describe. The choice of central value is, in the meantime, dependent upon the choice of software. The methodology described below will adopt the arithmetic mean as the central value, given that it is the input value in CMLCA. Correlating equations for geometric means are available as electronic supplementary material to this article. Dispersion measures should also correlate with the type of distribution (e.g. a geometric standard deviation to describe log-normally distributed data) and software used.

In order to apply the most appropriate moments to different sets of primary and secondary data, a decision tree was initially developed (**Fig. 3.3**). In the decision tree, priority is given to primary data (P1–3), assuming that they are more up to date and relevant, and provide a better level of

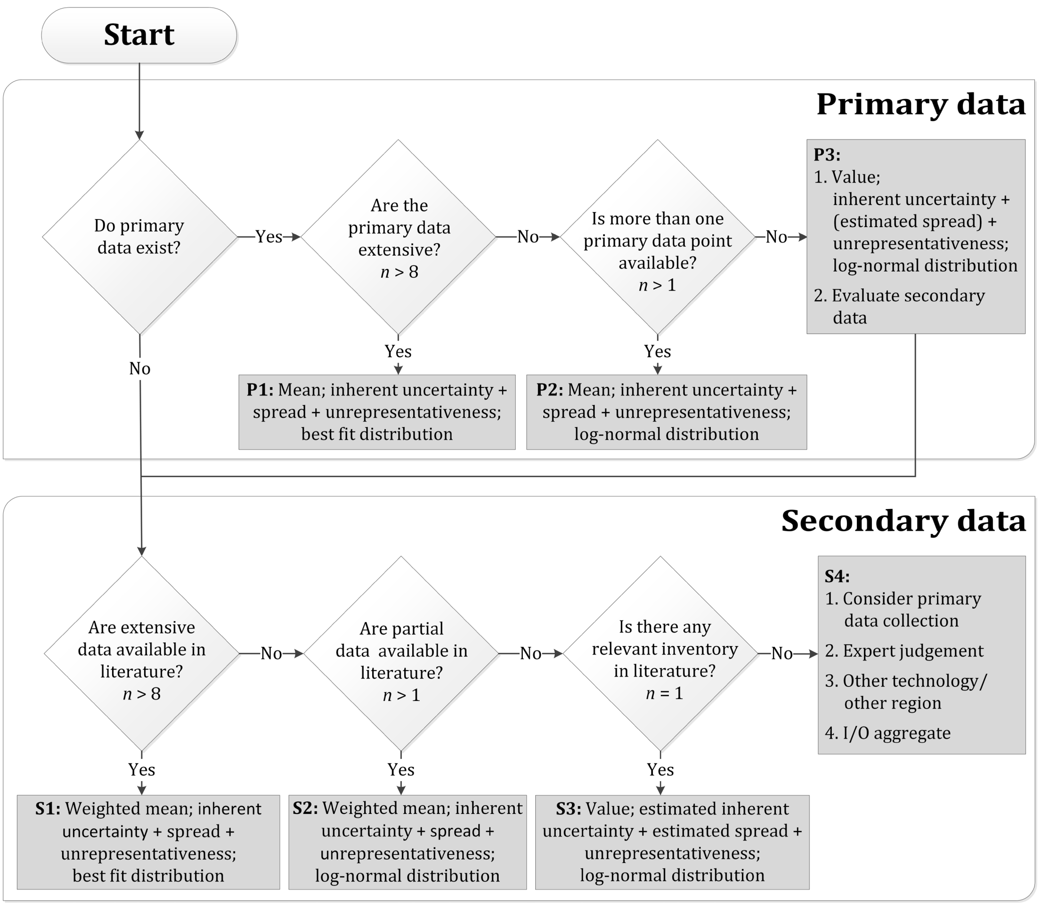

Fig. 3.3: Decision tree for sourcing unit process data, with regards to mean, inherent uncertainty, spread, unrepresentativeness and distribution.

understand- ing than secondary data. Where only one primary dataset is relevant (P3) to the scope of the study, spread can be neglected. However, if only one primary dataset is available (P3), the option of resolving to, or supplementing with, secondary data should be considered. For secondary data (S1–4), a weighting procedure amongst values is proposed, in order to acknowledge varying degrees of representativeness amongst secondary data sources. Where processes are unrepresented in literature (S4), four alternative options are suggested of which the one deemed to provide the most accurate estimate should be selected. The decision tree allows for more consistent data handling, while still partially relying upon expert judgement (particularly for secondary data) in order to approach the wide array of possible situations.

In order to more accurately determine the central value, we introduce a weighting procedure amongst secondary data points. The weighting procedure assumes that several reported values are available candidates for an inventory flow at the unit process level. The selection criteria for choosing values should be stated in the scope of the study, and the sample should preferably be well balanced (e.g. not all values from the same region). As each of the values will represent samples of different accuracy, we here encourage weighting based upon representativeness (σ^r), defined by the overall uncertainty factor, and inherent uncertainty (σ^u) where available for all values. This assures that more recent and extensive studies are given more emphasis, while also allowing for overlapping of inventories. Compiling and comparing data may also indicate if any cross-referencing exists amongst the secondary data sources, all of which should be removed from further analysis. Weighted means can be calculated using **Equation 1**, where x represents the vector of n values indexed by i, w the weighting factors (**Eq. 2**) and $\bar{x}_{(wt)}$ the weighted arithmetic mean. For the input parameter (σ^{u+r}) in the weighting factor, we recommend the square of the arithmetic standard deviation. However, in order to avoid bias from the scale of means where relative uncertainty factors are adopted, and to allow for weighting of true zero values (e.g. no fish in pond x when the question is "how many fish are there in the pond?"), $1/(\ln(\sigma_g^{u+r}))^2$ couzld be considered if relative geometric standard deviations are given or the square of the coefficient of variation $1/(CV^{u+r})^2$ for relative arithmetic standard deviations.

$$\bar{x}_{(wt)} = \frac{1}{\sum w_i} \sum w_i x_i \quad \textbf{Eq. 3.1} \qquad\qquad w = \frac{1}{(\sigma^{u+r})^2} \quad \textbf{Eq. 3.2}$$

The estimate for representativeness can be derived from a NUSAP pedigree with accompanying uncertainty factors. The pedigree matrix should evaluate all of the most relevant variables, and its complexity may differ depending upon the ambition and complexity of the parameter/model assessed (van der Sluijs *et al.* 2005). Pedigree criteria should, moreover, be explicitly defined, to avoid interpretation bias and ac- knowledge that information on data sometimes is lacking for certain pedigree criteria. Uncertainty factors should mean- while preferably be verified by real data. As an indicator for unrepresentativeness of weighted means, we recommend the use of the lowest uncertainty factor within a sample to characterise the unrepresentativeness of the weighted mean, given that this already has been accounted for in the weighting process.

As for inherent uncertainty, we naturally encourage the adoption of calculated arithmetic, or geometric (**Eq. 3.3**), standard deviations for primary site samples. Where standard deviations are reported around secondary data points, we recommend the adoption of the lowest reported inherent un- certainty, given the assumption that the increased sample results in more accurate values. Where inherent standard deviations remain unreported, estimates from related processes or basic uncertainties should be adopted. As for spread, the standard deviation amongst primary data values, or the values supporting each weighted mean, should be used.

$$\sigma_g = \exp\left(\sqrt{\frac{\sum_{i-1}^{n-1}\left(\ln\frac{x_i}{x_g}\right)^2}{n-1}}\right) \quad \textbf{Eq. 3.3}$$

In order to aggregate the uncertainty factors, the standard deviations all need to be on the same scale. The translation of standard deviations between the normal (σ_a) and the lognormal scale is therefore presented by **Eqs. 3.4** and **3.5**. Both of these equations, however, only provide approximate parameters.

$$\sigma_a \approx \frac{\bar{x}}{2}\left(\sigma_g - \frac{1}{\sigma_g}\right) \quad \textbf{Eq. 3.4}$$

$$\sigma_g \approx \sqrt{\frac{\bar{x}+\sigma_a}{\bar{x}-\sigma_a}} \quad \textbf{Eq. 3.5}$$

Assuming that inherent uncertainty (σ^u), spread (σ^s) and unrepresentativeness (σ^r) are independent and moreover described on the same scale, the overall dispersion (σ^o) can be calculated using either **Eq. (6)** for arithmetic standard deviations or **Eq. (7)** for geometric standard deviations in accordance with the combination rules by Frischknecht *et al.* (2007b). While **Eq. (7)** fulfills all the desired functions of combining geometric standard deviations, it is not universally recognised.

$$\sigma_a^{o^2} = \sigma_a^{u^2} + \sigma_a^{s^2} + \sigma_a^{r^2} \quad \textbf{Eq. 3.6}$$

$$\sigma_g^{o^2} = \exp\left(\sqrt{\left[\ln\left(\sigma_g^{u^2}\right)\right]^2 + \left[\ln\left(\sigma_g^{s^2}\right)\right]^2 + \left[\ln\left(\sigma_g^{r^2}\right)\right]^2}\right) \quad \textbf{Eq. 3.7}$$

Caution is needed with regard to zeroes on the lognormal scale, as negative or zero values for x are not accommodated. While missing values can be excluded from the equations, for true zero values, we recommend that they be substituted by a value of 10 % of the lowest non-zero value reported elsewhere for the variable. This ensures that the true zeroes remain the lowest value without introducing the complexity of, e.g. Box–Cox transformations (Ortiz and Arocha 2004). In cases where two alternative flows fill an identical function (e.g. generators and grid electricity), these may have to be treated individually with regard to their contribution. Templates for the recom- mended equations and unit process collection sheets are avail- able as electronic supplementary material to this article.

Table 3.3: A hypothetical list of values identified to represent a unit process flow.

Source	a	b	c	d
Value	1.6	1.7	1.0	0.9
Reported inherent standard deviation	0.16	n.a.	0.12	n.a.
NUSAP score	(3,2,1,2,1;2)	(2,2,2,3,1;3)	(1,3,1,3,3;2)	(2,2,4,2,4;1)
Sum of squared uncertainty factors, σ_g (Frischknecht et al. 2007b)	1.051	1.041	1.100	1.251
Sum of variances, σ_{CV} (Weidema et al. 2012)	0.002	0.001	0.008	0.041

3.3 A simple hypothetical example

In order to exemplify the proposed methodology, a hypothetical case will be used. Four values from secondary data sources (a–d) were assumed to represent a common unit process flow, each scaled towards a common reference flow, as is crucial before merging unit process data (**Table 3.3**). The pedigree and uncertainty factors proposed by Frischknecht *et al.* (2007b) and Weidema *et al.* (2012) were adopted in order to evaluate unrepresentativeness. Both of these documents evaluate the categories of reliability, completeness, temporal correlation, geographical correlation, and further technical correlation, as originally proposed by Weidema *et al.* (2012), with the addition of sample size in Frischknecht *et al.* (2007b). Sample size was again removed in Weidema *et al.* (2012), as default basic uncertainty factors were introduced. While the characteristics of the uncertainty factors in Frischknecht *et al.* (2007b) are not always clear, we here assume these uncertainty factors to be equivalent with geometric standard deviations (σ_g). The representativeness of each value is reported within brackets as pedigree scores together with the corresponding summed relative uncertainty factors.

In accordance to **Fig. 3**, the decision tree, a lognormal distribution was assumed. Using the method described above (**Eqs. 1, 2** and **4**), the weighted arithmetic mean was derived at 1.479, adopting the uncertainty factors of Frischknecht *et al.* (2007b), and 1.654 when consulting Weidema *et al.* (2012) (excluding inherent uncertainties due to incomplete reporting). Alternative weighting factors resulted in weighted means of 1.585 according to Frischknecht *et al.* (2007b) ($w_i = 1/\ln(\sigma_g^u + r)^2$), and 1.671 according to Weidema *et al.* (2012) ($w_i = 1/CV^2$). All of these are higher than the basic arithmetic mean of 1.30, as a result of the two larger values (A and B) being more representative. To calculate the overall deviation, we adopt the proportionally lowest reported inherent uncertainty ($\sigma_a^u = 0.16$ or $\sigma_g^u \approx 1.106$ using **Eq. 5**) and dimensioned pedigree estimate ($\sigma_a^r = 0.068$ (from $\sigma_g^r = 1.041$) or 0.0017 (1.7×0.001)) amongst the values, depending upon the methodology used. The spread can be derived amongst the values to $\sigma_a^s = 0.408$ or, alternatively, $\sigma_g^s = 1.381$ (using **Eq. 3**). Finally, the overall dispersion can be estimated at $\sigma_a^o = 0.443$ using **Eq. (6)** (assuming $\sigma_a^u = 0.16$, $\sigma_a^s = 0.408$ and $\sigma_a^r = 0.068$) or $\sigma_g^o = 1.406$ using **Eq. (7)** (and **5**) (assuming $\sigma_g^i = 1.106$, $\sigma_g^s = 1.381$ and $\sigma_g^r = 1.041$).

3.4 Discussion

Our proposed protocol presents a practical way to approach and organise primary and secondary data. While the procedure of critically evaluating data sources is time consuming, and resources often are limited, efforts can be restricted to the most influential parameters by initial scoping efforts and sensitivity analyses. By critically analysing the secondary inventory sources and weighting them towards a common mean, cross- referencing of outdated or estimated inventory flows is avoided. Horizontal averaging of data sources also allows for merging of inventories, thereby generating more complete unit process datasets. The proposed approach is especially useful for building more general processes, as primary data sources rarely represent national-level surveys, and production methods often differentiate geographically.

Defining and enclosing dispersion originating from inherent uncertainty, spread and unrepresentativeness is more fundamental than the choice of analytical method for propagating uncertainties (e.g. Monte Carlo analysis or Latin hypercube). To date, inherent uncertainties and spread have often been neglected or replaced by pedigree-generated uncertainty factors or default uncertainties. Even with the extension by Frischknecht *et al.* (2007b), NUSAP's pedigree approach, however, only estimates unrepresentativeness of data and complements, rather than replaces, inherent uncertainty or spread. The above proposed methodology enables for dispersions to be estimated for both primary and secondary data. This provides one step towards producing more accurate ranges in LCI results, while clearer definitions of which uncertainty parameters should be embedded at the unit process level are encouraged.

While we here assume the arithmetic mean for the central value, this choice needs to be made in accordance with the specified data manager. In the meantime, the produced LCI outputs may better be represented by the geometric mean. More extensive statistical testing of LCI conclusions is also recommended, using, e.g. analysis of variance. To improve the level of detail of dispersions and results, we encourage underlying datasets of primary data to be made available, or at least to include sample size, standard deviations, and a distribution around presented means or other central values. Actual inherent uncertainties could then be calculated. Moreover, the application of NUSAP's pedigree should also be extended beyond the averaging of data and also apply to the point of use of that data. This becomes relevant (see **Fig. 3.2**) when using ecoinvent processes for purposes they are not intended to represent (e.g. using the ecoinvent product "rice, at farm [US, 2001–2006]" instead of Chinese rice in 2013).

The quantitative adaptation of the pedigree goes beyond its original intent, but is also the only way to evaluate the quality of the often more than 4000+ processes commonly used in LCAs. We, however, encourage further advancements of the NUSAP approach within the field of LCA, especially the development of statistically supported uncertainty factors for individual sectors and/or regions, as categories of processes often experience inconsistent sensitivity towards the different types of correlation. For example, the rate of technological advancements in rapidly developing countries like China, or in high-tech industries (e.g. computer components), is often faster than in baseline cases (Williams *et al.* 2009). Its original function to evaluate uncertainties related to post-normal science should, however, not be forgotten. Moreover, the removal of sample size as an indicator based upon the introduction of default uncertainties may downplay its importance, especially for small samples. Sample size is a pivotal factor for any statistical model, but has so far played a relatively limited role in supporting LCA conclusions.

An expected advancement of ecoinvent v3 is parameterisation (Weidema *et al.* 2012), where raw data are made available for manipulation at the unit process level. The methodological advancements proposed here could be integrated in such parameterised LCI datasets to increase flexibility and transparency of data. Likewise, this protocol is useful when producing or adopting the surrogate global processes required in ecoinvent v3. However, more support behind the background and characteristics of the scale independent normal distributions, adopted in the data quality guideline, is encouraged.

The current simplified approach for selecting inherent un- certainties and unrepresentativeness around weighted means was the result of limitations in reporting on data in literature, where advancements are welcomed. Moreover, the weighting factor proposed for arithmetic means (standard deviations) become biased (favouring smaller values) by the relative uncertainties often proposed in available quantitative adoptions of NUSAP's pedigree. Better justified mathematical approaches in the field of LCA as a whole are therefore recommended. Future efforts are also encouraged towards more frequent application of goodness-of-fit tests to extensive datasets, in order to identify which of the available distributions best characterise data categories. Moreover, the under- standing and handling of covariance, where variables are correlated with each other, also remain limited. To date, as in this manuscript, covariance is often neglected which easily results in incorrect estimates of uncertainties when random sampling methods such as Monte Carlo are applied. Additional inaccuracy relates to the current benchmarking of temporal correlation to the time of data evaluation, where assessments of unrepresentativeness, in, e.g. databases, easily become outdated over time. Additional advances include the implementation of the Bayesian theorem where data are imputed (Björklund 2002) and meta-analysis of input data, rather than results (for more, please see the special issue on meta-analysis in J Ind Ecol (2012) 16:S1). Also, the advancement of statistical models, and introducing concepts such as statistical power, will allow for even stronger conclusions to be made and reintroduce the importance of sample size.

3.5 Conclusions

Increased objectivity and the inclusion of quantitative uncertainties are pressing issues in the field of LCA. If the community fails to address these issues, it may jeopardise its credibility and scientific integrity. While all the necessities today are available for the practical inclusion of uncertainties, greater efforts are needed to define the uncertainty parameters at the unit process level. For this, we have proposed a protocol for sourcing data, with the ambition of keeping the methodology amenable for the everyday LCA practitioner and limiting the resource investments needed. The protocol developed here is meant to help practitioners select the most representative and relevant data for their purposes and to quantify related uncertainties. To improve the quality of the data itself, improved reporting of primary data is necessary, as much of the under- lying information on inherent uncertainties currently is lost somewhere in this reporting process. Hopefully, the next generation of parameterised inventories will encourage the reporting of raw data, instead of point values. In the meantime, better reporting on the underlying characteristics of data as online resource to articles is encouraged. The resulting unit process parameters from the methodology proposed herein, alongside other advancements in the field of LCA, will hope- fully encourage more statistically rigid LCA conclusions.

Over the coming years, the here presented approach and the methodological considerations presented in (Henriksson *et al.* 2012c) will be implemented to evaluate a number of Asian aquaculture products exported to Europe, as part of the ongoing EU FP7-funded SEAT project. Additional advancements of the present methodology will also be made available in updated versions of the online resource of the present article (available at www.cml.leiden.edu/software/).

Acknowledgments

This work is part of the Sustaining Ethical Aquaculture Trade (SEAT) project, which is co-funded by the European Commission within the Seventh Framework Programme—Sustainable Development Global Change and Ecosystem (project no. 222889). http:// www.seatglobal.eu.

Chapter 4

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

Patrik JG Henriksson, Wenbo Zhang & Jeroen B Guinée

Accepted: 27 October 2014. International Journal of Life Cycle Assessment. Volume 20, Issue 2, pp. 185-195. DOI: 10.1007/s11367-014-0816-0

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

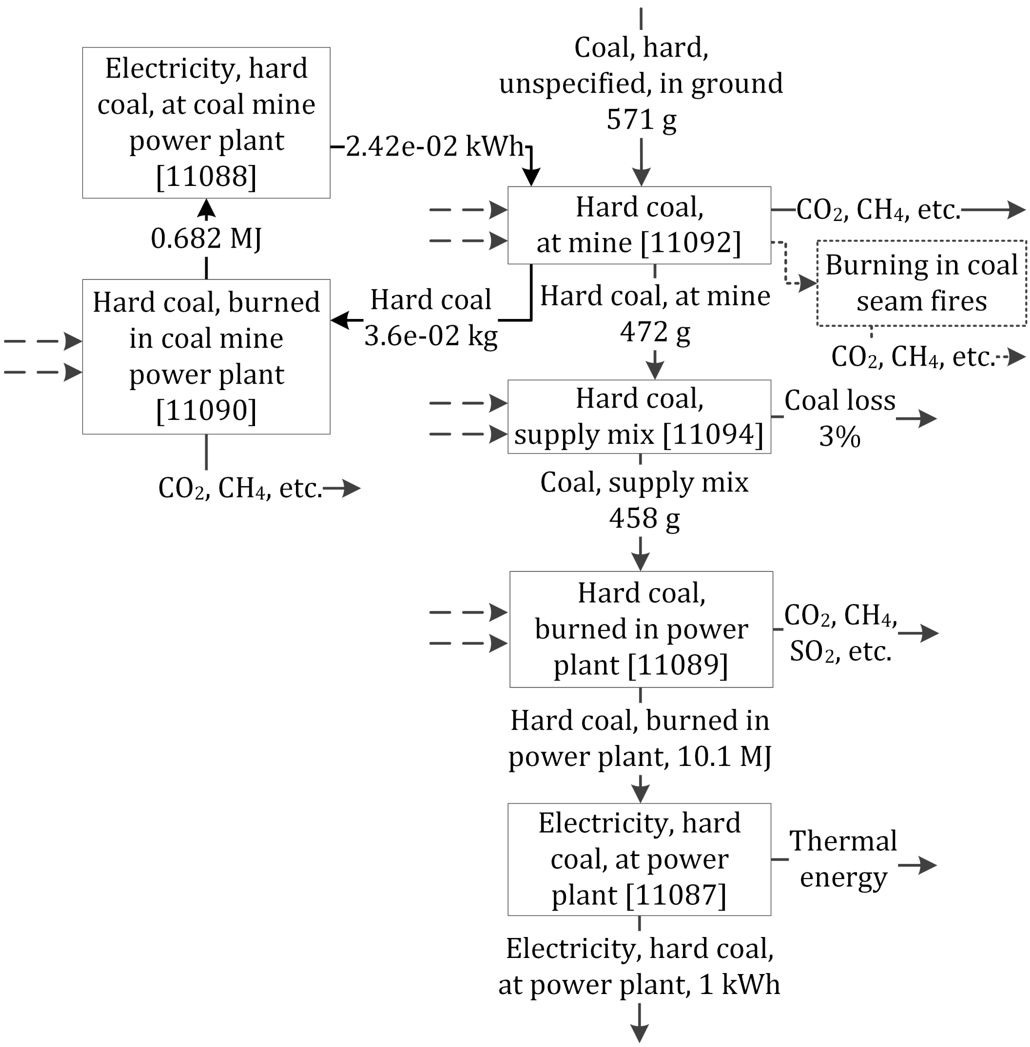

Fig. 4.1: Simplified process tree of Chinese electricity generation from coal in ecoinvent v2.2. Boxes indicate processes, solid lines product/environmental flows, dashed lines additional products not addressed in the present study, and dotted lines/boxes suggested flows/processes.

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).

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		
		$\bar{x}$	$\bar{x}$	CV	$\bar{x}$	CV	$\bar{x}$	CV	$\bar{x}$	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.

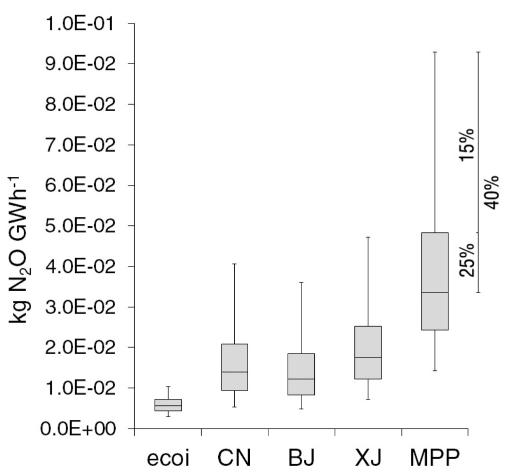

Fig 4.2: Box-and-whisker plot of the life cycle dinitrogen monoxide emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

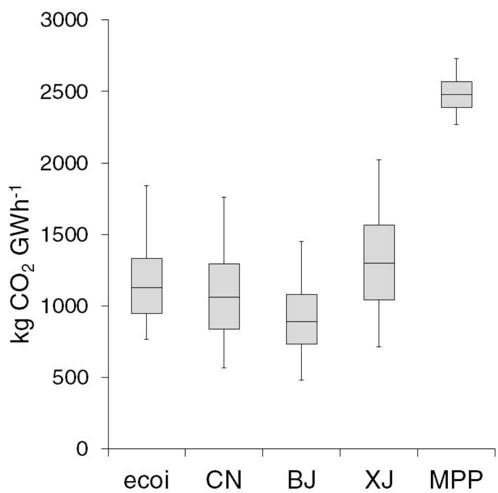

Fig 4.3: Box-and-whisker plot of the life cycle carbon dioxide emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

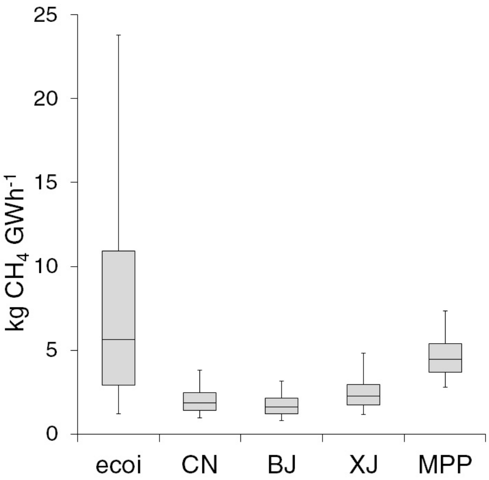

Fig 4.4: Box-and-whisker plot of the life cycle methane emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

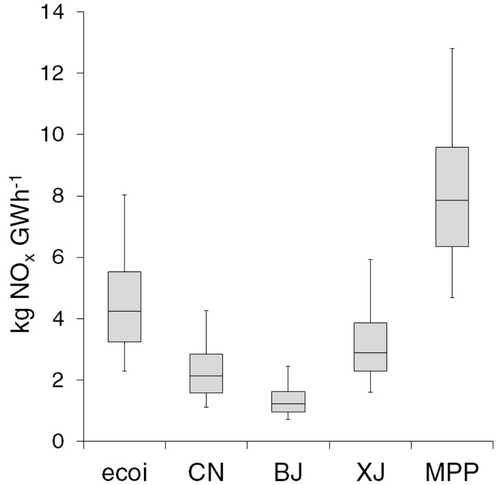

Fig 4.5: Box-and-whisker plot of the life cycle nitrogen oxides emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

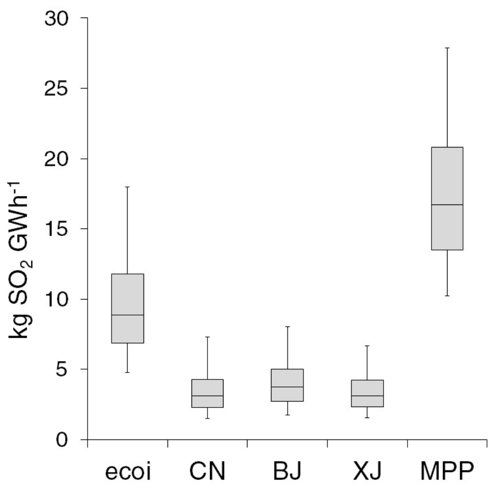

Fig 4.6: Box-and-whisker plot of the life cycle sulphur dioxide emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

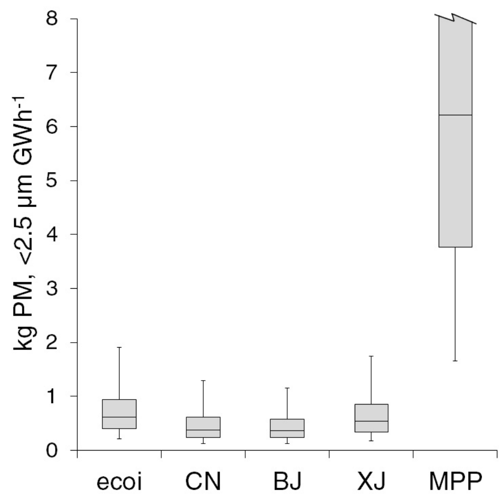

Fig 4.7: Box-and-whisker plot of the life cycle particulate emissions from the generation of 1 kWh of electricity at power plant, with the central line indicating the median, the box the 25th and 75th percentiles and the whiskers the 10th and 90th percentiles.

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

This work is part of the Sustaining Ethical Aqua- culture Trade (SEAT) project, which is co-funded by the European Commission within the Seventh Framework Programme—Sustainable Development Global Change and Ecosystem (project no. 222889) http:// www.seatglobal.eu. We also would like to extend our gratitude to René Kleijn who inspired us to write this article and to Reinout Heijungs for invaluable support.

Chapter 5

Product Carbon Footprints and Their Uncertainties in Comparative Decision Contexts

Patrik JG Henriksson, Reinout Heijungs, Hai M Dao, Lam T Phan, Geert R de Snoo & Jeroen B Guinée

Accepted: 30 January 2015. PLOSONE. Volume 10, Issue 3. DOI: 10.1371/journal.pone.0121221

Abstract

In response to growing awareness of climate change, requests to establish product carbon footprints have been increasing. Product carbon footprints are life cycle assessments restricted to just one impact category, global warming. Product carbon footprint studies generate life cycle inventory results, listing the environmental emissions of greenhouse gases from a product's lifecycle, and characterize these by their global warming potentials, producing product carbon footprints that are commonly communicated as point values. In the present research we show that the uncertainties surrounding these point values necessitate more sophisticated ways of communicating product carbon footprints, using different sizes of catfish (Pangasius spp.) farms in Vietnam as a case study. As most product carbon footprint studies only have a comparative meaning, we used dependent sampling to produce relative results in order to increase the power for identifying environmentally superior products. We therefore argue that product carbon footprints, supported by quantitative uncertainty estimates, should be used to test hypotheses, rather than to provide point value estimates or plain confidence intervals of products' environmental performance.

5.1 Introduction

Early enthusiasm about carbon footprinting resulted in the aim of calculating product carbon footprints (PCFs) for whole product assortments (Beattie 2012). The conclusions were intended for industry to improve the product's or service's lifecycle environmental performance, and for consumers to encourage more sustainable product procurements. These ambitions soon floundered after being faced with the challenges of high costs of collecting data and modeling PCFs, large time investments, and a lack of consensus on modeling choices (Beattie 2012). The 14067, 14040 and 14044 ISO standards for PCF and life cycle assessment (LCA), from which PCFs originate, provide the principles, minimum requirements and framework for conducting and reporting such studies (ISO 14040 2006; ISO 14044 2006; ISO 14067 2012). ISO 14040, for example, defines the phases of LCAs: goal and scope definition, life cycle inventory analysis (LCI), life cycle impact assessment (LCIA) and interpretation (ISO 14040 2006). In addition to ISO, numerous standards have been produced to harmonize methods based on the ISO standards (BSI 2008; JRC 2010b). Inventory databases and software solutions have also made it easier to calculate life cycle inventory results (e.g. kg CO_2, CH_4 and N_2O), and classify and characterize these into PCFs (kg CO_2-eq.). Results are commonly presented as absolute point values, which theoretically could be compared with each other much like nutritional facts (Vandenbergh *et al.* 2011). Simply communicating the quantitative information through carbon labels has, however, been called into question, as consumers lack a daily or annual allowance for greenhouse gases (GHGs), unlike for nutrients (Upham *et al.* 2011).

Another reason for not communicating GHGs as point values is the large uncertainties surrounding these quantitative estimates. PCFs of identical products can deviate by an order of magnitude between studies, even if they comply with the same methodological guidelines (de Koning *et al.* 2009). This is largely due to data sourcing and modeling assumptions (de Koning *et al.* 2009; Yoshida *et al.* 2014), but in some cases also to different characterization factors used to translate the environmental emissions into impacts (Hertwich *et al.* 2000). The characterization factors for carbon footprints are typically the global warming potentials (GWPs 100-year) reported by the IPCC, based upon the radiative forcing of different gases.

LCA studies are often used for comparative purposes, including consumer choice. In a comparative context, two issues should be solved. The first is the fact that a standard LCA yields results on several impact categories, and that the trade-off between these categories is a delicate issue, requiring weighting and/or multi-criteria analysis (Linkov and Seager 2011; Prado-Lopez *et al.* 2013). The second is the fact that uncertainties in a comparative analysis require a different strategy, due to the fact that part of the uncertainty may be shared between the product alternatives (de Koning *et al.* 2009). In our work, we focus on the carbon footprint, so on just one category. Therefore the first issue is outside our scope. The second issue, however, is of central concern to us. While previous approaches dealt with shared uncertainties, they did not make the step to hypothesis testing, and neither to the implications for the labeling of individual products.

Despite the known limitations and uncertainties of PCF estimates, GHG savings have still made their way into regulations where they are enforced on a point-value basis. California's Low Carbon Fuel Standard (California Air Resources Board 2012), for example, enforces 10% GHG savings for new fuels compared to a fossil fuel reference, and the EU's fuel quality directive (European Comission 2009) uses a 6% margin.

Already in the 1990s were dispersion estimates made for a number of LCI related emission parameters (Hanssen and Asbjørnsen 1996; Finnveden 1998). Around the same time, there were also several new methodologies suggested for how to include quantitative uncertainties in life cycle inventories (LCIs)(Weidema and Wesnaes 1996; Huijbregts 1998a; Huijbregts 1998b; Huijbregts *et al.* 2001). To date, however, the uncertainties considered have largely been limited to sensitivity analyses (van der Harst and Potting 2014), default inventory ranges (Huijbregts *et al.* 2003; Röös *et al.* 2010), characterization factors for one specific impact category (Lloyd and Ries 2007; van Zelm and Huijbregts 2013), or pedigree estimates (Kennedy *et al.* 1996; Frischknecht *et al.* 2007b). Pedigree estimates refer to a matrix of data quality indicators which evaluate the representativeness of the data used, which later are tentatively quantified using uncertainty factors based upon expert judgment or empirical data (Frischknecht *et al.* 2007b; Henriksson *et al.* 2013; Ciroth *et al.* 2013). Statistical testing of outcomes, in the meantime, is rare among LCA studies, and where consulted it is largely limited to quotients (A/B) (Mattila *et al.* 2011). **Table 5.1** summarizes a selection of LCA studies that take uncertainty into account. The table results show that this is the first study that evaluates empirical LCI uncertainty data, empirical LCIA uncertainty data, in a comparative analysis applying Monte Carlo dependent sampling and a hypothesis based significance test.

It is our belief that failure to explicitly and properly deal with uncertainties may result in counterproductive decisions, and that more extensive guidelines will merely reduce the number of flawed conclusions. Instead, the field of LCAs and PCFs needs to review some of the fundamentals of the scientific method, including statistically supported conclusions.

Statistically testing a hypothesis requires a predefined null hypothesis and quantification of uncertainties, two requirements that are rare in PCF studies. In comparative studies, the hypothesis conventionally presumes one product alternative to be better or equal to an alternative. The hypothesis is then critically evaluated using the appropriate statistical tests for the data under study. A product should consequently only be deemed beneficial if the null hypothesis can be statistically rejected.

Quantifying the dispersions around point values requires a variance and a distribution for unit process data and characterization factors, in addition to the central value (step 1). Next, a propagation method is needed (Heijungs and Lenzen 2013). In the present study Monte Carlo (MC) was used as it is the most commonly available propagation method and allows for post-hoc analyses. In a Monte Carlo, values are randomly sampled from the unit process distributions over a fixed number of iterations and aggregated into LCA results using an LCA matrix (step 2). This procedure produces a range of possible results, which in turn could be evaluated using different statistical tests and analyses (step 3). The outcomes are statistically supported environmental recommendations that can be communicated to policy makers or consumers through different channels (step 4).

Table 5.1: A selection of LCA studies which take uncertainty into account, detailing if distributions are based upon real data (empirical), or default/pedigree estimates (conjectural), propagation/sampling method, comparative study, the presence of a hypothesis and any significance test carried out.

Reference	Input uncertainty data					Output results	
	Unit process data	Characterization factors	Propagation method	Comparative analysis	Sampling method	Hypothesis	Significance test
Basset-Mens et al. 2009	Conjectural	No	Latin Hypercube	No	N/A	N/A	N/A
Bojacá and Schrevens 2010	Empirically based	No	Monte Carlo	No	N/A	N/A	N/A
Chen and Corson 2014	Partially Empirically based	N/A	Monte Carlo	Yes	Independent	None	N/A
Hauck et al. 2014	Empirically based	Empirically based	Monte Carlo	Yes	Unknown	None	N/A
Heijungs and Kleijn 2001	Conjectural	Conjectural	Monte Carlo	Yes	Dependent	n(A>B)=n(A<B)	Runs test
Heijungs et al. 2005	Conjectural	N/A	Taylor series	No	N/A	N/A	N/A
Heijungs et al. 2005	Conjectural	N/A	Monte Carlo	Yes	Dependent	n(A>B)=n(A<B)	Runs test
Heijungs and Lenzen 2013	Conjectural	Conjectural	Taylor series	No	N/A	N/A	N/A
Heijungs and Lenzen 2013	Conjectural	Conjectural	Monte Carlo	Yes	Independent	None	N/A
Hong et al. 2010	Conjectural	Empirically based	Taylor series	Yes	Independent	None	N/A
Hong et al 2010	Conjectural	Empirically based	Monte Carlo	Yes	Dependent	A/B=1	N/A
Huijbregts et al 2003	Empirically based	Empirically based	Monte Carlo	Yes	Dependent	A/B=1	N/A

Kennedy et al 1996	Conjectural	N/A	Monte Carlo	Yes	Independent	Median(A)= Median(B)	Tukey's test
de Koning et al 2009	Conjectural	Conjectural	Latin hypercube	Yes	Independent	None	N/A
Lo et al 2005	Empirically based	Empirically based	Monte Carlo	Yes	Independent	None	N/A
Malça and Freire 2010	Meta-analysis	N/A	Monte Carlo	No	N/A	N/A	N/A
Mattila et al. 2011	Empirically based	Yes, but source unknown	Monte Carlo	Yes	Dependent	A/B=1	N/A
Maurice et al. 2000	Largely Conjectural	No	Monte Carlo	Yes	Independent	None	N/A
Mutel et al. 2013	Conjectural	Empirically based	Monte Carlo	Yes	Independent	None	N/A
Röös et al. 2010	Conjectural	No	Monte Carlo	No	N/A	N/A	N/A
Röös et al 2011	Conjectural	No	Monte Carlo	No	N/A	N/A	N/A
Sonnemann et al. 2002	Conjectural	No	Monte Carlo	Yes	Dependent	None	N/A
Steinmann et al. 2014	Empirically based	Empirically based	Monte Carlo	No	N/A	N/A	N/A
Weber 2012	Meta-analysis	N/A	Monte Carlo	No	N/A	N/A	N/A
This study	Empirically based	Empirically based	Monte Carlo	Yes	Dependent	Median(A)= Median(B)	Wilcoxon

If results are to be used for comparisons, e.g. to decide if fish produced in larger corporate farms is better in terms of climate change impacts than fish produced in smaller family owned farms, the sampling procedure (step 2) for the products under study can be either dependent (correlated), where each product footprint builds upon the same sampled parameters, or independent (uncorrelated), where each product footprint builds upon a uniquely drawn set of random samples (**Fig. 5.1**) (Heijungs and Kleijn 2001; Hong *et al.* 2010; Imbeault-Tétreault *et al.* 2013). Independent sampling yields completely stochastic, incomparable results ("absolute results"), while dependent sampling produces results where all footprints are derived from the same set of sample values for both unit process data and characterization factors in each MC run. Thus, if the fish produced in larger corporate farms yield a very high outcome in a particular MC run, the fish produced in smaller family owned farms will most likely also yield a higher than average outcome, assuming that the two share many processes (e.g. electricity production, transportation processes, and disposal). Only the comparative difference between the results of each MC run, obtained by subtracting the sample result of one product from that of another, is therefore of importance in dependent sampling. We here label this as "relative results". For comparative purposes, dependent sampling is the only relevant option, and relative results can be a very useful way of presenting the LCA results for each sample. In addition, relative results allow for powerful paired statistical testing of null hypotheses (step 3). The outcomes would, in turn, be communicated as one product being better than one or more alternatives (step 4).

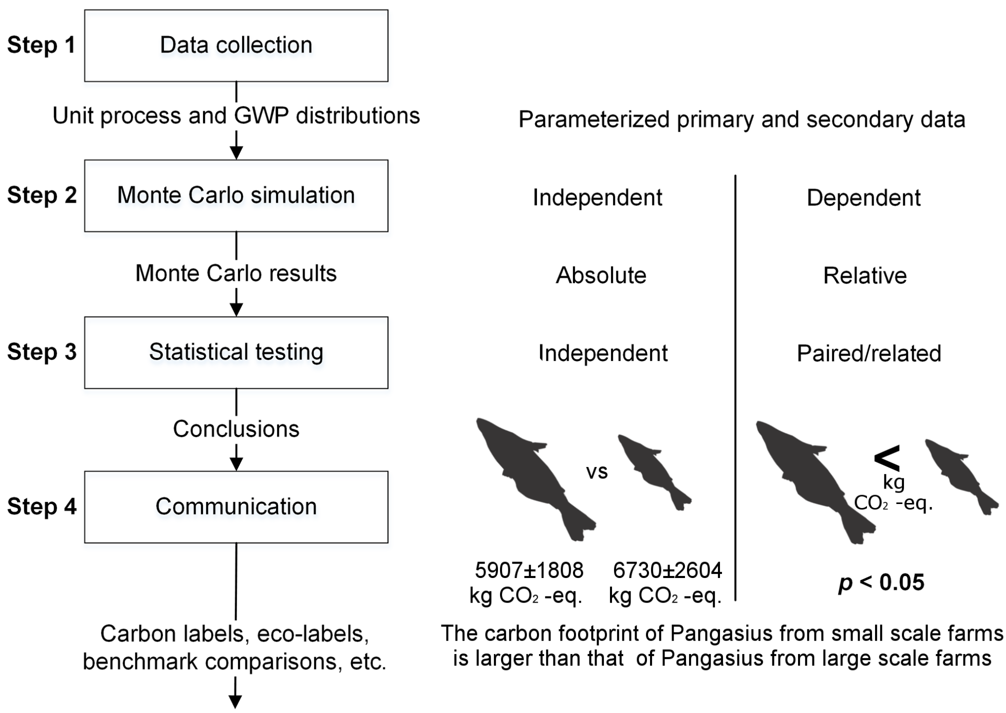

Fig. 5.1. Procedures for propagating dispersions in data into product carbon footprints.

In order to demonstrate the advantages of dependent sampling and to evaluate how to communicate PCFs with statistical tests, we use an LCA study of Vietnamese catfish (Pangasius spp.) fillets as an example (Henriksson *et al.* 2014a). The hypothesis explored was "Pangasius fish produced in larger corporate farms have smaller PCFs per unit of fish than those produced in smaller family-owned farms". This hypothesis builds upon the assumption that corporations generally monitor and manage their farms better than family-owned farms and rely more heavily upon commercial feeds tailored to Pangasius fish. Thus, the null hypothesis tested assumed that the mean PCF of 36 randomly sampled family-owned farms would be equal to that of 36 corporate farms. While the absolute overall dispersions remain large, we managed to identify significant trend differences between the different farming systems by using our proposed approach.

5.2 Methods

Data on the two farming systems and other related processes were collected between 2010 and 2013 as part of the EU FP7 SEAT project (Table S5.1-5.3, available online). Additional data were retrieved from the literature and the ecoinvent v2.2 database (www.ecoinvent.org). A complete description of the data used in the present research is available as supporting information and in SEAT deliverable D3.5 (Henriksson *et al.* 2014b). Unit process distributions and variances were developed using the protocol presented in Henriksson *et al.* (Henriksson *et al.* 2013), reflecting inherent uncertainties (inaccuracies in measurements and models), spread (variability resulting from averaging) and unrepresentativeness (mismatch between the representativeness and use of data). The Anderson-Darling goodness-of-fit test was used to identify the distributions best representing data, limited to the four available distributions and generically assumed lognormal data in ecoinvent v2.2 (Henriksson *et al.* 2013).

The inventory flows were characterized using the GWPs and uncertainty distributions (Table S5.4, available online) reported in the fifth IPCC assessment report (IPCC 2013; Myhre *et al.* 2013) (step 1). In introducing uncertainties to GWPs, problems arise by the fact that the GWP of CO_2 is 1 by definition (and thus has no uncertainty), while the GWPs of all other GHGs are normalized by that of CO_2. Underlying GWPs (in kg CO_2-eq. kg^{-1}) are the absolute GWPs (AGWPs), which express the time-integrated radiative forcing (in W m^{-2} yr^{-1} kg^{-1}) (Myhre *et al.* 2013). These AGWPs are uncertain, also for CO_2. By adopting the uncertainty distributions on the level of GWPs we assume that these GWP uncertainties are based on dependent sampling of AGWPs in the models used by IPCC, e.g. dividing the AGWP for CH_4 in each run by the AGWP for CO_2 in the same run, thus forming a distribution of GWPs for CH_4 and a point value of the GWP for CO_2. The fifth IPCC assessment report (IPCC 2013) does not specify if the uncertainty estimates in the GWP of GHGs have been obtained through dependent or independent sampling, but judging the values of the uncertainties, we believe that dependent sampling has been used, as it should have been. Based on this assumption and in order to stay close to the traditional carbon footprint, we choose to use the GWPs with related uncertainty information for our characterization calculations from the fifth IPCC report (IPCC 2013; Myhre *et al.* 2013), thereby maintaining the relative units and hence calculating carbon footprints in kg CO_2-eq. The standard deviations (σ) supporting these GWPs were back-calculated from the 90% uncertainty ranges (σ = (P95-P05) / (2*1.645)) presented in the fifth IPCC report (IPCC 2013; Myhre *et al.* 2013). For more details, please see Table S5.4 (available online) and Myhre *et al.* (Myhre *et al.* 2013).

Results were scaled to one tonne of fish and propagated over 1 000 MC simulations using dependent sampling (step 2) and the matrix-based algebra (Heijungs and Suh 2002a) implemented in the CMLCA v5.2 (www.cmlca.eu) software. Statistical tests were conducted in SPSS (v.21).

Of the two groups, family-owned farms were more reliant on farm-made feeds and agricultural byproducts (31% of all feeds) than large corporate farms, which almost exclusively (94%) relied upon commercial feeds. Apart from feeds, all other supporting processes differed only in quantity, meaning that they rely upon the same shared supply chain, and hence on the same drawn values in each MC run, as well as stochastic GWP. Emissions resulting directly from the fish ponds, however, were not shared between the two farming practices and therefore resulted in independently sampled values. For a more complete list of the data used and more specific results, see the supporting information to this article.

5.3 Results

Both ranges of results were associated with large dispersions (Figure S5.1, available online). From these, the mean difference between the two farming practices could be found by subtracting the result for fish from large corporate farms from that of fish from small family-owned farms for each MC run (**Fig. 5.2a**). The mean difference between results did not follow a normal distribution and we therefore tested the median difference using the non-parametric one-sample Wilcoxon Signed Rank test (step 3), showing a highly significant ($p < 0.001$) difference of 859 kg CO_2-eq. (see **Fig. 5.2b**), thus indicating a significantly larger median PCF for fish from family-owned farms compared to fish from corporate farms (step 4).

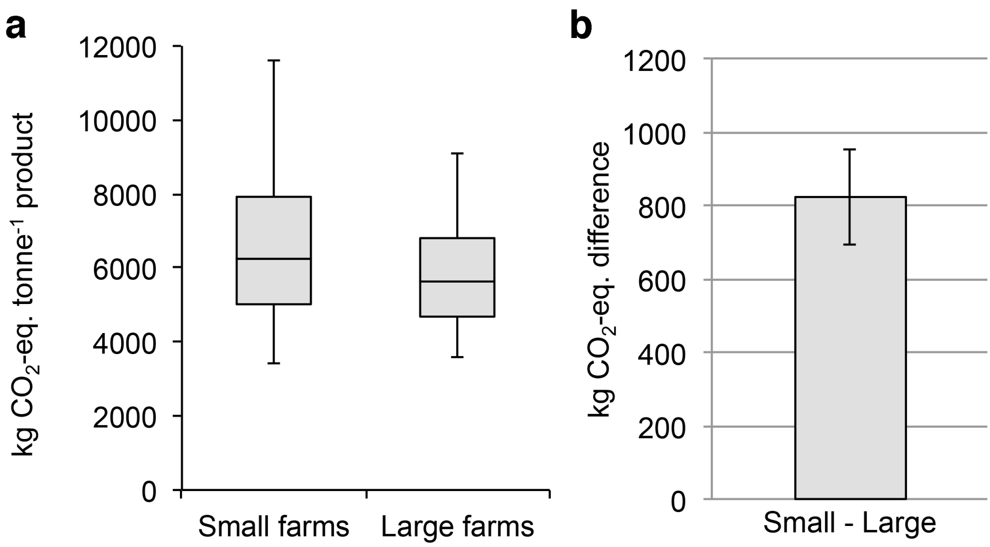

Fig. 5.2: Greenhouse gas emissions resulting from the production of one tonne of Pangasius fish in small and large farms. a, Box-and-whisker plot displaying the GHG emissions associated with fish from small (N=36) and large (N=36) sized Pangasius farms. Indicated are the median, the 25th percentile and 75th percentile (box), and the 10th and 90th percentiles (whiskers). b, Median difference between fish from small and large farms on a per MC run basis, subtracting the GHG from the large farms from that of the small farms. Error bars indicate the 95% confidence interval of the median differences.

5.4 Discussion

As inventory models are data limited, most data supporting PCFs are opportunistically collected, rather than following a random sampling design. Concepts such as experimental design and statistical inference are therefore largely ignored in most footprinting exercises. Modeling choices also influence outcomes, including the choices of emission models, model structure, and mathematical equations. Product footprints are thus highly influenced by conscious and unconscious choices, inducing statistical inference. Dependent sampling, however, reduces the effect of such choices, as the underlying choices remain largely consistent. The greater statistical power offered by paired statistical tests also reduces the risk of Type II statistical errors.

Only considering relative uncertainties is also favorable in situations where the origins of raw materials or products are untraceable. For example, aluminum derives from an energy intensive process and enters the global market from a pool of countries. The metal is then often traded, alloyed, worked up and assembled on geographically dispersed locations. The origin or origins of the aluminum raw material are therefore next to impossible to trace, while the resulting GHG emissions may differ with two orders of magnitude amongst different origins (e.g. China or Iceland) (Liu and Müller 2012). However, if only relative uncertainties are considered, the production of aluminum could be horizontally averaged to a global level while different aluminum products still could be compared with relatively high accuracy without simplifying the data.

Where requirements such as normally distributed populations and equal variances are fulfilled, a paired t-test is an appropriate test for comparing two products. However, in the case of a comparison involving three or more alternatives (e.g. small, medium, and large sized ponds), the paired comparison will not work due to the increased risk of type I errors. In such cases a test for related multiple comparisons should be used, two-way ANOVA being the most obvious choice, with an added Tukey test for post-hoc grouping into clusters of alternatives that differ significantly from one another. A non-parametric alternative for comparisons of more than two products is provided by the Friedman test. The clusters identified by the post-hoc test could serve as the basis for eco-labeling schemes, where each cluster represents a rank or a label (red, yellow or green), which easily could be communicated to e.g. consumers. Alternatively, a baseline product could be used for each product group (e.g. farmed salmon in the current example) to communicate results in ways more accessible to consumers.

5.5 Conclusions

Product footprints were created to meet the need to steer our consumer society towards more sustainable choices. However, carbon footprints constitute a highly politicized field of science, where the decision stakes are high and system uncertainties large (Ravetz 1999). PCFs will therefore always be subject to intense scrutiny. In response, by re-evaluating PCFs as a strictly relative indicator while acknowledging the level of underlying uncertainty, clusters of environmentally superior products or production systems may be identified with a level of confidence. Our conclusions can be extended to other approaches for assessing products in a comparative sense, including the water footprint (Hoekstra *et al.* 2011) and life cycle costing (Swarr *et al.* 2011).

Chapter 6

A comparison of Asian aquaculture products using statistically supported LCA

Patrik JG Henriksson, Andreu Rico, Wenbo Zhang, Sk Ahmad-Al-Nahid, Richard Newton, Lam T Phan, Zongfeng Zhang, Jintana Jaithiang, Hai M Dao, Tran M Phu, David C Little, Francis J Murray, Kriengkrai Satapornvanit, Liping Liu, Qigen Liu, M Mahfujul Haque, Froukje Kruijssen, Geert R de Snoo, Reinout Heijungs, Peter M van Bodegom & Jeroen B Guinée

Accepted: 29 October 2015. Environmental Science & Technology. DOI: 10.1021/acs.est.5b04634

Abstract

We investigated aquaculture production of Asian tiger shrimp, whiteleg shrimp, giant river prawn, tilapia and pangasius in Bangladesh, China, Thailand and Vietnam using life cycle assessments (LCAs), with the purpose of evaluating the comparative eco-efficiency of producing different aquatic food products. Our starting hypothesis was that different production systems are associated with significantly different environmental impacts, as the production of these aquatic species differs in intensity and management practices. In order to test this hypothesis, we estimated the systems global warming, eutrophication and freshwater ecotoxicity impacts. The contribution to these impacts and the overall dispersions relative to results were propagated using Monte Carlo simulations and dependent sampling. Paired testing showed significant ($p<0.05$) differences between the median impacts of most production systems in the intra-species comparisons, even after a Bonferroni correction. For the full distributions, instead of only the median, only for Asian tiger shrimp more than 95% of the propagated Monte Carlo results favored certain farming systems. The major environmental hot-spots driving the differences in environmental performance among systems were fishmeal from mixed fisheries for global warming, pond run-off and sediment discards for eutrophication, and agricultural pesticides, metals, benzalkonium chloride and other chlorine releasing compounds for freshwater ecotoxicity. The Asian aquaculture industry should therefore strive towards farming systems relying upon pelleted species-specific feeds, where the fishmeal inclusion is limited and sourced sustainably. Also, excessive nutrients should be recycled in integrated organic agriculture together with efficient aeration solutions powered by renewable energy sources.

6.1 Introduction

Aquaculture is the only solution for meeting the growing demand for aquatic products in a world where capture fishery catches have stagnated (Duarte *et al.* 2009; FAO 2014a). Asia is the main producing region with 88% of global aquaculture production by volume, and the European Union (EU) the largest single market with 36% of total world imports by value (FAO 2014a). However, while consumption trends have rapidly increased in the EU, concerns have been raised regarding the environmental sustainability of the fish and crustacean products imported from Asia. These concerns are associated with detrimental environmental consequences such as global warming, eutrophication, ecotoxicity, land-use and land-use change (LULUC), excessive energy use and freshwater use (Pelletier *et al.* 2006; Henriksson *et al.* 2012c; Jonell and Henriksson 2014).

The environmental impacts related to aquaculture commodities have been quantified in various life cycle assessment (LCA) studies (Henriksson *et al.* 2012c). However, only a handful of these have focused on Asian aquaculture. Four LCA studies have evaluated Vietnamese Pangasius catfish (Phong *et al.* 2011; Bosma *et al.* 2011; Huysveld *et al.* 2013; Henriksson *et al.* 2015a), three shrimp farming (Mungkung 2005; Cao *et al.* 2011; Jonell and Henriksson 2014), two Indonesian finfish (Pelletier and Tyedmers 2010b; Mungkung *et al.* 2013) and one Thai finfish (Pongpat and Tongpool 2013). Only three of these quantified the uncertainties related to results (Cao *et al.* 2011; Henriksson *et al.* 2014a; Jonell and Henriksson 2014). Little is therefore known about the level of confidence behind conclusions made in previous studies, despite the increasing importance of LCA results in policy contexts (Henriksson *et al.* 2015a). Seafood standards are, for example, starting to incorporate carbon footprints into their recommendations (Madin and Macreadie 2015) and a PAS2050 standard has been developed for seafood and other aquatic food products (BSI 2012). For such standards to be realistic and effective, differences in impacts need to be statistically substantiated.

In the present study, we performed life cycle assessments (LCAs) and statistically evaluated the environmental impacts for some of the most common Asian aquaculture commodities found on European markets (Henriksson *et al.* 2014a) (**Table 6.1**). From this selection, the most important producing regions and production systems were identified and evaluated (Henriksson *et al.* 2014a; Murray *et al.* 2014; Henriksson *et al.* 2014b). Noteworthy is that some of these production systems currently are not eligible for export due to existing import regulations into the EU (e.g. tilapia integrated with pigs in China). System characterization was based on farm scale, pond type, species combination and other features of the production systems (Henriksson *et al.* 2014a; Murray *et al.* 2014).

The present study builds upon the final LCA case study report (Henriksson *et al.* 2014a) of the Sustaining Ethical Aquaculture Trade project (www.seatglobal.eu), but also includes calculated freshwater ecotoxicity characterization factors (FAETPs) for a number of aquaculture related chemicals using the USEtox model, including uncertainty estimates for characterization factors (Rosenbaum *et al.* 2008).

Table 6.1: Farming systems evaluated in the study. The systems will hereon be referred to by the code or the characteristic in bold.

Country	Code	Species	Region	Key characteristics
Bangladesh	BD K	Giant river prawn	**Khulna**	Avg. of 2 kg fish coproduced per kg prawn
	BD B		**Bagerhat**	Avg. of 3.3 kg fish co-produced per kg prawn
	BD S&P		Both	**Integrated** with Giant tiger shrimp
	BD W	Asian tiger shrimp	**West**	Lower stocking density and not always fed, with fish
	BD E		**East**	Higher stocking density, no fish
	BD S&P		West	**Integrated** with Giant river prawn
China	CN HL	Whiteleg shrimp	Guangdong	Lined **high-level** ponds with pumped water exchange
	CN LL		Guangdong	**Low-level** earthen ponds with tidal water exchange
	CN GD	Tilapia	**Guangdong**	Intensive to semi-intensive farms, <30 post-larvae m^2
	CN HI		**Hainan**	Intensive to semi-intensive farms, <30 post-larvae m^2
	CN R		Both	Farmed in freshwater **reservoirs**
	CN IG		Guangdong	Ponds fertilized by **integrated** pigs on dikes
Thailand	TH E	Whiteleg shrimp	**East**	Electricity as main energy source on farm
	TH S		**South**	LPG as main energy source on farm
Vietnam	VN SI	Asian tiger shrimp	Soc Trang & Bac Lieu	**Semi-intensive** with <30 shrimp post-larvae stocked per m^2
	VN I		Soc Trang	**Intensive** with >30 shrimp post-larvae stocked per m^2
	VN I	Whiteleg shrimp	Ben Tre	Intensive with >30 shrimp post-larvae stocked per m^2
	VN S	Pangasius	An Giang & Can Tho	**Small** farms with no full-time labor
	VN M			**Medium** privately owned with full time labor
	VN L			**Large** corporate farms

In order to provide a level of confidence behind conclusions, the hypothesis "different production systems providing the same aquaculture commodity to European consumers are associated with different environmental impacts" was tested statistically. The null hypothesis tested assumed that the environmental lifecycle impacts of commodities originating from different aquaculture system were equal (e.g. system A = system B).

Two approaches were used when testing the differences between paired results as obtained in dependent sampling (Henriksson *et al.* 2015a), one using significance tests (H_0:m_A=m_B at α=0.05) and the other analyzing the percentage of Monte Carlo (MC) runs in which the difference was lower or higher than zero ($p(x_A-x_B<0)$ or $p(x_A-x_B>0)$) at p=0.95). This dual approach was chosen as each of them answers different questions; significance tests for the median analyze if the distribution of differences has a median that deviates significantly from zero, while MC frequencies indicate how often a type of farming system is expected to perform better than another. Given the large differences in nutritional, culinary and monetary value of the different species (Schau and Fet 2008), comparisons were only made across countries and systems, not across species.

6.2 Materials and methods

6.2.1 Goal and scope

The study aimed to evaluate the comparative eco-efficiency per functional unit of one tonne of frozen product for some selected aquaculture commodities commonly imported to Europe from Bangladesh, China, Thailand and Vietnam. The products surveyed were frozen peeled tail-on (PTO) whiteleg shrimp (Litopenaeus vannamei), PTO Asian tiger shrimp (Penaeus monodon), headless shell-on (HLSO) giant river prawn (Macrobrachium rosenbergii), tilapia fillets (mainly Oreochromis niloticus) and pangasius catfish fillets (Pangasianodon hypophthalmus). The production chains were modeled up to European ports, assuming that any processes (e.g. retailing, cooking and composting) downstream of this system boundary would be equivalent.

Three impact categories, global warming, eutrophication and freshwater toxicity, were evaluated. The selection of these represents a trade-off among access to good quality data (e.g. important emissions driving some impact categories could not be specified for Asian processes, such as halon causing ozone layer depletion or palladium resulting in abiotic resource depletion), avoidance of extensive multiple comparisons problems, diversity of inventory flows and impacts (e.g. acidification gave similar outcomes to global warming (Henriksson *et al.* 2014a)), and the different uncertainties they are subject to. Impacts were allocated among multiple co-products originating from the same process (e.g. fillets and heads from fish processing) based upon mass and economic proceeds (monetary value times mass), in order to evaluate the sensitivity of this highly influential methodological choice (Henriksson *et al.* 2012c) and to strengthen conclusions. These two allocation methods were chosen as they generally constitute two extreme outcomes and since they can be consistently applied to all allocation situations. Sensitivity in many other pivotal parameters of aquaculture LCAs (amount of feed used, emissions from agricultural fields and aquatic systems, characterization factors, etc.) (Henriksson *et al.* 2012c) were accounted for as part of the variable distributions and therefore considered in the statistical evaluation. Other modeling decisions that could influence outcomes (e.g. cut-off) were not evaluated in the present research as they were deemed to be of only limited importance to our comparative setup. For a more complete set of impact categories and methodological choices, please see Henriksson *et al.* (2014a), Henriksson *et al.* (2014b) and the supporting information of this article. This information is available free of charge via the Internet at http://pubs.acs.org/.

The data sourcing procedure was based upon the protocol presented in Henriksson *et al.* (2012a). Following this protocol, secondary data were weighted (in this study based upon the squared coefficient of variation, wt = $1/CV^2$) according to their inherent uncertainty (inaccuracies in measurements and models) and unrepresentativeness (mismatch between the representativeness and use of data), defined by the Numerical Unit Spread Assessment Pedigree and quantitative uncertainty factors in Frischknecht *et al.* (2007b). Overall dispersions were quantified as the sum of inherent uncertainty, spread (variability resulting from averaging) and unrepresentativeness, in accordance to the protocol (Henriksson *et al.* 2013). LCI models were constructed, propagated and characterized using the CMLCA 5.2 software (www.cmlca.eu) and subsequently aggregated towards the functional unit over 1000 MC simulations using dependent sampling (Henriksson *et al.* 2015a). Covariance was not accounted for in the current models because of methodological limitations. Distributions were tested using the Anderson-Darling goodness-of-fit test in the EasyFit v5.5 software (www.mathwave.com) and significance tests were conducted in SPSS v21 (for a more detailed description of the statistical approach, see supporting information).

The median impact of each system was pairwise tested against that of all other systems used to produce the same commodity, for all three impact categories. Since the distributions were quite skewed, we decided to test equality of medians with the non-parametric Wilcoxon signed-rank test rather than equality of means with means with a paired t-test. Significant differences were considered as $\alpha = 0.05$. However, since 216 comparisons were made among the five species and 20 systems, for two allocation factors and three impact categories, there is over 99.99% probability that at least one of our hypothesis would be a false positive (1-(1-0.05)^(36 comparisons*2 allocation factors*3 impact categories)). A Bonferroni correction was therefore implemented, adjusting the alpha level to $\alpha_b = 0.05/216 = 0.00023$.

The alternative approach, looking at the cumulative frequency of one alternative to be favorable to another according to the MC runs, was assumed to hold if cumulative frequencies were higher than 95%, as described by Heijungs and Kleijn (2001), and Huijbregts *et al.* (2003).

6.2.2 LCI data collection

Primary data for the current study involved several actors in the aquaculture value chains (**Fig. 6.1**). Initial data collection on basic farming practices was conducted between October 2010 and February 2011 for approximately 200 farmers for each species in each of the four countries (a total of about 1400 farmers were interviewed). Farm selection was performed by a random sampling design of farm clusters representing the most important production methods (Murray *et al.* 2014). From this dataset, 20 production systems were identified as systematically different based upon basic parameters such as feed used, energy sources and integrated species (Henriksson *et al.* 2014b) (**Table 6.1**). A follow-up in-depth survey was then conducted between 2011 and 2013 with focus on more LCI specific data and other actors in the aquaculture value chain, including feed mills, capture fisheries and agricultural producers. A complete set of data is available as supporting information to this article and as an annex to SEAT deliverable D3.5 (Henriksson *et al.* 2014b).

6.2.3 LCIA data

Eutrophying emissions were characterized based upon the Redfield ratio, assuming an average composition of phytoplankton biomass of 106 carbon atoms, 16 nitrogen atoms and 1 phosphorus atom, as suggested by Heijungs *et al.* (1992) and neglecting any uncertainty. Emissions resulting in global warming were characterized using the characterization factors and uncertainty estimates presented in the fifth IPCC report (IPCC 2013; Myhre *et al.* 2013). Characterization factors for freshwater ecosystem impacts were derived from Rosenbaum *et al.* (2008), or, for non-characterized

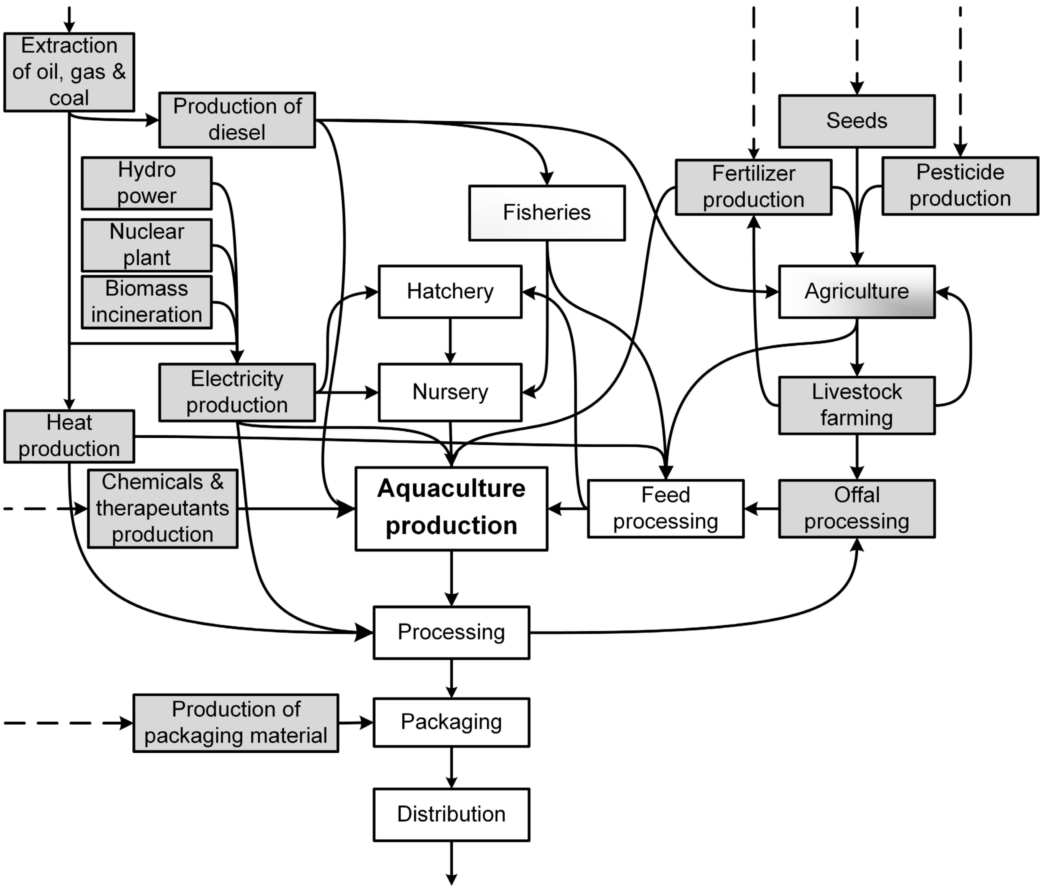

Fig 6.1: Simplified flow-chart of the processes included in this LCA, where arrows symbolize transportation, dashed lines indicate upstream processes, white filled boxes indicate processes modeled from primary data and grey fill boxes indicate processes modeled based upon secondary data.

chemicals used in aquaculture farming, calculated using the USEtox model. Ecotoxicity data for potentially toxic chemicals applied in aquaculture farms which were used in the model were primarily sourced from Rico *et al.*(Rico and Van den Brink 2014), and secondarily from the US Environmental Protection Agency's (EPA) ECOTOX database (cfpub.epa.gov; accessed 25-May-2014). For chemical characteristics, measured data were prioritized (primarily from sitem.herts.ac.uk/aeru/vsdb/atoz.htm; accessed 25-May-2014) before quantitative structure–activity relationships (QSARs) were used (toxnet.nlm.nih.gov, accessed 25-May-2014; Episuite v4.11 from US EPA). All chemicals applied to agricultural fields and ponds were assumed lost to the environment, in consistency with ecoinvent v2.2. For acute exposure EC50 and LC50 values were considered, and for chronic exposure NOECs and LOECs. Dispersions around the FEATPs were calculated as the sum of dispersions around acute and chronic effect concentrations within and among genera, and the unrepresentativeness of this data. No dispersions were, however, available for the FAETPs readily available in Rosenbaum *et al.* (2008).

6. 3 Results and interpretation

Significant conclusions among systems for each species are summarized below. Only conclusions that held for both allocation factors were considered. Relative differences as percentages and contribution analyses are available in the supporting information of this article. Dispersions related to the contribution analysis could unfortunately not be quantified using the present approach. These values are instead based upon the so-called baselines (point-value estimates), which in the current study were defined by arithmetic means, in line with the arithmetical structure of CMLCA (Heijungs and Suh 2002).

Asian tiger shrimp farming in Western Bangladesh was related to significantly lower median global warming and eutrophication impacts than all other systems, and also had the lowest median freshwater ecotoxic emissions alongside intensive farming in Vietnam (**Table 6.2**). This is explained by the fact that many Asian tiger shrimp farms in Western Bangladesh use limited feed and/or fertilizer inputs, resulting in a net sink for nutrients. The median eutrophying impacts of Bangladeshi farms in the east were, in the meantime, comparable with those from either of the Vietnamese shrimp farming systems, and worse with regards to freshwater ecotoxicity. Asian tiger shrimp integrated with prawn performed the worst for all impact categories except global warming. The poorer performance of the Bangladeshi systems with regards to toxicity was largely due to more extensive use of agricultural products as feed, for which pesticides are used. In Vietnam, intensive production of Asian tiger shrimp had significantly lower ecotoxicological and eutrophying impacts as compared to semi-intensive production, but similar global warming impacts.

Table 6.2: Ranking of the relative environmental performance related to Asian tiger shrimp at European consumers. VN = Vietnam; BD = Bangladesh; I = Intensive; SI = Semi-intensive; W = West; E = East; S&P = Shrimp and Prawn. Different superscripted letters indicate significantly different ranges identified using the Wilcoxon signed-rank test and different colors indicate ranges where more than 95% of the runs favored the green alternative over the red.

	Global warming		Eutrophication		Ecotoxicology	
Rank	Mass	Economic	Mass	Economic	Mass	Economic
Best	BD W[a]	BD W[a]	BD W[a]	BD W[a]	BD W[a]	BD W[a]
	BD E[b]	BD E[b]	BD E[b]	VN I[b]	VN I[b]	VN I[a]
	BD S&P[c]	VN SI[c]	VN I[c]	VN SI[c]	VN SI[c]	VN SI[b]
	VN I[d]	VN I[d]	VN SI[d]	BD E[c]	BD E[d]	BD E[c]
Worst	VN SI[d]	BD S&P[e]	BD S&P[e]	BD S&P[d]	BD S&P[e]	BD S&P[d]

For all three impacts, the median of related to the production of frozen peeled whiteleg shrimp were significantly larger for the Thai farms compared to the Vietnamese farms. Farming in low-level ponds in China was also related to lower median environmental impacts compared to farming in eastern Thailand. Chinese high and low-level farms (**Table 6.3**), however, had similar global warming and eutrophication impacts, while low-level farms were related to lower freshwater ecotoxicity impacts. The environmental impacts of whiteleg shrimp farming in China were also similar to farming in Vietnam, while the allocation factor used greatly influenced results due to a more extensive use of fishmeal from mixed fisheries and livestock byproducts in feeds. None of the impacts were significantly different when analyzing the entire distribution of differences between systems.

Table 6.3: Relative environmental performance of whiteleg shrimps at European consumers. VN = Vietnam; TH = Thailand; CN = China; I = Intensive; E = East; S = South; LL = Low-level; HL = High-level. Different superscripted letters indicate significantly different ranges identified using the Wilcoxon signed-rank test. For none of the comparisons, 95% of the runs favored one alternative over the other.

	Global warming		Eutrophication		Ecotoxicology	
Rank	Mass	Economic	Mass	Economic	Mass	Economic
Best	CN HL[a]	VN I[a]	VN I[a]	VN I[a]	CN LL[a]	VN I[a]
	CN LL[a]	CN LL[b]	CN LL[a]	CN LL[b]	CN HL[b]	CN LL[b]
	VN I[b]	CN HL[bc]	CN HL[a]	CN HL[b]	VN I[b]	CN HL[c]
	TH S[c]	TH S[bc]	TH S[b]	TH S[c]	TH S[c]	TH S[d]
Worst	TH E[d]	TH E[c]	TH E[b]	TH E[d]	TH E[d]	TH E[d]

Allocation also had a large influence on the outcomes of the Bangladeshi giant river prawn systems (**Table 6.4**). Farms where such prawn were polycultured with Asian tiger shrimp had more favorable median outcomes than prawn from Khulna province farmed without shrimp with regards to global warming and eutrophication, while the situation was the opposite in terms of freshwater ecotoxicity impacts. Distributions of differences did not differ among systems.

Table 6.4: Relative environmental performance of Giant River prawn at European consumers. BD = Bangladesh; B = Bagerhat; K=Khulna; S&P = Shrimp and Prawn. Different superscripted letters indicate significantly different ranges identified using the Wilcoxon signed-rank test. For none of the comparisons, 95% of the runs favored one alternative over the other.

	Global warming		Eutrophication		Ecotoxicology	
Rank	Mass	Economic	Mass	Economic	Mass	Economic
Best	BD B[a]	BD S&P[a]	BD S&P[a]	BD S&P[a]	BD B[a]	BD S&P[a]
	BD S&P[a]	BD B[b]	BD B[b]	BD K[b]	BD S&P[b]	BD B[b]
Worst	BD K[b]	BD K[b]	BD K[c]	BD B[c]	BD K[c]	BD K[b]

Among the Chinese tilapia systems, fillets from ponds in Guangdong were associated with significantly lower median impacts compared to fillets from Hainan (**Table 6.5**). The Hainan farms were also related to larger median eutrophication and ecotoxicity impacts than farms integrated with pigs and reservoir systems. Distributions of differences did not differ among systems.

Table 6.5: Relative environmental performance of tilapia fillets at European consumers. Tilapia. CN = China; GD = Guangdong; HI = Hainan; I = Integrated; R = Reservoir. Different superscripted letters indicate significantly different ranges identified using the Wilcoxon signed-rank test. For none of the comparisons, 95% of the runs favored one alternative over the other.

	Global warming		Eutrophication		Ecotoxicology	
Rank	Mass	Economic	Mass	Economic	Mass	Economic
Best	CN GD[a]	CN GD[a]	CN GD[a]	CN GD[a]	CN GD[a]	CN GD[a]
	CN R[b]	CN R[a]	CN INT[b]	CN INT[b]	CN INT[b]	CN R[a]
	CN INT[c]	CN INT[b]	CN R[c]	CN R[b]	CN R[b]	CN INT[b]
Worst	CN HI[d]	CN HI[b]	CN HI[d]	CN HI[c]	CN HI[c]	CN HI[c]

All evaluated environmental median impacts caused by the production of pangasius fillets were found to be significantly lower in the studied large-scale farms as compared to those calculated for small- and medium-scale farms. (**Table 6.6**). Small-scaled farms also resulted in significantly lower median eutrophication impacts than medium-scaled farms. Distributions of differences did not differ among systems.

Table 6.6: Relative environmental performance of Pangasius fillets at European consumers. VN = Vietnam; SL = Small; MD = Medium; LG = Large. Different superscripted letters indicate significantly different ranges identified using the Wilcoxon signed-rank test. For none of the comparisons, 95% of the runs favored one alternative over the other.

	Global warming	Eutrophication	Ecotoxicology			
Rank	Mass	Economic	Mass	Economic	Mass	Economic
Best	VN LG^{a}	VN LG^{a}	VN LG^{a}	VN LG^{a}	VN LG^{a}	VN LG^{a}
	VN SL^{b}	VN SL^{b}	VN SL^{b}	VN SL^{b}	VN SL^{b}	VN SL^{b}
Worst	VN MD^{b}	VN MD^{b}	VN MD^{c}	VN MD^{c}	VN MD^{b}	VN MD^{b}

6.4 Discussion

6.4.1 Analytical approach

Unlike previous comparisons of point-values, the current approach offered a level of confidence to support conclusions; and unlike previous comparisons of ranges (Cao *et al.* 2011), by only considering relative uncertainties, type II statistical errors (incorrectly accepting the null hypothesis) were reduced. Of the systems tested, most came out to differ significantly, despite the conservative Bonferroni correction (Narum 2006). This is largely due to the large sample size used (n=1000), a sample size deemed as sufficient, but not excessive. Historically, the number of MC iterations has been limited by computing power, and mathematical solutions for calculating the number of iterations needed to achieve a desired confidence level have even been proposed (so called sequential stopping boundaries) (Fay *et al.* 2007). One could therefore argue that by increasing the number of MC runs any hypothesis test on means or medians will always produce significant results. This, by the way, is not only true for Monte Carlo, but it is also a danger of large real samples, and it is an inherent characteristic of classical hypothesis testing (Cohen 1994). Using the alternative to significance tests showed that only the comparison of Asian tiger shrimp systems deviated in more 95% of the MC runs in their environmental impacts.

From a naive point of view, the two statistical approaches give contradictory answers, but in reality they answer different questions. The more suitable of the two approaches therefore depends upon the question needing answering, e.g. is the median of A significantly different from the median of B, or is a random pick of A demonstrably better than a random pick of B. Thus, while significance tests provide a conventional answer with respect to the median (or mean) impact, the proportional outcomes favoring a certain type of farming system might be more informative for a policy decision. In alternative words, statistical tests are about comparing distribution parameters, while the other approach is about a random pick from a distribution. While our belief is that operating within the paradigm of statistical hypotheses testing is too valuable to discard (Henriksson *et al.* 2015a), statistical significance should not always be taken at face value (Cohen 1994; McCloskey and Ziliak 1996; Doweyko 2008). However, differences that are proclaimed to be “significant” should be supported by statistical tests.

6.4.2 Aquaculture findings

Reflecting on previous aquaculture LCAs, many of the conclusions in the current research confirm the general outcomes of LCAs of fed aquaculture systems worldwide. Like tilapia and African catfish farming in Cameroon, eutrophication was mainly related to farm effluent (Ewoukem *et al.* 2012); and like most salmon farming, the provision of feed (including fisheries, agriculture and livestock) was related to most greenhouse gas emissions (Pelletier *et al.* 2009) (see Fig S1-S3). Lowering the feed conversion ratio would consequently offer environmental improvements, where formulated feeds tailored to the nutritional needs of each species served in portions ensuring high availability (e.g. floating pellets) should be promoted. Reductions in aquaculture impacts, moreover, require agriculture to switch to less toxic pesticides or adopt organic farming practices to the extent possible. Developing models for reusing pond effluents and sediments locally as fertilizers, as already practiced in traditional Chinese aquaculture, would also reduce the impacts of both agri- and aquaculture, as nutrients in modern aquaculture systems are largely lost to adjacent water bodies where they result in eutrophication. Production systems with limited environmental interactions that allow for nutrients to be captured, and the influence by external parasites and bacterial diseases to be reduced (thus reducing the reliance on and discharge of therapeutants) should therefore also be favored.

Use of wild fish in aqua-feeds is one of the major critiques of the aquaculture sector, based on both environmental and socioeconomic arguments (Naylor *et al.* 2000; Cao *et al.* 2015). In the present research this also stood out as one of the major causes for global warming and eutrophication for many systems (see Figure S1-S2). Limiting the inclusion and choosing more sustainable sources of fishmeal in feeds therefore need to be priorities for reducing the environmental impacts of farmed aquatic products, especially for shrimp. This goal can only be achieved if both feed producers and farmers, who often believe that larger fishmeal inclusions result in faster growth, recognize advancements in dietary substitution and supplements. A more sustainable source could be derived from processing byproducts, as much of these are still discarded (e.g. shrimp byproducts in Bangladesh). This would not only reduce pressure on wild fish stocks (Newton *et al.* 2014; Cao *et al.* 2015), but would also reduce eutrophying emissions at landfills and recycle nutrients (Phong *et al.* 2011). Lastly, it is important to always favor feed ingredients, terrestrial or aquatic, that do not compete with their direct use as human food, as malnutrition still is widespread in some regions of Asia and elsewhere.

Intensity of systems had no clear correlation with the impacts evaluated in the present study. Paddle-wheel aerators were, however, more intensively used in ponds with higher stocking densities, with consequent global warming impacts. Monitoring oxygen levels in ponds could therefore help optimizing the use of paddle-wheels, and more energy efficient forms of aeration should be developed and promoted. The use of coal to generate the electricity that powers aerators and other activities also needs to be curbed or improved, as does the electricity efficiency of freezers.

On-farm chemical use made only small contributions to the overall lifecycle freshwater ecotoxicity impacts, with the exception of benzalkonium chloride and other chlorine releasing compounds used as disinfectants. Chlorine is volatile and therefore used in large quantities, but the presence of organic matter leads to chlorinated compounds (e.g. halogenated hydrocharbons) that are more stable and induce long-term toxicity. The use of alternative, less toxic, biocidal or disinfection methods is therefore promoted.

6.4.3 Limitations and future research needs

When considering chemical and other emissions, it is important to acknowledge that LCA has limited capacity to account for spatio-temporal aspects in both the LCI and the LCIA phases (Guinée and Heijungs 1993; Pinsonnault *et al.* 2014). Thus, even if many of the local impacts related to the grow-out sites appeared not to exceed the buffering capacity of local ecosystems, they cannot be discounted as inconsequential. For example, with regards to therapeutant use in the present study, the peak predicted environmental concentrations for 61% of the treatments applied by grow-out farmers resulted in a risk quotient higher than one, implying a potential risk to important structural endpoints of aquatic ecosystems not accounted for in the LCAs (Rico and Van den Brink 2014). Similar for eutrophication, where discharge of sediments and/or sludge from post-harvested ponds could have severe ecological consequences through peaks in turbidity, oxygen depletion or ammonia toxicity. Neither are additive and synergistic effects of different stressors accounted for in current LCA methodology, highlighting the added value of adopting the refined spatio-temporal windows and mixture toxicity approaches currently used in risk assessment alongside LCA (Rico and Van den Brink 2014). A risk assessment approach could also provide better insights into other impacts that have been deemed as relevant for aquaculture LCAs (Ford *et al.* 2012), such as reduced dissolved oxygen levels, introduction of non-indigenous species, and spread of disease and parasites.

The large dispersions around the characterization factors for freshwater ecotoxicity originated partially from the eco-toxicological effect factors, with large discrepancies in experimental acute and chronic effect concentrations, and within and among genus. Chronic effects on different types of algae often expressed the largest irregularities. Many additional assumptions exist around the chemical properties, some of which had to be resolved using QSARs. Given that these values are purely based upon the theoretical properties of molecules, QSAR estimates can differ greatly from reality (Doweyko 2008). Many other parameters related to inventory and impact assessment models also lack confidence estimates (Nemecek and Schnetzer 2011; Hauschild *et al.* 2012), which in some cases were confidence estimates are almost impossible to quantify (Maurice *et al.* 2000; Björklund 2002). For example, in the present research no uncertainty estimates were assigned to the eutrophication potentials, as the uncertainty around the actual environmental consequences are hard to quantify given their complex nature and geographically specific context, with discrepancies induced by factors such as planktonic species assemblage, bioavailability of the nutrients, fate of emissions, abiotic factors and nutrient compositions in receiving environments (Ptacnik *et al.* 2010). More recent impact assessment methods that address these challenges by presenting country-, or even region-, specific characterization factors (Posch *et al.* 2008; Gallego *et al.* 2010) can, in the meantime, induce new uncertainty in the form of unknown locations of emissions.

In addition to this, uncertainties also arise from the limited number of distributions available to represent data in LCA at present and the general negligence of covariance (Maurice *et al.* 2000). Still, these are only some of the many assumptions made over the different phases of an LCA, where quantitative uncertainty estimates remain incomplete or undefined, resulting in a fragile pyramid where the ranges of results only capture part of the underlying uncertainty. Significant differences thus only consider the dispersions quantified, confirming the strict relative meaning of comparative LCAs (Henriksson *et al.* 2015a). Other types of uncertainties, including several methodological choices, may also be more easily illustrated by performing sensitivity analyses (Björklund 2002) until more sophisticated approaches become available (Jung *et al.* 2013; Beltran *et al.* 2014).

More extensive data on emissions related to LULUC are warranted, as the removal of mangrove for pond constructs is known to greatly influence both global warming and eutrophication results (Jonell and Henriksson 2014). More inventory and characterization data related to freshwater ecotoxicity are also invited, as many emissions with possible environmental effects had to be excluded from the present study due to resource constraints. The inclusions of infrastructure, its maintenance and waste disposal might, for example, alter the conclusions made related to freshwater ecotoxicity, as metals were a major driver for this impact category. Moreover, it is important to acknowledge that the data in the present research represents farming practices between 2010 and 2011, while aquaculture practices are notable for changing rapidly. For example, an outbreak of early mortality syndrome led to a rapid shift from Asian tiger shrimp to whiteleg shrimp for many Vietnamese farmers during the period of this research. Wild fish stocks, agricultural yields and monetary values are also variable over time. More extensive databases and better software that allow for more rapid data processing and invite practitioners to utilize methodological advancements are therefore desired, in order to promote more scientifically robust conclusions in future LCA studies.

Acknowledgements

This work is part of the Sustaining Ethical Aquaculture Trade (SEAT) project, which is co-funded by the European Commission within the Seventh Framework Programme—Sustainable Development Global Change and Ecosystem (project no. 222889). www.seatglobal.eu.

Chapter 7

General discussion and conclusions

7.1 Significant trends and environmental hot-spots in Asian aquaculture production chains

By using the LCA approach presented in the current research, several significant trends could be identified among the environmental impacts caused by different Asian aquaculture production systems. Most trends also persisted using both allocation methods, suggesting that many conclusions could be made with great confidence.

Among the conclusions reached, noteworthy was the importance of feed, with large GHG emissions from capture fishing boats, livestock farming and agriculture. Excess feed was also the major driver for eutrophication, and agricultural pesticides an environmental hot-spot for freshwater ecotoxicity. Together with the significantly lower environmental impacts of the large commercial pangasius farms, this indicates that farm management is strongly linked with the environmental performance of aquaculture production. While this might not be surprising, it highlights the importance of training small-scale farmers, where some of the recommendations in the present thesis should be considered.

In China, the non-integrated tilapia farms in Guangdong had significantly lower environmental impacts than the other systems, with the exception of reservoirs for global warming and ecotoxicity. This trend was again mainly a reflection the eFCRs at the farms, given that feed was the main driver behind most impacts. Promoting and distributing high quality pelleted feeds will therefore be essential, alongside better farm management and feeding practices, to reduce environmental impacts. This also holds true for whiteleg shrimp, where the Vietnamese production systems (eFCR=1.3) resulted in significantly lower emissions than either of the Thai shrimp farming systems (eFCR=1.5). There was, however, no clear correlation between intensity and environmental impacts. Future developments of the aquaculture sector therefore need to consider the consequences of land-use and land-use change, stressing that sustainble intensification is the way forward, but that these practices need to be evaluated, identified and promoted for all types of farmers.

Common environmental hot-spots apart from overfeeding in the different production chains included extensive use of fishmeal (especially from mixed fisheries), dumping of sediments into nearby environments, , landfilling of processing byproducts, high reliance on coal power, the use of certain therapeutants and inefficiently processed byproduct meals. Most of these can, however, be addressed by implementing better policies and farming practices, as well as educating all actors in the aquaculture value chain about the environmental impacts related to aquatic food products.

7.2 Irregularities in current aquaculture LCAs

Several LCA studies of aquaculture systems were already available when the present research commenced (2010). Since, the twelve studies originally reviewed in Henriksson *et al.* (2011) have been accompanied by several additional studies, many that focus on Asian farming systems (Cao *et al.* 2011; Hall *et al.* 2011; Bosma *et al.* 2011; Mungkung *et al.* 2013; Huysveld *et al.* 2013). A commonly observed malpractice among the reviewed studies was the mixing of processes from different background databases, since each database relies upon its unique set of methodological choices. The resulting impacts from different databases are therefore completely incomparable. For example, many studies consulted the processes for the production of fishmeal and other animal derived products in the LCAfood (lcafood.dk) alongside ecoinvent, and/or other LCI databases. The LCAfood database, however, constitutes a consequential LCI database that tries to account for market reactions to changes in demand. Some environmental emissions can therefore come out as negative (e.g. if a product substitutes an environmentally poor product), resulting in emissions completely incompatible to those of the attributional ecoinvent LCI database. This malpractice is partially to blame on software developers that often use the number of available processes as a marketing tool and therefore allow for databases to be mixed without providing inexperienced users with any sort of disclaimer. A simple remedy for this problem is therefore to disable the option of mixing different databases in software, or at least provide warnings to users who do so.

There was also a general lack of transparency into the inventory data used, making critical reviews difficult and reproducing results impossible. This goes against the core of the scientific theory and undermines the academic integrity of most LCA results. As Ioannidis (2012) phrases it: "Efficient and unbiased replication mechanisms are essential for maintaining high levels of scientific credibility". These concerns were amplified by the fact that most studies only present aggregated LCIA results, leaving no insight for reviewers or readers to critically evaluate the decisions made. Poor reporting on primary data also hampers the collective efforts of producing a more extensive LCI data library and obstructs any secondary use of that data (including citations). Since most LCI data have much effort invested into its collection, failing to sufficiently record this data is a waste of resources. More strict requirements by journals and reviewers could therefore transcend case studies beyond their current questionable usefulness (Klöpffer and Curran 2013). This reporting could easily be provided, without compromising the word limit of journals, as supporting information to articles. In the present research a spreadsheet was also developed for this purpose (available at cml.leiden.edu/software/software-quanlci.html), providing an easy way to record and report upon different data references and the dispersions related to them (Henriksson *et al.* 2012c).

Additional impact categories relevant to aquaculture and food production should also be better established within the LCA framework, including impacts on seafloors (Hornborg *et al.* 2012), impacts on food security (Garnett 2014) and impacts on biodiversity (Ford *et al.* 2012). It is, however, important that lifecycle thinking prevails when developing these. Meaning that an impact assessment framework should be applicable to the whole range of different processes causing the environmental damage, including agriculture, livestock, industrial processes, transportation, etc. For those methods that are not relevant to a lifecycle perspective, a risk assessment approach might better be applied as it also takes into account temporal aspects, ecosystems' carrying capacity and synergistic effects. Social life cycle assessments (SLCA) and life cycle costing (LCC) indicators also need to be developed, in order to support more holistic life cycle sustainability assessments (LCSA) (Guinée and Heijungs 2011). The implementation of LCSA might, for example, have provided a more balanced view of small-scale farming in the present research. Throughout the process of expanding the coverage of LCA it is also important to acknowledge that some impacts never will fit into a quantitative framework and therefore need to be communicated alongside LCA results, stressing that decisions should never be based on LCA results alone.

The main methodological topic of debate among the aquaculture LCAs reviewed was the use of different allocation methods. Several studies presented elaborate discussions on the topic (Pelletier and Tyedmers 2007; Fet *et al.* 2009; Avadí and Fréon 2013) and at least two articles have been dedicated solely to allocation in seafood LCAs (Ayer *et al.* 2007; Svanes *et al.* 2011). However, with the level of overall dispersions now quantified it is clear that choices regarding data sourcing often influence results more than the choice of an allocation factor. This becomes even more evident if only relative conclusions are considered (A>B), as significant trends tended to remain coherent across allocation methods. Thus shifting focus towards data quality.

7.3 Data quality improvement options for LCAs

LCA is a tool with inherent demarcation problems, where statistical inference is inadequate and confirmation bias inevitable. Results often build upon large quantities of data and outcomes from complex models supported by insufficient documentation, making the reproducibility of results next to impossible. In the meantime, results are generally presented in a way that induces high confidence, with comparisons of absolute results being commonplace even in scientific literature (Nijdam *et al.* 2012; Tilman and Clark 2014). Strengthening the scientific integrity of LCA studies and adding confidence behind conclusions were therefore identified as areas of priority in the present research.

Starting at the unit process level, we presented a protocol for horizontal averaging of data in **Chapter 3**, where all available datasets could be used and weighted towards a central moment, reducing the influence from data choices and consequently confirmation bias. In addition to this, a method for quantifying overall dispersions defined as the sum of inherent uncertainty, spread and unrepresentativeness was presented. Acknowledging resource constraints as a generic limitation of the data intensive LCA framework, much effort was invested into making the method accessible to the majority of LCA practitioners and understandable to their audiences. In the process of doing so, nomenclature was presented alongside a spread-sheet for calculating overall dispersions.

The importance of defining unit process data is often underestimated, as many unit process parameters act as multipliers during the propagation process, meaning that one erroneous parameter can result in completely skewed conclusions. The generally opportunistic sourcing of unit process parameters is therefore to be blame for much of the discrepancies seen around LCA results today (de Koning *et al.* 2009). This was initially illustrated using the example of soybeans, where we showed that different sourcing of unit process data among studies describing the same system (soybeans from Brazil) resulted in discrepancies among results with up to an order of magnitude (Henriksson *et al.* 2012b). In the meantime, additional layers of complexity (e.g. geographically specific impact categories, effect oriented impact categories, etc.) are constantly being added to the LCA framework (Hornborg 2012; Ford *et al.* 2012), stressing that a general shift from point-values towards distributions is needed.

The moments (central value, variance, etc.) describing distributions, both in unit process data and results, can be expressed in several ways, none of which is "correct". The most common practice in the field of LCA, to my knowledge, is to use the arithmetic mean as the central value. However, when looking across different inventory data sources in more detail, it often becomes evident that mixes of different indicators for the central value are used. This in conjunction with the use of default uncertainties or pedigree estimates fit to a lognormal distribution often results in strange outcomes. For example, assume that two values of 10 are arithmetic means, with one value being assigned a default variance of CV=0.1 and the other value a variance of CV=0.2, both fit to a lognormal distribution. As these values later are propagated into results, the arithmetic means of the two resulting ranges will diverge, as a result of describing a lognormal distribution with an arithmetic mean. If the median instead was used as the indicator for the central value, this deviation would be reduced (but still persist). This as the median is less influenced by extreme values that otherwise can have strong influence on arithmetic means, especially for small sample sizes. The median is also the basis of comparison in non-parametric tests, the only tests that could be correctly consulted in the present research. It is therefore recommended to adopt the median consistently for all LCA parameters and results, and adjust LCA software accordingly. The ultimate strive, however, should be to fit all data to its own distribution and allow for the most appropriate moments to represent this data.

7.4 Features of horizontal averaging and propagation of LCI data

In order to explore how data best could be horizontally averaged and propagated into LCI results, we used the simplified example (relative to the generally complex aquaculture production chains) of Chinese coal power in **Chapter 4**. Initially, the level of horizontal averaging, which historically has been based upon practical classifications such as geographical regions, products produced or production systems, was questioned. It was also shown how these types of classifications often force a diverse set of practices into the same unit process. For example, the existence of flue gas desulphurisation units in coal power plants proved far more influential on acidifying impacts than the capacity or location of the power plant. This demonstrated that spread could be greatly reduced by reclassifying data individually for each dataset, a rationale that also was adopted in the sixth chapter where a unique classification of grow-out farms was defined for each species and country. This feature was even more prominent for other unit processes encountered throughout this thesis work. For example, rice farming in Bangladesh was characterised by two to three different farming seasons (Amon, Aus or Boro). Each of these farming seasons were related to their own sets of farming practices, intensities of irrigation and yields. Consequently the environmental impacts related to the different harvests actually varied more among each other than compared to many neighbouring countries.

Once the unit process dataset had been defined, the LCI results needed to be propagated towards a common functional unit. Several methods for propagating results have been proposed, including Monte Carlo (MC) and first-order Taylor expansion (Huijbregts *et al.* 2001; Imbeault-Tétreault *et al.* 2013; Heijungs and Lenzen 2013). Of these, MC was decided as the most suitable for the pupose of the present research, as it is commonly available in software (Lloyd and Ries 2007) and allow for post-hoc analyses (e.g. goodness-of-fit tests and significance tests) (Heijungs and Lenzen 2013).

7.5 Identifying significant trends using LCA

Given the many methodological limitations and sources of uncertainty identified throughout **Chapter 2** to **4**, the critical question of "which conclusions can be drawn among ranges of LCA results?" remained. By resolving to the concept of dependent sampling, first roughly outlined by Huijbregts (2001) and later explored by Heijungs and Kleijn (2001) and Hong *et al.* (2010), paired results could be generated, allowing for more powerful paired significance tests. However, a prerequisite for applying any significance test is the establishment of a hypothesis, a rare feature in LCA studies. In **Chapter 5** we therefore stress the importance of defining a hypothesis in LCA studies, where significance tests can be used to test the LCA results and reject the null-hypothesis. By only considering the relative differences, one not only reduces the risk of committing a Type II statistical error (failing to assert what is present), but also ensures that identical methodological choices are maintained (with regards to functional unit, system boundaries, allocation, underlying database, impact assessment method, etc.).

The level of correlation of paired results is dependent upon the number of overlapping unit process. Comparing two different pangasius products from Vietnam therefore offers a greater level of correlation, and thus greater resolutions in comparisons, than comparing pangasius fillets from Vietnam with shrimp tails from China. This as a result of more unit processes being shared between the two pangasius value-chains (e.g. feed production, hatchery production, electricity generation, etc.) than between the pangasius value-chain and the Chinese shrimp value-chain.

7.6 Recommendations

7.6.1 Aquaculture

7.6.1.1 Improving feeding practices

Feed was the largest single driver behind most of the impact categories, either through the use of diesel in fishing boats, agricultural pesticides, field emissions or through nutrient effluents resulting from an excessive use of feed and fertilisers. Reducing the amount of feed used should therefore be a priority for the aquaculture sector.

Reducing the inclusion rates of fishmeal in feeds and sourcing fishmeal from sustainable sources are other priorities for lessening the environmental impact of Asian aquaculture chains. This as fishmeal has been associated with many negative consequences (Naylor *et al.* 2009), including overfishing (Pauly *et al.* 2003), physical damage on seafloors (Hornborg *et al.* 2012) and reducing protein availability for the world's poor (Jacquet *et al.* 2009). In the present research we also show that much of the fishmeal sourced regionally is associated with large GHG and eutrophying emissions. Moreover, all shrimp farming systems in the present research, except those in Bangladesh, required larger inputs of wild fish than shrimp produced. This indicates of a net loss in animal protein, pressures on wild fish stocks and competition with food availability. A partial solution for this problem was presented in Cao *et al.* (2015), where we showed that a more extensive use of processing byproducts in fishmeal production could satisfy between half and two-thirds of China's current fishmeal demand (Cao *et al.* 2015).

7.5.1.2 Reusing wastewater and sediments in agriculture

The grow-out site was the hot-spot for most eutrophication impacts as a result of effluents of wastewater and sediments. One of the most efficient ways to deal with these nutrient flows from aquaculture ponds is to reuse them in agricultural fields. This practice may also help to maintain the soil organic carbon on agricultural fields (Boyd *et al.* 2010; Wiloso *et al.* 2014) and reduce the addition of inorganic fertilisers. Treatment ponds and other types of effluent handling are also recommended, but considerations need to be made with regards to gases released from these instalments.

7.5.2 Aquaculture LCAs

7.5.2.1 Choosing a functional unit beyond farm-gate

Most of the aquaculture LCAs reviewed had set their system boundaries at farm-gate with a mass based functional unit of live fish. The consequence of these choices became that byproducts used in feeds (e.g. rice bran or MBM) were allocated large environmental burdens when mass or gross energy content was used as the basis for allocation, while the allocation towards the inevitable fish byproducts that ensue at fish processing remained unaccounted for. Where economic allocation was adopted the situation was the opposite, resulting in products having lower environmental impacts at farm-gate, but not necessarily as processed products (as the value of fillets or tails are much larger than those of the byproducts). Consequently, by choosing a functional unit beyond the processing stage, the discrepancies between the two allocation methods used in this study (mass and economic) were greatly reduced.

7.5.2.2 Land-use and land-use change related to aquaculture

Land-use and land-use change (LULUC) was not explored directly within this thesis. However, the research of Schoon (2013) and Jonell and Henriksson (2014) conducted in parallel to this work stress the importance of considering LULUC when evaluating the lifecycle of aquaculture products. This relates most directly to mangrove deforestation as a result of establishing new aquaculture ponds, but also LULUC impacts resulting from the provision of feed need to be considered. Middelaar *et al.* (2013), for example, concluded that the GHG emissions from land-use change (LUC) resulting from Brazilian soybean farming could be more than six times those resulting from operations.

7.5.3 Life Cycle Assessment

7.5.3.1 Standardising dispersions around LCA results

Producing and processing empirically quantified dispersions around LCA results is today practically doable for all LCA practitioners and should therefore become norm. Many improvements could, however, aid practitioners with this shift. Initially, the LCA community needs to agree upon one consistent nomenclature so that unit process data and results can be communicated in a correct way. Software developers also need to embrace this nomenclature and improve the existing options for including and analysing dispersions. This would include the options for more distributions or statistical moments (skewness, kurtosis, etc.), the propagation of unit process data alongside characterisation factors, paired sampling, multiple allocation factors, accounting for covariance, provide relevant statistical tests (e.g. goodness-of-fit, Wilcoxon test, Friedman test, etc.), R extensions, GPU support and more easily shared models/inventory data. This would also encourage better reporting of data and raise the standard of LCA as a science.

Improving statistical inference with the support of software is also necessary for managing big data in LCA (Cooper *et al.* 2013). The adoption of big data would reduce the incidence of flawed parameters in LCIs and ultimately harmonise results. It could also come to support long-term datasets and help to update parameters in real-time (Xu *et al.* 2015). The protocol developed presented in **Chapter 3** could be used for the integration of big data into LCA, as working with weighted mean based upon a pedigree approach could assure more objective representation of different parameters (Xu *et al.* 2015).

7.5.3.2 Structuring LCI models to address hypotheses

When adopting dependent sampling, the structuring of the unit process dataset becomes increasingly important. Given that only distributions in unit processes shared by production chains can be dependently sampled, the LCI modelling structure will influence the level of correlation among results. For example, **Fig. 7.1** demonstrates a hypothetical scenario where burning of diesel in two different fishing fleets has been separated into two country specific unit processes. Consequently, the distributions in the two unit processes can only be independently sampled. If the unit process dataset instead was modelled according to **Fig. 7.2**, the national label on emissions might be lost, but dependent sampling prevails. Similar thinking could be applied to all unit processes that rely upon fairly generic data, which also often is related to large spread (e.g. combustion of diesel in unknown engine, wastewater from processing plants, transportation distances, etc.). Constructing unit process datasets and LCI databases accordingly would therefore reduce relative uncertainties, even if absolute uncertainties might increase (by the use of more generic unit processes).

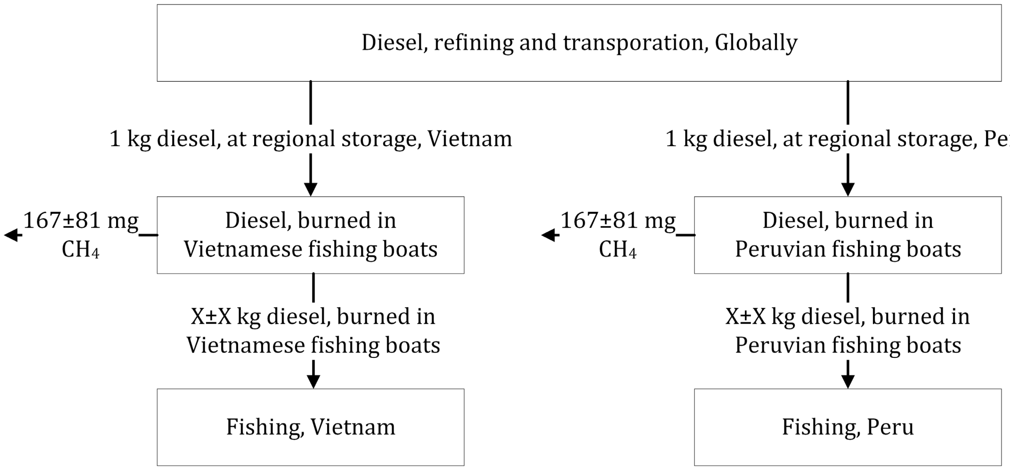

Fig. 7.1: Example of a unit process dataset using separate unit processes for the combustion of diesel in fishing boats.

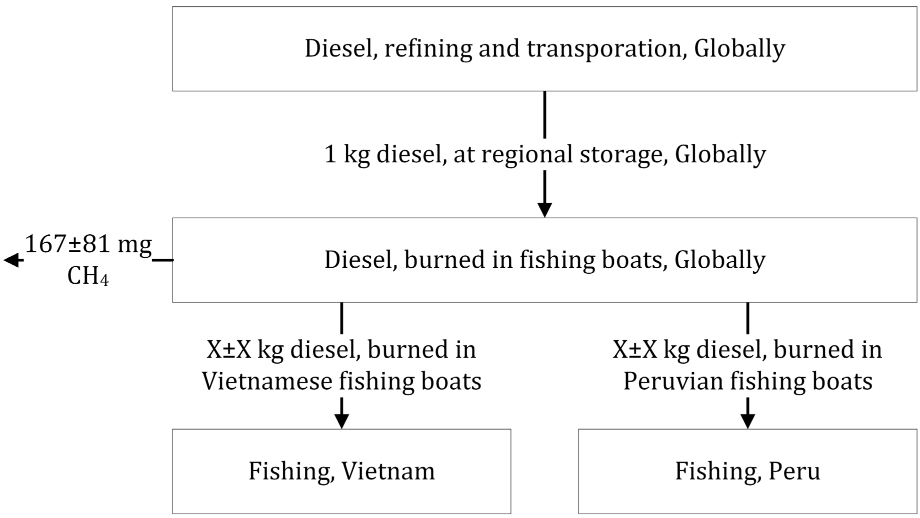

Fig. 7.2: Example of a unit process dataset using only one unit process for the combustion of diesel in fishing boats.

7.5.3.3 Achieving mass balanced LCI models

Since the appearance of computers, mathematical modelling has become the answer for evaluating most of our environmental concerns. Over time, these models have become increasingly complex, leaving ever less room for critical evaluations of the predicted outcomes (Pilkey and Pilkey-Jarvis 2007). LCA is a prime example of such an environmental modelling tool where one flawed parameter or erroneous decimal point can skew conclusions. Striving towards mass balanced LCI models could therefore greatly reduce the risk of such mistakes and logically makes great sense (inputs=outputs). Resolving the many challenges related to this (e.g. chemical reactions within processes) and providing software to support mass balanced models is therefore encouraged.

7.5.3.4 LCA as a science – confirmatory or exploratory

Exploratory research sets out to identifying indicators, rather than being a pathfinder (Tukey 1980). Confirmatory research, on the other hand, aims at identifying significant trends in stochastic environments. While the prior may provide highly valuable information, it does not do it with the same conviction as the latter. Throughout the present thesis, much doubt was shed on the confirmatory use of LCA results, but a more scientifically rigid approach to LCA was also presented. By adopting the suggested approach, LCA practitioners are allowed to achieve statistically supported conclusions, with a reduced chance of committing Type II statistical errors. It is, however, my personal belief that LCA should be used for both purposes, depending upon the goal of the study; where hot-spot analyses and system mapping may help formulate hypotheses for follow-up confirmatory LCAs. I also believe that methodological alternatives add confidence to LCA results, rather than erasing comparability. As was shown, absolute results are irrelevant, so fewer resources should be invested in seeking consensus on methodological choices through operational guidelines, PCR standards, etc. LCA results will always remain incomparable across studies and between LCA practitioners. Exploratory LCA case studies should therefore avoid comparisons with other studies apart from maybe building consensus around environmental hotspots. Finally, it is important to highlight that LCA is not a tool created to save individual species or unique locations, it is a tool crafted to steer societies (not individuals) towards more sustainable choices and actions.

Summary

This thesis aims to evaluate the environmental sustainability of European imports of selected farmed aquatic food products from Asia using life cycle assessment (LCA) studies. LCA is currently one of the most popular tools for benchmarking the environmental performance of product systems (e.g., for biofuels, food commodities, light bulbs, drink containers).

Imports of aquatic food products from Asia to Europe have been steadily increasing since the turn of the millennium, the result of fully exploited, or even overexploited, regional fish stocks, an overall increase in the demand for fish, and changing consumer preferences. A selection of four Asian countries (Bangladesh, China, Thailand and Vietnam) and five farmed species (Asian tiger prawn, whiteleg shrimp, freshwater prawn, tilapia and pangasius catfish) were chosen as representatives of the Asian aquaculture industry. This selection of countries and species covered farming systems ranging from extensive, using more passive farming techniques, to highly intensive production units relying on a diversity of auxiliary inputs (e.g. feed, oxygen, water and therapeutants).

Several LCA studies already had been carried out on aquaculture products, but few of these focused on Asian production. Moreover, the common practice was to only calculate LCA impacts as point-values. Comparisons could consequently not be statistically supported, resulting in decisions and even legislation deeming products superior to each other without any knowledge about the underlying uncertainty. Thus, in order to produce scientifically supported conclusions, the following main research question was defined:

Are there significant differences among the environmental impacts resulting from the production of Asian aquaculture commodities, and if so, what are the main causes?

As part of answering the main research question, four sub-questions (RQs) were also defined:

RQ1: Are there shortcomings in methods, data or coverage in existing aquaculture LCAs? (Chapter 2)

RQ2: Can variances be determined for unit process data in aquaculture LCAs? (Chapter 3)

RQ3: Can these variances be propagated into ranges of results? (Chapter 4)

RQ4: How can we determine if the LCA results of two systems fulfilling the same function are significantly different? (Chapter 5)

RQ1 is addressed in **Chapter 2**, where a review of previous aquaculture LCA studies is carried out. This review highlighted that most studies up to 2011 had focused on finfish in western countries. Another result showed that methodological choices varied greatly among the studies, with different choices for functional units, system boundaries, data, life cycle impact assessment methods and co-product allocation methods. Of these, allocation constituted the largest meth-

odological division, with most discussions focusing on energy based versus economic allocation. Moreover, inventory data were generally limited in sourcing and reporting among the different studies.

The issue of limited data quality (**RQ2**) is addressed in **Chapter 3**, where a protocol for horizontal averaging of unit process data is presented. The chapter explores previous estimates of quantitative uncertainties related to LCA results, and identifies three major sources that contribute to dispersions around LCA results; namely inherent uncertainty, spread (variability due to real differences among production practices) and unrepresentativeness (mismatch between the representativeness and use of data, generally quantified using the pedigree part of the Numerical Unit Spread Assessment Pedigree system). Collectively, these are referred to as overall dispersions. The protocol is based around a novel decision-tree detailing how to estimate overall dispersions for both primary and secondary data. Essential mathematical formulas are presented together with an excel template for calculating unit process parameters, allowing LCA practitioners to apply the estimation protocol for themselves.

In **Chapter 4**, the estimation protocol from **RQ2** is applied in practice to produce ranges of Life Cycle Inventory (LCI) results (**RQ3**). A case study of Chinese coal power was chosen as it presents a more limited set of unit process parameters than most aquaculture production case studies, making the links between unit process data and results more clearer. The outcome of this exercise highlighted some intrinsic challenges related to quantifying uncertainties around results. The level of horizontal averaging (e.g. geographical, technological, etc.) was initially shown to influence parameter estimates. Once ranges of results were propagated using Monte Carlo simulations, shortcomings related to the limited number of distributions available in LCA surfaced. The file format of unit process in ecoinvent v2.2 (ecospold v1) only allows for normal, lognormal, triangular and uniform distributions. In ecoinvent v2.2, the lognormal distribution is the default. However, once propagated, this skewed distribution easily results in physically impossible results (e.g. more carbon in emissions than coal burned). The most fundamental outcome of **Chapter 4**, however, was revealing the magnitude of the overall dispersions around LCI results, and as data sourcing cannot be harmonised in the same way as methodological choices, this complicates comparisons across LCA studies.

Once the relative meaning of LCA results was recognised, a statistical approach for identifying significant differences among results was needed (**RQ 4**). Chapter 5 therefore explored how LCA results can be propagated in a comparative context, with a subsequent statistical analysis. The findings showed that dependent sampling, yielding relative results, considerably reduced the dispersions among alternatives in comparative studies, especially for production chains that share many underlying unit processes. Dependently propagated results should, consequently, be analysed on a Monte Carlo run basis, rather than as absolute ranges. This allows for more powerful paired statistical tests to be used, such as the Wilcoxon Signed Rank test.

Based on the set of methodological components needed to reach statistically supported LCA conclusions, the hypothesis "different production systems are associated with different environmental impacts" was tested in **Chapter 6**. Allocation methods were approached as alternative ways of reaching results, rather than deeming one method superior another (**RQ1**). Since few

Asian processes were available in the ecoinvent v2.2 database, many had to be modelled using the **RQ2** protocol. This ensured that overall dispersions were defined for many supporting unit processes. As for the aquaculture farms, the averaging of primary data was based upon an evaluation of basic production parameters, such as feed use, energy sources and coproduced species. By challenging traditional classifications (such as countries) the spread around parameters could be reduced (**RQ3**). Processes were consequently averaged based upon practices, rather than nationality. Results were later propagated over 1000 Monte Carlo runs using dependent sampling. The outcomes were analysed using the Wilcoxon Signed Rank test and the cumulative frequencies of one alternative having lower global warming, eutrophication or freshwater ecotoxicity impacts than another on a pair-wise basis (**RQ4**).

In the end, the results showed that Asian tiger shrimp farming in Western Bangladesh resulted in significantly lower global warming and eutrophication impacts than any of the other Asian tiger shrimp system. These systems had lower feed inputs and feed is the major driver behind the three environmental impacts evaluated. Intensity, however, had no clear correlation with environmental impacts; neither did the median environmental impacts of Tilapia farming integrated with pigs differ from conventional tilapia farming. Tilapia farming on Hainan, however, was associated with increased environmental consequences compared to Guangdong, the result of different feed conversion ratios. Small and medium sized pangasius farms also had significantly larger environmental footprints than large farms, the result of poorer management and farm practices in small and medium farms.

Other common environmental hot-spots identified are fishmeal and fish oil in feeds, eutrophying effluents from farms, the use of benzalkonium chloride and other chlorine releasing compounds as disinfectants, and extensive use of paddle-wheels on shrimp farms. Aquaculture farmers in Asia should improve farm management by using pelleted feeds with low fishmeal content, limit their use of therapeutants and recycle more nutrients in agriculture.

Advocates of LCA should in the meantime, reflect upon how results have been viewed to date. Results cannot simply be compared across studies, even if they comply with the same methodological standard (e.g. ISO or ILCD). LCA studies should instead be used to test hypotheses, for which dependent sampling can offer higher resolution in comparisons and reduce the risk of type II statistical error (false negatives). The influence of the number of Monte Carlo runs and the different outcomes of the two statistical approaches used in **Chapter 6**, in the meantime, induces caution about type I statistical error (false positives). However, the two approaches answer different questions, one whether medians are significantly different, and the other whether an alternative is environmentally better than the other. From a policy makers point-of-view, cumulative frequencies might be more relevant as knowing whether one production chain is being better than another is clearly relevant. However, null-hypotheses assuming production chains differ in environmental impacts can only be discarded using significance tests.

Samenvatting

Het doel van dit proefschrift is om de milieuduurzaamheid te evalueren van gekweekte aquatische voedingsproducten, door middel van levenscyclusanalyses (LCA), met de nadruk op vanuit Azië naar Europa geïmporteerde producten. LCA is een van de meest gebruikte hulpmiddelen wanneer men de milieuprestaties van diverse productsystemen (bijvoorbeeld biobrandstoffen, levensmiddelen, lampen) wil vergelijken.

De invoer van aquatische voedingsproducten van Azië naar Europa is gestaag toegenomen sinds het begin van deze eeuw, als gevolg van zowel een volledig (en over-) geëxploiteerde regionale visstand, als een stijgende vraag naar vis, en tot slot vanwege veranderende consumentenvoorkeuren. Vier Aziatische landen (Bangladesh, China, Thailand en Vietnam) en vijf gekweekte zeediersoorten (Penaeus monodon, Litopenaeus vannamei, Macrobrachium rosenbergii, Tilapia spp. en Pangasius hypophthalmus) werden geselecteerd als representatieve afspiegeling van de Aziatische aquacultuur. Deze selectie aan landen en vissoorten omvat verschillende productiesystemen, variërend van extensieve (passievere productiemethoden) tot extreem intensieve viskwekerijen (waarbij de laatstgenoemde een breed scala aan hulpstoffen nodig heeft, zoals diervoeder, zuurstof, water en medicatie).

Er zijn al verscheidene LCA studies uitgevoerd over viskwekerijproducten, maar slechts enkele studies hebben zich specifiek gericht op Aziatische productie. Daarnaast werden de LCA resultaten van deze onderzoeken doorgaans uitgedrukt als absolute puntschattingen zonder onzekerheidsmarges. Dit maakt het onmogelijk om statistisch onderbouwde vergelijkingen tussen studies te maken, met als gevolg dat beslissingen en regelgeving in plaats daarvan worden gebaseerd op waarden met een potentieel hoge onzekerheid. Om wetenschappelijk onderbouwde conclusies te kunnen trekken is derhalve de volgende onderzoeksvraag gedefinieerd:

Zijn er significante verschillen tussen de milieueffecten van de geselecteerde Aziatische viskwekerijproducten, en indien ja, wat zijn de belangrijkste oorzaken hiervan?

Vier deelvragen zijn gepostuleerd om deze onderzoeksvraag (**RQ**) te ondersteunen:

RQ1: Zijn er tekortkomingen in methodische aanpak, de data of de spreiding en geografische dekking van bestaande LCA studies over viskwekerijen? (**Hoofdstuk 2**)

RQ2: Kunnen de varianties van de procesgegevens voor viskwekerij LCAs worden bepaald? (**Hoofdstuk 3**)

RQ3: Kunnen deze varianties worden doorgerekend naar varianties in LCA resultaten? (**Hoofdstuk 4**)

RQ4: Hoe kunnen we vaststellen of de LCA-resultaten van twee systemen met dezelfde functie significant van elkaar verschillen? (**Hoofdstuk 5**)

RQ1 wordt behandeld in **hoofdstuk 2** op basis van een review van bestaande aquacultuur LCA-studies. Dit literatuuroverzicht toont aan dat een meerderheid van de studies gepubliceerd vóór 2011 zich richtte op vinvis in Westerse landen. Tevens toont dit hoofdstuk aan dat de studies sterk verschilden in de gemaakte methodische keuzes, onder andere wat betreft de keuze van de functionele eenheid, de systeemgrenzen, de data, effectbeoordelingsmethoden en co-product allocatiemethoden. Allocatie zaaide de grootste verdeling onder de verschillende studies, waarbij de meeste discussie's zich richtten zich op alloceren op basis van energie of op basis van economische waarde. Daarnaast werd er weinig nieuwe data verzameld door de verschillende studies en schoot de rapportage van de gebruikte data tekort.

In **hoofdstuk 3** wordt de beperkte kwaliteit van beschikbare data besproken en een protocol gepresenteerd voor het horizontaal middelen van procesgegevens. In het hoofdstuk worden eerst eerdere benaderingen om de kwantitatieve onzekerheid van LCA resultaten te schatten besproken. Vervolgens worden drie belangrijkste bronnen geïdentificeerd die bijdragen aan de variantie in LCA resultaten: inherente onzekerheid, spreiding (variatie als gevolg van verschillen in productiewijzen) en gebrekkige representiviteit (discrepantie tussen de representativiteit en de toepassing van de data, gekwantificeerd met behulp van het "pedigree" deel van de "Numerical Unit Spread Assessment Pedigree"). Gezamenlijk worden deze drie bronnen aangeduid met algehele spreiding. Het protocol is gebaseerd op een nieuw ontwikkelde beslisboom die aangeeft hoe de algehele spreiding geschat kan worden voor zowel primaire als secundaire data. De essentiële wiskundige formules worden gepresenteerd samen met een Excel-template voor de berekening van procesparameters. Dit maakt het protocol ook toegankelijk voor andere uitvoerders van LCA studies.

In **hoofdstuk 4** wordt het bovengenoemde protocol toegepast in de praktijk voor het berekenen van Life Cycle Inventory (LCI) resultaten (**RQ3**). Als case studie zijn Chinese kolen gekozen omdat dit een wat kleiner productsysteem is met een daardoor beperktere set aan procesgegevens dan de meeste aquacultuur case studies. Hierdoor is het verband tussen procesgegevens en de LCA resultaten duidelijker. Het resultaat van deze oefening benadrukt de intrinsieke uitdagingen die samenhangen met de kwantificering van onzekerheden van LCA resultaten. De manier van horizontaal middelen (bijvoorbeeld geografisch of technologisch) had aanvankelijk invloed op de parameterschattingen. Pas nadat de spreiding in de LCA resultaten waren doorgerekend met Monte Carlo simulaties kwamen er een aantal tekortkomingen aan het daglicht die te maken hadden met het beperkte aantal beschikbare verdelingen welke gehanteerd worden voor LCA procesgegevens. Het bestandsformaat voor een proces in ecoinvent v2.2 (ecospold v1) laat alleen de keuze voor een normale, lognormale, driehoekige of uniforme verdeling toe. In ecoinvent v2.2 is de lognormale verdeling de standaard. Echter, na doorrekening resulteert een dergelijke scheve verdeling in fysiek onmogelijke resultaten (bijvoorbeeld meer koolstof in emissies dan mogelijk met de hoeveelheid verbrande kolen). De belangrijkste bevinding van hoofdstuk 4 ligt echter in het verkregen inzicht in de grootte van de algehele spreiding van LCI resultaten. Omdat het verzamelen van procesgegevens bovendien niet op dezelfde wijze kan worden geharmoniseerd als methodologische keuzes maakt dit vergelijkingen tussen verschillende LCA studies gecompliceerd.

Met de lessen over de relatieve betekenis van LCA resultaten uit hoofdstuk 3 in het achterhoofd, was de volgende stap het opzetten van een statistische methode om significante verschillen tussen resultaten te kunnen identificeren (**RQ4**). In **hoofdstuk 5** is daarom onderzocht hoe LCA resultaten kunnen worden doorberekend in een vergelijkende context, en hoe daarop vervolgens een statistische analyse kan worden toegepast. De bevindingen tonen dat zogenoemde 'afhankelijke' steekproeven de spreiding tussen de alternatieven van een vergelijkende studies verminderen, met name voor alternatieven met productieketens die veel achterliggende processen gemeen hebben. Resultaten op basis van afhankelijke steekproeven moeten vervolgens per Monte Carlo trekking vergeleken worden, in plaats van als absolute bereiken. Dit laat krachtigere gepaarde statistische testen toe, zoals de Wilcoxon Signed Rank toets.

Gebaseerd op de set van methodische componenten die nodig zijn om tot statistisch relevante LCA conclusies te komen, is vervolgens de volgende hypothese in **hoofdstuk 6** getoetst: "verschillende productiesystemen kunnen worden geassocieerd met verschillende milieueffecten". Allocatiemethoden werden daarbij behandeld als alternatieve manieren om resultaten te bereiken, in de plaats van één methode superieur te stellen aan de andere (**RQ1**). Omdat er slechts weinig typisch Aziatische processen beschikbaar zijn in de ecoinvent v2.2 database, moesten veel processen worden gemodelleerd met behulp van het protocol dat voor **RQ2** ontwikkeld was. Dit zorgde er voor dat het protocol ook op veel achtergrondprocessen uit de ecoinvent v2.2 database is toegepast. De gemiddelden voor de viskwekerijen zijn gebaseerd op een weging van de basis productieparameters, zoals voederverbruik, energiebronnen en coproduceerde vissoorten. De spreiding kon worden gereduceerd door traditionele classificaties (zoals landen) in twijfel te trekken; de processen werden vervolgens gemiddeld op basis van productiewijzen, in plaats van nationaliteit. Resultaten werden daarna gepropageerd over 1000 Monte Carlo runs, met behulp van afhankelijke steekproeven. De uitkomsten werden geanalyseerd met de Wilcoxon Signed Rank toets en op basis van de cumulatieve frequenties dat het ene alternatief paarsgewijs een lagere klimaat, eutrofiëring, of aquatische ecotoxiteit effectscore heeft in vergelijking met het andere alternatief (**RQ4**).

Uiteindelijk toonden de resultaten aan dat de Aziatische tijgergarnaal gekweekt in West Bangladesh een significant lagere klimaat- en eutrofiëringseffectscore had dan tijgergarnalen uit andere Aziatische kwekerijen. De productiesystemen in west Bangladesh hadden een lager voedergebruik, en voedergebruik is de grootste driver achter deze drie milieueffecten. Intensiteit, echter, had geen duidelijke correlatie met milieueffecten. De mediane waarden voor deze drie milieueffecten voor tilapiakwekerijen geïntegreerd met varkens verschilde ook niet significant met die van conventionele tilapiakwekerijen. Tilapiakwekerijen op Hainan, echter, hadden wel hogere milieuscores dan die in Guangdong, wat veroorzaakt werd door verschillende voederconversie waarden (FCRs). Kleine en middelgrote pangasiuskwekerijen bleken significant grotere milieueffecten te hebben dan de grotere kwekerijen, wat veroorzaakt werd door slechter management en kwalitatief lage kwekerijpraktijken in de kleine tot middelgrote kwekerijen.

Andere algemeen bekende hotspots die hier ook voren kwamen waren vismeel en visolie in voeder, eutrofiëring door effluenten uit de viskwekerijen, het gebruik van benzalkonium chloride en andere chloor-houdende stoffen zoals desinfec-tanten, en extensief gebruik van schepraden op garnaalkwekerijen. Viskwekers in Azië zouden hun management moeten verbeteren door meer geconcentreerd voeder in pellets te gebruiken met een laag vismeelgehalte, het gebruik van medicatie en antibiotica te reduceren en tot slot, het recyclen van nutriënten in de landbouw.

Voorstanders van de LCA methode zouden in de tussentijd eens goed moeten reflecteren op hoe men resultaten van LCA studies tot dusver heeft geïnterpreteerd. Resultaten van verschillende studies kunnen niet simpelweg met elkaar worden vergeleken, zelfs niet als zij voldoen aan dezelfde methodologische standaard (bijvoorbeeeld ISO of ILCD). LCA studies zouden in plaats daarvan moeten worden gebruikt om hypotheses te toetsen, waarbij afhankelijke steekproeven een hogere resolutie in vergelijkingen kunnen opleveren, en het risico voor type II statistische fouten kunnen reduceren. De invloed van het aantal Monte Carlo runs en de verschillende resultaten van twee statistische methoden die zijn toegepast in **hoofdstuk 6** kan ondertussen tot voorzichtigheid met betrekking tot type I statistische fouten. Echter, de twee methoden beantwoorden verschillende vragen. De ene methode beantwoordt de vraag of mediane waarden significant verschillend zijn, de andere of een alternatief aantoonbaar beter of slechter is dan de ander. Vanuit een beleidsmakerspersectief zijn cumulatieve frequenties wellicht relevanter, omdat het duidelijke relevantie heeft om te weten of de ene productieketen een betere milieuprestatie heeft dan de andere. Echter, nul-hypothesen die aannemen dat productieketens verschillen in centrale waarde van de milieueffecten kunnen enkel worden verworpen met significantietoetsen.

Glossary

CV	Coefficient of variation, the standard deviation divided by the mean
Dispersions	Any form of range around a variable, resulting from inherent uncertainty, spread or unrepresentativeness
eFCR	Economic feed conversion ratio (FCR), total weight of feed in/wet-weight of fish out
FCR	Feed conversion ratio, a measurement of weight gain efficiency with several different definitions. Please see eFCR
Fish	Collective term for finfish, molluscs, crustaceans and other aquatic animals
Inherent uncertainty	Uncertainties related to the inaccuracies of measurements or model at no level of horizontal averaging
LULUC	Land-use and land-use change (LULUC)
PCR	Product Category Rules
Primary data	Data collected specifically for the intended study and representing relevant suppliers (UNEP 2011)
Secondary data	Previously published data describing processes for the intended study at different levels of aggregation and representativeness (UNEP 2011)
Spread	Variability around an average resulting from horizontal averaging
Unit process	Smallest element considered in the life cycle inventory analysis for which input and output data are quantified
Unrepresentativeness	Uncertainty resulting from the level of representativeness

References

Ahamed F, Hossain MY, Fulanda B, *et al* (2012) Indiscriminate exploitation of wild prawn postlarvae in the coastal region of Bangladesh: A threat to the fisheries resources, community livelihoods and biodiversity. *Ocean Coast Manag 66:56–62*. doi: 10.1016/j.ocecoaman.2012.05.025

Aubin J, Papatryphon E, Vanderwerf H, *et al* (2006) Characterisation of the environmental impact of a turbot (Scophthalmus maximus) re-circulating production system using Life Cycle Assessment. *Aquaculture 261:1259–1268*. doi: 10.1016/j.*Aquaculture*.2006.09.008

Aubin J, Papatryphon E, Vanderwerf H, Chatzifotis S (2009) Assessment of the environmental impact of carnivorous finfish production systems using life cycle assessment. *J Clean Prod 17:354–361*. doi: 10.1016/j.jclepro.2008.08.008

Avadí A, Fréon P (2013) Life cycle assessment of fisheries: A review for fisheries scientists and managers. *Fish Res 143:21–38*. doi: 10.1016/j.fishres.2013.01.006

Ayer N, Tyedmers P (2009) Assessing alternative *Aquaculture* technologies: life cycle assessment of salmonid culture systems in Canada. *J Clean Prod 17:362–373*. doi: 10.1016/j.jclepro.2008.08.002

Ayer N, Tyedmers P, Pelletier N, *et al* (2007) Co-Product Allocation in Life Cycle Assessments of Seafood Production Systems: Review of Problems and Strategies Allocation, Co-product. *Int J Life Cycle Assess 12:480–487*.

Basset-Mens C, Kelliher FM, Ledgard S, Cox N (2009) Uncertainty of global warming potential for milk production on a New Zealand farm and implications for decision making. *Int J Life Cycle Assess 14:630–638*. doi: 10.1007/s11367-009-0108-2

Bayart J-B, Bulle C, Deschênes L, *et al* (2010) A framework for assessing off-stream freshwater use in LCA. *Int J Life Cycle Assess 15:439–453*. doi: 10.1007/s11367-010-0172-7

Beattie G (2012) Psychological effectiveness of carbon labelling. *Nat Clim Chang 2:214–217*. doi: 10.1038/nclimate1468

Belton B, Thilsted SH (2014) Fisheries in transition: Food and nutrition security implications for the global South. *Glob Food Sec 3:59–66*. doi: 10.1016/j.gfs.2013.10.001

Beltran A, Guinée J, Heijungs R (2014) A statistical approach to deal with uncertainty due to the choice of allocation methods in LCA. *9th Int. Conf. LCA Food. San Fransisco, USA, p 10*

Beveridge MCM, Phillips MJ, Macintosh DJ (1997) *Aquaculture* and the environment: the supply of and demand for environmental goods and services by Asian *Aquaculture* and the implications for sustainability. *Aquac Res 28:797–807*. doi: 10.1046/j.1365-2109.1997.00944.x

Björklund AE (2002) LCA Methodology Survey of Approaches to Improve Reliability in LCA. *Int J Life Cycle Assess 7:64–72*.

Bojacá CR, Schrevens E (2010) Parameter uncertainty in LCA: stochastic sampling under correlation. *Int J Life Cycle Assess 15:238–246*. doi: 10.1007/s11367-010-0150-0

Bosma R, Anh PT, Potting J (2011) Life cycle assessment of intensive striped catfish farming in the Mekong Delta for screening hotspots as input to environmental policy and research agenda. *Int J Life Cycle Assess 16:903–915*. doi: 10.1007/s11367-011-0324-4

Bouwman L, Goldewijk KK, van der Hoek KW, *et al* (2013) Exploring global changes in nitrogen and phosphorus cycles in agriculture induced by livestock production over the 1900–2050 period. *Proc Natl Acad Sci . 110:20882–20887*. doi: 10.1073/pnas.1012878108

Boyd CE, Wood CW, Chaney PL, Queiroz JF (2010) Role of *Aquaculture* pond sediments in sequestration of annual global carbon emissions. *Environ Pollut 158:2537–40*. doi: 10.1016/j.envpol.2010.04.025

BP (2013) BP Statistical Review of World Energy 2013. London, UK

BSI (2008) PAS 2050 - Specification for the assessment of the life cycle greenhouse gas emissions of goods and services. British Standards Institution. UK.

BSI (2012) PAS 2050-2 : 2012 Assessment of life cycle greenhouse gas emissions - Supplementary requirements for the application of PAS 2050:2011 to seafood and other aquatic food products.

Burgess MG, Polasky S, Tilman D (2013) Predicting overfishing and extinction threats in multispecies fisheries. *Proc Natl Acad Sci U S A 110:15943–8*. doi: 10.1073/pnas.1314472110

Burnham A, Han J, Clark CE, *et al* (2012) Life-cycle greenhouse gas emissions of shale gas, natural gas, coal, and petroleum. *Environ Sci Technol 46:619–27*. doi: 10.1021/es201942m

Cai W, Wang C, Jin Z, Chen J (2013) Quantifying baseline emission factors of air pollutants in China's regional power grids. *Environ Sci Technol 47:3590–7*. doi: 10.1021/es304915q

California Air Resources Board (2012) California Code of Regulations. Subchapter 10. Climate Change. Article 4. Regulations to Achieve Greenhouse Gas Emission Reductions. Subarticle 7. Low Carbon Fuel Standard. 121.

Cao L, Diana JS, Keoleian G, *et al* (2011) Life Cycle Assessment of Chinese Shrimp Farming Systems Targeted for Export and Domestic Sales. *Environ Sci Technol 45:6531–6538*. doi: 10.1021/es104058z

Cao L, Naylor RL, Henriksson PJG, *et al* (2015) China's *Aquaculture* and the world's wild fisheries. *Science (133-135) 347:133–135*.

Carlsson-Kanyama a (2003) Food and life cycle energy inputs: consequences of diet and ways to increase efficiency. *Ecol Econ 44:293–307*. doi: 10.1016/S0921-8009(02)00261-6

CCI (2010) China Coal Industry Yearbook 2008 (in Chinese). Coal Industry Publishing house, Beijing

CEC (2013a) China Electricity Council—information of coal power plant flue gas desulfurization denitration industry in 2012 (in Chinese). http://www.cec.org.cn/huanbao/jienenghbfenhui/ huanbaochanyejijishufuwu/chanyedongtai/chanyexinxi/2013-03- 20/99027.html. Accessed 15 Sep 2013

CEC (2011) China Electricity Council—basic data of power industry statistics in 2011 (in Chinese). http://www.cec.org.cn/d/file/ guihuayutongji/tongjxinxi/niandushuju/2013-04-19/34df3e56ce28a3cc02da66706e1b23b2.xls. Accessed 15 Sep 2013

CEC (2013b) China Electricity Council - January - August 2013 power industry statistics (in Chinese). http://www.cec.org.cn/d/file/guihuayutongji/tongjxinxi/ yuedushuju/2013-09-16/53ba811beba059a521e43879a1b4de09.xls. Accessed 15 Sep 2013

CEC (2013c) China Electricity Council—the electrostatic precipitator technology will become mainstream to reduce the PM2.5 from thermal power. http://www.cec.org.cn/xinwenpingxi/2013-08-01/ 106702.html. Accessed 1 Jan 2013

Cederberg C, Persson UM, Neovius K, *et al* (2011) Including carbon emissions from deforestation in the carbon footprint of Brazilian beef. *Environ Sci Technol 45:1773–9*. doi: 10.1021/es103240z

Chen X, Corson MS (2014) Influence of emission-factor uncertainty and farm-characteristic variability in LCA estimates of environmental impacts of French dairy farms. *J Clean Prod 81:150–157*. doi: 10.1016/j.jclepro.2014.06.046

Cheng Y-P, Wang L, Zhang X-L (2011) Environmental impact of coal mine methane emissions and responding strategies in China. *Int J Greenh Gas Control 5:157–166*. doi: 10.1016/j.ijggc.2010.07.007

Ciroth A, Muller S, Weidema B, Lesage P (2013) Empirically based uncertainty factors for the pedigree matrix in ecoinvent. *Int J Life Cycle Assess* doi: 10.1007/s11367-013-0670-5

Cohen J (1994) The earth is round (p<.05). Am Psychol 49:997–1003.

Cooper J, Noon M, Jones C, *et al* (2013) Big data in life cycle assessment. *J Ind Ecol 17:796–799*. doi: 10.1111/jiec.12069

Cordell D, Drangert J-O, White S (2009) The story of phosphorus: Global food security and food for thought. *Glob Environ Chang 19:292–305*. doi: 10.1016/j.gloenvcha.2008.10.009

Crespi V, Coche A (2008) Glossary of Aquaculture. FAO. Rome, Italy

Cui X, Hong J, Gao M (2012) Environmental impact assessment of three coal-based electricity generation scenarios in China. *Energy 45:952–959*. doi: 10.1016/j.energy.2012.06.063

d'Orbcastel ER, Blancheton J-P, Aubin J (2009) Towards environmentally sustainable

Aquaculture: Comparison between two trout farming systems using Life Cycle Assessment. *Aquac Eng 40:113–119*. doi: 10.1016/j.aquaeng.2008.12.002

Da Silva VP, van der Werf HMG, Spies A, Soares SR (2010) Variability in environmental impacts of Brazilian soybean according to crop production and transport scenarios. *J Environ Manage 91:1831–9*. doi: 10.1016/j.jenvman.2010.04.001

Dalgaard R (2008) LCA of soybean meal. *Int J Life Cycle Assess 13:240–254*. doi: 10.1065/lca2007.06.342

De Koning A, Schowanek D, Dewaele J, *et al* (2009) Uncertainties in a carbon footprint model for detergents; quantifying the confidence in a comparative result. *Int J Life Cycle Assess 15:79–89*. doi: 10.1007/s11367-009-0123-3

De Vries JW, Aarnink AJ a, Groot Koerkamp PWG, De Boer IJM (2013) Life cycle assessment of segregating fattening pig urine and feces compared to conventional liquid manure management. *Environ Sci Technol 47:1589–97*. doi: 10.1021/es302951a

Di X, Nie Z, Yuan B, Zuo T (2007) Life Cycle Inventory for Electricity Generation in China. *Int J Life Cycle Assess 12:217–224*.

Diana J (2009) *Aquaculture* production and biodiversity conservation. *Bioscience 59:27–38*. doi: 10.1525/bio.2009.59.1.7

Donato DC, Kauffman JB, Murdiyarso D, *et al* (2011) Mangroves among the most carbon-rich forests in the tropics. *Nat Geosci 4:293–297*. doi: 10.1038/ngeo1123

Dones R, Bauer C, Rööder A (2007) Kohle. In: Dones, R (Ed.) *et al.*, Sachbilanzen von Energiesystemen: Grundlagen für den ökologischen Vergleich von Energiesystemen und den Eindbezug von Energiesystemen in Ökobilanzen für die Schweiz. Final report ecoinvent No. 6-VI. Dübendorf, CH

Dones R, Zhou X, Tian C (2004) Life Cycle Assessment (LCA) of Chinese energy chains for Shandong electricity scenarios. *Int J Glob Energy Issues 22:199–224*.

Doweyko AM (2008) QSAR: dead or alive? *J Comput Aided Mol Des 22:81–9*. doi: 10.1007/s10822-007-9162-7

Duarte CM, Holmer M, Olsen Y, *et al* (2009) Will the Oceans Help Feed Humanity? *Bioscience 59:967–976*. doi: 10.1525/bio.2009.59.11.8

Edwards P, Tuan LA, Allan GL (2004) A survey of marine trash fish and fish meal as *Aquaculture* feed ingredients in Vietnam. ACIAR Working Paper No. 57. Canberra

Ellingsen H, Aanondsen S (2006) Environmental impacts of wild caught cod and farmed salmon - a comparison with chicken. *Int J Life Cycle Assess 1:60–65*.

European Comission (2009) Directive 2009/30/EC of the European Parliament and the Council. 26.

Ewoukem TE, Aubin J, Mikolasek O, *et al* (2012) Environmental impacts of farms integrating *Aquaculture* and agriculture in Cameroon. *J Clean Prod 28:208–214*. doi: 10.1016/j.jclepro.2011.11.039

FAO (2006) Livestock's long shadow: environmental issues and options. Communication Division - FAO, Rome, Italy

FAO (2014a) The State of World Fisheries and *Aquaculture* 2014. Rome, Italy

FAO (2014b) FishStat. http://www.fao.org/fishery/statistics/software/fishstatj/en

FAO (2010a) The state of world fisheries and *Aquaculture* 2010. Rome, Italy

FAO (2010b) Fisheries and *Aquaculture* Information and Statistics Service. In: Aquac. Prod. 1950–2008. http://www.fao.org/fishery/statistics/software/fishstat/en.

Fay M, Kim H, Hachey M (2007) On using truncated sequential probability ratio test boundaries for Monte Carlo implementation of hypothesis tests. *J Comput Graph Stat 16:946–967*.

Fet AM, Schau EM, Haskins C (2009) A Framework for Environmental Analyses of Fish Food Production Systems Based on Systems Engineering Principles. *Syst Eng*. doi: 10.1002/sys

Finkbeiner M (2009) Carbon footprinting—opportunities and threats. *Int J Life Cycle Assess 14:91–94*. doi: 10.1007/s11367-009-0064-x

Finnveden G (1998) Data Quality of Life Cycle Inventory Data - Rules of Thumb. *Int J Life Cycle Assess 3:65–66*.

Foley JA, Monfreda C, Ramankutty N, Zaks D (2007) Our share of the planetary pie. *Proc Natl Acad Sci U S A 104:12585–6*. doi: 10.1073/pnas.0705190104

Ford JS, Pelletier NL, Ziegler F, *et al* (2012) Proposed Local Ecological Impact Categories and Indicators for Life Cycle Assessment of *Aquaculture*. *J Ind Ecol 16:254–265*. doi: 10.1111/j.1530-9290.2011.00410.x

Frischknecht R, Althaus H, Bauer C, *et al* (2007a) The Environmental Relevance of Capital Goods in Life Cycle Assessments of Products and Services. *Int J Life Cycle Assess 1–11*. doi: http://dx.doi.org/10.1065/lca2007.02.309

Frischknecht R, Jungbluth N, Althaus H, *et al* (2007b) Overview and Methodology. ecoinvent report No. 1. Dübendorf

Funtowicz SO, Ravetz JR (1990) Uncertainty and quality in science for policy. Kluwer Academic Publishers, Dordrecht

Galford GL, Melillo JM, Kicklighter DW, *et al* (2010) Greenhouse gas emissions from alternative futures of deforestation and agricultural management in the southern Amazon. *Proc Natl Acad Sci*. doi: 10.1073/pnas.1000780107

Gallego A, Rodríguez L, Hospido A, Moreira MT (2010) Development of regional characterization factors for aquatic eutrophication. *Int J Life Cycle Assess 14:32–43*. doi: 10.1007/s11367-009-0122-4

Garnett T (2014) Three perspectives on sustainable food security: Efficiency, demand restraint, food system transformation. What role for life cycle assessment? *J Clean Prod 73:10–18*. doi: 10.1016/j.jclepro.2013.07.045

Gloria T, Russell A, Atherton J, *et al* (2006) Ecological Toxicity Methods and Metals. An examination of two case studies. *Int J Life Cycle Assess 11:26–33*. doi: 10.1065/lca2006.01.229

Godfray HCJ, Beddington JR, Crute IR, *et al* (2010) Food Security: The Challenge of Feeding 9 billion People. *Science 327:812–818*. doi: 10.1126/science.1185383

Goedkoop M, Spriensma R (1999) The Eco-indicator 99—A damage oriented method for Life Cycle Impact Assessment—Methodology Report. Amersfoort, Netherlands

Gómez DR, Watterson JD, Americano BB, *et al* (2006) IPCC 2006 Guidelines for National Greenhouse Gas Inventories, chapter 2: Stationary Combustion.

González-Rodríguez RM, Rial-Otero R, Cancho-Grande B, *et al* (2011) A review on the fate of pesticides during the processes within the food-production Chain. Crit Rev *Food Sci Nutr 51:99–114*. doi: 10.1080/10408390903432625

Grönroos J, Seppälä J, Silvenius F, Makinen T (2006) Life cycle assessment of Finnish cultivated rainbow trout. Boreal Environonment Res 11:401–414.

Guan D, Liu Z, Geng Y, *et al* (2012) The gigatonne gap in China's carbon dioxide inventories. *Nat Clim Chang 2:672–675*. doi: 10.1038/nclimate1560

Guinée JB, Gorrée M, Heijungs R, *et al* (2002) Handbook on Life Cycle Assessment: Operational Guide to the ISO Standards. Kluwer Academic Publishers, Dordrecht

Guinée JB, Heijungs R (1993) A proposal for the classification of toxic substances within the framework of life cycle assessment of products. *Chemosphere 26:1925–1944*. doi: 10.1016/0045-6535(93)90086-K

Guinée JB, Heijungs R (2011) Life Cycle Sustainability Analysis - Framing Questions for Approaches. *J Ind Ecol 15:656–658*. doi: 10.1111/j.1530-9290.2011.00398.x

Guinée JB, Heijungs R, Huppes G (2004) Economic Allocation: Examples and Derived Decision Tree. *Int J Life Cycle Assess 9(1):23–33*.

Guinée JB, Heijungs R, Huppes G, *et al* (2011) Life Cycle Assessment : Past, Present and Future. *Environ Sci Technol 45:90–96*.

Hall SJ, Delaporte A, Phillips MJ, *et al* (2011) Blue Frontiers: Managing the Environmental Costs of Aquaculture. Penang, Malaysia

Hanssen OJ, Asbjørnsen OA (1996) Statistical properties of emission data in life cycle assessments. *J Clean Prod 4:149–157*.

Hauck M, Steinmann ZJN, Laurenzi IJ, *et al* (2014) How to quantify uncertainty and variability in life cycle assessment: the case of greenhouse gas emissions of gas power generation in the US. *Environ Res Lett 9:074005*. doi: 10.1088/1748-9326/9/7/074005

Hauschild MZ, Goedkoop M, Guinée J, *et al* (2012) Identifying best existing practice for characterization modeling in life cycle impact assessment. *Int J Life Cycle Assess 18:683–697*. doi: 10.1007/s11367-012-0489-5

Heijungs R (1996) Identification of key issues for further investigation in improving the reliability of life-cycle assessments. *J Clean Prod 4:159–166*. doi: 10.1016/S0959-6526(96)00042-X

Heijungs R, Frischknecht R (2005) Representing Statistical Distributions for Uncertain Parameters in LCA. *Int J Life Cycle Assess 10:248–254*.

Heijungs R, Guinée J, Huppes G, *et al* (1992) Environmental life-cycle assessment of products - Guide and Backgrounds. Leiden, Netherlands

Heijungs R, Kleijn R (2001) Numerical Approaches Towards Life Cycle Interpretation. *Int J Life Cycle Assess 6:141–148*. doi: 10.1007/BF02978732

Heijungs R, Lenzen M (2013) Error propagation methods for LCA—a comparison. *Int J Life Cycle Assess 19:1445–1461*. doi: 10.1007/s11367-014-0751-0

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

Heijungs R, Suh S, Kleijn R (2005) LCA Methodology Numerical Approaches to Life Cycle Interpretation. *Int J Life Cycle Assess 10:103–112*. doi: 10.1065/lca2004.06.161

Henriksson P, Pelletier N, Troell M, Tyedmers P (2011) Life cycle assessment and its application to Aquaculture production systems. *Meyers RA Encycl Sustain Sci Technol 5893–5909*.

Henriksson PJG, Guinée JB, Heijungs R, *et al* (2012a) Draft inventory report A Protocol for Horizontal Averaging of Unit Process Data - Including Estimates for Uncertainty - SEAT Deliverable Ref: D 3.3.

Henriksson PJG, Guinée JB, Heijungs R, *et al* (2013) A protocol for horizontal averaging of unit process data - including estimates for uncertainty. *Int J Life Cycle Assess 19:429–436*. doi: 10.1007/s11367-013-0647-4

Henriksson PJG, Guinée JB, Heijungs R, de Koning A (2012b) A protocol for approaching uncertainties in life cycle inventories. In: Corson MS, van der Werf HM (eds) *Proc. 8th Int. Conf. Life Cycle Assess.* Agri-Food Sect. INRA, Saint-Malo, France, pp 193–197

Henriksson PJG, Guinée JB, Kleijn R, de Snoo GR (2012c) Life cycle assessment of *Aquaculture* systems—a review of methodologies. *Int J Life Cycle Assess 17:304–313*. doi: 10.1007/s11367-011-0369-4

Henriksson PJG, Zhang W, Nahid SAA, *et al* (2014a) Final LCA case study report - Results of LCA studies of Asian Aquaculture Systems for Tilapia, Catfish, Shrimp, and Freshwater prawn. SEAT Deliverable D3.5. Leiden, Netherlands

Henriksson PJG, Zhang W, Nahid SAA, *et al* (2014b) Final LCA case study report - Primary data and literature sources adopted in the SEAT LCA studies. SEAT Deliverable D3.5–Annex report. Leiden, Netherlands

Henriksson PJG, Zhang W, Guinée JB (2014c) Updated unit process data for coal-based energy in China including parameters for overall dispersions. *Int J Life Cycle Assess 20:185-195*. doi: 10.1007/s11367-014-0816-0

Henriksson PJG, Heijungs R, Dao HM, *et al* (2015a) Product carbon footprints and their uncertainties in comparative decision contexts. *PLoS One 10:10*. doi: 10.1371/journal.pone.0121221

Henriksson PJG, Rico A, Zhang W, *et al* (2015b) A comparison of Asian aquaculture products using statistically supported LCA. *Environ Sci Technol*. doi: 10.1021/acs.est.5b04634

Hertwich EG, Hammitt JK, Pease WS (2000) A Theoretical Foundation for Life-Cycle Assessment — Recognizing the Role of Values in Environmental Decision Making. *J Ind Ecol 4:13–28*. doi: 10.1162/108819800569267

Hoekstra AY, Chapagain AK, Aldaya MM, Mekonnen MM (2011) The Water Footprint Assessment Manual. Earthscan, London and Washington

Hong J, Shaked S, Rosenbaum RK, Jolliet O (2010) Analytical uncertainty propagation in life cycle inventory and impact assessment: application to an automobile front panel. *Int J Life Cycle Assess 15:499–510*. doi: 10.1007/s11367-010-0175-4

Hooper DU, Adair EC, Cardinale BJ, *et al* (2012) A global synthesis reveals biodiversity loss as a major driver of ecosystem change. *Nature 486:105–108*. doi: 10.1038/nature11118

Hornborg S (2012) Evaluating fisheries management from a Life Cycle perspective with new approaches to by-catch impacts. Licentiate thesis. ISBN: 91-89677-50-1

Hornborg S, Nilsson P, Valentinsson D, Ziegler F (2012) Integrated environmental assessment of fisheries management: Swedish Nephrops trawl fisheries evaluated using a life cycle approach. *Mar Policy 36:1193–1201*. doi: 10.1016/j.marpol.2012.02.017

Houghton J, Ding Y, Griggs D, *et al* (2001) Climate Change 2001: The Scientific Basis, Intergovernmental Panel on Climate Change (IPCC). Cambridge Univ Press, Cambridge, UK

Huijbregts M a. J, Gilijamse W, Ragas AMJ, Reijnders L (2003) Evaluating Uncertainty in Environmental Life-Cycle Assessment. A Case Study Comparing Two Insulation Options for a Dutch One-Family Dwelling. *Environ Sci Technol 37:2600–2608*. doi: 10.1021/es020971+

Huijbregts MA (1999) Life-cycle impact assessment of acidifying and eutrophying air pollutants. Calculation of equivalency factors with RAINS-LCA.

Huijbregts MAJ (1998a) Application of Uncertainty and Variability in LCA Part I : A General Framework for the Analysis of Uncertainty and Variability in Life Cycle Assessment. *Int J Life Cycle Assess 3:273–280*.

Huijbregts MAJ (1998b) Application of Uncertainty and Variability in LCA Part II : Dealing with Parameter Uncertainty and Uncertainty due to Choices in Life Cycle Assessment. *Int J Life Cycle Assess 3:343–351*.

Huijbregts MAJ (2001) Uncertainty and variability in environmental life-cycle assessment. University of Amsterdam

Huijbregts MAJ, Heijungs R, Hellweg S (2004) Conference Reports: 2nd Biannual Meeting of iEMSs. Complexity and Integrated Resource Management: Uncertainty in LCA. *Int J Life Cycle Assess 9:341–342*. doi: 10.1007/BF02979428

Huijbregts MAJ, Norris G, Bretz R, *et al* (2001) Framework for Modelling Data Uncertainty in Life Cycle Inventories. *Int J Life Cycle Assess 6:127–132*.

Huysveld S, Schaubroeck T, De Meester S, *et al* (2013) Resource use analysis of Pangasius *Aquaculture* in the Mekong Delta in Vietnam using Exergetic Life Cycle Assessment. *J Clean Prod*. doi: 10.1016/j.jclepro.2013.01.024

ILCD (2010) International Reference Life Cycle Data System (ILCD) Handbook: Analysing of existing Environmental Impact Assessment methodologies for use in Life Cycle Assessment. Ispra, Italy

Imbeault-Tétreault H, Jolliet O, Deschênes L, Rosenbaum RK (2013) Analytical Propagation of Uncertainty in Life Cycle Assessment Using Matrix Formulation. *J Ind Ecol 17:485–492*. doi: 10.1111/jiec.12001

Ioannidis JPA (2012) Why Science Is Not Necessarily Self-Correcting. *Perspect Psychol Sci 7:645–654*. doi: 10.1177/1745691612464056

IPCC (2013) The International Panel on Climate Change Working group I - Contribution to the IPCC fifth assessment report - Climate Change 2013: The physical science basis Final Draft Underlying Scientific-Technical Assessment.

Iribarren D, Moreira MT, Feijoo G (2010) Revisiting the Life Cycle Assessment of mussels from a sectorial perspective. *J Clean Prod 18:101–111*. doi: 10.1016/j.jclepro.2009.10.009

ISO 14040 (2006) ISO. Geneva, Switzerland

ISO 14044 (2006) Environmental management—Life cycle assessment— Requirements and guidelines. Geneva, Switzerland

ISO 14067 (2012) Greenhouse gases — Carbon footprint of products — Requirements and guidelines for quantification and communication. Geneva, Switzerland

Jacquet J, Hocevar J, Lai S, *et al* (2009) Conserving wild fish in a sea of market-based efforts. *Oryx 44:45*. doi: 10.1017/S0030605309990470

Jonell M, Henriksson PJG (2014) Mangrove-shrimp farms in Vietnam–comparing organic and conventional systems using life cycle assessment Corresponding author : *Aquaculture 1–19*.

JRC (2010a) International Reference Life Cycle Data System Handbook - Analysis of existing Environmental Impact Assessment methodologies for use in Life Cycle Assessment.

JRC (2010b) ILCD Handbook - General guide for LCA - Detailed guidance.

Jung J, Assen N, Bardow A (2013) Sensitivity coefficient-based uncertainty analysis for multi-functionality in LCA. *Int J Life Cycle Assess 19:661–676*. doi: 10.1007/s11367-013-0655-4

Kennedy DJ, Montgomery DC, Quay BH (1996) Data quality. *Int J Life Cycle Assess 1:199–207*. doi: 10.1007/BF02978693

Klöpffer W, Curran MA (2013) How many case studies should we publish, if any? *Int J Life Cycle Assess* 19:1–2. doi: 10.1007/s11367-013-0667-0

Kuenzer C, Zhang J, Tetzlaff A, *et al* (2007) Uncontrolled coal fires and their environmental impacts: Investigating two arid mining regions in north-central China. *Appl Geogr 27:42–62*. doi: 10.1016/j.apgeog.2006.09.007

Lazarevic D, Buclet N, Brandt N (2012) The application of life cycle thinking in the context of European waste policy. *J Clean Prod 1–9.* doi: 10.1016/j.jclepro.2012.01.030

Lebel L, Mungkung R, Gheewala SH, Lebel P (2010) Innovation cycles , niches and sustainability in the shrimp *Aquaculture* industry in Thailand. *Environ Sci Policy*. doi: 10.1016/j.envsci.2010.03.005

Liang X, Wang Z, Zhou Z, *et al* (2013) Up-to-date life cycle assessment and comparison study of clean coal power generation technologies in China. *J Clean Prod 39:24–31*. doi: 10.1016/j.jclepro.2012.08.003

Limpert E, Stahel WA, Abbt M (2001) Log-normal Distributions across the Sciences: Keys and Clues. *Bioscience 51:341–352*. doi: 10.1641/0006-3568(2001)051[0341:LNDATS]2.0.CO;2

Lin J, Pan D, Davis SJ, *et al* (2014) China's international trade and air pollution in the United States. *Proc Natl Acad Sci U S A 111:1736–41*. doi: 10.1073/pnas.1312860111

Lindquist B, Groenigen KJ, Adviento-Borbe MA, *et al* (2012) An agronomic assessment of greenhouse gas emissions from major cereal crops. *Glob Chang Biol 18:194–209*. doi: 10.1111/j.1365-2486.2011.02502.x

Linkov I, Seager TP (2011) Coupling multi-criteria decision analysis, life-cycle assessment, and risk assessment for emerging threats. *Environ Sci Technol 45:5068–74*. doi: 10.1021/es100959q

Liu G, Müller DB (2012) Addressing sustainability in the aluminum industry: a critical review of life cycle assessments. *J Clean Prod 35:108–117*. doi: 10.1016/j.jclepro.2012.05.030

Liu W, Lund H, Mathiesen BV (2013) Modelling the transport system in China and evaluating the current strategies towards the sustainable transport development. *Energy Policy 58:347–357*. doi: 10.1016/j.enpol.2013.03.032

Lloyd SM, Ries R (2007) Characterizing, Propagating, and Analyzing Uncertainty in Life-Cycle Assessment: A Survey of Quantitative Approaches. *J Ind Ecol 11:161–179*. doi: 10.1162/jiec.2007.1136

Lo S-C, Ma H-W, Lo S-L (2005) Quantifying and reducing uncertainty in life cycle assessment using the Bayesian Monte Carlo method. *Sci Total Environ 340:23–33*. doi: 10.1016/j.scitotenv.2004.08.020

Madin EMP, Macreadie PI (2015) Incorporating carbon footprints into seafood sustainability certification and eco-labels. *Mar Policy 57:178–181*. doi: 10.1016/j.marpol.2015.03.009

Malça J, Freire F (2010) Uncertainty Analysis in Biofuel Systems. *J Ind Ecol 14:322–334*. doi: 10.1111/j.1530-9290.2010.00227.x

Mattila T, Kujanpää M, Dahlbo H, *et al* (2011) Uncertainty and Sensitivity in the Carbon Footprint of Shopping Bags. *J Ind Ecol 15:217–227*. doi: 10.1111/j.1530-9290.2010.00326.x

Maurice B, Frischknecht R, Coelho-Schwirtz V, Hungerbühler K (2000) Uncertainty analysis in life cycle inventory. Application to the production of electricity with French coal power plants. *J Clean Prod 8:95–108*. doi: 10.1016/S0959-6526(99)00324-8

McCloskey D, Ziliak S (1996) The standard error of regressions. *J Econ Lit 34:97–114*.

Middelaar C van, Cederberg C, Vellinga T V, *et al* (2013) Exploring variability in methods and data sensitivity in carbon footprints of feed ingredients. *Int J Life Cycle Assess 18:768–782*. doi: 10.1007/s11367-012-0521-9

Morgan M, Henrion M (1990) Uncertainty: a guide to dealing with uncertainty in quantitative risk and policy analysis. Cambridge University Press, New York

Muir J (2005) Managing to harvest? Perspectives on the potential of *Aquaculture*. Philos *Trans R Soc Lond B Biol Sci 360:191–218*. doi: 10.1098/rstb.2004.1572

Mungkung RT (2005) Shrimp Aquaculture in Thailand: Application of Life Cycle Assessment to Support Sustainable Development, PhD thesis. PhD thesis

Mungkung RT, Aubin J, Prihadi TH, *et al* (2013) Life Cycle Assessment for environmentally sustainable *Aquaculture* management: a case study of combined *Aquaculture* systems for carp and tilapia. *J Clean Prod 57:249–256*. doi: dx.doi.org/10.1016/j.jclepro.2013.05.029

Murray FJ, Zhang W, Nietes-Satapornvanit A, *et al* (2014) Report on Boundary Issues. Deliverable 2.8 of the SEAT project. Stirling, United Kingdom

Mutel CL, de Baan L, Hellweg S (2013) Two-step sensitivity testing of parametrized and regionalized life cycle assessments: methodology and case study. *Environ Sci Technol 47:5660–7*. doi: 10.1021/es3050949

Myhre G, Shindell D, Bréon F-M, *et al* (2013) Anthropogenic and Natural Radiative Forcing Supplementary Information. In: Stocker T, Qin D, Plattner G-K, *et al* (eds) Clim. Chang. 2013 Phys. Sci. Basis. Contrib. Work. Gr. I to Fifth Assess. Rep. Intergov. Panel Clim. Chang. IPCC, p 44

Narum SR (2006) Beyond Bonferroni: Less conservative analyses for conservation genetics. *Conserv Genet 7:783–787*. doi: 10.1007/s10592-005-9056-y

Naylor R, Falcon W, Zavaleta E (1997) Variability and Growth in Grain Yields , 1950-94 : Does the Record Point to Greater Instability? *Popul Dev Rev 23:41–58*.

Naylor RL, Goldburg RJ, Primavera JH, *et al* (2000) Effect of *Aquaculture* on world fish supplies. *Nature 405:1017–1024*.

Naylor RL, Hardy RW, Bureau DP, *et al* (2009) Feeding *Aquaculture* in an era of finite resources. *Proc Natl Acad Sci U S A 106:15103–10*. doi: 10.1073/pnas.0905235106

NBS (2011) National Bureau of Statistics—China Electric Power Yearbook (in Chinese). China Statistical Press, Beijing

Nemecek T, Schnetzer J (2011) Methods of assessment of direct field emissions for LCIs of agricultural production systems. Data quality guideline for ecoinvent database version 3. Zurich

Newton R, Telfer T, Little D (2014) Perspectives on the utilization of *Aquaculture* coproduct in Europe and Asia: prospects for value addition and improved resource efficiency. *Crit Rev Food Sci Nutr 54:495–510*. doi: 10.1080/10408398.2011.588349

Nijdam D, Rood T, Westhoek H (2012) The price of protein: Review of land use and carbon footprints from life cycle assessments of animal food products and their substitutes. *Food Policy 37:760–770*. doi: 10.1016/j.foodpol.2012.08.002

Noceti P, Smith J, Hodges S (2003) An evaluation of tests of distributional forecasts. *J Forecast 22:447–455*. doi: 10.1002/for.876

Noor Uddin GM, Larsen MH, Guardabassi L, Dalsgaard A (2013) Bacterial flora and antimicrobial resistance in raw frozen cultured seafood imported to Denmark. *J Food Prot 76:490–499*. doi: 10.4315/0362-028X.JFP-12-402

Ortiz M, Arocha F (2004) Alternative error distribution models for standardization of catch rates of non-target species from a pelagic longline fishery: Billfish species in the Venezuelan tuna longline fishery. *Fish Res 70:275–297*. doi: 10.1016/j.fishres.2004.08.028

Ou X, Xiaoyu Y, Zhang X (2011) Life-cycle energy consumption and greenhouse gas emissions for electricity generation and supply in China. *Appl Energy 88:289–297*. doi: 10.1016/j.

apenergy.2010.05.010

Ou X, Yan X, Zhang X, Liu Z (2012) Life-cycle analysis on energy consumption and GHG emission intensities of alternative vehicle fuels in China. *Appl Energy 90:218–224*. doi: 10.1016/j.apenergy.2011.03.032

Papatryphon E, Petit J, Kaushik SJ, van der Werf HMG (2004) Environmental impact assessment of salmonid feeds using Life Cycle Assessment (LCA). *Ambio 33:316–23*.

Patzek TW, Croft GD (2010) A global coal production forecast with multi-Hubbert cycle analysis. *Energy 35:3109–3122*. doi: 10.1016/j.energy.2010.02.009

Pauly D, Alder J, Bennett E, *et al* (2003) The future for fisheries. *Science 302:1359–61*. doi: 10.1126/science.1088667

Pelletier N, Audsley E, Brodt S, *et al* (2011) Energy Intensity of Agriculture and Food Systems. *Annu Rev Environ Resour 36:223–246*. doi: 10.1146/annurev-environ-081710-161014

Pelletier N, Leip A (2013) Quantifying anthropogenic mobilization, flows (in product systems) and emissions of fixed nitrogen in process-based environmental life cycle assessment: rationale, methods and application to a life cycle inventory. *Int J Life Cycle Assess 19:166–173*. doi: 10.1007/s11367-013-0622-0

Pelletier N, Tyedmers P (2007) Feeding farmed salmon: Is organic better? *Aquaculture 272:399–416*. doi: 10.1016/j.Aquaculture.2007.06.024

Pelletier N, Tyedmers P (2010a) Forecasting potential global environmental costs of livestock production 2000-2050. *Proc Natl Acad Sci U S A 107:18371–4*. doi: 10.1073/pnas.1004659107

Pelletier N, Tyedmers P (2008) Life cycle considerations for improving sustainability assessments in seafood awareness campaigns. *Environ Manage 42:918–31*. doi: 10.1007/s00267-008-9148-9

Pelletier N, Tyedmers P (2010b) Life Cycle Assessment of Frozen Tilapia Fillets From Indonesian Lake-Based and Pond-Based Intensive *Aquaculture* Systems. *J Ind Ecol 14:467–481*. doi: 10.1111/j.1530-9290.2010.00244.x

Pelletier N, Tyedmers P, Sonesson U, *et al* (2009) Not All Salmon Are Created Equal: Life Cycle Assessment (LCA) of Global Salmon Farming Systems. *Environ Sci Technol 43:8730–6*. doi: 10.1021/es9010114

Pelletier NL, Ayer NW, Tyedmers PH, *et al* (2007) Impact Categories for Life Cycle Assessment Research of Seafood Production Systems: Review and Prospectus. *Challenges 12:414–421*.

Pelletier NL, Ayer NW, Tyedmers PH, *et al* (2006) Impact categories for life cycle assessment research of seafood production systems: Review and prospectus. *Int J Life Cycle Assess 12:414–421*. doi: 10.1065/lca2006.09.275

Pettersen J, Hertwich EG (2008) Critical review: Life-cycle inventory procedures for long-term release of metals. *Environ Sci Technol 42:4639–4647*. doi: 10.1021/es702170v

Phong LT (2010) Dynamics of sustainability in Integrated Agriculture-*Aquaculture* systems in the Mekong Delta. Wageningen University

Phong LT, de Boer IJM, Udo HMJ (2011) Life cycle assessment of food production in integrated agriculture–Aquaculture systems of the Mekong Delta. *Livest Sci 139:80–90*. doi: 10.1016/j.livsci.2011.03.015

Pilkey OH, Pilkey-Jarvis L (2007) Useless Arithmetic: Why Environmental Scientists Can't Predict the Future. Columbia University Press

Pinsonnault A, Lesage P, Levasseur A, Samson R (2014) Temporal differentiation of background systems in LCA: relevance of adding temporal information in LCI databases. *Int J Life Cycle Assess 19:1843–1853*. doi: 10.1007/s11367-014-0783-5

Pongpat P, Tongpool R (2013) Life Cycle Assessment of Fish Culture in Thailand: Case Study of Nile Tilapia and Striped Catfish. I*nt J Environ Sci Dev 4:608–612*. doi: 10.7763/IJESD.2013.V4.423

Posch M, Seppälä J, Hettelingh J-P, *et al* (2008) The role of atmospheric dispersion models and ecosystem sensitivity in the determination of characterisation factors for acidifying and eutrophying emissions in LCIA. *Int J Life Cycle Assess 13:477–486*. doi: 10.1007/s11367-008-0025-9

Prado-Lopez V, Seager TP, Chester M, *et al* (2013) Stochastic multi-attribute analysis (SMAA) as an interpretation method for comparative life-cycle assessment (LCA). *Int J Life Cycle Assess 19:405–416*. doi: 10.1007/s11367-013-0641-x

Ptacnik R, Andersen T, Tamminen T (2010) Performance of the Redfield Ratio and a Family of Nutrient Limitation Indicators as Thresholds for Phytoplankton N vs. P Limitation. *Ecosystems 13:1201–1214*. doi: 10.1007/s10021-010-9380-z

Ravetz JR (1999) What is Post-Normal Science. *Futures 31:647–653*.

Rico A, Minh T, Satapornvanit K, *et al* (2013) Use of veterinary medicines , feed additives and probiotics in four major internationally traded *Aquaculture* species farmed in Asia. *Aquaculture 412-413:231–243*. doi: 10.1016/j.*Aquaculture*.2013.07.028

Rico A, Van den Brink PJ (2014) Probabilistic risk assessment of veterinary medicines applied to four major *Aquaculture* species produced in Asia. *Sci Total Environ 468-469:630–41*. doi: 10.1016/j.scitotenv.2013.08.063

Rockström J, Steffen W, Noone K, *et al* (2009) Planetary Boundaries : Exploring the Safe Operating Space for Humanity. *Ecol Soc 14:33*.

Röös E, Karlsson H, Witthöft C, Sundberg C (2015) Evaluating the sustainability of diets–combining environmental and nutritional aspects. *Environ Sci Policy 47:157–166*. doi: 10.1016/j.envsci.2014.12.001

Röös E, Sundberg C, Hansson P-A (2010) Uncertainties in the carbon footprint of food products: a case study on table potatoes. *Int J Life Cycle Assess 15:478–488*. doi: 10.1007/s11367-010-0171-8

Röös E, Sundberg C, Hansson P-A (2011) Uncertainties in the carbon footprint of refined wheat products: a case study on Swedish pasta. *Int J Life Cycle Assess 16:338–350*. doi: 10.1007/s11367-011-0270-1

Rosema A, Genderen J, van Schalke H (1993) Environmental monitoring of coal fires in north China. Project Identification Mission Report. *BCRS 93–29*.

Rosenbaum RK, Bachmann TM, Gold LS, *et al* (2008) USEtox—the UNEP-SETAC toxicity model: recommended characterisation factors for human toxicity and freshwater ecotoxicity in life cycle impact assessment. *Int J Life Cycle Assess 13:532–546*. doi: 10.1007/s11367-008-0038-4

Ross S, Evans D, Webber M (2002) How LCA studies deal with uncertainty. *Int J Life Cycle Assess 7:47–52*. doi: 10.1007/BF02978909

Roy P, Nei D, Orikasa T, *et al* (2009) A review of life cycle assessment (LCA) on some food products. *J Food Eng 90:1–10*. doi: 10.1016/j.jfoodeng.2008.06.016

Sandweiss DH, Maasch KA, Chai F, *et al* (2004) Geoarchaeological evidence for multidecadal natural climatic variability and ancient Peruvian fisheries. *Quat Res 61:330–334*. doi: 10.1016/j.yqres.2004.02.008

Schau EM, Fet AM (2008) LCA Studies of Food Products as Background for Environmental Product Declarations. *Int J Life Cycle Assess 13:255–264*.

Schoon N (2013) A proposed method for including CO2 emissions resulting from LULUC of mangrove forests: A case study of *Aquaculture* shrimp in the Mekong Delta, Vietnam. Leiden University

Serlin RC (2000) Testing for Robustness in Monte Carlo Studies. *Psychol Methods 5:230–240*. doi: 10.1037/1082-989X.5.2.230

Smith P, Haberl H, Popp A, *et al* (2013) How much land-based greenhouse gas mitigation can be achieved without compromising food security and environmental goals? *Glob Chang Biol 19:2285–302*. doi: 10.1111/gcb.12160

Sonesson U, Mattsson B, Nybrant T, Ohlsson T (2005) Industrial processing versus home cooking: an environmental comparison between three ways to prepare a meal. *Ambio 34:414–421*. doi: 10.1579/0044-7447-34.4.414

Sonnemann G, Vigon B, Valdivia S, Rack M (2011) Global guidance principles for life cycle assessment databases - a basis for greener processes and products.

Sonnemann GW, Schuhmacher M, Castells F (2002) Uncertainty assessment by a Monte Carlo simulation in a life cycle inventory of electricity produced by a waste incinerator. *J Clean Prod*

11:279–292. doi: 10.1016/S0959-6526(02)00028-8

Steffen W, Richardson K, Rockström J, *et al* (2015) Planetary Boundaries: Guiding human development on a changing planet. *Science 347(6223):736*. doi: 10.1126/science.1259855

Steinmann ZJN, Hauck M, Karuppiah R, *et al* (2014) A methodology for separating uncertainty and variability in the life cycle greenhouse gas emissions of coal-fueled power generation in the USA. *Int J Life Cycle Assess*. doi: 10.1007/s11367-014-0717-2

Stoate C, Boatman ND, Borralho RJ, *et al* (2001) Ecological impacts of arable intensification in Europe. *J Environ Manage 63:337–365*. doi: 10.1006/jema.2001.0473

Su B, Ang BW (2013) Input–output analysis of CO2 emissions embodied in trade: Competitive versus non-competitive imports. *Energy Policy 56:83–87*. doi: 10.1016/j.enpol.2013.01.041

Su S, Li B, Cui S, Tao S (2011) Sulfur dioxide emissions from combustion in china: from 1990 to 2007. *Environ Sci Technol 45:8403–10*. doi: 10.1021/es201656f

Suh S, Lenzen M, Treloar GJ, *et al* (2004) System Boundary Selection in Life-Cycle Inventories Using Hybrid Approaches. *Environ Sci Technol 38:657–664*. doi: 10.1021/es0263745

Svanes E, Vold M, Hanssen OJ (2011) Effect of different allocation methods on LCA results of products from wild-caught fish and on the use of such results. *Int J Life Cycle Assess 16:512–521*. doi: 10.1007/s11367-011-0288-4

Swarr TE, Hunkeler D, Klöpffer W, *et al* (2011) Environmental life-cycle costing: a code of practice. *Int J Life Cycle Assess 16:389–391*. doi: 10.1007/s11367-011-0287-5

Tacon A, Metian M (2008) Global overview on the use of fish meal and fish oil in industrially compounded aquafeeds: Trends and future prospects. *Aquaculture 285:146–158*. doi: 10.1016/j.Aquaculture.2008.08.015

Thodesen J, Rye M, Wang Y-X, *et al* (2013) Genetic improvement of tilapias in China: Genetic parameters and selection responses in growth, pond survival and cold-water tolerance of blue tilapia (Oreochromis aureus) after four generations of multi-trait selection. *Aquaculture 396-399:32–42*. doi: 10.1016/j.Aquaculture.2013.02.010

Tian H, Cheng K, Wang Y, *et al* (2012) Temporal and spatial variation characteristics of atmospheric emissions of Cd, Cr, and Pb from coal in China. *Atmos Environ 50:157–163*. doi: 10.1016/j.atmosenv.2011.12.045

Tilman D, Clark M (2014) Global diets link environmental sustainability and human health. Nature. doi: 10.1038/nature13959

Tlusty M, Lagueux K (2009) Isolines as a new tool to assess the energy costs of the production and distribution of multiple sources of seafood. *J Clean Prod 17:408–415*. doi: 10.1016/j.jclepro.2008.08.001

Treyer K, Bauer C (2013) Life cycle inventories of electricity generation and power supply in version 3 of the ecoinvent database—part I: electricity generation. *Int J Life Cycle Assess*. doi: 10.1007/s11367-013-0665-2

Troell M, Naylor RL, Metian M, *et al* (2014) Does *Aquaculture* add resilience to the global food system? *Proc Natl Acad Sci 1–7*. doi: 10.1073/pnas.1404067111

Tukey JW (1980) We Need Both Exploratory and Confirmatory. *Am Stat 34:23–25*. doi: 10.2307/2682991

UNEP (2011) Global guidance principles for life cycle assessment databases—a basis for greener processes and products. UNEP/SETAC Life Cycle Initiative Report. Paris

Upham P, Dendler L, Bleda M (2011) Carbon labelling of grocery products: public perceptions and potential emissions reductions. *J Clean Prod 19:348–355*. doi: 10.1016/j.jclepro.2010.05.014

Van der Harst E, Potting J (2014) Variation in LCA results for disposable polystyrene beverage cups due to multiple data sets and modelling choices. *Environ Model Softw 51:123–135*. doi: 10.1016/j.envsoft.2013.09.014

Van der Sluijs JP, Craye M, Funtowicz S, *et al* (2005) Combining quantitative and qualitative measures of uncertainty in model-based environmental assessment: the NUSAP system. *Risk Anal 25:481–92*. doi: 10.1111/j.1539-6924.2005.00604.x

Van Dijk P, Zhang J, Jun W, *et al* (2011) Assessment of the contribution of in-situ combustion of coal to greenhouse gas emission; based on a comparison of Chinese mining information to previous remote sensing estimates. *Int J Coal Geol 86:108–119*. doi: 10.1016/j.coal.2011.01.009

Van Zelm R, Huijbregts MA (2013) Quantifying the trade-off between parameter and model structure uncertainty in life cycle impact assessment. *Environ Sci Technol 47:9274–80*. doi: 10.1021/es305107s

Vandenbergh M, Dietz T, Stern P (2011) Time to try carbon labelling. *Nat Clim Chang 1:4–6*.

Vanhonacker F, Altintzoglou T, Luten J, Verbeke W (2011) Does fish origin matter to European consumers?: Insights from a consumer survey in Belgium, Norway and Spain. *Br Food J 113:535–549*. doi: 10.1108/00070701111124005

Venkatesh A (2012) Towards Robust Energy Systems Modeling : Examining Uncertainty in Fossil Fuel-Based Life Cycle Assessment Thesis committee. Carnegie Mellon University

Verdegem M (2013) Nutrient discharge from *Aquaculture* operations in function of system design and production environment. *Rev Aquac 5:158–171*. doi: 10.1111/raq.12011

Wang C, Ducruet C (2014) Transport corridors and regional balance in China: the case of coal trade and logistics. J *Transp Geogr 40:3–16*. doi: 10.1016/j.jtrangeo.2014.08.009

Weber CL (2012) Uncertainty and Variability in Product Carbon Footprinting. *J Ind Ecol 16:203–211*. doi: 10.1111/j.1530-9290.2011.00407.x

Weidema B, Wesnaes MS (1996) Data quality management for life cycle inventories—an example of using data quality indicators. *J Clean Prod 4:167–174*. doi: 10.1016/S0959-6526(96)00043-1

Weidema BP, Bauer C, Hischier R, *et al* (2012) Overview and methodology. Data quality guideline for the ecoinvent database version 3. Ecoinvent Report 1. St. Gallen

Weidema BP, Morteson B, Nielsen P, Hauschild M (1996) Elements of an impact assessment of wheat production. Lyngby, Denmark

Williams ED, Weber CL, Hawkins TR (2009) Hybrid Framework for Managing Uncertainty in Life Cycle Inventories. *J Ind Ecol 13:928–944*. doi: 10.1111/j.1530-9290.2009.00170.x

Wiloso EI, Heijungs R, Huppes G (2014) A novel life cycle impact assessment method on biomass residue harvesting reckoning with loss of biomass productivity. *J Clean Prod 81:137–145*. doi: 10.1016/j.jclepro.2014.06.044

Winther U, Ziegler F, Hognes ES, *et al* (2009) Carbon footprint and energy use of Norwegian seafood products.

Xu G, Yang Y, Lu S, *et al* (2011) Comprehensive evaluation of coal-fired power plants based on grey relational analysis and analytic hierarchy process. *Energy Policy 39:2343–2351*. doi: 10.1016/j.enpol.2011.01.054

Xu M, Cai H, Liang S (2015) Big Data and Industrial Ecology. *J Ind Ecol 1–6*. doi: 10.1111/jiec.12241

Xu Y, Yang C-J, Xuan X (2013) Engineering and optimization approaches to enhance the thermal efficiency of coal electricity generation in China. *Energy Policy 60:356–363*. doi: 10.1016/j.enpol.2013.05.047

Yan X, Akiyama H, Yagi K, Akimoto H (2009) Global estimations of the inventory and mitigation potential of methane emissions from rice cultivation conducted using the 2006 Intergovernmental Panel on Climate Change Guidelines. *Global Biogeochem Cycles 23:15*. doi: 10.1029/2008GB003299

Yang C-J, Jackson RB (2013) China's synthetic natural gas revolution. *Nat Clim Chang 3:852–854*. doi: 10.1038/nclimate1988

Yoshida H, Clavreul J, Scheutz C, Christensen TH (2014) Influence of data collection schemes on the Life Cycle Assessment of a municipal wastewater treatment plant. *Water Res 56:292–303*. doi: 10.1016/j.watres.2014.03.014

Zhang B, Chen GQ (2010) Methane emissions by Chinese economy: Inventory and embodiment analysis. *Energy Policy 38:4304–4316*. doi: 10.1016/j.enpol.2010.03.059

Zhang J, Mauzerall DL, Zhu T, *et al* (2010) Environmental health in China: progress towards clean air and safe water. *Lancet 375:1110–9*. doi: 10.1016/S0140-6736(10)60062-1

Zhao Y, Nielsen CP, Lei Y, *et al* (2011) Quantifying the uncertainties of a bottom-up emission inventory of anthropogenic atmospheric pollutants in China. *Atmos Chem Phys 11:2295–2308*. doi: 10.5194/acp-11-2295-2011

Zhao Y, Wang S, Duan L, *et al* (2008) Primary air pollutant emissions of coal-fired power plants in China: Current status and future prediction. *Atmos Environ 42:8442–8452*. doi: 10.1016/j.atmosenv.2008.08.021

Zhao Y, Wang S, Nielsen CP, *et al* (2010) Establishment of a database of emission factors for atmospheric pollutants from Chinese coal-fired power plants. *Atmos Environ 44:1515–1523*. doi: 10.1016/j.atmosenv.2010.01.017

Curriculum vitae

Patrik JG Henriksson

Personal information

Date of birth: 14 November 1979

Place of birth: Lidingö Municipality, Stockholm County, Sweden

Patrik Henriksson's background is in marine biology, which he first studied at Lund University (Sweden), and later at University of British Columbia (Canada) and Bangor University (Wales). Patrik wrote his master thesis at the Department of System Ecology, Stockholm University. The focus of the MSc thesis was to evaluate the energy use in tropical aquaculture using Life Cycle Assessment. He started his PhD research in January 2010.

Undergraduate Studies

Marine Biology, Lund University, Sweden, 2-years. 2004-2006.

Marine Biology, University of British Columbia, Canada, 6 months. 2006.

System Ecology, Stockholm University, Sweden, 6 months. 2007.

Marine Biology, Bangor University, Wales, UK, 1 year. 2007-2008.

MSc

Energy use in Tropical Aquaculture, Department of System Ecology, Stockholm University. 2008-2009.

Awards

First Place - Student Oral Presentation Award, World Aquaculture Society's AQUA 2012 conference, Prague, Czech Republic

Publications, Peer-reviewed

Henriksson PJG, Rico A, Zhang W, Nahid SAA, Newton R, Phan LT, Zhang Z, Jaithiang J, Dao HM, Phu TM, Little DC, Murray FJ, Satapornvanit K, Liu L, Liu Q, Haque MM, Kruijssen F, de Snoo GR, Heijungs R, van Bodegom PM, Guinée JB (2015) A comparison of Asian aquaculture products using statistically supported LCA. Environ Sci Technol. doi: 10.1021/acs.est.5b04634.

Henriksson PJG, Troell M, Rico A (2015) Antibiotic use in aquaculture: Some complementing facts. *PNAS*. 10.1073/pnas.1508952112

Henriksson PJG, Heijungs R, Dao HM, Phan LT, de Snoo GR, *et al.* (2015) Product carbon footprints and their uncertainties in comparative decision contexts. *PLoS One.* 10.1371/journal.pone.0121221.

Cao L, Naylor RL, Henriksson PJG, Leadbitter D, Metian M, Troell M, Zhang W (2015) China's aquaculture and the world's wild fisheries. *Science 347: 133–135.* 10.1126/science.1260149.

Henriksson PJG, Zhang W, Guinée JB (2014) Updated unit process data for coal-based energy in China including parameters for overall dispersions. *Int J of LCA.* 10.1007/s11367-014-0816-0.

Jonell M, Henriksson PJG (2014) Mangrove–shrimp farms in Vietnam—Comparing organic and conventional systems using life cycle assessment. *Aquaculture*. 10.1016/j.aquaculture.2014.11.001

Henriksson PJG, Guinée JB, Heijungs R, de Koning A, Green DM (2013) A protocol for horizontal averaging of unit process data—including estimates for uncertainty. *Int J of LCA*. 10.1007/s11367-013-0647-4

Rico A, Phu TM, Satapornvanit K, Min J, Shahabuddin AM, Henriksson PJG, Murray F, Little DC, Dalsgaard A, Van den Brink PJ (2013). Use of veterinary medicines, feed additives and probiotics in four major internationally traded aquaculture species farmed in Asia. *Aquaculture 412-413: 231-243*. 10.1016/j.aquaculture.2013.07.028.

Troell M, Kautsky N, Beveridge M, Henriksson PJG, Primavera J, Rönnbäck P, Folke C (2013) Aquaculture. In Levin S (ed.) Encyclopedia of Biodiversity, second edition.

Nahid SAA, Henriksson PJG, Wahab MA (2013) Value-chain analysis of freshwater apple snail (Pila globosa) used for on-farm feeds in the freshwater prawn farming sector in Bangladesh. *Int J Agr Res, Innov & Tech, Vol. 3, pp. 22–30*. 10.3329/ijarit.v3i2.17840.

Carey N, Galkin A, Henriksson PJG, Richards JG, Sigwart JD (2013) Variation in oxygen consumption among 'living fossils'(Mollusca: Polyplacophora). *J Mar Biol Assoc UK 93:1, 197-207*. 10.1017/S0025315412000653.

Henriksson PJG, Guinée JB, Kleijn R, de Snoo GR (2011) Life cycle assessment of aquaculture systems—a review of methodologies. *Journal of Life Cycle Assessment 17:304-313*. 10.1007/s11367-011-0369-4

Henriksson PJG, Pelletier N, Troell M, Tyedmers PH (2011) Life Cycle Assessment and Its Application to Aquaculture Production Systems. In Meyers RA (ed.) Encyclopedia of Sustainability Science and Technology, Springer, pp. 5893-5909. 10.1007/978-1-4614-5797-8_191.

Pelletier N, Audsley E, Brodt S, Garnett T, Henriksson PJG, Kendall A, Kramer K-J, Murphy D, Nemecek T, Troell M (2011) Energy Intensity of Agriculture and Food Systems. *Annu. Rev. Environ. Resour. 36:7*, 1–7.24. 10.1146/annurev-environ-081710-161014.

Henriksson PJG, Mandic M, Richards JG (2009) The osmorespiratory compromise in sculpins: impaired gas exchange is associated with freshwater tolerance. *Physiol Biochem Zool. 81:3*, 310-319. 10.1086/587092.

Publications, Others

Henriksson PJG, Zhang W, Nahid SAA, Newton R, Phan LT, Dao HM, Zhang Z, Jaithiang J, Andong R, Chaimanuskul K, Vo NS, Hua HV, Haque MM, Das R, Kruijssen F, Satapornvanit K, Nguyen PT, Liu Q, Liu L, Wahab MA, Murray FJ, Little DC, Guinée JB (2014) Final LCA case study report - Results of LCA studies of Asian Aquaculture Systems for Tilapia, Catfish, Shrimp, and Freshwater prawn. SEAT Deliverable D3.5. 182 pp.

Henriksson PJG, Little DC, Troell M, Kleijn R (2010) Energy Efficiency Of Aquaculture - Life Cycle Assessment Useful In Evaluating Sustainability. *The Advocate, Global Aquaculture alliance. Vol. 13. Issue 5,* pp. 40-42.

Henriksson PJG, Little DC, Guinée JB, Kleijn R (2012) Life-cycle assessment and Aquaculture. Asian Aquaculture Network (AAN). Bangkok, Thailand. 2 pp.

Waley D, Newton R, Henriksson PJG, Thanh LP (2012) Sustainability of the Pangasius trade. *Aqua Culture Asia Pacific Magazine pp.32-35*

Acknowledgements

This thesis would not have been possible without the scientific and mental support of the following people, as well as the many whom I forget to mention.

Annick Lang, Mikael Printz and Nathalie Bax for directly contributing to the aesthetics of this thesis

Jeroen Guinée, Reinout Heijungs, Geert R de Snoo, René Kleijn, Arjan de Koning, Andreu Rico, Wenbo Zhang, Sk Ahmad-Al-Nahid, Richard Newton, Lam T Phan, Froukje Kruijssen, Jesper Clausen, Zongfeng Zhang, Jintana Jaithiang, Hai M Dao, Tran Phu, Phuong Nguyen, David Little, Francis Murray, William Leschen, Liping Liu, Qigen Liu, Ranjan Das, Abdul Wahab, Mohammad Haque, Kriengkrai, Arlene Satapornvanit, Peter van Bodegom, Darren Green, Douglas Waley, Ingrid Kelling, Oai Li Chen, Meen Che Hong, reviewers, commitee members and all others who directly helped with this research.

Max Troell, Michael Phillips, Malin Jonell, Nathan Pelletier, Peter Tyedmers, Friederike Ziegler, Sara Hornborg, Angel Avadi, Ian Vázquez-Rowe, Marc Metian, Jeffrey Richards, Rattanawan Mungkung, Joel Aubin, Erik Skontorp Hognes, Robert Parker, Steve Prescott, Aaron Shafer, Gustav Engström, Stephan Barthel, Britt Stikvoort, Carl Folke, other colleagues at the Beijer Institute, WorldFish and Stockholm Resilience Centre, and all others who gave me scientific support and inspiration.

Atiyo Ghosh, Fatima Drubi, Coen van der Giesen, Stefano Cucurachi, Laura Bertola, Jeroen Admiraal, Jiali Rui, Cilia Grebenstein, Angelica Mendoza, David Font, Benjamin Sprecher, Krijn Trimbos, Edi Wiloso, Sebastiaan Deetman, Lan Song, Oleksandra Ieromina, Kai Fang, Wenji Liao, Ether Philips, Jory Sjardijn, Susan van den Oever, Arnold Tukker, Natasha Järviö and all other CML staff.

Nathalie Bax, Leif, Lars, Lena, Tova Henriksson/Kyrö, Britt, Erik Holm, Annika, Amelie, Laura, Roger Prine, Margareta, Helena, Thomas Ritzler/Tenenbaum, Martina van Donge, Geert Terpstra, Fredrik, Marlene, Alma Håkansson/Cederheimer, Daniel Petri, Albert Wykman, Kimberly Ong, James Ede, Greg Goss, Milica Mandic, Chiara, Paolo, Tobia Marchetti/Concari, Alex, Luca Garcia, Kristian Molander-Söderholm, Ingmar Brouns, Eelco Bakker, Emma Constanza, Lijntje, Peter van den Hout, Eryn van Dijk, Philip, Lisa, Sam Johannessen/Dobring, Stefan Arkinger, Henrik Hultman, Jesper, Annelie, Elton Funck/Gaeyner, Michaela Thrun, Dan Svensson, Alex Edlund, Luis Morgado, Nicolas Davin, Robert Hattiga, Tonja, Lea van Gorp/Cucurachi, Naomi Banfield, Pablo Trujillo, Iris Maertens, Thijs Albers, Sonja Koeman, Loesje Hagens, Ramon van Geytenbeek, Eline Sumeru, Luciana Mesinas, Eelco Miedema, Bibi Eckhardt, Sandra Scanu, Ricardo Alanis, Gustav Ström, Mikael Fröberg, Alexandra Towns, Ibrahim Idrissa, Soumaila, Jenny Oscarsson, Lina Svanberg, Geert van Hoof, Ellen van den Berg, Pancake Batfish, Vincent Koorstra Marieke Elzakkers, Ivan Filé, Hendrik van den Brink, Patrick Defaix, Alex van Aken, Storm Patterson, Remco Wendt, Arjen Stobbe, Erik Sjöqvist, Jonas Andreasson, Danny Clayton, Kate Harrison, Johnny Redz, Baz Schat, Stephan Duynstee and all others who distracted me during these years.

Lastly I would like to thank all the farmers and non-farmers in Asia who took their valuable time to share their knowledge with me.