Streamlined Carbon Footprint Computation — Case Studies in the Food Industry

by

Yin Jin Lee

Bachelor of Science in Chemical and Biological Engineering,
University of Wisconsin–Madison (2009)

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Author ....
Engineering Systems Division
May 10, 2013

Certified by ....
Dr. Edgar Blanco
Research Director, Center of Transportation and Logistics
Thesis Supervisor

Accepted by ....
Olivier L. de Weck
Professor of Engineering Systems and Aeronautics and Astronautics
Chair, Engineering Systems Division Education Committee

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Abstract

One of the greatest barriers in product Carbon Footprinting is the large amount of time and effort required for data collection across the supply chain. Tesco's decision to downsize their carbon footprint project from the original plan of 70,000 house brand products to only a small fraction of them exemplifies the tradeoff between cost and good intention. In this thesis, we have merged salient characteristics from several recent works in this area to develop a fast and cheap method to calculate food carbon footprint accurately. We defined sources of uncertainty as data quality, data gaps and cut-off error, and quantified them. Firstly, quick judgment uncertainty was applied to assess data quality, reducing the time and the expertise needed. Secondly, we showed that it is feasible to use averaged proxies in a preliminary carbon footprint calculation to select the inputs with high impact. The analysis was streamlined by getting specific data only for a subset of high impact inputs while leaving the insignificant inputs represented by low resolution averaged proxies. Monte Carlo simulations and analytical solutions were introduced to account for the total variance of averaged proxies. We applied hierarchy structures to organize the existing emission factors to facilitate proxy selection, but found that the hierarchy required either expert knowledge for design or large numbers of emission factors to average out the inconsistencies within the same input types. Lastly, by integrating uncertainty calculation with iterative carbon footprint calculation, we demonstrated convergence of the calculated carbon footprint and its uncertainty results, providing firm support for our techniques of leaving less significant inputs represented by low resolution averaged proxies. The novel contribution of this work is the application of test sets to 1) prove that carbon footprints calculated using the streamlined approach converged quickly to a stable estimate even when the true values were beyond the range of the proxies, and 2) show an adaptive and justifiable way to select the minimal number of high impact inputs for further analysis.

Thesis Supervisor: Dr. Edgar Blanco

Title: Research Director, Center of Transportation and Logistics

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Part I

Introduction

Chapter 1

Motivation

The relationship between the food system and the climate is closely tied to the survival and well being of humans. As much as there is apprehension of the impact of climate change on future food supply, there is concern about the impact of the food system chain on the climate, especially when the estimates by IPCC (2007) showed that the agriculture industry contributed to 13.5% of global greenhouse gas emission in 2004 [1]. These concerns result in a growing demand of food carbon footprint analyses at the organizational, individual and product levels [2]. However, conventional carbon footprint analysis is expensive as it approaches the entire process in a bottom-up manner, demanding extensive data collection for the calculation of a carbon footprint estimate [3, 4]. In 2012, we witnessed Tesco ending their unsuccessful attempt to label 70,000 of their house products. The program failed because carbon footprint labels of products did not gain "critical mass" amongst Tesco's competitors, so the consumers were unable to compare the carbon footprint between brands. Another important factor that prohibited carbon footprint labeling was that each label required "a minimum of several months' work" [5]. At this rate, it would take companies many years to label all their products. Carbon footprint assessments have to be faster and cheaper.

There are several recent works that proposed new methodologies to compute environmental impact and its uncertainty effectively [6, 7, 4]. The new wave of methodologies focuses on using screening calculations as the first step to identify the product inputs with high carbon footprint contribution, allowing analysts to better allocate their data collection efforts on these inputs [6, 8]. In 2011, the Materials System Laboratory developed the Product Attribute to Impact Algorithm (PAIA) to calculate the carbon footprint of products, including the uncertainty, under the constraints of limited information [9]. *Structured Underspecification*, one of the steps in PAIA, can be useful for food carbon footprint calculation. In 2012, PepsiCo implemented carbon footprinting on a large scale using the Fast Carbon Footprint (FCF) tool developed by researchers at Columbia University [4]. The tool allowed PepsiCo to carry out carbon footprint assessments at the same rate products were designed [10]. As of now, there are few published case studies to support the effectiveness of these carbon footprint methods. Therefore, the objective of this thesis is to integrate the salient characteristics of Structured Underspecification and FCF to derive new knowledge and introduce novel techniques for food carbon footprinting.

1.1 Complexity of the food system

The food supply chain is a highly fragmented system consisting of formal, informal and nonmarket channels. Although all the supply chains consist of fundamentally similar stages including the manufacturing and distribution of inputs (seed, animal feed, fertilizers), agricultural outputs (crops and livestock), processing, packaging, distribution, preparation, and waste disposal, the traditional interactions across each segment of the supply chain are purely material and money exchanges [2, 11]. Businesses usually include many stages of procurement and distribution. In addition, the competition between businesses induces secrecy along the supply chain. Both the complex network of distribution and lack of transparency impede effort to trace the sources of food. To this point we have only described the complexity of the physical food system. To track the volume of greenhouse gases released throughout the food system will only add another thick layer of complexity to the existing puzzle! An accurate food carbon footprint would need to include emissions at the power plants providing energy to the facilities, the emissions of the farm vehicles, to the carbon dioxide trapped in soil, the gases emitted by the livestock, and the list goes on. To keep active records of all these activities and inputs would require technologies that could be too costly [2]. To complicate things even more, some of these measures are difficult to justify or quantify, and if they are quantifiable, they are variable [12].

1.2 Capturing the environmental impact of food

The structure of the food suply chain system did not include the need for compiling environmental impact data. To rebuild a data structure compatible with the complex food system requires exorbitant investments to measure and monitor the wide array of inputs and outputs that are almost impossible. Thus, researchers, governments and non-governmental organizations have been doing separate life cycle assessments (LCAs) on individual products for selected food instead (More information on LCA is provided in Section 2.1). The current best option to capture the environmental impact of food without real data collection is to rely on these published studies.

The individual carbon footprint studies are often based on purposeful assumptions to define the scale and scope, and are applicable only for specific geographical regions and technologies [2]. Further research was needed to translate the results of these works to information that is usable for consumers. Leveraging on numerous LCAs of food products published in the 1990s, Jungbluth structured the determinants in the food life cycle into five broad groups, namely, the type of product and agricultural practice, the processing for storage and distribution, distance and mode of transportation, the type and amount of packaging and lastly, the food preparation process [11]. He compared the different options within these stages and gave general guidelines about their relative environmental impact, with the objective to provide clear and simple instructions for environmentally concerned consumers. Other works attempt to compute the average carbon footprint of an individual from a specific country, such as India [13], and Finland [14]. While many of these works applied strategies to reduce the amount of real data needed in their own computation, to our knowledge, no work has introduced a methodology that is dedicated to computing the carbon footprint and the uncertainty of any combination of food in a meal, from the perspective of a food service provider or a consumer.

1.3 Barriers in product carbon footprinting

There are many challenges to compute general product carbon footprints quickly and accurately. Critical reviews of environmental impact assessment tools pointed to data availability and quality as one of the root causes that impose limitations to the system boundary definition, uncertainty analysis, and the adoption of the tools in general [15, 3, 16, 17].

System boundary is the extent of the life cycle that is included in the analysis. Reliable impact assessments need to be set at the right scale and depth, and ideally, have enough data to account for spatial, technology and temporal variability. Yet, data limitation pushes analysts to constrain their analysis to only as large as is needed for the objective of their studies [18]. Although limiting the system boundary is acceptable for specific cases, it is not applicable in product carbon footprinting. The main approach to reduce data demand in product carbon footprint calculation is to identify and exclude the less significant components. The practice to eliminate these components is also referred to as *cut-off* [6]. The way to select the cut-off boundary is still evolving (refer to Section 2.5.3).

The lack of data also prohibits conventional uncertainty analysis. Standard uncertainty propagation requires large data sets to gauge the spread of the inputs. Data limitation is perhaps partly why many LCAs do not include uncertainty calculations [19, 20]. Another barrier to uncertainty calculation is that there are so many sources of uncertainty that several papers were published to refine the definition of uncertainty [21, 22, 23, 16, 17, 20]. While there was an early solution to calculating uncertainty with limited data through the use of fuzzy sets [24], it had not been widely used. Recent developments in uncertainty calculations address the same problem with more intuitive mathematical structures that can be readily incorporated [25, 4].

Lastly, life cycle assessment results of the same product type are usually not consistent. While the International Standards (Section 2.2) allows analysts to apply justified assumptions for greater flexibility in their assessments, the flip side of the problem is that the results of the LCAs are often not comparable. This undermines the application of carbon footprints as a measure to compare between products. For example, Teehan and Kandlikar found that the carbon footprint of desktop computers from multiple separate studies had conflicting results because of differences in their underlying assumptions [26]. In response to the lack of data and consistency, many researchers have recommended further standardization of LCAs, and to establish large databases [16, 27, 17]. There is as yet, no food carbon footprint database available. If we were to compile emission factors from different studies, it is best to use many values to average out the variability, and also a methodology that can estimate the error of using multiple sources.

1.4 Thesis objectives

The food service sector is the point where the product is designed for the consumer, thus it has the highest control over the carbon footprint of the meal, but unfortunately, it is situated at the end of the supply chain and has limited control and knowledge over the source of the food. A methodology developed with a focus on food can help businesses in the food service sector better understand the hotspots in their menu, so they can design their dishes to minimize their carbon footprint. A more idealistic aim of the methodology is to provide a platform to compare the carbon footprints of different food options. To reach this tall order, the methodology has to be fast, cheap and accurate at the same time. For it to be fast, it could be built on a standardized database that would calculate estimates and uncertainties. For it to be cheap and accurate at the same time, screening calculations can assign significance to the inputs. Effort can be greatly reduced if we can focus our data collection effort on only a subset of all the inputs, with an understanding that these inputs are the ones that largely determine the final value of the carbon footprint.

1.4.1 The Galapagos Islands Ferry Tour case study

A food order list was requested from a company that organizes ferry tour packages around the Galapagos Islands in Ecuador. This case study was first done with little changes to the Product Attributes to Impact Algorithm devised by the Materials Systems Laboratory at the Massachusetts Institute of Technology, as described in the Master Thesis of Siamrut Patanavanich [7].

1.4.2 The Cambridge Bondir case study

Twenty restaurants that claimed to be environmentally friendly on their website were invited to take part in the research project with a letter accompanied with an example form (Appendix C-1 and C-3). Of the restaurants which replied, we only worked with Bondir. The dish Pasture Raised Red Broiler Chicken was selected for the study because the chef could provide most of the supply chain data. This case study was done with improvements to the methodology in the previous case study. The changes are summarized in Table 5.1.

1.5 Thesis structure

The thesis is broken down into two parts: first to review related works and to give a brief overview of our methodology, and second, to apply the methodology in case studies to evaluate the effectiveness of the methodology. In Chapter 2 we define the terminologies in carbon footprint analysis and point out the gaps in the current international and national standards that are still under research revisions. The review of existing solutions to uncertainty and data availability highlights the barriers to widespread application of carbon footprinting. The chapter ends with an introduction to the new paradigm in carbon footprinting and a general description of our approach to food carbon footprinting. In the following two chapters, we would present the case studies in the same sequence as the research process. In Chapter 3 we present the methodology that we adopt from an existing work and its application to calculate the carbon footprint of a food order list of a Galapagos Ferry Tour trip. The implementation and the results of the case study present several limitations of the existing methodology, thus a second case study was carried out to further test the methodology. Chapter 4 explains the revisions to address the limitations in the Galapagos Islands case study. The Bondir Cambridge case study also shifted the focus from a structured approach to a more general approach to show that several nascent techniques can be merged and applied to other combinations of food. Lastly, we conclude the thesis with Chapter 5 to compare the two case studies, assess the practical value of the revised methodology and how it can be further improved.

Chapter 2

Streamlined carbon footprint analyses

The applications of carbon footprint assessments include product labeling and informing decisions. Although most companies and businesses are aware of the importance of carbon footprints, product labeling has not been widespread because of its cost. Instead, many companies use carbon footprint analyses to identify the hotspots, the activities or the material inputs that have the greatest impact on the environment, of their product [3]. The companies can prioritize their attention to alleviating the impact from the hotspots, thus minimizing the carbon footprint effectively.

Over the last decades, the International Standards, and other international and national organizations have rolled out various guidelines to ensure that environmental impact assessments are reliable. Despite that these standards have made carbon footprint calculation easier by being increasingly clear about the steps, the cost and time needed for hiring external specialists and for data collection still prohibited widespread use of carbon footprint assessments. Thus, there is ongoing research effort to improve the efficiency of carbon footprint assessments without compromising the accuracy of these assessments significantly.

In this chapter, we first define the types of life cycle assessment, introduce the prominent international and national standards and protocols for carbon footprint assessments, and provide a basic understanding of carbon footprint calculations. Secondly, we provide the broad classification of streamlining methods, the approaches that are applied to reduce calculation and data collection needs. Thirdly, we describe the types of uncertainties typical in carbon footprint analyses and how they are calculated. Lastly, we discuss how recent developments decreased the data collection efforts of carbon footprint analyses and describe the contribution of this study.

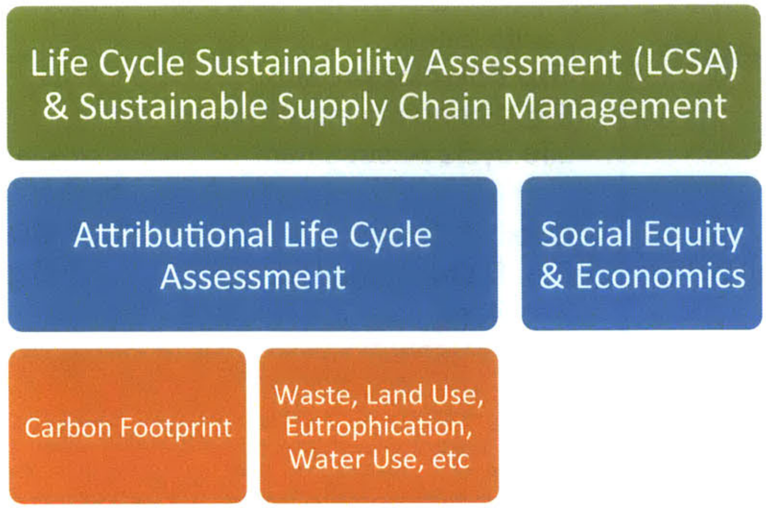
2.1 Life Cycle Assessments (LCA)

To be sustainable at different scopes and scales can lead to widely different interpretations. Figure 2-1 shows the scope hierarchy, starting from Life Cycle Sustainability Assessment [28] and Sustainable Supply Chain Management [29]. These perspectives emphasize the need to include economic, social and environmental aspects in the definition of sustainability. At the next level, Attributional Life Cycle Assessments examine all the inputs and outputs within the boundary of the life cycle to analyze the possible environmental impacts of products, [30] excluding considerations of the potential monetary cost or social impacts. At the bottommost level, carbon footprint analysis only looks at the climate change impacts of the product, which is only a subset of the overall environmental impacts, neglecting other potential issues such as eutrophication or waste. It is not uncommon to find cases where lower carbon footprint is equated to greater sustainability [31]. Although we will only focus on carbon footprint analysis in this thesis, the methodology that we have developed can be applied to other environmental impacts.

2.1.1 Depth and breadth of Life cycle assessment

There are two ways to scale Life Cycle Assessments (LCA) and Carbon Footprint (CF) assessments (Fig. 2-2). The depth describes how general the assessment is, and is usually dependent on the type of data that is available. For example, the carbon footprint of watermelons can be studied based on data at the aggregate sector level (EIO-LCA) [32] or it can be studied based on the activities and processes at a particular farm (Process-based LCA) [30]. The aggregated top-down and process-

Figure 2-1: A hierarchy to show the scopes of life cycle assessments that are commonly used to analyze the environmental impact of human activities or products.



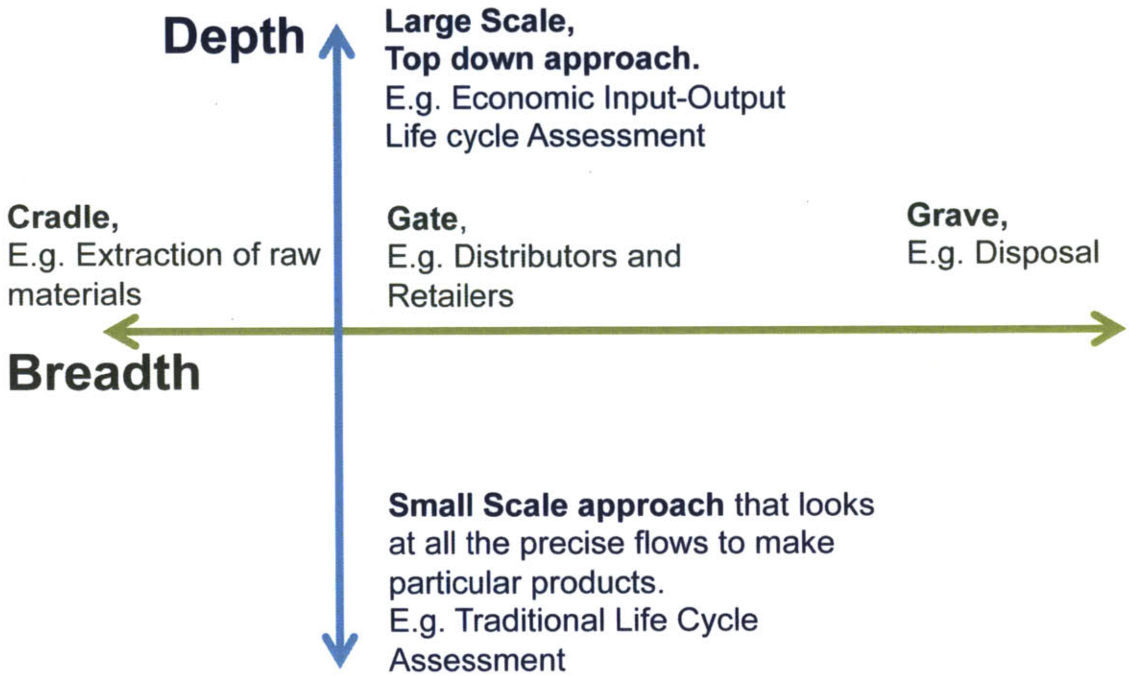
based bottom-up approach can complement each other to show the range of the impact [15]. The bottom-up process-based LCA approach is used for the case studies because the data we have is at the appropriate level. We are aware that this can underestimate the true carbon footprint because we have excluded the operations that do not directly affect the food production or preparation, such as the electricity used for lights at the restaurant. An EIO-LCA could have been done before the process-based LCA for results with greater accuracy.

The breadth describes the extent of the life cycle, which can be as complete as from the extraction of the raw materials to the final disposal of the product, conventionally called cradle-to-grave, or as short as the last mile delivery from the distribution center to the retail stores. The scope is limited to the production phase in the Galapagos Islands Ferry Tour case study, and is expanded to cradle-to-grave in the Cambridge Bondir case study.

2.2 Product carbon footprint

Carbon footprint, the total amount of greenhouse gases that was released during an activity, or in the production of a material, is only a subset of all the possible

Figure 2-2: Depth and breadth of Life Cycle Assessment and Carbon Footprint Analysis.



types of environmental impacts. The six greenhouse gases carbon dioxide (CO_2); methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFC), perfluorocarbons (PFC), and sulfur hexafluoride (SF_6) were converted to carbon dioxide equivalent (CO_{2eq}) using factors suggested by the Intergovernmental Panel on Climate Change [33]. For convenience, we adopt the term *attributable processes* (APs) from the GHG Product Protocol to refer to activities, materials, and energy flows that contribute to the carbon footprint of the product.

The traditional carbon computation approaches are usually based on established national or international standards, such as the International Standards 14040:2006, Life Cycle Assessment: Principles and Framework [34] and 14044:2006, Life Cycle Assessment [30], World Resources Institute GHG Protocol Product Standards [8] and the British Standard Institute PAS2050:2011 [35].

- ISO 14040\44 are part of a series of Environmental Management Systems published by the International Organization for Standardization (ISO). They provide a framework for life cycle assessment, a methodology to analyze the environmental impacts across the life cycle of activities or products. One subset of environmental impacts is greenhouse gas emissions, which is equivalent to carbon footprint.

- The PAS2050 was built on the ISO14040/44 standards to further describe the steps to calculate the greenhouse gas emissions of goods and services.
- The GHG Protocol Product Standard was built on both the ISO standards and PAS2050 to provide additional guidelines for consistent public reporting of the greenhouse gas emissions.

The ISO14044, PAS2050 and GHG Protocol require attributional and *process-based* LCAs. The attributional approach attempts to link greenhouse gas emissions and removals of the APs to a unit of the studied product [6]. Process-based means that the carbon footprint contribution has to be accounted by individual APs. Other ways to assess environmental impacts include the Economic Input Output Life Cycle Assessment (EIO-LCA), and the Hybrid Life Cycle Assessment (Hybrid LCA), which improves the process-based LCA by including elements from the EIO-LCA. [15].

2.3 Basics of carbon footprint calculations

Carbon footprint analysis can be complex because there are many intricacies that have to be defined and the details can be found within the standards mentioned in Section 2.2. If the details are decided, the fundamentals of the calculation can be done with rudimentary mathematical manipulations. To best simplify the mathematical operations, the Fast Carbon Footprint methodology has defined that the carbon footprint of an input CF_i is the product of the *emission factors* EF_i and its *driver(s)* $D_{i,j}$, where i is the index of the AP and j is the index of the type of driver (Eqn. 2.1) [4].

$$CF_i = EF_i \prod_j D_{i,j} \tag{2.1}$$

An emission factor, EF_i is the total amount of greenhouse gas that was emitted in the production of a unit of material i, or during a unit of activity i, and is expressed as $kgCO_{2eq}$ per unit weight of material, or per unit of activity. Carbon dioxide equivalent is a measure of the global warming impact of the greenhouse gases when normalized to that of the carbon dioxide gas [33]. The drivers are scalars that describe the magnitude of the input. Using examples from the two case studies in this report, the drivers can be the weight of food added to the dish, the duration of the activities and the distance between the origin and the destination of the food inputs. In this report, the term *data* can refer to both the *drivers*, and the *emission factors*.

2.3.1 Calculating the total carbon footprint

The total carbon footprint CF_{Total} of a product made of n APs is the sum of all the individual carbon footprints CF_i (Eq. 2.2).

$$CF_{Total} = \sum_{i}^{n} CF_i \tag{2.2}$$

Due to variability and uncertainties, the EF and D are not fixed numbers but random variables from different distributions. Thus, it is more appropriate to use the expected emission factors $\mathbf{E}[EF_i]$ and expected drivers $\mathbf{E}[D_i]$ to obtain the expected individual carbon footprint $\mathbf{E}[CF_i]$ and total carbon footprint $\mathbf{E}[CF_{Total}]$. The same operations are still the same as in Equation 2.1 and 2.2.

2.4 Streamlined carbon footprinting

Extensive work is required to obtain the emission factors of activities and materials and *streamlining* methods are often applied to reduce the amount of data needed. SETAC's 1999 streamlined LCA report classified streamlining approaches into two broad groups, namely, *scope limiting* and *surrogate data* [18]. *Scope limiting* refers to only looking at a part of the product life cycle. For example, if the aim of the study is to compare the carbon footprint of the same type of product from two different brands, the scope can be limited up to the production phase, assuming that the use phase and disposal phase emissions will be similar. *Surrogate data* refers to using existing published data as substitutes for the real data. This approach can reduce data collection effort substantially, [36] and was widely practised through the use of commercial software suites such as SimaPro, or databases such as the U.S. Life Cycle Inventory. However, the emission factors are specific to the location and context and the use of surrogate data will increase the uncertainty of the carbon footprint estimate.

Alternatively, Ong, Koh, et al. introduced a streamlined approach that first applied qualitative overview of the inputs into the product life cycle to identify the high impact inputs, referred to as the Set of Interest. Subsequently, a round of quantitative assessment was conducted with focus on the Set of Interest only [37]. The qualitative process requires expert knowledge, thus the application of this method is limited.

2.5 Uncertainty

Carbon footprints of products are only useful for influencing decision processes if there is information about the reliability of the estimates [35]. The reliability is usually measured by the range of uncertainty of the single point and the uncertainties can arise in many different ways in the context of carbon footprint assessments [17]. Huijbergt was the first to discuss the type of uncertainties in-depth in 1998 [21, 22]. Later, the reviews by Björklund [23], Reap [16], Ascough [17] and Lloyd [20] examined many LCA publications to further categorize the types of uncertainties.

Recently Williams argued that the *uncertainties in data*, *cutoff error*, *aggregate uncertainty*, *geographical uncertainty*, and *temporal uncertainty* are the five most important uncertainty types in process-based LCA [6]. *Uncertainties in data* can be due to the data quality and the data representativeness of the true value. Data quality describes the natural fluctuations or errors at the time of data collection, and data representativeness describes the appropriateness of using surrogate data to represent the real input. *Cutoff error* is further elaborated in Section 2.5.3. *Aggregate un-*

certainty is derived from situations when detailed data is not available, and values pertaining to a bigger group of entities are used instead. For example, when the data of the emissions from a particular plastic factory is not available, the emissions data from the plastic manufacturing industry is used instead. Lastly, emissions data is often location and temporal specific. For example, Roma Tomatoes grown in Indonesia in 2010 will have different environmental impacts from Roma Tomatoes grown in the same country in 1990 or Roma Tomatoes grown in Italy in 2010. Unfortunately, we may not always know where and when the Roma Tomatoes we consume are gathered (hopefully recently!), thus there is *geographical uncertainty*, and *temporal uncertainty*. In this work, we classified uncertainty into three general types, namely, uncertainty within data, uncertainty when dealing with data gaps, and lastly, cutoff errors, and proposed solutions to quantify them.

2.5.1 Uncertainty in data

The uncertainty within data that arises from the data quality is conventionally described using *Data Quality Indicators* that include technology representativeness, temporal representativeness, geographical representativeness, completeness and reliability [38]. It also encompasses randomness during the data collection process. A typical way to estimate the uncertainties based on the Data Quality Indicators is described in Section 3.2.2. However, Meinrenken et. al. pointed out that even the best-in-class carbon footprint assessments have at least $\pm 5\%$ error, thus they suggested that the uncertainty can be assigned a coefficient of variance based on judgment [4].

2.5.2 Data gaps

Food comes in many varieties. There are common food such as russet potatoes and feedlot beef globally and there are also many foods that are unique to individual regions. Most publications on the environmental impact of food focused on staple and common food. There could be many ingredients that do not have existing emissions data when the aim is to compute the carbon footprint of real meals. Instead of investing effort to collect the emissions data of all the ingredients, we can adopt solutions to overcome these data gaps. Data gaps are generally addressed in two ways [8, 2]. First is through the use of estimated data. The emission factor can be extrapolated from existing databases by leveraging on the characteristics of the AP, such as price [4] and location. Second is through the use of existing emission factors as surrogate data, or proxies, in the calculation. The proxies can be selected based on characteristics of the AP. The GHG Product Standards provided a few examples of suitable proxies [8]:

- Using data on apples as a proxy for all fruit
- Using data on PET plastic processes when data on the specific plastic input is unknown

Canals et.al. compared the effectiveness of using proxies versus extrapolating data to deal with data gaps for bio-based products and found out that using the averaged proxy is more accurate than scaled and single proxy, and faster than extrapolating data, which may need extensive expert knowledge. [2] Another reason against the use of single proxy is that experts may not select proxies better than amatuers [39]. Canals et. al. also noted that measuring uncertainty in data gaps is important because the environmental impact within crops can vary as much as between different crops [2].

2.5.3 Cutoff error

To reduce data collection effort in LCA, certain inputs and outputs can be excluded if they are likely to be insignificant. However, cutoff can result in the underestimation of the real total environmental impact and has to be done carefully [40]. The ISO14040/44 standards allow cutoff based on the weight and energy fraction of the AP with respect to the product, but these criteria do not always correlate to its environmental impacts (refer to Section 3.3.3). A third option is to perform the cutoff based on the fraction of environmental impact of the input over the total impact of the product but the way to obtain the fraction without data collection efforts was unclear [15]. PAS2050:2011 clarified this ambiguity by recommending a back-of-envelope calculation. Based on the rough calculation, the inputs and outputs that contribute to the last 1% of the total carbon footprint can be cutoff from the system boundary. [35] The rigid 1% cutoff may require redundant data collection effort. The most recent GHG Protocol Product Standard did not require fixed cutoff boundary, but instead suggested using screening processes in the calculation:

"The most effective way to perform screening is to estimate the emissions and removals of processes and process inputs using secondary data and rank the estimates in order of their contribution to the products' life cycle. Companies can then use this list to prioritize the collection of primary or quality secondary data on the processes and process inputs that have the largest impact on the inventory results"

However, uncertainty assessment was not given emphasis, but only "helpful" to identify processes that contribute to high uncertainty [8]. In addition, Suh and Williams supported the use of EIO-LCA estimates as the first screening step to cutoff the less significant processes because the top-down approach will include capital goods and operation-related emissions [15, 6]. It is an ongoing research effort to find a good screening approach that can identify the cutoff boundary and its uncertainty.

2.5.4 Methods to assess uncertainty

Two common ways to assess reliability are to use uncertainty analysis and sensitivity analysis. Uncertainty analysis is applied to propagate input uncertainties to the results and sensitivity analysis is applied to identify the uncertainty that has the greatest influence on the result [16]. Sensitivity analysis can indicate the APs that have the greatest leverage on the results, however, it does not inform the possible range of the final estimate [6]. The focus of this work will be uncertainty analysis.

2.6 A new paradigm

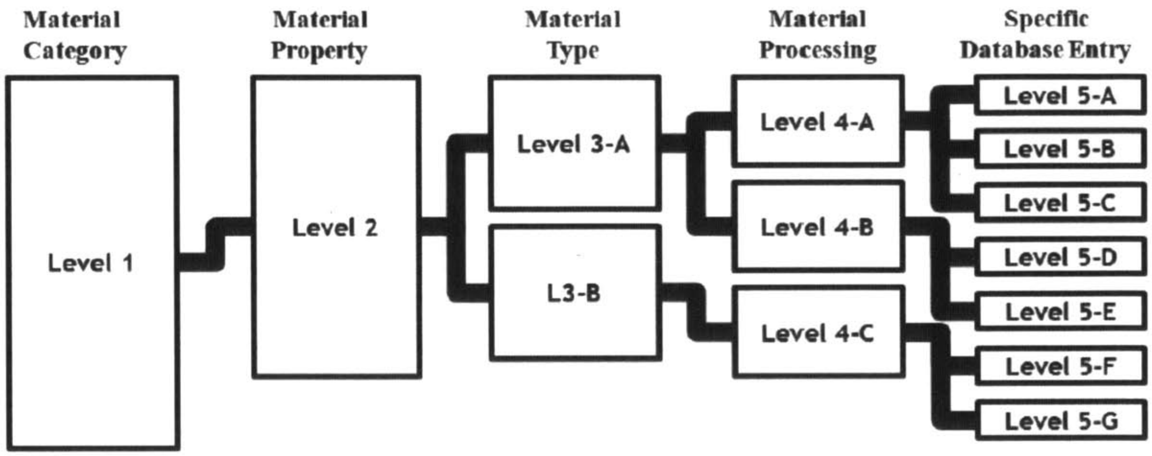
The recent developments in LCA have strong emphasis on its practicality, with particular focus on reducing data collection effort and accounting for uncertainty in the estimated results. *Structured Underspecification* addresses data gaps issues and cutoff boundary selection by providing a logical structure for proxy selection and uncertainty computation. The Fast Carbon Footprint tool speeds up the carbon footprint and uncertainty computation process by introducing a framework supported by analytical equations [4]. The *Hybrid Framework* promoted the use of iterative carbon footprint estimation with uncertainty analysis to ensure that results are accurate and precise [6]. All three proposals are founded on the perspective that data screening should be used to identify attributable processes that have relatively large impact on the absolute value or the uncertainty of the carbon footprint estimate.

2.6.1 Structured Underspecification

Structured Underspecification was specifically designed to remove the potential statistical biases due to erroneous surrogate selection and to capture the total uncertainty in using proxy data. It was first developed to classify material information with increasing specifications so that the LCA analysts can estimate the magnitude of uncertainty given the level of specification that is known. We will use an existing example to illustrate how structured specification works [7]. Figure 2-3 shows how a hierarchy structure is used to classify information of materials based on five levels of specifications, including, material category, material property, material type, material processing, and specific database entry. The material category refers to generic material types, such as metals, chemicals and minerals. In the material property level, the materials are further classified based on differences in their properties. For example, metals can be classified by whether they are ferrous or non-ferrous or alloys.

The appropriate number of proxies for a material will depend on the level of specificity. In Figure 2-3, if a material is identified up to the L2 specificity, then any of the database entries that are indexed as Level 5-A to G are qualified to be its

Figure 2-3: Illustration of the Structured Underspecification hierarchy levels. Adapted from [7].



proxy. If the material is further specified to Level 3-A, the possible proxies would be reduced to the database entries that are indexed as Level 5-A to E. Using multiple proxies will overestimate true uncertainty of the material carbon footprint, but it will represent the analysts' uncertainty in his or her carbon footprint estimate. The proxies are used for screening calculation to identify a small fraction of the APs that have significant contribution to the total carbon footprint, also referred to as the Set of Interest.

Streamlining in Structured Underspecification

The goal of Structured Underspecification is to determine the set of materials with the highest environmental impact, and this set of materials is referred to as the Set of Interest (SOI) [7]. A formal definition of SOI is the smallest number of material that can represent at least a threshold fraction of the total impact. The threshold fraction is referred to as the cut-off percentile, and the number of the APs in the Set of Interest will increase with a higher cut-off percentile. Another interpretation of the cut-off percentile is the cumulative percentage of carbon footprint that was contributed by the APs in the SOI. For example, the PAS2050 allowance to leave the APs that contribute to the last 1% of the carbon footprint is equivalent to a 99th percentile cut-off. The remaining APs make up the Set of Interest. Structured Underspecification calculates the total carbon footprints with Monte Carlo simulations. In this thesis, we would test the effectiveness of using a fixed cut-off percentile to determine the Set of Interest for total carbon footprint estimation.

2.6.2 Fast Carbon Footprinting

Fast Carbon Footprinting is a single approach that integrates uniform data structure, concurrent uncertainty analysis and EF estimation. For uniform data structure, a "one-data-structure-fits-all-products" model was proposed to calculate both the EF and the uncertainty with generic algorithm. Instead of an indepth uncertainty analysis, "Judged uncertainty" is used to assign coefficient of variations (CVs) for cases where the CVs cannot be determined otherwise, and the suggested benchmarks are shown in Table 2.1. A linear regression model was used to extrapolate a suitable emission factor from the database, and *Compounded uncertainty*, a system of equations, is used to quickly evaluate the carbon footprint estimate and its associated uncertainty using the extrapolated emission factors and the assigned CVs. Compounded uncertainty is further elaborated on in Appendix A.3.

The tool was developed to allow companies to calculate carbon footprint quickly and independently, with little assistance from external specialists. Its main objective is to provide guidance and insights for product designs and other decision-making processes. It utilizes the company's records as primary activity data, and emission factors from public databases. The tool is especially outstanding for its adaptation to standard enterprise software used by many companies (such as the SAP system) and it has been developed into an user-friendly interface that is applied by PepsiCo to identify hotspots at the product level [10].

2.6.3 Iterative carbon footprint estimation with uncertainty analysis

In his proposal for the *Hybrid Framework for Managing Uncertainty in Life Cycle Inventories* (Hybrid Framework), Williams puts a strong emphasis on uncertainty

Table 2.1: Rationale for categories of data type and their suggested assigned CV.

Assigned CV	Data type	Rationale/comment
Low (~5%)	■ Bill of materials (BOM) from enterprise resource planning (ERP)	■ 5% based on assumption that ERP data are of high accuracy (but with some remaining uncertainty, e.g., scrap and spill)
	■ Other primary activity data, such as transportation distances and type (road, rail, etc.), if collected reliably	■ Even non-ERP sourced data such as transportation distances can be very accurate, if drawn from a sufficiently large sample of logistics networks and freight partners. However, note that in such cases the CV can often be inferred directly from the data
	■ Factory energy consumptions (unless allocation ambiguities increase CV)	
Medium (~25%)	■ Secondary emission factors (EFs) obtained from public or commercial databases or other studies	■ 25% based on empirical benchmark CV for EFs (see Table S2 in supporting information on the Web). Note that EFs obtained from statistical models will carry those models' CV benchmarks
	■ Activity data such as shelf and refrigeration times, if specific to product and collected reliably ■ Proven and well-known disposal scenarios (e.g., recycling rates)	
High (~50%)	■ Country-specific default values for activity data (e.g., refrigeration, transportation) ■ Less reliable disposal scenarios (e.g., recycling rates)	■ 50% based on experience with authors' particular dataset. May be adjusted depending on the company's specific data environment
Extra high (e.g., factor 10)	■ Case-by-case basis only	■ For certain inputs, associated uncertainty will be far greater than 50% (e.g., EF of small amounts of unspecified flavoring)
	■ Usually encountered only for D_i that carry very small overall impact. Otherwise the CV would have to be reduced by further studies	■ We recommend treating such cases outside the standard CV propagation framework, e.g., by individual sensitivity tests. These may reveal such immaterial impacts that the uncertainty can simply be dealt with by assuming a very conservative average D_i (e.g., largest possible EF times 5) and then assigning a "low" CV

analysis and argued that:

"the future practice of hybrid LCI (Life Cycle Inventory) should include explicit iteration in which uncertainty is estimated before and after... The concept is to integrate the method [carbon footprint calculation in our context] with uncertainty assessment to explicitly reduce uncertainty."

He also projected that if the iterative steps were done,

"At some point the analyst decides that the result is sufficiently certain for the purpose of the study and the result of the iteration and uncertainty range become the final result."

However, further work is needed to characterize and quantify the different types of uncertainty in the LCA before this framework can be applied [6].

2.7 Overview of this thesis's methodology

The methodology was designed with the aim of overcoming data gaps, an ubiquitous problem in food carbon footprint calculations. The amount of real data required could be reduced by using averaged proxies to approximate the total carbon footprint. The averaged emission factor proxies were used for screening calculations to identify the attributable processes (APs) that have high impact, which we will refer to as the *Set of Interest.* Data collection effort was reduced because instead of collecting data for all the APs, analysts could just focus on the SOI and still obtain good carbon footprint estimates.

The research procedure to apply the methodology in food carbon footprinting consists of seven steps, namely:

1. Collecting the primary data, a list of APs of the product. The primary data refers to the list of APs that carry the product through its life cycle. It includes both the name of the process and its magnitude.

2. Establishing the system boundary of the study. The motivation of life cycle

assessments (LCAs) is to measure the environmental impact of products or activities within the scope boundaries. The size of the scope has to be justified because it can affect the conclusion of the assessments greatly. [15, 30]

3. Defining the functioning unit. Since the objective of the methodology was to facilitate carbon footprint calculation of the product, the functional units were selected to be the *total carbon footprint per food order* in the Galapagos Islands Ferry Tour case study and *per dish of Pasture Raised Red Broiler Chicken* for the Cambridge Bondir case study.

4. Compiling a database of emission factors.

5. Applying Structured Underspecification to classify the emission factors.

6. Selecting the appropriate proxies and judging their representativeness.

7. Calculating a preliminary total carbon footprint estimate with its uncertainty.

8. Screening for the APs that contribute significantly to the total carbon footprint, also called the *Set of Interest*, and,

9. Investing data collection effort on the *Set of Interest* to find a more accurate carbon footprint estimate.

The Galapagos Islands Ferry Tour case study used *Structured Underspecification* [7] exactly. Through the Galapagos Islands Ferry Tour case study we identified some limitations of Structured Underspecification, thus the methodology was revised with the concepts from *Fast Carbon Footprinting* and the *Hybrid Framework* in the Cambridge Bondir case study.

Part II

The Case Studies

Chapter 3

Galapagos Islands Ferry Tour Case Study

In this chapter, we calculated the carbon footprint of a food order list of a Galapagos Islands ferry tour. Despite an increasing availability of life cycle assessments (LCA) studies and resources, we found few carbon footprint studies that focused on produce from South America, and none that were focused on produce from Ecuador. Given the restriction, emission factor proxies had to be used. At this point of the research, *Structured Underspecification* was the best option to obtain the carbon footprint estimate and its associated uncertainty.

3.1 Problem definition and data preparation

3.1.1 Primary data of the Galapagos Islands Ferry Tour case study

The only information that was provided by the ferry tour company was a list of 142 food items with their order size and weight. (Appendix B.1) The order list included several items that were either too specific or too exotic that no existing proxies could be found. If possible, these items were substituted with similar food. For example, plantains, yucca and yogurt were represented using the emission factors of banana, potato and ice cream respectively. Processed foods that consist of several materials and required cooking processes such as the Custard Flan and Mondongo (a type of beef tripe soup) were excluded from the study because none of the emission factors in the database was similar. After this treatment, 48 items were excluded from the study and 31 items were substituted. Including the 31 items that were substituted, 94 items were used for the rest of the study. The uncertainties in the weight of the food items were all set at $\pm 1\%$.

3.1.2 System boundary of the Galapagos Islands Ferry Tour case study

Given that there was no other information on the production, delivery, preparation and disposal of the food items, the study was only focused on the greenhouse gases that were emitted when the food was produced at the source. The source can be a factory or a farm. This type of boundary is commonly referred to as cradle-to-gate. Although it is not a complete LCA, it is a good representation of the environmental impact because the production phase of food items dominates the carbon footprint of food compared to other supply chain processes [42] as long as the food is not transported by air [43].

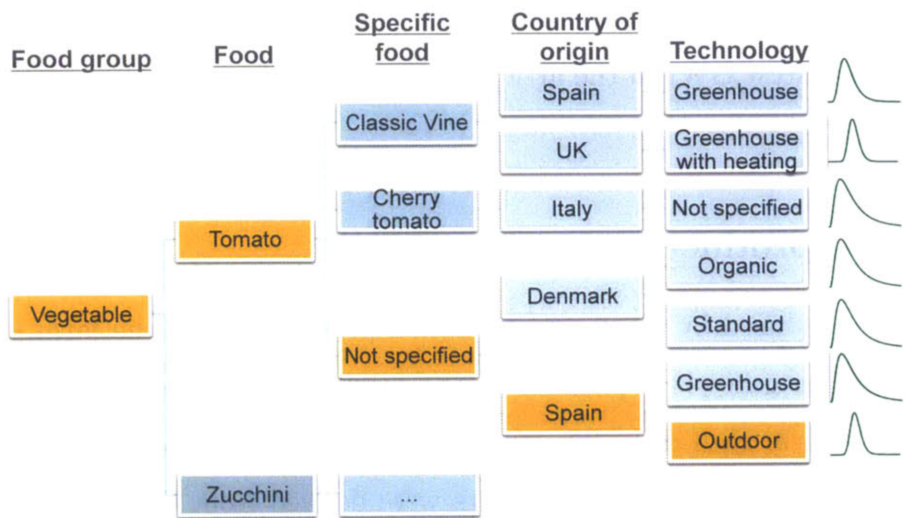
3.1.3 Functional unit

The functional unit is the *total carbon footprint per food order* in the Galapagos Islands Ferry Tour case study.

3.1.4 Emission factors data organization

The hierarchy levels in this work classify the emission factors in the database according to the ease of obtaining the information of the food from the perspective of the end-user. Please refer to Figure 3-1 for illustration; each single point emission factor in the database was placed at the right end of the hierarchy, at the *Technology* level. Each hierarchy level is referred to as the *level of specification* because it represents

Figure 3-1: The proposed hierarchy for the Galapagos Islands Ferry Tour case study consisted of five levels, namely, *Food Group*, *Food*, *Specific Food*, *Country of Origin* and lastly, *Technology*. The single point emission factors obtained from published sources are placed at the *Technology* level.



the amount of information that is known about the AP. Based on the information the analyst has about the AP he can move from the Food group level to the appropriate level of specification and select all the proxies that meet the requirement. If the analyst only knows that the AP is a tomato, he would use all the seven emission factors, regardless of the true species of the tomato, its country-of-origin, or the technology that was used to grow it, because all of them are qualified to be the proxy. If the analyst knows that the tomato is of the specie Classic Vine, he can use only the first two emission factors at the Technology level. With more information, the analyst could use a smaller number of proxies. However, it should be noted that a smaller number of proxies may not reduce the standard deviation because the environmental impact within crops can vary as much as between different crops [2]. The database of emission factors and their sources is in Appendix D.1.

3.1.5 Data structure

The emission factors compiled in the database were often calculated in separate studies that had different assumptions, and it was not ideal to compare them directly. We assumed that the differences were accounted for in the uncertainty of the individual CF, explained in Section 3.2.1. It was noted that the International Panel for Climate Change (IPCC) had revised the 100-years global warming potentials (GWP) factors of nitrous oxide and methane in 2001 and 2007 [44], and efforts were made to convert the GWP to the latest GWP if the article stated that it used the earlier IPCC GWP values.

3.1.6 Food production

The emissions produced by the food production processes up to the farm gates and the slaughterhouse gates is a product of the food production emission factor and the weight of food in each dish. The emission factors were converted to mass basis, $kgCO_{2eq}/kgfood$. When different products were derived from the same source, the carbon footprints were allocated to products by their relative cost. For example, since different beef parts have different market values, they would be allocated a carbon footprint proportional to their prices.

The sources of the food emission factors in our database had varied system boundaries in their analyses. Most of the studies covered from cradle to farm gate or production gate, a handful of them covered from cradle to retail and an even smaller number of them covered the entire life cycle. For the conversions of meat between different boundary definitions, we used the ratio 1 kg live weight = 0.81 kg carcass weight [45] = 0.56 kg bone free meat [46]. The emission factors for liquids that were expressed in terms of volume were converted to weight assuming that their density is the same as water, 1 kg/L.

3.2 Carbon footprint calculation

3.2.1 Uncertainty in each emission factor

Emission factors were usually reported as single point data [25]. Structured Underspecification assumed that each emission factor was the mean from separate distributions and represented it with the logarithm distribution. The spread of the distribution depended on the representativeness of the emission factor. An appropriate proxy would have a smaller spread whereas a poor proxy would have a wider spread. The quality was judged using the *Data Quality Indicators* in the Galapagos Islands Ferry Tour case study.

3.2.2 Data Quality Indicators

The Data Quality Indicators are widely used to assess the quality of data and are built into Samapro and Ecoinvent databases [50]. The indicating factors *Reliability*, *Completeness*, *Temporal*, *Geographic* and *Technological correlations* are described in the pedigree matrix [48, 8]. (Fig. 3.1)

Each of the five factors were rated using an indicator score from 1 to 5, where the score of 1 was assigned to the most appropriate and accurate data. These indicator scores were converted to uncertainty factors (Fig. 3.2) to calculate the square of the geometric standard deviation σ_g^2 based on Equation 3.1.

Table 3.1: Data Quality Indicators tabulated in the form of a pedigree matrix that can be used to assess the quality of data. Adapted from Frischknecht(2007) [51].

Indicator score	1	2	3	4	5	Remarks
Reliability	Verified data based on measurements	Verified data partly based on assumptions OR non-verified data based on measurements	Non-verified data partly based on qualified estimates	Qualified estimate (e.g. by industrial expert); data derived from theoretical information (stoichiometry, enthalpy, etc.)	Non-qualified estimate	verified means: published in public environmental reports of companies, official statistics, etc unverified means: personal information by letter, fax or e-mail
Completeness	Representative data from all sites relevant for the market considered over an adequate period to even out normal fluctuations	Representative data from >50% of the sites relevant for the market considered over an adequate period to even out normal fluctuations	Representative data from only some sites (<<50%) relevant for the market considered OR >50% of sites but from shorter periods	Representative data from only one site relevant for the market considered OR some sites but from shorter periods	Representativeness unknown or data from a small number of sites AND from shorter periods	Length of adequate period depends on process/technology
Temporal correlation	Less than 3 years of difference to our reference year (2000)	Less than 6 years of difference to our reference year (2000)	Less than 10 years of difference to our reference year (2000)	Less than 15 years of difference to our reference year (2000)	Age of data unknown or more than 15 years of difference to our reference year (2000)	less than 3 years means: data measured in 1997 or later; score for processes with investment cycles of <10 years; for other cases, scoring adjustments can be made accordingly
Geographical correlation	Data from area under study	Average data from larger area in which the area under study is included	Data from smaller area than area under study, or from similar area		Data from unknown OR distinctly different area (north america instead of middle east, OECD-Europe instead of Russia)	Similarity expressed in terms of enviornmental legislation. Suggestion for grouping: North America, Australia; European Union, Japan, South Africa; South America, North and Central Africa and Middle East; Russia, China, Far East Asia
Further technological correlation	Data from enterprises, processes and materials under study (i.e. identical technology)		Data on related processes or materials but same technology, OR Data from processes and materials under study but from different technology	Data on related processes or materials but different technology, OR data on laboratory scale processes and same technology	Data on related processes or materials but on laboratory scale of different technology	Examples for different technology: - steam turbine instead of motor propulsion in ships - emission factor B(a)P for diesel train based on lorry motor data Examples for related processes or materials: - data for tyles instead of bricks production - data of refinery infrastructure for chemical plants infrastructure
Sample size	>100, continous measurement, balance of purchased products	>20	> 10, aggregated figure in env. report	>=3	unknown	sample size behind a figure reported in the information source

Table 3.2: The default uncertainty factors for the pedigree matrix.

Indicator score	1	2	3	4	5
Reliability	1.00	1.05	1.10	1.20	1.50
Completeness	1.00	1.02	1.05	1.10	1.20
Temporal correlation	1.00	1.03	1.10	1.20	1.50
Geographical correlation	1.00	1.01	1.02		1.10
Further technological correlation	1.00		1.20	1.50	2.00
Sample size	1.00	1.02	1.05	1.10	1.20

$$\sigma_g^2 = e^{sqrt[ln(U_1)]^2+[ln(U_2)]^2+[ln(U_3)]^2+[ln(U_4)]^2+[ln(U_5)]^2+[ln(U_6)]^2+[ln(U_b)]^2} \tag{3.1}$$

where

U_1 = uncertainty factor of reliability

U_2 = uncertainty factor of completeness

U_3 = uncertainty factor of correlation

U_4 = uncertainty factor of geographical correlation

U_5 = uncertainty factor of technological correlation

U_6 = uncertainty factor of sample size

U_b = basic uncertainty factor

An Indicator score of three implies that the quality of the CF data as a surrogate was medium and a score of one implies that there was no uncertainty. Even though the Data Quality Indicators included technological and geographical correlation as part of the matrix, we recognized the *Country of Origin* and *Technology* as a part of the food specification and had included them in our classification hierarchy (Fig. 3-1). Thus, we assumed that the Indicator score is three for *Reliability*, *Completeness* and *Temporal correlation*, and one for the *Geographic* and *Technological correlation*. Based on this assignment, $\sigma_g^2 = 1.163$.

The distributions of the individual emission factors were assumed to be *logarithmic* with arithmetic mean, μ_{ar}, and standard deviation,σ_{ar}^2. The arithmetic parameters were calculated using Equation 3.2 and 3.3.

$$\mu_{ar} = \mu_g exp^{\frac{log^2(\sigma_g)}{2}} \tag{3.2}$$

$$\sigma_{ar} = \sqrt{exp^{2ln\mu_g + ln^2(\sigma_g)}(e^{ln^2(\sigma_g)} - 1)} \tag{3.3}$$

3.2.3 Proxy selection

Of the 94 food items in the food order list from the Galapagos Islands Ferry Tour, we were provided the characteristics of 82 items up to the *Food* level and 12 items up to the *Specific Food* level. There was no information about the country of origin and the technology that was used to produce the ingredients. At the *Specific Food* level, we filtered the surrogate data only if the listed food item stated it explicitly. For example, Beef liver from the food list was assigned to use the Beef knuckle emission factor because they were both cheap beef parts.

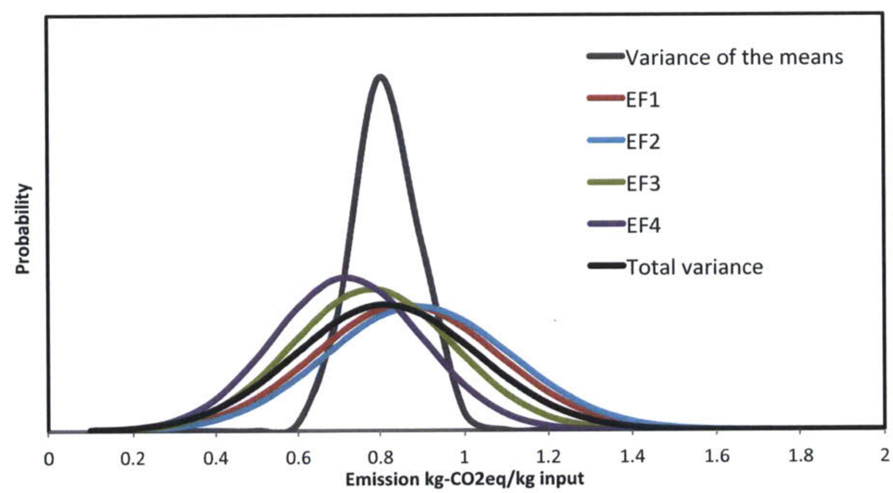
A few realistic assumptions were made to progress into the *Country of Origin* and *Technology* level. Statistics in FAO showed that most of the foods consumed in Ecuador in the past ten years were locally produced [52]. We assumed that the energy consumption in the farming process was dependent on the climate [53] and selected the emission factors from countries with Tropical and Mediterranean climate over those from countries with Temperate climate. For example, the preference for selection was in the order: Brazil$\gg$ India and Ghana$\gg$ Australia, Spain and Italy$\gg$ UK, Sweden, Denmark, Netherlands, Canada and USA. Statistics in FAO also showed that the total agricultural area in Ecuador decreased by 2.9% from 1989 to 2009 [52]. It was assumed that there was negligible land use change in Ecuador and any data with land use change was also excluded in the *Country-of-origin* level.

Lastly, we do not have any information about the technology used. For the sake of comparison, we picked one emission factor with conventional technology for each AP, to calculate the total carbon footprint at the *Technology* level.

3.2.4 Uncertainty in using proxies

The proxies were not the true values, and it was unlikely that any of them was exactly equivalent to the true emission factor. As a result, not only did we need to account for the uncertainty in the proxy, we needed to account for the potential error of choosing the wrong proxies. With Structured Underspecification, each proxy was assumed to be non-identical and had its own distribution. This assumption was appropriate because the proxies were taken from different sources (e.g. farms in China and farms in Italy) and the sources carried out their physical activities independently. The fact that they were non-identical random variables had to be emphasized because, if they were identical, we could assume that they were from the same population and the variance of the averaged proxy would be the variance of all the proxies.

Table 3.3: The uncertainty of an averaged proxy needs to consider the variance in the mean of the proxies and the variance within the proxies



To capture the real spread of the surrogate emission factors, it was assumed that all qualified emission factors had equal probability of being the most appropriate proxy thus the probability was a function of the known number of emission factors. (*e.g.* If we had four emission factors, the probability of each factor being selected was 1/4.) In the Galapagos Islands Ferry Tour case study, the "rand" function in Microsoft Office Excel was used to select the proxies at random. In each run, the selected proxy was fed into the total carbon footprint calculation. A total of 10,000 runs were carried out in each simulation.

3.2.5 Monte Carlo Simulation

We carried out 10,000 Monte Carlo simulations for the five levels of specifications using Oracle Crystal Ball. In each calculation run, individual food items were assigned one random surrogate emission factor that matched the level of specificity. The proxies were selected based on Structured Underspecification as described both in Section 2.6.1 and in Section 3.1.4. The total CF of the meal was calculated using Equation 2.2. The uncertainty was computed using the Data Quality Indicators as described in Section 3.2.2.

3.2.6 Screening for the Set of Interest

The Set of Interest was chosen to be the group of APs, or food items, that contributed to the first 90th percentile of the total carbon footprint for 75% of the runs. This cut-off was selected such that there were around 10-20 APs in the Set of Interest. The food items in the SOI of *Food* and *Specific Food* levels were updated with the same emission factors that were used to compute the total CF at the *Technology* level. By combining data from the lower level of specification with data from the higher level of specification, we created hybrid levels at the *Food* and *Specific Food* level, and labeled them as *Food-SOI* and *SFood-SOI* respectively. If the estimates of the hybrids are accurate, it would verify that we only have to find the exact emission factors of the SOI to obtain a good estimate of the total carbon footprint.

3.3 Results

3.3.1 Results at different levels of specification

Figure 3-2 shows the total carbon footprint of the food order list when all 94 food items were at the stated level of specification. That the means remained at around 670 ± 40 across all levels (Table 3.4) was a coincidence that the more appropriate

Table 3.4: The distributions of the total food carbon footprint of the food order list for the five levels of specification.

	Total carbon footprint of the food order list/ kg CO2e				
Levels	Food Group	Food	Specific food	Country of Origin	Technology
Maximum	11457	15648	12251	1412	916
Minimun	204	316	286	355	522
Median	623	725	647	675	655

proxies were moderate values. As the redundant emission factor proxies were removed with increasing specification, the spread of the total carbon footprint decreased.

In the first three levels, the group of outliers in the upper end were the simulations that included the beef emission factor with land use change impact in Brazil beef [55]. This emission factor is 26 times higher than average beef, thus the total carbon footprint of the simulated runs that included this emission factor was much higher than the other runs.

The reduction in the spread across the levels also indicated that the hierarchy was able to classify the emission factors reasonably well, such that the emission factors that were grouped together in the next level were closer values than the emission factors that were left out. The result in this section reflected that the carbon footprint estimate could be more accurate with more information about the attributable processes.

3.3.2 The Set of Interest (SOI)

The sets of food inputs that fell into the top 90% of the total food carbon footprint for more than 75% of the runs were identified and listed in Table 3.5. The number of inputs in the SOI increased at the higher levels because the number of proxies decreased and the carbon footprint of the individual inputs were more consistent. Comparing the SOI of *Food Group* and *Food*, although Potato and Minced meat were at the top of the SOI in *Food Group*, they fell out of the SOI completely in the *Food* level onwards. The *Food Group* level included proxies of vastly different magnitudes. Both Potato and Mince meat had large purchase weight, but have emission factors

Figure 3-2: The boxplots show the 25th, 50th and 75th percentile of the total food carbon footprint for the food order list at the five levels of specifications. The Country label represents the Country of Origin. The whiskers extend to the most extreme points that are within 1.5 interquartile ranges from the lower and upper quantiles.

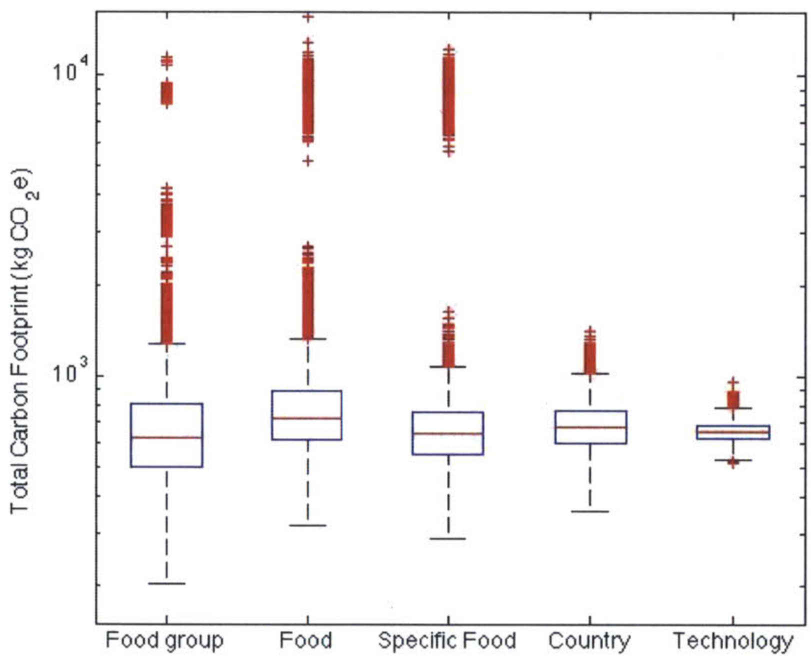


Table 3.5: The lists of food items that fell into the top 90% of the total food CF for more than 75% of the runs, for the five levels of specifications. The inputs that used surrogate data (e.g. Yogurt used the emission factor of Ice cream) are marked with *. The inputs that have interesting shifts between the levels are shaded in orange.

	Set of Interest				
Order of Impact	Food Group	Food	Specific food	Country of Origin	Technology
1	Beef	Beef	Beef	Beef	Beef
2	Fish	Fish	Fish	Fish	Rice
3	Chicken	Beef Tongue	Rice	Rice	Fish
4	Potato	Beef heart	Plant oil	Plant oil	Plant oil
5	Minced meat*	Beef liver	Parmesan cheese	Parmesan cheese	Sugarcane sugar
6	Sugarcane sugar	Rice	Tomato	Sugarcane sugar	Yogurt*
7	Yogurt*	Plant oil	Sugarcane sugar	Canned tuna	Parmesan cheese
8	Rice	Parmesan cheese	Canned tuna	Yogurt*	Canned tuna
9	Chicken eggs	Tomato	Yogurt*	Shrimp	Shrimp
10		Canned tuna	Shrimp	Mozarella cheese	Mozarella cheese
11		Yogurt*	Mozarella cheese	Tomato	Tomato
12		Shrimp	Chicken eggs	Chicken	Zucchini
13		Mozarella cheese	Chicken	Zucchini	String bean*
14		Zucchini	Zucchini	String bean*	Melons
15		String bean*	String bean*	Flour	Flour
16			Flour	Yellow cheese	Yellow cheese
17			Yellow cheese	Chicken eggs	Tomato fruit*
18					Watermelon

on the lower bound of their *Food Group.* Representing them by the average of their food group gave a false impression that they have high carbon footprint contribution. *Food Group* was not a useful level of specification and would be excluded from all other analyses.

Beef Tongue, Beef Heart and Beef Liver quickly fell out of the SOI as we moved from the Food to the Specific Food level. These beef parts were relatively inexpensive compared to the average beef, and were assigned the low emission factors for cheap beef at the Specific Food level. The SOI was quite consistent in the last three levels with some slight shuffling in the order. Tomato dropped from 6th to 11th at the Country of Origin level as many of the higher emission factors from the Temperate climate were removed. The countries with Temperate climate tend to use energy intensive greenhouses with heating for their tomato and thus have higher emission factors [53].

3.3.3 Weight fraction versus carbon footprint fraction

Figure 3-3 shows the average carbon footprint of the SOI as a fraction of the total carbon footprint $\frac{\mathbf{E}[CF_{SOI}]}{textbfE[CF_{Total}]}$ and the weight of the SOI as a fraction of the total weight $\frac{Weight_{SOI}}{Weight_{Total}}$. While on average the SOI contributed to 0.87 of the total carbon footprint, it only contributed to 0.38 of the total weight. This indicated that the food inputs in the SOI, especially Beef, Parmesan cheese and Yoghurt, had high carbon footprint per unit weight. On the other hand, the plant based foods were in the SOI because they were ordered in large volumes. The average carbon footprint of the SOI was slightly lower than 0.90 because the SOI were in the top 90th percentile for only over 75% of the simulations, instead of all the time. Weight of the AP was not a good predictor of its carbon footprint contribution.

3.3.4 Streamlining using the Set of Interest

The streamlined approach of only specifying the SOI to the *Techonology* level effectively reduced the range of the total carbon footprint. The carbon footprint range

Figure 3-3: The carbon footprint fraction $\frac{\mathbf{E}[CF_{SOI}]}{\mathbf{E}[CF_{Total}]}$ and weight fraction $\frac{Weight_{SOI}}{Weight_{Total}}$ of the SOI at the *Technology* level.

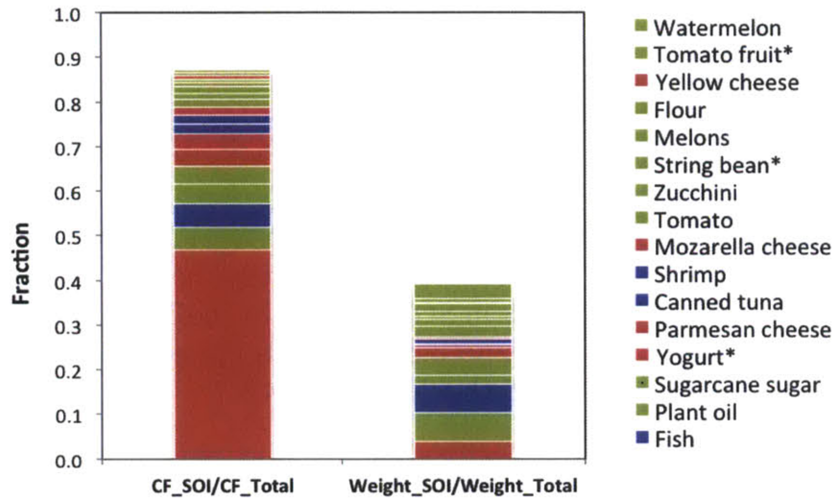


Table 3.6: The distributions of the total food carbon footprint of the food order list before and after streamlining using SOI. The maximums and minimums of the hybrids are very close to those at the Technology level.

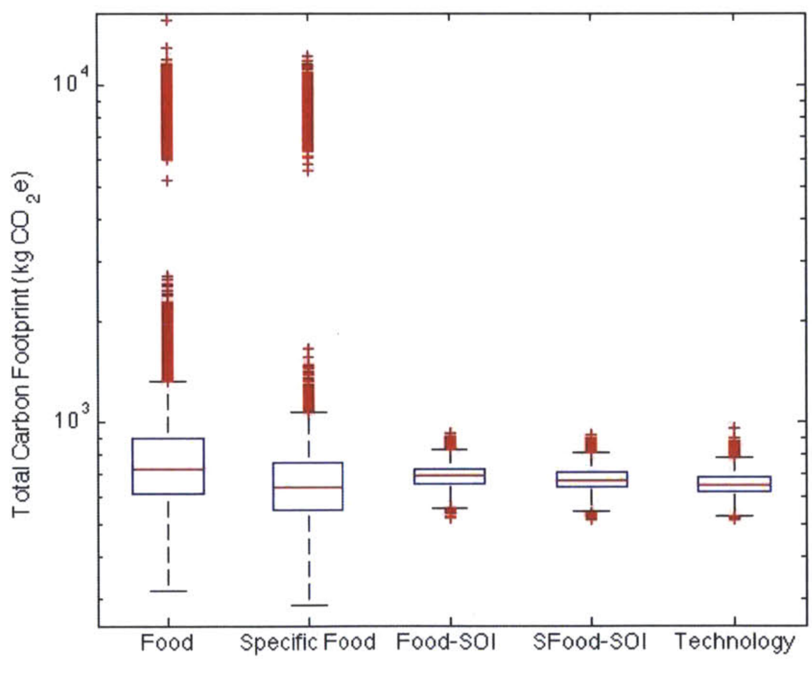
	Total carbon footprint of the food order list/ kg CO2e				
Levels	Food	Specific food	Food-SOI	SFood-SOI	Technology
Maximum	15648	12251	930	914	916
Minimun	316	286	523	518	522
Median	725	647	693	676	655

of the hybrids matched the CF range of the Technology level within the error (Fig. 3-4 and Table 3.6). The results reflected that it was possible to obtain an equally accurate range of the total carbon footprint without the knowledge of the country of origin and the technology for 79 out of the 94 items in the food order list. This could save substantial amount of effort needed to track the supply chain of the less significant foods.

3.3.5 Limitations of the study

Based on our results, we could infer that the approach to streamline using the SOI was reliable on two conditions:

Figure 3-4: The boxplots compare the distribution of the total food carbon footprint for the food order list before and after streamlining using the SOI. Food-SOI and SFood-SOI are the hybrids of the inputs in SOI specified at the Technology level with the remaining inputs at the Food and Specific food levels respectively. The range of the hybrids matches the range of the Technology level well.



1. the cut-off percentile has to be appropriate. It was fortuitous that the cut-off chosen was strict enough to select the attributable processes that affect the carbon footprint the greatest. The results of the hybrids may be worse if the cut-off percentile was lower than 90%. The research methodology could be improved such that the selection of the cut-off percentile was justifiable.

2. the hypothesized true emission factors (at the *Technology* level) has to be in the database that was used to compute the Food and Specific Food levels. The total carbon footprint calculated using existing emission factors does not show that the methodology would be accurate when the emission factors is unknown. In Chapter 4 we would test the effectiveness of the methodology using a test set consisting of emission factors that were not in the database used for the screening calculation.

Moreover, all the computation is based on simulation and most of the rationale behind the resulting spread is made from induction. In the next study, we will introduce the analytical solution to Structured Underspecification.

3.3.6 Summary

By compiling a database and organizing it in a hierarchy, we were able to estimate the carbon footprint of a meal with limited information. The carbon footprint estimate was more precise when we had more information on the food items, because the number of proxies used was reduced. We found that the *Food Group* level did not classify the food item well enough to reduce the variance within the level. Also, of the many food items in the order list, beef appeared to be the food that should be investigated most carefully. The total carbon footprint was changed drastically both when the land use beef emission factor was removed and when the lower beef emission factors were allocated to the cheaper beef parts.

While the SOI contributed to the majority of the total carbon footprint of the order list, their total weight was less than half of the total order weight. The weight of the inputs did not reflect the carbon footprint impact. When we only select the items by their contribution to the total carbon footprint, the hybrids that combined the Set of Interest specified at the *Technology* level with the rest of the food items specified at either the *Food* or the *Specific Food* levels derived carbon footprint estimates that were comparable to the estimate calculated with all 94 food items specified up to the *Technology* level. The SOI had only 15-16 food items. This implied that we only needed to invest our data collection effort on 15 out of 94 food items to get a good estimate of the total carbon footprint. Using the concept of SOI could help the Galapagos Islands ferry tour company save substantial data collection effort and give an equally accurate carbon footprint. We also found parts of the Structured Underspecification that can be further improved, and thus we carried out the next case study with several improvements.

Chapter 4

Cambridge Bondir's Red Broiler Chicken Case Study

The limitations in the Galapagos Tour Ferry Food case study motivated further developments of the food carbon footprinting methodology. A case study was done for a dish served at a restaurant in Boston. The chef from a local farm-house style restaurant, Bondir, provided all the details needed for a complete assessment. Chef Bond's ties with his food suppliers made it possible to collect more details than was possible in the Galapagos Islands Ferry Tour case study.

Several new ideas are incorporated to the food carbon footprint in this case study compared to the Galapagos Island case study. First, instead of using the pedigree matrix, we adopted the Fast Carbon Footprinting approach in assigning coefficient of variance (Section 2.6.2) to the emission factors and the primary data. Second, analytical solutions were introduced for Structured Underspecification. The analytical solutions help reduce computation time and improve the transparency in the individual component contribution. Third, instead of using a strict cut-off requirement for the Set of Interest, an iterative approach similar to that suggested by the Hybrid Framework (Section 2.6.3) was adopted. Fourth, the test set was used to test the performance of averaged proxies for carbon footprint estimation. The application of the test set was extended to broader random cases, and this is presented as standalone Section 4.9 and Section 4.10. Lastly, we introduced a metric that selects the number of attributable processes (APs) in the Set of Interest based on the degree the estimate converges to a stabilized value.

4.1 Problem definition

4.1.1 Primary data of the Cambridge Bondir case study

A detailed form with instructions was created to guide the chef in data collection (Appendix C-3). The information collected consisted of 105 APs in the dish's life cycle, namely, 39 ingredients (Appendix B.2), 36 packaging materials (Appendix B.3), 8 preparation processes (Appendix B.5), 21 transport trips (Appendix B.4) and 1 waste disposal (Appendix B.6). All weights and emission factors were assumed to be independent. The food items with astericks (*) at the *Specific Food* level did not have an appropriate emission factor in the database and were substituted with the food items listed at the *Food* level. There was no data for Mustard seeds, Sugar, Baking soda and Duck fats and they were assumed to be sourced from USA.

For the transportation stage, except for Black pepper and Olive oil, all other materials were from the United States. At the state level, we used 644km for all the local food ingredients, following the definition in the 2008 Congress Bill H.R.2419 [41]. It stated that local food has to be marketed at most 400 miles from the origin of the product. For distances at the *Town* and *Exact location* level, Google Maps was used to obtain the shortest travelling distance between the origin and the destination. The uncertainty in the weight of the primary data was uniformly set at $\pm 5\%$. It was also assumed that the trips were dedicated for delivery and that the return trips were with empty loads.

4.1.2 System boundary of the Cambridge Bondir case study

One of the aims of this case study was to work with an accessible company that could provide complete life cycle information. We referred to the life cycle stages suggested by Jungbluth, namely, the type of product and agricultural practice, the processing for storage and distribution, distance and mode of transportation, the type and amount of packaging and lastly, the food preparation process [11]. In this work, the processes for storage were regarded as part of the food production and waste disposal was added as the last stage. To sum up, the five stages that describe the life cycle of food were Food production, Packaging, Transport, Process and Waste disposal.

4.1.3 Functional unit

The functional unit is the *total carbon footprint per dish of Pasture Raised Red Broiler Chicken* for the Cambridge Bondir case study.

4.2 Data preparation

4.2.1 Emission factors data organization

The description of the hierarchies in the Cambridge Boston case study is in Table 4.1. The difference between the two case studies was that the Galapagos Islands Ferry Tour (Figure 3-1) used only the food production emission factors database and that its hierarchy had an additional Food group level. The Food group level was left out in the second case study because it was not effective in grading the emission factors. The definitions of the specification levels for the other stages were explained in Table 4.1. The levels of specification in the second case study were intentionally kept at four to five for all the stages of the life cycle, but it could be varied for other applications.

4.2.2 Data structure

The units for the emission factors were unified so that the data could be manipulated with ease. The emission factors had to share common units and be organized based on their characteristics. The rationale for converting the emission factors from published sources and primary data to the standardized units in the Cambridge Bondir case study is summarized in Table 4.2 and elaborated in the following subsection. The

Table 4.1: The levels of attribute specifications in the five product life cycle stages.

Life Cycle Stage	Specification Level	Name of level	Description
Food production	Level 1	Food	The common name that is associated with the food. E.g. Banana, Tomato.
	Level 2	Specific Food	Specific variety of the vegetable, or a particular cut of meat.
	Level 3	Origin	The country where the food was produced, such as where the farm or the factory was located.
	Level 4	Technology	The technology used to produce the food.
Packaging Material	Level 1	Material Class	The common class of the material type, such as Plastic, Glass and Paper based.
	Level 2	Application	How the material was used, such as in the form of a bottle or other formed container or a can.
	Level 3	Packaging Material	The specific chemical substance, such as Polyethylene Terephthalate (PET) or Aluminium
	Level 4	Specific Material	Other details such as country of manufacturing, and if the material was recycled or disposed at a landfill after use.
Transport Vehicle (Emission Factor)	Level 1	Mode of Transport	The Mode of Transport was broadly defined as Road, Air or Water.
	Level 2	Vehicle type	The vehicle type referred to the general type of vehicle, such as trucks, cars, or airplanes.
	Level 3	Fuel	The type of fuel used by the vehicle.
	Level 4	Other specifications	Other details that further define the vehicle, such as the model type, the engine efficiency and the road types. These details were clustered together because the emission factors of different vehicle types had different characteristics specified.
Process	Level 1	Process type	The thermal, mechanical and electrical processes used to prepare and clean-up the dish.
	Level 2	Application	If the equipment was built for Industry, Restaurant or Household use.
	Level 3	Energy source	The source of energy for the equipment. It was either gas or electricity.
	Level 4	Equipment	The exact equipment that was used for the process.
Waste disposal	Level 1	Waste type	Compostable, food waste, metal, etc.
	Level 2	Disposal Method	The type of treatment that was applied to store or remove the waste, e.g. incineration or landfill.
	Level 3	Country	The country in which the treatment takes place.
	Level 4	Waste management company	The waste management company that was in charge of the waste disposal.
Origin and destination locations (Driver)	Level 1	Country	
	Level 2	State	
	Level 3	Town	
	Level 4	Exact location	

databases of emission factors and their sources are in Appendix D.1 to D.6. The data treatment details for the emission factors in the food production stage was discussed in Section 3.1.6.

Table 4.2: The units and the equations that were used to calculate the emission of the attributable processes in the life cycle stage.

Life Cycle Stage	Data	Units	Description	Equation/ Characteristics needed	Source Type
Food production	Weight of food per dish	kg produce/ dish	Driver		Collected
	Agriculture Emission Factor	kg CO2e/ kg produce	Emission Factor		Published data
	CF for food input per dish	kg CO2e/ dish		Agriculture Emission Factor x Weight of food per dish	
Packaging Material	Weight of material per unit packaging	kg packaging material/ pack			Collected
	Weight of food per unit packaging	kg produce/ pack			Collected
	Weight of food per dish	kg produce/ dish			Collected
	Weight of packaging material per dish	kg packaging material/ dish	Driver	Weight of material per unit packaging x Weight of food per dish/ Weight of food per unit packaging	Calculated
	Packaging Material Emission Factor	kg CO2e/ kg packaging material	Emission Factor		Published data
	CF for food input per dish	kg CO2e/ dish		Packaging Material Emission Factor x Weight of packaging material per dish	
Transportation	Distance	km	Driver		Collected + Published
	Weight of food per dish	kg produce/ dish	Driver		Collected
	Allocated Transport Emission Factor	kg CO2e/ km* kg product	Emission Factor		Published data
	CF for food input per dish	kg CO2e/ dish		Distance x Allocated Transport Emission Factor x Weight of food per dish	
Process	Equipment operating time per dish	day/ dish	Driver		Collected
	Equipment Emission Factor	kg CO2e/ day	Emission Factor		Spec sheets
	CF for food input per dish	kg CO2e/ dish		Equipment Emission Factor x Equipment operating time per dish	
Waste	Weight of waste per dish	kg waste/ dish	Driver		Collected
	Disposal Emission Factor	kg CO2e/ kg waste	Emission Factor		Published data
	CF for food input per dish	kg CO2e/ dish		Disposal Emission Factor x Weight of waste per dish	

4.2.3 Packaging

The emissions from packaging is the product of the weight of the packaging per dish and the carbon footprint per kg of packaging. The unit of the packaging material emission factors was the carbon footprint per kg of packaging material used $kgCO_{2eq}/kgmaterial$. (Table 4.2) The scope of the emission factors includes the manufacturing phase and the end-of-life disposal of the material, thus solid waste was not listed as an AP.

Some published data only measure the carbon footprint of the raw material, while we needed the carbon footprint of the packaging material in the form it was in use. For example, the carbon footprint of the bottle was the sum of the emissions from the molding process and the emissions from the production of the plastic resins. The carbon footprint during the shaping process was the product of the emission factors of the molding processes (Table D.3) and the weight of the packaging material used.

Allocation

The driver was the weight of packaging material used per dish. The packaging material per pack of food was divided by the number of times the material was reused and the number of dishes it contributed to. We assumed that there was no uncertainty in these numbers. For example, the weight of the material in the plastic bucket used to carry the Duck fat was divided by the 12 times it was reused.

4.2.4 Transport

The emissions from a transportation process is the product of the allocated transport emission factor of the vehicle, and two drivers, the distance between the origin and the destination, and the weight of food per dish. (Table 4.2) The allocated transport emission factor was the carbon footprint that was emitted by the transportation vehicle per km travelled, allocated to each kg of produce carried by the vehicle $kgCO_{2eq}/km \cdot kgfood$ [47, 48]. The distances were tabulated in the form of a hierarchy too because the information of the source had different degrees of clarity.

Allocation

We assumed that the trips were dedicated for delivery, that each delivery trip delivered goods to Bondir solely. This would overestimate the emissions from the transportation module because the trucks delivered to more than one location in each trip. Based on previous knowledge that the carbon footprint of transportation contributed little to the total carbon footprint of prepared food [42, 43], the number of stops per delivery was neglected in the screening calculation. It could be further refined if it was shown to be significant. In addition, the calculation was simplified by assuming the same level of knowledge of the origin and destination, i.e. if we only know the state of origin of the food, we would only know the state of the destination.

4.2.5 Process

The process stage included all the mechanical and thermal processes that were applied for the storage or preparation or cleaning processes at the restaurant. It was assumed that the processes upstream of Bondir were negligible since the ingredients were freshly harvested. The energy demands of the equipment were recorded in terms of power consumption, a measure of energy use per unit time, thus the emission factor of equipment was $kgCO_{2eq}/day$ and the driver was the duration of the process, converted to the unit of day per dish (Table 4.2). The power ratings of the equipment were specified in kWh, and they were multiplied with the emission factor of power in the USA average, 0.595 $kgCO_{2eq}/kWh$ for electricity and 0.179 $kgCO_{2eq}/kWh$ for gas, and then multiplied by 24 hours per day, to obtain the emission factor in the units of $kgCO_{2eq}/day$ [49].

Allocation

Some food was made in bulk. For example, the chicken stock was for 40 servings. The carbon footprint of the heating process was then divided over the servings assuming that the number of servings was a fixed number without uncertainty.

4.2.6 Waste treatment

The emission factor of waste treatment was the amount of greenhouse gas emitted per kg of waste, $kgCO_{2eq}/kgwaste$. The emission factor from waste included the greenhouse gas that was emitted during waste treatment. (Table 4.2) The transportation of the food waste from the restaurant to the disposal site was omitted.

4.3 Data uncertainty

4.3.1 Judged uncertainty

In the Cambridge Bondir case study, the uncertainty in the emission factors was assigned based on the rationale proposed by the Fast Carbon Footprinting. Since even the most accurate estimates by the best-of-class calculations would have coefficient of variation (CV) of $\pm 5\%$, it was suggested that data collection efforts could be conserved by assigning variance based on the analyst's confidence in the data [4]. When compared to the pedigree matrix, this approach also cut down the number of judgments per emission factor from six uncertainty factors to one CV. Thus, in this work, the variance of the emission factors were assigned a CV of 25, 50 or 100% based on how similar it was to the ideal emission factor. If the proxy emission factors have the same characteristic as the AP at level 1 (e.g. the AP was tomato and the emission factors of tomato was used), it was assigned an uncertainty of $\pm 25\%$, if the proxy emission factors are not the exact AP as the real AP, but was judged similar in nature (e.g. the AP was duck fats and the emission factors of duck was used), it was assigned an uncertainty of $\pm 50\%$, lastly, if the proxy emission factors was totally different (e.g. the AP was salt, and the emission factor of sugar was used), it was assigned an uncertainty of $\pm 100\%$. The uncertainties in the emission factors for the APs are tabulated in Tables B.2 to B.6.

4.3.2 Proxy selection

Even though the APs were more specified in this case study, the database did not always have representative proxies at the highest level of specification. Some assumptions had to be made in selecting these sets of proxies. In cases where there was no proxy from the United States, proxies from Europe were selected. For the transportation stage, the trucks were assumed to have engines meeting the Euro 2 standards and the roads travelled were assumed to be motorways. There was only one proxy per AP at level 4 specification.

4.4 Analytical solutions to Structured Underspecification

4.4.1 Average emission factor and its uncertainty

In the Cambridge Bondir case study, an analytical solution was used in place of Monte Carlo simulations. To calculate the expected emission factor of AP_i, or the average of the proxies $\mathbf{E}[EF_i]$ and its variance $var(EF_i)$, let q be the number of proxies, and the emission factor of the kth proxy be EF_k. With Q indicating the selected proxy and $Q \in \{1, ..., k\}$, the expectation of emission factor EF_k of Q was $\mathbf{E}[EF_k|Q = k]$. The expected emission factor would be the averaged proxy,

$$\mathrm{E}[EF_i] = \mathbf{E}[\mathbf{E}[EF_k|Q]] = \frac{\sum_{k=1}^{q} \mathbf{E}[EF_k|Q = k]}{q} \tag{4.1}$$

The Law of Total Variance [54] was used to calculate the variance in the emission factor, EF_i. The derivation of the Law of Total Variance is in Appendix A.1.

$$var(EF_i) = \mathbf{E}[var(EF_k|Q)] + var(\mathbf{E}[EF_k|Q]) \tag{4.2}$$

The total variance can be interpreted as the sum of the average variances of the q proxies, and the variance between the mean of the q proxies. This variance $var(EF_i)$ was fed into Equation 4.3 to find the variance of the total carbon footprint CF_{Total}.

4.4.2 Total carbon footprint and its uncertainty

The estimated carbon footprint of the n APs for $i = 1, ..., n$, CF_i, is the product of the emission factors EF_i and its driver(s) $D_{i,j}$. (Eqn. 2.1). The total carbon footprint would be the sum of all the carbon footprints of the individual APs, CF_i. (Eqn. 2.2)

Since CF_i was a multiple of two or three random variables, we used the standard definition of variance [54] (Eqn. A.6) to derive the variance of the product of multiple random variables. For example, if the ith component had only one EF and one $D_{i,1}$, the variance of the ith carbon footprint CF_i would be equivalent to

$$\begin{aligned}
var(CF_i) &= var\Big(EF_iD_{i,1}\Big) \\
&= \Big(var(EF_i) + \mathbf{E}[EF_i]^2\Big)\Big(var(D_{i,1}) + \mathbf{E}[D_{i,1}]^2\Big) \\
&\quad -\Big(\mathbf{E}\big[EF_i\big]\Big)^2\Big(\mathbf{E}\big[D_{i,1}\big]\Big)^2 \\
&= \Big(\mathbf{E}\big[EF_i\big]\Big)^2 var(D_{i,1}) + \Big(\mathbf{E}\big[D_{i,1}\big]\Big)^2 var(EF_i) \\
&\quad +var(EF_i)var(D_{i,1}) \qquad (4.3)
\end{aligned}$$

Other combinations of emission factors and drivers could be derived using Equation A.6. Assuming that all CF_i were independent of each other, the variance of the CF_{Total} was the sum of variance of the n components:

$$var(CF_{Total}) = \sum_i^n var(CF_i) \qquad (4.4)$$

4.4.3 The pros and cons of analytical solutions

Unlike in the Monte Carlo simulations where the emission factors were stated to have logarithm distributions, the mean and standard deviation of the analytical solution to Structured Underspecification would be the same regardless of the distribution of the emission factors. While the equations do not provide information about the resulting distribution of the total carbon footprint, the logarithm distribution of the emission factors in the Monte Carlo simulations was an artifact adopted from the field of risk assessment (because it does not show negative values). The advantage of using analytical equations instead of Monte Carlo simulation was that the amount of data generated was greatly reduced. With 105 APs, the result was 105 pairs of CF_i and variances. On the other hand, if we had performed 10,000 Monte Carlo simulations, there would be 1050,000 pairs of CF_i and variances to analyse and store.

4.5 Test set

The use of test set to test prediction models is a widely used practice in Machine Learning and Data Mining. The available data set is split into two sets, one set for fitting the prediction model, and the other set to test the performance of the prediction model. This concept was imported to test the performance of Structured Underspecification. The test set was a set of emission factors that was judged to be the most representative emission factors in the database. It would verify that the methodology worked not only because the hypothetically best emission factors were already within the database, but because top contributors largely determined the total carbon footprint and the uncertainty. We would also check if the cut-off percentile of 99%, as recommended by PAS2050, was an effective way to obtain an accurate and precise carbon footprint estimate. In cases where there was only one available emission factor in the database, the emission factor was used both in the test set and as a proxy. The uncertainty in each test set emission factor was set at a coefficient of variance (CV) of $\pm 5\%$. They were assigned a low uncertainty because they were hypothetically true and accurate measurements. This uncertainty should represent the random fluctuations within measurements.

4.6 The Set of Interest

The definition of the Set of Interest was more flexible in this case study. Instead of using a strict percentile cut-off as in the first case study to select the Set of Interest, the Set of Interest was selected step-wise, starting from the AP with the highest impact. The impact of the AP could be its contribution to the total carbon footprint, or its contribution to the uncertainty of the total carbon footprint. If an AP was selected, effort would be invested to find out more about its characteristics. It would progress into a higher level of specification and use a smaller number of proxies while all other APs would use the same proxies as in the previous step:

1. Start *Iteration 0* by calculating the total carbon footprint at Level 1 specifica-

tion.

2. Rank the carbon footprint and the variance of the APs.

3. Replace the emission factor of the AP with the highest impact with the corresponding emission factor from the test set.

4. Recalculate the total carbon footprint and record it.

5. Repeat Step 3, but by updating the AP with the next highest impact based on the rankings from *Iteration 0* in Step 1.

This allowed us to examine the improvement in the carbon footprint estimate with every piece of new information about the characteristics of the AP. Since the uncertainty in test set data was set at $CV = \pm 5\%$, as compared to the proxies that have $CV = \pm 25, \pm 50, or \pm 100\%$, the variance of the carbon footprint estimate should decrease as all the emission factors proxies were updated by a single test set emission factor.

4.6.1 Extent vs Depth

Imagine that we have limited resources to carry out the data collection, we will need further understanding on how we choose the Set of Interest, and the levels of specification we need for each of the 105 APs. More explicitly, we need to decide whether it is reasonable to have some APs at the Level 1 specification, some at Level 2, and so on. There were many possible combinations of cut-off percentiles and levels of specification. We started with a screening calculation in which all the 105 APs were at Level 1 specification, referred to as *Iteration 0.* We considered a straightforward case where the specification of the APs could only be increased to one fixed level (Level 2, 3, and 4). The results would show us if it is more effective to invest our limited resources to gather shallow information about many APs, or if it is more effective to invest the same resources to gather in-depth specificiations about the APs with high impact.

4.6.2 Contribution to the total carbon footprint or total uncertainty

In general, uncertainty is derived from the lack of both accuracy and precision. In this context, accuracy refers to the closeness of the estimated carbon footprint to the real carbon footprint and precision refers to the spread of the estimated carbon footprint. After *Iteration 0*, the option was to either increase the accuracy or the precision of the carbon footprint estimate. To increase the accuracy, the Set of Interest has to be selected based on descending magnitude of individual carbon footprints, CF_i. To increase the precision, the Set of Interest has to be selected based on descending magnitude of individual carbon footprint variances, $var(CF_i)$. Both objectives were desirable and both approaches should converge to the same results, thus it was interesting to compare if one converges to the true total carbon footprint faster.

4.7 Results

4.7.1 Preliminary total carbon footprint estimate

The screening iteration, *Iteration 0* was calculated using all Attributable Processes (APs) with information at Level 1 specification. It represented the calculation that required the least information about the AP. The resulting total carbon footprint of a dish of Bondir's Red Broiler Chicken was $2.1 \pm 0.4 kgCO_{2eq}$. The agriculture and the process stages contributed the most to the total carbon footprint, 53 and 42% respectively. The process stage had high contribution because thermal processes are energy intensive, while material and transport had low contribution because the carbon footprint was allocated to multiple dishes. In addition, the majority of the packaging used plastic, which was light and had low carbon footprint impact.

The contribution from an individual AP calculated based on averaged proxies from specification Level 1 is shown in Table 4.3. The top ten APs are cooking processes and ingredients. The APs that contribute most to the carbon footprints are also the APs that contribute most to the variance. The top six APs contribute to as much as

Stage	%contribution
Agriculture	53%
Material	1%
Process	42%
Transport	7%
Waste	1%

60% of the total carbon footprint, and the 40th AP only contributes to 1g of the total carbon footprint. It is clear from the screening calculation that only a small fraction of the 105 APs have significant impact on the total carbon footprint.

4.7.2 Evaluation of the analytical solution

The expected total carbon footprint and standard deviation of *Iteration 0* calculated based on the analytical solution and a Monte Carlo simulation with 10,000 runs were only 0.4% and 2.4% apart respectively. (Table 4.4) Since the analytical solution was equivalent to the Monte Carlo simulation, the rest of the work was done using the equations only.

4.7.3 Cut-off percentile versus level of specification

Based on the results of *Iteration 0*, the APs that contribute to the cut-off percentiles of 20%, 40%, 60%, 80%, 90%, 95% and 99% were updated to level 2, level 3 and level 4 specifications. (Fig. 4-1) The *best possible* estimate calculated with all 105 APs at specification level 4 was used as a reference. Not surprisingly, updating the high impact APs with the level 4 proxies was the most effective way to converge to the best possible estimate that was calculated using level 4 proxies.

An interesting finding from Figure 4-1 is that the total carbon footprint estimates flattened after the APs which contributed to the top 80% of the carbon footprints were updated, indicating that updating the emission factors of the less significant APs provided negligible marginal improvement to the accuracy of the estimate. If so, there would be little need to expend resources to collect more information about these less significant APs. Resources should be focused on the more significant APs. Relying

Table 4.3: Results from the preliminary total carbon footprint calculation *Iteration 0*. The attributable processes that are highlighted in orange are the cut-offs for 20%, 40%, 60%, 80%, 90%, 95% and 99%

Rank	Index	Attributable Processes	Impact (kg)	Cumulative Impact %	Variance
1	P03	Baking chicken	3.54E-01	17.24%	2.09E-02
2	F01	Chicken	3.19E-01	32.78%	4.50E-02
3	F40	Water	1.77E-01	41.40%	3.72E-02
4	P04	Frying corncake	1.39E-01	48.18%	1.05E-02
5	P06	Cooking marfax beans	1.25E-01	54.29%	8.50E-03
6	F04	Duck Fat	1.23E-01	60.28%	9.86E-04
7	P05	Cooking chicken stock	8.34E-02	64.35%	3.78E-03
8	F26	Water	8.04E-02	68.27%	7.69E-03
9	P01	Cooling chicken	7.60E-02	71.98%	7.01E-04
10	F22	Pork	6.92E-02	75.35%	1.04E-03
11	TEF03	Chicken delivery	5.65E-02	78.11%	2.33E-02
12	F30	Ice	5.12E-02	80.61%	4.14E-04
13	F06	Eggs	4.55E-02	82.82%	8.15E-04
14	F25	Rape seed oil	4.17E-02	84.86%	1.13E-03
15	P02	Searing chicken	4.17E-02	86.89%	9.44E-04
16	F39	Hot water	2.88E-02	88.30%	3.48E-04
17	F14	Butter	2.88E-02	89.70%	7.50E-05
18	P07	Cooking collard greens	2.78E-02	91.06%	4.20E-04
19	F07	Milk	2.70E-02	92.38%	1.24E-03
20	TEF19	Olive oil delivery	2.17E-02	93.43%	4.71E-04
21	F38	Rape seed oil	1.86E-02	94.34%	2.24E-04
22	F08	Flour	1.62E-02	95.13%	2.14E-05
23	TEF20	Olive oil delivery	1.36E-02	95.79%	1.34E-03
24	TEF16	Duck fat delivery	1.36E-02	96.46%	1.34E-03
25	F15	Dried Pea	1.11E-02	97.00%	2.09E-05
26	F37	Wine	9.10E-03	97.44%	1.30E-05
27	Waste	Compost	8.00E-03	97.83%	1.09E-04
28	F09	Flour	7.20E-03	98.18%	4.22E-06
29	TEF04	Spice delivery	5.10E-03	98.43%	1.87E-04
30	TEF18	Olive oil delivery	4.30E-03	98.64%	6.28E-05
31	TEF06	Spice delivery	3.50E-03	98.81%	8.65E-05
32	TEF07	Spice delivery	2.50E-03	98.93%	4.60E-05
33	F10	Sugar	2.40E-03	99.05%	3.75E-06
34	TEF05	Spice delivery	2.00E-03	99.15%	1.20E-05
35	F29	Celery	1.80E-03	99.24%	5.40E-06
36	F17	Celery	1.80E-03	99.32%	5.40E-06
37	F05	Dried herbs	1.70E-03	99.41%	1.86E-07
38	F02	Salt	1.40E-03	99.48%	3.42E-07
39	TEF14	Spice delivery	1.10E-03	99.53%	8.83E-06
40	F27	Onion	1.00E-03	99.58%	3.21E-07
41	F16	Onion	1.00E-03	99.63%	3.21E-07
42	F32	Onion	9.00E-04	99.67%	2.54E-07
43	TEF08	Spice delivery	7.00E-04	99.71%	4.61E-07
44	TEF17	Vegetable delivery	7.00E-04	99.74%	1.52E-06
45	F28	Carrot	6.00E-04	99.77%	1.51E-07
46	F20	Chili	5.00E-04	99.79%	1.80E-08
47	F19	Sugar	5.00E-04	99.82%	1.58E-07
48	F03	Dried Pea	3.00E-04	99.84%	7.44E-09
49	TEF01	Flour delivery	3.00E-04	99.85%	3.50E-07
50	F18	Carrot	3.00E-04	99.87%	3.79E-08
51	F35	Salt	3.00E-04	99.88%	4.88E-08
52	F34	Chili	2.00E-04	99.89%	3.55E-09
53	TEF12	Spice delivery	2.00E-04	99.90%	3.73E-07
54	TEF11	Spice delivery	2.00E-04	99.91%	3.73E-07
55	TEF10	Spice delivery	2.00E-04	99.92%	3.44E-07
56	TEF09	Spice delivery	2.00E-04	99.93%	3.44E-07
57	M01	Plastic Film	2.00E-04	99.94%	8.79E-09
58	F23	Sugar	1.11E-04	99.95%	2.09E-09
59	F21	Dried Pea	1.11E-04	99.95%	2.09E-09
60	M25	Metal Can	9.95E-05	99.96%	2.49E-09
61	F33	Onion	9.06E-05	99.96%	2.54E-09
62	F13	Sugar	8.45E-05	99.97%	1.63E-09
63	M02	Paperbase Box	7.98E-05	99.97%	2.76E-09
64	F12	Sugar	6.16E-05	99.98%	2.47E-09
65	F11	Sugar	6.16E-05	99.98%	2.47E-09
66	TEF13	Spice delivery	5.67E-05	99.98%	2.33E-08
67	M04	Plastic Bucket	5.63E-05	99.98%	6.49E-10
68	F36	Dried Pea	4.94E-05	99.99%	4.12E-10
69	M07	Paperbase Box	4.13E-05	99.99%	7.41E-10
70	M06	Paperbase Box	3.57E-05	99.99%	0.00%
71	TEF15	Spice delivery	2.84E-05	99.99%	0.00%
72	TEF02	Herb delivery	2.59E-05	99.99%	0.00%
73	M05	Plastic Film	2.37E-05	99.99%	0.00%
74	F24	Dried Pea	2.22E-05	99.99%	0.00%
75	M15	Textile Bag	2.04E-05	100.00%	0.00%
76	M38	Metal Can	1.97E-05	100.00%	0.00%
77	M08	Paperbase Bag	1.58E-05	100.00%	0.00%
78	M19	Metal Can	1.19E-05	100.00%	0.00%
79	M03	Plastic Bottle	7.79E-06	100.00%	0.00%
80	M09	Paperbase Bag	7.04E-06	100.00%	0.00%
81	M27	Plastic Film	5.09E-06	100.00%	0.00%
82	M16	Plastic Film	5.09E-06	100.00%	0.00%
83	F31	Cabbage	4.50E-06	100.00%	0.00%
84	M10	Paperbase Bag	2.32E-06	100.00%	0.00%
85	M32	Plastic Film	2.01E-06	100.00%	0.00%
86	M11	Metal Can	1.87E-06	100.00%	0.00%
87	M14	Paperbase Packaging paper	1.69E-06	100.00%	0.00%
88	M22	Plastic Film	8.15E-07	100.00%	0.00%
89	P08	Dish washing	5.78E-07	100.00%	0.00%
90	M28	Plastic Film	4.08E-07	100.00%	0.00%
91	M17	Plastic Film	4.08E-07	100.00%	0.00%
92	M21	Plastic Bottle	3.65E-07	100.00%	0.00%
93	M12	Paperbase Box	2.65E-07	100.00%	0.00%
94	M29	Plastic Film	2.04E-07	100.00%	0.00%
95	M18	Plastic Film	2.04E-07	100.00%	0.00%
96	M23	Paperbase Box	1.56E-07	100.00%	0.00%
98	M13	Paperbase Box	1.54E-07	100.00%	0.00%
99	M20	Plastic Film	9.74E-08	100.00%	0.00%
100	M37	Plastic Bottle	8.15E-08	100.00%	0.00%
101	M33	Plastic Film	4.76E-08	100.00%	0.00%
102	M34	Plastic Film	4.02E-08	100.00%	0.00%
103	M24	Plastic Bottle	1.61E-08	100.00%	0.00%
104	M36	Plastic Bottle	1.22E-08	100.00%	0.00%
105	M31	Plastic Film	1.20E-08	100.00%	0.00%

Table 4.4: The expected total carbon footprint and standard deviation of Iteration 0 calculated based on the analytic solution and a Monte Carlo simulation with 10,000 runs

	Analytical solution	Monte Carlo simulation results
Mean	2.051	2.043
Standard Deviation	0.392	0.383

solely on the PAS2050 guideline to cutoff at the 99th percentile of the screening calculation would require the analyst to obtain accurate emission factors of the top 33 APs. Verification with the test set would show us if a cut-off percentile of 99% was too strict.

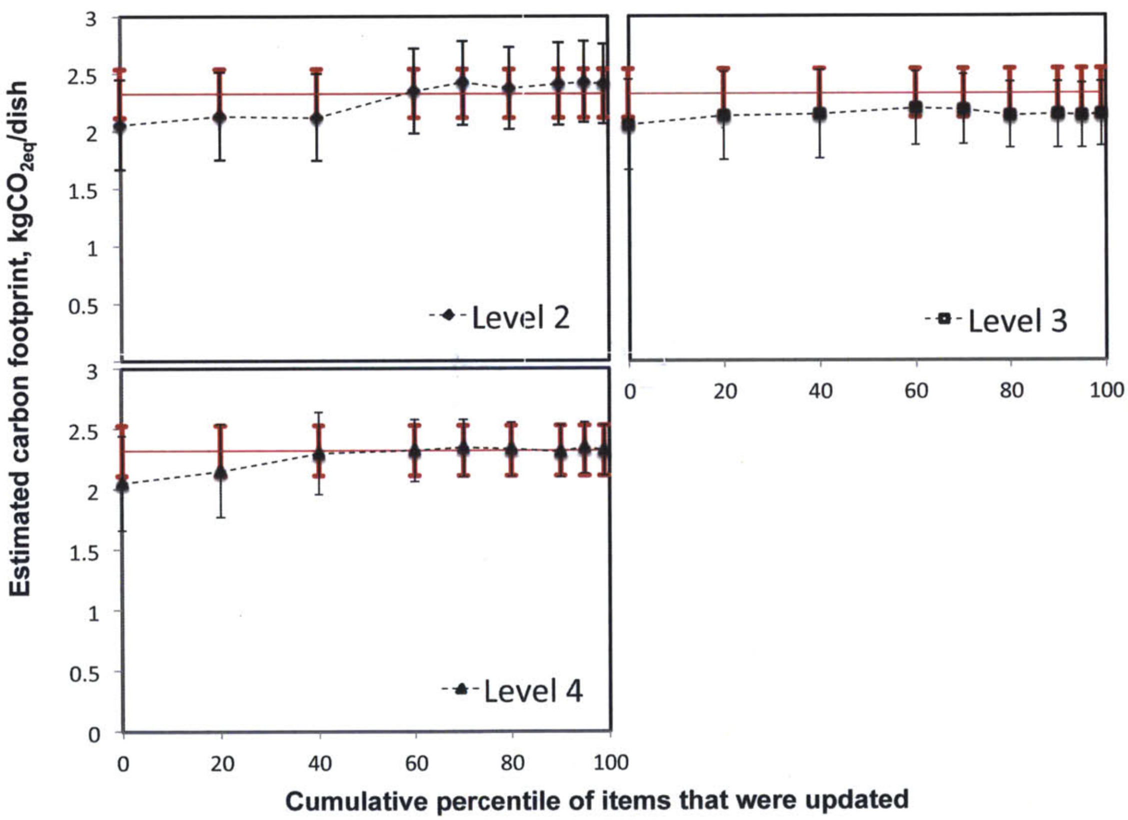


Figure 4-1: Starting from *Iteration 0*, the attributable processes that contributed the most to the total carbon footprint were updated with the proxies at level 2, 3 and 4 specifications. The red line is the best possible carbon footprint estimate that was calculated when all 105 APs were at specification level 4.

Increasing the number of APs that were specified at level 2 and 3 did not make the total carbon footprint estimate converge to the best possible result. Level 2 and 3 underestimate at the first 20% cut-off because the proxies for roasting chicken (P03) included emission factors of 31 $kgCO_{2eq}/day$ while and 44 $kgCO_{2eq}/day$ while the proxy at the level 4 specification was 44 $kgCO_{2eq}/day$ and again at 40% cut-off because the proxies for chicken (F01) at level 2 and 3 include emission factor between the range of 1 to 4 $kgCO_{2eq}/kg - chicken$ while the proxy at level 4 specification was 5.77 $kgCO_{2eq}/kg - chicken$. Level 2 eventually overestimates after 40% cut-off, because the tap water (F40) has proxies that were in the magnitude of 0.2-0.4 $kgCO_{2eq}/kg - water$ by the 3rd level, these values were removed and the average dropped to 0.0003 $kgCO_{2eq}/kg - water$. The greater value was derived from a LCA with included the emission during water treatment, while the lower value excluded that. This shows that the inconsistencies in LCA results exist and can pose problem when choosing proxies. The progression from level 2 and level 3 does not necessarily guarantee an improvement in the prediction because there can be wide variation in the emission factors even within the same level of specification. Neither was the estimate at level 3 any better than the estimate at *Iteration 0*.

4.7.4 Total carbon footprint of the Red Broiler Chicken

The significance of using the test set was to show that the carbon footprint estimate would converge quickly even when only a small fraction of the APs had the unknown true emission factors in the test set, while the rest of the APs were represented by proxies at specification level 1. Figure 4-2 shows that the carbon footprint estimate quickly converged as the APs with high impact were updated with the test set data.

Based on the blue curve in Figure 4-2, the carbon footprint estimates was $2.34 \pm 0.06 kgCO_{2eq}/dish$ when the top 33 AP were updated. The final estimate when all 105 APs were updated with the test set emission factors was also $2.34 \pm 0.06 kgCO_{2eq}/dish$. There could be a more cost-effective way to cut-off and still give an estimate that is as accurate as at the 99th percentile mandated by the PAS2050.

Lastly, the best possible estimate at the specification level 4 was $2.3 \pm 0.2 kgCO_{2eq}/dish$, which was more accurate and precise than the estimate at the Specification level 1 at $2.1 \pm 0.4 kgCO_{2eq}/dish$. However, there was no merit to this estimate because the

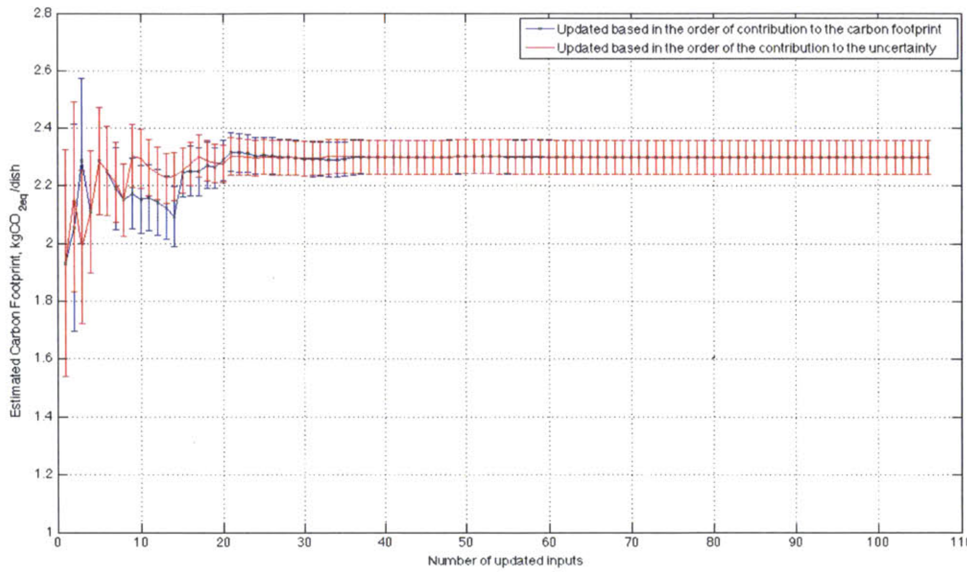


Figure 4-2: The total carbon footprint estimate of Bondir's Red Broiler Chicken dish. The APs with the highest impact to the total carbon footprint, both in terms of absolute contribution (blue line) and contribution to the uncertainty (red line), were updated with the emission factors from the test set step-wise.

level 4 proxies and the test set proxies were purposely selected with the intention that they should be very similar values.

4.8 Section take-away

The hierarchy was not effective at reducing the uncertainty of the Red Broiler Chicken dish. Wide variance persisted in the level 2 and 3 specifications of APs such as tap water and chicken, and as a result the estimate was inaccurate and imprecise when numerous APs were updated. The hierarchy was dropped, the case study departed from using Structured Underspecification and took a new turn. Without the complications of the levels, the questions became more fundamental, addressing general methodology questions such as:

1. How could averaged proxies be used to identify the Set of Interest (SOI)?
2. Would the estimate be accurate if we used averaged emission factor proxies for

the insignificant APs, and the best possible emission factor for the SOI only? would it work if the best possible emission factors are real emission factors that may not be within the range of the proxies?

3. Would the hybrids of averaged proxies and the best emission factors work for other meals than Red Broiler Chicken?

4.9 An important extension: Random test sets and meals

This section includes extensions to the Cambridge Bondir case study by applying different degrees of randomness to the methodology. Two sets of factors, namely, the test set emission factors, and the composition of the meal, were varied.

4.9.1 Random test sets

The selection of the test set was done based on judgement and there could have been bias in the selection such that the results would converge. Instead of fixing the test set by judgement, the proxies were randomly selected from the level 1 proxies. This would mean that the emission factor of a piece of chicken meat from India that was bred in a conventional method would be as likely to be the true emission factor as the emission factor of a piece of free range chicken meat from the United States. This step does not help us better estimate the total carbon footprint of the Red Broiler Chicken dish, but it would ensure that the result in Section 4.6.2 was not dependent on the selected test set.

4.9.2 Other ways to set cut-off boundaries

Moreover, the results from multiple random test set simulations could be used to identify a good size of the Set of Interest, by observing the average rate at which the simulations converge to a stable estimate. The goodness of convergence could be measured by two parameters, 1) the percentage difference of the total carbon footprint at *Iteration n* (CF_n) and the final carbon footprint estimate (CF_{final}), δ_n, where

$$\delta_n = \frac{CF_{final} - CF_n}{CF_{final}} \tag{4.5}$$

and 2) the value of the coefficient of variance at *Iteration n*, CV_n.

The tolerance for both δ_n and CV_n were set at 1% and 3% respectively, and β was defined as the xth consecutive time where δ_n was smaller than 1% and CV_n was smaller than 3%. The term x was set at 5. The requirement for the accuracy would be stricter if δ_n, CV_n are smaller and x is large. The average β could be obtained over multiple simulations.

4.9.3 Application to other meals

We further tested the usefulness of the methodology beyond the recipe at the Bondir restaurant. The driver of the AP and the APs in the meal were randomized to create new meals. These random meals were created by choosing any other 105 APs listed in the emission factor database in Appendix D.1 to D.6, based on their level 1 specifications (namely, Food, Material Class, Mode of Transport, Equipment type and Waste type). Thus the meal could be made up of 40 road trips, 10 air trips, 5 beef, 20 plastic, 30 various vegetables. The weights of the APs were varied uniformly between 0 to 0.01 kg. Distances were fixed at 100 km for simplification.

Consistent results for random meals would 1) support the use of averaged proxies as a reliable first step to identify the high impact APs in food, 2) confirm that the results could converge to a stable carbon footprint estimate even when only the high impact APs have the true emission factors and the other less significant APs are merely represented by the averaged proxies.

4.10 Results for Random test set

The results from 3 simulations of random test sets are shown in Figure 4-3. The carbon footprint estimates converged regardless of the test set, proving that the results in Section 4.7.4 were not dependent on the selected test set. In all three cases, the total carbon footprint estimates stablize when around 20 APs were updated with the test set values. The trend is the same for all other simulations, except for the runs which included the beef with land use change values (there were two values, one that is 26 times the average beef, and one that is 4 times the average beef). The extreme abnormality was removed for the rest of this study, but it was noted that analysts need to be aware of outliers while using averaged proxies.

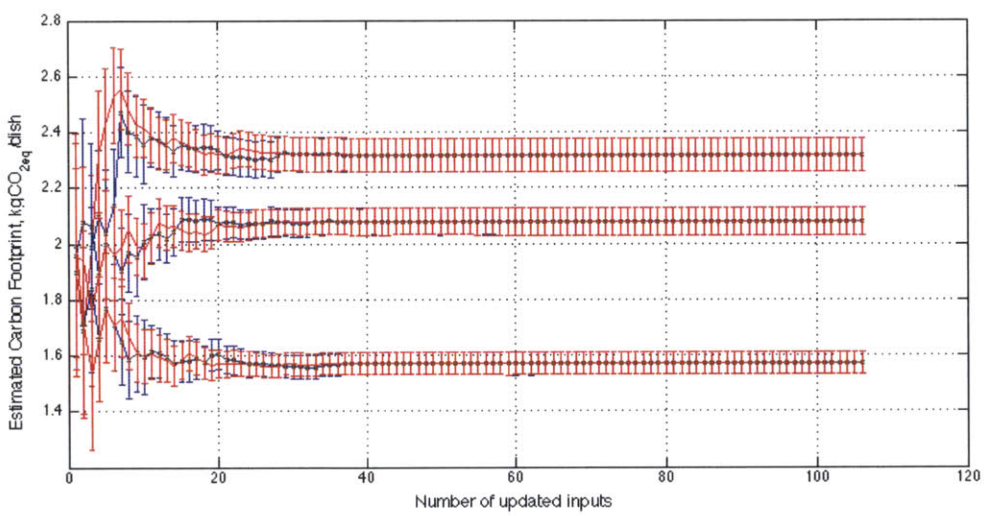


Figure 4-3: The results from four simulations of the total carbon footprint calculation with different test sets. Regardless of the test set, the carbon footprint estimate will converge when over 20 attributable processes were updated. The APs with the highest impact to the total carbon footprint, both in terms of absolute contribution (blue line) and contribution to the uncertainty (red line), were updated with the emission factors from the test set step-wise.

4.10.1 Adaptive cut-off boundaries

With an understanding that the better strategy to obtain an accurate carbon footprint estimate is to find the true emission factor of the highest impact APs from Section

4.7.3, the follow-up question is: how can we define the number of high impact APs, or the size of the Set of Interest based on our preferred accuracy? A potential answer is that we could use the database of emission factors to carry out numerous simulations with random test sets to find an average β based on our preferred δ_n, CV_n and x (Please refer to Section 4.9.2 for definitions).

The random test set is simulated for another 50 times with $\delta_n = 0.01$, $CV_n = 0.03$ and $x = 5$, and the averaged size for the Set of Interest, β, turned out to be 27. The estimate when $\beta = 27$ was $2.34 \pm 0.06 kgCO_{2eq}/dish$, similar to the final estimate. The absolute deviation of the estimated mean from the hypothetically true mean decreased from $\pm 16\%$ to less than $\pm 1\%$ and the uncertainty decreased from $\pm 20\%$ to ± 2.6 by the 27th iteration when the estimated uncertainty at the 105th iteration is $\pm 2.5\%$. Having the hypothetically true carbon footprint value of as few as 27 out of 105 APs could give us a good approximation of the hypothetically true mean and deviation of the total carbon footprint of the restaurant dish. Using the β can save us data collection affort for six less AP than if the 99th percentile cut-off was imposed. Should less accuracy is needed, and the parameters δ_n, CV_n could be increased and x can be decreased while selecting β. These parameters can be self-defined or standardized across the same industry.

4.10.2 Updating by contribution to the absolute carbon footprint or its uncertainty

The rate of convergence by either updating APs with high CF_i or APs with high $var(CF_i)$ was tested on the original test set in Figure 4-2. It appeared that the total carbon footprint calculated using the level of contribution to the total uncertainty as a means to identify the high impact APs stabilized faster. However, this may be dependent on the test set (which is selected by the author's judgement) and the trend may not be consistent if another test set was used. Thus we compared the two approaches using many random test sets. The βs were measured for different sets of δ_n, CV_n and x. Five hundred simulations were performed for each set of parameters.

The approach to update APs with high $var(CF_i)$ had smaller β_{CV} than to update APs with high $var(CF_i)$, $\beta_{var(CF_i)}$ in all three combinations of parameters is listed in Table 4.5. (Figure 4-4) To update APs in the order of their contribution to the uncertainty made the estimate converge faster on average. Even though these selected combinations of parameters and the strong overlap between the distribution of the betas were not strong evidence to prove that any one approach was clearly better, by rationale, the approach to update APs with high $var(CF_i)$ should converge faster. On top of the fact that it has already accounted for the uncertainty, the $var(CF_i)$ was proportional to the carbon footprint, CF_i (since $var(CF_i) = (CV * \cdot CF_i)^2$). Thus to update APs with high $var(CF_i)$ increased accuracy and precision at the same time.

When compared to the 99th percentile cut-off, the β cut-offs were often smaller, except for in the strictest case. The averages of the β were always smaller, showing that to use β would almost always reduce data collection effort while assuring that the carbon footprint has converged to a stable value.

Table 4.5: The sets of δ_n, CV_n and x to represent different levels of strictness. A CV of 0.035 is the lowest possible.

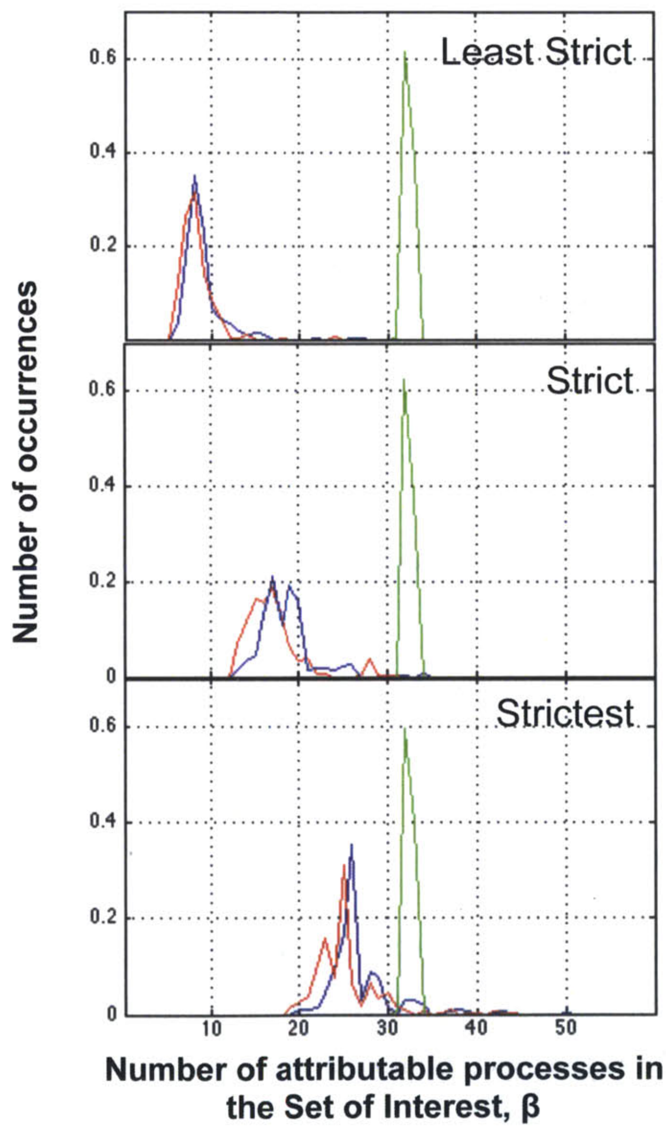
Relative strictness	δ_n	CV_n	x
Least strict	0.1	0.1	2
Strict	0.05	0.05	5
Strictest	0.01	0.035	7

4.11 Random meals

A meal was defined as any combination of 105 APs from the emission factor databases. The aim of this approach was to find out if the methodology would work in the same way if the meal consisted of the other inputs that were not included in the Red Broiler Chicken dish, such as beef, or pork.

The result was again positive. (Fig. 4-5) The total carbon footprint converged as a small fraction of the APs was updated. The screening calculation using average proxies was a viable first step to identify the APs that had high impact as it could

Figure 4-4: The distribution of βs at different levels of strictness. The y-axis is the number of occurences normalized by 500 simulations. The blue line is for $\beta_{var(CF_i)}$, the red line is for β_{CV} and the green line is the 99th percentile cut-off.



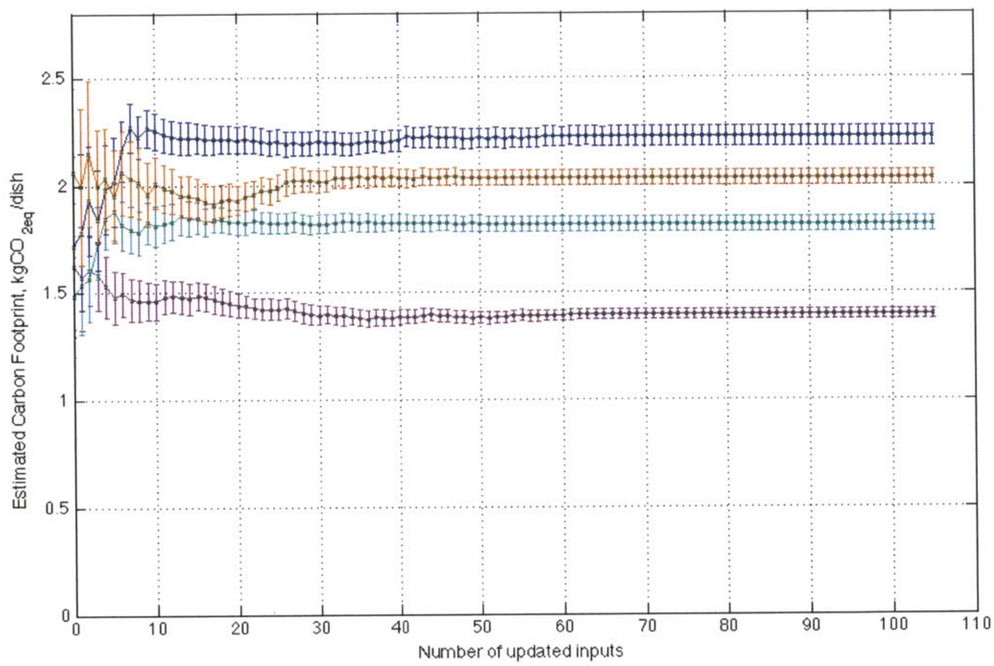


Figure 4-5: The results from four simulations of the total carbon footprint calculation of random meals. Regardless of the test set, the carbon footprint estimate will converge when over 20 attributable processes were updated.

reduce the data collection effort and estimate carbon footprint accurately. Given that there was a wider variation in random meals than in random test sets, we expected that the β derived using $\delta_n = 0.01$, $CV_n = 0.03$ and $x = 5$ from fifty random meal simulations should be larger than when the meal was fixed, and indeed, it was 36.

4.12 Summary

In this case study, we had effectively used the analytical solutions in place of the Monte Carlo simulations. Using the analytical solutions step-wise, we were able to observe how the total carbon footprint estimate converged as more APs were updated with less proxy emission factors. This trend persisted regardless of the level of specification, showing that increasing the precision of the insignificant APs did not have observable impacts on the accuracy or the precision of the total carbon footprint, and could be left unchanged. On the other hand, investments to collect accurate data of the high impact items would correct the total carbon footprint estimate in a few iterations. While a screening calculation using proxies at level 1 specification was a viable first step to identify the APs with high impacts, levels 2 and 3 may not be adequate at estimating an accurate food carbon footprint because there could still be wide variances between the emission factors within the same level. The database could be better organised using clustering techniques to ensure that the variances were lower in the higher levels.

Given that the streamlined approach was able to converge to the total carbon footprint even when the random test sets were used, we conclude that the average proxies were a good way to represent the hypothetically true carbon footprint. Also, regardless of whether the best emission factor is the test set or the level 4 specification, the most effective way is to focus only on the APs with high impact. Moreover, it was found that the convergence occurred more rapidly when the APs with high uncertainty $var(CF_i)$, instead of the APs with high carbon footprint contribution CF_i, were updated in each step because $var(CF_i)$ correlated with both the carbon footprint and the uncertainty of the AP.

When it comes to selecting the best cut-off boundary, the 99th percentile cut-off mandated by the standards was too strict. We found that using random test sets to find the cut-off size β was a more adaptive approach that can provide equally accurate food carbon footprint estimate. Lastly, this approach can be applied to other combination of food, packaging, transport, cooking processes and waste disposal to cut down data collection effort effectively. If a restaurant wants to compute the total carbon footprint in their dishes, instead of collecting data for all the APs that covered the life cycle of the food, or using the PAS2050 recommended solution to ignore only the last 1% of the carbon footprint impact, they could estimate their carbon footprint step-wise to choose an adaptive cut-off size based on the desired accuracy within the bounds of maximally possible accuracy.

Chapter 5

Conclusion

The ultimate objective of this thesis was to reduce the data collection efforts in carbon footprint analysis by using multiple proxies to obtain a refined carbon footprint estimate and its uncertainty. While the overall motivation was the same in the two case studies, they took on different trajectories and concluded on different notes. In this chapter we would review the key points that were brought up in the case studies, and how the research procedure could have been improved.

5.1 Summary of differences in the two case studies

The detailed differences in the research procedures between the two case studies are outlined in Table 5.1. The limitation of the application of Structured Underspecification in the Galapagos Islands case study was that the methodology did not guarantee that the final carbon footprint could be truly reflective of the real carbon footprint since the final estimate was calculated based on existing emission factors instead of true emission factors (the same as saying that a black cat is black.) An ensuing question was, would the hybrid of the specified Set of Interest and non-specified insignificant APs still predict well, if some of the true emission factors were out of the range of the existing proxies? Thus, in the second case study we used test sets to examine this question. The use of a test set could verify that the use of averaged proxies in Structured Underspecification can also work when the true emission factor may be out of the range of the existing proxies. The other notable improvement in the case study was the introduction of the step-wise approach to clearly illustrate the marginal improvement of increasing specification for one AP at a time. This improvement allowed us to calculate an adaptive boundary cut-off that could minimize data collection efforts.

Table 5.1: Differences between the Galapagos Islands Ferry Tour case study and the Cambridge Bondir case study.

Steps in the methodology	**Galapagos Islands Ferry Tour**	**Cambridge Bondir**
The system boundary	Only the food production phase, from cradle to farm gate, was included.	Included the five stages across the life cycle of the product. The stages were: food production, packaging, transport, processes, and disposal.
The functional unit	The food ordered for a ferry tour in the Galapagos Islands, Ecuador.	A dish of Pasture Raised Red Broiler Chicken served at Bondir, Cambridge.
The hierarchy structure and levels	The food production stage included five levels of specification, namely the Food group, Food, Specific Food, Country-of-origin and Technology.	Each of the five stages had four levels of specification. (Table 4.1)
Methods to quantify the uncertainty of the emission factors	The uncertainties of the proxies were quantified using the Data Quality Indicators (Section 3.2.2)	The uncertainties of the proxies were assigned a coefficient of variance directly.
Methods to obtain the total carbon footprint and its uncertainty	Monte Carlo simulations were used to estimate the expected total carbon footprint and its variance.	Analytical equations were used to calculate the expected total carbon footprint and its variance.
Methods to select the Set of Interest	The Set of Interest was selected using a fixed cut-off.	The size of the Set of Interest was selected step-wise, starting with a screening calculation. A test set was used to measure the effectiveness of the methodology.
Further work	Not applicable	The methodology was extended to multiple random meals.

5.2 The effectiveness of Structured Underspecification

The Galapagos Islands Ferry Tour case study applied *Structured Underspecification* and the concept of the *Set of Interest* to calculate the total carbon footprint of a food order list. The application of Structured Underspecification was to show that a hierarchy could classify emission factors such that analysts could choose multiple emission factors if there was not enough information or expertise to select one. We observed a distinct improvement in the prediction with increased specification. The results from the hybrids also supported the Set of Interest streamlined approach, which proposed that only a subset of the APs had to be specified to obtain a total carbon footprint relatively close to the total carbon footprint calculated if all APs were specified.

However, Structured Underspecification was shown to be less effective in the Cambridge Bondir case study when we apply the test set. We observed that when the high impact items were poorly specified at level 2 and 3, the total carbon footprint estimates never converge to the best possible estimate regardless of increased number of items in the Set of Interest.

5.2.1 Importance of well organized hierarchy

The performance of Structured Underspecification depended a lot on reducing variance with increasing levels of specifications. We witnessed great improvements in the Galapagos Islands Ferry Tour case study because the order list included beef, which has emission factors of three groups: Land use change ($7.5kgCO_{2eq}/kgmeat$ to $1025kgCO_{2eq}/kgmeat$), normal meat ($8kgCO_{2eq}/kgmeat$ to $45kgCO_{2eq}/kgmeat$), and cheap meat ($4kgCO_{2eq}/kgmeat$ to $4.2kgCO_{2eq}/kgmeat$). Since beef was a significant portion of the food consumed on the ferry tour, including normal and cheap meats, the variance of the total carbon footprint changed greatly as the generic beef was specified. On the other hand, the APs in the Red Broiler Chicken dish had only small changes in variances that were cancelled out by the effects of the other APs, such as in the level 2 prediction where the low averaged proxies of chicken was cancelled out by the high averaged proxies of tap water. Based on this result, it appeared that the variation of food emission factors within the same specie generally nullifies the effect of increasing specification and Structured Underspecification is less applicable in food industries.

5.3 Classification of uncertainty

While there were many types of uncertainty, this work broadly defined them to be uncertainties in data quality, data gaps and cut-off errors. We integrated uncertainty analysis of data quality and data gaps in the total carbon footprint calculations using the averaged proxies. These can represent the uncertainty from the perspective of an analyst who received the data as single point data. Data quality could be better refined if the Data Quality Indicators were used, however it can be more time consuming and may be better if they were used exclusively for the Set of Interest.

5.4 Judged uncertainty

The use of judged uncertainty in place of the Data Quality Indicators in the Cambridge Bondir case study reduces the number of values the analyst would need to judge from five indicator scores to one coefficient of variance, and removes the calculation steps needed to convert the indicator scores to arithmetic means and standard deviations. Even though computation work was simple, the reduction in the analyst judgement saved substantial labor time.

5.5 Use of averaged proxies

One of Structured Underspecification's advantages over the common concept of averaged proxies [25] was the way the variance of the averaged proxies was calculated.

Instead of taking the variance of all the proxies assuming that they belong to the same population, Structured Underspecification assumed that each proxy had its own distribution, capturing a more realistic and broader variance.

The later half of the Cambridge Bondir case study departed from the use of the hierarchy structure, but retained the use of averaged proxies. The streamlined approach was verified with multiple test sets, showing that it worked even when some of the test set emission factors may be outside of the range of the existing emission factors (excluding the extremely outlying emission factors).

5.5.1 Analytical solutions

This is the first work to introduce the Law of Total Variance for calculating the variance of averaged proxies considering that the proxies have separate distributions. The means and variances from the analytical solutions matched those of the Monte Carlo simulations. While the analytical solutions can cut down the computing time and the amount of data generated, it could not project the final distribution shape of the total carbon footprint. On the other hand the distribution obtained from the simulations was a shape that was adopted from the field of risk assessment, instead of the true distribution of the data. Either approach can be used based on the analyst's need.

5.6 Step-wise carbon footprint calculation

While the PAS2050 recommended a direct cut-off based on a screening calculation, the GHG protocol and the *Hybrid Framework* recommended a more flexible option where the data collection priority is assigned to the APs that have high impact on both the contribution and the uncertainty. Applying the two approaches in two separate case studies showed that the step-wise approach revealed more information about the marginal improvement of the carbon footprint estimate with incremental refinement of the data quality. This work firmly supported William's proposition that the integration of uncertainty analysis into carbon footprint estimate can allow the analyst to choose the appropriate point to end the carbon footprint analysis.

The results encouraged the protocols and standards to emphasize uncertainty analysis. Instead of giving priority to APs in the order of their contribution to the carbon footprint, giving priority to APs in the order of their contribution to the uncertainty increased the accuracy and the precision of the estimate simultaneously. Using uncertainty to order would avoid investigating an AP that contributed greatly to the total carbon footprint, but had little uncertainty. This work also approaches the screening calculations with process-based calculations, and we could have started with the top down approach using EIO-LCA to find out the hotspots. The process-based approach most likely underestimated the carbon footprint.

5.7 Cut-off boundaries

In the Galapagos Islands Ferry Tour case study, we found that weight was indeed not reflective of the environmental impact of APs. In the Cambridge Bondir case study, we compared the performance of using a fixed 1% cut-off or the adaptive set of interest size, β, and found that the 1% cut-off required more items to be further studied than if β was used. In general, both methods have their advantages. While βs allow adaptive and justifiable cut-off boundaries, 1% cut-off is a simpler concept to comprehend.

5.8 Application of test sets

The application of the test sets was the most novel contribution in this work. First, it proved that the step-wise approach would converge to the hypothetically true total carbon footprint even when only the SOI had the hypothetically true and new emission factors while the less significant APs were only represented by existing emission factor proxies. Secondly, using randomized test sets better gauged the right cut-off size because it accounted for the case when the real emission factors were not within the range of the existing emission factors.

In conclusion, by merging the popular concepts and recommendations that were suggested by different groups of researchers, we created a methodology to estimate food carbon footprint from the perspective of businesses in the food service sector. The aim of the work was to show that carbon footprint calculation can be fast, cheap and reliable at the same time. Although using published emission factors required substantial data collection from published documents, it saved the need to carry out real measurements in the field. After the database was compiled, the screening calculation was fast. Approximating uncertainty using the Fast Carbon Footprint rationale was practical and cut down the time needed to judge data quality. Lastly, to carry out the total carbon footprint calculation iteratively, or step-wise, to identify high impact items was verified to effectively cut down the data collection effort required while still obtaining relatively accurate and precise estimates. The step-wise approach clearly depicted the improvement with every revision to the emission factors, allowing the analyst to stop their investigation when the carbon footprint estimate converged to a desired accuracy and precision. In the future, the equations and database can be built into a user-friendly program such that anyone can carry out a calculation since no expert judgment is needed. Large corporations that want to obtain highly accurate carbon footprints can invest to obtain better carbon footprint data for only the high impact items. Further improvements to this approach can make carbon footprint labeling less daunting in the future.

Appendix A

Equations

A.1 Derivation of the Law of Total Variance

The difference between the condition expectation of the qualified emission factor $\widehat{EF_i}$ and the emission factor EF_i is defined as

$$\widetilde{EF_i} = \widehat{EF_i} - EF_i \tag{A.1}$$

If we are given Q, then $\mathbf{E}[\widetilde{EF_i}|Q] = 0$, and $\mathbf{E}[\widetilde{EF_i}] = 0$. $\widetilde{EF_i}$ and $\widehat{EF_i}$ is uncorrelated. [1] Rearranging Equation A.1, the variance of EF_i is

$$var(EF_i) = var(\widehat{EF_i}) + var(\widetilde{EF_i}) \tag{A.2}$$

To find $var(\widetilde{EF_i})$ we introduce $var(EF_i|Q)$ where

$$var(EF_i|Q) = \mathbf{E}[(X - \mathbf{E}[EF_i|Q])^2|Q] = E[\widetilde{EF_i}^2|Q] \tag{A.3}$$

and

$$var(\widetilde{EF_i}) = \mathbf{E}[\widetilde{EF_i}^2] - \mathbf{E}[\widetilde{EF_i}]^2 = \mathbf{E}[\widetilde{EF_i}^2|Y] = \mathbf{E}[var(EF_i|Q)] \tag{A.4}$$

using equations ??, A.2, A.4, we get

[1]Proof: $cov(\widetilde{EF_i}, \widehat{EF_i}) = \mathbf{E}[\widetilde{EF_i}\widehat{EF_i}] - \mathbf{E}[\widetilde{EF_i}]\mathbf{E}[\widehat{EF_i}] = 0$ because $\mathbf{E}[\widetilde{EF_i}] = 0$ and $\mathbf{E}[\widetilde{EF_i}\widehat{EF_i}]$ $= \widehat{EF_i}\mathbf{E}[\widetilde{EF_i}] = 0$

$$var(EF_i) = \mathbf{E}[var(EF_i|Q)] + var(\mathbf{E}[EF_i|Q]) \tag{A.5}$$

A.2 The Variance of the Product of Multiple Random Variables

The following definition can be used to derive the variance of the product of multiple random variables. Equation A.6 closely resemble the standard definition of variance ($var(X) = \mathbf{E}[X^2] - \mathbf{E}[X]^2$)]

$$\begin{aligned} var\Big(\prod_{i=1}^{m} X_i\Big) &= \mathbf{E}\Big[\prod_{i=1}^{m} X_i^2\Big] - \prod_{i=1}^{m}\Big(\mathbf{E}[X_i]\Big)^2 \\ &= \prod_{i=1}^{m} \mathbf{E}[X_i^2] - \prod_{i=1}^{m}\Big(\mathbf{E}[X_i]\Big)^2 \\ &= \prod_{i=1}^{m}\Big(var(X_i) + (\mathbf{E}[X_i])^2\Big) - \prod_{i=1}^{m}\Big(\mathbf{E}[X_i]\Big)^2 \end{aligned} \tag{A.6}$$

A.3 Compound Uncertainty

This part of the work is mainly to explained the work by Dr. Meinrenken in his paper *Fast Carbon Footprinting for Large Product Portfolios* using his explanations in the supporting information [?]. For simplification, we will represent both EF_i and $D_{i,j}$ as $D_{i,k}$ where in this context k is the index of both the emission factors and drivers of the ith component. By combining equations 2.2 and 2.1 and expanding the function about the sample mean $\overline{CF_{Total}}$ by Taylor series [2], we obtain

$$\begin{aligned} CF_{Total} &= \overline{CF_{Total}} + \sum_{i,k} \Delta CF_{i,k} \\ &= \overline{CF_{Total}} + \sum_{k} (D_k - \overline{D_k}) \frac{\partial CF_{Total}}{\partial D_k} \end{aligned} \tag{A.7}$$

and from this we derive that the variance in the total carbon footprint as a results of the variation in the driver $D_{i,k}$, expressed as $\Delta CF_{i,k}$, is equivalent to

$$\begin{aligned} var(\Delta CF_{i,k}) &= (D_{i,k} - \overline{D_{i,k}})^2 \Big(\frac{\partial CF_{Total}}{\partial D_k} \Big)^2 \\ &= \big(CF_{i,k} - \overline{CF_{Total}} \big)^2 \end{aligned} \tag{A.8}$$

The coefficient of variance of the total carbon footprint CF_{Total} is simply

$$CV_{CF_{Total}} = \frac{\sqrt{\sum_i^n \sum_k \big(CF_{i,k} - \overline{CF_{Total}} \big)^2}}{\overline{CF_{Total}}} \tag{A.9}$$

Note that $\overline{CF_{Total}}$ is the sample mean, which is equivalent to the expected total carbon footprint $\mathbf{E}[CF_{Total}]$ used in the previous section. It was expressed differently only because the sources have approached the question from different perspectives.

[2] Terms that are second order and above in the Taylor expansion are zero in this case. The Taylor series gives an exact answer.

Appendix B

Primary data

Table B.1: The order list that was provided by the Galapagos Islands Ferry Tour.

Item	Product	Substituted by	Order Weight (kg)	Included (Yes/No)
1	Sugar		14.00	Yes
2	Watermelon		11.49	Yes
3	Beef heart		1.36	Yes
4	Beef tongue		1.36	Yes
5	Beef liver		0.91	Yes
6	Canned tuna		0.74	Yes
7	Sliced ham	Pork ham	0.23	Yes
8	Whole cold cut		0.23	Yes
9	Flour		6.00	Yes
10	Wheat bread		2.50	Yes
11	Whole ham		0.23	Yes
12	Bacon		0.20	Yes
13	Potato		32.66	Yes
14	Fish		22.68	Yes
15	Rice		22.68	Yes
16	Beef		13.61	Yes
17	Grapefruit	Orange	11.70	Yes
18	Pineapple		9.79	Yes
19	Orange		9.72	Yes
20	Carrot		9.07	Yes
21	Tomato		9.07	Yes
22	Papaya	Banana	8.24	Yes
23	Yogurt	Ice cream	8.00	Yes
24	Oil		7.36	Yes
25	Green banana		7.30	Yes
26	Red onion		5.44	Yes
27	Babacos	Banana	5.40	Yes
28	Bread		5.00	Yes
29	Zucchini		5.00	Yes
30	Melons		4.65	Yes
31	Chicken		4.54	Yes
32	Plaintain	Banana	4.54	Yes
33	Shrimp		4.54	Yes
34	Yucca	Potato	4.54	Yes
35	Eggs		4.32	Yes
36	Butter		4.00	Yes
37	Cauliflower		3.93	Yes
38	Milk		3.84	Yes
39	Tomato fruit	Tomato	3.65	Yes
40	Turnip	Carrot	3.63	Yes
41	Bell pepper		3.38	Yes
42	Peach	Apple	3.28	Yes
43	Lettuce		3.03	Yes
44	Avocado	Apple	2.88	Yes
45	Mandarin orange		2.85	Yes
46	Lemon		2.81	Yes
47	Red apple		2.72	Yes
48	Pear	Apple	2.42	Yes
49	Spaghetti		2.40	Yes
50	Pearl onions		2.27	Yes
51	Radish	Carrot	2.27	Yes
52	String bean	Pea, fresh pod	2.27	Yes
53	Pickle	Cucumber	2.06	Yes
54	White cabbage		2.02	Yes
55	Parmesan cheese		2.00	Yes

Item	Product	Substituted by	Order Weight (kg)	Included (Yes/No)
56	Naranjillas	Orange	1.96	Yes
57	Grapes	Strawberry	1.81	Yes
58	Mince meat	Pork	1.81	Yes
59	Strawberry		1.81	Yes
60	Evaporated milk		1.64	Yes
61	Red cabbage		1.60	Yes
62	Condensed milk		1.59	Yes
63	Brocolli		1.56	Yes
64	Mushroom		1.52	Yes
65	Cream		1.50	Yes
66	Beans		1.36	Yes
67	Corn		1.36	Yes
68	Fava beans		1.36	Yes
69	Fresh green pea		1.36	Yes
70	Melloco	Legumme	1.36	Yes
71	Cookies	Bread	1.30	Yes
72	Bread crumbs	Bread	1.00	Yes
73	Mozarella cheese		1.00	Yes
74	Lentil	Dried pea	0.90	Yes
75	Cracker	Bread	0.90	Yes
76	Eggplant		0.90	Yes
77	Green asparagus		0.86	Yes
78	White asparagus		0.86	Yes
79	Sweet corn		0.68	Yes
80	White onion		0.61	Yes
81	Olive oil		0.46	Yes
82	Basil	Lettuce	0.45	Yes
83	Pork		0.45	Yes
84	Pork leg		0.45	Yes
85	Spinach	Lettuce	0.45	Yes
86	Chantilly	Cream	0.40	Yes
87	Ice cream		0.40	Yes
88	Yellow cheese		0.40	Yes
89	Aji (chilli type)	Chilli	0.34	Yes
90	Cilantro, celery, parsley		0.31	Yes
91	Peppermint	Lettuce	0.30	Yes
92	Green cherries	Strawberries	0.24	Yes
93	Red cherries		0.24	Yes
94	Cold cuts	Pork ham	0.23	Yes
95	Bottled water		36.00	No
96	Salt		4.00	No
97	Granola		2.50	No
98	Instant coffee		2.50	No
99	Corn flakes		2.40	No
100	Cooking red wine		2.00	No
101	Cooking white wine		2.00	No
102	Tomato salsa		1.95	No
103	Dried fruit		1.81	No
104	Marmalade		1.80	No
105	Meat pastry		1.80	No
106	Rum		1.50	No
107	Beef tripe soup		1.36	No
108	Honey		1.24	No
109	Quick corn meal		1.20	No
110	Achiote (condiment)		1.00	No

Item	Product	Substituted by	Order Weight (kg)	Included (Yes/No)
111	Corn meal		1.00	No
112	Tomato paste		1.00	No
113	Peanut		0.90	No
114	Pop corn		0.90	No
115	Heart of palm		0.82	No
116	Coffee		0.80	No
117	Lasagna		0.80	No
118	Noodle soup macaroni		0.80	No
119	Noodle soup tornillo pasta		0.80	No
120	Stuffed olives		0.72	No
121	Capers		0.50	No
122	Orange flavor drink powder		0.50	No
123	White vinegar		0.50	No
124	Peanut butter		0.49	No
125	Chinese sauce		0.48	No
126	Mustard		0.48	No
127	Olives		0.47	No
128	Vanilla		0.44	No
129	Jelly		0.40	No
130	Maicena grande (snack)		0.40	No
131	Sorbet		0.39	No
132	Custard flavor flan		0.32	No
133	Tostitos - doritos		0.30	No
134	Vanilla pudding		0.22	No
135	Cream of chicken soup		0.22	No
136	Raisins		0.22	No
137	Chicken bouillon		0.16	No
138	Baking powder		0.10	No
139	Black pepper		0.05	No
140	Cinnamon stick		0.05	No
141	Ground cinnamon		0.05	No
142	Herbal tea		0.05	No

Table B.2: Food production attributable processes to the Red Broiler Chicken dish. The food items with estericks (*) at the *Specific Food* level did not have an appropriate emission factor in the database and were substituted with the food items listed at the *Food* level

Food production					
	Food	**Specific food**	**Technology**	**Weight of food per dish (kg produce/dish)**	**Uncertainty (±x%)**
Chicken	Chicken		Organic, Open pasture	0.080	25
	Salt	Kosher salt*	Conventional	0.002	100
	Dried Pea	Black Pepper*	Organic	0.000	100
	Duck Fat		Conventional	0.030	50
	Dried herbs		Organic	0.002	100
Corn cake Batter 32 Servings	Eggs		Organic, Open pasture	0.011	25
	Milk	Buttermilk*	Conventional	0.018	50
	Flour	Cornflour	Sustainable	0.017	25
	Flour	All purpose flour	Conventional	0.007	25
	Sugar		Conventional	0.002	25
	Sugar	Baking powder*	Conventional	0.000	100
	Sugar	Baking soda*	Conventional	0.000	100
	Sugar	Kosher salt*	Conventional	0.000	100
	Butter		Conventional	0.004	25
Marfax 40 Servings	Dried Pea	Marfax Beans*	Conventional	0.013	50
	Onion		Organic	0.006	25
	Celery		Organic	0.003	100
	Carrot		Organic	0.003	25
	Sugar	Mollasses*	Conventional	0.001	100
	Chili		Organic	0.001	25
	Dried Pea	Mustard Seed*	Conventional	0.000	100
	Pork	Bacon	Organic, Open pasture	0.013	25
	Sugar	Kosher salt*	Conventional	0.000	100
	Dried Pea	Black Pepper*	Organic	0.000	100
	Rape seed oil	Olive oil*	Conventional	0.013	50
Chicken stock 8kg	Water	Tap water		0.500	25
	Onion		Organic	0.006	25
	Carrot		Organic	0.005	25
	Celery		Organic	0.003	100
	Ice			0.500	25
Collards 90 Servings	Cabbage	Collard greens	Organic	0.000	50
	Onion		Organic	0.006	25
	Onion	Garlic*	Organic	0.001	100
	Chili		Organic	0.000	25
	Salt	Kosher salt	Conventional	0.000	100
	Dried Pea	Black Pepper*	Organic	0.000	100
	Wine	Distilled vinegar*	Conventional	0.006	50
	Rape seed oil	Olive oil*	Conventional	0.006	50
Water for washing	Hot water			1.000	25
	Water			1.099	25

Table B.3: The type and the weight of the packaging material used to carry the ingredients in a dish of Pasture Raised Red Broiler Chicken at Bondir, Cambridge.

Packaging material								
	Specific food	Class	Application	Packaging Material	Specific Material	Material Driver (kg material/dish)	Uncertainty (±x%)	Times reused
Chicken	Chicken	Plastic	Film	PET		7.05E-05	25	0
	Kosher salt*	Paperbase	Box	Board		5.88E-05	25	0
	Black Pepper*	Plastic	Bottle	PET		2.67E-06	25	2
	Duck Fat	Plastic	Bucket	Molded container	PS	1.92E-05	25	12
	Dried herbs	Plastic	Film	PET		8.00E-06	25	0
Corn cake Batter 32 Servings	Eggs	Paperbase	Box	Board		2.64E-05	25	0
	Buttermilk*	Paperbase	Box	Board		3.05E-05	25	0
	Cornflour	Paperbase	Bag	Paper	Kraft paper	1.14E-05	25	0
	All purpose flour	Paperbase	Bag	Paper	Kraft paper	5.08E-06	25	0
	Sugar	Paperbase	Bag	Paper	Kraft paper	1.68E-06	25	0
	Baking powder*	Metal	Can	Aluminium		3.91E-07	25	0
	Baking soda*	Paperbase	Box	Board		1.95E-07	25	0
	Kosher salt*	Paperbase	Box	Board		7.18E-08	25	0
	Butter	Paperbase	Packaging paper	Paper - Kraft	Wax paper *	1.22E-06	100	0
Marfax 40 Servings	Marfax Beans*	Textile	Bag	Plastic film*	Burlap*	6.88E-06	100	0
	Onion	Plastic	Film	Mesh bag		1.72E-06	25	0
	Celery	Plastic	Film	PET		1.38E-07	25	0
	Carrot	Plastic	Film	PET		6.88E-08	25	0
	Mollasses*	Metal	Can	Aluminium		2.50E-06	25	0
	Chili	Plastic	Film	PET		2.75E-08	25	0
	Mustard Seed*	Plastic	Bottle	PET		1.25E-07	25	0
	Bacon	Plastic	Film	PET		2.75E-07	25	0
	Kosher salt*	Paperbase	Box	Board		1.15E-07	25	0
	Black Pepper*	Plastic	Bottle	PET		4.17E-09	25	2
	Olive oil*	Metal	Can	Aluminium		2.08E-05	25	0
Chicken stock 8kg	Tap water						25	
	Onion	Plastic	Film	Mesh bag		1.72E-06	25	0
	Carrot	Plastic	Film	PET		1.38E-07	25	0
	Celery	Plastic	Film	PET		6.88E-08	25	0
	Ice						25	
Collards 90 Servings	Collard greens	Plastic	Film	PET		8.16E-10	25	0
	Onion	Plastic	Film	Mesh bag		6.80E-07	25	0
	Garlic*	Plastic	Film	PET		1.36E-08	25	0
	Chili	Plastic	Film	PET		5.44E-09	25	0
	Kosher salt	Paperbase	Box	Board		1.13E-07	25	0
	Black Pepper*	Plastic	Bottle	PET		4.12E-09	25	2
	Distilled vinegar*	Plastic	Bottle	PET		1.63E-08	25	0
	Olive oil*	Metal	Can	Aluminium		4.12E-06	25	0

Table B.4: The type of vehicle used and the distance travelled to deliver the ingredients added to each dish of Pasture Raised Red Broiler Chicken at Bondir, Cambridge.

	Transportation - Vehicle					Distance									
						Origin			Destination			Distance (km)			
Supplier	Mode of transport	Vehicle type	Vehicle specification	Other conditions	Uncertainty (±x%)	State	Town	Exact place or address	State	Town	Exact place or address	State	Town	Exact place or address	Uncertainty (±x%)
Four star farms	Road	Truck < 7.5t		Diesel,MiniVan Toyato Sienna	25	USA,MA	North Field	496 Pine Meadow Rd North Field MA 01360	USA,MA	Cambridge	Bondir	644	134	137	5
Evas Garden		Truck 7.5 to 14t	Refrigerated	Diesel	25	USA,MA	Dartmouth	105 Jordan Road Dartmouth, MA	USA,MA	Cambridge	Bondir	644	108	112	25
Pete and Jan	Road	Passenger Car	Euro6	Diesel	25	USA,MA	Concord, MA	159 Wheeler Road Concord, MA 01742	USA,MA	Cambridge	Bondir	644	23.5	28.3	25
JN Kidd- All	Road	Truck			25	USA,MA	Weymouth	JN Kidd	USA,MA	Cambridge	Bondir	644	30.4	31.1	50
JN Kidd- Kosher salt	Road	Truck			25	USA,MI	Saint Clair		USA,NJ	Paterson		1349	947	955	50
JN Kidd- Kosher salt and distilled white vinegar	Road	Truck			25	USA,NJ	Paterson		USA,MA	Weymouth	JN Kidd	644	392	385	50
JN Kidd- Distilled white vinegar	Road	Truck			25	USA,NJ	Engelwood		USA,MA	Paterson		644	350	344	50
JN Kidd- Black pepper	Road	Ship			25	India		Kandir Port	USA,NJ	Elizabeth	Port	14907	14907	14907	50
JN Kidd- Black pepper	Road	Truck			25	USA,NJ	Elizabeth	Port	USA,NY	Brooklyn		644	34	33	25
JN Kidd- Black pepper	Road	Truck			25	USA,NY	Brooklyn		USA,MA	Weymouth	JN Kidd	644	367	368	50
JN Kidd- Molasses	Road	Truck			25	USA,NY	Brooklyn		USA,MA	Woburn		644	360	365	50
JN Kidd- Molasses	Road	Truck			25	USA,MA	Woburn		USA,MA	Weymouth	JN Kidd	644	45.1	43	50
JN Kidd- Mustard seed	Road	Truck			25	USA			USA,MA	Weymouth	JN Kidd	644	300	200	100
JN Kidd- Suger	Road	Truck			25	USA			USA,MA	Weymouth	JN Kidd	644	300	200	100
JN Kidd- Baking Soda	Road	Truck			25	USA			USA,MA	Weymouth	JN Kidd	644	300	200	100
Duck Fat	Road	Truck			25	USA			USA,MA	Weymouth	JN Kidd	644	392	200	100
SparrowArc farm	Road	Truck 7.5 to 14t	Refrigerated	Diesel	25	USA,ME	Unity	43 Fisher Rd Unity ME 04988	USA,MA	Cambridge	Bondir	644	349	333	25
Extravirgin-foods	Road	Truck 28 to 40t			25	Greece,Messenia	Kalamata		Greece,Attica	Athens	Pireus port	204	224	247	50
	Ship	Container ship			25	Greece,Attica	Athens	Pireus port	USA,MA	Boston	Boston port	7623	7700	7614	25
	Road	Truck 28 to 40t			25	USA,MA	Boston	Boston port	USA,MA	Watertown	71 Arlington Street Watertown, MA 02472	644	13.4	16.5	25
	Road	Pedal			25	USA,MA	Watertown	71 Arlington Street Watertown, MA 02472	USA,MA	Cambridge	Bondir	1	1	1	

Table B.5: The processes to prepare the Pasture Raised Red Broiler Chicken at Bondir, Cambridge.

Process and Equipment						
Food	**Equipment type**	**Energy source**	**Application**	**Equipment**	**Equipment operating time per unit produce (day/kg dish)**	**Uncertainty (±x%)**
Chicken	Cooler	Electricity	Restaurant	* divided by 200kg of other foodstuff	0.0050	25
	Cooktop	Gas	Restaurant	Thermatek TMD 36.6.1	0.0021	25
	Oven	Gas	Restaurant	Thermatek TMD 36.6.1	0.0104	25
Corncake	Cooktop	Gas	Restaurant	Thermatek TMD 36.6.1	0.0069	25
Chicken stock	Cooktop	Gas	Restaurant	Thermatek TMD 36.6.1	0.0042	25
Marfax	Cooktop	Gas	Restaurant	Thermatek TMD 36.6.1	0.0063	25
Collard greens	Cooktop	Gas	Restaurant	Thermatek TMD 36.6.1	0.0014	25
	Dishwasher	Electricity	Restaurant	Undercounter Dishwasher Champion 180degF	0.0001	25

Table B.6: The weight of food waste that was disposed for per dish of Pasture Raised Red Broiler Chicken at Bondir, Cambridge.

Waste						
	Waste type	**Disposal Method**	**Country**	**Waste Management**	**Weight of food per dish (kg produce/ dish)**	**Uncertainty (±x%)**
Waste	Compost	Landfill	USA		0.050	25

Appendix C

Outreach materials

Massachusetts Institute of Technology

MIT Center for Transportation & Logistics
Building E40-295

77 Massachusetts Avenue
Cambridge, Massachusetts
02139–4307

Phone 617–229-9068
Fax 617–253–4560
http://ctl.mit.edu

June 26, 2012

Jason Bond
Chef and Owner
Bondir
279A Broadway
Cambridge, MA 02139

Dear Jason,

I am a MIT PhD student at the School of Engineering. I am part of a research group under the supervision of Dr. Edgar Blanco (http://edgarblanco.mit.edu/) looking at environmental sustainability of products and their underlying supply chains.

One of the main barriers to engage a much broader audience is the complexity and uncertainty of the measurement and, ultimately, "labeling" of a product environmental attributes. Our current research focuses in developing and refine quick methods to calculate the carbon footprint of food products that could be widely adopted without sacrificing the quality of the calculation.

We would like to invite your establishment to participate in a summer study aiming to perform carbon footprint calculations of meals served at a Cambridge restaurant. The aim of our study is to apply and demonstrate the use of quick methods with real restaurant business data.

We expect our results and methods to be published in scientific journals. We will treat all data as confidential and results will not be associated with a recipe or restaurant. It also important to emphasize that we are **not aiming to compare** the relative environmental benefits of one establishment vs. another one based on our calculations.

Please let us know if you are interested in accepting our invitation to participate in this study by sending an e-mail to Yin Jin Lee (yinjin@mit.edu). I am attaching a brief description of the type of data required and a data collection template in the form of an excel spreadsheet document. As a token of appreciation, we will share the early results of our analysis with you as well as provide you with a private report summarizing the results of our calculation at no charge.

Thank you for your attention, and we look forward to collaborate with you.

Regards,

YinJin

Yin Jin Lee
PhD Student, MIT Center for Transportation & Logistics
yinjin@mit.edu

cc- Dr. Edgar Blanco, Research Director, MIT CTL(eblanco@mit.edu)

Appendix - Data Collection Summary

The following is a preliminary list of the data we would like to collect for the meal carbon footprint study:

- Restaurant menu
- Ingredient list of a few entrées with recommended quantities of preparation
- Purchase quantities (in kilograms, cases or bottles) of the selected ingredients in a typical week
- Description of the origin of ingredients (e.g. supplier, country and state)
- Description of the ingredients (e.g. organic, local and free range)
- Ingredient packaging types
- Mode of delivery of the product from farm to the restaurant (e.g. trucks or van)
- Preparation details (e.g. equipment used and cooking time)

We are open to re-adjust our data needs based on what is easily available at your establishment so that existing records are used whenever possible. A brief interview (less than 30 min) may be scheduled after all data has been collected to validate our analysis of any information provided.

Note: All information not in the public domain will be treated as confidential. Results will only be used for academic purposes and establishment names will not be associated with any published results.

Dish	German Pork Knuckle

Agricultural

Food, including the cut and the species	Weight or Volume	Units (lb or kg or oz etc)	Food country of origin	Technology
Pork Knuckle	200	g	USA	Free range, organic
Cherry tomato	50	g	USA	Organic, greenhouse
Flour	20	g	USA	Conventional

Process (before delivery to the restaurant, for processed food)

Food	Process	Process
Cherry Tomato	Sun dried	Drying under sun

Packaging

Food	Weight or Volume/ packaging	Units (lb or kg or oz etc)	Packaging material class	Packaging form	Packaging Material	Weight or area of packaging material	Unit of packaging material	Recycled?	% recycled
Pork Knuckle	5	kg	Plastic	Film	Low Density Polyethylene	5	g	No	
			Plastic	Foam	Polystyrene	20	g	No	
			Paper base	Box	Corrugated box	50 x 30	cm3	Yes	40
Cherry tomato	15.3	kg	Paper base	Box	Corrugated box	50 x 30	cm3	No	
Flour	1	kg	Plastic	Film	Unspecified	3	g	Unspecified	

Transport

Food	Mode of Delivery	Vehicle/ vehicle type	Engine/ Engine type	Fuel	Refrigerated	Goods Origin (Address or rough location)	Goods Destination (Address or rough location)	Empty truck on return trip?
Pork Knuckle	Road	Lorry/truck+trailer	US EPA Certified Smartway	Diesel	Yes	Address of Farm	Address of distribution center	No
	Road	Van < 3.5t	Unspecified	Diesel	Yes	Address of distribution center	Address of restaurant	Yes
Cherry tomato	Road	Lorry/truck+trailer	US EPA Certified Smartway Elite	Diesel	Yes	Orange County, California	LA Airport	
	Air	Medium haul	Unspecified	Petrol	Yes	LA Airport	MASS Airport	
	Road	Van < 3.5t	Unspecified	Diesel	Yes	Mass Airport	Restaurant	
Flour	Road					Farm, 23 Cottage Rd, Spring field, IL 23123	Distribution Center, 937 Windy Rd, Reading, OH 31234	
						Distribution Center, OH	Distribution Center, 472 Albany St, Cambridge MA 02139	

Preparation

Appliance used	Brand	Model	Duration	Duration unit	Heat/ Power source
Oven	Built-in	NA	30	min	Charcoal
Processor	KitchenAid	1234	3	min	Electricity

MIT- Center for Transportation and Logistics
Carbon Footprint Study in Collaboration with Bondir

Life Cycle Data Collection Form
August 2012

Introduction

Data collection is an important step in a carbon footprint study. Accurate and precise activity data will give reliable carbon footprint result. The purpose of this data collection form is to clearly define the type of information needed for a complete study, demonstrate how to fill the data collection form and lastly, provide a copy of the empty form. It will be easier to first look at the example and refer to the definitions when the fieldname is ambiguous. While filling the form, certain information may be difficult to obtain; if the information cannot be obtained, please write "Unknown". If the information is not applicable, please write "/".

Definitions

Module	Field	Description
Agriculture - This module is used to identify the carbon footprint that is associated with the production of the food.	Ingredient	Food, and species if available. Please include total tap water use, for both preparation and cooking too.
	Technology	The technology used to produce the food. Possible options (are not limited to): Conventional, Greenhouse with and without heating for vegetable, Organic, Free range for livestock and Artisan for fishing.
	Weight of food per dish	The weight of the ingredients added to one dish. This can be a rough estimate or it can be obtained by dividing the amount of meat purchased divided by the number of dishes sold.
	Weight percent of inedible parts	A weight percent of parts that is inedible. E.g. 5g of bones in 50g of Sardine = 10%.
Packaging material - This module is used to identify the carbon footprint that is associated with the material that was used to pack or prepare the food.	Packaging Material Class	See Packaging Helplist for possible options.
	Application	See Packaging Helplist for possible options.
	Packaging Material	See Packaging Helplist for possible options.
	Weight of material per unit packaging	Weight of one packaging material, whether the packaging is reused or not. A measured or estimated value is fine.
	Weight of food per unit packaging	A measured or estimated value is fine.
	Times reused	# of times the packaging is reused before it is disposed
	Packaging waste disposal type	Recycled or disposed as trash

Module	Fields	Description
Process & Equipment - This information is used to calculate the carbon footprint associated with the equipment used to store and prepare the ingredients and food.	Ingredients	List of all the food that was processed
	Process	Possible options (are not limited to): Freezing, Cooling, Boiling, Dehydrating, Mixing and Washing.
	Equipment type	Possible options (are not limited to): Walk-in Freezer or Cooler, Horizontal Freezer or Cooler, Gas Stove, Electric Stove, Gas Oven, Electric Oven, Blender, Mixer, Food Processor, Dehydrator and Dishwasher.
	Application	Possible options (are not limited to): Restaurant, Warehouse and Home.
	Capacity	In terms of dimensions or weight or volume
	Brand, Model Number	Brand and model number.
	Energy consumption of equipment	In specs sheet, or at the back of the equipment.
	Process time for each product	Estimated time the ingredient was processed. This entry can be descriptive. Example, a carrot may be in the fridge for an average of 6 hours. Another example, the dishwasher may run for 1.5 hours, regardless of how many dishes it holds.
	Total weight of product in each process	For continuous processes such as freezing, this refers to the estimated weight of products using the equipment for 1 day. For batch processes such as the mixer, this refers to the estimated total weight of mixed food in one run. As for the dishwasher, this refers to the average number of items in each wash. The value need not be precise.
Waste - This information is used to calculate the carbon footprint associated with the disposal of the food and water waste.	Type of waste	Food mainly. Do not need to break down the types of food if they go through the same type of disposal. Do not need to include packaging waste.
	Disposal Method	Possible options (are not limited to): Landfill, Incineration, Sink, Composting, Transferred to third party.
	Disposal center	All possible information about the disposal center. Such as the name of the waste management company and the location of the waste treatment plant.
	Weight of waste per dish	A rough estimation of the total food waste per dish, excluding the weight of the inedible part of the dish, will work.

Module	Fields	Description
Distance - This information is used to estimate the distance covered to deliver the goods from the farm or producers to the restaurant.	Ingredient	Food, and species if available
	Stop type	The purpose of the stop. Possible options (are not limited to): Farm, Producer, Distribution center, Warehouse, Port, Airport, Restaurant.
	Address or general location	The exact addresses of the farm, the distribution centers and the warehouse locations are preferred. If that is not possible, the preference for detail decreases as follows: the town, the state, and the country.
Transportation Vehicle - This information is used to identify the carbon footprint that is associated with the transportation vehicles.	Vehicle type	The trip starting from Stop #1 will be described in Stop #1 column. Possible options (are not limited to): Trucks, Vans, Passenger car, Airplanes, Container ship, Ferry, Rail.
	Fuel	Diesel, petrol, hybrid or biodiesel
	Make	Manufacturer or brand of vehicle
	Capacity	Any measure of the carrying capacity of the vehicle
	Year	The estimated manufactured year, or the age of the car. E.g. 2 or 10 years old.
	Refrigeration	Yes or No. If yes, how?
	Certification	Euro standard engine or Smartway Carrier Certification
	Capacity Utilization	An estimated percentage of the capacity of the vehicle that was in used during the delivery. E.g. One third full = 33%.
	Other conditions	Land transports traffic condition: Free flow, Jammed or Saturated. Rail terrain: Flat, Hilly or Mountainous.
	Return trip	Empty or partially filled

Packaging Helplist

Possible options for Materials

Application	Packaging material class	Packaging Material
Bottle Cap Molded container Foam Bag Film	Plastic	PET or PETE or Polyethylene terephthalate (Plastic #1) PE or Polyethylene (Plastic #2 and #4) PP or Polypropylene (Plastic #5) PS or polystyrene (Plastic #6)
Jar Bottle	Glass	White glass Green glass Brown glass Glass
Liquid packing Box Graphic paper Bag Packaging paper	Paper base	Board Corrugated Board Paper
Can	Metal	Tin steel can Aluminum Can

How to identify the plastic: Plastic Coding system

e.g.

Number	Abbreviation	Material/ Plastic name
1	PET or PETE	Polyethylene terephthalate
2	HDPE	High density polyethylene
3	PVC or V	Polyvinyl Chloride
4	LDPE	Low density polyethylene
5	PP	Polypropylene
6	PS	Polystyrene
7	Others or O	
Numbers other than 7	Unknown	Unspecified

Example – LCD Form Part 1

Please use separate sets of forms for each dish. If the information cannot be obtained, please write "Unknown", and if the information is not applicable, please write "/". Please use more forms if there is not enough space, and number the pages accordingly.

Dish name Pasture Raised Red Broiler Chicken

LCD Form - Part 1

Number of dishes sold in a day 40

Agriculture	Ingredient	Olive oil	/	Chicken	/	Potato	/
	Technology	Conventional	/	Free range Organic	/	Organic	/
	Weight of food per dish	10g	/	200g	/	120g	/
	Weight percent of inedible parts	/	/	5%	/	/	/
Packaging material	Packing Material Number	Material #1	Material #2	Material #1	Material #2	Material #1	Material #__
	Packaging Material Class	Paper base	Metal	Plastic	Paper base	Paper base	
	Application	Box	Formed container	Bag	Box	Box	
	Packaging Material	Paper	Tin	Unknown	Paper	Paper	
	Weight of material per unit packaging	20g	150g	5g			
	Weight of food per unit packaging	6 tins	2L	2 lbs	4 x 2 lbs chicken	5 lbs	
	Times reused	0	0	0	around 3	unknown	
	Packaging waste disposal type	Recycled	Recycled	Trash	Recycled	unknown	
Process & Equipment	Process Number	Process #1		Process #2		Process #3	
	Ingredients	Chicken, Olive oil		Chicken, Olive oil		Potato	
	Process	Sear		Roast in Oven		Roast in Oven	
	Equipment type	Gas stove		Gas Oven		Gas Oven	
	Application*	Restaurant		Restaurant			
	Capacity*	NA		10 cubic ft			
	Brand, Model Number*	Thermatek, TMD 36.6.1		Thermatek, TMD 36.6.1			
	Energy consumption of equipment*	Unknown		10 kW, turned on from 12noon to 10pm.			
	Process time for each product	2 min		30 min		20 min	
	Total weight of product in each process	200g		Average 2 kg of food when it is on.			
Waste	Waste Number	Waste #1		Waste #__		Waste #__	
	Type of waste	Food		/		/	
	Disposal Method	Compost		/		/	
	Disposal center	WM waste management, Massachusetts				/	
	Weight of waste per dish	0 to 5g		/		/	

Example – LCD Form Part 2

Dish name Pasture Raised Red Broiler Chicken

LCD Form - Part 2

Number of dishes sold in a day 40

Distance	Ingredient	Olive oil	/	/
	Stop Number	Stop #1	Stop #2	Stop #3
	Stop type	Producer factory	Origin Port	Destination Port
	Address or general location	Greece	Greece port	1100 Raymond Boulevard, Newark, NJ 07102
Transportation Vehicle	Vehicle type	Unknown	Container ship	Van
	Fuel	/	/	Diesel
	Make	/	/	Mercedes
	Capacity	/	/	7 t
	Year	/	/	5 years
	Refrigeration	/	/	None
	Certification	/	/	Smartway Carrier
	Capacity Utilization	/	/	100%
	Other conditions	/	/	Saturated road
	Return trip	/	/	Empty
Distance	Ingredient	/	Chicken	/
	Stop Number	Stop #4	Stop #1	Stop #2
	Stop type	Destination - restaurant	Farm	Destination - restaurant
	Address or general location	Bondir	Distribution Center, 937 Windy Rd, Reading, OH 31234	Bondir
Transportation Vehicle	Vehicle type	/	Passenger Car	/
	Fuel	/	Petrol	/
	Make	/	Renault	/
	Capacity	/	/	/
	Year	/	3 years old	/
	Refrigeration	/	Yes, back seat of the car.	/
	Certification	/	/	/
	Capacity Utilization	/	/	/
	Other conditions	/	Freeflow	/
	Return trip	/	/	/

LCD Form - Part 1

Dish name ____________________

Number of dishes sold in a day ____________________

Agriculture	Ingredient						
	Technology						
	Weight of food per dish						
	Weight percent of inedible parts						
Packaging material	Packing Material Number	Material #__	Material #__	Material #__	Material #__	Material #__	Material #__
	Packaging Material Class						
	Application						
	Packaging Material						
	Weight of material per unit packaging						
	Weight of food per unit packaging						
	Times reused						
	Packaging waste disposal type						
Process & Equipment	Process Number	Process #__		Process #__		Process #__	
	Ingredients						
	Process						
	Equipment type						
	Application*						
	Capacity*						
	Brand. Model Number*						
	Energy consumption of equipment*						
	Process time for each product						
	Total weight of product in each process						
Waste	Waste Number	Waste #__		Waste #__		Waste #__	
	Type of waste						
	Disposal Method						
	Disposal center						
	Weight of waste per dish						

Dish name ______________________

Number of dishes sold in a day ______________________

LCD Form - Part 2

Distance	Ingredient			
	Stop Number	Stop #__	Stop #__	Stop #__
	Stop type			
	Address or general location			
Transportation Vehicle	Vehicle type			
	Fuel			
	Make			
	Capacity			
	Year			
	Refrigeration			
	Certification			
	Capacity Utilization			
	Other conditions			
	Return trip			
Distance	Ingredient			
	Stop Number	Stop #__	Stop #__	Stop #__
	Stop type			
	Address or general location			
Transportation Vehicle	Vehicle type			
	Fuel			
	Make			
	Capacity			
	Year			
	Refrigeration			
	Certification			
	Capacity Utilization			
	Other conditions			
	Return trip			

Appendix D

Emission Factors

Table D.1: The source and specifications of the agriculture emission factors. Emission factors with source "C" are calculated using details from on the specs sheets of the equipment.

Source	Food	Food Specifications	Country of origin	Technology	kg CO2 eq GWP 100/ kg @ Farm-gate
[48]	Barley		Spain	Conventional	0.933
[56]	Barley	Spring Barley	Denmark	Conventional	0.637
[56]	Barley	Winter Barley	Denmark	Conventional	0.599
[48]	Barley		France	Conventional	0.561
[48]	Barley		Switzerland	Organic	0.545
[48]	Barley		Switzerland	Extensive	0.525
[48]	Barley		Germany	Conventional	0.49
[48]	Barley		Switzerland	Integrated Production	0.422
[56]	Barley	Spring Barley	Denmark	Organic	0.39
[56]	Barley	Winter Barley	Denmark	Organic	0.315
[48]	Maize	Starch	Germany		1.096
[48]	Maize		Switzerland	Integrated Production	0.606
[48]	Maize		USA		0.435
[48]	Maize		Switzerland	Organic	0.433
[56]	Oats	Flakes	Denmark	Conventional	0.651

[56]	Oats		Denmark	Conventional	0.553
[56]	Oats		Denmark	Organic	0.379
[57]	Rice		Thailand	Paddy	2.967
[13]	Rice	Basmati Rice	India	Paddy	1.515
[13]	Rice		India	Paddy	1.221
[48]	Rice		USA	Conventional	0.467
[58]	Rice	Brown rice	USA, California	Averaged	2.43
[58]	Rice	White rice	USA, California	Averaged	2.64
[56]	Rye	Flour	Denmark	Conventional	0.855
[56]	Rye		Denmark	Conventional	0.697
[56]	Rye		Denmark	Organic	0.61
[48]	Rye		Switzerland	Organic	0.532
[48]	Rye		Europe	Conventional	0.518
[48]	Rye		Switzerland	Extensive	0.424
[48]	Rye		Switzerland	Integrated Production	0.342
[48]	Sorghum	Sweet Sorghum	China	Conventional	0.29
[56]	Wheat	Flour	Denmark	Conventional	0.986
[48]	Wheat		Spain		0.763
[56]	Wheat		Denmark	Conventional	0.688
[48]	Wheat		Switzerland	Extensive	0.673
[48]	Wheat		France		0.625
[48]	Wheat		USA		0.603
[48]	Wheat		Switzerland	Organic	0.594
[48]	Wheat		Switzerland	Integrated Production	0.594
[48]	Wheat		Germany		0.553
[59]	Wheat	Winter wheat	UK		0.333
[56]	Wheat		Denmark	Organic	0.274
[56]	Lentil		USA, Idaho		0.54
[13]	Apple		India		0.331
[60]	Apple	Seasonal	Germany		0.112

[59]	Apple	Desert apple	UK		0.111
[58]	Apple	Fuji	USA, California	Conventional	0.18
[58]	Apple	Machintosh, Golden delicious	USA, California	Organic	0.26
[58]	Apple	Machintosh, Golden delicious	USA, California	Organic - Transitional	0.25
[58]	Apple	Granny Smith	USA, California	Conventional	0.11
[58]	Apple	Granny Smith, Macintosh	USA, California	Organic - Transitional	0.02
[58]	Apple	Granny Smith, Macintosh	USA, California	Organic	0.19
[13]	Banana		India		0.072
[61]	Lemon		Italy		0.166
[62]	Melon		Italy		1.375
[63]	Melon	Watermelon	Australia		0.38
[63]	Melon	Rock and Cantaloupe	Australia		0.25
[61]	Orange		Italy		0.24
[64]	Pineapple		Ghana	Organic	0.14
[64]	Pineapple		Ghana	Organic	0.12
[59]	Strawberry		UK	Greenhouse with heating	1.272
[65]	Strawberry		UK	Greenhouse with heating	0.85
[65]	Strawberry		Spain		0.35
[66]	Strawberry		Spain		0.349
[58]	Strawberry		USA, California	Conventional	0.34
[58]	Strawberry		USA, California	Organic	0.23

[58]	Strawberry		USA, California	Organic - Transitional	0.21
[58]	Blueberries	High Bush	USA, California	Conventional	0.83
[58]	Blueberries	High Bush	USA, California	Organic	0.73
[58]	Blueberries	High Bush	USA, California	Organic - Transitional	0.72
[58]	Grapes	Wine grapes, Chardonnay	USA, California	Conventional	0.27
[58]	Grapes	Wine grapes, Chardonnay	USA, California	Organic	0.25
[58]	Grapes	Wine grapes, Chardonnay	USA, California	Organic - Transitional	0.05
[58]	Grapes	Wine grapes, Cabernet Sauvignon	USA, California	Conventional	0.21
[58]	Grapes	Wine grapes, Cabernet Sauvignon	USA, California	Organic	0.17
[58]	Grapes	Wine grapes, Cabernet Sauvignon	USA, California	Organic - Transitional	0.17
[58]	Grapes	Raisin Grapes, Thompson Seedless	USA, California	Conventional	0.67
[58]	Grapes	Raisin Grapes, Thompson Seedless	USA, California	Organic	0.7
[58]	Grapes	Raisin Grapes, Thompson Seedless	USA, California	Organic - Transitional	0.67
[67]	Spaghetti		Italy		1.508
[48]	Rape seeds		USA	Conventional	1.869
[48]	Rape seeds		Germany	Conventional	1.327

[48]	Rape seeds		France	Conventional	1.279
[48]	Rape seeds		Switzerland	Extensive	1.083
[48]	Rape seeds		Switzerland	Integrated Production	1.046
[48]	Rape seeds		Germany	Conventional	0.898
[48]	Rape seeds		Switzerland	Organic	0.684
[48]	Palm kernel oil		Malaysia	Conventional	7.59
[48]	Palm oil		Malaysia	Conventional	3.21
[48]	Rape oil		Europe	Conventional	5.02
[48]	Rape oil		Switzerland	Conventional	4.55
[48]	Soyabean oil		Brazil	Conventional	4.08
[48]	Soyabean oil		Europe	Conventional	2.05
[48]	Soyabean oil		USA	Conventional	0.954
[48]	Coconut oil		Philippines	Conventional	0.475
[59]	Sugarbeet		UK		6.978
[68]	Sugarcane		Zambia		0.64
[68]	Sugarcane		Mauritius		0.26
[68]	Sugarcane		Zambia		0.21
[68]	Sugarcane		Zambia		0.092
[48]	Sugarcane		Brazil		0.021
[48]	Dried Pea		Spain	Conventional	1.274
[48]	Dried Pea		Switzerland	Integrated Production	1.021
[48]	Dried Pea		Switzerland	Organic	0.981
[48]	Dried Pea		France	Conventional	0.698
[48]	Dried Pea		Germany	Conventional	0.659
[56]	Dried Pea		Denmark	Conventional	0.486
[48]	Fava Bean		Switzerland	Integrated Production	1.052
[48]	Fava Bean		Switzerland	Organic	1.038
[69]	Beans		Scotland		0.05
[58]	Almond		USA, California	Conventional	2.47

[58]	Almond		USA, California	Organic	3.57
[58]	Almond		USA, California	Organic - Transitional	3.07
[58]	Walnut	Chandler	USA, California	Conventional	0.49
[58]	Walnut	Terminal bearing	USA, California	Organic	2.89
[58]	Walnut	Terminal bearing	USA, California	Organic - Transitional	1.92
[63]	Asparagus		Australia		2.54
[63]	Amaranth		China		0.105
[63]	Beetroot		Australia		0.24
[63]	Broccoli		Australia		1.73
[70]	Broccoli		Spain		0.2
[70]	Broccoli		Spain		0.8
[70]	Broccoli		UK		0.3
[70]	Broccoli		UK		0.35
[58]	Broccoli		USA, California	Conventional	0.36
[58]	Broccoli		USA, California	Organic	0.43
[58]	Broccoli		USA, California	Organic - Transitional	0.31
[63]	Cabbages		Australia		0.23
[71]	Cabbages	Chinese Cabbage	China	Conventional	0.135
[63]	Capsicums		Australia		0.59
[56]	Carrots		Denmark	Organic, with straw	0.209
[63]	Carrots		Australia		0.2
[56]	Carrots		Denmark	Organic, with straw	0.165

[56]	Carrots		Denmark	Organic, without straw	0.111
[56]	Carrots		Denmark	Conventional, with straw	0.101
[56]	Carrots		Denmark	Conventional, without straw	0.058
[59]	Carrots		UK		0.045
[63]	Cauliflowers		Australia		0.38
[59]	Cauliflowers		UK		0.279
[13]	Cauliflowers		India		0.028
[63]	Celery		Australia		0.18
[62]	Chillies		Italy		1.05
[63]	Chillies		Australia		0.66
[56]	Cucumbers		Denmark	Greenhouse with heating	4.348
[63]	Cucumbers		Australia		0.13
[27]	Cucumbers		Finland		3.745
[71]	Cucumbers		China	Conventional	0.043
[13]	Eggplant		India		0.031
[72]	Lettuce		Britain	Greenhouse with heating	2.549
[72]	Lettuce		Britain	Greenhouse with heating	2.549
[59]	Lettuce		UK	Greenhouse with heating	1.783
[60]	Lettuce		Germany	Greenhouse with heating	1.45
[63]	Lettuce		Australia		0.32
[72]	Lettuce		Britain	Outdoor	0.274
[72]	Lettuce		Britain	Outdoor	0.27
[72]	Lettuce		Spain	Outdoor	0.259
[72]	Lettuce		Spain	Outdoor	0.255
[60]	Lettuce		Germany	Outdoor	0.25
[72]	Lettuce		Britain	Greenhouse	0.184

[72]	Lettuce		Britain	Greenhouse	0.176
[58]	Lettuce	Iceberg	USA, California	Conventional	0.19
[58]	Lettuce	Leaf	USA, California	Organic	0.27
[58]	Lettuce	Leaf	USA, California	Organic - Transitional	0.15
[63]	Mushroom		Australia		0.06
[63]	Onion		Australia		0.21
[56]	Onion		Denmark	Dried	0.207
[56]	Onion		Denmark	Conventional	0.136
[59]	Onion		UK		0.072
[63]	Pea	Fresh pod	Australia		3.94
[63]	Pea	Shelled	Australia		2.46
[70]	Long green beans	Fresh pod	UK		0.28
[70]	Long green beans	Fresh pod	UK		0.207
[70]	Long green beans	Fresh pod	Uganda		0.138
[48]	Potato	Starch	Germany	Conventional	0.86
[63]	Potato		Australia		0.63
[63]	Potato		Australia		0.27
[73]	Potato		Ireland	Organic	0.202
[59]	Potato		UK		0.172
[56]	Potato		Denmark	Conventional	0.153
[48]	Potato		Switzerland	Organic	0.141
[48]	Potato		Switzerland	Integrated Production	0.133
[73]	Potato		Ireland	Conventional	0.122
[48]	Potato		USA	Conventional	0.115
[69]	Potato	Ware potatoes	Scotland	Organic	0.039
[13]	Potato		India		0.025
[27]	Potato	Starch	Finland		0.349

[27]	Potato	Russet Burbank	USA, South-western Idaho		0.32
[27]	Potato	Russet Burbank	USA, Eastern Idaho		0.185
[63]	Sweet corn		USA		1.38
[65]	Tomato	Baby Plum	UK	Greenhouse with heating	5.877
[65]	Tomato	Classic Vine	UK	Greenhouse with heating	5.077
[56]	Tomato		Denmark	Organic	4.947
[56]	Tomato		Denmark	Standard	3.437
[56]	Tomato		Denmark	Recirculated	3.437
[65]	Tomato	Baby Plum	Spain	Greenhouse	3.077
[65]	Tomato	Classic loose	UK	Greenhouse with heating	2.177
[74]	Tomato		Spain	Greenhouse	1.44
[74]	Tomato		Spain	Outdoor	1.42
[74]	Tomato		Spain	Outdoor	1.31
[62]	Tomato	Cherry Tomato	Italy		1.242
[74]	Tomato		Spain	Greenhouse	1.05
[65]	Tomato	Classic Vine	Spain	Greenhouse	0.977
[62]	Tomato		Italy		0.877
[65]	Tomato	Classic loose	Spain	Greenhouse	0.717
[63]	Tomato		Australia		0.22
[75]	Tomato		Spain	Greenhouse	0.25
[58]	Tomato		USA, California	Conventional, Furrow irrigation	0.23
[58]	Tomato		USA, California	Direct seeded for processing	0.1
[71]	Tomato		China	Conventional, Furrow irrigation	0.045

[71]	Spinach	Water Spinach	China	Conventional	0.014
[62]	Zucchini and squash		Italy		1.799
[63]	Zucchini and squash		Australia		1.17
[56]	Cod		Denmark	Sea	2.605
[56]	Flatfish		Denmark	Sea	7.209
[56]	Herring		Denmark	Sea	1.148
[56]	Industrial fish		Denmark	Sea	0.476
[56]	Mackerel		Denmark	Sea	0.336
[56]	Sand eel		Denmark	Sea	0.332
[56]	Trout		Denmark	Aquaculture (Standard)	3.576
[56]	Trout		Denmark	Aquaculture (100% circulation)	6.454
[56]	Trout		Denmark	Aquaculture (0% circulation)	2.528
[76]	Trout	Rainbow Trout	Finland	Cultivated	1.47
[13]			India		1.436
[77]	Anglerfish		Spain	Offshore, trawling	20.86
[77]	Atlantic pomfret		Spain	Offshore, lining	7.756
[77]	Bigeye tuna		Spain	Offshore, lining	40.9
[77]	Blue shark		Spain	Offshore, lining	7.489
[77]	Blue whiting		Spain	Coastal, trawling	3.423
[77]	Common cuttlefish		Spain	Offshore, trawling	6.39
[77]	Common ling		Spain	Offshore, lining	6.956

[77]	Common octupus		Spain	Offshore, varied	7.35
[77]	Conger eel		Spain	Offshore, lining	7.76
[77]	European Pilchard		Spain	Coastal, seining	1.56
[77]	Fork beard		Spain	Offshore, lining	12.5
[77]	Hake		Spain	Coastal, trawling	14.356
[77]	Hake		Spain	Offshore, lining	16.023
[77]	Hake		Spain	Offshore, trawling	15.467
[77]	Lesser flying squid		Spain	Offshore, varied	6.91
[77]	Mackerel	Atlantic horse mackerel	Spain	Coastal, trawling	2.88
[77]	Mackerel	Atlantic horse mackerel	Spain	Coastal, seining	1.96
[77]	Mackerel	Atlantic mackerel	Spain	Coastal, trawling	1.76
[77]	Mackerel	Atlantic mackerel	Spain	Coastal, seining	1.22
[77]	Mackerel	Chub mackerel	Spain	Coastal, seining	1.56
[77]	Mako shark		Spain	Offshore, lining	20.045
[77]	Megrim		Spain	Offshore, trawling	18.689
[77]	Other species		Spain	Coastal, trawling	4.52
[77]	Other species		Spain	Coastal, seining	1.56
[77]	Other species		Spain	Coastal, Artisanala and trolling	2.98
[77]	Other species		Spain	Offshore, varied	8
[77]	Porbeagle		Spain	Offshore, lining	20.045

[77]	Rock fish		Spain	Offshore, lining	13.88
[77]	Splendid alfonsino		Spain	Offshore, lining	7.756
[77]	Swordfish		Spain	Offshore, lining	28.48
[77]	Turbot		Spain	Aquaculture	43.112
[58]	Salmon		Norway	Farmed	3.41
[58]	Salmon		Chile	Farmed	4.83
[58]	Salmon		Canada	Farmed	4.18
[78]	Salmon		Norway	Farmed	3.58
[78]	Salmon		Chile	Farmed	4.6
[78]	Salmon		Canada	Farmed	4.74
[78]	Salmon		UK	Farmed	6.54
[56]	Mussels		Denmark	Sea	0.078
[77]	Mussels		Spain	Aquaculture	0.166
[77]	Norway lobster		Spain	Offshore, trawling	141.5
[56]	Norway lobster		Denmark	Sea	100.07
[56]	Shrimp or prawn		Denmark	Sea	4.86
[79]	Shrimp or prawn		Senegal, Ziguinchor	Trawling	63.334
[79]	Shrimp or prawn		Senegal, Ziguinchor	Artisanal	13
[46]	Beef		Brazil		41.033
[55]	Beef		Brazil	Includes new land use change	1063.92
[80]	Beef		Canada		18.291
[80]	Beef		Canada		22.2
[?]	Beef		Canada		30.775
[56]	Beef		Denmark	Conventional	38.712
[81]	Beef		Ireland	Both specialist beef farms and dairy breeds	20

[?]	Beef		Ireland	Suckler	43.964
[?]	Beef		Japan		32.827
[81]	Beef		Spain	Conventional	17.439
[82]	Beef		Sweden		22.759
[81]	Beef		UK	Lowland	22.862
[81]	Beef		UK	Non- organic	23.155
[81]	Beef		UK	Hill and upland	24.034
[81]	Beef		UK	Suckler	37.076
[83]	Beef		Brazil	new land use	225.4
[83]	Beef		Ireland	new land use	60.4
[83]	Beef	Veal	Netherlands	new land use	7.9
[83]	Beef	Beef cattle	Netherlands	new land use	20.8
[83]	Beef	Dairy cattle	Netherlands	new land use	11.7
[56]	Beef	Fillet	Denmark	Conventional	45.842
[56]	Beef	Flanchet	Denmark	Conventional	22.898
[56]	Beef	Foreend	Denmark	Conventional	25.142
[56]	Beef	Knuckle	Denmark	Conventional	4
[56]	Beef	Mince	Denmark	Conventional	4.282
[56]	Beef	Outside	Denmark	Conventional	22.835
[56]	Beef	Round	Denmark	Conventional	22.647
[56]	Beef	Steak	Denmark	Conventional	43.377
[56]	Beef	Steak	Denmark	Conventional	40.544
[56]	Beef	Tenderloin	Denmark	Conventional	69.542
[56]	Beef	Top round	Denmark	Conventional	43.279
[58]	Beef		USA, Idaho		15.12
[58]	Beef		USA, Nebraska		17.86
[58]	Beef		USA		20
[84]	Beef		USA	Feedlot	14.8
[84]	Beef		USA	Pastoral	8.1
[85]	Beef		USA	Feedlot	26.9
[85]	Beef		USA	Pastoral	34.9
[85]	Beef		USA	Backgrounding /Feedlot	29.45

[86]	Chicken	Cooled and packaged	Brazil	Large scale	1.4
[86]	Chicken	Cooled and packaged	Brazil	Small scale	1.7
[56]	Chicken		Denmark	Conventional	3.223
[86]	Chicken	Cooled and packaged	France	Label Rouge	3.9
[86]	Chicken	Cooled and packaged	France	Standard system	2.2
[81]	Chicken		France	Conventional	2.993
[13]	Chicken		India	Conventional	0.846
[82]	Chicken		Sweden	Conventional	3.447
[81]	Chicken		UK	Conventional	8.161
[81]	Chicken		Netherlands	Includes new land use change	9.786
[81]	Chicken		Netherlands	Includes new land use change	4.7
[81]	Chicken		UK	Free range	7.829
[27]	Chicken		Finland	Conventional	2.58
[58]	Chicken		UK	Conventional	4.6
[58]	Chicken		USA	Conventional	2.36
[58]	Chicken		UK	Conventional	3.1
[58]	Chicken		Canada, British Columbia	Conventional	3.99
[87]	Chicken		USA	Conventional	5.77
[87]	Chicken		USA	Organic or Free range	6.924
[56]	Chicken egg		Denmark	Conventional	2.813
[13]	Chicken egg		India		0.84
[81]	Chicken egg		Netherlands	Battery cage	5.571
[81]	Chicken egg		Netherlands	Aviary with outdoor run	6
[81]	Chicken egg		Netherlands	Deep litter	6.143

[81]	Chicken egg		Netherlands	Deep litter with outdoor run	6.571
[82]	Chicken egg		Sweden		2.029
[58]	Chicken egg		Canada, British Columbia	Large scale, free range	2.38
[58]	Chicken egg		USA, New Jersey	Large scale, confined	1.86
[58]	Turkey		Pennsylvania		5.24
[88]	Duck		Australia	Conventional	2.07
[?]	Duck		UK	Conventional	4.1
[89]	Pork		Austrailia	Conventional	4.77
[89]	Pork		Austrailia	Conventional	8.462
[45]	Pork		Canada		4.524
[45]	Pork		Canada		4.314
[45]	Pork		Canada		4.41
[56]	Pork		Denmark	Conventional	3.524
[56]	Pork		Denmark	Conventional	3.524
[89]	Pork		Denmark	Conventional	5.077
[56]	Pork		Denmark	Conventional	3.984
[56]	Pork		Denmark	Conventional	4.246
[56]	Pork		Denmark	Conventional	4.294
[56]	Pork		Denmark	Conventional	4.379
[81]	Pork		Finland	Good agricultural practice	4.391
[81]	Pork		Finland	Red label	6.681
[89]	Pork		France	Conventional	4.616
[81]	Pork		Netherlands	Conventional	6.558
[81]	Pork		Spain	Intensive	4.8
[82]	Pork		Sweden	Conventional	5.216
[89]	Pork		Sweden	Conventional	6.77
[89]	Pork		Sweden	Conventional	8.462
[81]	Pork		UK	Heavier finishing	9.354

[81]	Pork		UK	Outdoor breeding	9.739
[81]	Pork		UK	Conventional	9.785
[81]	Pork		UK	Indoor breeding	9.877
[83]	Pork		Netherlands	Includes new land use change	7.9
[58]	Pork		USA, Michigan	Average productivity	5.69
[58]	Pork		USA, Iowa	Confined	6.04
[58]	Pork		USA, Iowa	Some pasture	6.69
[58]	Pork		UK		6.4
[58]	Pork		US		3.8
[58]	Pork		UK		5.5
[56]	Pork	Bacon	Denmark	Conventional	3.264
[56]	Pork	Ham	Denmark	Conventional	3.264
[56]	Pork	Mince	Denmark	Conventional	3.26
[56]	Pork	Mince	Denmark	Conventional	3.282
[56]	Pork	Neck	Denmark	Conventional	3.266
[56]	Pork	Tenderloin	Denmark	Conventional	3.224
[13]	Sheep meat	Mutton	India		28.72
[83]	Sheep meat	Lamb	Netherlands	Includes new land use change	31.1
[58]	Sheep meat	Lamb	USA, Idaho		25.37
[58]	Sheep meat	Lamb	USA, Ohio	High productivity	19.39
[58]	Sheep meat	Lamb	USA, Ohio	Average productivity	21.42
[58]	Sheep meat	Lamb	UK		17.6
[58]	Sheep meat	Lamb	UK		28
[58]	Sheep meat	Lamb	New Zealand		31.35
[56]	Milk		Denmark	Conventional	0.965
[56]	Milk		Denmark	Conventional	0.809
[56]	Milk		Denmark	Conventional	0.779
[56]	Milk		Denmark	Organic	0.797

[56]	Milk		Denmark	Conventional	1
[56]	Milk		Denmark	Conventional	1.087
[56]	Milk		Denmark	Conventional	1.058
[56]	Milk		Denmark	Organic	0.974
[83]	Milk		Netherlands	Includes new land use change	1.6
[58]	Milk	Whole Milk	UK	Conventional	1.03
[58]	Milk	Whole Milk	US	Conventional	1.35
[58]	Milk	Whole Milk	UK	Conventional	1
[58]	Milk	Whole Milk	USA, Wisconsin	Conventional	1.02
[58]	Milk	2% milk	USA, Wisconsin	Conventional	0.67
[58]	Milk	Whole Milk	USA, Idaho	Conventional	1.1
[13]	Milk		India	Conventional	0.729
[56]	Milk	Full cream	Denmark	Conventional	1.146
[56]	Milk	Lowfat	Denmark	Conventional	1.218
[56]	Milk	Mini	Denmark	Conventional	1.253
[56]	Milk	Skimmed	Denmark	Conventional	1.265
[56]	Milk	Milk powder	Denmark	Conventional	9.119
[56]	Cheese		Denmark	Conventional	11.84
[27]	Cheese		Finland	Conventional	11.737
[58]	Cheese		USA, Wisconsin		9.09
[58]	Cheese		Sweden		8.8
[58]	Cheese		UK		9.8
[90]	Butter		Denmark		9.6
[90]	Butter		Germany		9
[90]	Butter		France		7.2
[58]	Yogurt	With 2% milk	USA, Wisconsin		0.79
[91]	Carbonated drinks		UK	Glass bottled	0.098

[91]	Carbonated drinks		UK	Aluminium canned	0.052
[91]	Carbonated drinks		UK	0.5 L bottle	0.078
[91]	Carbonated drinks		UK	2 L bottle	0.057
[83]	Tofu		Netherlands and Belgium	Includes new land use change	3.8
[83]	Tofu		Netherlands	Includes new land use change	2.4
[92]	Chocolate	Milk chocolate	Europe		3.05
[92]	Chocolate	Dark chocolate	Europe		1.45
[92]	Chocolate	White chocolate	Europe		3.5
[92]	Chocolate	Chocolate with sultanas	Europe		1.85
[93]	Chocolate	Milk chocolate	Sweden		2.6
[93]	Chocolate	Dark chocolate	Sweden		0.84
[94]	Cocoa powder		Ghana		0.323
[27]	Beer	Medium strength	Finland		0.108
[27]	Oat meal		Finland		0.625
[48]	Sugar from Sugarbeet		Switzerland	Conventional	0.973
[48]	Sugar from Sugarcane		Brazil	Conventional	1.86
[68]	Sugar from Sugarcane		Zambia		1.731
[68]	Sugar from Sugarcane		Mauritius		0.255
[90]	Margarine		UK		1.1
[90]	Margarine		Germany		1.32
[90]	Margarine		Spain		1.66
[90]	Spreadable		Denmark		7.4

[56]	Bread	Rye bread	Denmark	Conventional	0.707
[56]	Bread	Wheat bread	Denmark	Conventional	0.772
[60]	Bread		Germany		0.52
[56]	Bread	Rolls	Denmark	Conventional	0.861
[56]	Margarine		Denmark	Conventional	0.857
[95]	Ice cream		China		2.968
[95]	Ice cream		New Zealand		0.59
[13]	Indian Spice		India		0.845
[58]	Cooked Tuna		Pacific Ocean		3.23
[48]	Tap water		Switzerland		0.001
[48]	Tap water		Europe		0.001
[56]	Tap water		Denmark	Groundwater	0.171
[56]	Tap water		Denmark	Surface water	0.389
[56]	Tap water		Denmark		0.245
[96]	Tap water		USA		0.001
C	Ice		USA	280 Lb Manitowoc Ice Machine	0.133
C	Ice		USA	280 Lb Hoshizaki Ice Machine	0.104
C	Ice		USA	500 Lb Hoshizaki Ice Machine	0.07
C	Ice		USA	600 Lb Hoshizaki Ice Machine	0.072
C	Hot water		USA	GE SmartWater Electric Water Heater SE50M12AAG	0.032

C	Hot water		USA	Kenmore 50 gal. Short Natural Gas Water Heater	0.013
C	Hot water		USA	Kenmore 55 gal. Tall Electric Water Heater	0.035
C	Hot water		USA	Kenmore 30 gal. Tall Electric Water Heater	0.051
C	Hot water		USA	Rheem Fury 65 Gallon Electric Water Heater - 82V662	0.035
C	Hot water		USA	Rheem 22V50F1 Natural Gas Water Heater, 50 Gallon	0.013
[97]	Wine		Australia		1.47
[97]	Wine		France		1.07
[97]	Wine		Argentina		1.5
[97]	Wine		USA		1.93
[98]	Wine		North America		2.39
[98]	Wine		Europe		1.72

Table D.2: The source and specifications of the packaging material emission factors.

Source	Material class	Application	Packaging material	Specific material	kg CO2 eq/ kg Packaging material
[48]	Plastic	Bottle	PET	Polyethylene terephthalate, granulate, bottle grade, at plant/RER U	3.853

[48]	Plastic	Film	PET	Polyethylene terephthalate, granulate, amorphous, at plant/RER U	3.18
[?]	Plastic	Bottle	PET	PET bottles recycled FAL	2.809
[?]	Plastic	Bottle	PET	PET bottles FAL	4.07
[?]	Plastic	Bottle	PET	PET bottle grade I	3.919
[96]	Plastic	Bottle	PET	Virgin PET Bottle, Landfilled.	3.77
[96]	Plastic	Bottle	PET	25% Recycled PET Bottle, recycled at end of life	3.24
[?]	Plastic	Film	PET	PET amorph I	5.004
[48]	Plastic	Film	PE	Polyethylene, LLDPE, granulate, at plant/RER U	2.274
[48]	Plastic	Film	PE	Polyethylene, LDPE, granulate, at plant/RER U	2.532
[48]	Plastic	Film	PE	Polyethylene, HDPE, granulate, at plant/RER U	2.36
[?]	Plastic	Film	PE	PE (LLDPE) I	1.039
[?]	Plastic	Film	PE	PE (LDPE) I	1.554
[?]	Plastic	Film	PE	PE (HDPE) I	1.369
[48]	Plastic	Film	PE	Packaging film, LDPE, at plant/RER U	2.604
[?]	Plastic	Film	PE	LLDPE film recycled FAL	1.635
[?]	Plastic	Film	PE	LLDPE film FAL	2.235
[?]	Plastic	Film	PE	LDPE film recycled FAL	1.744
[?]	Plastic	Film	PE	LDPE film FAL	2.451
[?]	Plastic	Film	PE	HDPE bottles recycled FAL	2.699
[?]	Plastic	Bottle	PE	HDPE bottles FAL	3.316
[48]	Plastic	Film	PP	Polypropylene, granulate, at plant/RER U	2.403
[?]	Plastic	Film	PP	PP I	1.529
[?]	Plastic	Cap	PP	PP caps recycled FAL	3.119
[?]	Plastic	Cap	PP	PP caps FAL	3.75
[?]	Plastic	Molded container	PS	PS (GPPS) I	3.304

[?]	Plastic	Molded container	PS	PS (GPPS) FAL	3.512
[?]	Plastic	Molded container	PS	PS (GPPS) 100	
[?]	Plastic	Foam	PS	PS (EPS) recycled FAL	4.073
[?]	Plastic	Foam	PS	PS (EPS) I	3.368
[?]	Plastic	Foam	PS	PS (EPS) FAL	4.925
[48]	Plastic	Molded container	PS	Polystyrene, general purpose, GPPS, at plant/RER U	4.406
[48]	Plastic	Foam	PS	Polystyrene, expandable, at plant/RER U	4.068
Dettore, Christopher G 2009	Plastic	Bottle	PLA	Polylactic acid, landfill	1.29
[48]	Glass	Jar or Bottle	White glass	Packaging glass, white, at plant/RER U	0.833
[48]	Glass	Jar or Bottle	White glass	Packaging glass, white, at plant/DE U	0.57
[48]	Glass	Jar or Bottle	White glass	Packaging glass, white, at plant/CH U	0.541
[48]	Glass	Jar or Bottle	Green glass	Packaging glass, green, at plant/RER U	0.817
[48]	Glass	Jar or Bottle	Green glass	Packaging glass, green, at plant/DE U	0.496
[48]	Glass	Jar or Bottle	Green glass	Packaging glass, green, at plant/CH U	0.509
[48]	Glass	Jar or Bottle	Brown glass	Packaging glass, brown, at plant/RER U	0.839
[48]	Glass	Jar or Bottle	Brown glass	Packaging glass, brown, at plant/DE U	0.552
[48]	Glass	Jar or Bottle	Brown glass	Packaging glass, brown, at plant/CH U	0.66
[?]	Glass	Bottles	Glass	Glass bottles recycled FAL	0.546

[?]	Glass	Bottles	Glass	Glass bottles FAL	0.937
[48]	Paper base	Liquid packing	Board	Liquid packaging board, at plant/RER U	0.614
[48]	Paper base	Box	Board	Solid bleached board, SBB, at plant/RER U	2.61
[48]	Paper base	Box	Board	Solid unbleached board, SUB, at plant/RER U	0.916
[48]	Paper base	Box	Board	Whitelined chipboard, WLC, at plant/RER U	1.087
[48]	Paper base	Box	Corrugated Board	Corrugated board base paper, kraftliner, at plant/RER U	0.673
[48]	Paper base	Box	Corrugated Board	Corrugated board base paper, semichemical fluting, at plant/RER U	1.04
[48]	Paper base	Box	Corrugated Board	Corrugated board base paper, testliner, at plant/RER U	0.824
[48]	Paper base	Box	Corrugated Board	Corrugated board base paper, wellenstoff, at plant/RER U	0.822
[48]	Paper base	Box	Corrugated Board	Corrugated board, fresh fibre, single wall, at plant/CH U	1.041
[48]	Paper base	Box	Corrugated Board	Corrugated board, fresh fibre, single wall, at plant/RER U	1.001
[48]	Paper base	Box	Corrugated Board	Corrugated board, mixed fibre, single wall, at plant/CH U	0.962
[48]	Paper base	Box	Corrugated Board	Corrugated board, mixed fibre, single wall, at plant/RER U	0.951
[48]	Paper base	Box	Corrugated Board	Corrugated board, recycling fibre, double wall, at plant/CH U	0.977
[48]	Paper base	Box	Corrugated Board	Corrugated board, recycling fibre, double wall, at plant/RER U	0.97
[48]	Paper base	Box	Corrugated Board	Corrugated board, recycling fibre, single wall, at plant/CH U	0.998

[48]	Paper base	Box	Corrugated Board	Corrugated board, recycling fibre, single wall, at plant/RER U	0.997
[?]	Paper base	Box	Corrugated Board	Corrugated cardboard FAL	2.191
[?]	Paper base	Graphic	Paper	Newspaper 100% recycled FAL	1.678
[?]	Paper base	Graphic	Paper	Newspaper virgin fiber FAL	2.745
[?]	Paper base	Graphic	Paper	Paper towels 100% recycled FAL	4.642
[?]	Paper base	Graphic	Paper	Paper towels virgin FAL	4.393
[48]	Paper base	Graphic	Paper	Paper, newsprint, 0% DIP, at plant/RER U	1.326
[48]	Paper base	Graphic	Paper	Paper, newsprint, at plant/CH U	0.833
[48]	Paper base	Graphic	Paper	Paper, newsprint, at regional storage/CH U	0.962
[48]	Paper base	Graphic	Paper	Paper, newsprint, at regional storage/RER U	1.303
[48]	Paper base	Graphic	Paper	Paper, newsprint, DIP containing, at plant/RER U	1.087
[48]	Paper base	Graphic	Paper	Paper, recycling, no deinking, at plant/RER U	0.835
[48]	Paper base	Graphic	Paper	Paper, recycling, with deinking, at plant/RER U	1.569
[48]	Paper base	Graphic	Paper	Paper, wood-containing, LWC, at regional storage/CH U	1.491
[48]	Paper base	Graphic	Paper	Paper, wood-containing, LWC, at regional storage/RER U	1.527
[48]	Paper base	Graphic	Paper	Paper, wood-containing, supercalendred (SC), at regional storage/CH U	1.162
[48]	Paper base	Graphic	Paper	Paper, wood-containing, supercalendred (SC), at regional storage/RER U	1.199

[48]	Paper base	Graphic	Paper	Paper, woodcontaining, LWC, at plant/RER U	1.416
[48]	Paper base	Graphic	Paper	Paper, woodcontaining, supercalendred (SC), at plant/RER U	1.09
[48]	Paper base	Graphic	Paper	Paper, woodfree, coated, at integrated mill/RER U	1.122
[48]	Paper base	Graphic	Paper	Paper, woodfree, coated, at non-integrated mill/RER U	1.181
[48]	Paper base	Graphic	Paper	Paper, woodfree, coated, at regional storage/CH U	1.192
[48]	Paper base	Graphic	Paper	Paper, woodfree, coated, at regional storage/RER U	1.267
[48]	Paper base	Graphic	Paper	Paper, woodfree, uncoated, at integrated mill/RER U	0.852
[48]	Paper base	Graphic	Paper	Paper, woodfree, uncoated, at non-integrated mill/RER U	1.48
[48]	Paper base	Graphic	Paper	Paper, woodfree, uncoated, at regional storage/CH U	1.209
[48]	Paper base	Graphic	Paper	Paper, woodfree, uncoated, at regional storage/RER U	1.323
[?]	Paper base	Packaging paper	Paper	Kraft bleached FAL	2.413
[48]	Paper base	Packaging paper	Paper	Kraft paper, bleached, at plant/RER U	1.701
[48]	Paper base	Packaging paper	Paper	Kraft paper, unbleached, at plant/RER U	0.856
[?]	Paper base	Packaging paper	Paper	Kraft unbleached 100% rec.FAL	1.239
[?]	Paper base	Packaging paper	Paper	Kraft unbleached FAL	1.254
[?]	Metal	Can	Tin steel can	Tin plate 100%scrap B250(98)	3.005
[?]	Metal	Can	Tin steel can	Tin plate 100%scrap D B250(98)	3.109

[?]	Metal	Can	Tin steel can	Tin plate 20% scrap B250	4.632
[?]	Metal	Can	Tin steel can	Tin plate 20% scrap D B250	4.652
[?]	Metal	Can	Tin steel can	Tin plate 50% scrap B250	4.026
[?]	Metal	Can	Tin steel can	Tin plate 50% scrap D B250	4.077
[?]	Metal	Can	Tin steel can	Tin plate 80% scrap B250	3.409
[?]	Metal	Can	Tin steel can	Tin plate 80% scrap D B250	3.492
[?]	Metal	Can	Tin steel can	Tin plate B250	5.036
[48]	Metal	Can	Tin steel can	Tin plated chromium steel sheet, 2 mm, at plant/RER U	7.85
[48]	Metal	Can	Aluminum Can	Aluminium alloy, AlMg3, at plant/RER U	9.262
[99]	Metal	Can	Aluminum Can		
[100]	Textile	Cloth	Wool	Wool for sweater	

Table D.4: The source and specifications of the transportation material emission factors.

Source	Mode of Transport	Vehicle type	Fuel	Vehicle Specification , Capacity Utilization , Other conditions	Allocated Transport EF (kg CO2e/km. kg load)
[48]	Air	Freight Aircrafts	NA	Medium haul , NA , NA	0.002
[48]	Air	Freight Aircrafts	NA	Long haul , NA , NA	0.002

[48]	Air	Freight Aircrafts	NA	Unspecified , NA , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	Saab 340B , 0.5 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	Saab 340B , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	Saab 340B , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	ATR 42-300 Freighter , 0.5 , NA	0.004
[47]	Air	Freight Aircrafts	Jet-A1	ATR 42-300 Freighter , 0.75 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	ATR 42-300 Freighter , 1 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	AN-26 Freighter , 0.5 , NA	0.005
[47]	Air	Freight Aircrafts	Jet-A1	AN-26 Freighter , 0.75 , NA	0.004
[47]	Air	Freight Aircrafts	Jet-A1	AN-26 Freighter , 1 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	F-27-500 , 0.5 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	F-27-500 , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	F-27-500 , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	BAe-146-200 , 0.5 , NA	0.004
[47]	Air	Freight Aircrafts	Jet-A1	BAe-146-200 , 0.75 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	BAe-146-200 , 1 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	L-188 Electra Freighter , 0.5 , NA	0.004

[47]	Air	Freight Aircrafts	Jet-A1	L-188 Electra Freighter , 0.75 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	L-188 Electra Freighter , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B737-300QC Freighter , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B737-300QC Freighter , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B737-300QC Freighter , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B737-300SF , 0.5 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	B737-300SF , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B737-300SF , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	A320 Freighter , 0.5 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	A320 Freighter , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	A320 Freighter , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	AN-12 , 0.5 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	AN-12 , 0.75 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	AN-12 , 1 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	B727-200 Freighter , 0.5 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	B727-200 Freighter , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B727-200 Freighter , 1 , NA	0.002

[47]	Air	Freight Aircrafts	Jet-A1	TU-204-100C , 0.5 , NA	0.004
[47]	Air	Freight Aircrafts	Jet-A1	TU-204-100C , 0.75 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	TU-204-100C , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B757SF , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B757SF , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B757SF , 1 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	B757-200SF , 0.5 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	B757-200SF , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B757-200SF , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	A310-300 Freighter , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	A310-300 Freighter , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	A310-300 Freighter , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B757-200F , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B757-200F , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B757-200F , 1 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	A300-B4 Freighter , 0.5 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	A300-B4 Freighter , 0.75 , NA	0.003

[47]	Air	Freight Aircrafts	Jet-A1	A300-B4 Freighter , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	A300-B4 Freighter , 0.5 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	A300-B4 Freighter , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	A300-B4 Freighter , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	IL-76MD , 0.5 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	IL-76MD , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	IL-76MD , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	DC-8-63F , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	DC-8-63F , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	DC-8-63F , 1 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	DC-8-73F , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	DC-8-73F , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	DC-8-73F , 1 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	B767-300 Freighter , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B767-300 Freighter , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B767-300 Freighter , 1 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	A300-600F , 0.5 , NA	0.002

[47]	Air	Freight Aircrafts	Jet-A1	A300-600F , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	A300-600F , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B767-300F , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B767-300F , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B767-300F , 1 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	DC-10-30F , 0.5 , NA	0.003
[47]	Air	Freight Aircrafts	Jet-A1	DC-10-30F , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	DC-10-30F , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	DC-10-30 Freighter , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	DC-10-30 Freighter , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	DC-10-30 Freighter , 1 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	MD-11 Freighter , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	MD-11 Freighter , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	MD-11 Freighter , 1 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	MD-11F , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	MD-11F , 0.75 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	MD-11F , 1 , NA	0.001

[47]	Air	Freight Aircrafts	Jet-A1	B747-400 Freighter , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B747-400 Freighter , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B747-400 Freighter , 1 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	B747-200F , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B747-200F , 0.75 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B747-200F , 1 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B747-400F , 0.5 , NA	0.002
[47]	Air	Freight Aircrafts	Jet-A1	B747-400F , 0.75 , NA	0.001
[47]	Air	Freight Aircrafts	Jet-A1	B747-400F , 1 , NA	0.001
[47]	Air	Belly Aircrafts	Jet-A1	A320 Belly , 1 , NA	0.002
[47]	Air	Belly Aircrafts	Jet-A1	A320 Belly , 0.5 , NA	0.003
[47]	Air	Belly Aircrafts	Jet-A1	A320 Belly , 1 , NA	0.003
[47]	Air	Belly Aircrafts	Jet-A1	A320 Belly , 0.5 , NA	0.003
[47]	Air	Belly Aircrafts	Jet-A1	A330-300 Belly , 1 , NA	0.002
[47]	Air	Belly Aircrafts	Jet-A1	A330-300 Belly , 0.5 , NA	0.002
[47]	Air	Belly Aircrafts	Jet-A1	A330-300 Belly , 1 , NA	0.002
[47]	Air	Belly Aircrafts	Jet-A1	A330-300 Belly , 0.5 , NA	0.002

[48]	Rail	Average Train	Diesel powered	NA , NA , NA	0.001
[48]	Rail	Average Train	Electric powered	NA , NA , NA	0.001
[48]	Rail	Average Train	Mixed power	NA , NA , NA	0.001
[48]	Rail	Average Train	Mixed power	NA , NA , NA	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Bulk , 0.6 , Flat terrain	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Average , 0.5 , Flat terrain	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Volume , 0.4 , Flat terrain	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Shuttle train , 0.5 , Flat terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Bulk , 0.6 , Flat terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Average , 0.5 , Flat terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Volume , 0.4 , Flat terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Shuttle train , 0.5 , Flat terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Bulk , 0.6 , Flat terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Average , 0.5 , Flat terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Volume , 0.4 , Flat terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Shuttle train , 0.5 , Flat terrain	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Bulk , 0.6 , Hilly terrain	0.001

[47]	Rail	Short Train	Electric powered	Cargo type, Average , 0.5 , Hilly terrain	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Volume , 0.4 , Hilly terrain	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Shuttle train , 0.5 , Hilly terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Bulk , 0.6 , Hilly terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Average , 0.5 , Hilly terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Volume , 0.4 , Hilly terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Shuttle train , 0.5 , Hilly terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Bulk , 0.6 , Hilly terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Average , 0.5 , Hilly terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Volume , 0.4 , Hilly terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Shuttle train , 0.5 , Hilly terrain	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Bulk , 0.6 , Mountainous terrain	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Average , 0.5 , Mountainous terrain	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Volume , 0.4 , Mountainous terrain	0.001
[47]	Rail	Short Train	Electric powered	Cargo type, Shuttle train , 0.5 , Mountainous terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Bulk , 0.6 , Mountainous terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Average , 0.5 , Mountainous terrain	0.001

[47]	Rail	Average Train	Electric powered	Cargo type, Volume , 0.4 , Mountainous terrain	0.001
[47]	Rail	Average Train	Electric powered	Cargo type, Shuttle train , 0.5 , Mountainous terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Bulk , 0.6 , Mountainous terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Average , 0.5 , Mountainous terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Volume , 0.4 , Mountainous terrain	0.001
[47]	Rail	Long Train	Electric powered	Cargo type, Shuttle train , 0.5 , Mountainous terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Bulk , 0.6 , Flat terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Average , 0.5 , Flat terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Volume , 0.4 , Flat terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Shuttle train , 0.5 , Flat terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Bulk , 0.6 , Flat terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Average , 0.5 , Flat terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Volume , 0.4 , Flat terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Shuttle train , 0.5 , Flat terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Bulk , 0.6 , Flat terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Average , 0.5 , Flat terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Volume , 0.4 , Flat terrain	0.001

[47]	Rail	Long Train	Diesel	Cargo type, Shuttle train , 0.5 , Flat terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Bulk , 0.6 , Hilly terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Average , 0.5 , Hilly terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Volume , 0.4 , Hilly terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Shuttle train , 0.5 , Hilly terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Bulk , 0.6 , Hilly terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Average , 0.5 , Hilly terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Volume , 0.4 , Hilly terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Shuttle train , 0.5 , Hilly terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Bulk , 0.6 , Hilly terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Average , 0.5 , Hilly terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Volume , 0.4 , Hilly terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Shuttle train , 0.5 , Hilly terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Bulk , 0.6 , Mountainous terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Average , 0.5 , Mountainous terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Volume , 0.4 , Mountainous terrain	0.001
[47]	Rail	Short Train	Diesel	Cargo type, Shuttle train , 0.5 , Mountainous terrain	0.001

[47]	Rail	Average Train	Diesel	Cargo type, Bulk , 0.6 , Mountainous terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Average , 0.5 , Mountainous terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Volume , 0.4 , Mountainous terrain	0.001
[47]	Rail	Average Train	Diesel	Cargo type, Shuttle train , 0.5 , Mountainous terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Bulk , 0.6 , Mountainous terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Average , 0.5 , Mountainous terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Volume , 0.4 , Mountainous terrain	0.001
[47]	Rail	Long Train	Diesel	Cargo type, Shuttle train , 0.5 , Mountainous terrain	0.001
[48]	Road	Truck 14 to 28t	Diesel	NA , 0.5 , NA	0.001
[48]	Road	Truck 28 to 40t	Petrol	NA , 0.5 , NA	0.001
[48]	Road	Truck 28 to 40t	Petrol	NA , 1 , NA	0.001
[48]	Road	Truck 28 to 40t	Diesel	Euro 3 , 0.5 , NA	0.001
[48]	Road	Truck 28 to 40t	Diesel	Euro 4 , 0.5 , NA	0.001
[48]	Road	Truck 28 to 40t	Diesel	Euro 5 , 0.5 , NA	0.001
[48]	Road	Truck 14 to 28t	Diesel	Euro 3 , 0.5 , NA	0.001
[48]	Road	Truck 14 to 28t	Diesel	Euro 4 , 0.5 , NA	0.001
[48]	Road	Truck 14 to 28t	Diesel	Euro 5 , 0.5 , NA	0.001

[48]	Road	Truck 14 to 28t	Diesel	NA , 0.5 , NA	0.001
[48]	Road	Truck 14 to 28t	Diesel	NA , 1 , NA	0.001
[48]	Road	Truck 14 to 28t	BioDiesel	Euro 3 , 0.5 , NA	0.001
[48]	Road	Truck 7.5 to 14t	Diesel	NA , 0.5 , NA	0.001
[48]	Road	Truck < 7.5t	Diesel	NA , 0.5 , NA	0.001
[48]	Road	Truck < 7.5t	Diesel	NA , 1 , NA	0.001
[48]	Road	Truck 7.5 to 14t	Diesel	NA , 0.5 , NA	0.001
[48]	Road	Truck 7.5 to 14t	Diesel	NA , 1 , NA	0.001
[48]	Road	Truck < 7.5t	Diesel	Euro 3 , 0.5 , NA	0.001
[48]	Road	Truck < 7.5t	Diesel	Euro 4 , 0.5 , NA	0.001
[48]	Road	Truck < 7.5t	Diesel	Euro 5 , 0.5 , NA	0.001
[48]	Road	Truck 7.5 to 14t	Diesel	Euro 3 , 0.5 , NA	0.001
[48]	Road	Truck 7.5 to 14t	Diesel	Euro 4 , 0.5 , NA	0.001
[48]	Road	Truck 7.5 to 14t	Diesel	Euro 5 , 0.5 , NA	0.001
[48]	Road	Passenger Car	Diesel	Euro 3 , NA , NA	0.004
[48]	Road	Passenger Car	Diesel	Euro 4 , NA , NA	0.003
[48]	Road	Passenger Car	Diesel	Euro 5 , NA , NA	0.003

[48]	Road	Passenger Car	Diesel	NA , NA , NA	0.004
[48]	Road	Passenger Car	Diesel	NA , NA , NA	0.004
[48]	Road	Passenger Car	Diesel	NA , NA , NA	0.004
[48]	Road	Passenger Car	Diesel	NA , NA , NA	0.004
[48]	Road	Passenger Car	Ethanol Diesel	Euro 3 , NA , NA	0.004
[48]	Road	Passenger Car	BioDiesel	Euro 3 , NA , NA	0.002
[48]	Road	Passenger Car	Methanol	Euro 3 , NA , NA	0.001
[48]	Road	Passenger Car	Natural gas	Euro 3 , NA , NA	0.004
[48]	Road	Passenger Car	BioDiesel	Euro 4 , NA , NA	0.004
[48]	Road	Passenger Car	BioDiesel	Euro 4 , NA , NA	0.004
[48]	Road	Passenger Car	Petrol	Euro 3 , NA , NA	0.004
[48]	Road	Passenger Car	Petrol	Euro 4 , NA , NA	0.004
[48]	Road	Passenger Car	Petrol	Euro 5 , NA , NA	0.004
[48]	Road	Passenger Car	Petrol	NA , NA , NA	0.004
[48]	Road	Passenger Car	Petrol	NA , NA , NA	0.004
[48]	Road	Passenger Car	Petrol	NA , NA , NA	0.004
[48]	Road	Passenger Car	Petrol	NA , NA , NA	0.004

[48]	Road	Passenger Car	BioDiesel	Euro 3 , NA , NA	0.003
[48]	Road	Passenger Car	Petrol	NA , NA , NA	0.004
[48]	Road	Passenger Car	Petrol	NA , NA , NA	0.004
[48]	Road	Bus	Diesel	NA , NA , NA	0.019
[48]	Road	Tram	Electricity	NA , NA , NA	0.008
[48]	Road	Trolley bus	Electricity	NA , NA , NA	0.006
[48]	Road	Truck < 7.5t	Petrol	NA , NA , NA	0.001
[48]	Road	Truck < 7.5t	Petrol	NA , NA , NA	0.001
[47]	Road	Truck < 7.5t	Diesel	80-ties , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro1 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro2 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro3 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro4 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro5 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	80-ties , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro1 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro2 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro3 , 0.5 , Freeflow, Motorway	0.001

[47]	Road	Truck 7.5 to 14t	Diesel	Euro4 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro5 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	80-ties , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro1 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro2 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro3 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro4 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro5 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	80-ties , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro1 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro2 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro3 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro4 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro5 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	80-ties , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro1 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro2 , 0.5 , Freeflow, Motorway	0.001

[47]	Road	Truck 28 to 40t	Diesel	Euro3 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro4 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro5 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	80-ties , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro1 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro2 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro3 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro4 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro5 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	80-ties , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro1 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro2 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro3 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro4 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro5 , 0.5 , Freeflow, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	80-ties , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro1 , 0.5 , Saturated, Motorway	0.001

[47]	Road	Truck < 7.5t	Diesel	Euro2 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro3 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro4 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro5 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	80-ties , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro1 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro2 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro3 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro4 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro5 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	80-ties , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro1 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro2 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro3 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro4 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro5 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	80-ties , 0.5 , Saturated, Motorway	0.001

[47]	Road	Truck 14 to 28t	Diesel	Euro1 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro2 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro3 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro4 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro5 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	80-ties , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro1 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro2 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro3 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro4 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro5 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	80-ties , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro1 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro2 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro3 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro4 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro5 , 0.5 , Saturated, Motorway	0.001

[47]	Road	Truck 50 to 60t	Diesel	80-ties , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro1 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro2 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro3 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro4 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro5 , 0.5 , Saturated, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	80-ties , 0.5 , Stop and go, Motorway	0.002
[47]	Road	Truck < 7.5t	Diesel	Euro1 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro2 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro3 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro4 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro5 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	80-ties , 0.5 , Stop and go, Motorway	0.003
[47]	Road	Truck 7.5 to 14t	Diesel	Euro1 , 0.5 , Stop and go, Motorway	0.002
[47]	Road	Truck 7.5 to 14t	Diesel	Euro2 , 0.5 , Stop and go, Motorway	0.002
[47]	Road	Truck 7.5 to 14t	Diesel	Euro3 , 0.5 , Stop and go, Motorway	0.002
[47]	Road	Truck 7.5 to 14t	Diesel	Euro4 , 0.5 , Stop and go, Motorway	0.001

[47]	Road	Truck 7.5 to 14t	Diesel	Euro5 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	80-ties , 0.5 , Stop and go, Motorway	0.002
[47]	Road	Truck 14 to 26t	Diesel	Euro1 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro2 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro3 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro4 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro5 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	80-ties , 0.5 , Stop and go, Motorway	0.002
[47]	Road	Truck 14 to 28t	Diesel	Euro1 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro2 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro3 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro4 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro5 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	80-ties , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro1 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro2 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro3 , 0.5 , Stop and go, Motorway	0.001

[47]	Road	Truck 28 to 40t	Diesel	Euro4 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro5 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	80-ties , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro1 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro2 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro3 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro4 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro5 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	80-ties , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro1 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro2 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro3 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro4 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro5 , 0.5 , Stop and go, Motorway	0.001
[47]	Road	Truck < 7.5t	Diesel	80-ties , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro1 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro2 , 0.5 , Freeflow, Urban Road	0.001

[47]	Road	Truck < 7.5t	Diesel	Euro3 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro4 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro5 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	80-ties , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro1 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro2 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro3 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro4 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro5 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	80-ties , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro1 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro2 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro3 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro4 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro5 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	80-ties , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro1 , 0.5 , Freeflow, Urban Road	0.001

[47]	Road	Truck 14 to 28t	Diesel	Euro2 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro3 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro4 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro5 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	80-ties , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro1 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro2 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro3 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro4 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro5 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	80-ties , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro1 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro2 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro3 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro4 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro5 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	80-ties , 0.5 , Freeflow, Urban Road	0.001

[47]	Road	Truck 50 to 60t	Diesel	Euro1 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro2 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro3 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro4 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro5 , 0.5 , Freeflow, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	80-ties , 0.5 , Saturated, Urban Road	0.002
[47]	Road	Truck < 7.5t	Diesel	Euro1 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro2 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro3 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro4 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro5 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	80-ties , 0.5 , Saturated, Urban Road	0.002
[47]	Road	Truck 7.5 to 14t	Diesel	Euro1 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro2 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro3 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro4 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro5 , 0.5 , Saturated, Urban Road	0.001

[47]	Road	Truck 14 to 26t	Diesel	80-ties , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro1 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro2 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro3 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro4 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro5 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	80-ties , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro1 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro2 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro3 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro4 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro5 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	80-ties , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro1 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro2 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro3 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro4 , 0.5 , Saturated, Urban Road	0.001

[47]	Road	Truck 28 to 40t	Diesel	Euro5 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	80-ties , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro1 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro2 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro3 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro4 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro5 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	80-ties , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro1 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro2 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro3 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro4 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro5 , 0.5 , Saturated, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	80-ties , 0.5 , Stop and go, Urban Road	0.002
[47]	Road	Truck < 7.5t	Diesel	Euro1 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro2 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro3 , 0.5 , Stop and go, Urban Road	0.001

[47]	Road	Truck < 7.5t	Diesel	Euro4 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro5 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	80-ties , 0.5 , Stop and go, Urban Road	0.003
[47]	Road	Truck 7.5 to 14t	Diesel	Euro1 , 0.5 , Stop and go, Urban Road	0.002
[47]	Road	Truck 7.5 to 14t	Diesel	Euro2 , 0.5 , Stop and go, Urban Road	0.002
[47]	Road	Truck 7.5 to 14t	Diesel	Euro3 , 0.5 , Stop and go, Urban Road	0.002
[47]	Road	Truck 7.5 to 14t	Diesel	Euro4 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro5 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	80-ties , 0.5 , Stop and go, Urban Road	0.002
[47]	Road	Truck 14 to 26t	Diesel	Euro1 , 0.5 , Stop and go, Urban Road	0.002
[47]	Road	Truck 14 to 26t	Diesel	Euro2 , 0.5 , Stop and go, Urban Road	0.002
[47]	Road	Truck 14 to 26t	Diesel	Euro3 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro4 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro5 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	80-ties , 0.5 , Stop and go, Urban Road	0.002
[47]	Road	Truck 14 to 28t	Diesel	Euro1 , 0.5 , Stop and go, Urban Road	0.002
[47]	Road	Truck 14 to 28t	Diesel	Euro2 , 0.5 , Stop and go, Urban Road	0.001

[47]	Road	Truck 14 to 28t	Diesel	Euro3 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro4 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro5 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	80-ties , 0.5 , Stop and go, Urban Road	0.002
[47]	Road	Truck 28 to 40t	Diesel	Euro1 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro2 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro3 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro4 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro5 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	80-ties , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro1 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro2 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro3 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro4 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro5 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	80-ties , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro1 , 0.5 , Stop and go, Urban Road	0.001

[47]	Road	Truck 50 to 60t	Diesel	Euro2 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro3 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro4 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro5 , 0.5 , Stop and go, Urban Road	0.001
[47]	Road	Truck < 7.5t	Diesel	80-ties , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro1 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro2 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro3 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro4 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro5 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	80-ties , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro1 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro2 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro3 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro4 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro5 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	80-ties , 0.5 , Freeflow, Rural Road	0.001

[47]	Road	Truck 14 to 26t	Diesel	Euro1 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro2 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro3 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro4 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro5 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	80-ties , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro1 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro2 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro3 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro4 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro5 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	80-ties , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro1 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro2 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro3 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro4 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro5 , 0.5 , Freeflow, Rural Road	0.001

[47]	Road	Truck 40 to 50t	Diesel	80-ties , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro1 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro2 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro3 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro4 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro5 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	80-ties , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro1 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro2 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro3 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro4 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro5 , 0.5 , Freeflow, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	80-ties , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro1 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro2 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro3 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro4 , 0.5 , Saturated, Rural Road	0.001

[47]	Road	Truck < 7.5t	Diesel	Euro5 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	80-ties , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro1 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro2 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro3 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro4 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro5 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	80-ties , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro1 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro2 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro3 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro4 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro5 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	80-ties , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro1 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro2 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro3 , 0.5 , Saturated, Rural Road	0.001

[47]	Road	Truck 14 to 28t	Diesel	Euro4 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro5 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	80-ties , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro1 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro2 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro3 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro4 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro5 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	80-ties , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro1 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro2 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro3 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro4 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro5 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	80-ties , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro1 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro2 , 0.5 , Saturated, Rural Road	0.001

[47]	Road	Truck 50 to 60t	Diesel	Euro3 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro4 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro5 , 0.5 , Saturated, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	80-ties , 0.5 , Stop and go, Rural Road	0.002
[47]	Road	Truck < 7.5t	Diesel	Euro1 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro2 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro3 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro4 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck < 7.5t	Diesel	Euro5 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	80-ties , 0.5 , Stop and go, Rural Road	0.003
[47]	Road	Truck 7.5 to 14t	Diesel	Euro1 , 0.5 , Stop and go, Rural Road	0.002
[47]	Road	Truck 7.5 to 14t	Diesel	Euro2 , 0.5 , Stop and go, Rural Road	0.002
[47]	Road	Truck 7.5 to 14t	Diesel	Euro3 , 0.5 , Stop and go, Rural Road	0.002
[47]	Road	Truck 7.5 to 14t	Diesel	Euro4 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 7.5 to 14t	Diesel	Euro5 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	80-ties , 0.5 , Stop and go, Rural Road	0.002
[47]	Road	Truck 14 to 26t	Diesel	Euro1 , 0.5 , Stop and go, Rural Road	0.001

[47]	Road	Truck 14 to 26t	Diesel	Euro2 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro3 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro4 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 14 to 26t	Diesel	Euro5 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	80-ties , 0.5 , Stop and go, Rural Road	0.002
[47]	Road	Truck 14 to 28t	Diesel	Euro1 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro2 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro3 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro4 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 14 to 28t	Diesel	Euro5 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	80-ties , 0.5 , Stop and go, Rural Road	0.002
[47]	Road	Truck 28 to 40t	Diesel	Euro1 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro2 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro3 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro4 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 28 to 40t	Diesel	Euro5 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	80-ties , 0.5 , Stop and go, Rural Road	0.001

[47]	Road	Truck 40 to 50t	Diesel	Euro1 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro2 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro3 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro4 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 40 to 50t	Diesel	Euro5 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	80-ties , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro1 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro2 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro3 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro4 , 0.5 , Stop and go, Rural Road	0.001
[47]	Road	Truck 50 to 60t	Diesel	Euro5 , 0.5 , Stop and go, Rural Road	0.001
[48]	Water	Barge Tanker	Diesel	NA , NA , NA	0.001
[48]	Water	Barge	Diesel	NA , NA , NA	0.001
[48]	Water	Transoceanic Freight ship	Heavy Fuel Oil	NA , NA , NA	0.001
[48]	Water	Tanker	Heavy Fuel Oil	NA , NA , NA	0.001
[47]	Water	RORO Cargo	NA	Modern , 0.88 , NA	0.001
[47]	Water	RORO Cargo	Residual Oil	Car transporters , 0.7 , NA	0.001

[47]	Water	Container ship	Marine Diesel Oil	Inland , 0.5 , NA	0.001
[47]	Water	Container ship	Residual Oil	Feeder Small , 0.8 , NA	0.001
[47]	Water	Container ship	Residual Oil	Feeder A type , 0.8 , NA	0.001
[47]	Water	Container ship	Residual Oil	Panamax , 0.8 , NA	0.001
[47]	Water	Container ship	Residual Oil	Post Panamax , 0.8 , NA	0.001
[47]	Water	Tanker	Marine Diesel Oil	Inland , 0.5 , NA	0.001
[47]	Water	Tanker	Residual Oil	Coastal Tanker , 0.5 , NA	0.001
[47]	Water	Tanker	NA	Product/Chem , 0.55 , NA	0.001
[47]	Water	Tanker	NA	Large , 0.6 , NA	0.001
[47]	Water	Dry Bulk	Residual Oil	Inland WW , 0.5 , NA	0.001
[47]	Water	Dry Bulk	Residual Oil	Coastal , 0.67 , NA	0.001
[47]	Water	Dry Bulk	Residual Oil	Handy Size , 0.67 , NA	0.001
[47]	Water	Dry Bulk	Residual Oil	Ocean , 0.67 , NA	0.001
[47]	Water	General Cargo	Residual Oil	Inland WW , 0.5 , NA	0.001
[47]	Water	General Cargo	Residual Oil	Coastal , 0.71 , NA	0.001
[47]	Water	General Cargo	Residual Oil	Handy Size , 0.71 , NA	0.001
[47]	Water	General Cargo	Residual Oil	Ocean , 0.71 , NA	0.001

Table D.3: The emission factors of the molding processes

Source	Shaping process	kg CO_{2eq}	Unit
[48]	Extrusion plastic film	0.429	/kg plastic
[48]	Blow moulding/RER U	0.89195872	/kg plastic
[48]	Foaming, expanding/RER U	0.69257704	/kg plastic
[48]	Aluminium product manufacturing, average metal working/RER U	3.3360709	/kg metal
[48]	Steel product manufacturing, average metal working/RER U	1.7921457	/kg metal

Table D.5: The source and specifications of the process emission factors.

Source	Equipment type	Application	Energy Source	Equipment	Equipment EF (kgCO2e/ day)
Product website	Oven	Domestic	Electricity	GE Cafe 30" Built-In Double Convection Wall Oven	29.995
Product website	Oven	Domestic	Electricity	GE Profile 30" Built-In Single/Double Convection Wall Oven	31.423
Product website	Oven	Domestic	Electricity	GE Profile 30" Built-In Single/Double Convection Wall Oven	24.282
Product website	Oven	Domestic	Electricity	GE Profile Advantium 120V - 30 in. Wall Oven	25.71
Product website	Oven	Domestic	Electricity	Oven, LG LRE3023ST	48.563
Product website	Oven	Domestic	Gas	Oven, LRG3091ST	18.256
Product website	Oven	Domestic	Gas	Gas range, Kenmore Model 70402	21.404
Product website	Oven	Restaurant	Gas	Vulcan-Hart (V36-1) - 36 Gas Open Burner, 4 burners	44.067
Product website	Oven	Restaurant	Gas	Southbend (S36D) - 36" Gas Open Burner, 6 Burners	44.067
Product website	Oven	Restaurant	Gas	Wolf (C72-SS-12B-N) - 72 Gas Open Burner, 12 Burners	44.067

Product website	Oven	Restaurant	Gas	U.S. Range (X24-4L) - 24" Open Burner Sunfire, 4 Burners	31.476
Product website	Oven	Restaurant	Gas	Vulcan-Hart (36-S-6B-P) - 36 Open Burner Endurance, 6 Burners	44.067
Product website	Oven	Restaurant	Gas	Thermatek TMD 36.6.1	37.771
Product website	Oven	Domestic	Electricity	GE Cafe 30" Built-In Double Convection Wall Oven	51.419
Product website	Oven	Domestic	Electricity	GE Profile Advantium 120V - 30 in. Wall Oven	25.71
Product website	Oven	Domestic	Electricity	Oven, LG LRE3023ST	59.989
Product website	Oven	Domestic	Gas	Oven, LRG3091ST	16.997
Product website	Oven	Domestic	Gas	Gas range, Kenmore Model 70402	21.404
Product website	Cooktop	Domestic	Electricity	Inductor Cooktop, LSCI365ST	12.888
Product website	Cooktop	Domestic	Electricity	Inductor Cooktop, LSCI365ST	9.452
Product website	Cooktop	Domestic	Electricity	Inductor Cooktop, LSCI365ST	4.726
Product website	Cooktop	Domestic	Electricity	Inductor Cooktop, LSCI365ST	12.888
Product website	Cooktop	Domestic	Electricity	Inductor Cooktop, LSCI365ST	6.015
Product website	Cooktop	Domestic	Gas	Gas Cooktop, LSCG306ST	11.458
Product website	Cooktop	Domestic	Gas	Gas Cooktop, LSCG306ST	23.922
Product website	Cooktop	Domestic	Gas	Gas Cooktop, LSCG306ST	15.109

Product website	Cooktop	Domestic	Gas	Gas Cooktop, LSCG306ST	6.296
Product website	Cooktop	Domestic	Gas	Gas range, Kenmore Model 70402	11.332
Product website	Cooktop	Restaurant	Gas	Thermatek TMD 36.6.1	44.067
Product website	Cooktop	Restaurant	Gas	Vulcan-Hart (V36-1) - 36 Gas Open Burner, 4 burners	35.253
Product website	Cooktop	Restaurant	Gas	Southbend (S36D) - 36" Gas Open Burner, 6 Burners	35.253
Product website	Cooktop	Restaurant	Gas	Wolf (C72-SS-12B-N) - 72 Gas Open Burner, 12 Burners	37.771
Product website	Cooktop	Restaurant	Gas	U.S. Range (X24-4L) - 24" Open Burner Sunfire, 4 Burners	37.771
Product website	Cooktop	Restaurant	Gas	Vulcan-Hart (36-S-6B-P) - 36 Open Burner Endurance, 6 Burners	40.29
Product website	Oven	Domestic	Electricity	GE Cafe 30" Built-In Double Convection Wall Oven	35.708
Product website	Oven	Domestic	Electricity	GE Profile 30" Built-In Single/Double Convection Wall Oven	18.568
Product website	Oven	Domestic	Electricity	GE Profile Advantium 120V - 30 in. Wall Oven	13.926
Product website	Cooktop	Domestic	Electricity	Inductor Cooktop, LSCI365ST	0.43
Product website	Cooler	Restaurant	Electricity	Top Mount 4X5X6 Norlake KLB45-CR , CPB050DC-A	11.995
Product website	Cooler	Restaurant	Electricity	Top Mount 6X12X6 Norlake KLB612-CR , CPB075DC-A	18.406
Product website	Cooler	Restaurant	Electricity	Top Mount 6X6X6 Norlake KLB66-CR , CPB050DC-A	11.995

Product website	Cooler	Restaurant	Electricity	Top Mount 6X12X7 Norlake KLB77612-CR , CPB075DC-A	18.406
Product website	Cooler	Restaurant	Electricity	Top Mount 6X6X7 Norlake KLB7766-CR , CPB050DC-A	11.995
Product website	Cooler	Restaurant	Electricity	Top Mount 8X8X7 Norlake KLB7788-CR , CPB075DC-A	18.406
Product website	Cooler	Restaurant	Electricity	Top Mount 8X8X6 Norlake KLB88-CR , CPB050DC-A	11.995
Product website	Freezer	Restaurant	Electricity	Top Mount 4X5X6 Norlake KLF45-CR , CPF060DC-A	15.567
Product website	Freezer	Restaurant	Electricity	Top Mount 6X12X6 Norlake KLF612-CR , CPF150DC-A	25.032
Product website	Freezer	Restaurant	Electricity	Top Mount 6X6X6 Norlake KLF66-CR , CPF075DC-A	20.062
Product website	Freezer	Restaurant	Electricity	Top Mount 6X12X7 Norlake KLF77612-CR , CPF150DC-A	25.032
Product website	Freezer	Restaurant	Electricity	Top Mount 6X6X7 Norlake KLF7766-CR , CPF100DC-A	19.943
Product website	Freezer	Restaurant	Electricity	Top Mount 8X8X7 Norlake KLF7788-CR , CPF150DC-A	25.032
Product website	Freezer	Restaurant	Electricity	Top Mount 8X8X6 Norlake KLF88-CR , CPF100DC-A	19.943
Product website	Dishwasher	Restaurant	Electricity	Undercounter Dishwasher Champion 250degF	0.018
Product website	Dishwasher	Restaurant	Electricity	Undercounter Dishwasher Champion 220degF	0.013
Product website	Dishwasher	Restaurant	Electricity	Undercounter Dishwasher Champion 180degF	0.003
Product website	Dishwasher	Restaurant	Electricity	Undercounter Dishwasher Jet Tech 140degF	0.007

Product website	Dishwasher	Restaurant	Electricity	Undercounter Dishwasher Jet Tech 220degF	0.015
Product website	Dishwasher	Restaurant	Electricity	Undercounter Dishwasher Moyer Diebel (201LT) 140degF	0.003
Product website	Dishwasher	Restaurant	Electricity	Door Type Dishwasher Insinger 180degF	0.002
Product website	Dishwasher	Restaurant	Electricity	Door Type Dishwasher Insinger 220degF	0.006
Product website	Dishwasher	Restaurant	Electricity	Door Type Dishwasher Jackson 140degF	0.004
Product website	Dishwasher	Restaurant	Electricity	Door Type Dishwasher Fagor (FI-120W) 140degF	0.002

Table D.6: The source and specifications of the waste treatment emission factors.

Source	Type of waste	Disposal Method	Country	Method specification	Disposal EF kg CO2e/kg waste
[101]	Compost	Landfill	Australia		0.002
[101]	Paper and cardboard	Landfill	Australia		0.003
[101]	Garden and green	Landfill	Australia		0.002
[101]	Wood	Landfill	Australia		0.002
[101]	Textiles	Landfill	Australia		0.002
[101]	Sewage	Landfill	Australia		0.001
[48]	Compost	Incineration	Switzerland		0.032
[48]	Compost	Incineration	Switzerland		0.016
[48]	Municipal	Landfill	Switzerland		0.56
[48]	Compost	Composting	Switzerland		0
[48]	Compost	Covered fermentation	Switzerland		0.041
[48]	Compost	Anaerobic digestion	Switzerland		0.258

[48]	Compost	Covered fermentation	Switzerland		0.015
[48]	Sewage	Waste water treatment	Switzerland	Residence	0.435
[48]	Sewage	Waste water treatment	Switzerland	Unpolluted, Class 2	0.332
[48]	Sewage	Waste water treatment	Switzerland	Class 1	0.316
[48]	Sewage	Waste water treatment	Switzerland	Class 2	0.37
[48]	Sewage	Waste water treatment	Switzerland	Class 3	0.403
[48]	Sewage	Waste water treatment	Switzerland	Class 5	0.479
[48]	Sewage	Waste water treatment	Switzerland	Class 4	0.439
[48]	Sewage	Waste water treatment	Switzerland	Unpolluted, Class 3	0.3
[102]	Compost	Landfill	USA		0.001
[102]	Compost	Landfill	USA	No recovery	0.002
[102]	Compost	Landfill	USA	Flaring	0.001
[102]	Compost	Landfill	USA	Energy recovery	0.001

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