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Yin Jin Lee, Xu Yang and Edgar Blanco

Abstract— **We proposed a methodology based on life cycle assessment streamlining techniques to estimate the carbon footprint (CF) of a meal. The methodology was applied to estimate the meal CF of twenty-four people on a 4-days Galapagos Island tour using over three hundred existing Life Cycle Analysis (LCA) results in the food industry. In spite of the abundance of food LCA studies, there were very little food CF studies on food produced in South America or Ecuador. By combining established and novel life cycle assessment streamlining techniques, we demonstrated how to (a) calculate the uncertainty associated with the use of surrogate CF data, (b) carry out a preliminary carbon footprint calculation using surrogate data to identify a subset of components that contributes the greatest CFs to the product, which we called the set of interest (SOI) and, (c) greatly reduce the uncertainty in the CF results using only exact CFs for the SOI in addition to the surrogate CFs of the other food items. In general, this methodology can systematically cut down the time and resources that are needed to collect all the emission data in the production of food in a meal, but to focus on only a small handful of food items that impact the total CF, provided that the surrogate CF database is large enough to include the true CF.**

Index Terms— **Food carbon footprint, LCA, Probabilistic Underspecification of life cycle assessment.**

I. Introduction

THE carbon footprint (CF) of food is a concern of most environmentally conscious consumers. In the last decade, there has been an increased interest in the CF of food products, evident by the many published news items and papers that provide guidelines for consumers to reduce their individual food CF. Consumers can now estimate their food CF using online calculators [1], [2]. These resources provide general guidance for consumer decisions, however, they are of questionable accuracy, with application for specific regions and do not include uncertainty in the CF calculations.

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Positioned at the lower end of the supply chain, the typical barrier consumers (and downstream manufacturers) meet is that they have the knowledge of the components that are included in the final product (e.g. a meal) but very little detail required for a complete LCA analysis. Complete LCAs require environmental information from the extraction of the raw material to the final disposal of the product. However, it is unconventional to exchange this information between the suppliers and buyers. This makes it increasingly difficult to obtain necessary details for a cradle to gate LCA as we move down the supply chain. In addition, the effort needed to track the emission across the life cycle of products often overshadow the tangible benefits of quantifying the environmental impact [3]. The discontinuation of the carbon labeling by one of the world's largest retailer, Tesco, in the January of 2012 demonstrated the difficulty of pledges to label broad ranges of products [4]. Thus, it is important to find cost-effective ways to overcome these barriers, especially if end-consumers are expected to change their buying patterns to include environmental dimensions.

In this paper, we demonstrate a possible solution to calculate the CF from the consumer perspective, using information on the food consumed by twenty-four people on a 4-days Galapagos Islands (Ecuador) tour. Despite an increasing availability of studies and resources, we found that there is a much smaller set of life cycle assessments (LCA) that focused on South America produce, and even fewer that were focused on Ecuador in particular. As mentioned earlier, this is a common problem faced by downstream members of the supply chain. To solve this problem efficiently, we need a methodology that can help us identify the food items that are significant to the total food CF, using currently available information.

This paper is organized as follows. Section II gives an overview of Life Cycle Assessment (LCA) in food as well as a review of methodologies to streamline and estimate uncertainty in LCA calculations. Section III describes the proposed methodology by introducing a hierarchical approach to describe components of a meal and its relationship with the uncertainty of the CF. In Section IV, we apply the proposed methodology to the Galapagos tourist meal plan, introducing the "set of interest" to efficiently reduce the uncertainty on the carbon footprint estimation. We conclude in Section V describing some limitations and further refinements to the proposed approach.

II. Background

A. Food life cycle assessments and carbon footprint

The carbon footprint (CF) of a product is a measure of the amount of greenhouse gases (GHG) that is generated throughout the product's lifecycle [5]. The GHG emission is usually calculated in LCA and quantified in terms of their global warming potential (GWP) according to the IPCC guidelines [6]. There are numerous sources of the CF of food products in the form of scientific studies, national reports, or in public and commercial databases. They were usually calculated based on a varied set of guidelines. Established LCA standards and guidelines include the international standards ISO 14040 [7] and ISO 14044 [8], or practical guidelines by international organizations and universities such as the SETAC Code of Practice [5] and the Dutch operation guidelines by Centrum Milieukunde Leiden (CML), Leiden University [9]. In 2008, the British Standards Institute introduced the PAS2050 to outline a systematic methodology to audit GHG emission specifically [10]. Other than the general LCA guidelines, Mila Canal outlined a LCA methodology specifically for vegetable production and consumption [11].

Besides papers on the LCA of individual food items, there are also studies that provide consumer advice for environmentally sound decision. Jungbluth broke down the life cycle of food products into modules and compared the Eco-indicator 95+ points for the product characteristics that might occur in each module. Through their comparisons, they concluded that the environmental impact of meat, air transported food products and vegetable produced in greenhouses with heating have higher impact than their respective alternatives whereas packaging has minor importance [12]. Blonk *et al.* reported similar findings [13]. Other resources extend from giving advice to providing simplified CF calculation tools online, which users can use to calculate their food carbon footprint. Although these platforms are convenient to use, they have explicitly stated that the values are only applicable for use in a stated country, and do not provide the uncertainty and variability in the final calculated number.

B. Streamline strategies

Streamline techniques are strategies that are applied to reduce the effort needed in LCA. Streamlining can be done through limiting the scope of the life cycle analysis or through the use of surrogate data [5]. The scope can be limited by examining only specific parts of the life cycle, thereby eliminating the need to track the emissions in the upstream processes or in the downstream processes. The practice of using surrogate data is widespread with many LCA analysts relying on databases such as the Ecoinvent [14] to substitute for the information they lack.

Using surrogate data in LCA calculations can give rise to uncertainty in the results. Weidema *et al.* have classified the various types of uncertainty qualitatively and proposed a way to estimate them quantitatively [15]. They developed a pedigree matrix that combines the description of the appropriateness of the surrogate data and assigned indicator scores that can be translated into a logarithmic uncertainty distribution. The pedigree matrix is also applicable for the food CF surrogate data in our methodology.

C. Probabilistic Underspecification

In situations where it is desirable to calculate the total CF of a product accurately with minimal effort, we need strategies that can allow us to identify and focus on the major contributors to the CF. Patanavanich introduced the use of structured probabilistic underspecification to estimate the range of cumulated energy distribution (CED) of assembled products [16]. The structure took the form of a hierarchy in which the materials were classified based on their physical characteristics at each level. The hierarchy structure is useful for situations when the materials are underspecified because the analyst can avoid choosing a less appropriate surrogate data but instead, include all possible options and calculate a range of the possible CED. As the material becomes more specific, less surrogate data is needed and the range of the CED decreases. They used the preliminary calculations of the total CED at a less specific level to identify the components that had the highest contribution to the product CED and carried out further streamlined LCA by specifying just the identified components.

In the attempt to calculate the total CF for twenty-four people on a 4-days Galapagos Island tour, we found ourselves in a typical downstream manufacturer conundrum. We neither have LCA data of the food consumed in Ecuador nor the time and resources required to calculate the exact CF. Thus we propose a revised structured probabilistic underspecification hierarchy specific for food CF calculations and illustrate how it is applied. This methodology can be extended to any meal.

III. Methods

A. Hierarchy structure

The basis of the hierarchy is to classify the food based on observable characteristics. The proposed hierarchy consists of five levels, namely, Food Group, Food, Specific Food, Country of Origin and lastly, Technology. Food Group represents the lowest resolution information of a food item (e.g. Meat, Vegetable). Food is the common name used to describe the food (e.g. tomato). Specific Food describes the variety of the vegetable, or a particular cut of meat. Technology refers to the technology used to produce the food. An example using Tomato is shown in Fig. 1. The food characteristics in the first three levels are easily obtainable by the consumer, compared to the Country of Origin and the Technology. Appendix 1 includes more examples of several common food and their classifications according to the proposed hierarchy.

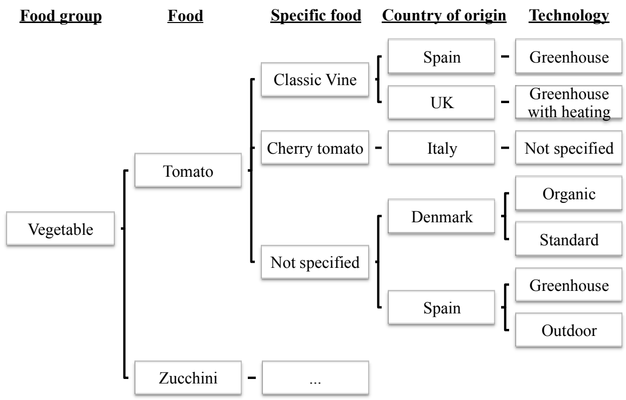

Fig. 1. The hierarchy structure of tomato is used to demonstrate how the specification increases across the five levels of specification.

B. *Database compilation*

We compiled 309 surrogate CFs in the form of the global warming potential over 100 years (GWP100) in a database. Sources that contributed more than 5 CO_2 equivalent or GWP100 emission data are listed in Table I. Even though the CF cited in these articles were calculated using different guidelines, and it was not ideal to compare them directly, we assumed that the differences in their resulting CF were accounted for in the uncertainty range of the individual CF, explained in the next section. It was noted that IPCC had revised the GWP of nitrous oxide and methane in 2001 and 2007 [6], and efforts were made to convert the GWP to the latest GWP if the article stated that it used the earlier IPCC GWP values.

The LCAs of the food CFs in our database have varied system boundaries. Since most of food LCA covered from cradle to farm gate or production gate, a handful of the food LCA covered from cradle to retail and an even smaller number of food LCA accounts for the entire life cycle, we set our system boundary to the CF of food from cradle to farm gate or factory gate. Although it is not a complete LCA, it is a good representation of the impact of the food items because the production phase of food items dominates the CF of food, compared to other supply chain processes such as transport [25], as long as the food is not transported by air. For the conversions of meat between different boundary definitions, we used the ratio 1kg live weight = 0.81 kg carcass weight [26] = 0.56 kg bone free meat [27].

There was no appropriate surrogate data for the processed food (e.g. Flan, a type of pie, and Mondongo, a type of beef tripe soup) thus we limited the scope of our studies to meats, vegetables, dairy products, fish and baked products and excluded most processed foods. Of the remaining 94 products, we were unable to find the exact food CF for 26 items such as Yogurt, String bean, Tomato fruit, Plantain, and Avocado. We did not exclude them from the analysis because their total weight was substantial (16%). Instead, surrogate data of another food from the same genus were used (e.g. Plantain was represented by Banana), or, if there was no food that is from the same genus, the surrogate data of another food that shared physical similarities were used (e.g. Yogurt was represented by Ice cream because both were dairy based and require refrigeration).

C. *Uncertainty*

In this study, we referred to the classification of uncertainty as introduced by M. Huijbregts [28], B. Weidema [15], and S. Patanavanich [16], and classified the sources of uncertainty in our CF calculation as the following:

Type i: The individual CF data in our database introduced uncertainty when used as a surrogate data. This could be due to the reliability of the information used in their calculation, the level of completeness of their data collection, the temporal correlation between the CF data and our analysis. We accounted for these uncertainties using the pedigree matrix proposed by B. Weidema [15]. The pedigree matrix also included technological and geographical correlation of the surrogate data, but we recognized the Country of Origin and technology as a part of the food specification and included them in our classification hierarchy instead (refer to the hierarchy section above). We assumed that the indicator score is three for reliability, completeness and temporal correlation, and one for the geographic and technological correlation. An indicator score of three implies that the quality of the CF data as a surrogate is medium and a score of one implies that there is no uncertainty.

Type ii: The uncertainty in the CF as a result of using

TABLE I. The titles of the publications used for data compilation and the types of carbon footprint (CF) data obtained

Title	Number of CF data (Food group)	Study includes CF from these countries	Published Year	Reference No.
LCA dk	16 (Dairy), 1 (Egg), 26 (Meat),17 (Fish), 4 (Shellfish), 13 (Cereal), 1 (Pulses), 12 (Vegetable), 5 (Bread)	Mainly Denmark	Around 2000	[17]
Ecoinvent	23 (Cereal), 8 (Plant oil), 7 (Pulses), 2 (Sugar), 4 (Vegetable)	Mainly Switzerland	1996- 2004	[14]
Carbon footprints of Indian food items	1 (Egg), 2 (Meat), 3 (Cereal), 2 (Fruit), 3 (Vegetable)	India	2009	[18]
Environmental Assessment of Two Pork Supply Chains Using Life Cycle Assessment	6 (Meat)	Australia, Denmark, France and Sweden	2010	[19]
Comparing environmental impacts for livestock products: A review of life cycle assessments	4 (Egg), 17 (Meat)	Netherlands, Ireland, Spain, UK, France and Finland	2010	[20]
Collection of Proceedings from LCAFood2010 Conference	4 (Meat), 8 (Fruit), 18 (Vegetable)	Various	2010	[21]
An assessment of greenhouse gas emissions from the Australian vegetables industry	2 (Fruit), 20 (Vegetable)	Australia	2010	[22]
Environmental Footprint and Sustainability of Horticulture (including Potatoes) – A Comparison with other Agricultural Sectors	1 (Cereal), 2 (Fruit), 5 (Vegetable)	UK	2006	[23]
Updating the carbon footprint of the Galician fishing activity (NW Spain)	31 (Fish), 2 (Shellfish)	Spain	2011	[24]

multiple surrogate data was accounted through the creation of a combined distribution through the application of Monte Carlo Simulation.

D. Calculation of the total CF

The total CF of the meal was calculated by summing the multiple of the weight of the food and the CF of the food. We assumed that there is ±1% uncertainty in the weight. We carried out 10,000 Monte Carlo simulations using Oracle Crystal Ball. In each calculation run, individual food items were assigned one random surrogate CF data that matches the level of specificity. The distributions of the individual CF data were assumed to logarithmic with arithmetic mean, μ_{ar}, and standard deviation, σ_{ar}. The arithmetic parameters were calculated using (1) and (2). The surrogate CF data was used as the geometric mean μ_g and geometric standard deviation σ_g = 1.163.

$$\mu_{ar} = \mu_g \exp^{\frac{\log^2(\sigma_g)}{2}} \quad (1)$$

$$\sigma_{ar} = \sqrt{\exp^{2\ln\mu_g + \ln^2(\sigma_g)}\left(\exp^{\ln^2(\sigma_g)} - 1\right)} \quad (2)$$

Out of the 94 food items in the food order list from the Galapagos Island Ferry Tour, 82 items were originally characterized up to the Food level and only 12 items were originally characterized up to the Specific Food level. This is typical to consumer level knowledge of meals. 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 because they were both cheap beef parts. Even though no information about the country or place of origin of the food items was given, in order to demonstrate how the structured hierarchy could reduce the uncertainty in the total food CF, we made a few realistic assumptions so as to progress into the Country of Origin and Technology level for purposes of the study. Statistics in FAO showed that most of the foods consumed in Ecuador in the past years were locally produced [29]. We assumed that the energy consumption in the farming process is dependent on the climate, which is true in the case of horticulture [30]. Thus at the Country of Origin level, the surrogate CF data from countries with tropical and Mediterranean climate have preference over those with temperate climate. Data from Brazil, India, Australia, Spain and Italy, Ghana remained to be use as surrogate and data from UK, Sweden, Denmark, Netherland, Canada and USA were filtered out. There is one CF data that included land use change impact in Brazil beef and it was 26 times the CF of Brazil beef without land use change [31]. We removed this data at the Country of Origin level too, assuming that beef grown with land use change was of a negligible proportion, because FAOSTAT statistics showed that the total agricultural area in Ecuador decreased by 2.9% from 1989 to 2009 [29]. At the technology level, it was ideal that we had one "correct" CF that could reflect the exact CF of food from Ecuador. However, we did not have this data, and for the sake of comparison in this study, we picked inputs with conventional technology for calculation.

E. Selecting the Set of Interest (SOI)

The result that we obtained at the Food and Specific Food level relied on many surrogate data in their calculation. It served as a preliminary screening of the food list, from which we could identify the "Set of Interest" (SOI) and eventually obtain an accurate CF efficiently by focusing our effort to resolve the CF of only the items in the SOI. In this study, the SOI was defined as the items that fell into the top 90% of the total CF for more than 75% of the 10,000 simulations.

To test the effectiveness of this strategy at Food and Specific Food level, we updated the surrogate data with the same inputs that we used to compute the total CF at the technology level. By doing so, we created hybrid levels of the Food and Specific Food level, which we called Food-SOI and SFood-SOI respectively. In real practice, we will only have to spend time to find the exact CF of the SOI and assume that the surrogate data is acceptable for the other components.

IV. Results and Discussion

A. Total carbon footprint and its uncertainty

The structured underspecification methodology allows us to include all appropriate surrogate CF data in the food carbon footprint (CF) calculation. Even without the exact CF information, we can find out the preliminary CF as long as we have a database of surrogate CF. The resulting total CF distributions of all the five levels indeed decrease with increasing specificity (Fig. 2.). The medians at the first three levels fall within ±11% of the median at the Technology level largely because the extreme data points cancelled out (Table II). In the first three levels, the outliers at the upper end

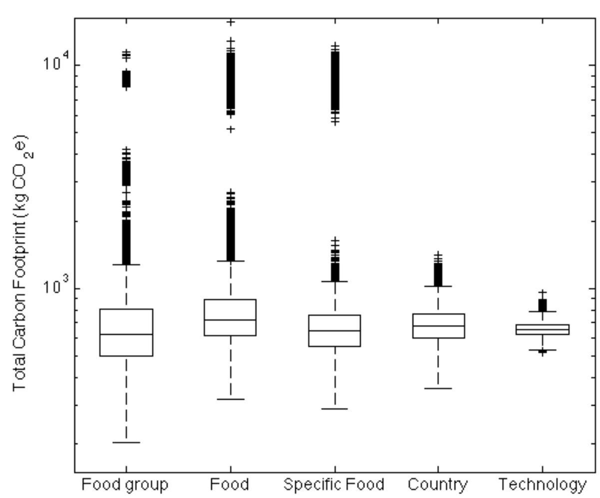

Fig. 2. The boxplots show the 25th, 50th and 75th percentile of the total food CF for twenty-four people on a 4-days Galapagos Island tour at the five levels of specifications. (The Country label represents the Country of Origin) The whiskers extend to the most extreme points that are within 1.5 interquartile ranges from the lower and upper quantiles. The resulting total CF distributions of all the five levels indeed decrease with increasing specificity.

TABLE II. The distributions of the total food CF for twenty-four people on a 4-days Galapagos Island tour for the five levels of specifications. The median of the Food Group level is close to the median at the Technology level because the extreme data points canceled out.

	Total carbon footprint of the food order list/ kg CO_2e				
Levels	Food Group	Food	Specific food	Country of Origin	Technology
Maximum	11457	15648	12251	1412	916
Minimum	204	316	286	355	522
Median	623	725	647	675	655

of the uncertainty range are the runs that included the beef CF using land use change as surrogate(s). The tail of outliers disappears at the Country of Origin level when we removed the land use change CF data from the surrogate list.

B. *Set of Interest (SOI)*

The sets of food items that fall into the top 90% of the total food CF for more than 75% of the runs are listed in Table III. The list explains how the CF ranges of the individual food items vary with increasing product specifications. The number of items in the SOI increases at the higher levels because the number of surrogates used in the calculation is decreased and the CFs of the individual items become more consistent. Although Potato and Minced meat are at the top of the SOI in Food Group, they fall out of the SOI completely in the higher levels, indicating that the Food Group level is not accurate enough to be used as a basis for further investigations. Beef Tongue, Beef Heart and Beef Liver are listed in the top five items at the Food level but fall out of the SOI when they are assigned as cheap beef at the Specific Food level. Thus the cost allocations of CF have great influence on the CF of different beef parts based on the existing data.

The SOI is 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 because many of the tomato with higher CF are from the countries with temperate climate, and they tend to use greenhouse with heating, which are very energy intensive [30].

C. *Streamlining using the SOI*

The aim of streamlining is to reduce the effort required to collect details for accurate CF calculation. Streamlining using the SOI is effective if it allows the user to identify the main contributors to the CF, focus the effort to collect details for only these main contributors, and be able calculate the range of possible CF as accurately as if there is complete information. We have enough information from the food list from Food Group up to the Specific Food level but we will only apply the streamline approach on the Food and Specific Food level because we have shown that the SOI at the Food Group level is inaccurate. The new levels are labeled Food-SOI and SFood-SOI, the hybrids of the Food and Specific Food levels, respectively.

The streamline approach effectively reduced the range of CF. The CF range of the hybrids matches the CF range of the Technology level well (Fig. 3. and Table IV). We have shown in this particular test, we can find an accurate range of the total CF of the food order list without the knowledge of the country of origin and technology for 79 items out of the 94 items in the food order list. This can save substantial amount of effort needed to track the supply chain of these foods. We note that our CF range at the technology level is a combination of a highly selective list of surrogates and not the exact total food CF for twenty-four people on a 4-days Galapagos Island tour. Nonetheless, based on our results, we can infer that the approach to streamline using SOI can be highly accurate if one

TABLE III. The lists of set of interest, the items that fall into the top 90% of the total food CF for more than 75% of the runs, for the five levels of specifications. The items that use other food CF surrogate data (e.g. Yogurt used Ice cream CF) are marked with *. The items that have interesting patterns in the list are shaded in grey.

	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

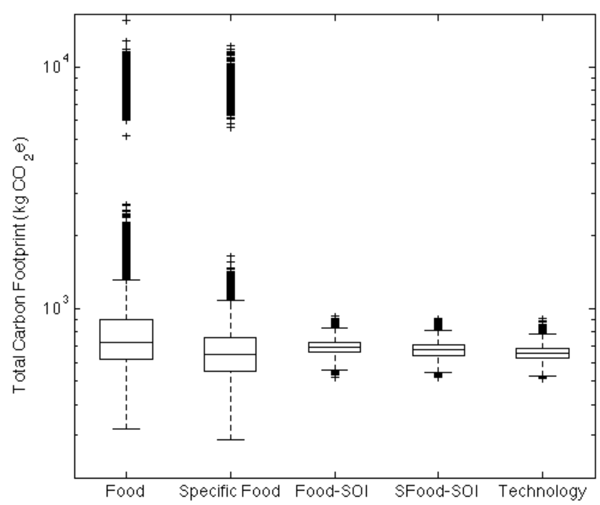

Fig. 3. The boxplots compares the distribution of the total food CF for twenty-four people on a 4-days Galapagos Island vacation before and after streamlining using SOI. Food-SOI and SFood-SOI are the hybrids of the items in SOI specified at the Technology level with the remaining items at the Food and Specific food levels respectively. The CF range of the hybrids matches the CF range of the Technology level well.

TABLE IV. The distributions of the total food CF for twenty-four people on a 4-days Galapagos Island vacation 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 CO_2e				
Levels	Food	Specific food	Food-SOI	SFood-SOI	Technology
Maximum	15648	12251	930	914	916
Minimum	316	286	523	518	522
Median	725	647	693	676	655

condition is met: the exact CF of the all the individual items falls within the combined range of the surrogate data. This can be possible if the database is large. It may be argued that the range of CF at the technology level is still quite high. This is due to the uncertainty in the item weights, which is unavoidable and the uncertainty in the appropriateness of the individual surrogate, listed as Type I uncertainty in Methods part C. Type i uncertainty can be reduced if the LCAs of the surrogate data are done in a uniformly reliable manner.

V. Conclusion

By combining the pedigree matrix and the probabilistic underspecification to streamlined LCA techniques, we have developed a methodology that can be used to calculate the carbon footprint of a meal with limited information about the supply chain of the items in the meal. We demonstrated that we could estimate the range of food CF accurately and efficiently. If we have a database with surrogate CF ranges that is broad enough to include the true CF of all the items in the meal, instead of having to find out the exact CF of all the items in the meal, we only need to find the exact CF of the items in the SOI. We can further test the robustness of this methodology by obtaining the real CF data from Ecuador or apply it in other meals where the real LCA data is more easily obtainable.

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