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Carbon Hotspots in the Food and Beverage Industry: Insights from Analyzing the Product Portfolio of a Global Packaged Consumer Goods Company

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Abstract

Some efforts to streamline and accelerate product-level life cycle assessments (LCA) with regards to greenhouse gas emissions (product carbon footprinting, PCF) rely on first grouping products into categories and then building simplified LCA models around emission hotpots. This requires, among others, fundamental understanding of how much such hotspots can vary from product to product, across brands, and country of origin. Here, we apply a novel fast LCA methodology to first quantify and then analyze PCFs of 3,335 stock keeping units (SKUs) of a global food snack and beverage company. We find that the often cited dominance of the supply chain's contribution to the total footprint is valid for large portfolios of products in aggregate (75%-93% contribution). However, this does not remain universally valid when analyzing individual brands and SKUs: At SKU level, the metric varies widely, from 9% (smallest supply chain contribution) to nearly 100%. For 254 of the 3,335 SKUs, less than 50% of overall emissions originate in the supply chain. SKU-level carbon intensity (PCF divided by net SKU weight) varies widely as well, in our sample from 0.1 to 70. It also varies within brands, indicating a design challenge for stream-lined models. SKU-average carbon intensityvaries between ~0.4 (beverages) to ~4 (some baked snacks). The portfolio-level footprint (3,335 SKUs in our sample) is highly concentrated: 4% of SKUs contribute 50% of annual GHG; 2.5% of the 6,040 acquired individual raw materials contribute 40% of annual GHG from all raw materials, the majority of the 2.5% being agricultural ingredients.

Keywords: Product carbon footprint (PCF); portfolio; supply chain; hotspots; life cycle assessment; agricultural ingredients, streamlined LCA, product category rules

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Introduction

Product life cycle assessment (LCA)(SAIC, 2006)has come a long way, from one of its earliest uses in a globally operating beverage company (to compare the relative environmental impacts of glass versus plastic packaging(Hunt et al., 1998)) to being the methodological backbone of the current Product Environmental Footprint (PEF) initiative of the European Commission. Specifically in product carbon footprinting (PCF), a sub-discipline of LCA, some of LCA's challenges (Reap et al., 2008b, a) have been overcome or at least alleviated, partially through the emergence of more detailed footprinting standards (Draucker et al., 2011) and further by improved awareness of and approaches to data quality issues (Lloyd and Ries, 2007, Ciroth and Meinrenken, 2014). In business applications, concepts of LCA and Industrial Ecology more generally have been shown to lead to competitive advantages (Hoffman et al., 2014). Respective case studies, e.g., (Meinrenken et al., 2014), are consistent with an apparent correlation between sustainability efforts and stock performance amongst S&P 500 companies (Carbon Disclosure Project, 2014). While strictly speaking this is a correlation without proof of causation, companies may infer with near certainty that efforts towards sustainability at least do not seem to be detrimental to more traditional measures of business performance.

For many companies, however, the majority of their environmental impacts are believed to originate in their supply chain (i.e., up- and downstream of their own operations); and here insights from methodologies such as LCA have proven challenging (O'Rourke, 2014). Whereas companies almost routinely track energy consumptions of their own operations, and quantify associated greenhouse gas (GHG) emissions referred to as scope 1 and 2, methodologies to analyze the hundreds and thousands of products and supply chains that make up each company's footprint are typically not yet at a company's disposal. This is because traditional LCA is usually considered too complex to be applied at such scale (Meinrenken et al., 2012b).

To address this, a number of recent studies focus on streamlining the PCF process. These focus either on simplifying the methodology itself and thus requiring fewer data entries and analytical steps, e.g., (Graedel, 1998, Hunt, Boguski et al., 1998, Hochschorner and Finnveden, 2003, Verghese et al., 2010, Arena et al., 2013). Or they focus on exploiting existing company IT systems and data science methodologies to carry out the LCA to the same level of detail, however with less time and personnel requirements(Meinrenken et al., 2013).

One recurring set of questions in such work are around "hotspots", i.e. the source for the majority of GHG contributions, and whether these can be generalized across products, product types, or regions. If hotspots can indeed be generalized, this could aid in streamlining LCA models for certain product categories(Ingwersen and Stevenson, 2012), for example, by focusing most of the LCA effort on pre-determined parts of a product type's life cycle while only approximating or even disregarding others. Likewise, it would facilitate quantifying the life cycle carbon reductions from introducing supply chain optimizations (Meinrenken et al., 2014) such as using low-carbon fuels (Lackner et al., 2010, Meinrenken and Lackner, 2014, 2015, Meinrenken, 2015). For example, are hotspots usually or always up- or downstream of a company's own operations; for packaged consumer goods, are packaging materials or actual product content the higher contributors; can this vary between brands of the same company, across regions, etc.? Such analyses have not yet been widely available because typically only a small number of products of any particular company have been analyzed via LCA (typically 10-20 (Cremmins, 2014)).

Here, we investigate above questions systematically by applying a recently introduced fast PCF approach to a dataset of 3,335 stock keeping units (SKUs) of a globally operating packaged consumer goods company that specializes in food snacks and beverages.

Materials and Methods

Life Cycle Assessment (LCA)

The <u>goal and scope</u> of the LCA was to first carry out a PCF, according to the latest GHG Protocol standard (GHG-Protocol, 2011), for each of the 3,335 SKUs in a large scale PCF project carried out for a global packaged consumer goods company (food snack and beverage sector). The <u>LCA inventory data</u> is described in detail in below section " LCA Inventory Data for Sample Portfolio".

All attributable life cycle stages (cradle-to-grave) were included for each SKU. PCFs were obtained for the six standard GHGs, with the impact calculation being on a 100 year global warming potential (GWP) horizon (expressed as CO_2e). The ultimate objective was to then analyze these PCFs with regards to the hotspot characteristics described in *Introduction.*

Fast PCF Methodology

As laid out in detail previously, the product carbon footprint of a single SKU *i* is calculated as follows (Meinrenken et al., 2011a, Meinrenken et al., 2011b, Meinrenken et al., 2012a, Meinrenken et al., 2012b, Meinrenken, Garvan et al., 2013, Meinrenken, Sauerhaft et al., 2014):

$$pcf_i = \sum_j \prod_k D_{i,j,k} \ , \qquad 1)$$

where pcf_i denotes the footprint of a single SKU *i* (amount of CO_2e); *j* the particular inventory item for which greenhouse gases (GHG) are specified (e.g., a certain packaging material, ingredient, transportation, energy use, etc.); and $D_{i,j,k}$the value of driver*k* for this particular inventory item *j* and product *i.* The annualized carbon footprint of one SKU is thus given as:

$$PCF_i = D_{i,0,0} \cdot pcf_i , \qquad 2)$$

where PCF_i denotes the annualized footprint, pcf_i as above, and $D_{i,0,0}$ the number of individual items produced of SKU *i* per year. The total annual footprint of any portfolio of multiple SKUs is thus:

$$PCF_{Portfolio} = \sum_i PCF_i = \sum_i D_{i,0,0} \cdot pcf_i \ , \qquad 3)$$

where $PCF_{Portfolio}$ denotes the aggregate footprint of a particular set of SKUs chosen to be part of a portfolio. For example, these may be all SKUs belonging to a certain brand, of a specific product type, or those manufactured in a certain country.

Finally, all drivers are screened for their contribution to the aggregated uncertainty of PCF and, where necessary, their sources reviewed and updated and thus driver uncertainty reduced (Meinrenken, 2013, Ciroth and Meinrenken, 2014).

LCA Inventory Data for Sample Portfolio

The life cycle inventory data was extracted from the company's enterprise resource planning (ERP) system (data of year 2011), with facility data (manufacturing plant energy and water consumptions) pulled from separate systems and secondary data added manually for some $Db_{i,j,k}$(Meinrenken, Kaufmann et al., 2012b). The data covered 3,335 SKUs (2 were excluded based on outliers in $Db_{i,0,0}$), 196 brands, 5 countries, and spanned the product types food snack (savory and sweet) as well as beverage (carbonated and non-carbonated). An overview is shown in Table 1.

While this constitutes a rather large dataset (large number of SKUs), it is not comprehensive in that it does not cover every single SKU in each brand, nor does it cover all brands in a particular country. The dataset is therefore a sample that does not reflect the company's total annual footprint but instead gives a representative spread of PCFs across a wide range of SKUs, brands, product types, and countries. The dataset is therefore ideal for the goal and scope of this study.

Table 1: Characteristics of 3,335 Stockable Units (SKUs) Contained in Sample Portfolio

	Brazil	China	Germany	Mexico	USA	**Portfolio**
Product type(s)	Food	Beverage	Beverage	Food	Food & Bev.	Food & Bev.
Number of brands	28	9	5	46	108	196
Number of SKUs	299	836	92	815	1293	3335
Average annual production per SKU	8,988,760	400,464	216,759	105,048	490,815	1,128,218
Average net weight per SKU [kg]	0.9	11.3	70.0	4.4	30.2	17.6
Number of pack. materials*	301	841	93	820	1301	3356
Number of ingredients*	241	673	74	656	1041	2684
Annual GHG (2011) [MegaTons CO_2e]	0.73	1.93	0.11	1.29	8.62	12.68
GHG confidence interval**	N/a***	N/a	N/a	N/a	N/a	±13%

*Estimated from total number of materials and SKU breakdown; **one standard deveation; *** confidence intervals for country, brand, or SKU-level obtainable via fast PCF methodology, however intervals are smaller than GHG variation between SKUs and brands, thus not shown.

Calculations and Analyses

As described previously (Meinrenken, Kaufmann et al., 2012b), the cradle-to-grave LCA inventory is organized into 8 different life cycle stages: S_1: procurement of packaging materials; S_2: procurement of ingredients; S_3: inbound transportation; S_4: manufacturing in company's facilities; S_5: outbound transportation of finished SKU; S_6: warehousing and retail; S_7: consumer use phase; and S_8: end of life. In the analyses presented in this work, we refer to S_1 and S_2 collectively as "raw material acquisition", and S_3 and S_5 through S_8 as "other supply chain" (Figure 2). We thus calculate $\chi_{Supply\ chain}$, the portion of the footprint arising from anywhere in the supply chain (up- or down stream of company's facilities) as a portion of the total footprint (Figure 5):

$$\chi_{Supplychain} = \frac{\left(\sum_{l=1-8} S_l\right) - S_4}{\sum_{l=1-8} S_l}, \qquad 4)$$

Finally, we define carbon intensity (*CI*) of any footprint as:

$$CI = \frac{\sum_i D_{i,0,0} \cdot pcf_i}{\sum_i D_{i,0,0} \cdot w_i}, \qquad 5)$$

where pcf_i denotes the footprint of a single SKU i (as above), S_i as above, and w_i denotes the net weight (i.e., excluding any packaging materials) of that SKU, and $Db_{i,0,0}$ above. *CI* can be calculated for any set of SKUs, ranging from a single SKU to entire portfolios of SKUs.

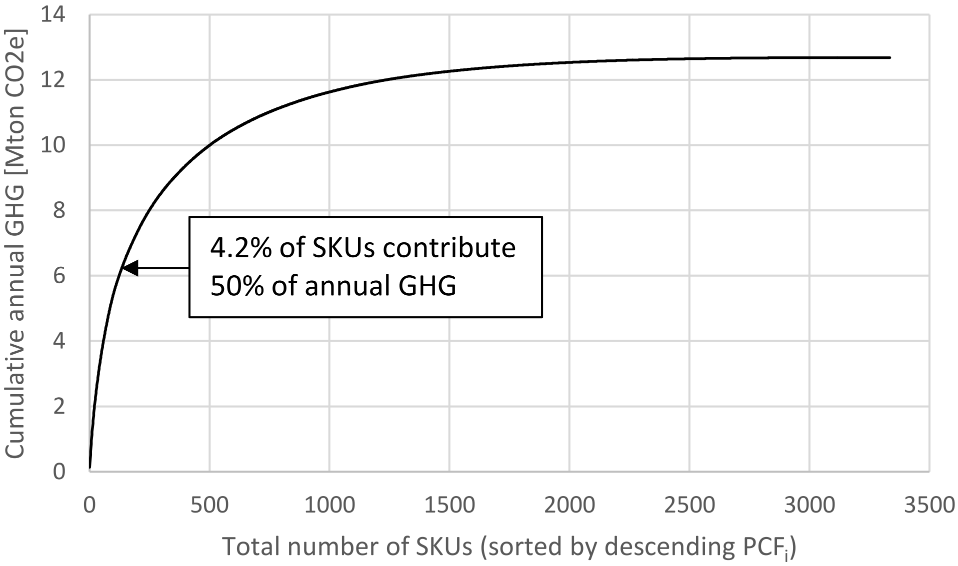
Results

Portfolio-Level Analyses

We first observe that the portfolio footprint is highly concentrated, meaning that relatively few SKUs contribute the majority of the portfolio's annual GHG. In the specific case of our sample portfolio of 3,335 SKUs, only 140 or 4.2% of all 3,335 SKUs with the largest PCF_i contribute 50% of $PCF_{Portfolio}$.

This is shown in Figure 1, which plots the cumulative *PCF* (vertical axis) as a function of the number of SKUs included in the count (horizontal axis), once SKUs have been sorted by increasing PCF_i. In other words, the company's annual carbon footprint across all of its products is highly concentrated in relatively few SKUs. A priori, this could be due to either the pcf_i being highly unevenly distributed, or the annual production numbers $D_{i,0,0}$ being highly uneven (or both). This is therefore investigated further in the subsequent results.

Figure 1: Cumulative Annual GHG Versus Number of Included SKUs



Next we investigated whether there are hotspots of annual GHG in certain materials rather than others. Similar to the above concentration of the footprint arising from relatively few SKUs, many raw materials that the company procures are used across many SKUs simultaneously. As a result, when focusing on the footprint in stages S_1 and S_2 alone, the footprint is similarly concentrated, with 40% of GHG stemming from just 15 individual materials (or 2.5% of all 6,040 materials used across all 3,335 SKUs). This is shown in Table 2 which is sorted by decreasing material amount used annually in the portfolio of 3,335 SKUs.

Table 2: Contribution of Materials in Supply Chain to Portfolio Footprint

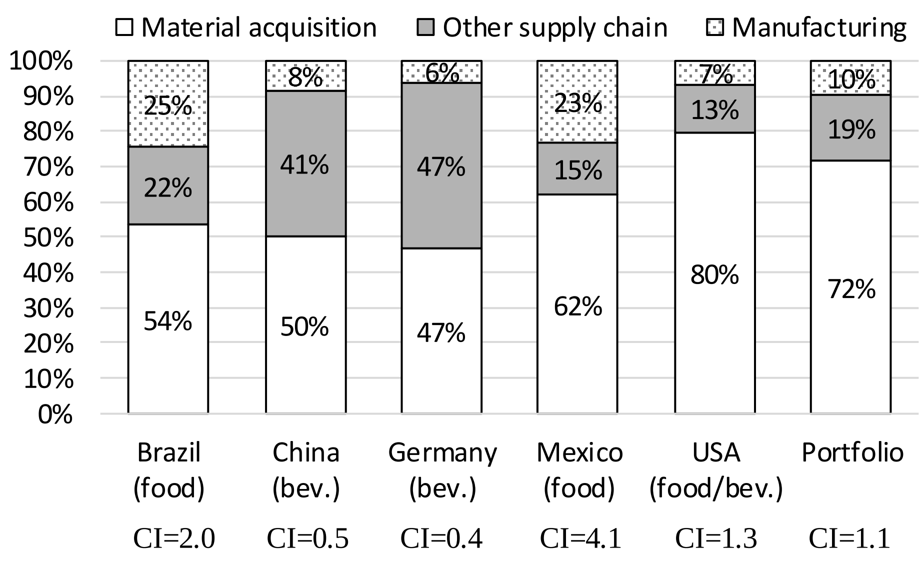
Rank (by material amount)	Material	Country where used in SKU	Annual GHG [Mton CO2e]	% of total GHG S_1+S_2 [cumu-lative]
1	Raw fruit Type A	USA	0.527	4.16%
2	Raw fruit Type B	USA	0.581	8.74%
3	Purchased juice	USA	0.243	10.65%
4	Fruit pulp	USA	0.124	11.63%
5	Beverage base mix	USA	3.178	36.69%
6	Sugar	China	0.049	37.08%
7	Salmon	Mexico	0.014	37.19%
8	Oats	USA	0.010	37.27%
9	Fructose syrup	China	0.162	38.54%
10	Purified water	USA	0.096	39.30%
11	Flavor essence	USA	0.006	39.35%
12	Liquid sucrose	USA	0.062	39.84%
13	Lemon/lime essense	USA	0.016	39.96%
14	Potatoes	Brazil	0.011	40.05%
15	Orange essence	USA	0.005	40.09%
…	…	…	…	…
6040	…	…	…	100.00%

In combination, the results shown in Figure 1 and Table 2 mean that companies can address large portions of their annual footprint by focusing on a small portion of their SKUs, and, with respect to their upstream footprint in stages S_1 and S_2 (i.e., material acquisition), on a small number of their raw materials.

Next we sought to characterize how much of the company's total footprint is driven by supply-chain-related versus non supply-chain-related stages of the lifecycle. This is shown in Figure 2: In every of the 5 countries sampled, non-supply chain related GHG emissions (i.e., from the manufacturing stage S_4) account for at most 25% of annual GHG. However, this can change widely from country to country, and is strongly correlated with the predominant product type in each country and the carbon intensity. For example, PCF in Germany (beverages) has the lowest contribution of S_4 (6%, carbon intensity (*CI*) 0.4) whereas PCF in Brazil has the highest contribution of S_4 (25%, *CI* 2.0).

Focusing only on the upstream portion of the supply chain (i.e. raw material acquisition), contributions range from 47% (Germany) to 80% (USA) of total annual GHG emissions. In summary, when focusing on highly aggregate portfolios such as entire countries, we find that supply-chain-related materials and processes such as transportation do dominate the overall footprint. However, the degree of this dominance varies from country to country. It is most likely mainly driven by the product type in question and, to a lesser extent, by its country of origin.

Figure 2: Breakdown of Annual GHG to Life Cycle Stages

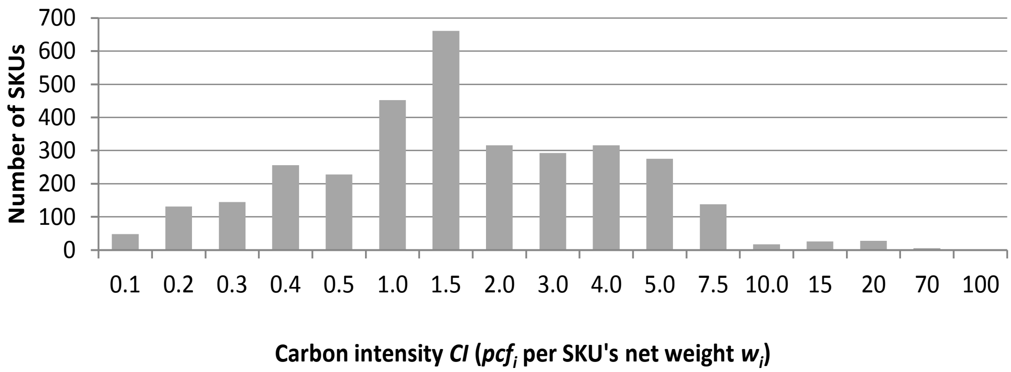


SKU-Level Analyses

Above results are at the level of portfolios (i.e., *PCF* rather than *pcf*) and are therefore affected by the annual SKU productions $D_{i,0,0}$ of each SKU *i*. They are therefore less insightful for a company if it wants to understand GHG hotspots in individual SKUs, be this in order to streamline the LCA process of such SKUs, in order to identify GHG reduction opportunities, or both. In subsequent analyses, we therefore strip out the effect of annual SKU productions and focus on the *pcf* of single SKUs.

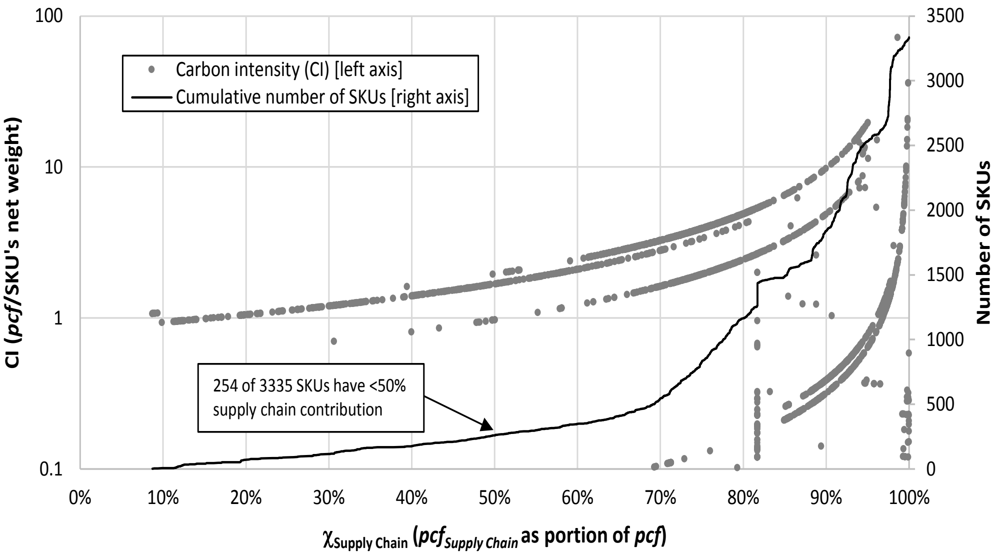
First, we find that the country-level variation in carbon intensity (*CI*) found above (ranging from 0.4 to 4; or factor 10) masks a much broader range of possible *CI* of individual SKUs. SKU by SKU, *CI* can range from as low as 0.1 to as high as 70 (factor 700). This is shown in Figure 3.

Figure 3: Range and Distribution of SKU-Level Carbon Intensity in Portfolio



We then sought to investigate the underlying reasons and possible trends for the wide range of SKU-level *CI*s. We find a strong correlation between *CI* of a SKU on one hand and $\chi_{Supply\ chain}$ on the other (i.e., the footprint portion that originates from the supply chain, *Methods*). This is shown in Figure 4: Across the 3,335 SKUs, $\chi_{Supply\ chain}$ ranges from a minimum of 9% to nearly 100%, and as a general trend, larger $\chi_{Supply\ chain}$ correlates with larger *CI*. Also shown in Figure 4 is the fact that SKUs whose supply chain contributes at most half to the total footprint *pcf* may not be the norm, but are by no means rare exceptions: 254 or ~8% of all SKUs have such untypically small $\chi_{Supply\ chain}$ (Figure 4, right vertical axis, plots cumulative number of SKUs as function of ascending $\chi_{Supply\ chain}$, horizontal axis).

Figure 4: Distribution of SKUs Versus $\chi_{\mathbf{Supply\ Chain}}$ and Impact on Carbon Intensity (CI)

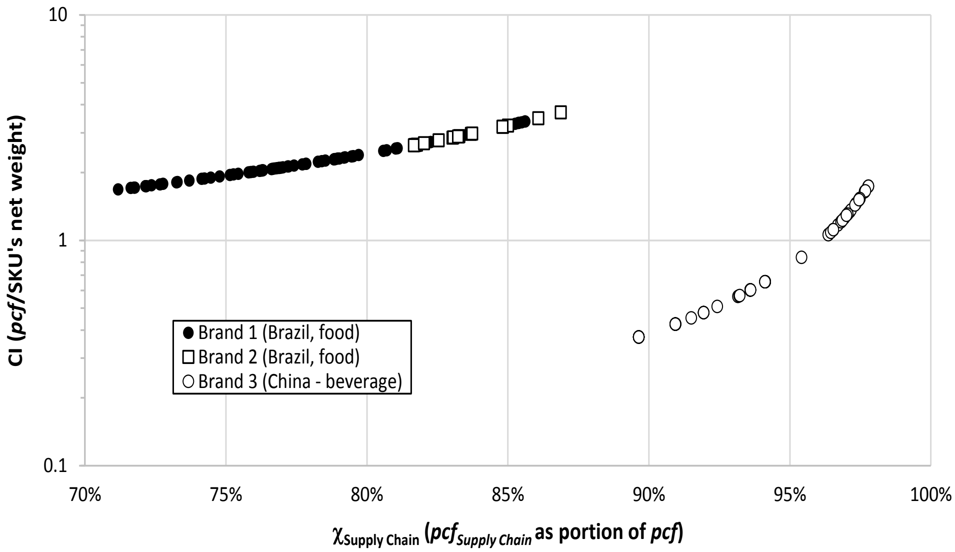


While Figure 4shows a general trend between SKUs' *CI* and $\chi_{Supply\ chain}$, it also shows that this trend is not uniform. Rather, there appear to be subgroups of SKUs in the portfolio, each with their own distinct dependence between *CI* and $\chi_{Supply\ chain}$.

Our final results are therefore devoted to elucidating the SKU characteristics that underly some of this variation in *CI* and $\chi_{Supply\ chain}$ dependence. Figure 5 shows excerpts of the 3,335 SKUs shown in Figure 4, with each SKU data point further identified by country and brand (brands are anonymized to protect company's data confidentiality). We find that each country, and within each country each brand, has its own distinct quantitative relationship between between *CI* and $\chi_{Supply\ chain}$. Furthermore, countries and brands differ strongly as to the overall range of *CI* and $\chi_{Supply\ chain}$. For example, SKUs of a beverage brand in China have *CIs* from 0.2 to 2.0 with $\chi_{Supply\ chain}$ ranging from ~90% to ~98%. In contrast, $\chi_{Supply\ chain}$ of SKU's of two particular food brands in Brazil are all below 87%, with one brand staying entirely above 82% while the other brand ranging as low as 72%. However, the *CI* of the majority of the SKUs of those two brands in Brazil are actually higher than those of the China sample.

Further analyses showed that the underlying reason for this variation is not just the product type: Food snacks can be expected to have higher *CI* than beverages, simply because of their typically more resource intensive formulation and manufacturing. But, to a lesser extent, the country affects the dependence between *CI* and $\chi_{Supply\ chain}$ as well (SKU-level results not shown, aggregate results shown in Table 2).

Figure 5: Variation of $\chi_{Supply\ Chain}$ and Carbon Intensity (CI) within and across Brands



Discussion

Summary and Conclusions

We present a first of its kind dataset of PCFs for 3,335 SKUs which were calculated using a novel footprinting methodology, using an analytic approach to uncertainty propagation (Meinrenken, Ramesh et al., 2011b, Meinrenken, Kaufmann et al., 2012b, Meinrenken, 2013) rather than Monte Carlo approach (Meinrenken et al., 1997, Zheng and Meinrenken, 2013, Zheng et al., 2014b, a, Zheng et al., 2015). Furthermore, each SKU's footprint captures SKU interactions (Macheret et al., 1995, Macheret et al., 1996, Gillespie et al., 1997) that arise from byproducts and/or promotional SKUs (which comprise multiple other SKUs in the portfolio).

When focusing on aggregate, annual GHG across SKU portfolios, we find that previously published observations, for example the importance of the supply chain, e.g. (O'Rourke, 2014), and the agricultural sector, are confirmed: Across the entire sample of 3,335 SKUs, material acquisition comprise 71% of the total footprint, followed by 19% from other supply chain activities and 10% from manufacturing in company's facilities. When broken down to countries and product sectors, footprints from the supply chain (i.e., everything except company's own manufacturing) can range from 75% to 93%. Raw material acquisition always remains the single highest contributing stage in this breakdown. Still focusing on aggregate, annual GHG, a minority of SKUs and a minority of acquired materials comprise the majority of the footprint, leading to a lumpy portfolio with respect to GHG.

This picture changes when drilling down further to the footprint of individual brands and single SKUs: Here, dominance of raw material acquisition is not generally true anymore. Rather, for 254 of the 3,335 SKUs, GHG emissions from the supply chain contribute less than 50% to the total footprint. As a general trend, higher contribution from the supply chain drives higher overall carbon intensity of a SKU. However, the nature of this relationship varies across countries and brands.

In particular, the carbon intensity varies strongly even for different SKUs of the same brand, indicating that it may be challenging (albeit not impossible) to adopt simplified, stream-lined LCA models to categories of products (because they may vary by SKU (e.g., packaging type) and/or country of origin).

Limitations and Future Improvement of Analytic Framework

First, the observed correlation between a SKU's carbon intensity (*CI*) on one hand and its footprint contribution from the supply chain on the other is likely further enhanced by the fact that our current model quantifies the footprint of company's manufacturing, for most SKUs, as directly proportional to a SKU's net weight (with a slope varying by country and product type). In the future, having more SKU-specific manufacturing resource data available, this will lead to a less systematic correlation.

However, the general trend will most likely remain, given that the range of carbon intensities (0.1 to 70 at SKU level) is most likely much larger than the variation in manufacturing resource consumption per net weight.

Second, the degree of concentration of the company's total footprint onto only a few SKUs and acquired raw materials is naturally specific to this company's specific SKU and brand structure as well as the specific countries and brands contained in the sample dataset. However, the dataset of 3,335 SKUs was so broad and diverse, that it must be considered highly likely that other global food and beverage companies of the larger packaged consumer goods sector exhibit similarly lumpy footprint patterns.

Finally, the predictive algorithm employed to estimate GHG emission factors (EF) for many materials (*Methods*) could be improved. When employed across entire portfolios, its accuracy is sufficient to demonstrate the large variability of hotspots across brands and SKUs, as shown in this work. However, pinpointing the exact hotspots in specific SKUs would require more scrutinized EFs.

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