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Critical Appraisal of Life Cycle Impact Assessment Databases for Agri-food Materials

Ricardo F.M. Teixeira

<heading level 1>Summary

Simplified Life Cycle Assessment is an attempt to expedite standard LCA methodology. One common simplification is to use secondary databases comprised of results, instead of inventories, from previous LCA studies to avoid data collection and speed up calculations. This article contains an assessment of the depth and variance in such databases, using descriptive analyses and clustering of 2,276 published global warming potential (GWP) weighted emissions records for agri-food products. Tables with mean and standard deviation for each product were generated and can be used in the future by LCA practitioners. The analysis of the datasets shows that clustering emissions by product name explains 55% of the variance in the database, while geographic region and method of production of the material explain only 2%. Significant gaps in the richness and comprehensiveness of databases available are also identified; data unavailability is one of the main reasons for uncertainty. The conclusion is thus that the use of secondary databases looks promising but there are still challenges to overcome regarding the depth of databases.

<heading level 1>Keywords

Life cycle assessment, Global Warming Potential, Agri-food products, Classification tree, Uncertainty.

<heading level 1>Introduction

Life Cycle Assessment (LCA) underwent four decades of methodological development to become one of the leading methodologies for environmental metrics. Once an academic tool, LCA now stands on the brink of being recognized as a major strategic management and decision-making tool by businesses (Verdantix 2011). The product-level LCA market in the European Union alone totaled a record $27.9 million in 2011, and is expected to grow 31-45% per year to reach $103.3 million by 2015, excluding consultancy services sold together with software (Verdantix 2012).

The food and beverages sector comes up as the fourth most important today, with around 11% of the total business value. It may become the third biggest business-driving sector by 2015, and represent over 13% of the total investment in LCA (Verdantix 2012). Food companies indicate as motivations for using sustainability metrics (1) external pressure, and (2) improving internal management (Schaltegger and Burritt 2010). External pressure may be the result of mandates from customers and/or the prospect of upcoming legislation. The labeling program currently being piloted by the French government (ADEME 2011) was the first large scale initiative of this sort. As for internal management, there are examples of LCA helping companies understand their own industrial metabolism and induce cost-savings (Iasevoli and Massi 2012).

Yet some researchers believe that standard-compliant LCA can be too complex, time consuming and costly for generalized implementation (Rex and Baumann 2008); moreover, when used for labeling, it is of doubtful utility due to difficulties in comparability (McKinnon 2010). An average food company would find such an endeavor challenging since the agri-food sector is highly fragmentized - 99% of all

companies are small and medium sized enterprises (SMEs) (Tarabella and Burchi 2011) and even relatively small companies possess vast product lines.

Many applications of LCA use simplified approaches that fall behind standardized methods (Verdantix 2011) – classified as Simplified LCA. Early reviews from Weitz et al. (1996) and Graedel (1998) define simplification and streamlining possibilities to help alleviate the main hurdle identified by LCA practitioners in surveys (Cooper and Fava 2006, Teixeira and Pax 2011) and verified empirically (Balkau and Sonnemann 2009): the time and resources required to collect primary data. Primary data is defined as "directly measured or collected data representative of activities at a specific facility or set of facilities" (EC 2013).

One simplification is to focus just on one impact assessment indicator, commonly greenhouse gas (GHG) emissions in Product Carbon Footprint (PCF) studies. The GHG Protocol (WRI/WBCSD 2011) established a popular methodology consistent with life cycle thinking for product-level assessment that includes only GHG emissions (Finkbeiner, 2009). This simplification does not alleviate many of the challenges posed to companies who adopt LCA as an in-house management tool, as illustrated by the anecdotal example from Tesco, a UK-based retailer. Tesco launched a program to calculate Product Carbon Footprints (PCF), obtained using a full LCA framework, for all 70,000 private label products (Clare and Little 2011), and eventually suspended the project after around 500 products had been analyzed. In a Guardian (2012) article, Tesco argues that the project did not get critical mass from retailers joining in the venture, and several months were required to calculate the PCF for just one product (the chain adds about 125 new products per year to the shelves). So, they switched to a product-portfolio approach (Guardian 2013).

Another common simplification is gathering available secondary data from generic databases and using them as surrogates for primary data (Hur et al. 2005). Secondary data is defined as "data that is not directly collected, measured, or estimated, but rather sourced from a third-party life-cycle-inventory database" (EC 2013). Pre-established emission factors quantify, for example, the Global Warming Potential (GWP) weighted emissions of processes or products. An emission factor sums the mass of GHG emissions for a given reference flow which is usually the mass of final product (Amani and Schiefer 2011). GWP are used to convert the mass of each GHG to an equivalent mass of CO_2. These factors are, in fact, single Life Cycle Impact Assessment (LCIA) measurements determined in previous studies, used as kg CO_2-equivalents (or CO_2e) per kg of product.

Simplified methodologies and tools that use these principles have been proposed (Bocken et al. 2009; Zah et al. 2009) particularly for internal management and quick hotspot assessment. Hotspot assessment, or *screening*, is usually recommended as the first stage of any LCA. It is crucial for companies to understand where to focus efforts in terms of impact reduction or data collection (Matthews et al. 2008). Hur et al. (2005) tested 11 simplified LCA methods against a simple matrix containing qualitative information only (Wenzel 1998), concluding that primary data was essential to maintain the accuracy of results, but only for hotspot stages of the lifecycle. Amani and Schiefer (2011) have surveyed 25 simplified LCA calculators. Although not all of them show promise in replacing full fledged LCA, some streamlined methods based on simple algorithms can be as accurate (up to 90%) as a complete application (Bala et al. 2010). In terms of results, Graedel (1998, cit. in Lifset 2006) argued that simplified LCA can provide around 80% of the findings from LCA, and studies such as Bala et al. (2010) and Teixeira et al. (2013) are encouraging for simplified methodologies. Rex and

Baumann (2008) also exemplify the usefulness of simplified LCA to a company who uses results mostly for internal management.

Still, proponents of simplified LCA base their assessment on specific case study applications. Others argue that since activity data (that is, "data that are specific to the process being considered, as opposed to generic data" – EC 2013) are a function of time, geographic region and production methods, it is virtually impossible to match products with ready-made emission factors (Hur et al. 2005). For agricultural products, yield is usually the main contributor to uncertainty in LCA results (Röös et al. 2010). Besides, simplifications contradict the essential spirit of ISO 14040 (ISO 1997), the first and still major LCA framework, which recommends the use of emissions-base unit processes, includes a mandatory Life Cycle Inventory (LCI) stage, mandates a multi-indicator approach, and includes strict directives on data quality. Other standards today also include similar requirements – such as the British PAS 2050:2011 (BSI 2011), the French BP X30-323 (AFNOR-ADEME 2010), and the EU's ILCD Handbook (JRC 2010). By violating standardization, simplified LCA may jeopardize comparative assertions.

Simplification is thus potentially suited if results are not meant to be communicated and are used only internally. Uncertainty in the results is acceptable if trends and hotspots are correctly identified and companies discover where they should focus their efforts. The main issue in these cases is to determine how reliable LCIA databases are, in order to assess how methodological simplifications can impact results. The test cannot consist of single-product concrete simplified LCA applications since these are always case-specific and no general conclusions can be drawn. This study is motivated by this question, formulated generically: how meaningful are simplified LCIA databases?

In this article I propose an alternative approach to help assess the reliability of secondary LCIA databases used during hotspot assessment or quick preliminary analysis. The approach consists of a critical analysis of databases. I start with a thought experiment: one random, inexperienced simplified LCA practitioner chooses at random an emissions record from a database using only the food material as prior knowledge. The practitioner would then match only basic information to choose a record from a sub-sample of the database. "Food material", as defined in the Method section, can be strictly defined as the name of the material (in which case the sub-sample of records would be those sharing the same generic name) or include basic information about production method and region. I hypothesize two necessary conditions for reliability: (1) the databases are rich (number of records) and comprehensive (diversity of records) enough to enable that (2) if the experiment is repeated and the practitioner selects records multiple times for the same material, results are similar. I propose that criterion (2) can be defined as being equivalent to saying that the standard deviation between records of the same type is lower than the mean (which is an arbitrary cut-off point). The objective of this work is to assess these two conditions.

<heading level 1>Method

My approach to the thought experiment consists of a descriptive and statistical analysis of carbon emissions records for agri-food products. To make results as general as possible, heterogeneity is maximized using a compilation of secondary databases from different sources. Similar types of materials are clustered using a classification tree.

<heading level 2>Database

The Carbonostics tool database (Carbonostics 2011) was used. It compiles 2,276 pre-recorded final LCIA results for CO_2e emissions from data providers such as ADEME (2010), CleanMetrics (2010), CLM (2010), the Danish LCA Food Database (LCA Food DK 2011), DEFRA (2012), ecoinvent (2012) and ESU (2012). The list of records and data suppliers can be found as Supplementary Information. I use this database since the amount and heterogeneity of records included are higher than found in Amani and Schiefer‘s (2011) survey of tools. Choosing a commercial database also helps the basic premise of our study, which is carried out from a random user’s standpoint.

The original database has a set of attributes attached, namely (1) the agri-food product category, (2) the agri-food product type, (3) the agricultural production method, and (4) the geographic region. There are finer classifications of records (distinction between types, different geographical aggregation), but those were not used due to lack of records. Overall, there are 10 category attributes, 323 type attributes, 4 production method attributes and 7 geographical attributes, with a total of 344 attributes distributed among four categorical independent variables:

- Category – a macro aggregation of 10 product families: dairy, fruits, grains, legumes/seeds/nuts (henceforth designated as “legumes” only, for simplicity), meat and poultry (henceforth designated as “meat” only), miscellaneous, oils, processed foods (“processed” from here on), seafood and vegetables.
- Type – a disaggregation of products in each category. Product types included are listed in Supplementary Information.

- Production method – one of four generic methods: 1) organic production, according to international organic production standards; 2) integrated production (IP), according to the IP norm; 3) greenhouse, for off-season agricultural products - seafood products from aquaculture were labeled as "greenhouse", since the concepts are related; and 4) conventional, defined as average unregulated production, unspecified methods of production. The "conventional" label is used in practice for all products that do not match any of the first three methods.
- Geographic region – a geographic division of the World similar to continents, namely Africa, Asia, Oceania, Europe, North America and South America. Some records have global validity.

Since variables are categorical, they could either be translated in a set of 344 binary variables, or remain as string variables. I tested both alternatives but since results are similar I show only the latter.

Potentially, other degrees of freedom related to the LCI of each record could be introduced, such as inclusion of transportation steps. Data were not filtered to remove these inconsistencies to maximize variance and replicate the error an inexperienced user would make if selecting an inappropriate record. Nevertheless there was prior removal of data because the database was peer-reviewed and validated by the Swiss NGO MyClimate (2012). This removal is a limitation to the maximization of heterogeneity but it is consistent with the premise of estimating the error made when a user chooses a record at random.

The model consisted of one dependent variable which is GWP_{100} (i.e., GWP-weighted emissions measured for a 100-years horizon, as defined in Pandey et al. 2011).

The mean of GWP_{100} is designated in the results by $\bar{C}$, measured in kg CO_2e per kg of material. For simplicity, units are omitted henceforth. Results are shown as "$\bar{C}$ *(SD, N)*", where SD is the standard deviation of the corresponding $\bar{C}$ and *N* is the number of observations. Final results indicate also 95% confidence intervals, shown as "$\pm \Delta C$", where ΔC delimits the bounds of the interval outside of which there is a probability of 5% or less of finding the sample mean, assuming normality in the distribution.

<heading level 2>Analysis method

The analysis was divided in three stages: (1) direct interpretation of the dataset, (2) exploratory data analysis using categorical regression, and (3) data clustering. Each stage is summarily described next. Further methodological information can be found in Supplementary Information.

<heading level 3>Direct interpretation

The first stage used descriptive statistics for the number and distribution of records. Products in the database were compared with products sold in each geographic region in the World. A preliminary analysis of standard deviations and assessment of outliers also took place.

<heading level 3>Exploratory data analysis

Since the attributes are depicted by categorical variables represented by a text string, it was deemed appropriate to employ categorical regression estimation with optimal scaling using alternating least squares (Liang et al. 1992). Instead of disentangling the strings by coding categorical data as a set of binary variables (in this case 344 would be needed), it assigns numerical values to each variable. This process estimates one coefficient for each of the four independent variables (category, type, geographic region and production method). The coefficients do not express the size of

the difference or the hierarchy between variables (for example, comparing type of material and geographic region) and can only be interpreted as having ordinal meaning within each variable. A coefficient of 2 for one attribute and a coefficient of 1 for another attribute in the same variable mean higher CO_2e emissions for the first attribute (but not that emissions are twofold). After coefficients were obtained, a linear regression model was then set up using the transformed (quantified) variables following Equation 1:

$$\bar{C} = \beta_1 Ca + \beta_2 T + \beta_3 M + \beta_4 R + \varepsilon, \quad (1)$$

where *Ca* is the quantified variable for product category, *T* the variable for product type, *M* for production method, *R* for geographical region and β_i (i = [1,4]) are the regression coefficients. This model helps assert the relevance of each independent variable in emissions.

<heading level 3>Data clustering

I used the Chi-squared Automatic Interaction Detection (CHAID) decision tree technique (Kass 1980), in its exhaustive-CHAID variant (Biggs et al. 1991). At each step, CHAID selects the independent variable (the data attributes) that interacts more strongly with the dependent variable (GWP_{100}) (IBM, 2010) – thus the idea of a tree that, in each iteration, branches into two or more groups. The final nodes of the tree correspond to the most disaggregated statistically significant clustering of attributes. Three analyses were worked out: (1) first including only production method and geographical region as independent variables, (2) then adding categories to the mix, and (3) finally including also the type attributes. Categories “Processed Foods” and “Miscellaneous” were excluded from the second analysis since they represent highly heterogeneous products that can hardly be meaningfully clustered.

<heading level 1>Results

<heading level 2>Dataset

Table 1 shows the mean GWP_{100} and standard deviations for categories, depending on production method and geographic region. The vast majority of materials are from conventional production (*N*=1874) in Europe (*N*=1769). Some categories such as fruits, grains, legumes and meat have a higher fraction of records from North America, but Asian and African records are always the minority. Only vegetables have a significant number of records for production systems other than conventional.

There is a mismatch between the number of records in each geographic region and category and the main products in each region of the World, considering the list of top commodities produced in the World compiled by FAO (FAOSTAT 2013). Out of the top-20 commodities (in economic value), only 9 are in the top-20 for number of records in the database (data for this analysis can be found as Supplementary Information). One of them – sugar cane – only has two records available, and two others – cotton and buffalo milk – have no records available. The same can be said if commodities are ranked by production and not economic value.

This effect is not due to bias from any specific data provider. CLM, ESU and data collected in journal publications are the main sources (see Supplementary Information for more details). For these, the distribution among categories is very similar. Next, the main sources are ADEME, CleanMetrics, the Danish LCA Food database, FCRN and PROBAS. These sources have a larger quantity of vegetables records but there is a good representation of all groups.

Regarding the standard deviation within each group, Figure 1 plots this statistic (for types of products) against the number of records in each group (ignoring

distinctions of production method and geographic region). Visual inspection shows a tendency for larger classes to have distributions with lower standard deviation. Beef is an outlier.

All distributions of records per category fail Kolmogorov-Smirnov and Shapiro-Wilk (Shapiro et al. 1965) tests of normality ($p<0.05$). Since categories are highly heterogeneous entities, the records at the higher and lower end of the spectrum are not necessarily outliers, but rather specific types of products that are atypical of their product category. All records falling outside the confidence range refer to specific types of products. To cite two examples, in the dairy category all outliers are records for butter and in the meat and poultry category all outliers correspond to beef and lamb (graphical visualization of outliers can be found in supplementary materials).

<heading level 2>Exploratory data analysis

Exploratory data analysis conducted using the optimal scaling method ranked emissions data and provides insight on the individual contribution of each data label to carbon emissions. Table 2 presents the transformed variables. The category with highest contribution to CO_2e emissions is Meat and Poultry. Fruits, grains and vegetables have the lowest unitary emissions. Regarding production method, greenhouse production is the lead contributor. Emissions from greenhouse production are mainly due to energy use, which seems to be approximately independent of the type of product being produced. Emissions from organic production and IP are lower.

Original and transformed variables are only weakly correlated (Table 3). For original variables, geographic region is negatively correlated with all variables, meaning that the less emitting products have a slight tendency to be produced in higher emissions regions. This effect is not significant, since transforming variables is enough to turn the

sign of the correlation coefficient positive for categories. In both cases, the correlation is always close to zero. Note that while this is true in general, data for specific product types are correlated with production methods and regions (they are only produced in one method or in one region).

Regression analysis (adjusted R^2=0.64) using transformed variables shows that the category and type of product have the highest beta regression coefficient (Table 4). Production method and geographic region, though still statistically significant (p=0.0000), are lower contributors to CO_2e emissions.

<heading level 2>Data clustering

Results in this section were obtained from decision trees using the CHAID method. A graphical representation of a decision tree is presented as Supplementary Information. All results mentioned were extracted from the final notes of the trees, which contain the statically significant clusters.

<heading level 3>Production method and geography

If production method is forced as the first variable to be singled out, then only conventional production is further separated according to geography. The lowest GWP_{100} corresponds to conventional products in North America and Asia (p=0.000) with $\bar{C}$=2.20 (5.18, 332), followed by organic and IP products, with $\bar{C}$=2.24 (4.58, 318). Conventional production in North America, which is the majority in the database, have significantly lower emissions than in other regions. The highest emissions correspond to South American and Asian conventional products with $\bar{C}$=5.98 (10.95, 94), followed by greenhouse products with $\bar{C}$=5.35 (5.86, 84). Standard deviation is higher than the mean for all end nodes.

If geographic region is forced as the first variable, the final end nodes are very similar. If no variable is forced first, then the first end nodes to emerge refer to production method. This concurs with the conclusions from the categorical regression analysis in Table 4 – production method is more relevant to determine emissions than geography. Also, the within-node variance is 43.28. Since the standard deviation of the initial data is 6.65 (total variance of 44.21), the proportion of variance explained by the geographic region and production method is only 2%.

<heading level 3>Product categories

Figure 2 shows the results (mean and 95% confidence interval) for the final nodes of the classification tree obtained when categories are added to the analysis as an independent variable together with production method and region. Results in table format can be seen in Table 5. The within-node variance is 33.3, and so the proportion of variance explained after introducing categories is now 25%.

Category name was the first variable selected; in this analysis categories explain more about emissions than the other variables included. Apart from categories, meat and poultry products are the only products divided according to geographic region. This means that emissions from meat depend more on the production region than on method of production. This may be a result of different assumptions going into studies of meat production in different countries. In South America it is standard to add land use change emissions to meat LCAs (Cederberg et al. 2011). All other categories are divided according to the production method, except for seafood and dairy where no differentiation is statistically significant. Overall, 12 significant clusters were obtained ($p<0.10$).

Meat products from South America, Asia and Oceania present the highest emissions (*N*=35), but greenhouse legumes, fruits and grains (*N* = 6) have the highest variation and their emissions can be as high as those from meat. This may, however, be due to the small sample size. Emissions from greenhouse products in these categories are the double of emissions from greenhouse vegetables.

<heading level 3>Product types

Results for the final nodes of the classification tree obtained when types are used instead of categories can be found as Supplementary Information. There were 24 such nodes, representing as many significant clusters ($p<0.10$). Within the cluster of products with the highest emissions (Beef, Mints, Lobster, Essential oil, Lamb, Mutton, Lamb shanks and roasted potatoes, Cress, Fishsticks, Tempe, Ice cream; *N*=115) are mostly meat products. Meat and seafood abound in the second highest emissions cluster (Shrimp, Aroma, Butter, Veal, Turbot, Sheep, Goat, Flaxseed, Oysters, Haddock, Sweeteners, Gammon; N=74). Other meat products have lower emissions; for example, chicken is part of the tenth cluster. The same is true of vegetables: celery is on the fourth cluster while potatoes are on the twenty-first. This model has the lowest within-node variance (19.55), meaning that the proportion of variance explained after introducing types is 56%.

Each cluster contains products from multiple categories, in the sense that products were grouped without prior knowledge about what category of product they are. Results can be found as Supplementary Information for when categories were included in the analysis simultaneously with type and forced as first pick so that all types in a cluster correspond to categories that are themselves clustered together. This caused more separation between products, and instead of 24 there were 47 significant

clusters. The within-node variance is only slightly higher (19.76), and so the proportion of variance explained is 55%. This percentage is lower than when categories were excluded, but categories were selected first by the method (before types). Categories being selected first is an indication that the variance of emissions for records within the same category is lower than for records in different categories, or in other words of low within-group variance for categories (relative to the rest of the database).

In this last case, lobster rises to the top as the product with highest emissions. Three meat products, namely beef, lamb and mutton come in second with $\bar{C}$=21.09 (14.54, 101). Other meat products like veal, bacon, sheep and goat are in fourth place with $\bar{C}$=13.03 (4.8, 20), while pork, turkey and pheasant are on cluster 14 with $\bar{C}$=5.39 (2.0, 70) and eggs, chicken or duck from North America are even further down on cluster 32 with $\bar{C}$=1.22 (1.25, 27).

An important observation is that the products with highest unit emissions ($\bar{C}$ > 3.5) show no differentiation for location, and production method is only relevant to distinguish greenhouse products. Production region and method matter only for the types with lowest emissions ($\bar{C}$ < 3.5). Overall, the effect of product types overrules the effect of production method and region.

Since this last analysis provides smaller clusters, some of the 95% confidence intervals get larger than when using only categories or only types (N decreases in most clusters). While in the first analysis (categories only) the interval for 5 out of 12 (42%) clusters was more than one third of the mean, in the second analysis (types only) 5 out of 24 (21%) were above the 1/3 mark, and in this third analysis (first categories then types) it is 12 out of 47 (25%). In all three analyses, only clusters with N < 20 have intervals larger than a third of the mean; so, the cause can be traced to low number of

records. For example, for lobster, shrimp and flatfish the reason for the high variability has to do with under-representation in the database.

Sometimes the effect of a small sample hides a second effect of true differentiation within equal types. For example, the highest variation is found for water with $\bar{C}$=0.02 (0.02, 16), due to the heterogeneity of water products in the database (bottled, tap). Another example is coffee, where the main issue is mixing data from different data providers using conflicting assumptions, such as including soil carbon or not. In these cases it would be important to go one step beyond types (to sub-types), but since many of these diverse clusters are constrained by data availability such is not yet possible.

<heading level 1>Discussion

In this article I apply several statistical methods to evaluate the accuracy and representativeness of available secondary databases for simplified LCA. I chose GWP as the indicator, not due to a bias towards the importance of this indicator, but rather because of data availability. As put by Weidema et al. (2008), carbon footprints are more appealing due to their popularity and simplicity, which makes them easily communicable. Ideally more criteria should be included in studies (Finkbeiner 2009), but since secondary databases for carbon are much larger the sole use of GWP is reinforced.

Results show a clear bias in the database towards conventional production in Europe. While it is possible to make the case that “conventional” is dominant due to being a broad label that includes many different systems of production, the same cannot be said of the bias for European records. The distribution among types is equally biased. I crossed the distribution of records per type with the list of top commodities produced

in the World compiled by FAO (FAOSTAT 2013) to assess if the most important commodities are covered in the database. In principle, it is not necessary that the most valuable commodities have more records available; even for top commodities, production may be concentrated in just a few regions of the World and/or technological heterogeneity may be small between the different regions. In the absence of other correlates, the rank in economic value and production can at least be used to assess if the distribution among product types in the database is at least sufficient to offer users more alternatives for the materials more likely to be of interest to practitioners.

Crossing the lists yielded a significant mismatch between commodities with the highest economic value in the World and the types in the database. These results could be interpreted as a consequence of the bias in the database towards Europe: since Europe is disproportionately overrepresented, it could be that commodities produced elsewhere are underrepresented. This is not, however, the case. If we take only Europe into consideration (results not shown here) there is only data for the top, most important materials, not for the rest of the top-20 list.

It could also be argued that what is relevant is not if for each region the distribution of records among types is consistent with the most important commodities, but rather if for each type of commodity the distribution among regions is consistent with the most common places of production. So I looked at the top three types (in terms of number of records) in the database, namely milk, beef and bread, the majority of which for European conditions. For (cow) milk, 79.0% of records are European (68 out of 86); for beef, the percentage is 82.7% (67 out of 81); for milk is 92.1% (70 out of 76). FAOSTAT (2013) data show a very different picture. The United States of America, India and China together produce more than two thirds of the World's milk.

For meat and bread there is no data available, but it is implausible that Europe produces a share equivalent to its share of records in the database.

On the flipside though, this bias is unlikely to influence results, which show that geographic region is rarely significant – and also production method. As more data becomes available, it will become evident if this happens because method and region are not significant for emissions or if it is a statistical consequence of the current gaps in databases. In conclusion, the depth of current databases is currently insufficient due to the bias towards conventional production in Europe.

The mismatch in record types is also not due to a particular data provider. No clear bias can be identified in the sub-database respecting to each provider in terms of the categories included, as made clear by visual inspection. It is also not the case that classification-tree clusters are aggregating records according to database. One independent variable for data provider was included and dropped (and is thus not presented in results) because it was never selected at the 10% significance level. This can be confirmed by crossing the types in some clusters and checking how many different databases are represented. The beef, lamb and mutton cluster (N=101) has data from 11 data providers. This is typically the case for clusters comprised of many records. Smaller clusters usually contain data from more than one source, albeit less than larger ones; for example the type lobster, with only 7 observations, has data from 4 providers.

I also analyzed variation within each cluster. It was expected that the standard deviation of the distribution should be lower if the sample is larger; in this case, it would be possible to suggest that it is mostly lack of data that limits the statistical analysis of the database, and not the inherent composition of the data. If, however,

standard deviations were not responsive to sample sizes, this could potentially mean that new records would introduce additional variability in the distribution. Visual inspection of the data provided some intuition why cluster size, and not inherent variability, is the most likely candidate to explain standard deviations. This observation was later confirmed since only clusters with $N < 20$ have intervals larger than a third of the mean.

The model explaining a higher share of the original variance includes material types. That share is 55%. To go beyond that, sub-type differentiation (or more information about the LCI of each record) might be required. This was not done here due to the thought experiment that configures the research question; plus, the consideration of more detailed classifications would be impossible for categories with less records. Lack of data is a common factor for clusters with high variance. Thus, the main barrier to using secondary emissions records databases for simplified LCA identified in this article is lack of data, not endogenous heterogeneity.

Lack of data is a major problem in LCA (Amani and Schiefer 2011). Notarnicola et al. (2012) used SCOPUS, an abstract and citation database, to search the expression “life cycle assessment” and found that over 4,500 scientific articles were published on the topic between 1999 and 2010. They also found that only 40 (~0.1%) were related to agriculture and food, which is less than the value of the agri-food LCA market sector. Only 6% of agri-food LCA practitioners claim to always have their studies peer-reviewed, while 26% have never submitted a study for any form of external review; most of the studies in the sector are only used in response to internal business demand (Teixeira and Pax 2011). It is crucial to promote publication of LCA results and expansion of databases.

The importance of material types also shows that categories are not a sufficient unit of abstraction. As an example, the category Meat and Poultry is not homogenous. Some meat products such as beef are on the higher end of GWP_{100} results, while others such as chicken are on the lower end. It is highly unlikely that a category for all meat can be accurately depicted using this approach. The same is true for seafood – lobster alone is the product with higher emissions, but that is missed when lobster is considered a part of a broader category. Categories are, however, important units of aggregation for similar products. The model that includes categories and types is displays a better fit to the data. The reason is that if categories are included, then types can be interpreted as deviations from the category mean. Such a model is more parsimonious than one that needs to treat types unattached from categories. Despite the biases identified, if the variation between types of products within each category was at least similar to the variation between types of products in different categories, then categories would be irrelevant. Since this is not the case, categories provide models with meaningful information.

The results of analyses similar to the work presented in this article can fit several purposes for the LCA community, of which I outline six. First, they can be used as a reference or benchmark in future LCA studies. If a LCA of an agri-food product does not fall within an established range, an explanation must be provided on why the product analyzed has specific characteristics that make it differ from others. A second use is for the environmental assessment of large-scale agricultural policies. The results of changes in production and land use per country are not often assessed in terms of their life cycle consequences. Using emission factors and the yearly balance sheets of agri-food production per country, it would be possible to build a tool that helps assess trends and assists in the interpretation of policy choices. These data cannot, however, be

used for process optimizations, since changes in the original numbers will change the structure of the database and comparisons must be updated. Results are also useful for hybrid input-output analysis (IO-LCA), which uses data at this level of detail. Naturally, simplified LCA methods and tools can also use this dataset for screening calculations, as well as streamlined simple algorithms such as presented by Bala et al. (2010). Although aggregated data can hardly replace individual data records, it will be very useful to suppress data gaps or make informed choices between available emission records. For example, practitioners sometimes must prioritize production method or geographic method as the main criterion to select a surrogate record. Since those methodological choices will be part of future Product Category Rules (PCR) in the agri-food sector, these aggregated results can also help PCR developers set category-specific rules and hierarchies for data quality. An even more specific use is to help LCA practitioners determine a product-specific hierarchy for data quality criteria. For example, if records from a certain category are very sensitive to geographic region, then that attribute must be privileged when choosing from secondary databases.

Data tables obtained in this work cannot yet be directly employed for most of these uses. This work set out to be a first step to assess if the use of secondary emission factors in LCA is a sound procedure, using the data available. Previous studies had already identified the need for LCA data that covers more products and more regions, as well as other indicators besides GWP. This study provides a procedure to assess which products and regions should be priority, as well as quantitative assessment of existing databases. The models applied here cannot be extrapolated to new data or other products because the reach of the databases is not yet sufficient to establish a wide baseline of products and methods in each region. When sufficient data is available, this procedure

(or eventually more sophisticated statistical methods) can be employed to hash through the uncertainties and obtain more accurate results.

<heading level 1>Conclusions

This article sets out test the case when an average LCA practitioner approaches a LCIA database to select one GWP_{100} record randomly for a given material (knowing only its name) and uses it in PCF calculations. The results provide evidence that the user would probably:

- Need to know enough about the material to characterize the type, since an analysis at the category level would be too uncertain.
- Not find enough data for all materials necessary, due to the mismatch between availability of records and most important materials;
- Often find reliable estimates for those records that would match the needs, considering that the type of material alone explains 55% of the variance in the data, and since only 25% of clusters obtained have a 95% confidence interval larger than one third of the mean and those are typically under-represented in terms of data quantity;
- Find that geographic region and production method are rarely significant to the choice of record.

So, regarding the two conditions for trustworthiness laid out in the Introduction, the practitioner would (1) find severe lacks in the richness and comprehensiveness of the databases, and (2) find that the error from selecting records randomly would depend on the type of record chosen, but rarely be higher than 100% of the mean for each type of material. The conclusion is thus that there are significant challenges to overcome regarding data availability for secondary LCIA databases to fulfill their promise as a

credible simplification in LCA. Current projects underway to develop LCA food databases should take the limitations identified in this study into consideration when deciding priorities for dataset coverage.

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<heading level 1>About the author

Ricardo Teixeira was VP Technology at Bluehorse Associates in Neuilly-Sur-Seine, France at the time the majority of the article was written. He is currently a Post-Doc researcher at the University of Antwerp in Belgium.

Address correspondence to:
University of Antwerp, Department of Biology
Research Group of Plant and Vegetation Ecology

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Campus Drie Eiken, Universiteitsplein 1

B-2610 Wilrijk, Belgium

ricardo.teixeira@uantwerpen.be

< http://www.ua.ac.be/main.aspx?c=ricardo.teixeira/>

Figure 1 – Standard deviation in GWP_{100}-weighted emissions in the database, sorted by type of material and plotted against the number of records in the same category.

GWP_{100} - Greenhouse gas emissions weighted using Global Warming Potential measured for a 100-years horizon (kg CO_2e per kg of material).

Figure 2 – Mean and 95% confidence interval for final nodes of the exhaustive-CHAID classification tree for CO_2e emissions including product categories, production method and geographical region as independent variables, ordered from highest to lowest emissions.

Clusters – 1: Meat and Poultry; South America, Asia & Oceania. 2: Meat and Poultry; Europe. 3: Legumes/Seed/Nuts; Greenhouse. 4: Seafood & Dairy. 5: Vegetables; Greenhouse. 6: Oils & Legumes/Seeds/Nuts; Conventional. 7: Meat and Poultry; Africa & North America. 8: Vegetables; Conventional. 9: Fruits & Grains; Conventional. 10: Legumes/Seeds/Nuts; Integrated Production. 11: Oils, Legumes/Seeds/Nuts, Vegetables, Fruits & Grains; Organic. 12: Vegetables, Fruits & Grains; Integrated Production.

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Table 1 – Mean and standard deviation per product category, depending on two control variables (production method and geographic region).

Categories	Totals	Production methods				Geographical regions					
		Conventional	Greenhouse	IP	Organic	Africa	Asia	Europe	North America	Oceania	South America
All	3.595 (6.648, 2276)	3.746 (6.939, 1874)	5.354 (5.855, 84)	1.603 (3.598, 91)	2.501 (4.895, 227)	3.671 (8.008, 52)	2.826 (6.288, 43)	3.733 (6.533, 1769)	2.075 (5.052, 231)	6.666 (9.717, 20)	5.709 (11.175, 76)
Dairy	5.135 (5.598, 207)	5.248 (5.551, 174)	-	2.817 (3.548, 3)	4.711 (6.089, 30)	6.053 (5.275, 6)	0.836 (0.139, 3)	5.271 (5.779, 170)	4.532 (4.803, 17)	3.867 (5.311, 3)	5.273 (5.21, 7)
Fruits	0.985 (1.902, 195)	0.829 (0.876, 168)	9.185 (9.26, 4)	0.289 (0.139, 7)	0.868 (1.635, 16)	0.725 (0.813, 2)	0.142 (0.106, 6)	1.177 (2.509, 103)	0.689 (0.926, 46)	0.523 (0.471, 6)	0.38 (0.141, 3)
Grains	0.927 (1.249, 183)	0.98 (1.097, 138)	10.974 (- , 1)	0.399 (0.131, 10)	0.57 (0.57, 34)	0.465 (0.01, 2)	1.606 (1.034, 4)	0.971 (1.368, 140)	0.652 (0.522, 31)	-	0.465 (0.01, 2)
Legumes	1.946 (4.338, 150)	2.085 (4.645, 126)	9.154 (- , 1)	0.79 (0.39, 8)	0.911 (1.341, 15)	7.446 (16.93, 6)	0.39 (0.323, 3)	1.619 (3.035, 93)	2.672 (3.137, 30)	-	0.979 (0.383, 7)
Meat	10.242 (11.251, 335)	10.538 (11.673, 291)	-	9.125 (6.555, 10)	8.039 (8.109, 34)	0.809 (1.575, 4)	12.623 (20.591, 3)	10.12 (10.582, 283)	2.073 (2.74, 13)	13.452 (12.098, 8)	15.766 (18.581, 19)
Miscellaneous	3.756 (8.953, 93)	3.428 (8.749, 83)	21.033 (20.449, 2)	5.968 (- , 1)	2.396 (3.012, 7)	-	4.318 (2.953, 6)	3.448 (7.29, 65)	13.299 (28.806, 5)	10.296 (- , 1)	3.042 (- , 1)
Oils	2.767 (5.362, 69)	2.945 (5.626, 62)	-	-	1.191 (0.934, 7)	1.582 (0.727, 2)	1.97 (0.933, 6)	3.321 (6.573, 45)	1.439 (0.506, 9)	-	2.105 (1.055, 5)
Processed	2.037 (2.911, 377)	2.143 (3.009, 339)	-	0.965 (0.497, 8)	1.127 (1.739, 30)	1.641 (1.88, 17)	0.385 (0.202, 4)	2.025 (2.904, 314)	2.56 (4.061, 16)	0.598 (- , 1)	2.262 (2.947, 21)
Seafood	5.328 (7.52, 168)	5.24 (7.69, 150)	5.822 (6.398, 16)	8.535 (- , 1)	7.443 (- , 1)	18.356 (17.027, 3)	6.608 (8.059, 5)	5.022 (7.288, 149)	5.335 (4.79, 9)	-	9.27 (- , 1)
Vegetables	1.668 (2.98, 499)	1.525 (2.804, 343)	4.294 (3.881, 60)	0.27 (0.187, 43)	0.751 (2.385, 53)	1.816 (3.385, 10)	0.137 (0.004, 3)	1.667 (3.005, 407)	1.361 (2.368, 55)	0.071 (- , 1)	1.813 (3.386, 10)

Results are presented in the form "$\bar{C}(SD, N)$", where by $\bar{C}$ is the mean GWP_{100} (kg CO_2e per kg of material) and *SD* its corresponding standard deviation, and *N* is the number of observations. IP – Integrated Production; "Legumes" – Legumes/Seeds/Nuts; "Meat" – Meat and Poultry; "Processed" – Processed Foods.

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Table 2 – Transformed variables "Category", "Production method" and "Geographic region" after categorical regression, in descending order of contribution to the variable "CO_2e emissions".

Variable	Attribute	Quantification
Category	Meat and Poultry	1.86
	Miscellaneous	0.84
	Dairy	0.76
	Seafood	0.75
	Vegetables	-0.26
	Oils	-0.27
	Legumes/Seeds/Nuts	-0.53
	Grains	-0.84
	Processed Foods	-1.02
	Fruits	-1.11
Production Method	Greenhouse	4.91
	Conventional	-0.08
	Organic	-0.69
	Integrated Production	-1.22
Geographic region	Europe	0.40
	Oceania	-0.16
	South America	-0.17
	Global	-0.28
	Africa	-1.07
	North America	-1.67
	Asia	-5.44

Table 3 – Correlations between independent variables, using original and transformed (Trans.) variables.

Variable	Category		Name		Production method		Geographical region	
	Original	Trans.	Original	Trans.	Original	Trans.	Original	Trans.
Category	1.000	1.000	.100	.029	.003	-.006	-.088	.087
Type	.100	.029	1.000	1.000	.033	-.025	-.022	-.025
Production method	.003	-.006	.033	-.025	1.000	1.000	-.114	-.030
Geographical region	-.088	.087	-.022	-.025	-.114	-.030	1.000	1.000
Eigenvalue	1.183	1.095	1.039	1.024	.937	.989	.840	.892

Table 4 – Results of the regression model using transformed variables (categorical regression).

Variable	Standardized Coefficients		Degrees of freedom	Sigma
	Beta	Standard Error*		
Category	.497	.051	9	0.000
Type	.636	.033	318	0.000
Production method	.146	.022	3	0.000
Geographical region	.063	.018	6	0.000

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* Bootstrap (1000) estimate. Dependent variable: CO_2e emissions. R^2: 0.693; Adjusted-R^2: 0.640.

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Table 5 - Final clustered nodes of the exhaustive-CHAID classification tree for CO_2e emissions including product categories, production method and geographical region as independent variables.

Cluster #	Category(ies)	Production Method	Geographic Region	Mean	Std. Dev.	N	p-value	95% Confidence Interval
1	Meat	All	South America Asia Oceania	15.34	15.78	35	0.01	(10.11, 20.57)
2	Meat	All	Europe	10.12	10.58	283	0.01	(8.89, 11.35)
3	Legumes, Fruits, Grains	Greenhouse	All	9.48	7.21	6	0.06	(3.71, 15.25)
4	Seafood, Dairy	All	All	5.22	6.52	375	0.00	(4.56, 5.88)
5	Vegetables	Greenhouse	All	4.29	3.88	60	0.06	(3.31, 5.28)
6	Oils, Legumes	Conventional	All	2.37	4.99	188	0.00	(1.66, 3.08)
7	Meat	All	Africa North America	1.78	2.53	17	0.01	(0.57, 2.98)
8	Vegetables	Conventional	All	1.53	2.80	343	0.00	(1.23, 1.82)
9	Fruits, Grains	Conventional	All	0.90	0.98	306	0.00	(0.79, 1.01)
10	Legumes	IP	All	0.79	0.39	8	0.00	(0.52, 1.06)
11	Oils, Legumes, Vegetables, Fruits, Grains	Organic	All	0.76	1.75	125	0.06	(0.45, 1.07)
12	Vegetables, Fruits, Grains	IP	All	0.29	0.18	60	0.00	(0.25, 0.34)

Dependent variable: CO_2e emissions. Std. Dev. – Standard Deviation; N – Number of observations; IP – Integrated Production; “Legumes” – Legumes/Seeds/Nuts; “Meat” – Meat and Poultry; “Processed” – Processed Foods.

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<heading level 1>Appendix 1 – Supplementary information

Two documents accompany the present article and can be found online. The first Supplementary Information file contains Figures and Tables that illustrate results. The second Supplementary Information file contains a table with the description of all records used in the analysis and the corresponding data provider as indicated in the Carbonostics database. The GWP_{100}-weighted emissions records are not included because some data are proprietary and cannot be freely reproduced.

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