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Uncertainty Implications of Hybrid Approach in LCA: Precision versus Accuracy

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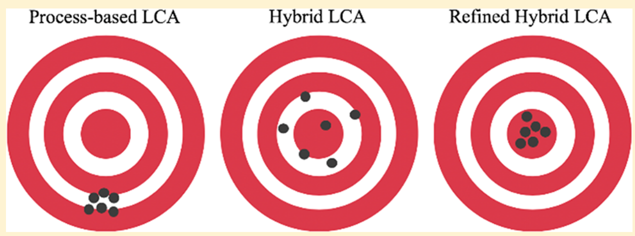
Supporting Information

ABSTRACT: The hybrid approach in Life Cycle Assessment (LCA) that uses both input-output and process data has been discussed in the context of mitigating truncation error and burdens of data collection. However, the implication of introducing input-output data on the overall uncertainty of an LCA result has been debated. In this study, we selected an existing process LCA, performed a Monte Carlo simulation after hybridizing each truncated flow at a time, and analyzed the dispersion and position of the distribution in the results. The results showed that hybridization effectively moved the mean of the life cycle greenhouse gas (GHG) emissions 38% higher while maintaining the standard deviation within the 0.62−0.78 range (relative standard deviation, 3−4%). We identified key activities contributing to the overall uncertainty and simulated the potential effect of collecting higher quality supplier-specific data for those activities on the overall uncertainty. The results showed that replacing as few as 10 of the largest uncertainty contributors with high precision supplier-specific data substantially narrowed the distribution. Our results suggest that hybridizing truncated inputs improves accuracy of LCA results without compromising their precision, and prioritizing supplier-specific data collection can further enhance precision in a cost-effective manner.



INTRODUCTION

Process life cycle assessment (LCA) has been the dominant approach in LCA.[1−3] Among the 30 most cited LCA studies according to the Thomson Reuter's Web of Science published since 2010, only two used the input-output (IO) approach, two used the hybrid approach, and the rest employed the process LCA approach (see Table 1S; a full list can be found in the SI).

Despite the dominance of process LCA, it has been repeatedly pointed out that the process LCA approach may suffer from truncation error,[4−8] which refers to the error due to the "impact not covered by the system boundary of the LCA".[2] Previous research showed that truncation error varies widely across sectors[12] and that modeling and methodological factors significantly influence the magnitude of truncation error. Lave and colleagues (1995), for example, used a paper cup example to show that with a process LCA approach less than half of the environmental discharges are accounted for and then demonstrated the usefulness of IO analysis to address this issue.[6] Treloar analyzed truncation error (1997) in the Australian residential building sector, demonstrating that the energy intensities of the processes one, two, and three stages upstream were 40.9%, 27.1%, and 7.61%, respectively (12.4% were the building's direct emissions).[7] Lenzen (2001) investigated truncation error in a broader range of applications, demonstrating that across sectors and product types truncation error was estimated at 50% in process LCA studies.[8] Ward and his colleagues (2017) reported a range of 30−80% truncation error across their modeling scenarios.[2]

These estimates of truncation errors are the result of simulations mostly using input-output tables as a proxy. In reality, the magnitude of truncation error in a given LCA can hardly be measured in an empirical setting, because no data is collected for truncated flows, and thus their contribution to the overall LCA result is unknown; if they are known, there is no reason to truncate them.[9−11] Furthermore, cutoff decisions are made often inconsistently across LCA studies, making the effort to standardize the procedure of measuring truncation error a challenge.[2]

The hybrid LCA approach has been recommended in the literature as a means to reduce the truncation error of process LCA or to improve precision of input-output analysis.[2,13−15] Questions still remain about the overall uncertainty implications of adding IO data to a process LCA using the hybrid LCA approach. Recently, two publications have drawn opposite conclusions about the implications of the hybrid LCA approach on the accuracy of LCA study results; one study concluded that "hybrid life cycle assessment (LCA) does not necessarily yield more accurate results than process-based LCA", while a commentary to the article concluded that "hybrid life cycle assessment (LCA) will likely yield more accurate results than process-based LCA".[30,31] One of the reasons for such contrasting views is that there is a trade-off

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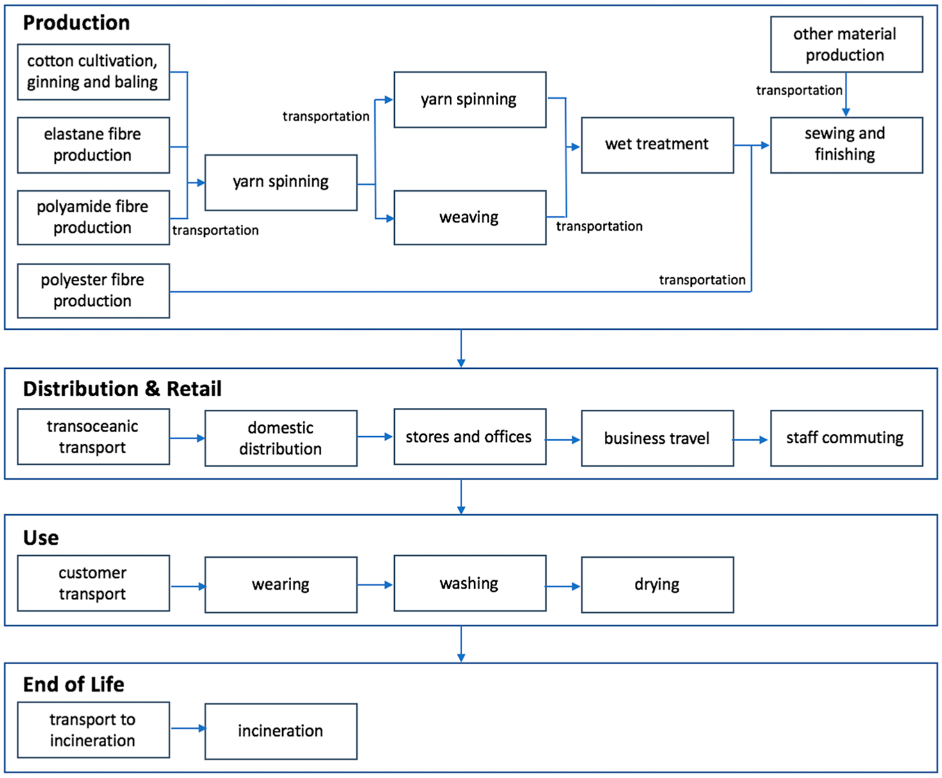

Figure 1. High-level process flow diagram for the life-cycle of a jacket (based on Roos et al. 2015[19]).

between a more complete system definition and additional variability in input-output LCA data due to sector aggregation,[9,16] the net effect of which has not been empirically tested in the literature.

This trade-off can be characterized as an accuracy vs precision dilemma. Accuracy is the closeness of the estimates to the true value.[17] Precision is the closeness of agreement among estimates.[17] Truncation errors tend to result in an underestimation in the result. Therefore, on the one hand, the higher the truncation error, the lower the accuracy of an LCA result. While the hybrid approach may be able to improve the accuracy of an LCA result by mitigating truncation errors, the generally wider distribution of input-output LCA data, on the other hand, would exacerbate precision in an LCA result.

This paper aims to answer the question "how do the accuracy benefits of hybridization weigh against precision costs?" by using a case study. The answer to the question is likely to be case dependent, and therefore drawing a general conclusion would be a challenge. Therefore, the objective here is to gain insight on the interplay between precision and accuracy by means of a case study rather than by the generalization of the relationship.

METHODOLOGY AND DATA

Study Design. Our study was conducted in three steps: (a) select a process LCA case study and run Monte Carlo simulation (MCS) with all available process data and parametric uncertainty characterization, (b) hybridize the LCA study by filling in data gaps with IO data and run MCS after the addition of data to each process, and (c) identify the top contributors to uncertainty and reduce the parametric uncertainty values of these highest contributors to simulate further data collection and refining of the LCA, and run MCS again after the refinement of each process. Each of the three steps is described in its own subsection below. This approach aligns well with the recommendation from the literature to employ an iterative process for the use of the hybrid LCA methodology with assessment of uncertainty.[9,10,33] The iterative approach leads to a gradual refinement and highlights the optimized improvement of the overall study results when refinement is used in combination with the hybrid LCA approach. Each MCS included 1000 runs, varying each parameter randomly within the log-normal distribution of values possible, based on its geometric standard deviation (GSD). A GSD is a measure of spread applied to log-normal distributions. GSDs are commonly used to characterize parametric uncertainty in LCA (including ecoinvent and CEDA), where a significant portion of the data are log-normally distributed.

The uncertainty of the results at each of the three steps (a, b, c) was interpreted in the context of both precision (standard deviation of the MCS results) and accuracy (evidence of reduced truncation error). The following sections describe each of the three steps and a high-level overview of the computations involved. A more comprehensive explanation of the data utilized and mathematical analysis including detailed matrix equations and Matlab codes can be found in the Supporting Information.

a. Case Study Selection and Process LCA Reconstruction. Several criteria were used to select the case study for this analysis: (1) the example needed to be from the "real world", not purely hypothetical, (2) the product needed to have a complex supply chain that required a laborious data collection effort, and (3) the "complete" set of unit processes in the process LCA needed to be published. A study published by the Mistra Future Fashion Consortium, titled "Environmental assessment of Swedish fashion consumption", was selected.[19] This study, commissioned by Mistra Future Fashion, analyzed

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five generic Swedish garments, and the jacket was chosen for our analysis due to its material and supply chain complexity in comparison to the others.

The Mistra Future Fashion study had several goals, including the assessment of potential consequences of proposed interventions in future scenarios;[19] however, in our study, we focus on one aspect of the study's goal: to map the baseline environmental impact of one use of an average jacket. Unit processes and material flows, 193 in total, were provided by the Mistra study's author and used to generate the process flow diagram for the life cycle of a jacket. Ecoinvent was employed as the primary source of background data LCI in the Mistra study, but one specific version of the database was not used consistently throughout. For the purpose of this study, we use ecoinvent v3.1 (more details on data sources are described below). The Mistra study includes 10 different impact categories with characterization methods used according to the ILCD guidelines. Of the impact categories they included, we selected the climate change impact measured in Global Warming Potential 100 (GWP_{100} in $kgCO_2eq$) as the example for our analysis. In the Mistra study, sensitivity analysis is used to consider different scenarios that may significantly influence the overall results, such as different use phase scenarios (i.e., washing at different frequencies). Aside from scenario uncertainty, no other uncertainty was assessed or characterized in the Mistra study. The study is reasonably complete and well documented, but uncertainty was not quantified. We use the jacket from the Mistra study as the case study for our analysis to shed light on the usefulness of uncertainty assessment to understand the likeliness of outcomes and how system boundary decisions influence the overall results.

Figure 1 displays a high-level process flow diagram for the life cycle of the jacket, modeled directly after the Mistra study report.[19] In reality, there were 193 processes included in both the Mistra study and in the process-based LCA and subsequent uncertainty analysis in step (a) of our study. The processes and individual impact contributions for the process-based LCA are listed in Table 5S in the Supporting Information. Many of the Mistra study defined processes included are aggregate processes (also referred to as system processes or rolled-up processes) that connect a series of other unit processes but do not have direct impacts themselves, such as the process "weaving" which draws together "production of electricity mix", "production of modified starch", and "disposal, textile", which itself flows into the larger processes of "production of woven polyamide" and "production of woven polyester". This process is a good example of one that omits processes such as "warehousing and storage" and "business support services" that are typically considered to be negligible in process LCAs.

Using the process LCA approach, the technology matrix (A) and environmental exchange matrix (B) were generated based on the processes and emissions reported in the Mistra study. After compiling all of the jacket's unit processes from the Mistra study, the authors used the ecoinvent v3.1 data set to gather reported upstream process data. ${A_p}^u$ was generated with the subset of the Mistra study's upstream unit processes that were available in ecoinvent v3.1, and these processes were linked to the full technology matrix in ecoinvent v3.1 (A_p) and the corresponding environmental exchanges matrix (B_p), as noted in eq 1. The total life-cycle impact calculated in step (a),$LCIA_p$, is then given by

$$LCIA_P = [C][B \quad B_p]\begin{bmatrix} I - A & 0 \\ -{A_p}^u & I - A_p \end{bmatrix}^{-1}\begin{bmatrix} y \\ 0 \end{bmatrix} \tag{1}$$

where y represents the functional unit in the Mistra study (use of one jacket) and the C matrix includes the characterization factors to transform the emissions associated with the life cycle inventory into one life cycle impact based on the TRACI methodology (climate change impact measured in $kgCO_2eq$). The original matrix notation that the ecoinvent database follows is the A^{-1} form for the total direct and indirect requirements as presented in Heijungs and Suh (2002)[22] and Suh (2004),[13] instead of $(I - A)^{-1}$ form used here. In this paper, however, we follow the $(I - A)^{-1}$ form for the sake of simplicity.

The uncertainty characterization values (GSDs) were extracted from the ecoinvent v3.1 database, and a Monte Carlo simulation was performed by randomly varying each parameter based on its distribution, ultimately generating 1000 results for $LCIA_P$. The median and standard deviation of these 1000 results were calculated as a means of measuring the precision of the result. The values in the technology matrix (A), environmental exchange matrix (B), and upstream cutoff matrix (A_p^u) did not accompany GSDs in the Mistra study, and we have assumed that their GSD is 1. Similarly, our analysis did not include characterized uncertainty for the characterization matrix (C). We recognize that overall uncertainty estimates are likely underestimated without accounting for the variation in these matrices.

b. Hybridization Process. In this study, we used the tiered hybrid LCA approach to hybridize the Mistra case study,[1,13] first identifying the upstream processes that may have been excluded during boundary selection. The authors of the Mistra study reported the omission of certain upstream processes that are commonly excluded from process LCA calculations: "Generally, manufacturing of machinery and equipment are not included in the models unless there has been a specific reason for doing so".[19] LCA databases, such as ecoinvent, however, aim to incorporate capital goods including machinery and equipment within the system boundary, while the degree of success may vary widely across unit processes and databases.

To determine the magnitude of these and similar processes that are typically excluded, the direct economic flows into the sectors relevant for the jacket's production were analyzed using the CEDA 5 input-output LCA database. Five sectors were considered in the analysis to be directly relevant to the jacket's upstream production: (1) fiber, yarn, and thread mills, (2) fabric mills, (3) textile and fabric finishing and fabric coating mills, (4) other textile product mills, and (5) apparel manufacturing. By analysis of only the inputs into these five sectors, the average contribution of each commodity was determined, and the contributions were ranked. Only the inputs contributing at least 0.1% of the total cost to produce each output of the five jacket-related sectors were included in the hybridization, and the sectors that overlapped with the process LCA data used in step (a) were excluded. For example, the contribution of the "fabric mills" commodity was not included in the hybridization, since several fiber production processes were already included in the Mistra study's LCA; however, the "management of companies and enterprises" commodity was not already included in the process LCA and so was added using input-output data during the hybridization.

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Table 3S in the Supporting Information contains the list of sectors identified during the aforementioned analysis and those included in the hybridization process (36 in total).

After establishing the baseline process LCA scenario and results in step (a), the additional upstream processes identified from analyzing the jacket-related sectors in the CEDA database were added through the integrated hybrid approach.[13] However, as discussed in Suh and Huppes (2005), the integrated hybrid approach and the tiered hybrid approach[1] would, in this particular case, generate identical results, as there are no feedback loops between the input-output and process systems through the downstream cutoff matrix.[18,32] The price of the jacket, estimated at $40 USD, was used to quantify the size of the contribution of each upstream process, since the contribution of each commodity per USD jacket production was previously determined. The magnitude for each of these commodities were modeled as upstream processes in the $A_{IO}{}^{u}$ matrix and then linked to the CEDA technology matrix data (A_{IO}) and environmental exchanges data (B_{IO}) using the hybrid approach.

Using the tiered hybrid approach, both the processes using process-based data and those using input-output data were modeled as upstream processes ($A_p{}^{u}$ and $A_{IO}{}^{u}$, respectively) to distinguish between the two data sets (both matrices are included in the Supporting Information). The overall computation using the tiered hybrid approach is given by

$$LCIA_H = [C][B \quad B_p \quad B_{IO}]\begin{bmatrix} I - A & 0 & 0 \\ -A_p{}^{u} & I - A_p & 0 \\ -A_{IO}{}^{u} & 0 & I - A_{IO} \end{bmatrix}^{-1}\begin{bmatrix} y \\ 0 \\ 0 \end{bmatrix} \tag{2}$$

which represents the total life cycle impact generated by the jacket in step (b) of our study.[1,13] No uncertainty information was provided for the price of the jacket itself; however, the uncertainty distributions for the contribution of each of the commodities to the jacket-related sectors (standard deviation of the average of all five sectors) and the CEDA data inputs (GSDs) are used, along with the uncertainty information for the environmental exchanges from ecoinvent (GSDs), to vary parameters during the Monte Carlo simulations. Just as in step (a), the median and standard deviation of these 1000 results were calculated for comparison. It is important to note that without characterized uncertainty for the jacket, overall uncertainty is likely underestimated in the study.

c. Iterative Refinement of Hybrid LCA Results. Progressive replacement of more uncertain, secondary data sets by less uncertain primary data sets was simulated in two steps: (1) identification of the major uncertainty contributors, and (2) simulating the effects of replacing those major uncertainty contributors by primary data. First, in order to identify the major uncertainty contributors, a local sensitivity analysis was performed to identify the sensitivity of the results to the variation of each upstream process (from both process-based and IO data sources). Monte Carlo simulations were run by varying all of the parameters associated with one process and calculating the standard deviation of the results when only the uncertainty of that process was included. This exercise was repeated for all of the processes, and the standard deviations of the results (100 simulations each) were compared. The use of IO data, which is holistic in nature due to a top-down modeling approach, using the hybrid approach, is currently the only streamlined approach to LCA that addresses the truncation error prevalent in all process LCAs. The focus of this paper is on the implications of the hybrid approach for uncertainty, and the authors recognize that there are several available methods to optimize refinement of the results once truncation error has been properly addressed. These alternatives include the sensitivity analysis method based on first-order approximation discussed in Heijungs and Suh (2002)[22] or the probabilistic triage method presented in Olivetti et al. (2013),[33] both of which could be complementary to the methods presented in this paper. The sensitivity analysis results are included in the Supporting Information (Table 4S), and the calculated uncertainty distributions for each process were used to rank the processes on the basis of how sensitive the results were to the variance introduced by each process. Second, the progressive collection of primary data for and replacement of those top uncertainty contributors was simulated by running a Monte Carlo simulation with 1000 runs (same as with steps (a) and (b)) by using eq 2 each time a process was refined by eliminating the parametric uncertainty associated with that one parameter, simulating the collection of primary data to fill in the data gap. A new Monte Carlo simulation was run each time a new process was refined, and the processes determined to be the highest contributors to uncertainty were refined one-by-one in the rank order described above. The median and standard deviation of each of these Monte Carlo simulation results were calculated to measure how the precision of the results changed with each refinement.

Data Sources. The appendices of the Mistra study included tables with all of the processes utilized and the flows between the processes for the jacket (on pages 90−132). This data was manually extracted from the report, as it was in PDF form, and replicated in an excel spreadsheet format. After determining that our initial results did not match that of the Mistra study, we contacted the authors and they provided a more complete set of unit processes and material flows, which is now incorporated into our case study. The Supporting Information (SI) of our study includes this more complete set of data in the "A_mistra" matrix in the excel workbook. This workbook in the SI describes in detail what ecoinvent and CEDA data were utilized as well as the background calculations. It is notable that our reconstruction of the Mistra study for the global warming potential of the jacket did not reproduce the exact same result that the original report presented; however, this 7% difference may be attributed to the use of only ecoinvent v3.1 in our study (as opposed to drawing from several ecoinvent versions) and the TRACI method for characterization instead of the ILCD guidelines used in the Mistra study's calculations.

The ecoinvent v3.1 database is used as the primary source of process-based LCI data in this study. Ecoinvent v3.1 contains over 11000 unit processes, and uncertainty information in the form of distribution of parameters is provided for each unit process data.[23] The distribution of parameters in the ecoinvent database are derived from an estimate of basic uncertainty (stochasticity) and several other criteria incorporated through a pedigree matrix approach, which translates reliability, completeness, temporal correlation, geographic correlation, and further technology correlation into a distribution.[24] The information on distribution of the underlying parameters at a unit process level can be used to simulate the overall distribution in the LCA results.[20,21,25]

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The pedigree approach has been developed to incorporate both quantitative and qualitative dimensions of uncertainty into one numeric indicator of uncertainty.[26] The pedigree approach has been criticized for its subjectivity and reliance on expert judgment;[27] however, viable alternatives to incorporate the inherent uncertainties in LCA are lacking.

The Comprehensive Environmental Data Archive (CEDA) database is the source of all input-output data used in this study.[28] CEDA 5 represents over 430 industrial sectors, commodities, and the linkages between them according to a 2014 base year. GSD values for individual parameters in CEDA are derived from the same pedigree approach used to estimate uncertainty for the parameters in ecoinvent to ensure comparability. In general, GSD values in CEDA are higher than those in ecoinvent due to the uncertainty caused by aggregation error. The median GSD in ecoinvent v3.1 is 1.2 while that for CEDA 5 is 1.8. Despite the fact that CEDA GSDs are generally higher than that of ecoinvent, the median GSDs for CEDA and ecoinvent data utilized in our analysis were quite similar (median GSD from CEDA = 1.3, median GSD from ecoinvent = 1.4). This is likely because the ecoinvent data in this study was utilized for the more complex processes, such as the production of various chemicals, while CEDA data was used for many processes that predominantly required energy consumption, such as warehousing and business services. While the median GSDs were comparable, Figure 2 demonstrates that the ecoinvent data used in this study has a broader range of parameter uncertainty (GSD values); therefore, we cannot conclude that IO data is always more uncertain than process-based data.

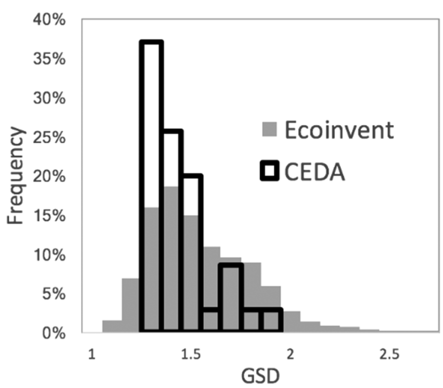

Figure 2. Histogram of geometric standard deviation (GSD) values for all process (ecoinvent) and input-output (CEDA) data used in the study (does not include the processes that had no quantified uncertainty or GSD = 1).

It is important to note that while the GSD values for each CEDA process used in our study were comparable to those of ecoinvent, there was additional uncertainty introduced through the use of IO data. As described in section (c) of the methodology, the contribution of each upstream process was based on an average of the total direct and indirect inputs of each commodity to the five jacket-related sectors in the CEDA 5 database. The standard deviation of these five contributions (relative standard deviation ranging from 0.03−1.11 for each commodity) was included in the MCSs by varying each of the CEDA-based technology (A) matrix parameters according to these corresponding standard deviations. Therefore, the overall uncertainty introduced through the use of CEDA data is higher than that of the ecoinvent inputs, but the broad range of GSD values in ecoinvent demonstrates that process-based LCA input data is not without uncertainty on its own.

RESULTS

The mean greenhouse gas emissions of the process LCA for one jacket in step (a) was 15.9 kg CO_2eq. As previously mentioned, this is slightly (7%) lower than the reported results in the original Mistra study; the use of different versions of ecoinvent database and characterization factor data are likely to explain the difference. Using the hybrid LCA approach, input-output data was then used to fill in all the upstream data gaps during step (b). IO data was used for 36 additional processes (bringing the total to 229), a list of which is included in Table 3S in the Supporting Information. The overall impact increased considerably after hybridization (21.9 kg CO2eq, or a 38% increase from step (a)), demonstrating a reduction in truncation error using the hybrid approach. Despite the large increase in the mean greenhouse gas emissions, the top five contributing processes do not change. This is expected, given that system boundaries and cut-offs in a process LCA should be defined to include the most significant unit processes in the life cycle.

Resulting probability distributions from the Monte Carlo simulations are portrayed in Figure 3 for each of the steps described in the study design: (a) process LCA approach using only the available process data, (b) hybrid LCA approach with all available process data and IO data to fill in the upstream data gaps, and (c) refined hybrid LCA approach by reducing the uncertainty (individual GSD values) of the top-ten highest contributors to overall uncertainty. The standard deviation of the characterized results for climate change impact changed from 0.62 (a) to 0.75 (b) by the inclusion of IO data using the hybrid approach. After refining the top ten processes that contribute to uncertainty, the precision improved dramatically (standard deviation in (c) = 0.11) and the median remained closer to that of the unrefined hybrid LCA than of the baseline process LCA results (median of (a) = 15.9, (b) = 21.9, (c) = 21.7). Of the top-ten processes identified through a sensitivity analysis as the highest contributors to overall uncertainty, four were using process-based data and six were unit processes using input-output data, indicating that the higher expected uncertainty associated with the IO data used in the hybrid approach did not overpower the process LCA results.

Step-wise analysis of hybridization and refinement of the jacket LCA case study showed improvement of both accuracy and precision made possible with the hybrid LCA approach. To elaborate on the hybridization process (step (b)), the hybridization was repeated with only one data gap filled in with IO data at a time, prioritizing the larger data gaps first. The point of this exercise was to demonstrate how the uncertainty changes, both in precision and accuracy, with the inclusion of each additional input-output process. Figure 4 displays the climate change impact results generated using MCS after each additional data gap is filled in with IO data using the hybrid method (left of the blue vertical line) as well as those results after each of the processes contributing most to overall uncertainty are refined (right of the blue vertical line). Precision improvements alone could be achieved without the use of the hybrid approach; however, accuracy would be difficult to address since truncation error is a prevalent outcome in the process-based approach to LCI data collection. Improving precision when using only the process LCA approach would therefore refine the results around a value

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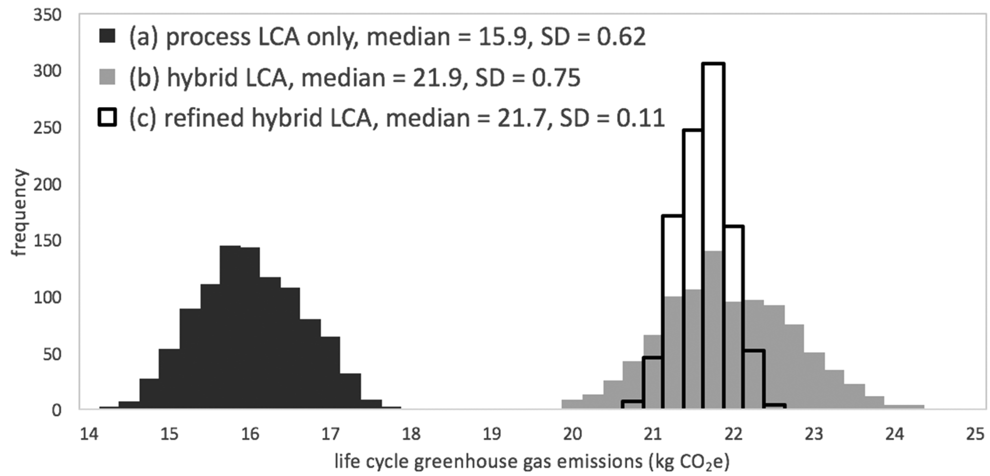

Figure 3. Histograms of LCA results based on Monte Carlo simulation (MCS) at each study step: (a) process LCA only, (b) hybrid LCA with input-output (IO) data to fill in gaps, and (c) refined hybrid LCA with reduced geometric standard deviations (GSDs) for top ten processes contributing most to overall uncertainty.

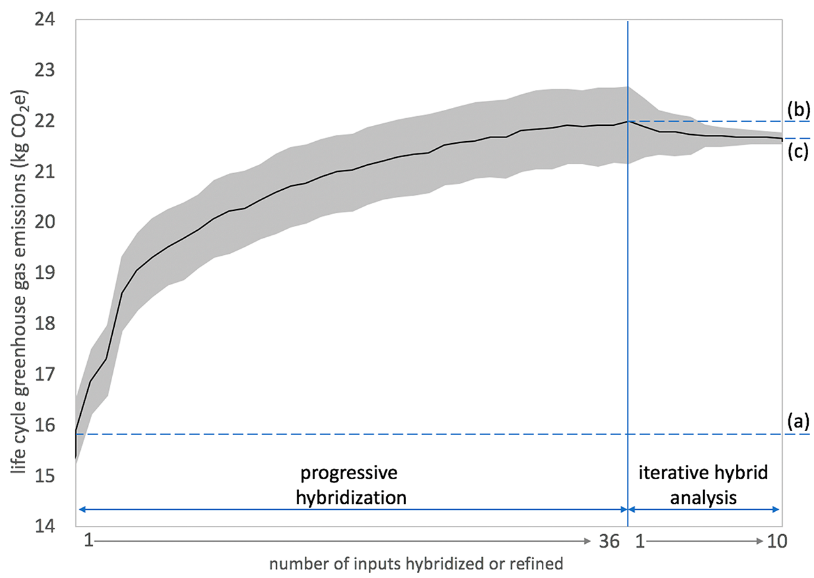

Figure 4. Progression of life cycle impact assessment (LCIA) results using the iterative hybrid LCA approach (gray represents the standard deviation of the Monte Carlo simulation (MCS) results at each step; black line represents the median of the MCS results). Median values: (a) = 15.9, (b) = 21.9, (c) = 21.7.

that was knowingly inaccurate due to the underestimation caused by truncation error.

■ DISCUSSION

This study assessed the uncertainty implications of the hybrid LCA approach through the lens of interplay between precision and accuracy. We selected an existing process LCA and used Monte Carlo simulation to analyze the shape and position of the distribution in the results after hybridizing one flow at a time. An application of the hybrid approach resulted in 38% higher mean and median life-cycle GHG emissions. The standard deviation remained consistently in the 0.62−0.78 range throughout the hybridization process. The magnitude of truncation error from undocumented cut-offs and system boundary decisions is unknown, but it is likely that what has been accounted for in our study is a subset of the total truncation.

It is notable that truncation error is unidirectional, meaning that it is always presented as an underestimation bias, while the errors in the input-output data or other proxy data for cut-offs are generally random.[4,29] When it comes to refinement of data to improve the quality of an LCA result, the simple distinction between IO or process cannot serve as the guide for choosing data; best quality data considering both precision and accuracy should be prioritized regardless of whether the data at hand is from an IO LCA database or from a process LCA database. In doing so, an LCA analyst should consider the trade-offs between precision and accuracy; i.e., inclusion of less precise data should be considered if its benefits of improving system completeness and accuracy outweigh the cost. For example, if one process contributes an overwhelming majority of the total impacts, it may be unwise to use input-output data, since the introduction of less precise data for that process may spread the range of possible results too broad to be useful in decision making. The decisions associated with data selection have to be based on the scope and objective of the LCA study.

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Furthermore, prioritizing the largest contributors to overall uncertainty can substantially reduce the time and resources needed for further improvement in the quality of LCA results. We therefore recommend the iterative hybrid procedure,[10] starting from the rough but complete picture and progressively refining the key contributors to overall uncertainty.

Our study is limited by the existing uncertainty distribution data from both ecoinvent and CEDA. The subjectivity of the pedigree approach and reliance on expert judgment to estimate certain contributors to these uncertainties are also recognized as a limitation, and future research should focus on developing more objective and scientific alternatives to measure parameter uncertainty in both process-based and IO data sets.

While our work attempted to capture and assess uncertainty more holistically than typical LCA studies, not all sources of uncertainty could be included in our assessment. Specifically, uncertainty associated with the technology matrix was not presented in the Mistra study and therefore not included in our analysis. Additionally, the uncertainty of the characterization factors in impact assessment was outside the scope of our study. Future work should address how to measure these sources of uncertainty as well.

■ ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge on the ACS Publications website at DOI: 10.1021/acs.est.9b00084.

An expanded discussion of uncertainty classifications and applications of uncertainty in LCA, including a literature review and brief synthesis of how uncertainty has been used in LCA in the time period 2010−2018. Tables containing results from the analysis to identify cut-offs using the CEDA database in step (b), as well as the results of the local sensitivity analysis in step (c) (PDF)

All matrices and underlying equations used to generate results are included in a supplemental excel workbook to ensure the reproducibility of the study. (XLSX)

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Notes

The authors declare no competing financial interest.

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