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A critical perspective on uncertainty appraisal and sensitivity analysis in life cycle assessment

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Conflict of interest statement

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Keywords

Life cycle assessment, uncertainty analysis, sensitivity analysis, knowledge quality assessment, stochastic and epistemic uncertainty, industrial ecology

Abstract

In this study, we review approaches for uncertainty appraisal in the life cycle assessment literature. We cover the acknowledgement of stochastic and epistemic uncertainty in uncertainty and sensitivity analysis and knowledge quality assessment, respectively.

Consistent with previous works, our findings indicate that uncertainty is only appraised in few studies on life cycle assessment. Most of these contributions cover only one of the phases of life cycle assessment, mainly the life cycle inventory. Less attention has been devoted to the phases of goal and scope definition and life cycle impact assessment.

Additionally, in most studies, uncertainty analysis and sensitivity analysis have been applied independently, as wrongly assumed they cover different uncertainty spaces. We also identify the scope for improvement in the appraisal of epistemic uncertainty and the correct definition of the probability distribution of the uncertain factors. We conclude by highlighting studies in which sensible practices have been adopted, identifying open challenges, and suggesting possible ways forward.

1 Introduction

Life Cycle Assessment (LCA) aims to account for the environmental aspects and potential impacts of a given system throughout its life cycle (International Organization for Standardization, 2006a, 2006b). While the methodology has been conceived to support informed decision-making, its application is associated with methodological and communication challenges. These include knowledge quality and its appraisal (Ross et al., 2002; Zampori et al., 2016), normative choices (Scrucca et al., 2020), and their effects on LCA outcomes (Sala et al., 2020; Yoshida et al., 2013), as well as in terms of impacts of policy interventions (Reale et al., 2017).

Arguably, uncertainty analysis (UA) and sensitivity analysis (SA) are among the most relevant ones. Yet a proper appraisal of uncertainty in LCA is challenging due to complicated accountings that includes hundreds to hundreds of thousands flows. These are handled by software that, in the majority of the cases, offer only a limited possibility of adequately running UA and SA within the environment. Further tools and techniques are required, along with the necessary skills that may not align with the expertise of practitioners.

Uncertainty was already a subject of discussion in the early days of LCA formalization within SETAC (Society of Environmental Toxicology and Chemistry)(Fava et al., 1994), alongside with uncertainty appraisal (defined as 'reliability')[1] (Heijungs (1994). In 1998, a SETAC-Europe LCA Working Group on 'Data Availability and Data Quality' was formed (Huijbregts et al., 2001). Early LCA scholars were already aware of the potential misuse of LCA results (Lloyd and Ries, 2007; Ross et al., 2002). Ross et al. (2002) scrutinised a pool consisting of 30 LCA studies published after 1997 and found that the assessment of uncertainty was largely overlooked.

Three recent literature reviews (Bamber et al., 2020; Igos et al., 2019; Michiels and Geeraerd, 2020) (see Supporting Information Table S1) and a book chapter (Rosenbaum et al., 2018) further investigated this issue. Bamber et al. (2020) reviewed recent LCA literature and found that UA was not widespread (less than 20% of the sample) and that, even when it was applied, the focus was often only on parameter-related uncertainty.

Both Bamber et al. (2020) and Igos et al. (2019) concluded by recommending increased reporting, implementation, and treatment of uncertainty in LCA studies; and advocating for the support of peer reviewers, editors, LCI databases, Life Cycle Impact Assessment (LCIA) methods, and LCA software developers in raising awareness and disseminating good practices. Michiels and Geeraerd (2020) recommend the use of Monte Carlo simulations to visualise uncertainty and variability ratios and/or total sensitivity indices through global sensitivity analysis (GSA).

Although the above reviews offered meaningful insights, none adequately discussed the suitability of the proposed approaches for the intended goals of uncertainty appraisal in LCA. The selection of UA/SA approach is, however, non-trivial and deserves thorough scrutiny. The present study aims to fill this gap by critically assessing current practices and recommendations in LCA (see Supporting Information Table S1). The objective of this study is twofold:

i. To characterise current LCA practices in terms of UA/SA approach and the appraisal of epistemic uncertainty by structuring reflections according to ISO phases.

ii. To critically examine current practices from the perspective of UA/SA practitioners.

2 Methods

2.1 Definitions

In this study, we adopt the distinction between epistemic and stochastic uncertainty (Walker et al., 2003), whereby the former is the lack of representativeness of a model or the lack of consistency across its components, whereas stochastic (or ontic) uncertainty is the variability of data and relationships (Igos et al., 2019). Additionally, epistemic uncertainty relates to those aspects that are beyond full quantification, whereas stochastic uncertainty can in principle be fully quantified.

Stochastic uncertainty is generally explored through quantitative UA and SA, while epistemic uncertainty can be partially explored through knowledge quality assessment, or through stochastic methods, to ascertain the effects of different methodological choices. However, epistemic uncertainty cannot be reduced to plain stochastic uncertainty. Approaches for knowledge quality assessment provide an analysis and diagnostic of uncertainty in the knowledge base of complex (environmental) policy problems (Funtowicz and Ravetz, 1990; Ravetz, 1971; van der Sluijs et al., 2005). It is commonly believed that more knowledge is a means towards uncertainty reduction, although this may not be the case (van der Sluijs et al., 1998). Knowledge and uncertainty do not necessarily span commensurable dimensions, and seeking more knowledge may actually result in an increase in uncertainty.

Uncertainty characterises the following LCA phases: goal and scope definition, LCI, and LCIA. The appraisal of uncertainty is conducted in the interpretation phase (Heijungs and Kleijn, 2001; Laurent et al., 2020). For this reason, in this study, we discuss uncertainty sources accordingly. The intepretation phase may also add further uncertainty in terms of the value-laden nature of the involved stakeholders, as discussed in Section 3.3. Nevertheless, the nature of uncertainty differs across LCA phases. In particular, the goal and scope phase is often characterised by epistemic uncertainty related to the framing of the assessment; this encompasses aspects such as selecting the functional unit, system boundaries, truncation threshold, and modelling and assessment techniques (e.g., system expansion or substitution; consequential or attributional LCA).

[1] We thank a reviewer for pointing us to these contributions.

The LCI and LCIA phases are often characterised by both stochastic and epistemic uncertainty. In the inventory phase, epistemic uncertainty is mostly concerned with the quality of LCI data and the underlying production process of this information. The LCIA phase relies on impact assessment models that, in turn, are affected by normative choices, and thus by epistemic uncertainty. The choice of impact assessment indicators may also reflect a normative choice, and likewise the modelling assumptions associated with background inventories.

UA and SA are both technical approaches for the quantitative appraisal of uncertainty. UA quantifies the range of output uncertainty, which can then be apportioned onto the input parameters and modelling hypotheses through SA (Figure 1). Various approaches for SA have been proposed in the literature, and a major distinction can be drawn between One-variable-at-a-time SA (OAT-SA) and GSA. The former is carried out by varying one input parameter at a time, leaving the others fixed. Conversely, the latter is based on experimental designs where all the parameters move together. In this way, GSA allows inferences to be drawn about interactions among parameters, which are unaddressed in an OAT context. Higher-order interactions occur in non-additive models, which is the standard setting in LCA, whereby the mathematical relations among input factors are beyond mere additions and subtractions.

[Figure 1 – about here]

2.2 Bibliometric search

A literature search was performed in Scopus on 10 August 2020 and updated on 25 October 2021, with the keywords *life cycle AND uncertainty AND sensitivity analysis* in the *Article Title, Abstract,* and *Keywords* fields. The search was also extended with the keywords *life cycle AND (uncertainty OR sensitivity analysis)* to ensure the inclusion of articles that addressed either UA or SA. This search resulted in ~9,000 papers, of which the majority was filtered out because not written in English or out of scope. We discarded articles on techno-economic analyses, life cycle cost estimations, or other life-cycle assessments that did not cover the environmental impact assessment, where LCA did not play a pivotal role, or where uncertainty and sensitivity analysis where used at another analytical level.

The total sample resulted in a total of 344 scientific articles, 80 of which had a methodological/theoretical scope. The full list of documents is presented in *Supporting Material*. A limitation of the Scopus search is that so-called grey literature (e.g., technical reports and policy documents) was omitted from the pool of documents searched.

Figure 2 shows the change in the number of documents produced over time, on a yearly basis. The first LCA study that explicitly analysed uncertainty was a conference paper published in 1995 (Chen, 1995). Following that, publication was intermittent until the mid-2000s, after which the number of articles began to ramp up to around 30 per year in 2016, with fairly stable production thereafter. In relative terms, over the total production of LCA papers, the relative ratio has been mainly stable around a few percentage points.

[Figure 2 – about here]

3 Results

In this section, we describe the methodological choices of LCA practitioners for uncertainty appraisal in the different phases of LCA. The numbers of contributions across LCA's phases are detailed in Figure 3. The lion's share is associated with the inventory phase, with around 60% of the total contributions. This reaches more than 90% if one acknowledges the contribution also dealing with LCIA (14%) or goal and scope definition (13%), or these three dimensions altogether (3%). The purely theoretical/methodological contributions are excluded from this counting given their scope. The specific figures for each phase are discussed in the following subsections.

[Figure 3 – about here]

3.1 Goal and scope definition

50 studies acknowledged a form of uncertainty in one/two aspects of the goal and scope definitions, as per the details presented in Figure 4a.

[Figure 4 – about here]

Most contributions simply qualitatively discussed the option of considering variable system boundaries, although several studies also produced quantitative figures, such as by performing system expansion (Eranki and Landis 2019). In one of these, Schmidt and Pahl-Wostl (2007) acknowledged uncertainty in their system boundary depending on the local characteristics of the system inquired into.

In the literature, uncertainty in the functional unit definition has mainly been examined in terms of multiple functional units; different coefficients for the production scaling factors (Wenker et al., 2016); replacement rates (e.g., number of polyethylene shoppers replaced by an individual cotton bag in Mattila et al., 2011); spaces (area), time (life-years), and service (occupancy), along with their possible combinations in a building (de Simone Souza et al., 2021); or end-uses (Wang et al. 2018).

3.2 Life cycle inventory

Almost 280 articles assessed uncertainty in the LCI phase (Figure 4b). As regards the uncertainty associated with the background system, most of the studies assessed the effect of different carbon intensities of the electricity mix. Some authors considered a country's carbon intensity against the carbon intensities of the whole international electric grid, or against other reference countries with particularly low or high carbon intensities; or they examined hourly variable rates against the yearly average (Pannier et al. 2018). Other studies extended this approach to heat generation (Tonini et al., 2012) or the composition of transformer oil (e.g., soybean versus other possible compositions (Mason et al., 2006)). A few studies also included uncertainty in the background process from the used inventories (typically, the ecoinvent database). Cox et al. (2018) fully characterised the uncertainty of the background against the foreground.

In the foreground system, uncertainty is associated to the inventory inflows and the related outflows in the process/system under study. When not available from primary data, it has been common practice in the literature to resort to inventory figures along with their uncertainty.

Modelling the uncertainty ranges for emission factors is a less frequent practice. Deng et al. (2017b) tested different approaches by assessing nitrogen-related field emissions in a cultivation through the denitrification-decomposition approach and benchmarked it against the IPCC standard figure.

3.3 Life cycle impact assessment

This phase has received far less attention compared to LCI: Only 69 studies acknowledged uncertainty at the impact assessment phase (Figure 4c).

Several studies acknowledged the effect of the variability of the time horizon investigated. Guo and Murphy (2012) applied this approach to three impact categories (global warming potential, ozone depletion, and human toxicity). De Rosa et al. (2018) and Reisinger et al. (2017) discussed the volatility of actual CO_{2eq} emissions due to uncertainty in the different time horizons of the characterisation factors, static vs. dynamic accounting for the emissions, and land-use change.

Seppälä et al. (2004) proposed a temporally and spatially variable estimate of the characterisation factors for eutrophication based on different hypotheses of impact, in the context of Finland's emissions. Maia de Souza et al. (2016) analysed the effect on the LCA outcome rankings using different LCIA methods. Specifically, the authors compared ReCiPe with a hierarchist approach to IMPACT 2002 + VQ2.2. Bueno et al. (2016) considered 5 different LCIA methods and Wang et al. (2020) 6 for the human health impact category. Chen et al. (2021) characterised the LCIA in terms of i) the total emission values across inventories; ii) the coverage of substances in the methods; iii) the characterisation factors associated to these substances in impact methods.

In the normalisation and weighting phase, Pang et al. (2015) and Wang et al. (2018) assessed different perspectives on the environmental endpoint dependent upon the relative weight attached to the different impact categories. Belboom et al. (2013) and Smetana et al. (2019) studied the sensitivity of the output to the actual point at which the impact was evaluated (midpoint vs. endpoint). Ravikumar et al. (2018) simultaneously examined the effects of uncertainty in three impact categories (marine eutrophication, climate change, and metal depletion) and weighting criteria (ReCiPe impact assessment method against hierarchy perspective with variable weights). Meyer et al. (2017) assessed uncertainty in the weighting for an impact of special interest (environmental noise).

French and Geldermann (2005) posited that uncertainty appraisal should take into account the values attached to different impact categories by stakeholders. Thies et al. (2019) agreed with this, arguing that the full phases of normalisation through weighting attribution and final interpretation are confronted with important difficulties linked to value-ladenness and preferences (Alanne et al., 2007). Approaches beyond manuals and software have been proposed to address these dimensions, including resorting to composite indicators (Nardo et al., 2005) and/or multi-criteria assessments (Agarski et al., 2016; Munda, 2004).

3.4 Contributions involving more than one phase

Several contributions acknowledged uncertainty across the phases of LCA (Figure 2). For instance, multiple authors considered uncertainty at the foreground and characterisation phases (Alyaseri and Zhou, 2019; Carless et al., 2016; De Marco et al., 2018; Van Zelm and Huijbregts, 2013), while Belboom et al., (2013); Cox et al., (2018); Cucurachi et al., (n.d.); Guo and Murphy, (2012); Pannier et al., (2018); Thévenot et al., (2018) also included the background phase. Palazzo and Geyer (2019) considered the whole modelling assumptions in a consequential LCA study.

Hernández-Padilla et al. (2017) highlighted the issue of the adequateness of using data from different geographical areas by considering uncertainty in electricity mix (background); wastewater treatment processes (foreground); and, local characterisation factors for the impact assessment. In the research, uncertainty in the normalisation phase was also acknowledged by comparing the results under different impact assessment methods. Patouillard et al. (2019) also dealt with spatial variability at the level of background, foreground, and impact assessment.

3.5 Stochastic uncertainty: Uncertainty analysis

In this section, we assess the methodological choices of the LCA practitioners in running UA. UA was performed in 217 studies, two-thirds of which were based on Monte Carlo simulations (Figure 5a). The simulations were executed on random combinations of input parameters sampled from their assumed input distributions. The output of Monte Carlo simulations is also a distribution of the possible values of output. 47 articles resorted to a min-(mean)-max range inquiry by testing the effects of sampling the parameters at the mean and the extreme of their distributions on the output uncertainty. 7 studies performed an analytical propagation of the uncertainty, and half of these benchmarked against Monte Carlo simulations. Finally, 8 studies appraised uncertainty only qualitatively.

[Figure 5 – about here]

As regards Monte Carlo simulations, the typical number amounted to 10,000, although the figures varied from 300 (Muñoz et al., 2020) to 10,000,000 (Wong et al., 2016). In the vast majority of cases, simulations were directly run on the input parameters' uncertainty ranges, although pre-filtering by removing non-influential parameters and feeding only the relevant ones into the Monte Carlo-based UA was performed through regression (Hsu et al., 2010; Jaxa-Rozen et al., 2021) or OAT-SA (Chiu and Lo 2018).

On sampling schemes, three studies used a Latin hypercube (Jaxa-Rozen et al., 2021; Khang et al., 2017; Mckay et al., 2000), in which the range of variability of the input parameters was more efficiently explored through a design that allowed a more uniform coverage of the uncertainty input space. The range approach can also be used by setting the input parameters at the extreme of their range of variability. Bawden et al. (2016) and Chen et al. (2018) made use of the range approach as a means of dealing with potentially unreliable LCA inventory data so as to avoid making any judgment about the probability of different occurrences.

Only a minority of studies justified the shape (Sabará, 2021) and range of the input parameter distributions fed into the UA and/or SA. 4 studies used statistical testing to define the most appropriate distribution shape for the input parameters based on their data population (Aktas and Bilec, 2012; De Marco et al., 2018; Goulouti et al., 2020; Guo and Murphy, 2012). Analogously, Barjoveanu et al. (2020a) tested the effects of distribution shape (normal, uniform, or triangular) and range (by doubling the standard deviation in a normal distribution), and evaluated how uncertainty in the output was affected in a ceteris paribus context (i.e., when all other parameters were fixed). To produce representative figures, Quinn et al. (2020) defined weighed distributions for several foreground parameters dependent on the mass associated with each specific data point.

Most studies used standard distributions from life cycle inventories (*tout court* or to compensate for the lack of primary data), whose shape and ranges were rarely adjusted to the specific context investigated. The adopted shape was almost exclusively lognormal, while the range was mainly defined based on the Pedigree approach (for more details, see Section 3.8). A notable exception is the work of Beylot et al. (2018), who resorted to triangular instead of lognormal shapes upon the parameters' physical incompatibility with this distribution shape. Normal and triangular shapes were the primary alternatives to the adoption of lognormal, while uniform, PERT, or beta distributions were more rarely used.

The uncertainty of the output was frequently conveyed in terms of statistical features of the output distributions (percentiles, quartiles, standard deviation, min-median-max, 90% or 95% confidence intervals, and relative error or coefficient of variation on the mean). Probabilities of rankings of output alternatives are less practiced, although they do play a role in comparative studies. In terms of visual outputs, whisker box plots were the typical chart selected, along with the probability distribution functions drawn from the Monte Carlo runs. Violine plots or cumulative distribution functions were less commonly used.

3.5.1 Use of pedigree matrices

Kennedy et al. (1996), Weidema and Wesnæs (1996), and then Weidema et al. (2013) proposed the use of pedigree matrices as proxies to estimate stochastic uncertainty. In this approach, the pedigree score is translated into a factor that, in combination with the standard deviation of a given parameter and under the assumption of a certain density function shape, provides an estimate of stochastic uncertainty. The rationale is the following: the lower the knowledge quality, the weaker the pedigree and the larger the stochastic uncertainty entailed. The implementation of this approach to the scale of LCI databases has been successful to the point that it is now at the foundation of the proposed uncertainty ranges for parameters in the major LCI commercial databases and software (e.g. Frischknecht and Jolliet, 2017; Weidema et al., 2013).

The reliability and commensurability (Cooper and Kahn, 2012) of the use of the pedigree score to appraise stochastic uncertainty has been scrutinised in the literature (Ciroth et al., 2016; Cooper and Kahn, 2012; Lin et al., 2015; Mohajerani et al., 2018; Muller et al., 2016a). Kennedy et al. (1996) also tested how the statistical properties attributed to a given pedigree influenced the results through an OAT-SA in a sort of meta-sensitivity analysis exercise. Ciroth et al. (2016) sought to provide empirical grounding for standard deviation coefficients based on a pedigree analysis of distribution shapes other than normal and lognormal. Qin et al. (2020) used the pedigree-based approach for investigation on LCIA models.

Yet, it is important to remind that the original developers and proponents of the pedigree matrix approach (Funtowicz and Ravetz, 1990; van der Sluijs et al., 2005) designed it as a knowledge quality assessment tool.

3.6 Uncertainty apportionment: Sensitivity analysis

SA was slightly more widespread than UA (Figure 5b). Most SA studies involved OAT approaches, with almost 190 contributions. Practitioners used various terms to refer to this approach: derivative, Taylor expansion, perturbations, etc. While slightly conceptually different, the logic of these approaches is the same: vary a single input parameter and evaluate its effect on the output variable(s), either numerically (perturbations), analytically (derivatives, Taylor expansion), or both. The range of variability of the individual parameters is fixed in either directions or only increased by 5-30%. Alternatively, more points may be studied, such as 95% variation of the input range at a 5% resolution (Quinn et al., 2020). Just above 20 studies performed GSA, with a further 8 studies running both analyses, OAT-SA and GSA, mainly in a comparative fashion.

One of the approaches included in the 'other' category in Figure 5b is a sensitivity metric known as the First-order Reliability Method (FORM) (Riesch-Oppermann and Brückner-Foit, 1988) used by Wei et al. (2016). Other approaches to SA may be only qualitative.

OAT-SA has been frequently adopted in LCA to check the robustness of modelling assumptions. Mattick et al. (2015) ran an anticipatory LCA to estimate the potential impact of future in-vitro meat cultivation. Benoist et al. (2012), Moreira et al. (2014), Safaei et al. (2015), and Tu and McDonnell (2016) performed OAT-SA even when the computational effort to resort to large Monte Carlo random sampling from the input parameters was made. Hanandeh and El-Zein (2010) embedded SA into Monte Carlo simulations, whereby all parameters but one were kept fixed. Ziyadi and Al-Qadi (2019) applied Bayesian inference to determine parameter uncertainty and surrogate models to propagate the uncertainty of model parameters and model form in a Monte Carlo setting. An extension of OAT/analytic approaches was presented in von Pfingsten et al. (2017). In their research, the authors introduced a method based on second-order analytical uncertainty to overcome the limitations of a simple first-

order Taylor expansion, in which only first-order derivatives are computed, and concluded that the second-order approach was more accurate in computing parameter sensitivities.
The sensitivity measures proposed in the literature include the use of the Spearman rank correlation coefficient (Carless et al., 2016; Lee et al., 2011; Mattinen et al., 2015; Palazzo and Geyer, 2019; Pfister et al., 2016; Ross and Cheah, 2017) and other measures of input-output covariance (Zhang et al., 2016). These measures were used in approximately 20 studies. Spearman's rank correlation coefficient may also be produced in a global context, yet this does not allow the estimation of higher-order interactions across parameters. The latter are accounted for in the so-called total-order Sobol' indices (Homma and Saltelli, 1996). This variance-based sensitivity metric was used along with first-order Sobol' indices (Sobolʹ, 2001) in 9 studies. Other GSA approaches have also been tested, including the Fourier Amplitude Sensitivity Test (FAST) (Saltelli et al., 1999), which was adopted in 2 studies (Chen et al., 2005; De Koning et al., 2010), and the polynomial chaos expansion (Sudret, 2008), which resorts to orthogonal polynomials to approximate the model response surface, in Galimshina et al. (2019). 8 studies used moment-independent GSA (Borgonovo, 2007), which is a method that does not rely on any specific statistical moment when apportioning the effect of input uncertainty onto the output.

As regards comparative approaches, Di Lullo et al. (2020) compared a Sobol'-based GSA and OAT Morris method to evaluate a model for the emissions produced by crude oil extraction from different oil fields. The authors concluded that the latter was computationally advantageous, although the range of output uncertainty (i.e., in terms of its variance) by applying the two different methods was not quantified.

3.7 Epistemic uncertainty and its appraisal

Epistemic uncertainty is only partially knowable (by its own definition), therefore, the methods and techniques that support its appraisal in LCA focus on the assessment of quality of knowledge and its fitness for purpose.
In the goal and scope phase, epistemic uncertainty results from modelling assumptions such as the following: the definition of the functional unit (Avadí et al., 2020; Barjoveanu et al., 2020b; Feiz et al., 2020) and system boundaries; the cut-off and allocation rules; the choice of marginal suppliers between the attributional and consequential, static or dynamic approaches; and, indirect consequential effects. For example, the truncation of economic activities in the accounting of LCA input-output processes has been questioned in the literature as it would lead to an underestimation of environmental impacts (Jiang et al., 2014; Majeau-Bettez et al., 2011). In comparative LCA, this aspect may not necessarily affect all products equally because they may be manufactured in different industrial sectors. This bias may be even more serious when estimating the absolute impact due to this mismatch, with top-down information coming from the underrepresented (or even completely neglected) economic sectors.
The vast majority of the contributions that address epistemic uncertainty, either implicitly or explicitly, have done so by focusing on the LCI phase. This has been achieved by accounting for the quality of LCI datasets by means of qualitative discussion or the use of off-the-shelf pedigree coefficients, through the development and application of data quality assessment systems or pedigree produced by expert judgement (Beylot et al., 2018; Fazio et al., 2015; Henriksen et al., 2020; Li et al., 2020) integrated with new data through Bayesian inference (Muller et al., 2016b); use of alternative inventories (Röder et al., 2014); combination of alternative distribution shapes (Lacirignola et al., 2017; Larsson Ivanov et al., 2019); use of fuzzy logic (Benetto et al., 2006a; Tan, 2008; Tan et al., 2002); and, use of alternative methods for the imputation of missing data (Geisler et al., 2004).
In the LCIA phase, epistemic uncertainty relates to the selection of a particular method; the normative aspects embedded within LCIA models (Qin et al., 2020), such as in terms of accounting at mid- and end-points or different impact assessment methods, and impact weighting (Igos et al., 2019). Forcing incommensurable environmental impacts – let alone social aspects – into a single indicator is challenging (Benini and Sala, 2016), to the extent that only few studies addressed epistemic uncertainty in the LCIA phase (Avadí et al., 2020; Benetto et al., 2006b; Milani et al., 2011; Petrakopoulou and Tsatsaronis, 2014).
In the next subsections, we discuss the main approaches used in the reviewed set of papers to handle epistemic uncertainty and the question of how this has been linked to stochastic uncertainty.

3.7.1 Data quality indicators

According to the approach proposed by Weidema and Wesnæs (1996), criteria such as reliability, completeness, and technological, temporal, and geographical representativeness are used to characterise the quality of LCI datasets based on expert judgment and evaluation. A 'pedigree' coefficient represents the level of quality of a given dataset, and it is estimated according to a structured approach.

Applications of the pedigree matrix approach are found in the US Environmental Protection Agency guidance document for LCI data quality assessment (Edelen and Ingwersen, 2016) and the European Commission Handbook (Joint Research Centre, 2010). These documents cover six data quality indicators, along with a five-point scale and minimum entry-level requirements for datasets to support science-for-policy applications.

Maia de Souza et al. (2016) used the pedigree score to transparently single out areas with a low score to report on the limitations of their study. Henriksen et al. (2020) proposed a new framework to assess the pedigree coefficient, which acknowledged the actual pace of development of industrial sectors and their adjustment to more demanding normative frameworks. This involved estimating the actual distance between inventory data and the current figures in the system represented.

3.7.2 Fuzzy logic

Fuzzy logic has also been proposed to handle epistemic uncertainty (Clavreul et al., 2012; Gavankar and Suh, 2014). This approach merges experts' beliefs with quantitative data to obtain potential ranges for parameters. The use of fuzzy logic has been proposed throughout the phases of LCA, including at the level of inventory (Ardente et al., 2004; Heijungs and Tan, 2010; Sabará, 2021; Tan, 2008; Tan et al., 2002); impact assessment (Benetto et al., 2006a, 2006b; Potting et al., 2006); and interpretation (Benetto et al., 2008).

Fuzzy logic is a good candidate for expressing epistemic uncertainty, because fuzzy sets can express vagueness (e.g., imprecise and non-numerical data) (Clavreul et al., 2013) more effectively than probability distributions, for instance by translating linguistic uncertainty levels into ranges of plausible outcomes (Tan, 2008). Despite its computational easiness, the number of applications of fuzzy logic in LCA is limited due to fuzzy logic's lack of capacity to deal with correlated parameters, the limited acquaintance of LCA developers and practitioners with this concept, and the lack of compatibility in major commercial software (Tan, 2008). Further research is necessary to assess how fuzzy sets can be used in combination with stochastic uncertainty (Tan, 2008), and whether SA techniques for estimating sensitivity indices could be extended to fuzzy LCA models.

4 Discussion

Despite the growing number of publications on the subject, the appraisal of uncertainty in the LCA literature still appears limited and widely characterised by questionable practices. The methodological developments published in the literature seem to be rather isolated exercises with very few practical applications. This is witnessed by the large resort to OAT-SA approaches instead of GSA (see Section 3.7). An overview of the main issues encountered is presented in the sections below, as well as in Table 1, along with reflections on possible remedies.

Table 1: Issues and remedies for uncertainty appraisal in LCA

Issue	What	Why is this a problem?	Remedy	Who should act by setting minimum requirements?
Downplay uncertainty (stochastic) (Section 3)	UA is separately characterised across LCA phases	Uncertainty is deflated in LCA and outcomes are unreliable, especially in comparative studies and labelling	Fullest possible characterisation of UA across all phases	Researchers; Practitioners; Editors of scientific journals.
Garbage-in garbage-out (stochastic) (Section 3.6)	Resort to one-size-fits-all (default) approaches for addressing lack of knowledge on probability distributions of, for example, all factors given the same percentage error	Could render UA or SA (even GSA) perfunctory as assumed probability distribution functions ranges and shapes do not reflect real states of knowledge on uncertainty	Avoid the use of pedigree scores as proxies for uncertainty characterisation, and justify distribution shapes and ranges	Dataset developers; Software developers; Researchers; Practitioners; Editors of scientific journals.

Independent and confusing UA and SA (stochastic) (Sections 3.6 and 7)	UA and SA are run separately	Miscommunication and confusing outcomes, and interactions among factors are lost	Adequate exploration of the option space through GSA	Software developers; Researchers; Practitioners; Editors of scientific journals.
Inadequacy and misuse of knowledge quality assessment tools (epistemic) (Section 3.8)	Inflation of epistemic and stochastic uncertainty by misuse of DQI/pedigree approaches	Overemphasis of stochastic uncertainty, downplay of epistemic uncertainty, and lack of appraisal of the fitness for purpose	Use of DQI/pedigree approaches to assess and discuss quality entry levels, and application of the diagnostic diagram for appraisal and communication	Researchers; Practitioners; Editors of scientific journals.

Issue 1: Downplay uncertainty

A fairly common practice that we identified involves separately characterising uncertainty across the different phases of LCA (Section 3). However, in so doing, stochastic uncertainty may be severely downplayed as only a tiny portion of the option space would actually be explored by neglecting interactions across the phases of LCA (Saltelli and Annoni, 2010). When considering uncertainty in the characterisation phase, this can span several orders of magnitude, up to more than twenty (Chen et al., 2021; De Schryver et al., 2013; Deng et al., 2017a; Roy et al., 2014; Schryver et al., 2011; Van Zelm et al., 2009; Van Zelm and Huijbregts, 2013). The same may occur by using figures from development labs in LCA (up to seven orders of magnitudes according to Li et al., 2014) and projecting these to a full-scale industrial application. One immediate implication of this finding is that only assessments where the differences among options are pronounced can be considered meaningful. However, few contributions acknowledge that overlapping output uncertainty ranges may challenge ranking reliability in a comparative analysis (Mendoza Beltran et al., 2018; Muñoz et al., 2014). A conservative approach may involve reporting the results in terms of the probability of one option being better – that is to say, less impactful – than the compared option.

Simultaneous variations of the uncertain input parameters and assumptions in Monte Carlo simulations, when coupled to GSA, enable the full exploration and characterisation of the uncertainty space. Nevertheless, satisfactory examples of its use in LCA are still scarce (Sections 3.6 and 3.7) to extent that even a comprehensive review of LCA (Ling-Chin et al., 2016) omitted the possible use of Sobol' sensitivity indices in LCA.
Performing GSA requires time-consuming simulations, which may be prohibitive for a complex LCA. Additionally, the practice of simplifying UA by focusing on the influential factors before a GSA (Aui et al., 2019; Groen et al., 2017; Röder and Thornley, 2018; Van der Harst and Potting, 2014) is unlikely to produce reliable results. This is because it is to be seen how this uncertainty would propagate with the uncertainty at play in all the LCA phases. In running an SA only on key parameters (Tao et al., 2022), the mean is confused with the uncertainty; one can know the effect of the input parameters on the output by running the model. However, the question of how parameter uncertainty affects output uncertainty is determined by running an SA. Thus, the key parameters can only be known after running an SA. The same caveat applies when running an uncertainty analysis in a context of reduced uncertainty by firstly varying only a subset of parameters and then opening up the option space by varying more (De Koning et al., 2010). The opposite would actually be recommendable: namely, let the model freely vary and then simplify it by fixing the non-influential parameters (Saltelli et al., 2008).

Issue 2: Garbage-in garbage-out

Another issue is represented by the shapes and ranges of the probability distributions of the modelled parameters fed into UA and SA (Sections 3.6 and 3.7). In many LCA studies, the following distributions are typically considered: distributions with standard deviation equal to the mean or to fixed ratios across parameters, or as per the pedigree coefficients (Section 3.8) (Kennedy et al., 1996; Weidema and Wesnæs, 1996); and, lognormal distributions. This shape is typically selected because distributions of this kind are already available in life cycle inventories; allow for the accounting of data skewness; and avoid negative figures (that could be randomly extracted from e.g., normal distributions) (Mattila et al., 2011). However, it is important to recognise that this approach is prone to the Garbage-in Garbage-out (GIGO) phenomenon (Funtowicz and Ravetz, 1990; Saltelli et al., 2013), which can invalidate UA or (G)SA even in a synthetic case study (Groen et al., 2017).

Issue 3: Independent and confusing UA and SA

A frequent practice identified in the reviewed studies was the independent running of UA and SA, which is tantamount to assuming that the uncertainty appraised using these approaches belongs to different categories (Sections 3.6 and 3.7). Logic would dictate that the uncertainty space is the same for the two analyses. For instance, Guo and Murphy (2012) ran independent UA on inventory data and OAT-SA on the time horizon of the impact categories, but these two analyses are necessarily correlated. For this reason, they should be run in tandem rather than independently. Studies were also found in the literature that performed SA before UA (Cherubini et al., 2018; Eranki and Landis, 2019). Even when accounting for the impact of the same parameters, one can find that different uncertainty ranges are used in SA and UA (Li et al., 2014). Some authors even mistook UA for SA (Bernstad Saraiva et al., 2016; Bisinella et al., 2017; Capello et al., 2008; Esteban et al., 2014; Meneses et al., 2016; Poujol et al., 2020; Xu et al., 2018) or vice versa (Amonkar et al., 2019).

Remedy to issues 1-3: Approaches to handle computational burden

In LCA, the order of magnitude of the analysed flows challenges the effective implementation of GSA. However, some of these flows (e.g., those related to the same production process) may be correlated, which would partially reduce the dimensionality of the problem. Effective methods to deal with correlated variables in GSA have also been proposed (Kucherenko et al., 2012). Patouillard et al., (2020, 2019), and Wei et al., (2015a) presented another valid approach by running GSA on grouped inventory data and impact categories to reduce the problem's dimensionality. Meta-models can also assist in reducing the computational burden of cumbersome LCA accountings in a GSA setting (Galimshina et al., 2019).

GSA may also assist LCA practitioners in simplifying the adopted model by fixing non-influential parameters (Saltelli et al., 2008). This approach was showcased in Padey et al. (2013), who first ranked the input parameters as per their Sobol' total sensitivity indices through GSA, and fixed those with the lowest indices because their values do not influence the output variance. In a non-global context, such an analysis could result in erroneously fixing too many or too few parameters, thus downplaying the output uncertainty or wasting computational resources, respectively (Pannier et al., 2018).

Issue 4: Inadequacy and misuse of knowledge quality assessment tools

In general, the LCA studies reviewed in this work did reflect on epistemic uncertainty qualitatively, yet most of the studies neglected important aspects such as the quality – or fitness for purpose – of the methodological choices in relation to the goal and scope of the assessment. A very limited number of studies discussed how alternative methodological or value-laden choices would compare against outcomes (Section 3.8).
LCA developers have explored several avenues to estimate missing uncertainty values associated with LCI due to the scattered nature of statistical information, which stems from the large number of flows and processes involved in LCA. However, it may be unwarranted to translate qualitative information into commensurable metrics and then to a range of probability/possibility estimates (Gavankar and Suh, 2014). Contrary to what was proposed by Weidema and Wesnæs (1996), the quality of a parameter (e.g., underpinning theoretical vs. empirical foundation) or its geographical representativeness says little about whether its standard deviation should be increased by a factor 2, 10, or 100, and it does not indicate which shape the probability distribution functions should have. The variability of a certain phenomenon might have literally nothing to do with the quality of the underpinning mode of measurement/estimation. Even if an empirical relation is established for specific circumstances (e.g., a given database, see Ciroth et al., 2016), it is rather unclear why this should be assumed out for other processes and databases.

Epistemic uncertainty may significantly influence modelled quantities, but it cannot be reduced to stochastic uncertainty. Adopting the pedigree coefficient as a multiplicative proxy has a mere psychological effect. It reassures practitioners and decision-makers by making uncertainty seemingly manageable, providing a sense of confidence in LCA. Nevertheless, epistemic and stochastic uncertainty are simply two different domains. Their conflation into stochastic uncertainty entails two risks: first, it can lead to a skewed or completely biased (stochastic) UA and SA (Issue 2); and second, it undermines the importance of the appraisal of epistemic uncertainty. However, this approach has become the norm across the LCA community.

Remedy to issue 4: Use of diagnostic diagrams

Appraisals of stochastic and epistemic uncertainty should be retained and used in a complementary way. Tools such as diagnostic diagrams can help to appraise epistemic uncertainty against the stochastic uncertainty apportioned in SA (Pye et al., 2018; Van Der Sluijs et al., 2005) (Figure 6). The y-axis represents a measure of the sensitivity of the output to the variation of input factors (e.g., Sobol's sensitivity indices), while the x-axis represents the score of a knowledge quality assessment scheme (e.g., pedigree score and data quality indicators). Understandably, weak pedigree values and high sensitivity indices would lead to the identification of most problematic inputs and assumptions, seek for remedies or alternatives, and enact proper uncertainty communication. All in the interest of assessing the quality of information on the parameters affecting the output uncertainty the most (Cooper and Kahn, 2012; Lewandowska et al., 2004).

[Figure 6 – about here]

Epistemic uncertainty could be addressed most effectively through the extended participation of peers, deliberation. By acknowledging the perspectives of different stakeholders and recognising what is in their interests in a production process, different choices may be adopted and discussed (e.g., on the allocation factors (Fedele et al., 2014)). In so doing, different interpretations of the figures may be possible, which means that LCA could be open to a quantitative storytelling perspective (Kuc-Czarnecka et al., 2020), and be used as such in conflicted contexts.

Finally, when epistemic uncertainty is unbearable (i.e., weak pedigrees for plenty of the assessed relations), one may simply refrain from quantifying and, instead, develop the discussion merely around qualitative terms (Sala et al., 2015, p. 2).

5 Conclusions

In this study, we reviewed LCA studies that have appraised and apportioned uncertainty in their modelling activity. We identified a number of issues as follows: i) most articles merely focused on uncertainty at the LCI phase, neglecting the other LCA phases; ii) UA and SA were typically run as independent assessments; iii) the input parameters for which uncertainty was acknowledged were mainly selected based on their effect on the LCA output (thereby confusing the mean with its uncertainty); iv) SA was often run one-factor-at-a-time, which overlooks interactions among parameters; v) the terminology associated with uncertainty communication was frequently misused by confusing uncertainty appraisal with its apportionment; vi) the pedigree coefficient for data quality assessment was also misused by translating it into a multiplicative coefficient to define the ranges of the input parameters' probability distributions; and finally, vii) a significant gap exists between state-of-the-art methodologies and commonly adopted practices in LCA studies.

Based on these findings, it is reasonable to conclude that UA and SA, as well as knowledge quality appraisal, in LCA are insufficient in a large proportion of the published scientific literature. This does not necessarily reflect the practices of the whole community. Much work is needed to ensure that LCA studies can be used for policy support and that the risk of misinterpretation is minimised. We understand the implicit trade-off of exhaustively acknowledging uncertainty and the resulting risk of being incapable of ranking options due to largely overlapping outcome ranges. However, adequate uncertainty appraisal and apportionment should be regarded as a basic requirement at any scientific journal for publishing LCA-based papers, as well as for product assessment and labelling schemes. This aspect should play a crucial role in the future agenda on uncertainty appraisal, apportionment and communication in LCA. Developing a more coherent and holistic view on this issue is a necessary and promising avenue to explore further, as well as fostering collaboration with UA and SA practitioners.

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9 Supporting Material

A full list of the studies considered in this review is available from the Supporting Material repository (*Zenodo*).

10 Figure legends

Figure 1: Uncertainty/sensitivity analysis workflow, adapted from Saltelli et al. (2008).

Figure 2: Scopus search on yearly LCA, uncertainty, and sensitivity analysis (primary axis) vs. percentage over total contributions on LCA (secondary axis). Dotted lines are the five-year averages of these trends. The underlying data are available from the Supporting Material repository (*Zenodo*).

Figure 3: Uncertainty appraisal across LCA phases. The underlying data are available from the Supporting Material repository (*Zenodo*).

Figure 4: a) Uncertainty appraisal at the goal and scope phase; b) Uncertainty appraisal at the inventory phase; c) Uncertainty appraisal at the impact assessment phase. The underlying data are available from the Supporting Material repository (*Zenodo*).

Figure 5: a) Technical aspects of uncertainty appraisal across LCA phases; b) Sensitivity analysis across LCA phases. The underlying data are available from the Supporting Material repository (*Zenodo*).

Figure 6: Instance of diagnostic diagram.