

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

Article

Accepted Version

Lo Piano, Samuele ORCID logo ORCID: <https://orcid.org/0000-0002-2625-483X> and Benini, Lorenzo (2022) A critical perspective on uncertainty appraisal and sensitivity analysis in life cycle assessment. *Journal of Industrial Ecology*, 26 (3). pp. 763-781. ISSN 1088-1980 doi: <https://doi.org/10.1111/jiec.13237> Available at <https://centaur.reading.ac.uk/103875/>

It is advisable to refer to the publisher's version if you intend to cite from the work. See [Guidance on citing](#).

To link to this article DOI: <http://dx.doi.org/10.1111/jiec.13237>

Publisher: Wiley

All outputs in CentAUR are protected by Intellectual Property Rights law, including copyright law. Copyright and IPR is retained by the creators or other copyright holders. Terms and conditions for use of this material are defined in the [End User Agreement](#).

[www.reading.ac.uk/centaur](http://www.reading.ac.uk/centaur)

**CentAUR**

Central Archive at the University of Reading

Reading's research outputs online

1 **Article type: 4a** - Advances in industrial ecology methods (life cycle  
2 assessment)

3  
4

# 5 A critical perspective on uncertainty appraisal and sensitivity 6 analysis in life cycle assessment

7 Samuele Lo Piano<sup>1,\*</sup>, Lorenzo Benini<sup>2</sup>

8

9 1) Corresponding author: [samuele.lopiano@reading.ac.uk](mailto:samuele.lopiano@reading.ac.uk), School of the Built Environment, University of  
10 Reading, Reading, United Kingdom.

11 2) [lorenzo.benini@eea.europa.eu](mailto:lorenzo.benini@eea.europa.eu), European Environment Agency, Copenhagen, Denmark.

12  
13

## 14 **Conflict of interest statement**

15 The authors declare no conflict of interest.

16

## 17 **Keywords**

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

20

## 21 **Abstract**

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

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

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

34

## 35 **1 Introduction**

36 Life Cycle Assessment (LCA) aims to account for the environmental aspects and potential impacts of a given system  
37 throughout its life cycle (International Organization for Standardization, 2006a, 2006b). While the methodology  
38 has been conceived to support informed decision-making, its application is associated with methodological and  
39 communication challenges. These include knowledge quality and its appraisal (Ross et al., 2002; Zampori et al.,  
40 2016), normative choices (Scrucca et al., 2020), and their effects on LCA outcomes (Sala et al., 2020; Yoshida et al.,  
41 2013), as well as in terms of impacts of policy interventions (Reale et al., 2017).

42 Arguably, uncertainty analysis (UA) and sensitivity analysis (SA) are among the most relevant ones. Yet a proper  
43 appraisal of uncertainty in LCA is challenging due to complicated accountings that includes hundreds to hundreds  
44 of thousands flows. These are handled by software that, in the majority of the cases, offer only a limited possibility

45 of adequately running UA and SA within the environment. Further tools and techniques are required, along with  
46 the necessary skills that may not align with the expertise of practitioners.  
47 Uncertainty was already a subject of discussion in the early days of LCA formalization within SETAC (Society of  
48 Environmental Toxicology and Chemistry)(Fava et al., 1994), alongside with uncertainty appraisal (defined as  
49 'reliability')<sup>1</sup> (Heijungs (1994). In 1998, a SETAC-Europe LCA Working Group on 'Data Availability and Data  
50 Quality' was formed (Huijbregts et al., 2001). Early LCA scholars were already aware of the potential misuse of  
51 LCA results (Lloyd and Ries, 2007; Ross et al., 2002). Ross et al. (2002) scrutinised a pool consisting of 30 LCA  
52 studies published after 1997 and found that the assessment of uncertainty was largely overlooked.  
53 Three recent literature reviews (Bamber et al., 2020; Igos et al., 2019; Michiels and Geeraerd, 2020)  
54 (see Supporting Information Table S1) and a book chapter (Rosenbaum et al., 2018) further investigated this issue.  
55 Bamber et al. (2020) reviewed recent LCA literature and found that UA was not widespread (less than 20% of the  
56 sample) and that, even when it was applied, the focus was often only on parameter-related uncertainty.  
57 Both Bamber et al. (2020) and Igos et al. (2019) concluded by recommending increased reporting,  
58 implementation, and treatment of uncertainty in LCA studies; and advocating for the support of peer reviewers,  
59 editors, LCI databases, Life Cycle Impact Assessment (LCIA) methods, and LCA software developers in raising  
60 awareness and disseminating good practices. Michiels and Geeraerd (2020) recommend the use of Monte Carlo  
61 simulations to visualise uncertainty and variability ratios and/or total sensitivity indices through global sensitivity  
62 analysis (GSA).  
63 Although the above reviews offered meaningful insights, none adequately discussed the suitability of the proposed  
64 approaches for the intended goals of uncertainty appraisal in LCA. The selection of UA/SA approach is, however,  
65 non-trivial and deserves thorough scrutiny. The present study aims to fill this gap by critically assessing current  
66 practices and recommendations in LCA (see Supporting Information Table S1). The objective of this study is  
67 twofold:

- 69 i. To characterise current LCA practices in terms of UA/SA approach and the appraisal of epistemic  
70 uncertainty by structuring reflections according to ISO phases.
- 71  
72 ii. To critically examine current practices from the perspective of UA/SA practitioners.

## 74 **2 Methods**

### 75 **2.1 Definitions**

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

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

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

---

<sup>1</sup> We thank a reviewer for pointing us to these contributions.

97 The LCI and LCIA phases are often characterised by both stochastic and epistemic uncertainty. In the inventory  
98 phase, epistemic uncertainty is mostly concerned with the quality of LCI data and the underlying production  
99 process of this information. The LCIA phase relies on impact assessment models that, in turn, are affected by  
100 normative choices, and thus by epistemic uncertainty. The choice of impact assessment indicators may also reflect  
101 a normative choice, and likewise the modelling assumptions associated with background inventories.  
102 UA and SA are both technical approaches for the quantitative appraisal of uncertainty. UA quantifies the range of  
103 output uncertainty, which can then be apportioned onto the input parameters and modelling hypotheses through  
104 SA (Figure 1). Various approaches for SA have been proposed in the literature, and a major distinction can be  
105 drawn between One-variable-at-a-time SA (OAT-SA) and GSA. The former is carried out by varying one input  
106 parameter at a time, leaving the others fixed. Conversely, the latter is based on experimental designs where all the  
107 parameters move together. In this way, GSA allows inferences to be drawn about interactions among parameters,  
108 which are unaddressed in an OAT context. Higher-order interactions occur in non-additive models, which is the  
109 standard setting in LCA, whereby the mathematical relations among input factors are beyond mere additions and  
110 subtractions.

111  
112 [Figure 1 – about here]

113  
114  
115

## 2.2 Bibliometric search

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

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

127 Figure 2 shows the change in the number of documents produced over time, on a yearly basis. The first LCA study  
128 that explicitly analysed uncertainty was a conference paper published in 1995 (Chen, 1995). Following that,  
129 publication was intermittent until the mid-2000s, after which the number of articles began to ramp up to around  
130 30 per year in 2016, with fairly stable production thereafter. In relative terms, over the total production of LCA  
131 papers, the relative ratio has been mainly stable around a few percentage points.

132  
133

[Figure 2 – about here]

## 3 Results

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

140  
141  
142

[Figure 3 – about here]

143  
144

145 **3.1 Goal and scope definition**

146 50 studies acknowledged a form of uncertainty in one/two aspects of the goal and scope definitions, as per the  
147 details presented in Figure 4a.

148

149 [Figure 4 – about here]

150

151 Most contributions simply qualitatively discussed the option of considering variable system boundaries, although  
152 several studies also produced quantitative figures, such as by performing system expansion (Eranki and Landis  
153 2019). In one of these, Schmidt and Pahl-Wostl (2007) acknowledged uncertainty in their system boundary  
154 depending on the local characteristics of the system inquired into.

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

160

161 **3.2 Life cycle inventory**

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

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

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

177

178 **3.3 Life cycle impact assessment**

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

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

186 Seppälä et al. (2004) proposed a temporally and spatially variable estimate of the characterisation factors for  
187 eutrophication based on different hypotheses of impact, in the context of Finland's emissions. Maia de Souza et al.  
188 (2016) analysed the effect on the LCA outcome rankings using different LCIA methods. Specifically, the authors  
189 compared ReCiPe with a hierarchist approach to IMPACT 2002 + VQ2.2. Bueno et al. (2016) considered 5 different  
190 LCIA methods and Wang et al. (2020) 6 for the human health impact category. Chen et al. (2021) characterised the  
191 LCIA in terms of i) the total emission values across inventories; ii) the coverage of substances in the methods; iii)  
192 the characterisation factors associated to these substances in impact methods.

193 In the normalisation and weighting phase, Pang et al. (2015) and Wang et al. (2018) assessed different perspectives  
194 on the environmental endpoint dependent upon the relative weight attached to the different impact categories.  
195 Belboom et al. (2013) and Smetana et al. (2019) studied the sensitivity of the output to the actual point at which  
196 the impact was evaluated (midpoint vs. endpoint). Ravikumar et al. (2018) simultaneously examined the effects of  
197 uncertainty in three impact categories (marine eutrophication, climate change, and metal depletion) and weighting

198 criteria (ReCiPe impact assessment method against hierarchy perspective with variable weights). Meyer et al.  
199 (2017) assessed uncertainty in the weighting for an impact of special interest (environmental noise).

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

### 206 **3.4 Contributions involving more than one phase**

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

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

### 218 **3.5 Stochastic uncertainty: Uncertainty analysis**

219 In this section, we assess the methodological choices of the LCA practitioners in running UA. UA was performed in  
220 217 studies, two-thirds of which were based on Monte Carlo simulations (Figure 5a). The simulations were  
221 executed on random combinations of input parameters sampled from their assumed input distributions. The  
222 output of Monte Carlo simulations is also a distribution of the possible values of output. 47 articles resorted to a  
223 min-(mean)-max range inquiry by testing the effects of sampling the parameters at the mean and the extreme of  
224 their distributions on the output uncertainty. 7 studies performed an analytical propagation of the uncertainty,  
225 and half of these benchmarked against Monte Carlo simulations. Finally, 8 studies appraised uncertainty only  
226 qualitatively.

227  
228 [Figure 5 – about here]  
229

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

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

241 Only a minority of studies justified the shape (Sabará, 2021) and range of the input parameter distributions fed  
242 into the UA and/or SA. 4 studies used statistical testing to define the most appropriate distribution shape for the  
243 input parameters based on their data population (Aktas and Bilec, 2012; De Marco et al., 2018; Goulouti et al.,  
244 2020; Guo and Murphy, 2012). Analogously, Barjoveanu et al. (2020a) tested the effects of distribution shape  
245 (normal, uniform, or triangular) and range (by doubling the standard deviation in a normal distribution), and  
246 evaluated how uncertainty in the output was affected in a ceteris paribus context (i.e., when all other parameters  
247 were fixed). To produce representative figures, Quinn et al. (2020) defined weighed distributions for several  
248 foreground parameters dependent on the mass associated with each specific data point.

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

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

262

### 263 3.5.1 Use of pedigree matrices

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

272 The reliability and commensurability (Cooper and Kahn, 2012) of the use of the pedigree score to appraise  
273 stochastic uncertainty has been scrutinised in the literature (Ciroth et al., 2016; Cooper and Kahn, 2012; Lin et al.,  
274 2015; Mohajerani et al., 2018; Muller et al., 2016a). Kennedy et al. (1996) also tested how the statistical properties  
275 attributed to a given pedigree influenced the results through an OAT-SA in a sort of meta-sensitivity analysis  
276 exercise. Giroth et al. (2016) sought to provide empirical grounding for standard deviation coefficients based on a  
277 pedigree analysis of distribution shapes other than normal and lognormal. Qin et al. (2020) used the pedigree-  
278 based approach for investigation on LCIA models.

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

281

282

## 283 3.6 Uncertainty apportionment: Sensitivity analysis

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

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

295 OAT-SA has been frequently adopted in LCA to check the robustness of modelling assumptions. Mattick et al.  
296 (2015) ran an anticipatory LCA to estimate the potential impact of future in-vitro meat cultivation. Benoist et al.  
297 (2012), Moreira et al. (2014), Safaei et al. (2015), and Tu and McDonnell (2016) performed OAT-SA even when the  
298 computational effort to resort to large Monte Carlo random sampling from the input parameters was made.  
299 Hanandeh and El-Zein (2010) embedded SA into Monte Carlo simulations, whereby all parameters but one were  
300 kept fixed. Ziyadi and Al-Qadi (2019) applied Bayesian inference to determine parameter uncertainty and  
301 surrogate models to propagate the uncertainty of model parameters and model form in a Monte Carlo setting. An  
302 extension of OAT/analytic approaches was presented in von Pfingsten et al. (2017). In their research, the authors  
303 introduced a method based on second-order analytical uncertainty to overcome the limitations of a simple first-



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

318 As regards comparative approaches, Di Lullo et al. (2020) compared a Sobol'-based GSA and OAT Morris method  
319 to evaluate a model for the emissions produced by crude oil extraction from different oil fields. The authors  
320 concluded that the latter was computationally advantageous, although the range of output uncertainty (i.e., in  
321 terms of its variance) by applying the two different methods was not quantified.  
322

### 323 **3.7 Epistemic uncertainty and its appraisal**

324 Epistemic uncertainty is only partially knowable (by its own definition), therefore, the methods and techniques  
325 that support its appraisal in LCA focus on the assessment of quality of knowledge and its fitness for purpose.

326 In the goal and scope phase, epistemic uncertainty results from modelling assumptions such as the following: the  
327 definition of the functional unit (Avadí et al., 2020; Barjoveanu et al., 2020b; Feiz et al., 2020) and system  
328 boundaries; the cut-off and allocation rules; the choice of marginal suppliers between the attributional and  
329 consequential, static or dynamic approaches; and, indirect consequential effects. For example, the truncation of  
330 economic activities in the accounting of LCA input-output processes has been questioned in the literature as it  
331 would lead to an underestimation of environmental impacts (Jiang et al., 2014; Majeau-Bettez et al., 2011). In  
332 comparative LCA, this aspect may not necessarily affect all products equally because they may be manufactured in  
333 different industrial sectors. This bias may be even more serious when estimating the absolute impact due to this  
334 mismatch, with top-down information coming from the underrepresented (or even completely neglected)  
335 economic sectors.

336 The vast majority of the contributions that address epistemic uncertainty, either implicitly or explicitly, have done  
337 so by focusing on the LCI phase. This has been achieved by accounting for the quality of LCI datasets by means of  
338 qualitative discussion or the use of off-the-shelf pedigree coefficients, through the development and application of  
339 data quality assessment systems or pedigree produced by expert judgement (Beylot et al., 2018; Fazio et al., 2015;  
340 Henriksen et al., 2020; Li et al., 2020) integrated with new data through Bayesian inference (Muller et al., 2016b);  
341 use of alternative inventories (Röder et al., 2014); combination of alternative distribution shapes (Lacirignola et  
342 al., 2017; Larsson Ivanov et al., 2019); use of fuzzy logic (Benetto et al., 2006a; Tan, 2008; Tan et al., 2002); and,  
343 use of alternative methods for the imputation of missing data (Geisler et al., 2004).

344 In the LCIA phase, epistemic uncertainty relates to the selection of a particular method; the normative aspects  
345 embedded within LCIA models (Qin et al., 2020), such as in terms of accounting at mid- and end-points or different  
346 impact assessment methods, and impact weighting (Igos et al., 2019). Forcing incommensurable environmental  
347 impacts – let alone social aspects – into a single indicator is challenging (Benini and Sala, 2016), to the extent that  
348 only few studies addressed epistemic uncertainty in the LCIA phase (Avadí et al., 2020; Benetto et al., 2006b; Milani  
349 et al., 2011; Petrakopoulou and Tsatsaronis, 2014).

350 In the next subsections, we discuss the main approaches used in the reviewed set of papers to handle epistemic  
351 uncertainty and the question of how this has been linked to stochastic uncertainty.  
352

#### 353 **3.7.1 Data quality indicators**

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

358 Applications of the pedigree matrix approach are found in the US Environmental Protection Agency guidance  
 359 document for LCI data quality assessment (Edelen and Ingwersen, 2016) and the European Commission Handbook  
 360 (Joint Research Centre, 2010). These documents cover six data quality indicators, along with a five-point scale and  
 361 minimum entry-level requirements for datasets to support science-for-policy applications.  
 362 Maia de Souza et al. (2016) used the pedigree score to transparently single out areas with a low score to report on  
 363 the limitations of their study. Henriksen et al. (2020) proposed a new framework to assess the pedigree coefficient,  
 364 which acknowledged the actual pace of development of industrial sectors and their adjustment to more demanding  
 365 normative frameworks. This involved estimating the actual distance between inventory data and the current  
 366 figures in the system represented.

### 367 368 **3.7.2 Fuzzy logic**

369 Fuzzy logic has also been proposed to handle epistemic uncertainty (Clavreul et al., 2012; Gavankar and Suh, 2014).  
 370 This approach merges experts' beliefs with quantitative data to obtain potential ranges for parameters. The use of  
 371 fuzzy logic has been proposed throughout the phases of LCA, including at the level of inventory (Ardente et al.,  
 372 2004; Heijungs and Tan, 2010; Sabará, 2021; Tan, 2008; Tan et al., 2002); impact assessment (Benetto et al., 2006a,  
 373 2006b; Potting et al., 2006); and interpretation (Benetto et al., 2008).

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

## 382 **4 Discussion**

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

388  
389 **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.

390

391

### Issue 1: Downplay uncertainty

392

393

394

395

396

397

398

399

400

401

402

403

404

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.

405

406

407

408

409

410

411

412

413

414

415

416

417

418

419

420

421

### Issue 2: Garbage-in garbage-out

422

423

424

425

426

427

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.,

428 normal distributions) (Mattila et al., 2011). However, it is important to recognise that this approach is prone to  
429 the Garbage-in Garbage-out (GIGO) phenomenon (Funtowicz and Ravetz, 1990; Saltelli et al., 2013), which can  
430 invalidate UA or (G)SA even in a synthetic case study (Groen et al., 2017).

431

### 432 **Issue 3: Independent and confusing UA and SA**

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

### 443 **Remedy to issues 1-3: Approaches to handle computational burden**

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

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

### 457 **Issue 4: Inadequacy and misuse of knowledge quality assessment tools**

458 In general, the LCA studies reviewed in this work did reflect on epistemic uncertainty qualitatively, yet most of the  
459 studies neglected important aspects such as the quality – or fitness for purpose – of the methodological choices in  
460 relation to the goal and scope of the assessment. A very limited number of studies discussed how alternative  
461 methodological or value-laden choices would compare against outcomes (Section 3.8).

462 LCA developers have explored several avenues to estimate missing uncertainty values associated with LCI due to  
463 the scattered nature of statistical information, which stems from the large number of flows and processes involved  
464 in LCA. However, it may be unwarranted to translate qualitative information into commensurable metrics and  
465 then to a range of probability/possibility estimates (Gavankar and Suh, 2014). Contrary to what was proposed by  
466 Weidema and Wesnæs (1996), the quality of a parameter (e.g., underpinning theoretical vs. empirical foundation)  
467 or its geographical representativeness says little about whether its standard deviation should be increased by a  
468 factor 2, 10, or 100, and it does not indicate which shape the probability distribution functions should have. The  
469 variability of a certain phenomenon might have literally nothing to do with the quality of the underpinning mode  
470 of measurement/estimation. Even if an empirical relation is established for specific circumstances (e.g., a given  
471 database, see Ciroth et al., 2016), it is rather unclear why this should be assumed out for other processes and  
472 databases.

473

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

481  
482  
483  
484  
485  
486  
487  
488  
489  
490  
491  
492  
493  
494  
495  
496  
497  
498  
499  
500  
501  
502  
503  
504  
505  
506  
507  
508  
509  
510  
511  
512  
513  
514  
515  
516  
517  
518  
519  
520  
521  
522  
523  
524  
525  
526  
527  
528  
529  
530  
531

#### **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.

## **6 Acknowledgments**

We thank Andrea Saltelli and Serenella Sala for the useful comments they provided on an earlier draft version of this manuscript. We also thank our manuscript's three anonymous reviewers for their careful appraisal. The content of this article does not reflect the official opinion of the European Environment Agency. Responsibility for the information and views expressed in this article lies solely with the authors.

## 532 **7 Funding information**

533 This study did not receive any private or public funding.

534

## 535 **8 References**

- 536 Agarski, B., Budak, I., Vukelic, D., Hodolic, J., 2016. Fuzzy multi-criteria-based impact category weighting in life  
537 cycle assessment. *Journal of Cleaner Production* 112, 3256–3266.  
538 <https://doi.org/10.1016/j.jclepro.2015.09.077>
- 539 Aktas, C.B., Bilec, M.M., 2012. Impact of lifetime on US residential building LCA results. *International Journal of Life*  
540 *Cycle Assessment* 17, 337–349. <https://doi.org/10.1007/s11367-011-0363-x>
- 541 Alanne, K., Salo, A., Saari, A., Gustafsson, S.-I., 2007. Multi-criteria evaluation of residential energy supply systems.  
542 *Energy and Buildings* 39, 1218–1226. <https://doi.org/10.1016/j.enbuild.2007.01.009>
- 543 Alyaseri, I., Zhou, J., 2019. Handling uncertainties inherited in life cycle inventory and life cycle impact assessment  
544 method for improved life cycle assessment of wastewater sludge treatment. *Heliyon* 5, e02793.  
545 <https://doi.org/10.1016/j.heliyon.2019.e02793>
- 546 Amonkar, Y., Chowdhury, N., Song, Y., Wu, J.S., Vaidya, P., Meinrenken, C.J., 2019. Life cycle GHG emission  
547 comparison of infant nursing using breast milk versus formula. *Journal of Environmental Accounting and*  
548 *Management* 7, 61–75. <https://doi.org/10.5890/JEAM.2019.03.005>
- 549 Ardente, F., Beccali, M., Cellura, M., 2004. F.A.L.C.A.D.E.: a fuzzy software for the energy and environmental balances  
550 of products. *Ecological Modelling* 176, 359–379. <https://doi.org/10.1016/j.ecolmodel.2003.11.014>
- 551 Aui, A., Li, W., Wright, M.M., 2019. Techno-economic and life cycle analysis of a farm-scale anaerobic digestion plant  
552 in Iowa. *Waste Management* 89, 154–164. <https://doi.org/10.1016/j.wasman.2019.04.013>
- 553 Avadí, A., Marcin, M., Biard, Y., Renou, A., Gourlot, J.-P., Basset-Mens, C., 2020. Life cycle assessment of organic and  
554 conventional non-Bt cotton products from Mali. *Int J Life Cycle Assess* 25, 678–697.  
555 <https://doi.org/10.1007/s11367-020-01731-x>
- 556 Bamber, N., Turner, I., Arulnathan, V., Li, Y., Zargar Ershadi, S., Smart, A., Pelletier, N., 2020. Comparing sources and  
557 analysis of uncertainty in consequential and attributional life cycle assessment: review of current practice  
558 and recommendations. *Int J Life Cycle Assess* 25, 168–180. [https://doi.org/10.1007/s11367-019-01663-](https://doi.org/10.1007/s11367-019-01663-1)  
559 [1](https://doi.org/10.1007/s11367-019-01663-1)
- 560 Barjoveanu, G., Pătrăuțanu, O.-A., Teodosiu, C., Volf, I., 2020a. Life cycle assessment of polyphenols extraction  
561 processes from waste biomass. *Scientific Reports* 10, 13632. [https://doi.org/10.1038/s41598-020-](https://doi.org/10.1038/s41598-020-70587-w)  
562 [70587-w](https://doi.org/10.1038/s41598-020-70587-w)
- 563 Barjoveanu, G., Teodosiu, C., Bucatariu, F., Mihai, M., 2020b. Prospective life cycle assessment for sustainable  
564 synthesis design of organic/inorganic composites for water treatment. *Journal of Cleaner Production* 272,  
565 122672. <https://doi.org/10.1016/j.jclepro.2020.122672>
- 566 Bawden, K.R., Williams, E.D., Babbitt, C.W., 2016. Mapping product knowledge to life cycle inventory bounds: a case  
567 study of steel manufacturing. *Journal of Cleaner Production* 113, 557–564.  
568 <https://doi.org/10.1016/j.jclepro.2015.10.014>
- 569 Belboom, S., Digneffe, J.-M., Renzoni, R., Germain, A., Léonard, A., 2013. Comparing technologies for municipal solid  
570 waste management using life cycle assessment methodology: A Belgian case study. *International Journal*  
571 *of Life Cycle Assessment* 18, 1513–1523. <https://doi.org/10.1007/s11367-013-0603-3>
- 572 Benetto, E., Dujet, C., Rousseaux, P., 2008. Integrating fuzzy multicriteria analysis and uncertainty evaluation in life  
573 cycle assessment. *Environmental Modelling & Software* 23, 1461–1467.  
574 <https://doi.org/10.1016/j.envsoft.2008.04.008>
- 575 Benetto, E., Dujet, C., Rousseaux, P., 2006a. Possibility Theory: A New Approach to Uncertainty Analysis? (3 pp).  
576 *Int J Life Cycle Assessment* 11, 114–116. <https://doi.org/10.1065/lca2005.06.212>
- 577 Benetto, E., Dujet, C., Rousseaux, P., 2006b. Fuzzy-Sets Approach to Noise Impact Assessment (7 pp). *Int J Life Cycle*  
578 *Assessment* 11, 222–228. <https://doi.org/10.1065/lca2005.06.213>
- 579 Benini, L., Sala, S., 2016. Uncertainty and sensitivity analysis of normalization factors to methodological  
580 assumptions. *International Journal of Life Cycle Assessment* 21, 224–236.  
581 <https://doi.org/10.1007/s11367-015-1013-5>
- 582 Benoist, A., Dron, D., Zoughaib, A., 2012. Origins of the debate on the life-cycle greenhouse gas emissions and  
583 energy consumption of first-generation biofuels - A sensitivity analysis approach. *Biomass and Bioenergy*  
584 40, 133–142. <https://doi.org/10.1016/j.biombioe.2012.02.011>
- 585 Bernstad Saraiva, A., Davidsson, Å., Bissmont, M., 2016. Lifecycle assessment of a system for food waste disposers  
586 to tank - A full-scale system evaluation. *Waste Management* 54, 169–177.  
587 <https://doi.org/10.1016/j.wasman.2016.04.036>
- 588 Beylot, A., Muller, S., Descat, M., Ménard, Y., Villeneuve, J., 2018. Life cycle assessment of the French municipal solid  
589 waste incineration sector. *Waste Management* 80, 144–153.  
590 <https://doi.org/10.1016/j.wasman.2018.08.037>

591 Bisinella, V., Götze, R., Conradsen, K., Damgaard, A., Christensen, T.H., Astrup, T.F., 2017. Importance of waste  
592 composition for Life Cycle Assessment of waste management solutions. *Journal of Cleaner Production* 164,  
593 1180–1191. <https://doi.org/10.1016/j.jclepro.2017.07.013>

594 Borgonovo, E., 2007. A new uncertainty importance measure. *Reliability Engineering & System Safety* 92, 771–  
595 784. <https://doi.org/10.1016/j.res.2006.04.015>

596 Bueno, C., Hauschild, M.Z., Rossignolo, J.A., Ometto, A.R., Mendes, N.C., 2016. Sensitivity analysis of the use of Life  
597 Cycle Impact Assessment methods: a case study on building materials. *Journal of Cleaner Production* 112,  
598 2208–2220. <https://doi.org/10.1016/j.jclepro.2015.10.006>

599 Capello, C., Hellweg, S., Hungerbühler, K., 2008. Environmental assessment of waste-solvent treatment options:  
600 Part II: General rules of thumb and specific recommendations. *Journal of Industrial Ecology* 12, 111–127.  
601 <https://doi.org/10.1111/j.1530-9290.2008.00009.x>

602 Carless, T.S., Griffin, W.M., Fischbeck, P.S., 2016. The environmental competitiveness of small modular reactors: A  
603 life cycle study. *Energy* 114, 84–99. <https://doi.org/10.1016/j.energy.2016.07.111>

604 Chen, R.W., 1995. Method and case study of integrating engineering analysis with LCA for material selection and  
605 its uncertainty, in: IEE Conference Publication. pp. 88–93.

606 Chen, X., Griffin, W.M., Matthews, H.S., 2018. Representing and visualizing data uncertainty in input-output life  
607 cycle assessment models. *Resources, Conservation and Recycling* 137, 316–325.  
608 <https://doi.org/10.1016/j.resconrec.2018.06.011>

609 Chen, X., Matthews, H.S., Griffin, W.M., 2021. Uncertainty caused by life cycle impact assessment methods: Case  
610 studies in process-based LCI databases. *Resources, Conservation and Recycling* 172, 105678.  
611 <https://doi.org/10.1016/j.resconrec.2021.105678>

612 Chen, Y., McRae, G.J., Gleason, K.K., 2005. Directly addressing uncertainty in ESH evaluation, in: IEEE International  
613 Symposium on Electronics and the Environment. pp. 31–35.

614 Cherubini, E., Franco, D., Zanghelini, G.M., Soares, S.R., 2018. Uncertainty in LCA case study due to allocation  
615 approaches and life cycle impact assessment methods. *International Journal of Life Cycle Assessment* 23,  
616 2055–2070. <https://doi.org/10.1007/s11367-017-1432-6>

617 Chiu, S.L.H., Lo, I.M.C., 2018. Identifying key process parameters for uncertainty propagation in environmental life  
618 cycle assessment for sewage sludge and food waste treatment. *Journal of Cleaner Production* 174, 966–  
619 976. <https://doi.org/10.1016/j.jclepro.2017.10.164>

620 Ciroth, A., Muller, S., Weidema, B., Lesage, P., 2016. Empirically based uncertainty factors for the pedigree matrix  
621 in ecoinvent. *Int J Life Cycle Assess* 21, 1338–1348. <https://doi.org/10.1007/s11367-013-0670-5>

622 Clavreul, J., Guyonnet, D., Christensen, T.H., 2012. Quantifying uncertainty in LCA-modelling of waste management  
623 systems. *Waste Management* 32, 2482–2495. <https://doi.org/10.1016/j.wasman.2012.07.008>

624 Clavreul, J., Guyonnet, D., Tonini, D., Christensen, T.H., 2013. Stochastic and epistemic uncertainty propagation in  
625 LCA. *Int J Life Cycle Assess* 18, 1393–1403. <https://doi.org/10.1007/s11367-013-0572-6>

626 Cooper, J.S., Kahn, E., 2012. Commentary on issues in data quality analysis in life cycle assessment. *International  
627 Journal of Life Cycle Assessment* 17, 499–503. <https://doi.org/10.1007/s11367-011-0371-x>

628 Cox, B., Mutel, C.L., Bauer, C., Mendoza Beltran, A., Van Vuuren, D.P., 2018. Uncertain Environmental Footprint of  
629 Current and Future Battery Electric Vehicles. *Environmental Science and Technology* 52, 4989–4995.  
630 <https://doi.org/10.1021/acs.est.8b00261>

631 Cucurachi, S., Blanco, C.F., Steubing, B., Heijungs, R., n.d. Implementation of uncertainty analysis and moment-  
632 independent global sensitivity analysis for full-scale life cycle assessment models. *Journal of Industrial  
633 Ecology* n/a. <https://doi.org/10.1111/jiec.13194>

634 De Koning, A., Schowanek, D., Dewaele, J., Weisbrod, A., Guinée, J., 2010. Uncertainties in a carbon footprint model  
635 for detergents; Quantifying the confidence in a comparative result. *International Journal of Life Cycle  
636 Assessment* 15, 79–89. <https://doi.org/10.1007/s11367-009-0123-3>

637 De Marco, I., Riemma, S., Iannone, R., 2018. Uncertainty of input parameters and sensitivity analysis in life cycle  
638 assessment: An Italian processed tomato product. *Journal of Cleaner Production* 177, 315–325.  
639 <https://doi.org/10.1016/j.jclepro.2017.12.258>

640 De Rosa, M., Pizzol, M., Schmidt, J., 2018. How methodological choices affect LCA climate impact results: the case  
641 of structural timber. *International Journal of Life Cycle Assessment* 23, 147–158.  
642 <https://doi.org/10.1007/s11367-017-1312-0>

643 De Schryver, A.M., Humbert, S., Huijbregts, M.A.J., 2013. The influence of value choices in life cycle impact  
644 assessment of stressors causing human health damage. *Int J Life Cycle Assess* 18, 698–706.  
645 <https://doi.org/10.1007/s11367-012-0504-x>

646 de Simone Souza, H.H., de Abreu Evangelista, P.P., Medeiros, D.L., Albertí, J., Fullana-i-Palmer, P., Boncz, M.Á.,  
647 Kiperstok, A., Gonçalves, J.P., 2021. Functional unit influence on building life cycle assessment. *Int J Life  
648 Cycle Assess* 26, 435–454. <https://doi.org/10.1007/s11367-020-01854-1>

649 Deng, Y., Li, J., Qiu, M., Yang, F., Zhang, J., Yuan, C., 2017a. Deriving characterization factors on freshwater ecotoxicity  
650 of graphene oxide nanomaterial for life cycle impact assessment. *International Journal of Life Cycle  
651 Assessment* 22, 222–236. <https://doi.org/10.1007/s11367-016-1151-4>

652 Deng, Y., Paraskevas, D., Cao, S.-J., 2017b. Incorporating denitrification-decomposition method to estimate field  
653 emissions for Life Cycle Assessment. *Science of the Total Environment* 593–594, 65–74.  
654 <https://doi.org/10.1016/j.scitotenv.2017.03.112>

655 Di Lullo, G., Gemechu, E., Oni, A.O., Kumar, A., 2020. Extending sensitivity analysis using regression to effectively  
656 disseminate life cycle assessment results. *Int J Life Cycle Assess* 25, 222–239.  
657 <https://doi.org/10.1007/s11367-019-01674-y>

658 Edelen, A., Ingwersen, W., 2016. Guidance on Data Quality Assessment for Life Cycle Inventory Data (No.  
659 EPA/600/R-16/096). US Environmental Protection Agency, Cincinnati.

660 Eranki, P.L., Landis, A.E., 2019. Pathway to domestic natural rubber production: a cradle-to-grave life cycle  
661 assessment of the first guayule automobile tire manufactured in the United States. *International Journal*  
662 *of Life Cycle Assessment* 24, 1348–1359. <https://doi.org/10.1007/s11367-018-1572-3>

663 Esteban, B., Riba, J.-R., Baquero, G., Puig, R., Rius, A., 2014. Environmental assessment of small-scale production of  
664 wood chips as a fuel for residential heating boilers. *Renewable Energy* 62, 106–115.  
665 <https://doi.org/10.1016/j.renene.2013.06.041>

666 Fava, J., Jensen, A.A., Lindfors, L., Pomper, S., De Smet, B., Warren, J., Vigon, B., 1994. Life-Cycle Assessment Data  
667 Quality: A Conceptual Framework, SETAC Books. Society of Environmental Toxicology and Chemistry and  
668 SETAC Foundation for Environmental Education, Pensacola, FL - USA.

669 Fazio, S., Garraín, D., Mathieux, F., De la Rúa, C., Recchioni, M., Lechón, Y., 2015. Method applied to the background  
670 analysis of energy data to be considered for the European Reference Life Cycle Database (ELCD).  
671 *Springerplus* 4. <https://doi.org/10.1186/s40064-015-0914-x>

672 Fedele, A., Mazzi, A., Niero, M., Zuliani, F., Scipioni, A., 2014. Can the Life Cycle Assessment methodology be adopted  
673 to support a single farm on its environmental impacts forecast evaluation between conventional and  
674 organic production? An Italian case study. *Journal of Cleaner Production* 69, 49–59.  
675 <https://doi.org/10.1016/j.jclepro.2014.01.034>

676 Feiz, R., Johansson, M., Lindkvist, E., Moestedt, J., Pålédal, S.N., Svensson, N., 2020. Key performance indicators for  
677 biogas production—methodological insights on the life-cycle analysis of biogas production from source-  
678 separated food waste. *Energy* 200, 117462. <https://doi.org/10.1016/j.energy.2020.117462>

679 French, S., Geldermann, J., 2005. The varied contexts of environmental decision problems and their implications  
680 for decision support. *Environmental Science and Policy* 8, 378–391.  
681 <https://doi.org/10.1016/j.envsci.2005.04.008>

682 Frischknecht, R., Jolliet, O. (Eds.), 2017. Global Guidance for Life Cycle Impact Assessment Indicators Volume 1.  
683 UNEP/SETAC Life Cycle Initiative, Paris.

684 Funtowicz, S.O., Ravetz, J.R., 1990. *Uncertainty and Quality in Science for Policy*. Springer Science & Business Media,  
685 Berlin, Heidelberg.

686 Galimshina, A., Hollberg, A., Moustapha, M., Sudret, B., Favre, D., Padey, P., Lasvaux, S., Habert, G., 2019. Probabilistic  
687 LCA and LCC to identify robust and reliable renovation strategies. *IOP Conf. Ser.: Earth Environ. Sci.* 323,  
688 012058. <https://doi.org/10.1088/1755-1315/323/1/012058>

689 Gavankar, S., Suh, S., 2014. Fusion of conflicting information for improving representativeness of data used in LCAs.  
690 *International Journal of Life Cycle Assessment* 19, 480–490. <https://doi.org/10.1007/s11367-013-0673-2>

691

692 Geisler, G., Hofstetter, T.B., Hungerbühler, K., 2004. Production of Fine and Speciality Chemicals: Procedure for the  
693 Estimation of LCIs. *International Journal of Life Cycle Assessment* 9, 101–113.  
694 <https://doi.org/10.1007/BF02978569>

695 Goulouti, K., Padey, P., Galimshina, A., Habert, G., Lasvaux, S., 2020. Uncertainty of building elements' service lives  
696 in building LCA & LCC: What matters? *Building and Environment* 183, 106904.  
697 <https://doi.org/10.1016/j.buildenv.2020.106904>

698 Groen, E.A., Bokkers, E.A.M., Heijungs, R., de Boer, I.J.M., 2017. Methods for global sensitivity analysis in life cycle  
699 assessment. *Int J Life Cycle Assess* 22, 1125–1137. <https://doi.org/10.1007/s11367-016-1217-3>

700 Guo, M., Murphy, R.J., 2012. LCA data quality: Sensitivity and uncertainty analysis. *Science of the Total Environment*  
701 435–436, 230–243. <https://doi.org/10.1016/j.scitotenv.2012.07.006>

702 Hanandeh, A.E., El-Zein, A., 2010. Life-cycle assessment of municipal solid waste management alternatives with  
703 consideration of uncertainty: SIWMS development and application. *Waste Management* 30, 902–911.  
704 <https://doi.org/10.1016/j.wasman.2009.12.026>

705 Heijungs, R., 1994. A generic method for the identification of options for cleaner products. *Ecological Economics*  
706 10, 69–81. [https://doi.org/10.1016/0921-8009\(94\)90038-8](https://doi.org/10.1016/0921-8009(94)90038-8)

707 Heijungs, R., Kleijn, R., 2001. Numerical approaches towards life cycle interpretation five examples. *International*  
708 *Journal of Life Cycle Assessment* 6, 141–148. <https://doi.org/10.1007/BF02978732>

709 Heijungs, R., Tan, R.R., 2010. Rigorous proof of fuzzy error propagation with matrix-based LCI. *Int J Life Cycle*  
710 *Assess* 15, 1014–1019. <https://doi.org/10.1007/s11367-010-0229-7>

711 Henriksen, T., Astrup, T.F., Damgaard, A., 2020. Data representativeness in LCA: A framework for the systematic  
712 assessment of data quality relative to technology characteristics. *Journal of Industrial Ecology* n/a.  
713 <https://doi.org/10.1111/jiec.13048>



714 Hernández-Padilla, F., Margni, M., Noyola, A., Guereca-Hernandez, L., Bulle, C., 2017. Assessing wastewater  
715 treatment in Latin America and the Caribbean: Enhancing life cycle assessment interpretation by  
716 regionalization and impact assessment sensibility. *Journal of Cleaner Production* 142, 2140–2153.  
717 <https://doi.org/10.1016/j.jclepro.2016.11.068>

718 Homma, T., Saltelli, A., 1996. Importance measures in global sensitivity analysis of nonlinear models. *Reliability  
719 Engineering & System Safety* 52, 1–17. [https://doi.org/10.1016/0951-8320\(96\)00002-6](https://doi.org/10.1016/0951-8320(96)00002-6)

720 Hsu, D.D., Inman, D., Heath, G.A., Wolfrum, E.J., Mann, M.K., Aden, A., 2010. Life cycle environmental impacts of  
721 selected U.S. Ethanol production and use pathways in 2022. *Environmental Science and Technology* 44,  
722 5289–5297. <https://doi.org/10.1021/es100186h>

723 Huijbregts, M.A.J., Norris, G., Bretz, R., Citroth, A., Maurice, B., Von Bahr, B., Weidema, B., De Beaufort, A.S.H., 2001.  
724 Framework for modelling data uncertainty in life cycle inventories. *International Journal of Life Cycle  
725 Assessment* 6, 127–132. <https://doi.org/10.1007/BF02978728>

726 Igos, E., Benetto, E., Meyer, R., Baustert, P., Othoniel, B., 2019. How to treat uncertainties in life cycle assessment  
727 studies? *International Journal of Life Cycle Assessment* 24, 794–807. <https://doi.org/10.1007/s11367-018-1477-1>

729 International Organization for Standardization, 2006a. ISO 14040:2006 Environmental management — Life cycle  
730 assessment — Principles and framework, Second Edition. ed. International Organization for  
731 Standardization, Geneva.

732 International Organization for Standardization, 2006b. ISO 14044:2006 Environmental management — Life cycle  
733 assessment — Requirements and guidelines, First Edition. ed. International Organization for  
734 Standardization, Geneva.

735 Jaxa-Rozen, M., Pratiwi, A.S., Trutnevyte, E., 2021. Variance-based global sensitivity analysis and beyond in life  
736 cycle assessment: an application to geothermal heating networks. *Int J Life Cycle Assess* 26, 1008–1026.  
737 <https://doi.org/10.1007/s11367-021-01921-1>

738 Jiang, Q., Li, T., Liu, Z., Zhang, H., Ren, K., 2014. Life Cycle Assessment of an engine with input-output based hybrid  
739 analysis method. *Journal of Cleaner Production* 78, 131–138.  
740 <https://doi.org/10.1016/j.jclepro.2014.04.003>

741 Joint Research Centre, 2010. International Reference Life Cycle Data System (ILCD) Handbook - General guide for  
742 Life Cycle Assessment - Provisions and Action Steps (Text No. 24378 EN LB-NA-24378- EN- C).  
743 Publications Office of the European Union, Luxembourg.

744 Kennedy, D.J., Montgomery, D.C., Quay, B.H., 1996. Data quality: Stochastic environmental life cycle assessment  
745 modeling: A probabilistic approach to incorporating variable input data quality. *International Journal of  
746 Life Cycle Assessment* 1, 199–207.

747 Khang, D.S., Tan, R.R., Uy, O.M., Promentilla, M.A.B., Tuan, P.D., Abe, N., Razon, L.F., 2017. Design of experiments for  
748 global sensitivity analysis in life cycle assessment: The case of biodiesel in Vietnam. *Resources,  
749 Conservation and Recycling* 119, 12–23. <https://doi.org/10.1016/j.resconrec.2016.08.016>

750 Kuc-Czarnecka, M., Lo Piano, S., Saltelli, A., 2020. Quantitative Storytelling in the Making of a Composite Indicator.  
751 *Soc Indic Res* 149, 775–802. <https://doi.org/10.1007/s11205-020-02276-0>

752 Kucherenko, S., Tarantola, S., Annoni, P., 2012. Estimation of global sensitivity indices for models with dependent  
753 variables. *Computer Physics Communications* 183, 937–946. <https://doi.org/10.1016/j.cpc.2011.12.020>

754 Lacirignola, M., Blanc, P., Girard, R., Pérez-López, P., Blanc, I., 2017. LCA of emerging technologies: addressing high  
755 uncertainty on inputs' variability when performing global sensitivity analysis. *Science of The Total  
756 Environment* 578, 268–280. <https://doi.org/10.1016/j.scitotenv.2016.10.066>

757 Larsson Ivanov, O., Honfi, D., Santandrea, F., Strippel, H., 2019. Consideration of uncertainties in LCA for  
758 infrastructure using probabilistic methods. *Structure and Infrastructure Engineering* 15, 711–724.  
759 <https://doi.org/10.1080/15732479.2019.1572200>

760 Laurent, A., Weidema, B.P., Bare, J., Liao, X., Souza, D.M. de, Pizzol, M., Sala, S., Schreiber, H., Thonemann, N., Verones,  
761 F., 2020. Methodological review and detailed guidance for the life cycle interpretation phase. *Journal of  
762 Industrial Ecology* 24, 986–1003. <https://doi.org/10.1111/jiec.13012>

763 Lee, B., Trcka, M., Hensen, J.L.M., 2011. Embodied energy of building materials and green building rating systems -  
764 A case study for industrial halls. *Sustainable Cities and Society* 1, 67–71.  
765 <https://doi.org/10.1016/j.scs.2011.02.002>

766 Lewandowska, A., Foltynowicz, Z., Podlesny, A., 2004. Comparative LCA of Industrial Objects: Part 1: LCA Data  
767 Quality Assurance - Sensitivity Analysis and Pedigree Matrix. *International Journal of Life Cycle  
768 Assessment* 9, 86–89. <https://doi.org/10.1007/BF02978567>

769 Li, B., Gao, X., Li, J., Yuan, C., 2014. Life cycle environmental impact of high-capacity lithium ion battery with silicon  
770 nanowires anode for electric vehicles. *Environmental Science and Technology* 48, 3047–3055.  
771 <https://doi.org/10.1021/es4037786>

772 Li, D., Wang, Y., Liu, Y., Sun, S., Gao, Y., 2020. Estimating life-cycle CO2 emissions of urban road corridor  
773 construction: A case study in Xi'an, China. *Journal of Cleaner Production* 255, 120033.  
774 <https://doi.org/10.1016/j.jclepro.2020.120033>

775 Lin, Z., Nikolakis, V., Ierapetritou, M., 2015. Life cycle assessment of biobased p-xylene production. *Industrial and*  
776 *Engineering Chemistry Research* 54, 2366–2378. <https://doi.org/10.1021/ie5037287>

777 Ling-Chin, J., Heidrich, O., Roskilly, A.P., 2016. Life cycle assessment (LCA) - From analysing methodology  
778 development to introducing an LCA framework for marine photovoltaic (PV) systems. *Renewable and*  
779 *Sustainable Energy Reviews* 59, 352–378. <https://doi.org/10.1016/j.rser.2015.12.058>

780 Lloyd, S.M., Ries, R., 2007. Characterizing, Propagating, and Analyzing Uncertainty in Life-Cycle Assessment: A  
781 Survey of Quantitative Approaches. *Journal of Industrial Ecology* 11, 161–179.  
782 <https://doi.org/10.1162/jiec.2007.1136>

783 Maia de Souza, D., Lafontaine, M., Charron-Doucet, F., Chappert, B., Kicak, K., Duarte, F., Lima, L., 2016. Comparative  
784 life cycle assessment of ceramic brick, concrete brick and cast-in-place reinforced concrete exterior walls.  
785 *Journal of Cleaner Production* 137, 70–82. <https://doi.org/10.1016/j.jclepro.2016.07.069>

786 Majeau-Bettez, G., Strømman, A.H., Hertwich, E.G., 2011. Evaluation of process- and input-output-based life cycle  
787 inventory data with regard to truncation and aggregation issues. *Environmental Science and Technology*  
788 45, 10170–10177. <https://doi.org/10.1021/es201308x>

789 Mason, J.E., Fthenakis, V.M., Hansen, T., Kim, H.C., 2006. Energy payback and life-cycle CO<sub>2</sub> emissions of the BOS in  
790 an optimized 3.5MW PV installation. *Progress in Photovoltaics: Research and Applications* 14, 179–190.  
791 <https://doi.org/10.1002/pip.652>

792 Mattick, C.S., Landis, A.E., Allenby, B.R., Genovese, N.J., 2015. Anticipatory Life Cycle Analysis of In Vitro Biomass  
793 Cultivation for Cultured Meat Production in the United States. *Environmental Science and Technology* 49,  
794 11941–11949. <https://doi.org/10.1021/acs.est.5b01614>

795 Mattila, T., Kujanpää, M., Dahlbo, H., Soukka, R., Myllymaa, T., 2011. Uncertainty and Sensitivity in the Carbon  
796 Footprint of Shopping Bags. *Journal of Industrial Ecology* 15, 217–227. <https://doi.org/10.1111/j.1530-9290.2010.00326.x>

797  
798 Mattinen, M.K., Nissinen, A., Hyysalo, S., Juntunen, J.K., 2015. Energy Use and Greenhouse Gas Emissions of Air-  
799 Source Heat Pump and Innovative Ground-Source Air Heat Pump in a Cold Climate. *Journal of Industrial*  
800 *Ecology* 19, 61–70. <https://doi.org/10.1111/jiec.12166>

801 Mckay, M.D., Beckman, R.J., Conover, W.J., 2000. A Comparison of Three Methods for Selecting Values of Input  
802 Variables in the Analysis of Output From a Computer Code. *Journal of Quality* 42, 55–61.  
803 <https://doi.org/10.1080/00401706.2000.10485979>

804 Mendoza Beltran, A., Chiantore, M., Pecorino, D., Corner, R.A., Ferreira, J.G., Cò, R., Fanciulli, L., Guinée, J.B., 2018.  
805 Accounting for inventory data and methodological choice uncertainty in a comparative life cycle  
806 assessment: the case of integrated multi-trophic aquaculture in an offshore Mediterranean enterprise. *Int*  
807 *J Life Cycle Assess* 23, 1063–1077. <https://doi.org/10.1007/s11367-017-1363-2>

808 Meneses, M., Torres, C.M., Castells, F., 2016. Sensitivity analysis in a life cycle assessment of an aged red wine  
809 production from Catalonia, Spain. *Science of the Total Environment* 562, 571–579.  
810 <https://doi.org/10.1016/j.scitotenv.2016.04.083>

811 Meyer, R., Benetto, E., Igos, E., Lavandier, C., 2017. Analysis of the different techniques to include noise damage in  
812 life cycle assessment. A case study for car tires. *International Journal of Life Cycle Assessment* 22, 744–  
813 757. <https://doi.org/10.1007/s11367-016-1188-4>

814 Michiels, F., Geeraerd, A., 2020. How to decide and visualize whether uncertainty or variability is dominating in  
815 life cycle assessment results: A systematic review. *Environmental Modelling & Software* 133, 104841.  
816 <https://doi.org/10.1016/j.envsoft.2020.104841>

817 Milani, A.S., Eskicioglu, C., Robles, K., Bujun, K., Hosseini-Nasab, H., 2011. Multiple criteria decision making with life  
818 cycle assessment for material selection of composites. *Express Polymer Letters* 5, 1062–1074.  
819 <https://doi.org/10.3144/expresspolymlett.2011.104>

820 Mohajerani, A., Ukwatta, A., Setunge, S., 2018. Fired-clay bricks incorporating biosolids: Comparative life-cycle  
821 assessment. *Journal of Materials in Civil Engineering* 30. [https://doi.org/10.1061/\(ASCE\)MT.1943-5533.0002308](https://doi.org/10.1061/(ASCE)MT.1943-5533.0002308)

822  
823 Moreira, M., Gurgel, A.C., Seabra, J.E.A., 2014. Life cycle greenhouse gas emissions of sugar cane renewable jet fuel.  
824 *Environmental Science and Technology* 48, 14756–14763. <https://doi.org/10.1021/es503217g>

825 Muller, S., Lesage, P., Ciroth, A., Mutel, C., Weidema, B.P., Samson, R., 2016a. The application of the pedigree  
826 approach to the distributions foreseen in ecoinvent v3. *Int J Life Cycle Assess* 21, 1327–1337.  
827 <https://doi.org/10.1007/s11367-014-0759-5>

828 Muller, S., Lesage, P., Ciroth, A., Mutel, C., Weidema, B.P., Samson, R., 2016b. The application of the pedigree  
829 approach to the distributions foreseen in ecoinvent v3. *Int J Life Cycle Assess* 21, 1327–1337.  
830 <https://doi.org/10.1007/s11367-014-0759-5>

831 Munda, G., 2004. Social multi-criteria evaluation: Methodological foundations and operational consequences.  
832 *European Journal of Operational Research* 158, 662–677. [https://doi.org/10.1016/S0377-2217\(03\)00369-2](https://doi.org/10.1016/S0377-2217(03)00369-2)

833  
834 Muñoz, I., Flury, K., Jungbluth, N., Rigarlsford, G., Canals, L.M., King, H., 2014. Life cycle assessment of bio-based  
835 ethanol produced from different agricultural feedstocks. *International Journal of Life Cycle Assessment*  
836 19, 109–119. <https://doi.org/10.1007/s11367-013-0613-1>

837 Muñoz, I., Soto, A., Maza, D., Bayón, F., 2020. Life cycle assessment of refractory waste management in a Spanish  
838 steel works. *Waste Management* 111, 1–9. <https://doi.org/10.1016/j.wasman.2020.05.023>

839 Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., 2005. Tools for Composite Indicators Building (No. EUR 21682 EN).  
840 Joint Research Centre, Ispra (Va), Italy.

841 Padey, P., Girard, R., le Boulch, D., Blanc, I., 2013. From LCAs to Simplified Models: A Generic Methodology Applied  
842 to Wind Power Electricity. *Environ. Sci. Technol.* 47, 1231–1238. <https://doi.org/10.1021/es303435e>

843 Palazzo, J., Geyer, R., 2019. Consequential life cycle assessment of automotive material substitution: Replacing steel  
844 with aluminum in production of north American vehicles. *Environmental Impact Assessment Review* 75,  
845 47–58. <https://doi.org/10.1016/j.eiar.2018.12.001>

846 Pang, B., Yang, P., Wang, Y., Kendall, A., Xie, H., Zhang, Y., 2015. Life cycle environmental impact assessment of a  
847 bridge with different strengthening schemes. *International Journal of Life Cycle Assessment* 20, 1300–  
848 1311. <https://doi.org/10.1007/s11367-015-0936-1>

849 Pannier, M.-L., Schalbart, P., Peuportier, B., 2018. Comprehensive assessment of sensitivity analysis methods for  
850 the identification of influential factors in building life cycle assessment. *Journal of Cleaner Production* 199,  
851 466–480. <https://doi.org/10.1016/j.jclepro.2018.07.070>

852 Patouillard, L., Collet, P., Lesage, P., Tirado Seco, P., Bulle, C., Margni, M., 2019. Prioritizing regionalization efforts  
853 in life cycle assessment through global sensitivity analysis: a sector meta-analysis based on ecoinvent v3.  
854 *Int J Life Cycle Assess.* <https://doi.org/10.1007/s11367-019-01635-5>

855 Patouillard, L., Lorne, D., Collet, P., Bulle, C., Margni, M., 2020. Prioritizing regionalization to enhance interpretation  
856 in consequential life cycle assessment: application to alternative transportation scenarios using partial  
857 equilibrium economic modeling. *Int J Life Cycle Assess.* <https://doi.org/10.1007/s11367-020-01785-x>

858 Petrakopoulou, F., Tsatsaronis, G., 2014. Can carbon dioxide capture and storage from power plants reduce the  
859 environmental impact of electricity generation? *Energy and Fuels* 28, 5327–5338.  
860 <https://doi.org/10.1021/ef500925h>

861 Pfister, S., Vionnet, S., Levova, T., Humbert, S., 2016. Ecoinvent 3: assessing water use in LCA and facilitating water  
862 footprinting. *International Journal of Life Cycle Assessment* 21, 1349–1360.  
863 <https://doi.org/10.1007/s11367-015-0937-0>

864 Potting, J., Hertel, O., Schöpp, W., Bastrup-Birk, A., 2006. Spatial Differentiation in the Characterisation of  
865 Photochemical Ozone Formation: The EDIP2003 Methodology. *Int J Life Cycle Assessment* 11, 72–80.  
866 <https://doi.org/10.1065/lca2006.04.014>

867 Poujol, B., Prieur-Vernat, A., Dubranna, J., Besseau, R., Blanc, I., Pérez-López, P., 2020. Site-specific life cycle  
868 assessment of a pilot floating offshore wind farm based on suppliers' data and geo-located wind data.  
869 *Journal of Industrial Ecology* 24, 248–262. <https://doi.org/10.1111/jiec.12989>

870 Pye, S., Li, F.G.N., Petersen, A., Broad, O., McDowall, W., Price, J., Usher, W., 2018. Assessing qualitative and  
871 quantitative dimensions of uncertainty in energy modelling for policy support in the United Kingdom.  
872 *Energy Research & Social Science* 46, 332–344. <https://doi.org/10.1016/j.erss.2018.07.028>

873 Qin, Y., Cucurachi, S., Suh, S., 2020. Perceived uncertainties of characterization in LCA: a survey. *Int J Life Cycle*  
874 *Assess.* <https://doi.org/10.1007/s11367-020-01787-9>

875 Quinn, R.J., Ha, H., Volk, T.A., Brown, T.R., Bick, S., Malmshemer, R.W., Fortier, M.-O.P., 2020. Life cycle assessment  
876 of forest biomass energy feedstock in the Northeast United States. *GCB Bioenergy* 12, 728–741.  
877 <https://doi.org/10.1111/gcbb.12725>

878 Ravetz, J.R., 1971. *Scientific knowledge and its social problems*. Oxford University Press.

879 Ravikumar, D., Seager, T.P., Cucurachi, S., Prado, V., Mutel, C., 2018. Novel Method of Sensitivity Analysis Improves  
880 the Prioritization of Research in Anticipatory Life Cycle Assessment of Emerging Technologies.  
881 *Environmental Science and Technology* 52, 6534–6543. <https://doi.org/10.1021/acs.est.7b04517>

882 Reale, F., Cinelli, M., Sala, S., 2017. Towards a research agenda for the use of LCA in the impact assessment of  
883 policies. *Int J Life Cycle Assess* 22, 1477–1481. <https://doi.org/10.1007/s11367-017-1320-0>

884 Reisinger, A., Ledgard, S.F., Falconer, S.J., 2017. Sensitivity of the carbon footprint of New Zealand milk to  
885 greenhouse gas metrics. *Ecological Indicators* 81, 74–82. <https://doi.org/10.1016/j.ecolind.2017.04.026>

886 Riesch-Oppermann, H., Brückner-Foit, A., 1988. First- and second-order approximations of failure probabilities in  
887 probabilistic fracture mechanics. *Reliability Engineering & System Safety* 23, 183–194.  
888 [https://doi.org/10.1016/0951-8320\(88\)90108-1](https://doi.org/10.1016/0951-8320(88)90108-1)

889 Röder, M., Thornley, P., 2018. Waste wood as bioenergy feedstock. Climate change impacts and related emission  
890 uncertainties from waste wood based energy systems in the UK. *Waste Management* 74, 241–252.  
891 <https://doi.org/10.1016/j.wasman.2017.11.042>

892 Röder, M., Whittaker, C., Thornley, P., 2014. How certain are greenhouse gas reductions from bioenergy? Life cycle  
893 assessment and uncertainty analysis of wood pellet-to-electricity supply chains from forest residues.  
894 *Biomass and Bioenergy* 79, 50–63. <https://doi.org/10.1016/j.biombioe.2015.03.030>

895 Rosenbaum, R.K., Georgiadis, S., Fantke, P., 2018. Uncertainty Management and Sensitivity Analysis, in: Hauschild,  
896 M.Z., Rosenbaum, R.K., Olsen, S.I. (Eds.), *Life Cycle Assessment: Theory and Practice*. Springer  
897 International Publishing, Cham, pp. 271–321. [https://doi.org/10.1007/978-3-319-56475-3\\_11](https://doi.org/10.1007/978-3-319-56475-3_11)

- 898 Ross, S., Evans, D., Webber, M., 2002. How LCA studies deal with uncertainty. *Int J LCA* 7, 47.  
899 <https://doi.org/10.1007/BF02978909>
- 900 Ross, S.A., Cheah, L., 2017. Uncertainty Quantification in Life Cycle Assessments: Interindividual Variability and  
901 Sensitivity Analysis in LCA of Air-Conditioning Systems. *Journal of Industrial Ecology* 21, 1103–1114.  
902 <https://doi.org/10.1111/jiec.12505>
- 903 Roy, S., Lien, S., Krieger, T., 2014. Process engineering for environmental footprinting, in: *Process Development*  
904 *Symposium 2014: Solving Today's Global Challenges*. pp. 29–42.
- 905 Sabará, M.A., 2021. Uncertainties in Life Cycle Inventories: Monte Carlo and Fuzzy Sets Treatments, in: De Cursi,  
906 J.E.S. (Ed.), *Proceedings of the 5th International Symposium on Uncertainty Quantification and Stochastic*  
907 *Modelling*. Lecture Notes in Mechanical Engineering. Springer International Publishing, Cham, pp. 177–  
908 197. [https://doi.org/10.1007/978-3-030-53669-5\\_14](https://doi.org/10.1007/978-3-030-53669-5_14)
- 909 Safaei, A., Freire, F., Henggeler Antunes, C., 2015. Life-cycle greenhouse gas assessment of nigerian liquefied  
910 natural gas addressing uncertainty. *Environmental Science and Technology* 49, 3949–3957.  
911 <https://doi.org/10.1021/es505435j>
- 912 Sala, S., Benini, L., Mancini, L., Pant, R., 2015. Integrated assessment of environmental impact of Europe in 2010:  
913 data sources and extrapolation strategies for calculating normalisation factors. *International Journal of*  
914 *Life Cycle Assessment* 20, 1568–1585. <https://doi.org/10.1007/s11367-015-0958-8>
- 915 Sala, S., Laurent, A., Vieira, M., Van Hoof, G., 2020. Implications of LCA and LCIA choices on interpretation of results  
916 and on decision support. *Int J Life Cycle Assess* 25, 2311–2314. <https://doi.org/10.1007/s11367-020-01845-2>
- 917
- 918 Saltelli, A., Annoni, P., 2010. How to avoid a perfunctory sensitivity analysis. *Environmental Modelling & Software*  
919 25, 1508–1517. <https://doi.org/10.1016/j.envsoft.2010.04.012>
- 920 Saltelli, A., Guimaraes Pereira, Â., Sluijs, J.P.V. der, Funtowicz, S., 2013. What do I make of your latinorum?  
921 Sensitivity auditing of mathematical modelling. *IJFIP* 9, 213. <https://doi.org/10.1504/IJFIP.2013.058610>
- 922 Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. *Global*  
923 *Sensitivity Analysis: The Primer*. Wiley.
- 924 Saltelli, A., Tarantola, S., Chan, K.P.-S., 1999. A Quantitative Model-Independent Method for Global Sensitivity  
925 Analysis of Model Output. *Technometrics* 41, 39–56. <https://doi.org/10.1080/00401706.1999.10485594>
- 926 Schmidt, S., Pahl-Wostl, C., 2007. Modeling biowaste flows for life-cycle assessment: Calculation of the potential  
927 and collected weight of kitchen and garden waste. *Journal of Industrial Ecology* 11, 181–199.  
928 <https://doi.org/10.1162/jiec.2007.1141>
- 929 Schryver, A.M.D., Zelm, R. van, Humbert, S., Pfister, S., McKone, T.E., Huijbregts, M.A.J., 2011. Value Choices in Life  
930 Cycle Impact Assessment of Stressors Causing Human Health Damage. *Journal of Industrial Ecology* 15,  
931 796–815. <https://doi.org/10.1111/j.1530-9290.2011.00371.x>
- 932 Scrucca, F., Baldassarri, C., Baldinelli, G., Bonamente, E., Rinaldi, S., Rotili, A., Barbanera, M., 2020. Uncertainty in  
933 LCA: An estimation of practitioner-related effects. *Journal of Cleaner Production* 268, 122304.  
934 <https://doi.org/10.1016/j.jclepro.2020.122304>
- 935 Seppälä, J., Knuutila, S., Silvo, K., 2004. Eutrophication of Aquatic Ecosystems: A New Method for Calculating the  
936 Potential Contributions of Nitrogen and Phosphorus. *International Journal of Life Cycle Assessment* 9, 90–  
937 100. <https://doi.org/10.1007/BF02978568>
- 938 Smetana, S., Schmitt, E., Mathys, A., 2019. Sustainable use of *Hermetia illucens* insect biomass for feed and food:  
939 Attributional and consequential life cycle assessment. *Resources, Conservation and Recycling* 285–296.  
940 <https://doi.org/10.1016/j.resconrec.2019.01.042>
- 941 Sobol', I.M., 2001. Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates.  
942 *Mathematics and Computers in Simulation*, The Second IMACS Seminar on Monte Carlo Methods 55, 271–  
943 280. [https://doi.org/10.1016/S0378-4754\(00\)00270-6](https://doi.org/10.1016/S0378-4754(00)00270-6)
- 944 Sudret, B., 2008. Global sensitivity analysis using polynomial chaos expansions. *Reliability Engineering & System*  
945 *Safety, Bayesian Networks in Dependability* 93, 964–979. <https://doi.org/10.1016/j.res.2007.04.002>
- 946 Tan, R.R., 2008. Using fuzzy numbers to propagate uncertainty in matrix-based LCI. *Int J Life Cycle Assess* 13, 585.  
947 <https://doi.org/10.1007/s11367-008-0032-x>
- 948 Tan, R.R., Culaba, A.B., Purvis, M.R.I., 2002. Application of possibility theory in the life-cycle inventory assessment  
949 of biofuels. *International Journal of Energy Research* 26, 737–745. <https://doi.org/10.1002/er.812>
- 950 Tao, M., Cheng, W., Nie, K., Zhang, X., Cao, W., 2022. Life cycle assessment of underground coal mining in China.  
951 *Science of The Total Environment* 805, 150231. <https://doi.org/10.1016/j.scitotenv.2021.150231>
- 952 Thévenot, A., Rivera, J.L., Wilfart, A., Maillard, F., Hassouna, M., Senga-Kiesse, T., Le Féon, S., Aubin, J., 2018.  
953 Mealworm meal for animal feed: Environmental assessment and sensitivity analysis to guide future  
954 prospects. *Journal of Cleaner Production* 170, 1260–1267. <https://doi.org/10.1016/j.jclepro.2017.09.054>
- 955 Thies, C., Kieckhäfer, K., Spengler, T.S., Sodhi, M.S., 2019. Operations research for sustainability assessment of  
956 products: A review. *European Journal of Operational Research* 274, 1–21.  
957 <https://doi.org/10.1016/j.ejor.2018.04.039>

958 Tonini, D., Hamelin, L., Wenzel, H., Astrup, T., 2012. Bioenergy production from perennial energy crops: A  
959 consequential LCA of 12 bioenergy scenarios including land use changes. *Environmental Science and*  
960 *Technology* 46, 13521–13530. <https://doi.org/10.1021/es3024435>

961 Tu, Q., McDonnell, B.E., 2016. Monte Carlo analysis of life cycle energy consumption and greenhouse gas (GHG)  
962 emission for biodiesel production from trap grease. *Journal of Cleaner Production* 112, 2674–2683.  
963 <https://doi.org/10.1016/j.jclepro.2015.10.028>

964 Van der Harst, E., Potting, J., 2014. Variation in LCA results for disposable polystyrene beverage cups due to  
965 multiple data sets and modelling choices. *Environmental Modelling and Software* 51, 123–135.  
966 <https://doi.org/10.1016/j.envsoft.2013.09.014>

967 van der Sluijs, J., van Eijndhoven, J., Shackley, S., Wynne, B., 1998. Anchoring Devices in Science for Policy: The Case  
968 of Consensus around Climate Sensitivity. *Soc Stud Sci* 28, 291–323.  
969 <https://doi.org/10.1177/030631298028002004>

970 Van Der Sluijs, J.P., Craye, M., Funtowicz, S., Kloprogge, P., Ravetz, J., Risbey, J., 2005. Combining Quantitative and  
971 Qualitative Measures of Uncertainty in Model-Based Environmental Assessment: The NUSAP System. *Risk*  
972 *Analysis* 25, 481–492. <https://doi.org/10.1111/j.1539-6924.2005.00604.x>

973 van der Sluijs, J.P., Craye, M., Funtowicz, S., Kloprogge, P., Ravetz, J.R., Risbey, J., 2005. Combining Quantitative and  
974 Qualitative Measures of Uncertainty in Model-Based Environmental Assessment: The NUSAP System. *Risk*  
975 *Analysis* 25, 481–492. <https://doi.org/10.1111/j.1539-6924.2005.00604.x>

976 Van Zelm, R., Huijbregts, M.A.J., 2013. Quantifying the trade-off between parameter and model structure  
977 uncertainty in life cycle impact assessment. *Environmental Science and Technology* 47, 9274–9280.  
978 <https://doi.org/10.1021/es305107s>

979 Van Zelm, R., Huijbregts, M.A.J., Posthuma, L., Wintersen, A., Van De Meent, D., 2009. Pesticide ecotoxicological  
980 effect factors and their uncertainties for freshwater ecosystems. *International Journal of Life Cycle*  
981 *Assessment* 14, 43–51. <https://doi.org/10.1007/s11367-008-0037-5>

982 von Pfingsten, S., Broll, D.O., von der Assen, N., Bardow, A., 2017. Second-Order Analytical Uncertainty Analysis in  
983 Life Cycle Assessment. *Environ. Sci. Technol.* 51, 13199–13204. <https://doi.org/10.1021/acs.est.7b01406>

984 Walker, W.E., Harremoës, P., Rotmans, J., Sluijs, J.P. van der, Asselt, M.B.A. van, Janssen, P., Krauss, M.P.K. von, 2003.  
985 Defining Uncertainty: A Conceptual Basis for Uncertainty Management in Model-Based Decision Support.  
986 *Integrated Assessment* 4, 5–17. <https://doi.org/10.1076/iaij.4.1.5.16466>

987 Wang, J., Tingley, D.D., Mayfield, M., Wang, Y., 2018. Life cycle impact comparison of different concrete floor slabs  
988 considering uncertainty and sensitivity analysis. *Journal of Cleaner Production* 189, 374–385.  
989 <https://doi.org/10.1016/j.jclepro.2018.04.094>

990 Wang, Z., Osseweijer, P., Posada, J.A., 2020. Human Health Impacts of Aviation Biofuel Production: Exploring the  
991 Application of Different Life Cycle Impact Assessment (LCIA) Methods for Biofuel Supply Chains.  
992 *Processes* 8, 158. <https://doi.org/10.3390/pr8020158>

993 Wei, W., Larrey-Lassalle, P., Faure, T., Dumoulin, N., Roux, P., Mathias, J.-D., 2016. Using the Reliability Theory for  
994 Assessing the Decision Confidence Probability for Comparative Life Cycle Assessments. *Environmental*  
995 *Science and Technology* 50, 2272–2280. <https://doi.org/10.1021/acs.est.5b03683>

996 Wei, W., Larrey-Lassalle, P., Faure, T., Dumoulin, N., Roux, P., Mathias, J.-D., 2015. How to Conduct a Proper  
997 Sensitivity Analysis in Life Cycle Assessment: Taking into Account Correlations within LCI Data and  
998 Interactions within the LCA Calculation Model. *Environ. Sci. Technol.* 49, 377–385.  
999 <https://doi.org/10.1021/es502128k>

1000 Weidema, B.P., Bauer, C., Hischier, R., Mutel, C., Nemecek, T., Reinhard, J., Vandebo, C.O., Wernet, G., 2013. Overview  
1001 and methodology. Data quality guideline for the ecoinvent database version 3, Ecoinvent Report 1(v3).  
1002 The Ecoinvent Centre, St. Gallen.

1003 Weidema, B.P., Wesnæs, M.S., 1996. Data quality management for life cycle inventories—an example of using data  
1004 quality indicators. *Journal of Cleaner Production* 4, 167–174. [https://doi.org/10.1016/S0959-6526\(96\)00043-1](https://doi.org/10.1016/S0959-6526(96)00043-1)

1005

1006 Wenker, J.L., Achenbach, H., Diederichs, S.K., Rüter, S., 2016. Life Cycle Assessment of Wooden Interior Doors in  
1007 Germany: A Sector-Representative Approach for a Complex Wooden Product According to EN 15804  
1008 Methodology. *Journal of Industrial Ecology* 20, 730–742. <https://doi.org/10.1111/jiec.12296>

1009 Wong, A., Zhang, H., Kumar, A., 2016. Life cycle assessment of renewable diesel production from lignocellulosic  
1010 biomass. *International Journal of Life Cycle Assessment* 21, 1404–1424.  
1011 <https://doi.org/10.1007/s11367-016-1107-8>

1012 Xu, L., Pang, M., Zhang, L., Pogonietz, W.-R., Marathe, S.D., 2018. Life cycle assessment of onshore wind power  
1013 systems in China. *Resources, Conservation and Recycling* 132, 361–368.  
1014 <https://doi.org/10.1016/j.resconrec.2017.06.014>

1015 Yoshida, H., Christensen, T.H., Scheutz, C., 2013. Life cycle assessment of sewage sludge management: A review.  
1016 *Waste Management and Research* 31, 1083–1101. <https://doi.org/10.1177/0734242X13504446>

1017 Zampori, L., Saouter, E., Castellani, V., Schau, E., Cristobal, J., Sala, S., 2016. Guide for interpreting life cycle  
1018 assessment result (JRC Report No. JRC104415). JRC, Luxembourg.

1019 Zhang, Y.-R., Wu, W.-J., Wang, Y.-F., 2016. Bridge life cycle assessment with data uncertainty. *International Journal*  
1020 *of Life Cycle Assessment* 21, 569–576. <https://doi.org/10.1007/s11367-016-1035-7>  
1021 Ziyadi, M., Al-Qadi, I.L., 2019. Model uncertainty analysis using data analytics for life-cycle assessment (LCA)  
1022 applications. *International Journal of Life Cycle Assessment* 24, 945–959.  
1023 <https://doi.org/10.1007/s11367-018-1528-7>  
1024  
1025

1026

## 9 Supporting Material

1027 A full list of the studies considered in this review is available from the Supporting Material repository ([Zenodo](#)).  
1028

1029

## 10 Figure legends

1030 **Figure 1:** Uncertainty/sensitivity analysis workflow, adapted from Saltelli et al. (2008).  
1031

1032

1032 **Figure 2:** Scopus search on yearly LCA, uncertainty, and sensitivity analysis (primary axis) vs. percentage over  
1033 total contributions on LCA (secondary axis). Dotted lines are the five-year averages of these trends. The underlying  
1034 data are available from the Supporting Material repository ([Zenodo](#)).

1035 **Figure 3:** Uncertainty appraisal across LCA phases. The underlying data are available from the Supporting Material  
1036 repository ([Zenodo](#)).  
1037

1038

1038 **Figure 4:** a) Uncertainty appraisal at the goal and scope phase; b) Uncertainty appraisal at the inventory phase; c)  
1039 Uncertainty appraisal at the impact assessment phase. The underlying data are available from the Supporting  
1040 Material repository ([Zenodo](#)).  
1041

1042

1042 **Figure 5:** a) Technical aspects of uncertainty appraisal across LCA phases; b) Sensitivity analysis across LCA  
1043 phases. The underlying data are available from the Supporting Material repository ([Zenodo](#)).  
1044

1045

1045 Figure 6: Instance of diagnostic diagram.