Chapter 11
Uncertainty Management and Sensitivity Analysis

Ralph K. Rosenbaum, Stylianos Georgiadis and Peter Fantke

Abstract Uncertainty is always there and LCA is no exception to that. The presence of uncertainties of different types and from numerous sources in LCA results is a fact, but managing them allows to quantify and improve the precision of a study and the robustness of its conclusions. LCA practice sometimes suffers from an imbalanced perception of uncertainties, justifying modelling choices and omissions. Identifying prevalent misconceptions around uncertainties in LCA is a central goal of this chapter, aiming to establish a positive approach focusing on the advantages of uncertainty management. The main objectives of this chapter are to learn how to deal with uncertainty in the context of LCA, how to quantify it, interpret and use it, and how to communicate it. The subject is approached more holistically than just focusing on relevant statistical methods or purely mathematical aspects. This chapter is neither a precise statistical method description, nor a philosophical essay about the concepts of uncertainty, knowledge and truth, although you will find a little bit of both. This chapter contains (1) an introduction of the essential terminology and concepts of relevance for LCA; (2) a discussion of main sources of uncertainty and how to quantify them; (3) a presentation of approaches to calculate uncertainty for the final results (propagation); (4) a discussion of how to use uncertainty information and how to take it into account in the

R.K. Rosenbaum (✉)
IRSTEA, UMR ITAP, ELSA Research Group and ELSA-PACT—Industrial Chair for Environmental and Social Sustainability, 361 rue Jean-François Breton, BP 5095, 34196 Montpellier, France
e-mail: ralph.rosenbaum@irstea.fr

S. Georgiadis
Department of Applied Mathematics and Computer Science, Technical University of Denmark, Kongens Lyngby, Denmark

S. Georgiadis
Global Decision Support Initiative, Technical University of Denmark, Kongens Lyngby, Denmark

P. Fantke
Division for Quantitative Sustainability Assessment, Department of Management Engineering, Technical University of Denmark, Kongens Lyngby, Denmark

M.Z. Hauschild et al. (eds.), *Life Cycle Assessment*,
DOI 10.1007/978-3-319-56475-3_11

interpretation of the results; and finally (5) a discussion of how to manage, communicate and present uncertainty information together with the LCA results.

Learning Objectives
After studying this chapter, the reader should be able to:

- Explain the importance and usefulness of addressing uncertainty in LCA
- Distinguish types and sources of uncertainty and variability and explain important misconceptions of uncertainty in the context of LCA
- List the dominating sources of uncertainty in a typical LCA
- Explain the relevant concepts and vocabulary of uncertainty
- Analyse sensitivity, uncertainty and variability and use these insights to reduce overall uncertainty when performing an LCA
- Express and communicate uncertainty in an appropriate way, catering to the purpose of the analysis
- Apply uncertainty information in results interpretation and decision support

11.1 Introduction

The British mathematician, science historian, author and inventor Jacob Bronowski wrote that "Knowledge is an unending adventure at the edge of uncertainty". This is a perfect motto and inspiration for this chapter. Before learning how to deal with uncertainty in the context of LCA, how to quantify it, interpret and use it, or communicate it, which are the main objectives of this chapter, it is useful to truly understand the concept of uncertainty in a broader sense. It is for that reason that we have chosen to approach the subject much more holistically than just focusing on relevant statistical methods, mathematical aspects and the like. This chapter is neither a precise statistical method description, nor a philosophical essay about the concepts of uncertainty, knowledge and truth, although you will find a little bit of both.

First of all, uncertainty is always there, it is the elephant in the room no matter what we are doing or talking about. From individuals to the entire humanity, from a child to a stock market broker to the most accomplished Nobel laureate, many of our daily efforts are related to knowing more, doing better, being more precise and more accurate. Acquiring knowledge and information and reducing the uncertainty around them is a driving force behind all human advancement, mobilising incredible amounts of resources worldwide. It is in fact one (if not the) driving force behind most things we do.

Uncertainty is also often the elephant in the room when people talk about or apply LCA. It is always there but some may fear it and ignore it deliberately, some may use it to criticise or even discredit LCA. An oversimplified understanding of uncertainty is a good part of the problem's root in both cases. Uncertainty is indeed frequently perceived as potentially discrediting LCA and its results as being too uncertain, unreliable, and insufficiently capable of distinguishing the compared options. The often considerable resources required for quantifying and managing uncertainty in an LCA study is an important barrier for their adequate consideration. Nevertheless, the presence of uncertainties of different types and from numerous sources in LCA results is a fact and ignoring them may be more detrimental than managing them in an integrated manner which allows their meaningful use to quantify and improve the precision of a study and the robustness of its conclusions.

LCA practice sometimes suffers from an imbalanced perception of uncertainties and their use in justifying modelling choices and omissions (e.g. excluding impact categories due to their perceived uncertainty). Identifying prevalent misconceptions, in some cases "myths", around uncertainties is another central goal of this chapter. The ambition is to help balancing the discussions around uncertainty in LCA and establish a positive discourse that focuses on the advantages of uncertainty management. Proper uncertainty management allows for more robust results and conclusions in support of science-based decision-making, grounded on the (accurate) recognition and discussion of inevitable and ubiquitous uncertainties.

Consider the following conceptual and simplified example to illustrate how fundamentally useful uncertainty assessment and management are in LCA. Figure 11.1 shows the results of an LCA study, performing a comparison of two alternative options A and B, for a given impact category like water use for example. The point estimate (i.e. reproducible, single value output from the LCA model without considering variations in inputs) impact score is 4 for option A and 6 for option B, which may suggest that option *A* is preferable, i.e. less environmentally impacting, over option *B* by a factor of 1.5. However, considering the uncertainties (including correlations between both options), the impact scores can be shown as superposed distributions as demonstrated in Fig. 11.1 (even though this may not be the best way to compare scenarios as discussed later in this chapter). Where the distributions are overlapping, option *B* has certain chances to be preferable over option *A*, the opposite of the conclusion drawn above from only looking at the point estimates. The more the distributions overlap, the higher the chances that option *A* may not be preferable to option *B*. In the left plot, there is a relatively small overlap of both distributions, and hence a relatively low chance to take the wrong decision when preferring option *A* over option *B*. In the centre plot, it is essentially impossible to discern the impact scores of both options and the chances to make the wrong conclusion would be high, no matter which option is chosen. In the right plot, the dispersions of both options are different (which will usually be the case in practice) and need to be evaluated in order to derive more reliable results. How to deal with such cases is discussed further-on in the chapter. That means that if the uncertainty cannot be further reduced (e.g. by using more certain data or models), both options are basically equal in terms of their potential environmental impact on water use.

The consideration and communication of uncertainties related to results obtained via modelling and/or measurements is vital for their correct interpretation. This is

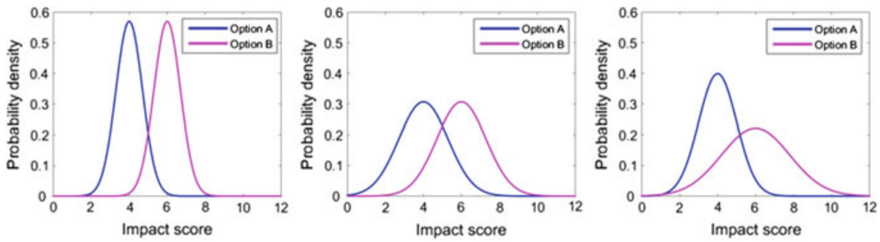

Fig. 11.1 Illustrative comparison of impact scores from two options *A* and *B* with the point estimates of 4 and 6, respectively, in all graphs, but with different uncertainties, low in the *left*, high in the *centre* and mixed in the *right* graph

often hampered by the difficulty to assign and propagate uncertainty information of the usually numerous parameters of a model as required by uncertainty assessment methods. This problem becomes even more apparent when modelling large systems as usually done in LCA, not to mention that there is more to overall uncertainty of a model result than just what parameters contribute. In current daily LCA practice, this often leads to complete omission of this important and integral aspect of any model result, while it may potentially influence or even change the conclusions of a study.

Uncertainty thus refers to everything we do not know and we cannot be certain about, regardless whether we are aware of it or not. In order to create a common basis of understanding when using technical terms and vocabulary around uncertainty, a thorough definition of important terms and concepts will be provided as starting point in the following section.

11.2 Essential Concepts and Definitions

In order to provide an accessible and operational angle on the subject, we have deliberately chosen to use simplified terminology and explanations that do not always capture everything there is to say. The focus of this chapter is on what is relevant for LCA students and practitioners, not on covering all aspects around statistical concepts, terms and definitions. For many concepts there may be multiple terms that are used synonymously in literature and in some cases there may not even be consensus on specific terms and their definition, such as what a sensitivity analysis exactly is for example. The implicit imprecision may be shocking to experts in statistics, but avoiding to capture the full complexity substantially helps getting a first grasp and understanding of the main concepts and how they are used in LCA practice, which is the main purpose of this chapter.

11.2.1 Defining Uncertainty, Variability and Sensitivity

The term **uncertainty** is used with a fairly large variation in its definition, including or excluding (somewhat) adjacent concepts like variability and sensitivity. It is therefore difficult if not impossible to give a universally valid and accepted definition of uncertainty. For the sake of defining a common understanding within the scope of this book, we use the definition of uncertainty as comprising everything we do not know, expressed as *the probability or confidence for a certain event to occur*. More precisely, the "unknown" includes both random and systematic errors (of estimating, measuring or collecting data), mistakes, and epistemological (or epistemic) uncertainty (i.e. lack of scientific knowledge and consequent misinterpretations). To put it a bit bluntly, uncertainty in principle describes the degree to which we may be off from the truth. In reality it is of course impossible for us to know that, otherwise we would not have to face uncertainty since we would know the truth (and we will avoid attempting to define what "truth" itself means). Therefore, in practice we define *reference points* that we assume to represent truth or at least to be close to it. A typical example for such a reference point would be a measurement. If we trust the measuring method and protocol we trust that a measurement represents a sort of truth at a specific point in space and time and the difference between a modelled estimate and a corresponding measured value is then used as an indicator for uncertainty. Ciroth et al. (2004) discuss and nicely illustrate this discrepancy between measured and true value and what uncertainty represents in that respect.

It is then important to keep in mind that the measured value inevitably comes with its own uncertainty due to possible measurement errors (and mistakes) and due to the uncertainty of how suitable the measurement method and how representative the sampling was regarding the actual "truth". Uncertainty can thus be quantified and reduced by knowing more, which usually requires us to invest more resources in order to gain more knowledge (e.g. by performing additional measurements or collecting more data and refining the model). However, no matter how many resources we have available, we can never be certain that we have eliminated (or at least minimised) uncertainty.

In order to define **variability**, let's take the example of body weight distributions in a human population. Many observations we can make will always have more than one value, as soon as we measure more than one sample (i.e. a sub-set of data points from a population of measured data), human body weight being an intuitive example. We are thus faced with a natural variability that simply represents the variety or spread in the data that we will always observe. With enough resources at hand that allow us to take every possible sample, we can perfectly well measure and quantify this variability, but we can never reduce it. In the context of LCA, we are typically faced with three different types of variability: (1) temporal variability (e.g. seasonal changes in temperature), (2) spatial or geographical variability (e.g. population density in different regions), and (3) inter-individual variability of humans, animals, other species (e.g. differences in diets) or technologies.

In LCA practice, the terms variability and uncertainty are often not distinguished or overarching one another (i.e. variability is often included as one aspect of uncertainty). However, for their important differences described before, it is recommendable and good practice to quantify and maintain both well separated as this will allow us to put this information to good use when interpreting and improving LCA results. We will come back to that later.

The **sensitivity** of a model describes the extent to which the variation of an input parameter or a choice (e.g. time horizon in the functional unit) leads to variation of the model result. A model is sensitive toward a parameter if a small change in this parameter will result in a large change in the model result, whereas a model is insensitive toward a parameter if any change in this parameter will have no (or negligible) effect on the model result (which in certain cases might indicate that this parameter may not be needed in the model, or at least that it is not an important input parameter for this particular value of the model result). Sensitivity may be analysed for both continuous and discrete input parameters, and it can also be analysed for choices leading to discrete sets of input values. For example, the choice of LCIA method is always a discrete choice between a certain number of fixed options (i.e. available methods). It is worth noting that the term sensitivity is used in various and inconsistent ways throughout literature and no agreement on its exact definition exists. Two main uses could be distinguished: (1) For some authors sensitivity includes the effect of uncertainty and thus considers the range of variation of input parameters as a function of their uncertainty (which hence needs to be known), varying them all at the same time. This is also called *global sensitivity analysis* and is essentially what this chapter refers to as uncertainty analysis. (2) Others define sensitivity solely as the effect of a certain change in input on the output applying a predefined variation without considering the uncertainty. This is analysed by varying one parameter at a time and also called *local sensitivity analysis*. In the context of this book and many publications in the LCA community, sensitivity only describes the variation of a result due to variation of an input or choice, without considering its uncertainty, i.e. local sensitivity.

11.2.2 Defining Accuracy and Precision in the LCA Context

When talking about uncertainty, a number of terms are often used in conjunction or interchangeably which seem to be synonyms but in fact are not. Two such terms are accuracy and precision. The definition of these terms in general English dictionaries varies to some extent, the Oxford English Dictionary for example defines accuracy as technical noun being “The degree to which the result of a measurement, calculation, or specification conforms to the correct value or a standard” and precision as technical noun being “Refinement in a measurement, calculation, or specification…”. Therefore, both terms are independent and while accuracy refers to the correctness of a value, precision relates to the relationship among multiple measurements or calculation results. It is therefore useful to have a closer look at the actual meaning of these terms in a technical or scientific context and what they imply for LCA. Accuracy describes the closeness of a measured or modelled value to its “true” value. Precision represents the quality of being reproducible in amount or performance (i.e. any repetition of a calculation, experiment, model run, etc. gives a similar result when precise or a wide spread when imprecise), but a reproducible result does not necessarily have to be very accurate or even “true”. In consequence, the accuracy of a model result may be high while its precision can be low as illustrated in Fig. 11.2. This means that the average of such model results will still represent meaningful information even though the results’ spread (i.e. the standard deviation) may be large. In contrast, a very precise measurement or model

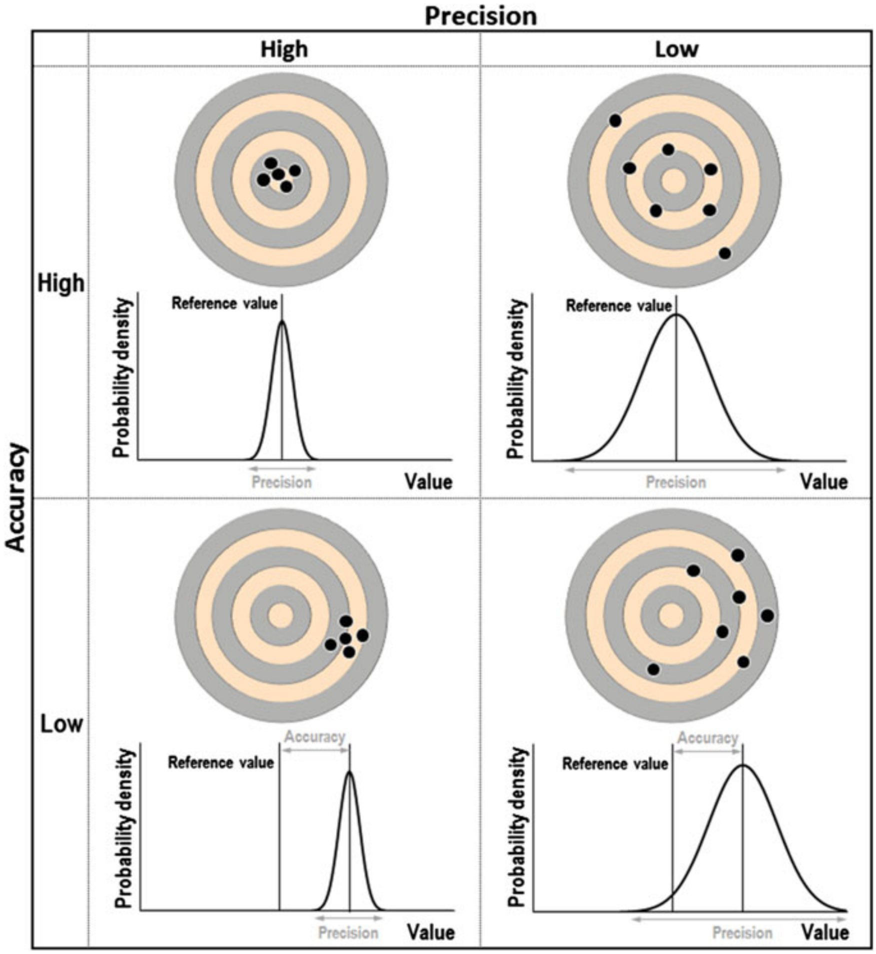

Fig. 11.2 Illustration of precision and accuracy

result (i.e. with a small standard deviation) is not necessarily meaningful if it comes with low accuracy regarding the information one is actually looking for.

In the LCA context, this can be illustrated using the different time horizons of the global warming potential (GWP). When intending to capture potential impacts from global warming of greenhouse gas (GHG) emissions, the GWP is integrated over 20, 100 and until the 4th IPCC Assessment Report (IPCC 2007) even over 500 years. It is intuitive that precision decreases with an increasing time horizon due to the assumptions necessary to model and predict far into the future, but does accuracy also automatically decrease with longer time horizons?

In order to answer that question, we need to consider that most GHGs stay much longer in the atmosphere than 20 years. GWP20 is a very precise and probably accurate indicator for the cumulative radiative forcing (i.e. the capacity to absorb energy, which can be measured in the lab) of a molecule during 20 years, but it neglects that this molecule may still be active long after. It is thus a very inaccurate indicator for the total potential contribution of the molecule to global warming, which is what we are usually interested in for an LCA study (unless the goal and scope definition requires a focus on short-term impacts). Therefore, implicitly assuming that GWP20 quantifies the (total) potential contribution of an emission to global warming bears a risk of interpreting LCA results wrongly in spite of using an indicator that is very precise, as it is inaccurate for the objective at hand (Fig. 11.3).

This example may seem somewhat obvious, but there are many other instances of exactly this type of confusion that can be found in current LCA practice. Another example is the comparison of the uncertainty of indicator results from different impact categories. The GWP is generally perceived as a fairly certain midpoint indicator whereas human toxicity is seen as a very uncertain midpoint indicator, an argument that is sometimes used to justify the omission of toxicity characterisation from an LCA study. It is worth reflecting whether this direct comparison of uncertainties makes sense by looking at the environmental relevance of what both indicators are actually quantifying.

We discussed in Chap. 10 that GWP is the time-integrated radiative forcing of a substance per unit mass emitted. The input data required to calculate it are relatively

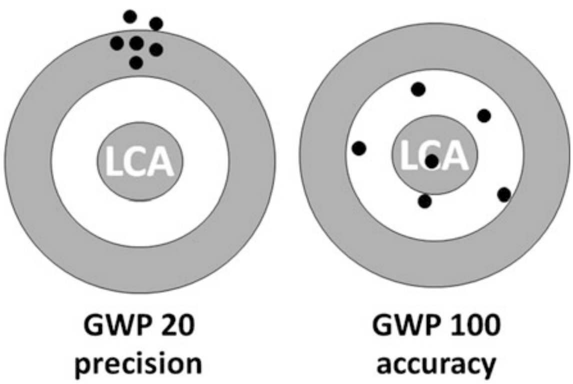

Fig. 11.3 GWP20 more precise but less accurate from an LCA perspective than GWP100

straightforward to measure and well reproducible in a laboratory, or in other words it is a *precise* indicator. It indicates the potential absorption of energy in molecules in the atmosphere, but it does not inform us on its impact on the environment or human health, or in other words it is *not accurate* regarding the goal of quantifying potential environmental impacts. Most toxicity midpoint indicators, however, quantify statistically how many disease cases (or affected species) may potentially occur in a human (or ecosystem) population per mass emitted. Therefore, toxicity indicators are much more representative regarding the consequences of a potential impact than GWP, or in other words a toxicity midpoint indicator has a higher environmental relevance than GWP and may thus actually be more accurate than GWP, while being less precise. Only the inherent, and most likely often unconscious, assumption of causal links between radiative forcing—increased temperature—melting polar caps—rising sea levels—more extreme weather events—loss of agricultural yield—increased competition for food—starvation and possibly even war—and thus effects on human health makes this indicator useful for LCA, but does it make it actually less uncertain for indicating a potential environmental or human health impact?

The argument of too high uncertainty of toxicity indicators thus refers to their precision (reproducibility), but not necessarily to their accuracy (in representing environmental impacts) and may hence be misleading. In addition, the spread between the highest and the lowest values for an indicator may differ widely between impact categories. Given that the toxicity-related impact categories cover several thousand elementary flows (i.e. chemical emissions) with different environmental mechanisms, related variability is higher by several orders of magnitude than for impact categories only covering a handful of elementary flows (e.g. climate change including ~50 chemicals). An example of the relationship between uncertainty around results for a single chemical and spread of results across chemicals is given in Chap. 31, Fig. 31.7.

In LCA, uncertainty should always be referring to what a study aims to quantify. The environmental relevance of indicators varies greatly among impact categories and is also a source of uncertainty towards the conclusions of a study. Just because this uncertainty is not quantified or even somewhat unconscious, that does not mean that it is not present. Hence, a direct comparison of purely precision-related uncertainty among midpoint indicators is not meaningful unless the compared indicators have a similar level of accuracy (i.e. environmental relevance).

This brings us to another common misconception about the uncertainty of LCA indicators, namely the choice of using midpoint or endpoint indicators. The typical trade-off between both options is that a midpoint indicator result will be more precise but less environmentally relevant, while it will be the opposite for an endpoint indicator (i.e. less precise but more environmentally relevant). Therefore, endpoint indicators are typically perceived as more uncertain based on their usually lower precision (due to a larger number of choices and hypotheses involved in their modelling compared to midpoint indicators). When considering environmental relevance as a measure of accuracy and a type of uncertainty (as discussed further below), it is important to keep in mind that midpoint indicators have a large portion of (unquantified or unperceived/unconscious) uncertainty due to their lower environmental relevance compared to endpoint indicators. As depicted in Fig. 11.4, overall uncertainty may increase or decrease from a midpoint to an endpoint indicator of a given impact category, depending on the uncertainty of models and parameters used for endpoint modelling.

However, Weidema (2009) pointed out that this "figure implies that it is possible to make a trade-off between relevance and uncertainty, in which the overall error is minimised … [and] … that the consequences of the decision will be less uncertain if the decision is taken at the point where the overall error is minimised—that is, at a midpoint […] (e.g., at the level of CO_2-equivalents)", which is a common perception among LCA practitioners and clients. Weidema then rightfully argues that "When the decision is implemented, however, the consequences occur not only at the level of the midpoint but also at the level of the endpoint (the decision will result in lost species and lost lives). This implies that the apparently low uncertainty of the decision at midpoint does not reduce the uncertainty of the consequences of the decision at endpoint level, which are still as uncertain as indicated at the bottom of [the] figure […]. If the consequences at endpoint level (e.g., lost species and lost lives) are what we really are interested in (as implied by the maximum relevance), then taking the decision at the midpoint level (e.g., CO_2-equivalents) is simply the same as ignoring the true uncertainty of the consequences of the decision." In other words, if minimal or avoided environmental consequences are the objective of a

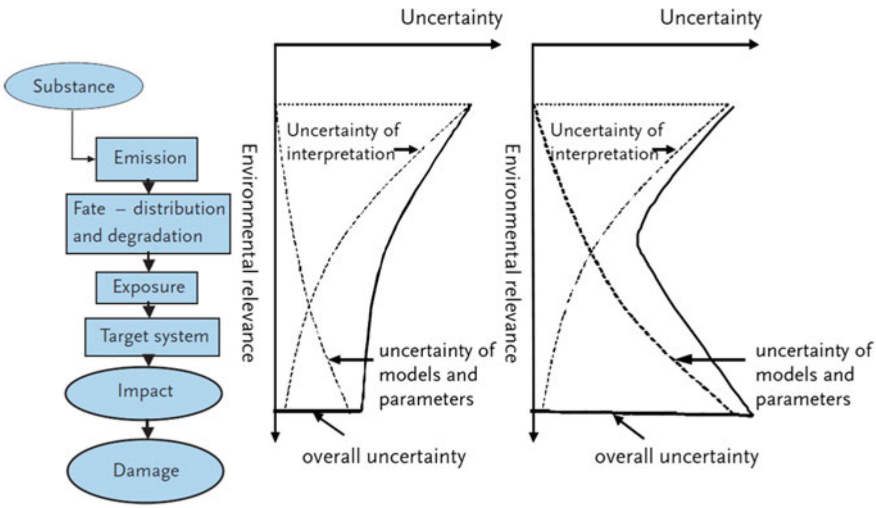

Fig. 11.4 Conceptual representation of how overall uncertainty may decrease (*middle*) or increase (*right*) from midpoint to endpoint (*damage*) in an impact pathway (*left*); uncertainty of interpretation and uncertainty of models and parameters contribute to different extents to overall uncertainty on midpoint (early in the impact pathway) and on endpoint/damage level (end of the impact pathway) while environmental relevance increases [taken from Hauschild and Potting (2005)]

decision, choosing midpoint indicators because they can be quantified with higher precision will still not avoid the uncertainty of that decision's environmental consequences since a midpoint indicator is less relevant (representative) for the environmental consequences to be avoided. Weidema (2009) entertainingly compares this flawed logic as being "representative of the situation of the drunk who, when asked why he was searching for his keys under the streetlight although he had lost them in the dark alley, responded that it was easier to see under the light". In consequence, the overall uncertainty of endpoint indicators may not (always) be much different to that of midpoint indicators from a decision-support perspective as indicated in Fig. 11.4 where the development in the "overall uncertainty" accompanying the decision may sometimes be lowest at the damage level, when the reduction in interpretation uncertainty, going from midpoint to damage, more than compensates the increase in model and parameter uncertainty of the applied characterisation model.

Hopefully, these examples illustrate that when discussing uncertainties between LCA indicators (of different impact categories or between midpoint and endpoint level), all types of uncertainty combined with the related concepts of precision and accuracy need to be considered or else the risk of oversimplifying and comparing apples and oranges is imminent, which may lead to unjustified and wrong conclusions.

The very purpose of any model is to represent a simplification of reality, but what is the right level of simplification? In order to establish a useful model, a meaningful level of complexity is required. As illustrated in Fig. 11.5 adapted from Ciroth (2004), the overall error (of representing reality) of a model is, among other, a function of the error due to an inaccurate representation of reality (too complex model with, e.g. too many input parameters and algorithms that introduce each their own uncertainty) and the error due to ignoring too much of the complexity of reality (too simplistic model). Accordingly, balancing both will yield the lowest overall model-related error. This is known as the parsimony principle, i.e. as simple as possible and as complex as necessary, and intuitively is a suitable leitmotif for LCA.

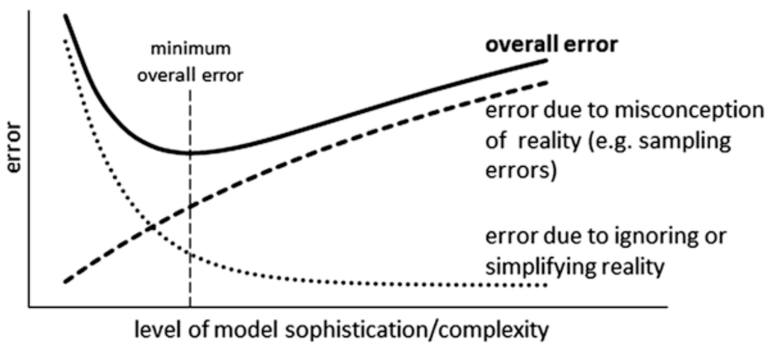

Fig. 11.5 Too complex modelling can have a similar error of representing reality as too simplistic modelling [modified from Ciroth (2004)]

Simplicity is often perceived as a desirable quality of a model making it easy to understand and less data demanding. Complexity on the other hand is frequently perceived as cumbersome, non-transparent and data intensive. However, rejecting complexity as such, without regarding its relevance and influence on the decision at hand, will of course be simpler and also lead to a decision, but it may not be a decision fulfilling the LCA objective of choosing an environmentally preferable option. In other words, it may be a more precise but less accurate and thus a potentially misleading decision. Given the inherent (i.e. unavoidable) complexity of environmental processes and our still limited knowledge of them, the principle of "It is better to be vaguely right than exactly wrong" (Read 1920) is a much cited and useful angle when discussing uncertainties in LCA, thereby also acknowledging that we should never design our models more complex than necessary to avoid "paralysis by analysis" potentially leading to no operational model at all and, hence, to no decision (support).

11.2.3 Representing Uncertainty

The probabilistic nature of uncertainty of the studied process or object is conceptualised by a probability distribution. The probability distribution of a continuous variable is described by a distribution function, usually the probability density function (PDF—not to be confused with the abbreviation PDF for Potentially Disappeared Fraction of species as used in Chap. 10). In practice, the PDF of an input parameter x is estimated by the values x_i measured over a sample, ranging from a minimum to a maximum value. Hence, the probability is approximated by the relative frequency when enough values are sampled. For example, when measuring the body weight of individuals in a human population of several thousand people, we will always find a range of values with a minimum value given by the lightest and a maximum value given by the heaviest individual(s) among those measured. Drawing the full range of measured values on the x axis and how often each of these values occurs (=their relative frequency) on the y axis results in a distribution function (a PDF) as illustrated in Fig. 11.6.

The shape of this function varies substantially depending on the frequency of the values of a variable. Many shape patterns have been clearly defined and termed, distinguishing continuous distributions such as normal, log-normal, or beta, and discrete ones such as binomial, Poisson, or hypergeometric, the latter being characterised by a probability mass function (PMF). When representing uncertainties, these names are used to describe the **type of distribution** and are an essential element when addressing the uncertainty of a (measured or estimated) parameter or the model output. Various methods exist to fit a continuous or a discrete distribution over a set of values.

Generally, important measures to describe uncertainties of an input parameter x or the model output are the *standard deviation* for the spread of a distribution, and for the central tendency of a distribution the arithmetic mean (or average), the

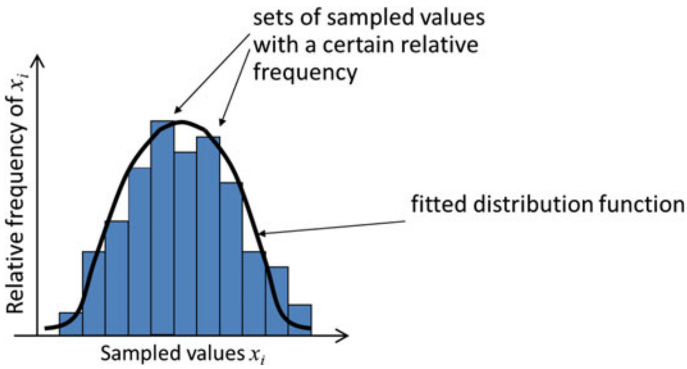

Fig. 11.6 Fitting of a distribution to a set of values for a variable

median, and (more rarely) the mode. The **arithmetic mean** or **average** of a sample is calculated as the sum of all values divided by the total count of all values. The **mode** is the most frequent (i.e. most probable) value within the dataset, and the **median** is the value separating the upper 50% and the lower 50% of all values when ranked in order of their magnitude. In a perfectly normally distributed dataset, the average, median, and mode are identical, whereas in any skewed distribution (e.g. a log-normal distribution) these central tendency measures have different values. However, the mean has the disadvantage to be very susceptible to outliers (unusually small or large values within a dataset) and skewed data. Therefore, the mean does not represent the best central value in skewed distributions (e.g. log-normal), whereas the median is less affected by the skewness of a dataset. The variation of the sample values is most commonly described by the (sample) **standard deviation.** The PDF or PMF are sufficient to fully characterise the distribution of an input parameter, but it is not always evident to derive these functions. Then the combined knowledge of the average (or median) and the (sample) standard deviation can provide a useful description of the behaviour of a parameter.

In-between the minimum and the maximum values of the range, we will find all sampled values and measures of central tendency for a probability distribution, like the *average* and the *median* body weight in the previous example. For the quantification of uncertainty, we usually do not use the entire range between these two extrema, but rather a sub-set of (more representative) values. Figure 11.7a represents a normal distribution for an input parameter x with known parameters μ (=mean) and σ (=standard deviation). Integrating under the curve of the normal distribution from negative to positive infinity, the area is 1 (i.e. 100%). Consequently, the probability for a value drawn from this distribution to fall in the range $\pm\infty$ is 100%. Obviously, this is not useful in terms of describing the uncertainty of a parameter.

In the context of environmental modelling (including LCA) the typically used uncertainty range is the 95% interval as given in Fig. 11.7a as shaded area for a

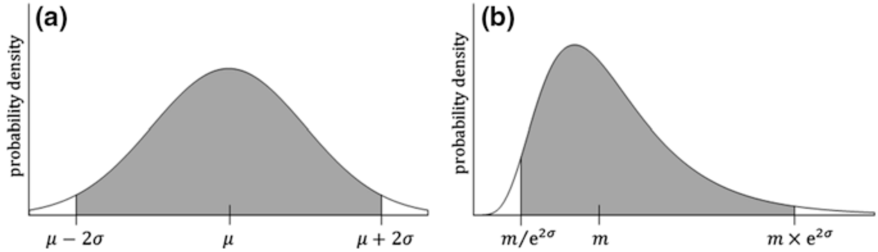

Fig. 11.7 **a** Normal distribution and **b** log-normal distribution with 95% uncertainty interval ranges *shaded in grey*

normally distributed input parameter. This 95% uncertainty interval can be interpreted as the range of values within which (approximately) 95% of all randomly measured values can be found. When the distribution function is known, we can also say that any sampled (or measured) value one may take in the future will fall within this range with 95% chances. Assuming a normal distribution for our example on body weight, this means that 95% of all measured weights from our population will fall within this range and that if picking randomly a person from that population, one will have 95% chances that this person has a body weight within this range of values and only 5% chances to pick a person lighter or heavier than that. The limits of the uncertainty interval are referred to via various names such as upper and lower bounds or **2.5th (lower bound) and 97.5th (upper bound) percentiles**. Other used uncertainty intervals for normally distributed variables are the 68 and the 99.7% intervals.

The link between measures of central tendency (especially the mean and median) and dispersion (standard deviation) of an input parameter x with the upper and lower uncertainty bounds is detailed in the following. Going back to the normal distribution in Fig. 11.7a with mean value μ and standard deviation σ, the 95% uncertainty interval (approximately) corresponds to the interval range between $\mu - 2\sigma$ and $\mu + 2\sigma$. The limits of this interval are the 2.5th percentile (2.5th %ile) as the lower bound at $\mu - 2\sigma$ and the 97.5th %ile as the upper bound at $\mu + 2\sigma$. Integrating over a range within $\pm\sigma$ from the mean value μ, the resulting value is 0.6826; hence, the probability for a value to fall within the range $\pm\sigma$ around the mean is approximately 68%. This range is called the 68% (sometimes 65%) uncertainty interval. You may have guessed it by now, the 99.7% uncertainty interval is then bounded by $\mu - 3\sigma$ on the lower and $\mu + 3\sigma$ on the upper end of the distribution.

If an input parameter x is log-normally distributed with population parameters μ and σ, it means that the natural logarithm of the parameter follows a normal distribution. This distribution is often observed for measurements of environmental input parameters and hence frequently used in environmental modelling. The median value m of the log-normal distribution is identical to the **geometric mean** e^{μ}, while the mean of the distribution is $e^{\mu + \sigma^2/2}$. The mean is larger than the median as this distribution is right skewed. For a log-normally distributed input parameter, the corresponding distribution and the 95% uncertainty interval are depicted in Fig. 11.7b. The 95% uncertainty interval (approximately) corresponds to the integration over the range $m/e^{2\sigma}$ to $m \times e^{2\sigma}$. The exponential term is thereby defined as the **squared geometric standard deviation**:

$$\mathrm{GSD}^2 \triangleq e^{2\sigma}. \tag{11.1}$$

With that, the GSD^2 is used to define the 2.5th and 97.5th %iles, i.e. the 95% uncertainty interval bounds, of a log-normal probability distribution around the median m of x as

$$\text{Probability}\left\{\frac{m}{\mathrm{GSD}^2} < x < m \times \mathrm{GSD}^2\right\} \approx 0.95. \tag{11.2}$$

The uncertainty intervals as discussed above should be distinguished from the confidence intervals. In practice, a population parameter (mean, median or standard deviation) is often unknown. In statistical data analysis, **confidence intervals** are usually calculated, that is the estimated range of values that frequently contains the "true" value of the unknown population parameter, if the sampling procedure is repeated. We need here to clarify some common misconceptions around the interpretation of confidence intervals. For our example on body weight, suppose a 95% confidence interval for the unknown true mean weight that ranges from a to b ($a < b$). The statements "95% of the population weighs between a and b kilograms" or "There is a 95% chance that the mean weight of the population lies between a and b kilograms" are false. The correct interpretation is "If we were to repeat the weight measurement over and over, then 95% of the time, on average, the confidence intervals contain the true mean weight." The latter does not refer directly to a property of the population parameter, but a property of the procedure itself. Two useful further readings on common misconceptions and misinterpretations of confidence intervals and other statistical methods and parameters are the papers from Greenland et al. (2016) and Hoekstra et al. (2014). For a further study of confidence intervals, and all the concepts presented in this section as well, the reader can refer to bibliography in probability and statistics, e.g. Walpole et al. (2012).

The type of distribution is an important element to precisely describe the uncertainty of a parameter. The simplifying assumption of a certain type of distribution (in LCA typically log-normal), instead of attempting to identify the exact distribution, is very useful when little or no information is available about a parameter or when using simplified, approximate analytical uncertainty propagation methods. However, this is sometimes met with criticism by practitioners who would like to integrate uncertainty information into their LCA studies using the exact distribution type. While from a purely statistical point of view this is the ideal, the very large number of variables and their distributions for individual inventory data and characterisation factors used to quantify the uncertainty of an impact score, will often result in a normal distribution of the impact score. This phenomenon is called the "central limit theorem" which states that the arithmetic mean of a sufficiently large number of independent values will be approximately normally distributed, regardless of the underlying input distributions (Pólya 1920). Although, this theorem requires certain conditions to be fulfilled (e.g. independence of the included parameters, existence of a finite expected value and standard deviation for each parameter), it is reasonable to assume these conditions to be fulfilled by most unit processes in LCI. This practical assumption offers several ways to significantly and parsimoniously simplify uncertainty quantification in the LCA context with a likely acceptable loss of precision when assuming one or only a few distribution types for LCA input parameters.

11.3 Addressing Uncertainty in LCA

11.3.1 Types and Sources of Uncertainty and Variability in LCA

There is no shortage of classifications of uncertainty types in literature, ranging from only two or three classes up to ten or more different types. A very useful classification for LCA was published by Huijbregts (1998) and comprises the following classes:

1. Temporal variability (e.g. seasons),
2. Spatial variability (e.g. population density, climate conditions),
3. Variability between objects (e.g. between different individuals),
4. Parameter uncertainty (e.g. inaccuracy, lack or non-representativeness of input data and model parameters),
5. Model (structure) uncertainty (e.g. algorithms in process and characterisation models),
6. Uncertainty due to choices (e.g. definition of functional unit and system boundaries, selection of LCIA method),

to which Björklund (2002) added:

7. Epistemological uncertainty (e.g. lack of relevant knowledge),
8. Mistakes (e.g. choosing the wrong substance or process due to similar names as references, unit conversions or unclear units like tons vs. metric tons/tonnes),

and to which we add:

9. Relevance uncertainty (e.g. environmental relevance, accuracy or representativeness of an indicator towards an area of protection).

Huijbregts (1998) also provided an illustrative list of examples of sources of uncertainty for each type and per LCA phase, which was slightly modified by

Björklund (2002) and by the authors of the present chapter and which is shown in Table 11.1. A classification of uncertainty types widely used in many fields of application distinguishes only three different types: parameter, model, and scenario uncertainty. Most of the nine uncertainty types listed above are essentially sub-classes of these three types as indicated in Table 11.1. Parameter uncertainty comprises variability and uncertainty in model input parameters. Model uncertainty indicates the uncertainty of the model itself via setup, initial and boundary conditions defined, variables/indicators taken into account, and equations used. Scenario uncertainty can be interpreted as uncertainty in the application and use of the model and its results under predefined conditions and assumptions. Whereas parameter and model uncertainty only contribute to the uncertainty of the numerical model results, scenario uncertainty may also contribute to uncertainty in the interpretation of the model results and, hence, that of a consequent decision as illustrated in Fig. 11.9.

For a number of reasons, parameter uncertainty and variability is the uncertainty type that is best considered in current LCA practice and it is what most people refer to when discussing uncertainty in LCA. With occasional, rare exceptions, the few published LCA studies that include uncertainty, essentially consider parameter uncertainty and variability. This kind of uncertainty is estimated in LCI databases such as ecoinvent and in some LCIA methods such as Impact World+ or LC-Impact, and LCA software allows to include the respective calculations in an LCA study. It is also a source of uncertainty that practitioners can address by improving data quality and representativeness, e.g. using primary data for foreground processes, or via spatialised LCA. This can be illustrated using three axes of data representativeness as discussed by Weidema et al. (2003), which constitute a three-dimensional space as shown in Fig. 11.8. LCI data may thus be too detailed, too un-specific, or too non-representative along one, two, or all three axes. Their distance on each axis to the range of data needed thereby represents their uncertainty.

It is important to keep in mind that most types of uncertainty and variability listed in Table 11.1 will contribute, to varying degrees, to the overall uncertainty of a quantitative LCA result (i.e. impact score). Just because parameter uncertainty is essentially the most accessible one and therefore the most frequently assessed or discussed type of uncertainty, it does not mean that it is always the most important (i.e. most contributing) one. The ninth type in the list above (uncertainty related to environmental relevance, accuracy or representativeness) refers to how completely all relevant processes are included in a model, notably to how completely an environmental mechanism is represented in a given characterisation model for a given category midpoint or endpoint (as illustrated in Fig. 11.4). Note that completeness and representativeness relate directly to the goal and scope of an LCA, e.g. the GWP model may be perfectly representative and complete if the goal of a study is to calculate a carbon footprint, while it may be incomplete and of low (environmental) relevance if the goal is to quantify the contribution of an activity to climate change-related human health impacts. For this reason, uncertainty related to environmental relevance or representativeness (i.e. termed here as relevance uncertainty in line with Paparella et al. 2013) cannot be part of the model

Table 11.1 Examples of sources of uncertainty and variability for each type of uncertainty per LCA phase

Uncertainty type		LCA phase				
		Goal and scope definition	Inventory analysis	Choice of impact categories and classification	Characterisation	Weighting and normalisation
Variability	Temporal variability	Inherent variations in the studied system	Differences in yearly emission factors	Inconsistent time horizons between impact categories	Time horizon or change in environmental characteristics over time	Change of social preference over time
	Spatial variability		Regional differences in emission factors	Regional differences in relevance of an impact category	Regional differences in environmental, ecological sensitivity or characteristics	Regional differences in distance to (political) targets
	Variability between objects		Differences in technology between factories which produce the same product	Differences among technologies in relevance of an impact category	Differences in environmental, ecological and human characteristics	Differences in individual preferences when using a panel method
Parameter uncertainty			Inaccurate, non-representative or no inventory data		Uncertainty in lifetimes of substances	Inaccurate normalisation data

(continued)

Table 11.1 (continued)

Uncertainty type		LCA phase				
		Goal and scope definition	Inventory analysis	Choice of impact categories and classification	Characterisation	Weighting and normalisation
Model uncertainty	Model structure uncertainty		Linear instead of nonlinear modelling, assuming continuous emissions	Impact categories are not known; Contribution of impact category is not known	Linear instead of nonlinear modelling, assuming steady-state conditions	Weighting criteria are not operational
	Uncertainty due to choices	Choice of system boundaries	Choice of allocation methods			
Scenario uncertainty		Choice of functional unit	Choice of technology level	Leaving out known impact categories	Choice of the characterisation method(s)	Choice of normalisation reference system or weighting method
Relevance uncertainty		Environmental relevance and representativeness required for decision		Completeness of (relevant) impact categories covered	Representativeness of an indicator regarding a given area of protection	Neglecting the influence of normalisation or weighting factors on results when interpreting them
Epistemological uncertainty		Ignorance about relevant aspects of studied system	Ignorance about modelled processes	Ignorance about relevant impact mechanisms	Ignorance about relevant environmental processes	Ignorance about relevant priorities
Mistakes		Any	Any	Any	Any	Any

Extended from Huijbregts (1998) and Björklund (2002)

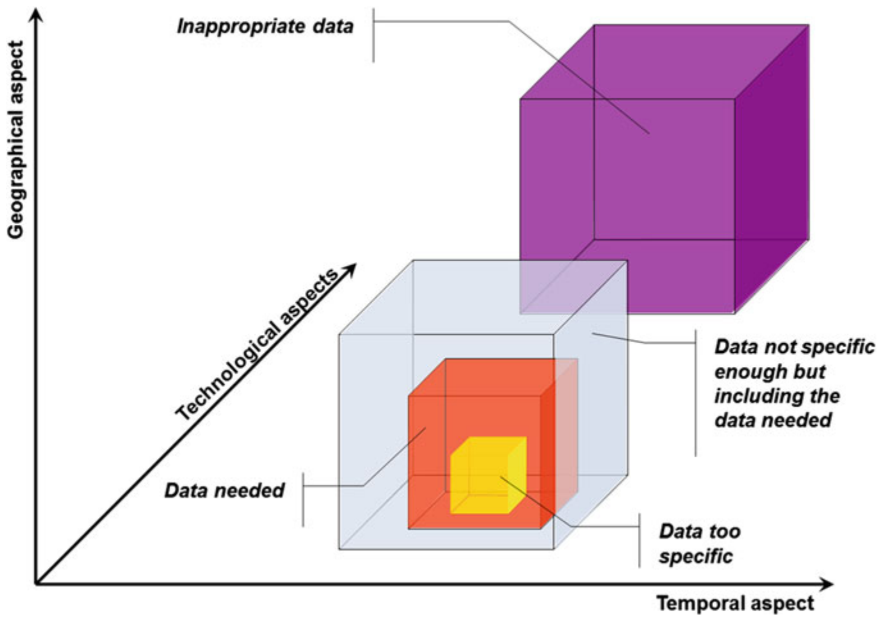

Fig. 11.8 Three aspects of data representativeness in LCA based on Weidema et al. (2003)

uncertainty, which is an intrinsic property of a model result and does not depend on how it is used or interpreted.

Uncertainties and variabilities are typically discussed regarding their importance for the uncertainty of a numerical model output or result, i.e. a number with its standard deviation and eventually a distribution function, which describes the uncertainty of the underlying tool and its result. This does however not consider what this result is being used for, which decision it supports and how it is being interpreted in the context of this decision. In order to also be able to represent and discuss additional sources of uncertainty related to results interpretation and the decision context, the concept of *relevance uncertainty* may be helpful. The more representative an indicator is for a given environmental (or social or economic) problem or damage, the lower the uncertainty on its interpretation, as discussed before. As shown in Fig. 11.9, this may be called the relevance uncertainty, which essentially contributes to the uncertainty of a conclusion or decision, but not to that of the numerical model result. Weidema (2009) pointed this out by stating that "Perhaps the cause of the logical error in the interpretation of (Fig. 11.4) … is that it requires that relevance (or uncertainty of interpretation) can be measured in the same unit as uncertainty of measurement, which is, in fact, not possible. Relevance is what we look for; uncertainty addresses the reliability of our measurement. When we are deciding how to measure what we look for, it is irrelevant how precisely we can measure what we do not look for".

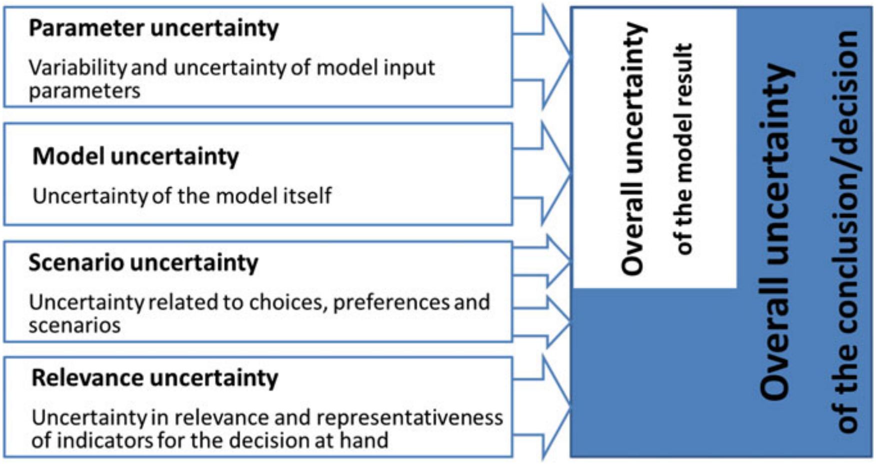

Fig. 11.9 Types of uncertainty and their contribution to result and decision uncertainty

This can be illustrated via a simple example on the use of indicators. Before leaving the house in the morning, many people check the outdoor temperature. What will be the uncertainty of this information? We can probably assume it to be low, so it is a very certain indicator value. However, the real question behind may not be what the value of the current temperature is, but what would be the adequate way to dress for the day. This decision requires a number of indicators, among other temperature, but also wind speed (or chill factor), rainfall and the predictions of those parameters for the rest of the day. Now the uncertainty of these indicator values is probably already a bit higher than that of the current temperature, but that's not all, since the decision at hand is the choice of clothes. This however comes with its own uncertainty on the interpretation of the link between preferable clothes and the available indicator values for temperature, wind speed, precipitation, all with their respective predictions and related uncertainties. The overall uncertainty of the decision is therefore dependent not only on the contributions from the indicator values but also on their interpretation and on how to conclude from them to choosing among a range of options for pants, jumpers, shoes, and jackets.

To translate this example into the world of LCA, one could ask "What is the GWP100 of 1 litre biodiesel?" and most practitioners will be able to answer this question (using a number of assumptions and choices) with reasonable certainty. However, a typical LCA goal is not the quantification of a given indicator, but the support of a decision like "Is biodiesel environmentally preferable to fossil diesel?". To answer that question, multiple indicators besides GWP100 such as land use, (pesticide-related) toxicity, eutrophication and others will have to be calculated. The resulting midpoint or endpoint indicator values, respectively, have their uncertainties and comparing them among both diesel types also adds uncertainty. However, the overall uncertainty of the answer to the question of preference is also affected by how the link between the differences of the indicator values and their representation of environmental consequences is interpreted.

Completeness refers to a parsimonious balance between simplicity and complexity (as discussed above in relation to Fig. 11.5), not to the need to include everything. The same parsimony principle also applies to the related balance between parameter and model uncertainty. In essence, a too simple model will be missing important processes and thus have high scenario and relevance uncertainty due to low environmental relevance, but will have low parameter and model uncertainty. A too complex model, in contrast, may need many (uncertain or unknown) parameters and may imprecisely represent some processes (high model uncertainty), but will also be more (environmentally) relevant, i.e. low uncertainty on representativeness. Similar to Fig. 11.5, overall uncertainty will thus, again, be lowest when both extremes are well balanced, the model being as simple as possible and as complex as necessary (i.e. following the parsimony principle), representing well all significantly influential processes (van Zelm and Huijbregts 2013). This is another example why the assumption of low uncertainty for a simple model, just because it needs few parameters, is incorrect and misleading.

When discussing uncertainty or error in LCA, it is also important to be aware of the implications of random versus systematic errors. In most fields where uncertainty assessment is addressed, the goal is to be precise on an absolute indicator, like temperature or weight for example, which aims to respectively indicate how hot or cold or how light or heavy something or someone is. With some exceptions, the goal in LCA is usually to compare (even a hotspot analysis is essentially a comparison between all processes within a product system) and provide a relative indicator of how much better or worse an option is compared to another, as opposed to indicating how good or how bad something is in absolute terms. In such a comparative context, a systematic error—affecting all compared objects in the same way—may have little importance for the interpretation of results and drawing conclusions. It will just shift all results up or down systematically. It thus affects the result in absolute terms (i.e. the numbers are all higher or lower), but not in relative terms (i.e. the quantitative difference between compared objects remains largely the same). This is frequently ignored when LCA is being criticised as too uncertain, essentially because people tend to interpret its uncertainty in absolute terms and compare it with the absolute uncertainty of other methods like quantitative risk assessment for example, whereas much of the absolute uncertainty does not contribute to the uncertainty of the difference between compared alternatives, which will be further discussed in Sect. 11.4.2. This is also related to why LCA results represent *potential impacts* and (usually) not predictions of observable impacts (see discussion and definition in Chap. 10).

11.3.2 Uncertainty Quantification and Propagation Methods

A quantitative uncertainty management is still a rare sight in LCA practice. If integrated, the most commonly considered types of uncertainty are parameter uncertainty and variability. Parameter uncertainty for example is captured in uncertainty estimates for inventory data such as given in the ecoinvent database.

The quantification of uncertainty refers to the task of establishing a quantitative measure of uncertainty for (1) a specific source of uncertainty in an LCA (e.g. a mean value, standard deviation, and distribution type for a variable or an other uncertain aspect), and (2) the overall uncertainty of an LCA as a result of the combination of specific sources of uncertainty. The latter is achieved using uncertainty propagation methods.

Having discussed the types and sources of uncertainty and variability that are relevant for LCA, the question arises how to quantify them in order to consider and manage them during the assessment process. Some uncertainty types may be more straightforward to quantify statistically than others (e.g. variability of measurable parameters, uncertainty due to some choices), some can be estimated but may be very difficult to quantify (e.g. model uncertainty) and those that relate to the unknown cannot be quantified at all (e.g. mistakes, epistemological uncertainty, and environmental relevance). The latter can (and should) be considered qualitatively during the interpretation of LCA results (see Chap. 12). In consequence, the quantitative overall estimated uncertainty of a model result is both incomplete and uncertain in itself. This however does not make this information useless, but it is essential to consider when interpreting results including their uncertainty.

Several methods to quantify the (quantifiable) uncertainty elements of an LCA have been proposed and implemented to some extent into LCA. Among these methods are reporting uncertainty intervals, analysing parameter variability and/or different scenarios, translating qualitative data quality 'pedigree criteria' into a numerical pedigree matrix, using fuzzy data sets, applying analytical uncertainty propagation, conducting numerical, probabilistic simulations based on e.g. Monte Carlo analysis, using Bayesian statistics, or a combination of some of these methods. The following sections describe three methods that are already used in LCA: (1) the semi-quantitative pedigree matrix approach used for example by ecoinvent for the quantification of variability and uncertainty of LCI data; (2) Monte Carlo simulation used in LCA software like SimaPro, GaBi, openLCA, and the more explorative/educational LCA tools CMLCA and Brightway 2; and (3) Taylor series expansion used in CMLCA. A broader overview of selected quantitative uncertainty propagation methods in the context of LCA or the comparison of specific methods can be found in Lloyd and Ries (2007), Heijungs and Huijbregts (2004), or Groen et al. (2014).

Pedigree Matrix Approach

Information about the uncertainty associated with elementary flows is often not available or difficult to quantify for the hundreds to thousands of flows in a typical LCI. To nevertheless address uncertainty related to LCI results, a simplified semi-quantitative procedure can be used and is implemented into the ecoinvent database and also used by ILCD (EC-JRC 2010). It quantifies (exclusively) parameter uncertainty via combining two different kinds of uncertainty:

(1) Basic uncertainty due to variation and stochastic error of the values for elementary flows, from measurement uncertainties, activity specific variations, temporal variations, etc. This is quantified either using statistical methods when sufficient data are available, or via a simplified approach assuming a log-normal distribution, establishing an approximation that reflects the lack of sufficient information to calculate a more precise estimate.

(2) Additional uncertainty based on data quality indicators using a qualitative assessment of "reliability", "completeness" and representativeness in terms of "temporal correlation", "geographical correlation", and "further technological correlation". These quality indicators are assigned different scores expressing for each value different degrees of data quality and uncertainty and are represented by a numerical value (1, 2, 3, etc.) for each data quality and uncertainty degree. The lower a score for any quality indicator, the higher is the data quality and/or the lower the data-related uncertainty. As illustrated in Fig. 11.10, combining data indicators in rows with the scores for each indicator in columns gives the so-called "pedigree matrix" considering additional uncertainty (uncertainty due to using imperfect data).

Originally, the semi-quantitative pedigree matrix approach was proposed by Funtowicz and Ravetz (1990) in a framework for managing "all sorts of uncertainty" and later adapted to LCI modelling by Weidema and Wesnæs (1996) as being integrated into ecoinvent. The concept of the pedigree matrix is shown for the data quality indicator "reliability" of the data sources in Fig. 11.10. Combining data quality indicators with their respective scores gives a set of uncertainty factors aggregated into (geometric) standard deviations based on assuming log-normally distributed data in ecoinvent 2. These uncertainty factors are based on expert judgment, without (documented) empirical foundation and have been updated with a more empirical approach by Ciroth et al. (2016) based on analysing LCA studies and data with focus on industrial processes separately for each data quality indicator. Furthermore, in ecoinvent 3 the mathematical framework has been developed to also calculate uncertainty factors for distributions other than log-normal from the coefficient of variation chosen as a universal measure of variability and defined as the ratio between the arithmetic standard deviation and mean for all distributions (Muller et al. 2016).

The pedigree matrix based approach was also applied in LCIA for estimating input data uncertainty for toxicity characterisation by Fantke et al. (2012). In this context, the matrix columns represent data-related base uncertainty and the matrix rows represent spatiotemporal data variability. This application and the framework

Qualitative scoring

indicator score / indicator	1	2	3	4	5 (default)
reliability	verified data based on measurements	Verified data partly based on assumptions *or* non-verified data based on measurements	Non-verified data partly based on qualified estimates	Qualified estimate (e.g. by industrial expert)	Non-qualified estimate

Uncertainty factors (ecoinvent 2) based on expert judgment

indicator score / indicator	1	2	3	4	5 (default)
reliability	1.00	1.05	1.10	1.20	1.50

Tentative uncertainty factors (ecoinvent 3) based on empirical foundation

indicator score / indicator	1	2	3	4	5 (default)
reliability	1.00	1.54 (interim)	1.61	1.69	(n.a.)

Fig. 11.10 Excerpt from the ecoinvent 3 pedigree matrix showing scores for the data quality indicator "reliability" of the data source [adapted from Ciroth et al. (2016)] and how the scores are translated into numerical uncertainty factors based on expert judgement (for ecoinvent 2) or based on empirical data (for ecoinvent 3). The full matrices contain scores for five different indicators

laid out by Muller et al. (2016) demonstrate that the semi-quantitative pedigree approach can be flexibly applied to different aspects of an LCA study based on a diversity of different data lacking fully quantifiable uncertainty information.

Numerical Uncertainty Propagation

The most widely used uncertainty propagation method is a numerical approach called Monte Carlo simulation (sometimes also referred to as Monte Carlo analysis). It is available in all major LCA software (although not in all respective versions). Its basic principle is the repetition of model calculations (i.e. iterations) using values for each input parameter sampled from its defined probability distribution. A Monte Carlo simulation is outlined as follows:

Step 1: generate samples of random values for all input variables;
Step 2: apply the model on the generated values to calculate the model output in terms of LCA results;
Step 3: analyse statistically the model output.

The model output can therefore be represented by a probability distribution instead of a single value. An insufficient number of iterations will result in an unreliable empirical distribution of the output variable that may neither consider the full (or at least sufficiently representative) range of output values possible, nor represent the true shape of the distribution. In consequence, the distribution type will not be stable and the uncertainty will therefore be imprecisely estimated.

The accuracy of a Monte Carlo analysis increases as the number of iterations becomes larger. However, there is no generic approach to determine when the number of iterations is 'large enough'. Consequently, the number of iterations may vary among practitioners and also among studies performed by the same practitioner. The number of simulations does not dependent on the number of input parameters, but, in practice, the more complex a (LCI) model is, the more time-consuming a Monte Carlo simulation becomes, which may affect the total number of iterations. Instead of pre-defining the necessary number of iterations, it may be more efficient to run a few tests using an increasing number of simulations until the uncertainty measures (mean, standard deviation or eventually the distribution shape) does not change above an 'acceptable' difference, when further increasing the number of iterations. With enough experience, the number of required iterations can be identified based on the type or complexity of a study.

While the basic, iterative principle is the same for any implementation of Monte Carlo simulation, the sampling method (i.e. how the values from the distribution of an input parameter are sampled) can vary. The simplest sampling method is called "simple random sampling" (SRS), sometimes also "Monte Carlo sampling", and it randomly samples a value from the entire distribution of a parameter, as many times as the number of iterations set. Another, more optimised sampling approach is "Latin hypercube sampling" (LHS), which is a stratified sampling method that first divides a distribution into segments of equal probability and randomly samples one value from each segment. Subsequently, for each iteration, one of these pre-sampled values is randomly selected and used as input parameter value. If correctly set up, this allows a better representation of extreme values (close to upper and lower bounds of the distribution) and can significantly reduce the amount of iterations required as it needs less iterations in order to create a sufficiently representative amount of combinations of the different input parameter values. There are several specialised, further optimised variants of this sampling technique, including for example Median Latin Hypercube sampling, which samples the median of each segment instead of a random value. For most LCA applications with its many distributions and multiple sources of variance contributing to the result's overall uncertainty, there will often be no difference or particular advantage in using LHS compared to SRS. Only when a small amount (typically less than five) of input parameters contributes most to the overall output uncertainty, the advantage of LHS may be tangible. For an overview on simulation and sampling approaches, see e.g. Ross (2012).

Since all inputs are assumed to vary independently and thus in principle any combination of input values is possible, Monte Carlo simulation as described above implies mutual independence of all input parameters. In LCA however, many input parameters are correlated, i.e. if one parameter has an increased value any correlated parameter will consequently have a value that is higher or lower by a specific factor. This dependency of two or more parameters can be expressed using covariance or a correlation coefficient, which can be incorporated into a Monte Carlo simulation so that no impossible combinations of input values are sampled. This will typically lead to a reduction (sometimes an increase) in output uncertainty that can be very large compared to assuming input parameter independence and it is therefore essential to consider. Note that, when correlations exist, appropriate conditional distributions are required. The difficulty in LCA practice is to identify and, even more so, to quantify input parameter correlations, which may be numerous and not typically provided in LCI databases. For a single scenario, Groen and Heijungs (2017) analysed the importance of correlation in uncertainty and sensitivity analysis in LCA. They compared two approaches to include correlation of input parameters and demonstrated that the risk of ignoring correlation can be quantified. They found that in some cases it may not be necessary to quantify and consider correlation and that the risk of ignoring it can be included in the uncertainty analysis and thus be considered for the quantification of the robustness of the results and the consequent decision. One possible way of identifying and managing input parameter correlation is described in the Supporting Information of Fantke et al. (2012).

A note to avoid confusion: LCA (and other) literature sometimes refers to Monte Carlo and Latin Hypercube (with or without further specification whether simulation, analysis or sampling is meant) as if they were two distinct alternative sampling methods. As described above however, both belong to the family of Monte Carlo simulations and the difference is the sampling method.

Analytical Uncertainty Propagation

The most classic, simple and well-established analytical approach to uncertainty analysis, which is widely used in physical sciences and engineering, is the first-order approximation or Gaussian approximation, named after its famous developer Carl Friedrich Gauss. Morgan and Henrion (1990) described how a first-order approximation can be derived from the Taylor series (i.e. the representation of a function as an infinite sum of terms calculated from its derivatives at a given point), a technique based on a Taylor series expansion of the function relating model input parameters to model results (output). They extended this to a number of special cases, essentially allowing a wider application. This method uses linear first-order equations within a fully multiplicative set of parameters assuming independence of all relevant inputs.

In this method, relative (normalised local) sensitivity coefficients $S_{\hat{x}}$ are defined for each input variable x, calculated from the change of model output y (∂ output) per relative change of input variable x (∂ input) and evaluated at the point $x = \hat{x}$:

$$S_{\hat{x}} \triangleq \frac{\partial\,\text{output}/\text{output}}{\partial\,\text{input}/\text{input}} = \left.\frac{\partial y/y}{\partial x/x}\right|_{x=\hat{x}} \tag{11.3}$$

Model output uncertainty, represented by the corresponding squared geometric standard deviation of model output, GSD_y^2, can be described by its variance, $\text{var}[\ln(y)]$, i.e. the variation around its mean value. Output variance depends on the variance of all model input variables, $\mathrm{var}[\ln(x_i)]$ (Morgan and Henrion 1990). If we use the fact that the variance of any input variable is related to its $\mathrm{GSD}^2_{x_i}$ by $\mathrm{var}[\ln(x_i)] = [\ln(\mathrm{GSD}_{x_i})]^2$, we can express model output uncertainty via its GSD^2_y as a function of $\mathrm{GSD}^2_{x_i}$ of model input:

$$\mathrm{GSD}^2_y = \exp\left(2 \times \sqrt{\sum_{i=1} \mathrm{var}[\ln(x_i)]}\right) = \exp\left(\sqrt{\sum_{i=1} \left[\ln\left(\mathrm{GSD}^2_{x_i}\right)\right]^2}\right) \qquad (11.4)$$

The $\mathrm{GSD}^2_{x_i}$ for the different input variables need to be known or can be approximated e.g. for log-normally distributed data from the 95% uncertainty interval by $\mathrm{GSD}^2 = \sqrt{97.5\mathrm{th}\%\mathrm{ile}/2.5\mathrm{th}\%\mathrm{ile}}$ (see also Fig. 11.7b and Eqs. 11.1 and 11.2) to ultimately arrive at an overall model output uncertainty using this analytical uncertainty quantification approach.

In the LCA context, this method was first proposed for use in LCI (Heijungs 1996, 2002, 2010; Heijungs et al. 2005). Based on this, application to LCA was demonstrated by Ciroth et al. (2004) for a virtual case and by Hong et al. (2010) for the real case of the carbon footprint of a car part comparing several scenarios and considering the dependency of many LCI and LCIA parameters shared by the considered scenarios, which is essential when comparing them. Imbeault-Tétreault et al. (2013) applied it to a complete LCA comprising 881 unit processes with 689 elementary flows comparing two scenarios and considering their dependencies. Different implementations of this method are possible, dealing in different ways with the limitations of this approach based on different underlying assumptions as compared and critically discussed by Heijungs and Lenzen (2014).

Comparisons with the results from Monte Carlo simulation which is considered to be the reference method for uncertainty propagation in LCA, consistently found good accordance between both methods applied to LCA (Ciroth et al. 2004; Hong et al. 2010; Imbeault-Tetreault et al. 2013; Heijungs and Lenzen 2014).

The main advantages of the analytical approach are its relative simplicity and calculation speed. The uncertainty is instantly calculated, whereas Monte Carlo simulation may take several minutes for small systems and few iterations to hours or even days of calculation time for complex systems and many iterations. For a typical LCA and a reasonable number of iterations, half an hour up to several hours on a modern computer can be expected. This is a major drawback towards routine uncertainty assessment in LCA and a central motivation for the authors mentioned above to explore analytical approaches for use in LCA. On the other hand, analytical methods are limited to predominantly simple (i.e. linear and continuous) models. An overview of strengths and weaknesses of analytical versus numerical methods in LCA was derived by Heijungs and Lenzen (2014) and is summarised in Table 11.2. It is worth mentioning that the analytical approach does not provide information about the distribution type of its result, only the standard deviation, but in LCA, a log-normal distribution is often assumed for the output similarly to the

Table 11.2 Comparison of main strengths and weaknesses of analytical and numerical uncertainty propagation methods

	Analytical: Taylor series expansion	Numerical: Monte Carlo simulation
Uncertainty information required per parameter	Standard deviation	Standard deviation, distribution type, parameter(s) describing the distribution
Uncertainty information obtained for model result	Standard deviation	Standard deviation, distribution type, further statistical analysis (e.g. median, interquartile range, etc.)
Applicability	Linear (almost), continuous functions; small uncertainties; no covariance (unless considered in additional term)	Linear and nonlinear, continuous and discrete functions; small and large uncertainties; no covariance (unless considered in additional term)
Calculation time	Instantly	Several minutes to hours
Capturing correlation of input parameters	Possible	Possible
Advantages	• Fast calculation time (i.e. seconds) • Distribution type and parameters of inputs not required • Useful screening approach	• Distribution type and parameters or outputs determined • Flexible and widely applicable including to complex models
Disadvantages	• Distribution type and parameters or outputs not determined • Fairly rigid and limited to simple linear models • Less widely applicable than Monte Carlo	• Long (sometimes very long) calculation time (i.e. hours to days) • More input information required

input parameters. Heijungs and Lenzen (2014) concluded that both methods should be implemented in LCA software and used complementarily in LCA, in order to profit from their respective advantages.

Quantification of Sensitivity

Sensitivity can be quantified using perturbation analysis (although often also referred to as sensitivity analysis, a term which is not clearly defined and used in different ways in literature, including or excluding uncertainty). Perturbation analysis can be performed numerically by varying an input parameter (e.g. by a fixed amount, a percentage, a standard deviation, or between a minimum and a maximum) and observing the resulting change in model output relative to the result using the unchanged input parameter (Heijungs 1994). The sensitivity S is then the ratio of the relative change in output divided by the relative change in input as given in Eq. 11.3. There are also analytical approaches available to provide this analysis (Heijungs 1994, 2002, 2010). The illustrative case study of an LCA on window frames in Chap. 39) identifies sensitive parameters calculating sensitivity ratios using Eq. 11.3 and also runs two sensitivity scenarios to test the influence of central assumptions in the study concerning the choice of geographical location (Danish vs. average European residence) and the decision whether to go for a design with a two-layered or a three-layered window pane.

If the input is not a parameter but a discrete choice (e.g. system boundaries, allocation rules, functional unit, LCIA method), a so-called scenario analysis evaluates the change in the result for each alternative considered (or meaningful) for a given choice. In this case Eq. 11.3 cannot be applied and a change in a choice may entail a change in several (correlated or mutually independent) input parameters, such as the case for the choice of LCIA method, which will usually change all characterisation factors. The analysis of the influence of a choice on the result is therefore referred to as scenario analysis, with each choice representing a possible scenario. Although they are formally two different types of analysis, a scenario analysis can be seen as a sort of sensitivity analysis, but for discrete changes in (often multiple) inputs instead of variation of one continuous parameter value at a time. A scenario analysis is also often used to represent different possibilities, e.g. future developments or best-case/worst-case scenarios, of how a number of parameters may change.

11.4 Interpretation and Use of Uncertainty Information

Once the uncertainties of input parameters, models, choices, etc., have been quantified and propagated, so that the results are not calculated deterministically but probabilistically (i.e. accompanied with a standard deviation and eventually a distribution of output values), the obtained information on uncertainty in the result can be used to improve (i.e. reduce) the uncertainty of important inputs and to enhance the interpretation and the robustness of conclusions drawn. This can be done in several, mostly complementary ways discussed in the following sections. We first discuss how to interpret uncertainty, variability, and sensitivity information, respectively, as the results of an uncertainty assessment in the LCA context. Then, we discuss the combined use of them and how to use the information obtained to reduce the uncertainty of an LCA study and the robustness of its conclusions.

11.4.1 Interpreting Uncertainty, Variability, and Sensitivity

As discussed, the sensitivity analysis points out those input parameters that have an important influence on the result, while the uncertainty analysis (including variability) provides information on the spread of the result due to the spread in input data and other sources of uncertainty. An input parameter may be very uncertain, but if the model output is insensitive to this parameter, the uncertainty of the input parameter will not contribute to that of the result (since no change in its value changes the model result) and improving the certainty of this parameter with better input data will bring no improvement to the robustness of the result and would thus be wasted effort. On the other hand, the model result may be very sensitive to an input parameter that is very certain, in which case it would depend on their degree of certainty and sensitivity whether or not better data would still improve the result's robustness. From this illustration it is clear that neither the sensitivity nor the uncertainty of a parameter should be interpreted on their own, whereas the combination of both allows a meaningful judgement of the importance of a parameter regarding the model output. This can be illustrated plotting both aspects as illustrated in Fig. 11.11, which shows both cases described above plus the two cases of (1) complete insensitivity combined with complete certainty of a parameter, which makes it negligible regarding its importance for the output uncertainty, and (2) high sensitivity combined with high uncertainty of a parameter, which will identify the primary parameters to focus data collection and improvement (i.e. reducing parameter uncertainty) on in order to obtain the largest gains in result certainty. This basic concept is useful to keep in mind when identifying dominant sources of uncertainty for any model result.

The concept of identifying and ranking sources of uncertainty, like input parameters, unit processes, or characterisation factors, in terms of their contribution to uncertainty in LCA results is called 'identification of significant issues in the Interpretation phase (see Chap. 12) but also referred to as key issue analysis, importance analysis or uncertainty contribution analysis, which is not to be confused with the impact contribution analysis or dominance analysis frequently used in LCA that identifies the unit processes most contributing to an impact score. It is useful for identification of important sources of uncertainty, where better information or data would directly improve the certainty of the result and hence the robustness of the conclusion. It can be applied to focus data acquisition and model refinement, ensuring that additional effort in getting better data or improving models actually contributes to more robust results. This also relates back to the discussion above on precision and accuracy, confirming that improving precision

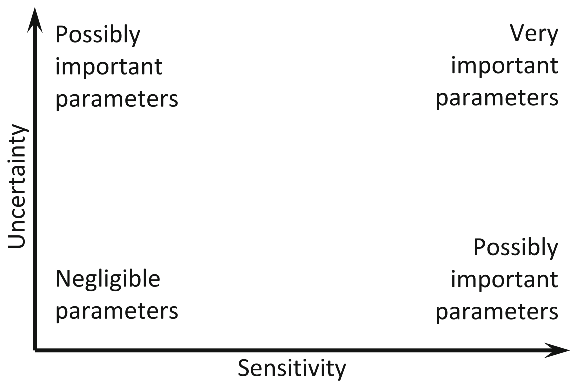

Fig. 11.11 Combining uncertainty of and sensitivity toward an input parameter to identify its importance in terms of contribution to overall uncertainty of the model result [based on Heijungs (1996)]; instead of parameters, any source of uncertainty in LCA could be identified, including for example characterisation factors

by finding more precise data does not automatically result in lower uncertainty if those data are not central to the impact score they are used to model.

Combining the information gathered via key issue analysis with that from impact contribution analysis, helps identifying unit processes that contribute significantly to (1) the impact score of a highly local or regional impact category (e.g. eutrophication, toxicity, land use, or water use, see Chap. 10) and (2) the uncertainty of that impact score. This can be used to apply a smart, partial regionalisation of the LCI model and its LCIA characterisation. Instead of using spatially resolved LCI and LCIA data for the entire LCA (which is resource intensive and thus usually prohibitive for both the practitioner and the LCA software used), only the identified unit processes and elementary flows are regionalised using primary input data and regionalised LCIA characterisation factors (or derived, representative archetypes of them). If the uncertainty and variability information of the underlying elementary flows and characterisation factors has been kept separate (i.e. not been combined into a single uncertainty distribution), this will result in a (substantially) lower overall uncertainty of the impact score, since the contribution from spatial variability will be eliminated (or at least reduced) by using spatially resolved data and characterisation factors for these processes. This method allows a parsimonious consideration of complexity due to spatial variability and rewards the practitioner's additional effort directly by a lower overall uncertainty and hence a more robust result and conclusion. The same approach can also be applied to temporal variability, i.e. using temporally explicit data instead of annual averages when it sufficiently influences the result's uncertainty, e.g. for water consumption.

11.4.2 Relevance of Uncertainty When Comparing Scenarios

So far we have discussed various aspects related to assessing the uncertainty of a single scenario, i.e. the environmental profile of one option, without comparing two or more alternative options, the latter being one of the most frequent applications of LCA. In the case of a comparative LCA however, there is an additional aspect to consider: the correlation of numerous input parameters between the compared scenarios, where many processes (i.e. electricity, fuel, transport, etc.) and almost all characterisation factors will be the same in several or all compared scenarios. When comparing two scenarios, the focal point is thus not on how large the value of an impact score is but what the difference (or the ratio) between two impact scores (i.e. between two scenarios or compared systems) is. Consequently, instead of the absolute uncertainty of a single impact score, the uncertainty of the difference (or ratio) between two impact scores needs to be assessed, because the uncertainty of correlated parameters will be the same in both scenarios and thus not contribute to the uncertainty of the difference between the scenarios. In other words, comparing two scenarios and their respective uncertainties (e.g. by simply overlaying both distributions) without considering correlation, the uncertainty will be (strongly) overestimated, which may be misleading and result in the wrong conclusion. Note that in the illustrative case study presented in Chap. 39, it was not possible to consider the correlations between the compared scenarios, due to software limitations. The technical possibilities for uncertainty analysis vary between available LCA software and may also evolve (i.e. improve) from older to newer versions. Choosing LCA software that supports the requirements of a proposer uncertainty analysis is therefore essential. The uncertainty analysis presented in the illustrative case study is a screening level analysis and considers in its interpretation that uncertainty in the comparison of scenarios is overestimated due to lacking consideration of correlations.

There are two frequently used ways to compare the impact scores of two scenarios A and B, calculating the difference $A - B$, or the ratio A/B. When using the difference, the result can be $A - B < 0$ when A has a lower impact score than B ($A < B$), it can be $A - B = 0$ when $A = B$, or it can be $A - B > 0$ when $A > B$. The second way works similarly, with $A/B < 1$ when $A < B$, $A/B = 1$ when $A = B$, or $A/B > 1$ when $A > B$. In both cases the environmentally preferable option for a given impact category (i.e. compared impact scores) is easily identified. The uncertainty of the difference or ratio can be quantified using covariance or correlation coefficients, which can be assessed with both numerical and analytical uncertainty propagation methods. When using Monte Carlo simulation, it is also straightforward to calculate the above difference or ratio pairing the results from the iterations from each scenario. This will result in a number of iterations where $A > B$ and some where $A < B$ unless one scenario is always better than the alternative over its entire range of uncertainty. This can then be interpreted as the frequencies of each case, i.e. $x\%$ of iterations where $A > B$ and $y\%$ of iterations where $A < B$, with x and y representing the respective probability given that enough iterations where calculated. This means that it is possible to calculate the probability of A being environmentally preferable over B and vice versa as illustrated in Fig. 11.12. For example, if A is better than B in 25% of the simulated cases, there will be 75% where B is better than A. The conclusion may thus be that B is better than A with 75% likelihood, or in other words with a 25% probability to be wrong.

In a decision support context, the probability of one alternative being preferable over another is an essential measure of robustness of a recommendation and eventually an information that only uncertainty assessment can provide. If the decision is to choose one option over all other alternatives, there is a substantial added value for the decision maker if the probability for this to be wrong can be quantified. It helps, among other, to provide perspective on the robustness of an environmental gain of a certain option relative to other measures such as costs for example. If a higher investment is required but the probability that this really is an environmentally preferable option is very high, the investment may be easier to justify. Several authors demonstrated how to apply this in LCA (Hong et al. 2010; Wei et al. 2016) and the following section provides an example where this approach was also used to enhance the interpretation of results and express the robustness of the conclusions.

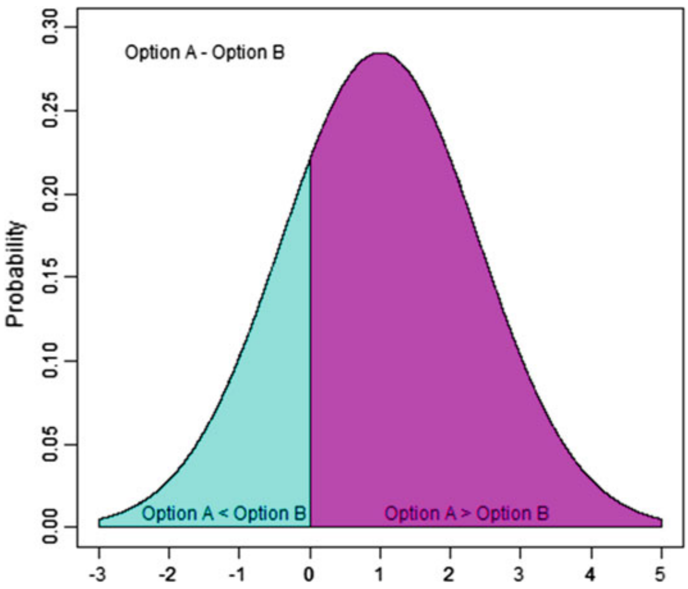

Fig. 11.12 Uncertainty of the difference between two scenarios *A* and *B*

The example is a real case comparing different, functionally equivalent solutions for hand dryers in public restrooms (Quantis 2009). The study compared the (1) XLERATOR Hand Dryer (high-speed air flow) to (2) conventional hand dryers (low-speed air flow), (3) paper towels with virgin paper, and (4) paper towels with 100% recycled paper. The functional unit was to dry 260,000 pairs of hands. The study was performed by Quantis' Boston office, commissioned by Excel Dryer Inc., underwent critical review according to ISO 14040/14044 and has been published (available via exceldryer.com). It is in many ways a classical LCA study, but what makes it stand out as an interesting example is that for climate change impacts, an uncertainty assessment was performed in order to determine the confidence in the conclusions regarding the preferable solution.

Using the analytical propagation method, output uncertainty was calculated for the climate change results of all four scenarios as shown in Fig. 11.13. Even though it may be tempting to compare the distributions directly, the latter do not consider dependency and thus overestimate the uncertainty of the difference between scenarios when comparing them. They do, however, indicate the uncertainty of each scenario individually with the XLERATOR showing the lowest spread, which is due to the fact that many primary data are used that the commissioner has direct access to, whereas the input data for alternative scenarios are estimated or taken from other sources and secondary data, thus increasing their uncertainty. The XLERATOR shows the lowest impact score and very little overlap with the uncertainty range of the alternative scenarios. This allows a first conclusion that it is very certain that this is the preferable alternative among the compared options,

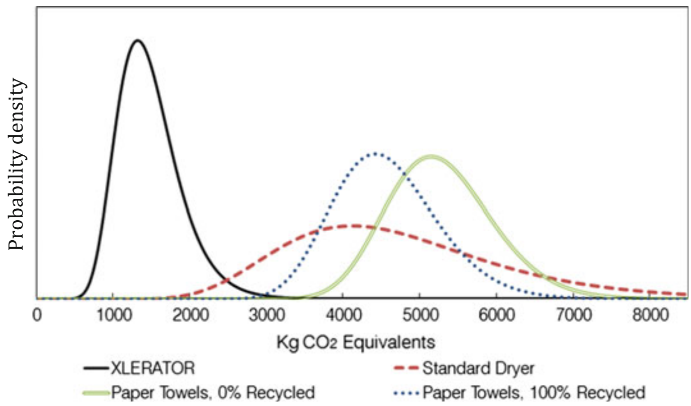

Fig. 11.13 Probability distributions (probability density functions) for the climate change impact scores of four compared alternatives to dry hands (Quantis 2009)

because the uncertainty range can only be smaller when considering the dependency of parameters between the alternatives.

In order to gain deeper insights into the uncertainty when comparing these alternatives, a paired comparison between two scenarios at a time was performed. A selection of the results is shown in Fig. 11.14. As discussed above, the ratio of two study results can be used to compare them and determine whether or not one of the two alternatives is environmentally preferable. It is clearly demonstrated that the XLERATOR consistently has the lowest impact score and that the probability that this is the wrong conclusion is virtually zero. In other words, according to the uncertainty analysis, it is 100% certain that the XLERATOR is the most preferable among all considered options regarding climate change impacts.

It is an important question to ask which aspects of uncertainty have been considered and how completely the uncertainty has been captured. If important sources of uncertainty that are independent between scenarios have been omitted, the uncertainty of the ratio between two scenarios may well be larger and the conclusion would be less robust. Assuring a complete consideration of important sources of uncertainty contributing to the difference between two scenarios is essential in order to fully trust the resulting measure of confidence in concluding the preference of one scenario over another.

The comparison of other scenarios provides examples of less certain outcomes. The comparison of standard dryer and virgin paper towels shows that a part of the resulting distribution of the ratio between both scenarios is larger than 1. According to the numerical results provided in the report, there is a 24% chance that virgin paper towels have a lower climate change impact than standard dryers. Consequently, there is a 76% chance that standard dryers are less impacting than virgin paper towels. When comparing standard dryer and recycled paper towels, the uncertainty distribution of the ratio between both is almost equally spread around 1, which means that there are about 50% chance for both possible conclusions. In that

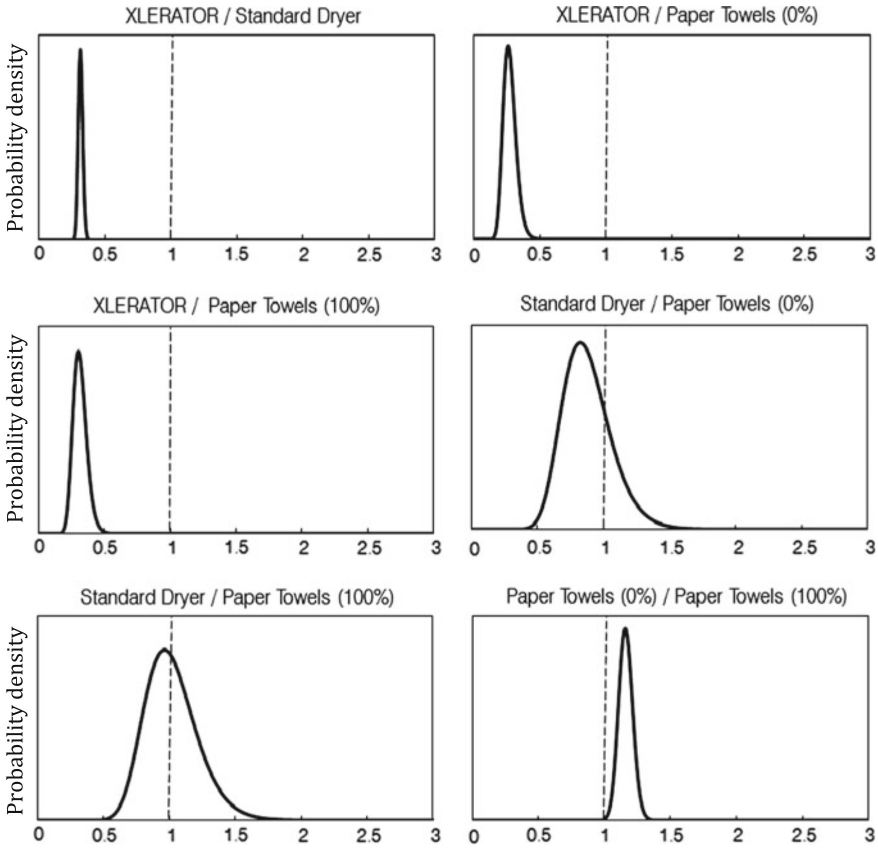

Fig. 11.14 Paired comparison of the climate change impact score ratio of alternative scenarios including uncertainty (Quantis 2009)

case, both scenarios have to be considered essentially equal and no conclusion regarding their (difference in) climate change impact can be drawn. Comparing the two paper towel options, it appears that recycled paper towels are the less impacting alternative, but the distribution of the ratio between both is close to 1. Additionally, the report states that a number of potentially important and independent uncertainties have not been quantified, such as "the methodological issues relating to allocating for recycled content and that the data used do not include impacts for the processing of the recycled paper". Hence, the range of the uncertainty distribution of the ratio between both scenarios may be larger and the conclusion of preference for the 100% recycled paper towels may be less robust.

In order to derive concrete conclusions if one option is better than (preferable to) another one, the observed differences need to be examined in statistical terms. The two most used statistical tools to examine if their difference is statistically significant are confidence intervals and hypothesis testing.

There is still room for improvement, but this study is an excellent example of how uncertainty analysis strengthens the robustness and the trust in the conclusions of an LCA. Besides showing the added value of uncertainty assessment and interpretation, it also illustrates the feasibility of quantifying and managing uncertainty in LCA.

11.5 Communication of Uncertainty

Besides quantifying and improving the robustness of an LCA and its conclusions, the question of how to communicate this beyond the practitioners directly involved in the study is fundamentally important and may often be more complex than anticipated. Like any communication it needs to be adapted to the target audience and will have to look very differently if targeting the general public, high-level decision/policy makers, or fellow practitioners and it will depend on the goal and scope of the LCA itself and, thus, differ if the goal was, e.g. to support the eco-design of a product or the overall environmental performance of a company. The following set of questions is useful to address in order to identify a meaningful uncertainty communication strategy:

1. Who is the target audience and how familiar is this audience with LCA and its aspects of uncertainty?
2. What exactly should be communicated in relation to uncertainty?
3. How should uncertainty results be represented?

11.5.1 Who? Identifying the Target Audience

Before choosing which uncertainty information should be conveyed, with how much detail and how exactly, it is essential to identify the target audience(s) of this information and adapt the communication strategy accordingly. Each potential target audience will understand and interpret uncertainty information differently in function of how familiar they are with underlying methodology, sources, types and meaning of uncertainty. There are many ways of classifying target audiences, but several main target groups (not necessarily always applying to all LCA reporting situations) may be:

- LCA experts, e.g. other practitioners, scientists, etc., who are very familiar with the subject. This may well be the easiest case, since little or no selection of uncertainty information, or a particularly adapted presentation will be required in most cases.
- Informed stakeholders with expertise regarding the LCA, the studied subject or the indicators considered (e.g. environmental, social, or economic), such as

NGOs, competitors, governmental agencies, etc. This target group will be able to access the core issues of an LCA and its uncertainty as long as some guidance and transparency regarding uncertainty are provided and the information is presented in a way that does not require in-depth expertise and routine.
– The general public, like NGOs, consumers, workers, or neighbours of a production site, will usually need as much pre-selection, pre-digestion and simplification of uncertainty information as possible.
– High-level decision makers in a company or national/international policy-context will not be familiar with technical details around the LCA study and uncertainty analysis. They have little time to spend on understanding any details and need to know quickly what the implications of the underlying uncertainties are for their decision(s). They may want to know which uncertainties are considered and how certain they can be regarding the robustness of the LCA results.
– Medium-level decision-makers such as regional or local policy-makers, or industrial production managers may require to be presented with uncertainty information somewhere in-between high-level decision-makers and the general public, depending on the context.
– The commissioner(s) of an LCA may fall into any of these groups and will have a particular interest in the uncertainty of its results.

It may well be that an LCA study needs to address several of these target groups and that a meaningful compromise needs to be found. A good way to deal with multiple target groups' needs is to prepare an adapted presentation for each target group, e.g. via an executive summary (for high-level) and a technical summary (for medium-level and informed stakeholders), or via dedicated reports or at least interpretation and discussion chapters for a given target group. The LCA report on window frames provided as an illustrative case study in Chap. 39 provides both an executive summary and a technical summary addressing different target groups for the report.

11.5.2 What? Selecting Which Information Is Relevant to Communicate

There are many aspects related to uncertainty that could be communicated but need to be selected depending on the target group of the information and what they can and need to do with it, but also considering the importance of transparency:

1. Assumptions and hypotheses underlying a study, including simplifications and generalisations;
2. Representativeness of information, models, and data used;
3. General level of scientific knowledge and understanding about important aspects of a study, particularly for new issues or approaches used;

4. Subjective, ethical or moral values and choices implicitly or explicitly included in the study;
5. Aspects that have not been considered (for whatever reason) but that may be important;
6. Types and sources of uncertainty that have been quantified;
7. Types and sources of uncertainty that have not been quantified but that are expected to be important contributors to overall uncertainty of results and/or conclusions;
8. How exactly uncertainties have been quantified and propagated;
9. Types of analyses that have been performed to consider uncertainty (e.g. sensitivity, uncertainty, uncertainty contribution, scenario analysis, etc.);
10. Uncertainty management and reduction strategies applied;
11. Robustness of the numerical results eventually including the quantitative uncertainty of some or all of them and a list of the most sensitive underlying assumptions and data;
12. Robustness of the conclusions and recommendations, eventually including quantitative measures and a list of the most sensitive underlying assumptions, data and choices;
13. Implications and consequences of the uncertainty underlying the results and/or conclusions.

It is important to keep in mind that communication of uncertainty does not necessarily imply its quantification using sophisticated methodology and substantial resources. The absolute minimum of a qualitative discussion of some or all aspects listed above can and should always be provided by a practitioner.

11.5.3 How? Representing Uncertainty Effectively

This section is largely inspired by a report from Wardekker et al. (2013), which nicely summarises the essential aspects around representing uncertainty. Although not specifically adapted to LCA, further details and insights beyond the selection in this chapter may be found there. When communicating LCA results, in which ever way, it is important to be aware that it is the responsibility of the author(s) (i.e. the practitioner, sometimes also the commissioner) to consider and adapt to the target audience. It is clearly insufficient to focus on a scientifically correct and complete presentation of results and related uncertainty, leaving the responsibility of their correct interpretation solely to the (target) audience. When choosing a way to express and represent uncertainty, it is thus important to keep in mind that the target audience may interpret it very differently than intended. Only using point estimates or deterministic results and conclusions, without mentioning any uncertainty, already bears the risk of unintentional interpretations. This will be even more the case when including uncertainty information, where it is well possible that referring to a low probability of an environmental consequence to occur may result in unintentional focus and unrest about this unexpected risk. It is also possible that evoking a high probability of adverse effects may not be noticed as an issue of concern, just because it was presented as something of a certain probability and not as the (almost) certain environmental consequence of an act or decision. In other words, the same uncertainty information may result in opposite interpretations by different readers. While this is difficult to fully foresee and avoid, paying attention to such details when preparing a presentation or report can help avoiding unintentional or wrong interpretation when considering the target audience's context and interpretation capacity.

Wording and phrasing are essential elements in this context. For example, a non-technical audience may not be familiar with the meaning and implication of terms like risk, probability or likelihood. The expression of uncertainty in a positive way versus a negative way can make an important difference. To illustrate this, the following two phrases express the same uncertainty information in an LCA comparing two alternatives *A* and *B*, but in a very different way: (1) "there is a 10% risk that choosing option *B* may be the wrong decision" versus "there is a chance of 90% that option *B* is the best option".

Besides paying attention to how an information is phrased (sent), it also plays an important role how the information is received, which Wardekker et al. (2013) describe via three effects of distortion:

- "Availability: matters that easily come to mind are generally regarded as occurring more frequently or more likely to occur than matters that are more obscure. A strong focus on a specific issue (in the media) may result in people regarding it as more likely to occur.
- Confirmation: once a view has been adopted, new information will be interpreted on the basis of this view. It is difficult to change people's views.
- Overconfidence: people are often too certain of their own judgement. This applies to the general public as well as to scientists."

The exact place in a report or presentation where uncertainty information is included is worth some consideration. Numerous options exist, but each solution may bear its particular risk of failure to communicate uncertainty, like a dedicated chapter stating all there is to state, may be easily ignored because it is little inviting to read, or an annex containing all relevant information may never be read, as it is not part of the main body of the report and therefore may not be considered relevant by some readers. It may be a good idea to spread uncertainty information meaningfully in different parts of the report, a concept referred to as progressive disclosure of information (PDI) which employs the concept of layers of information, distinguishing "outer layers (e.g. press release, summary, [oral presentations]) [that] refer to non-technical information, uncertainties integrated into the message, emphasis on context, implications and consequences" and "inner layers (e.g., appendices, background report, [or specific section like introduction, conclusion, recommendations]) [containing] detailed technical information, uncertainties discussed separately, emphasis on types, sources and the extent of uncertainty)"

(Wardekker et al. 2013). Different layers can be used that are adapted to specific target groups and uncertainty information to communicate. In any case, conclusions and recommendations should always directly include relevant and central information regarding uncertainty.

There are different, often complementary ways to present uncertainty information:

- Qualitatively (e.g. reporting sources of uncertainty and their potential influence on results);
- Descriptively (e.g. reporting central tendencies like mean and variability around the mean);
- Graphically (e.g. visualising uncertainty information in graphs);
- Numerically (e.g. reporting ranges, probability distributions of results values or statistical results).

Presenting uncertainty information in a verbal or descriptive way is useful, as it allows direct integration with the results and conclusions, especially for non-quantitative information and may be retained more easily than numerical information by most readers. It is particularly well suited for inclusion with outer layers (e.g. report summary). Such a description of uncertainties may be based on a quantified evaluation or even just on a qualitative appreciation of uncertainty. In any case, it is important to keep in mind that many terms typically used to describe uncertainty are quite imprecise and prone to vary in perception and interpretation among individuals, e.g. large, small, important, significant, etc. It is essential to use these terms consistently with the same meaning throughout a report and that they match numerical results, if available. They may even be explicitly defined, e.g. very likely = 90–99% probability, likely = 80–89% and so on.

If quantified, uncertainty information can also be communicated numerically, e.g. in tables, as standard deviations, minimum and maximum bounds, ranges, uncertainty and confidence intervals, probabilities, comparison with other studies or measurements, etc. This is useful especially for application in inner layers of information, such as a report appendix. A frequent mistake in this case is the communication of results and quantified uncertainties with a “false precision” showing too many digits. This practice suggests a very precise quantification of uncertainty that is most likely not defendable in an LCA context. For example, considering a typical standard deviation of a global warming impact score, a value of 2.49678 is essentially the same as 2.5 and in fact even the same as 3. The opposite may also exist, when a “false imprecision” is used to express numerical results so vaguely that they could mean anything, or are immune to criticism, but not very helpful for decision support.

Graphical representation of uncertainty can be provided in many different ways, e.g. using error (or uncertainty) bars or bands, box plots, probability distributions, coefficients of variation, confidence intervals, etc. This has the advantage that a lot of information can be aggregated and shown in a concise and structured way, allowing to capture a lot of uncertainty information in a short time and single graph.

This is illustrated in Fig. 11.15 which shows an example of a box plot (or whisker plot) of the spread of freshwater ecotoxicity characterisation factors for 2499 organic chemicals and 4 emission compartments from USEtox 2.02 (see Chap. 10 for further information regarding freshwater ecotoxicity characterisation factors). The boxes efficiently illustrate that 90% of the characterisation factors fall within the range of five to six orders of magnitude, whereas the difference between the lowest and highest characterisation factors (grey dots) is in the range of 16–19 orders of magnitude. Although the actual shape of the uncertainty distribution cannot the seen, it is visible that the distribution is skewed towards higher values with the median (the value at 50%) being in the upper range of values and not in the centre.

However, graphical representation of uncertainty also bears the risk of being suggestive, easily misinterpreted, or too complex. One of the most common ways to represent uncertainty is to plot the probability distributions of the output variables, as presented in Fig. 11.13 and discussed in Sect. 11.4.2. Alternatively to PDFs in Fig. 11.13, the Cumulative Distribution Functions (CDFs) of the outputs could be derived in order to characterise uncertainty. Another tool to represent uncertainty are the so-called probability boxes, based on a probability bounds approach (Karanki et al. 2009). The book "Environmental Decisions in the Face of Uncertainty" from the Institute of Medicine (IOM 2013) contains a useful overview and more in-depth discussion on graphical and other representations of uncertainty. For example, a frequent mistake when representing uncertainty in LCA is the use of error bars. Figure 11.16 illustrates this with error bars that we added to the original graph from the Quantis study discussed above, so that the resulting graph below represents uncertainty in an alternative way to Fig. 11.13. This representation of uncertainty can be seen in numerous LCA publications and presentations. The error bars here represent the absolute uncertainty of each compared option, but they do not consider interdependence of uncertainties between scenarios. However, by presenting them next to each other, Fig. 11.16 suggests that the error bars can be

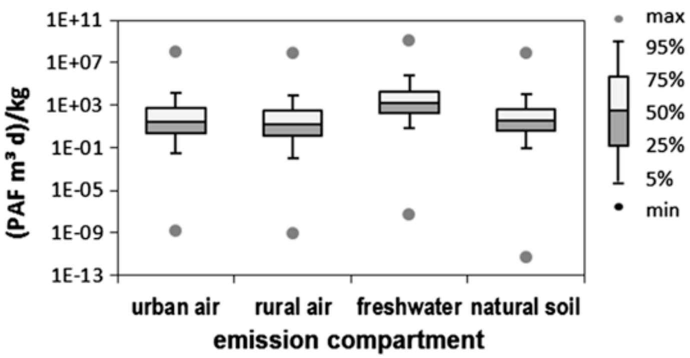

Fig. 11.15 *Box* or *whisker plot* of freshwater ecotoxicity characterisation factors for 2499 organic chemicals and 4 emission compartments from USEtox 2.02

directly compared among each other in order to determine if the uncertainty allows to visually distinguish these options. As discussed above, only the uncertainty of the difference (or ratio) for each paired comparison among these options (which will be smaller while only considering the uncertainty of the difference (or ratio) between two options) will truly allow to determine whether both options are distinguishable or essentially equal. The useful way of using error bars in this example would therefore be to present one for each pairing of these compared options, parallel to Fig. 11.14.

When using graphs, the scale of an axis should always reflect the underlying uncertainty. This is particularly important in LCA, where many impact scores may have an uncertainty spanning from one to several orders of magnitude, in which case it would be misleading to present them on a linear scale. In such cases, the results should preferably be shown using a log-scale, which will only emphasise larger differences between impact scores. Contrary to a frequent perception, this has nothing to do with data manipulation, since scores can still be identified by their exact value. It simply avoids over-exaggeration of very small differences that may look very large on a linear scale while (almost) disappear on a log-scale. A similar effect of over-exaggeration is achieved when zooming into a certain range of an axis, e.g. only showing the highest values from 80 to 100%, which will show differences between two points as much larger compared to the full range of the axis.

As indicated above, these approaches are complementary and should be used as such. Sometimes a repetition of the same (important) information via two different ways and at two different places in a report may be preferable over a concise, non-repetitive communication.

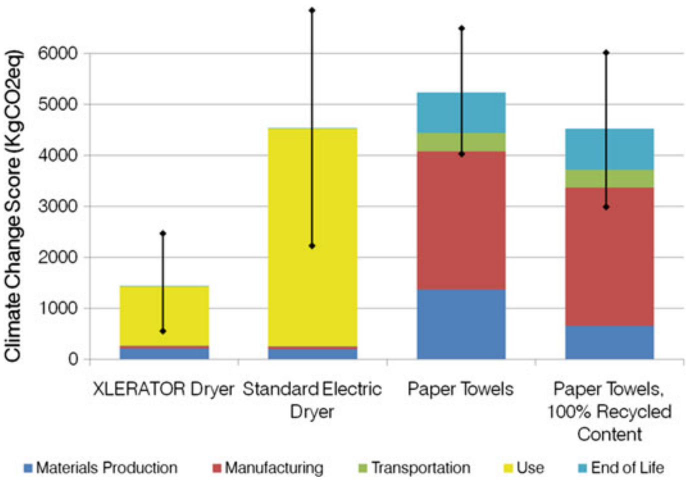

Fig. 11.16 Uncertainty bars for the climate change impact scores of four compared alternatives to dry hands (figure adapted from Quantis (2009) by adding error bars for illustrative purposes)

11.6 Management of Uncertainty

The strategy of how to consider and manage uncertainties in an LCA study depends on a number of factors that will determine what is feasible. The most important limitation is likely the availability of resources (time and/or budget) to collect additional information in order to quantify, represent and reduce uncertainty. Accessibility and level of operationalisation of the technical aspects of uncertainty assessment (e.g. databases providing default uncertainties for background LCI data and LCIA characterisation factors, LCA software providing ways to efficiently propagate uncertainties) is also frequently named as a potential barrier. In any case, there is always a minimum of uncertainty management that will be feasible without requiring important resources. In many scientific fields, uncertainty is managed using a tiered approach with each tier (or level of detail) progressively increasing the requirements and sophistication of uncertainty assessment and management. A particular advantage of such an approach is that it allows an iterative improvement and refinement of uncertainty management from a first qualitative listing of uncertainty sources, to a first quantitative estimation and screening, up to a sophisticated full uncertainty assessment as a study advances. This type of approach caters nicely to the iterative nature of LCA (see Sect. 6.3) and allows the LCA practitioner to adapt the extent of uncertainty management in a study to the available resources, instead of suggesting that uncertainty management always has to be done using the most complex approaches or not at all if resources are too limited to allow for a quantitative approach.

An example for such a tiered approach is the Guidance on Characterizing and Communicating Uncertainty in Exposure Assessment from the World Health Organisation (WHO 2008). It proposes four progressive tiers with increasing complexity from tier 0 (the absolute minimum) to tier 3 (the most sophisticated level):

Tier 0: Screening uncertainty analysis
Tier 1: Qualitative uncertainty analysis
Tier 2: Deterministic uncertainty analysis
Tier 3: Probabilistic uncertainty analysis

While the details of this framework are adapted to chemical exposure assessment, its underlying principle of iteratively increasing sophistication and complexity is a useful inspiration for LCA. Figure 11.17 shows the different levels of detail for each tier, from no uncertainty analysis (point estimate) at the bottom to probabilistic uncertainty analysis at the top.

An expert working group of the UNEP-SETAC Life Cycle Initiative on uncertainty management in LCA drafted a similar framework for LCA during a series of workshops between 2009 and 2012, which is a useful starting point

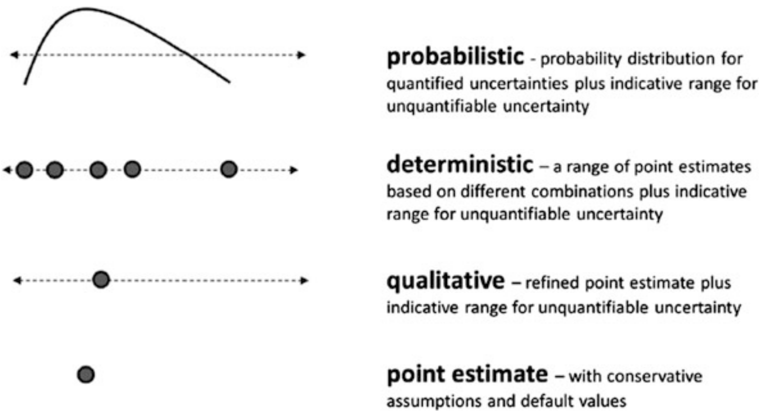

Fig. 11.17 Levels of detail for tiered uncertainty management strategies [taken from Paparella et al. (2013)]

towards integration of uncertainty management into LCA practice. They proposed five tiers:

Tier 0: Minimum transparency with a clear definition of what is considered a notable difference between scenarios for each impact category;

Tier 1: Screening level focusing on identification of important sources of parameter uncertainty providing information on importance and sensitivity of parameters, choices, assumptions, etc.;

Tier 2: Qualitative and semi-quantitative uncertainty assessment of important sources of uncertainty with systematic identification and description of uncertainties for all parameters, choices and assumptions including parameter and scenario uncertainty;

Tier 3: Quantitative uncertainty assessment of all sources of uncertainty with systematic quantification of uncertainties and variability for all parameters, choices and assumptions accounting for all quantifiable uncertainties;

Tier 4: Fully probabilistic LCA representing all relevant sources of influence by fully characterised uncertainty and variability separately.

In essence, different levels of sophistication are possible when establishing a strategy to integrate uncertainty management into a study and it is not always the most sophisticated level that is required. Compared to completely ignoring uncertainty, even a basic (e.g. qualitative) consideration is already better than nothing and a good and essential first step to pinpoint sources of uncertainty in the results of any LCA study. This helps to be conscious about potential pitfalls and misinterpretation when making a decision based on the conclusions of a study. It should also be noted that a tiered uncertainty assessment framework essentially serves as an orientation providing coherence for different levels of sophistication of uncertainty assessment.

It groups those elements of an uncertainty assessment that can be combined meaningfully on each level.

11.7 Perspectives

Uncertainty and variability are inherent properties of LCA, all its models, data, assumptions, and choices that are required when performing an LCA. Uncertainty is not the enemy, but it is unavoidable and its assessment can be helpful when put to good use for improving and interpreting LCA results. Uncertainty and its reduction is the very reason for the iterative nature of LCA and should hence be used as a guiding principle for the changes applied during each iteration of an LCA. Uncertainty and variability have many sources, some of which are quantifiable, while others are not, but all need to be considered when interpreting and discussing results and the robustness of a conclusion.

In order to be successfully applied in LCA, uncertainty assessment requires some knowledge of the underlying principles and methods as well as a set of tools supporting:

1. Quantification and storage of uncertainty, variability, and correlation or interdependence of inputs, models, assumptions, etc.
2. Propagation of input uncertainties to model output uncertainty
3. Tools for sensitivity, uncertainty, uncertainty contribution analysis and scenario comparison
4. Skilled interpretation and communication of relevant uncertainty information

Even though uncertainty assessment is an additional procedure to handle and provide resources for when conducting an LCA, it has multiple uses that will help ensuring that resources spent on the iterative improvement of the study actually contribute to a tangible improvement in uncertainty of the results and their enhanced interpretation in order to provide robust conclusions. Uncertainty assessment can notably be used to:

- Identify sources of uncertainty that dominantly contribute to the uncertainty of results
- Effectively target the iterative improvement of data, models and assumptions towards those elements that dominate the result(s) and their uncertainty
- Identify processes and elementary flows where archetypical or spatially explicit LCI and LCIA data will significantly reduce the uncertainty of the results due to the integration of spatial (or temporal) variability into the LCA
- Enhance the interpretation of results, e.g. which alternatives are truly different and which are not
- Quantify the confidence in the robustness of a conclusion or the probability of being wrong

Not only does the assessment and management of uncertainty in LCA provide a lot of opportunities and advantages, but ignoring it actually bears potentially important risks. For example, resources spent to improve the study may be inefficiently used when improving data and models with limited contribution to result uncertainty (e.g. when results are not sensitive to changes in inputs). Conclusions drawn from deterministic results may not only lack robustness but actually be misleading (e.g. when differences between results are not significant, i.e. falling within the uncertainty ranges of results).

From today's perspective, a lot can be done already to consider uncertainty, with many LCI databases and the first LCIA methods providing uncertainty estimates for their data, and most LCA software providing functionality to propagate those into the results. When exploring those options, it is important to be aware of the limitations that most if not all LCA software (while writing this book in 2016) does not provide the possibility to consider LCIA uncertainties, which may not always be obvious to the user. Running the uncertainty analysis will thus essentially propagate the uncertainties from the LCI database and result in a very incomplete quantification of uncertainty that may be missing many important sources on the LCIA side. Using this kind of uncertainty information to establish whether or not two alternatives have significantly different impact scores may still provide misleading conclusions and a false impression on their robustness due to its bias towards LCI uncertainty. To overcome this limitation, updates of LCIA methods will (increasingly) provide uncertainty estimates for characterisation factors (Bulle et al., in review).

With high uncertainties being a frequent, critical argument towards LCA, it is worth asking if LCA results are actually more uncertain than those from other assessment tools. No doubt that the precision of LCA results will be inferior to that of many other environmental assessment tools, especially the local and site-specific ones. This has a lot to do with scale, since LCA typically models entire supply chains that will usually be global, involve many processes about which little information is available, covering a broad range of environmental indicators and impact categories, and often spanning considerable time periods (defined in the duration of the functional unit) to be represented. The combination of large spatiotemporal scales and the complexity due to broad inventory flow and impact coverage, which is unique to LCA among environmental assessment tools, is the source of a lot of variability and uncertainty due to e.g. aggregating over larger spatial or temporal space and is thus simply a function of the space considered and data available. However, as discussed in this chapter, contrary to most environmental assessment tools, LCA does not attempt to predict absolute impacts, but rather focuses on the relative difference in potential impacts between alternatives, although exceptions exist, such as Environmental Product Declarations (EPD) which are "stand-alone" environmental profiles. Any systematic error and source of variability or uncertainty will usually have little influence on the uncertainty of the difference between alternatives. Therefore, the focus in LCA is accuracy and not necessarily precision.

While this chapter provides an overview of a range of aspects around uncertainty management in LCA, we recommend the cited literature for those readers looking for more in-depth insights into specific aspects. For further reading beyond literature cited above we recommend the following: Deeper insights on uncertainty representation in the context of LCA were published by Heijungs and Frischknecht (2005). For log-normally distributed parameters, Strom and Stansbury (2000) discuss the determination of distribution information from minimal literature information and provide a comprehensive overview on log-normal distributions. Heijungs and Kleijn (2001) further discuss contribution analysis, perturbation analysis, uncertainty analysis, comparative analysis, and discernibility analysis. De Schryver et al. (2011) explore how value choices in LCIA influence the uncertainty of (human health) characterisation factors. Clavreul et al. (2013) combine probability and possibility theories to represent stochastic and epistemic uncertainties in a consistent manner in LCA. Even though it does not discuss life cycle assessments and has a more risk-assessment based focus, a useful read regarding environmental decision making under uncertainty including aspects of communication and management of uncertainty is the book "Environmental Decisions in the Face of Uncertainty" from the Institute of Medicine (IOM 2013) which is freely available via The National Academies Press (NAP) website.

When discussing LCA indicators and results, we should be at least as critical, if not even more critical when presented with no or small uncertainties as we are when presented with large, but properly quantified uncertainties. Or to say it more eloquently with the words of physicist and Nobel laureate Richard P. Feynman: "What is not surrounded by uncertainty cannot be the truth".

Acknowledgements The authors gratefully acknowledge the support from Jon Dettling (Quantis) for allowing us to use their study as an example.

References

Björklund, A.: Survey of approaches to improve reliability in LCA. Int. J. Life Cycle Assess. **7**, 64–72 (2002). doi:10.1007/BF02978849

Bulle, C., Margni, M., Kashef-Haghighi, S., Boulay, A.-M., Bourgault, G., De Bruille, V., Cao, V., Fantke, P., Hauschild, M.Z., Henderson, A., Humbert, S., Kounina, A., Laurent, A., Levasseur, A., Liard, G., Patouillard, L., Rosenbaum, R.K., Roy, P.-O., Shaked, S., Jolliet, O.: IMPACT World+: A Globally Regionalized Life Cycle Impact Assessment Method (in review)

Ciroth, A.: Uncertainties in life cycle assessment. Int. J. Life Cycle Assess. **9**, 141–142 (2004). doi:10.1007/BF02994186

Ciroth, A., Fleischer, G., Steinbach, J.: Uncertainty calculation in life cycle assessments—A combined model of simulation and approximation. Int. J. Life Cycle Assess. **9**, 216–226 (2004). doi:10.1007/BF02978597

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

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

De Schryver, A.M., van Zelm, R., Humbert, S., Pfister, S., McKone, T.E., Huijbregts, M.A.J.: Value choices in life cycle impact assessment of stressors causing human health damage. J. Ind. Ecol. **15**, 796–815 (2011). doi:10.1111/j.1530-9290.2011.00371.x

EC-JRC: European Commission-Joint Research Centre—Institute for Environment and Sustainability: International Reference Life Cycle Data System (ILCD): Handbook—General guide for Life Cycle Assessment—Detailed guidance. First edition March 2010. EUR 24708 EN. Publications Office of the European Union, Luxembourg (2010)

Fantke, P., Wieland, P., Juraske, R., Shaddick, G., Itoiz, E.S., Friedrich, R., Jolliet, O.: Parameterization models for pesticide exposure via crop consumption. Environ. Sci. Technol. **46**, 12864–12872 (2012). doi:10.1021/es301509u

Funtowicz, S.O., Ravetz, J.R.: Uncertainty and Quality in Science for Policy. Kluwer Academic Publishers, Dordrecht (1990)

Greenland, S., Senn, S.J., Rothman, K.J., Carlin, J.B., Poole, C., Goodman, S.N., Altman, D.G.: Statistical tests, P values, confidence intervals, and power: a guide to misinterpretations. Eur. J. Epidemiol. **31**, 337–350 (2016). doi:10.1007/s10654-016-0149-3

Groen, E.A., Heijungs, R.: Ignoring correlation in uncertainty and sensitivity analysis in life cycle assessment: what is the risk? Environ. Impact Assess. Rev. **62**, 98–109 (2017). doi:10.1016/j.eiar.2016.10.006

Groen, E.A., Heijungs, R., Bokkers, E.A.M., de Boer, I.J.M.: Methods for uncertainty propagation in life cycle assessment. Environ. Model Softw. **62**, 316–325 (2014). doi:10.1016/j.envsoft.2014.10.006

Hauschild, M.Z., Potting, J.: Spatial Differentiation in Life Cycle Impact Assessment: The EDIP2003 Methodology. The Danish Ministry of the Environment, Environmental Protection Agency, Copenhagen (2005)

Heijungs, R.: A generic method for the identification of options for cleaner products. Ecol. Econ. **10**, 69–81 (1994). doi:10.1016/0921-8009(94)90038-8

Heijungs, R.: Identification of key issues for further investigation in improving the reliability of life-cycle assessments. J. Clean. Prod. **4**, 159–166 (1996). doi:10.1016/S0959-6526(96)00042-X

Heijungs, R.: The use of matrix perturbation theory for addressing sensitivity and uncertainty issues in LCA. In: Proc. Fifth Int. Conf. EcoBalance—Pract. tools thoughtful Princ. Sustain., 6–8 Nov 2002, Tsukuba, Japan (2002)

Heijungs, R.: Sensitivity coefficients for matrix-based LCA. Int. J. Life Cycle Assess. **15**, 511–520 (2010). doi:10.1007/s11367-010-0158-5

Heijungs, R., Frischknecht, R.: Representing statistical distributions for uncertain parameters in LCA: relationships between mathematical forms, their representation in EcoSpold, and their representation in CMLCA. Int. J. Life Cycle Assess. **10**, 248–254 (2005). doi:10.1065/lca2004.09.177

Heijungs, R., Huijbregts, M.A.J.: A review of approaches to treat uncertainty in LCA. Trans. 2nd Bienn. In: Meet. Int. Environ. Model. Softw. Soc. iEMSs, Osnabrück, Ger, pp 332–339 (2004)

Heijungs, R., Kleijn, R.: Numerical approaches towards life cycle interpretation five examples. Int. J. Life Cycle Assess. **6**, 141–148 (2001). doi:10.1007/BF02978732

Heijungs, R., Lenzen, M.: Error propagation methods for LCA—a comparison. Int. J. Life Cycle Assess. **19**, 1445–1461 (2014). doi:10.1007/s11367-014-0751-0

Heijungs, R., Suh, S., Kleijn, R.: Numerical approaches to life cycle interpretation—The case of the Ecoinvent'96 database. Int. J. Life Cycle Assess. **10**, 103–112 (2005). doi:10.1065/lca2004.06.161

Hoekstra, R., Morey, R.D., Rouder, J.N., Wagenmakers, E.-J.: Robust misinterpretation of confidence intervals. Psychon. Bull. Rev. **21**, 1157–1164 (2014). doi:10.3758/s13423-013-0572-3

Hong, J., Shaked, S., Rosenbaum, R.K., Jolliet, O.: Analytical uncertainty propagation in life cycle inventory and impact assessment: application to an automobile front panel. Int. J. Life Cycle Assess. **15**, 499–510 (2010). doi:10.1007/s11367-010-0175-4

Huijbregts, M.A.J.: Application of uncertainty and variability in LCA Part I: a general framework for the analysis of uncertainty and variability in life cycle assessment. Int. J. Life Cycle Assess. **3**, 273–280 (1998). doi:10.1007/BF02979835

Imbeault-Tetreault, H., Jolliet, O., Deschênes, L., Rosenbaum, R.K.: Analytical propagation of uncertainty in LCA using matrix formulation. J. Ind. Ecol. **17**, 485–492 (2013). doi:10.1111/jiec.12001

IOM: Environmental Decisions in the Face of Uncertainty. The National Academies Press, Washington, DC (2013)

IPCC: Climate change 2007—the physical science basis. Intergovernmental Panel on Climate Change (2007)

Karanki, D.R., Kushwaha, H.S., Verma, A.K., Ajit, S.: Uncertainty analysis based on probability bounds (P-box) approach in probabilistic safety assessment. Risk Anal. **29**, 662–675 (2009). doi:10.1111/j.1539-6924.2009.01221.x

Lloyd, S.M., Ries, R.: Characterizing, propagating, and analyzing uncertainty in life-cycle assessment: A survey of quantitative approaches. J. Ind. Ecol. **11**, 161–179 (2007). doi:10.1162/jiec.2007.1136

Morgan, M.G., Henrion, M.: Uncertainty: A Guide Dealing with Uncertainty in Quantitative Risk and Policy Analysis. Cambridge University Press, Cambridge (1990)

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

Paparella, M., Daneshian, M., Hornek-Gausterer, R., Kinzl, M., Mauritz, I., Muhlegger, S.: Uncertainty of testing methods—what do we (want to) know? ALTEX **30**, 131–144 (2013)

Pólya, G.: Über den zentralen Grenzwertsatz der Wahrscheinlichkeitsrechnung und das Momentenproblem. Math. Z. **8**, 171–181 (1920). doi:10.1007/BF01206525

Quantis: Comparative Environmental Life Cycle Assessment of Hand Drying Systems: The XLERATOR Hand Dryer, Conventional Hand Dryers and Paper Towel Systems. Salem, MA (2009)

Read, C.: Logic: Deductive and Inductive, 4th edn. Simkin and Marshall, London (1920)

Ross, S.: Simulation, 5th edn. Academic Press, Cambridge (2012)

Strom, D.J., Stansbury, P.S.: Determining parameters of logs from minimal information. Am. Ind. Hyg. Assoc. J. **61**, 877–880 (2000). doi:10.1080/15298660008984601

van Zelm, R., Huijbregts, M.A.J.: Quantifying the trade-off between parameter and model structure uncertainty in life cycle impact assessment. Environ. Sci. Technol. **47**, 9274–9280 (2013). doi:10.1021/es305107s

Walpole, R.E., Myers, R.H., Myers, S.L., Ye, K.: Probability and Statistics for Engineers and Scientists, 9th edn. Prentice Hall, Englewood Cliffs (2012)

Wardekker, J.A., Kloprogge, P., Petersen, A.C., Janssen, P.H.M., van der Sluijs, J.P.: Guide for Uncertainty Communication, PBL Netherlands Environmental Assessment Agency, The Hague, The Netherlands (2013)

Wei, W., Larrey-Lassalle, P., Faure, T., Dumoulin, N., Roux, P., Mathias, J.-D.: Using the reliability theory for assessing the decision confidence probability for comparative life cycle assessments. Environ. Sci. Technol. **50**, 2272–2280 (2016). doi:10.1021/acs.est.5b03683

Weidema, B.P.: Avoiding or ignoring uncertainty. J. Ind. Ecol. **13**, 354–356 (2009). doi:10.1111/j.1530-9290.2009.00132.x

Weidema, B.P., Wesnæs, M.S.: Data quality management for life cycle inventories—an example of using data quality indicators. J. Clean. Prod. **4**, 167–174 (1996). doi:10.1016/S0959-6526(96)00043-1

Weidema, B.P., Frees, N., Petersen, E., Øllgaard, H.: Reducing uncertainty in LCI, Danish Environmental Protection Agency, Copenhagen, Denmark (2003)

WHO (2008) Guidance Document on Characterizing and Communicating Uncertainty in Exposure Assessment. International Programme on Chemical Safety (IPCS), World Health Organization (WHO), Geneva

Author Biographies

Ralph K. Rosenbaum LCA expert and environmental modeller focusing on LCIA development since early 2000s. Contributed to several UNEP/SETAC working groups towards global harmonisation of LCA methodology. Interested in LCIA modelling of emissions and water/soil resource use, operationalisation of uncertainty management and spatial differentiation.

Stylianos Georgiadis Background in Applied Mathematics, focusing on stochastic and statistical modelling with application in urban water systems, food risk assessment, reliability and queueing models. Interested in uncertainty quantification in risk management, life cycle assessment and decision analysis.

Peter Fantke Develops methods for LCIA, health impact assessment and chemical alternatives assessment since 2006. Has contributed to UNEP/SETAC LCIA working groups and is USEtox Manager. Interested in quantifying and characterising chemical emissions, uncertainty analysis, consumer exposure, chemical substitution and model parameterisation.