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A Tier-Wise Method for Evaluating Uncertainty in Life Cycle Assessment

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Abstract: As a decision support tool, life cycle assessment (LCA) is prone to multiple uncertainties associated with the data, model structures, and options offered to practitioners. Therefore, to make the results reliable, consideration of these uncertainties is imperative. Among the various classifications, parameter, scenario, and model uncertainty are widely reported and well-acknowledged uncertainty types in LCA. There are several techniques available to deal with these uncertainties; however, each strategy has its own pros and cons. Furthermore, just a few of the methods have been included in LCA software, which restricts their potential for wider application in LCA research. This paper offers a comprehensive framework that concurrently considers parameter, scenario, and model uncertainty. Moreover, practitioners may select multiple alternatives depending on their needs and available resources. Based on the availability of time, resources, and technical expertise three levels—basic, intermediate, and advanced—are suggested for uncertainty treatment. A qualitative method, including local sensitivity analysis, is part of the basic approach. Monte Carlo sampling and local sensitivity analysis, both of which are accessible in LCA software, are suggested at the intermediate level. Advanced sampling methods (such as Latin hypercube or Quasi-Monte Carlo sampling) with global sensitivity analysis are proposed for the advanced level.

Keywords: life cycle assessment; framework development; uncertainty analysis; sensitivity analysis

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1. Introduction

Life cycle assessment (LCA) is among the frequently applied methodologies for evaluating the environmental aspects and impacts of a system (i.e., product, service, or process) and is often used as a decision support tool [1,2]. It analyzes the environmental repercussions of a system across its complete life cycle and has already been applied in various fields such as product improvement, eco-labelling, business planning, and policy development [3,4]. There are several sources of uncertainty in LCA. For instance, in the different phases of LCA, methodological choices such as defining the functional unit, selection of system boundaries, allocation procedures, the particular time horizon, etc. are unavoidable and result in several types of uncertainty. The treatment of these uncertainties is crucial to enhance the robustness and credibility of the obtained results.

The data presented in Figure 1 was retrieved from the Scopus using the 'Article title, Abstract, Keywords' search option until 2021 and the defined keywords were 'life cycle assessment', 'LCA', and 'uncertainty' with 'And' operator. The number of publications in 2022 is not included; however, an upward trend is expected for 2022 for both categories. From this figure, it can be clearly observed that LCA has been used extensively by the scientific community during the last three decades, with more than 2000 LCA papers published annually after 2018. However, only a few of these (not more than 5 to 10 percent) mentioned the word 'uncertainty' in the title, abstract or keywords. Even within these relatively few studies, some have mentioned uncertainty only in the context of future direction for further analysis. This indicates that less attention has been paid to uncertainty calculation by the LCA practitioners.

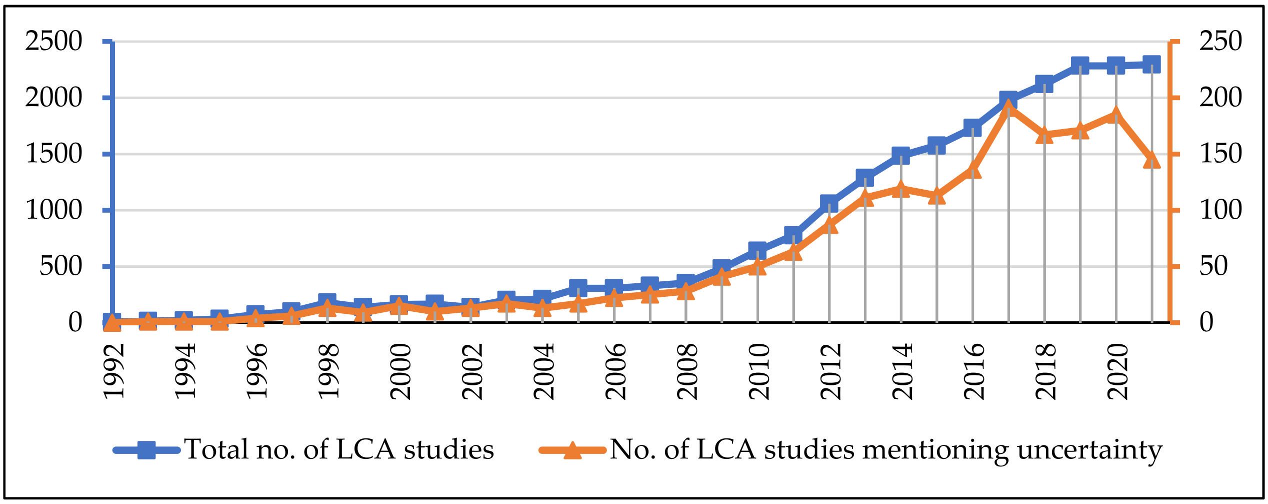

Figure 1. A number of LCA studies published annually (Note: Scopus is the data source).

The environmental implications of a system or a product can be evaluated with the help of LCA while considering the complete life cycle, which includes different stages, i.e., extraction of raw materials, production, usage, and end-of-life phase [5]. Considering the complete life cycle and multiple impact categories ensures that environmental improvements can be planned without relegating the negative impacts to other life cycle phases or other areas of protection. LCA studies usually comply with the general framework prescribed by the International Organization for Standardization (ISO) in ISO 14040 [6] and ISO 14044 [5]. Even when studies comply with these standards, differences in normative choices for the same product system might lead to conflicting outcomes [7]. As a result, international standards have been criticized as being excessively ambiguous [8,9]. This flexibility, on the other hand, is required to enable the application of these standards across diverse systems with varying characteristics. Other reasons for possible differences include the use of non-representative data, assumptions, and data gaps, all of which have led to criticism of the reliability of LCA outcomes [10]. The reliability of LCA is also affected by many other factors, e.g., dependency on data from various unit operations, diverse sources, several countries, data that is not gathered for LCA purposes, and biased methodological choices [10,11]. For instance, spatial variability can affect the atmospheric fate factor and soil sensitivity factor [12]. Furthermore, the presentation of LCA results is usually done as point estimates, which may lead to faulty decisions based on a misleading sense of accuracy regarding the environmental profile of a system [13]. Hence, there is a dire need for practical recommendations to facilitate the LCA practitioners so that the uncertainties associated with their analyses can be adequately addressed.

In 1992, a workshop by the Society of Environmental Toxicology and Chemistry (SETAC) first pointed out the importance of uncertainty in LCA in a data quality context (Fava 1994). Furthermore, a working group (i.e., the SETAC LCA) was founded in the early 1990s by the LCA community on data availability and data quality and recognized the need of embracing uncertainty [14,15]. The International Organization for Standardization has defined uncertainty analysis in ISO 14044 [5] as "a systematic procedure to quantify the uncertainty introduced in the life cycle inventory (LCI) results due to the cumulative effects of model imprecision, input uncertainty and data variability". In general, uncertainty either refers to the absence of sufficient knowledge or ambiguous information; however, in comparison, variability represents the quality of data which is heterogeneous in nature [16]. Despite the different meanings, the approaches used to deal with uncertainty and variability exhibit a large overlap. The standard suggests using probability distributions and ranges to support LCI conclusions to address uncertainties. LCA studies necessitate a vast quantity of data and assumptions at each stage of the analysis, making it difficult to identify and eventually propagate the uncertainty. As a result, a majority of LCA case studies still ignore uncertainty due to less knowledge/expertise and a lack of resources [17–19].

This quick overview of probable causes of uncertainty demonstrates that an LCA analysis is susceptible to a number of variables that could compromise the result's reliability. Various in-depth studies, such as Lloyd and Ries [20], Igos et al. [18], or Bamber et al. [19] on uncertainty identification, propagation, and characterization in LCA have been conducted, but a consistent approach has yet to be developed. Furthermore, the ISO 14040 [6] and ISO 14044 [5] standards do not provide any guidelines on how to conduct uncertainty analysis to support the LCA results. Although increasing emphasis has been dedicated to uncertainty analysis among the LCA community in recent years, there is still a need for a robust framework. The primary objective of this review is to propose a framework based on an updated overview of the available approaches for uncertainty treatment in LCA. Using the proposed stepwise approach, LCA practitioners can make informed decisions to propagate uncertainty in their analyses according to their available resources and constraints. The objectives of this study are summarized as follows:

- ➢ To summarize the sources and types of uncertainty;
- ➢ To list the possible ways to treat uncertainty in LCA;
- ➢ To characterize the common and best practices found in the previous literature;
- ➢ To discuss the pro and cons of applying the available approaches;
- ➢ To propose a tier-wise framework for uncertainty treatment.

2. Methodology

To fulfil the objectives of this study, a systematic literature review approach was adopted. However, some reference documents were provided in Table 1, focusing on uncertainty propagation, characterization, and/or reporting methods. Further, related references were provided in the subsequent sections. The procedure followed in this article consisted of four steps—questions preparation, literature identification, inclusion or exclusion criteria, and finally, classification and analysis of the selected studies. All of the steps are further explained below.

Step 1: Questions preparation

The following research questions were formulated by keeping in view the defined objectives:

- What are the main classes and types of uncertainty considered in LCA studies?
- What types of methods were chosen for uncertainty treatment in LCA studies?
- What are the pros and cons of using these approaches for uncertainty treatment?
- How was the uncertainty characterized and reported in the literature?
- The answers to these questions are provided in the results and discussion sections.

Step 2: Literature identification

Different databases (i.e., Scopus, ResearchGate, and Google Scholar) were used for the identification of the literature. The keywords 'life cycle assessment' 'LCA', and 'uncertainty' were searched in the title, abstract and author-specified keywords of the papers to ensure that the study is conducted from a life cycle perspective.

Step 3: Inclusion or exclusion criteria

The following criteria were used to include or exclude a study in the review:

- Only reference documents, peer-reviewed research articles (i.e., proposed methodologies or methods, and review articles and/or case studies), dissertation, and book chapters were selected;
- The articles in which uncertainty treatment approaches were not considered were excluded.

Step 4: Classification and analysis

This step included the categorization of considered studies keeping in view the following aspects: types of uncertainties (defined and/or applied in the selected studies), methods used for uncertainty propagation, characterization, and reporting. Furthermore, keywords related to the questions raised in Step 1 were also searched throughout the papers.

Table 1. Reviewed literature for uncertainty analysis qualification and quantification.

Reference	Type	Summary of the Content
Huijbregts [21]	Methodologies or Methods	Proposed a framework and classification of uncertainties.
Huijbregts et al. [22]	Case study (article)	Offers a broad approach for quantifying LCA uncertainties (i.e., parameter, scenario, and model) and illustrates it with a case study.
ISO 14040 [6] and ISO 14044 [5]	Reference documents	Provides a standard definition of uncertainty analysis in LCA but does not stipulate a framework for treatment while explicitly mentioning the treatment process as "Either ranges or probability distributions are used to determine uncertainty in the results".
Lloyd and Ries [20]	Review article	Surveyed 24 LCA studies that employed quantitative uncertainty analysis and summarized the available practices for uncertainty characterization and propagation.
Clavreul et al. [23]	Case study	The uncertainties particular to waste in LCA contexts were presented, as well as numerous approaches for uncertainty analysis. In addition, a comprehensive methodology for quantifying the uncertainty was also proposed.
Groen [2]	Dissertation	An in-depth analysis of variability and uncertainty in the LCA outcomes, using multiple approaches.
Igos et al. [18]	Review article	The approaches for identifying, characterizing, propagating (uncertainty analysis), understanding the impacts (sensitivity analysis), and communicating uncertainty were discussed.
Rosenbaum et al. [15]	Book chapter	Discusses how to assess, analyze, and convey uncertainties in LCA contexts.
Mendoza Beltran [17]	Dissertation	A deeper picture of the significance of multiple sources of uncertainty in LCA is offered by highlighting various sources of uncertainty.
Bamber et al. [19]	Review article	Common sources of uncertainty and techniques to address them were outlined, and their frequency of use was assessed.

3. Results and Discussion

This section includes the uncertainty classification, propagation, characterization, and communication of uncertainty in LCA studies. The following aspects of the selected studies were evaluated: the types of uncertainties, methods used for uncertainty propagation, and criteria for uncertainty characterization and reporting in LCA. Furthermore, based on the available information, three tiers have been proposed to incorporate uncertainty analysis in LCA studies.

3.1. Uncertainty Classification

Several attempts to include uncertainty in LCA have been made in recent decades, suggesting that LCA practitioners are becoming more conscious of the topic's importance and influence. Numerous classifications have been identified in the literature regarding uncertainty types, ranging from two or three classes to ten or more [15,24]. In the late 1990s, Huijbregts [21] proposed a general framework by distinguishing three types in particular: parameter uncertainty, uncertainty due to normative choices, and model uncertainty as presented in Table 2.

Table 2. Typologies used in literature to classify the uncertainty.

Author(s)	Classification	Description
Huijbregts [21]	Parameter uncertainty	Defined as error in parametric quantities, inadequate or outdated measurements (corresponding to unrepresentativeness of the data), or no data (generally corresponding to lack of data).
	Scenario uncertainty	Defined as the structuring of several options in order to compare results for various normative choices connected with functional units, weighting factors, and/or allocation procedures, and so on.
	Model uncertainty	Model uncertainty is introduced due to emissions aggregation in the inventory analysis and deriving characterization factors using linear modeling.
Basset-Mens et al. [25]	Intra-system variability	Uncertainty inside a considered system.
	Intersystem variability	Uncertainty between different systems under consideration.
Clavreul et al. [23]	Epistemic uncertainty	The insufficient knowledge, which is simply referred to as uncertainty.
	Stochastic uncertainty	Spatial, temporal, and technological unpredictability (mostly known as variability).
Igos et al. [18]	Quantity uncertainty	Further classified into epistemic (lack of data) and ontic (variability) uncertainty.
	Model structure and context uncertainty	The formulation of alternate scenarios to analyze findings based on different assumptions is a popular way to differentiate the two (e.g., allocation procedures, geographic resolution, or supplier choice).

Björklund [10] extended Huijbregts' [21] approach by subdividing parameter uncertainty into uncertainties due to data inaccuracy, data gaps, and unrepresentative data. She further elaborated on additional uncertainty categories (e.g., epistemological uncertainty, uncertainty due to mistakes, and estimations). Rosenbaum et al. [15] introduced relevance uncertainty, which is more closely linked to an indicator's environmental relevance or representativeness towards an area of protection. However, this is a contribution to the interpretation side but not the numerical model output. Basset-Mens et al. [25] defined intra-system variability as uncertainty within a product system and intersystem variability as uncertainty between different product systems. Clavreul et al. [23] classified uncertainty as epistemic uncertainty (i.e., the insufficient knowledge which is simply referred to as uncertainty) and stochastic uncertainty (i.e., spatial, temporal, and technological unpredictability) mostly known as variability in LCA. Igos et al. [18] classified uncertainty into two main classes: 1) quantity uncertainty, and 2) model structure and context uncertainty. In short, many studies have investigated uncertainty and classified it by considering different perspectives. However, the classification of uncertainty in LCA as parameter, scenario, and model uncertainties, is generally acknowledged and widely applied [19,20,26].

3.2. Uncertainty Propagation

Several methods for the treatment of uncertainty have been reported in the surveyed literature (qualitative such as pedigree, quantitative such as sampling, analytical methods, etc.). Analytical methods, fuzzy data sets, and stochastic and scenario modeling were among the different methods identified in a previous survey conducted by Lloyd and Ries [20]. Bamber et al. [19] surveyed a large LCA dataset to analyze the approaches used to treat uncertainties in both attributional and consequential LCA. Igos et al. [18] also made an in-depth discussion on sampling methods, fuzzy logic, analytical and statistical methods, and sensitivity analysis approaches. This review not only discusses the available approaches comprehensively in the context of considered classifications of uncertainty but also tries to fill the information gaps identified in the previous literature.

3.2.1. Parameter Uncertainty

In general, parameter uncertainty (also known as uncertainty in data) refers to the uncertainty in seen or measured values caused by the stochastic nature of the system, as well as data quality uncertainty. As noted in the literature reviews conducted by Bamber et al. [19] and Lloyd and Ries [20], this review also found that the parameter was the most widely reported uncertainty source while the other key sources of uncertainty were typically missed. The different methods (i.e., qualitative and quantitative) used to treat parameter uncertainty including pedigree matrix, sampling methods, analytical methods, statistical methods, and sensitivity analysis are discussed below.

Pedigree Matrix

This is a qualitative method to propagate parameter uncertainty; the idea was proposed by Weidema and Wesnæs [27] and has since been improved and utilized in research [10,28]. It has also been included in the ecoinvent database [29]. Weidema and Wesnæs [27] specified five qualities of the dataset (i.e., reliability, completeness, temporal, geographic, and technical correlations), and Frischknecht et al. [29] added sample size to this list. Weidema et al. [30] once again omitted the sample size after introducing the default factors for uncertainty. In this method, data quality indicators are converted to probability distributions by using a 'default' lognormal distribution to describe the data quality indicator value. Each indicator is further separated into five levels (i.e., with a score ranging from 1–5), and a predefined uncertainty factor is assigned against each score in terms of geometric standard deviation [11,29]. A few types of LCA software (i.e., openLCA and CMLCA) facilitate the propagation of uncertainty using this approach.

Ciroth et al. [11] applied the pedigree method to analyze uncertainties associated with the empirical outcomes using the ecoinvent database and discovered that the pedigree approach tended to underestimate inherent uncertainties. Another study, conducted by Yang et al. [31] to analyze the spatial disparities in intermediate flows of LCI data considering key crops in the United States with the help of the pedigree approach revealed that the uncertainty is significantly underrated in the ecoinvent database. Furthermore, by conducting a survey, Qin et al. [32] also evaluated the level of acceptability of the pedigree approach as a method of characterizing uncertainty in LCA. Qin et al. [32] also analyzed uncertainty in the LCI and characterization phases using the pedigree approach. However, the intended objective and validity of this quantitative use of the pedigree scheme may be questioned because it only evaluates the dataset quality while disregarding any inherent uncertainty or dispersion of the data [7]. Furthermore, despite other benefits, the pedigree system relies on subjective expert judgments, raising questions regarding its legitimacy and usefulness [32]. On the other hand, despite strong criticisms regarding its reliability and subjectivity, this approach is still a helpful tool to propagate parameter uncertainty. The pedigree matrix could be a useful option (especially for data which is only represented by a single value) to propagate uncertainty.

Sampling Methods

A quantitative approach can be adopted to address parameter uncertainty by using sampling methods such as Monte Carlo, Quasi-Monte Carlo, or Latin Hypercube. With the development of Monte Carlo sampling in the mid-19th century, the use of sampling methods to propagate uncertainty began [24]. Furthermore, Monte Carlo is one of the more well-adopted methods used by the LCA community for parameter uncertainty propagation [18–20]. It randomly changes uncertain parameters; however, the variation is limited by the distributions specified for the considered parameter. Repeated calculations provide an expected output value distribution that represents the combined parameter uncertainty. Latin Hypercube sampling (also known as stratified sampling) operates in the same way as Monte Carlo sampling with only one difference. In this method, a parameter uncertainty distribution is split into several non-overlapping intervals, each with an equal probability. Furthermore, a number is drawn randomly from the predefined distribution, resulting in more exact random samples and a faster convergence rate than Monte Carlo. Morris and Mitchell [33] and Tarantola et al. [34] proposed significant improvements to the original Latin Hypercube method, viz., maximin Latin Hypercube sampling and Latin supercube sampling. The Quasi-Monte Carlo method uses pseudo-random numbers for sampling; which is the only exception which makes it different from Monte Carlo sampling [35]. Quasi-random numbers are deterministic numbers that are evenly distributed for a particular distribution function [34]. A flowchart to propagate uncertainty through sampling methods is presented in Figure 2. As indicated in the figure, after LCA modeling (which includes goal and scope definition, inventory analysis, impact assessment, and identification of parameter contribution), the process of uncertainty propagation through the sampling method requires the parameter distribution details. The uncertainty characterization can further be done based on the data quality or distribution of the parameters (i.e., significant inputs and outputs). Further discussion on the uncertainty characterization approaches is presented in Section 3.3.

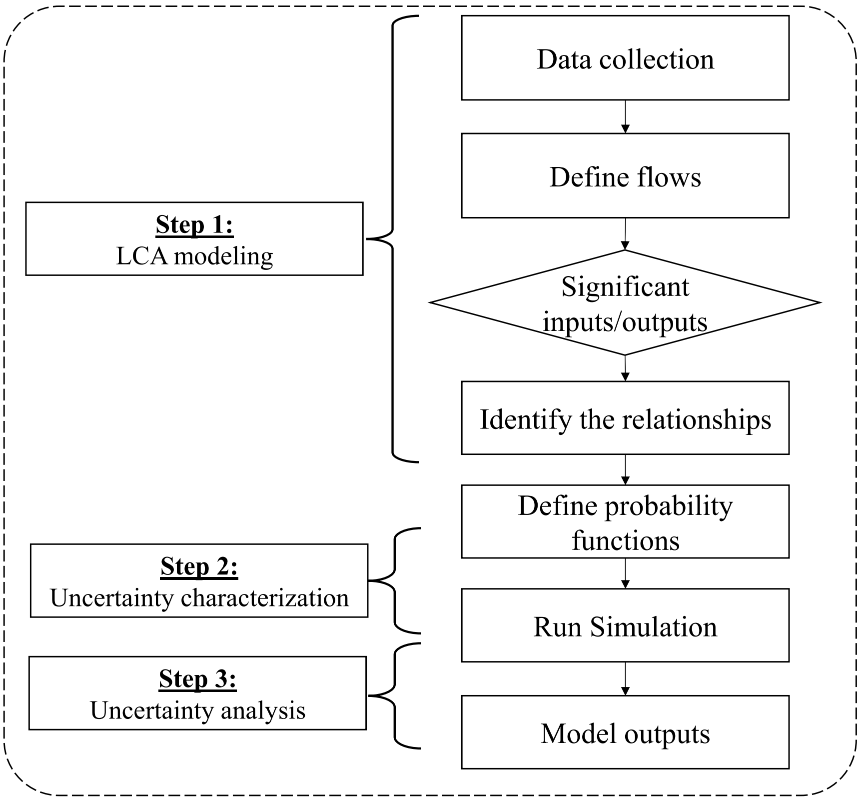

Figure 2. General flowchart to propagate uncertainty through sampling methods.

In order to achieve representative findings, Monte Carlo sampling (i.e., generally available in all LCA software) necessitates a large number of simulations (i.e., ranging from 1000 to 10,000 runs) making this approach time-intensive [18]. On the other hand, Heijungs [36] recommended that the number of runs employed in simulation should equal to the sample size used for the input parameters. Furthermore, Heijungs also recommended that Monte Carlo sampling should not be employed at all if input parameters are evaluated through the pedigree approach. Furthermore, it is easier to deal with sampling methods if a correlation among the parameters exists. Bojacá and Schrevens [37] investigated the correlations between parameters by testing the covariance of the inventory data. In this study, a multivariate normal distribution was used rather than using a single univariate distribution for correlated parameters. In essence, sampling methods seem to be a promising option to operationalize uncertainty analysis in LCA. However, the advanced sampling methods (i.e., Latin Hypercube sampling or Quasi-Monte Carlo sampling), are employed less frequently since practitioners have to rely on non-LCA software (i.e., Oracle Crystal Ball, MATLAB, or SimLab).

Analytical Methods

The Gaussian approximation, proposed by German mathematician Carl Friedrich Gauss, is the oldest and most well-known mathematical approach for uncertainty propagation. Morgan and Henrion [38] demonstrated how to obtain a first-order approximation using the Taylor series expansion of a function that connects model input parameters and model outputs. At a given point, a function is calculated using derivatives and represented as a sum of unlimited terms. This method is based on the assumption that all critical inputs are independent and linear.

Heijungs [39] was the first one to suggest this approach in the LCA context. Ciroth et al. [40] demonstrated its application to LCA by considering a virtual case. Hong et al. [41] extended this work by applying it to a real-world problem for the carbon footprint evaluation of vehicle parts, in which they compared many scenarios. Hong et al. [41] and Imbeault-Tétreault et al. [42] used this approach to calculate global warming potential using lognormal distributions of data and characterization factors. This adaptation is advantageous as most probability distributions (e.g., in the ecoinvent database) used in LCA are lognormal. This approach is also incorporated in CMLCA software and Heijungs and Lenzen [43] applied it using input–output tables. Furthermore, Groen and Heijungs [44] critically examined the feasibility of different implementation approaches and analyzed the correlations while considering a general case study. However, analytical methods are typically limited to linear and continuous models. While comparing sampling and analytical methods, both approaches used for LCA consistently showed good agreement [41–43]. The main merits of the analytical approach are its simplicity and speed of calculation. The time-intensive nature of Monte Carlo is a significant issue when it comes to regular uncertainty assessment in LCA.

Statistical Methods

Bayesian statistics—This approach relies on empirical data, e.g., the available information of sample data and a prior distribution. Since the selection of a distribution is also conditional to the available information or group of experts, the primary function of this approach is to provide estimates that properly reflect the genuine state of knowledge while avoiding severe cognitive and motivational biases. As previously indicated, Monte Carlo sampling is a standard approach for parameter uncertainty propagation. The distributions of unknown parameters must be given explicitly in traditional Monte Carlo sampling. The information provided to Monte Carlo simulation may be updated and relevance assessed by combining it with Bayesian inference. As a result, Bayesian inference is expected to address the issues resulting from a lack of knowledge, in addition to providing a framework for integrating judgmental information with observational data to estimate uncertain parameters. Bayesian Monte Carlo analysis has not been widely used for life cycle assessment as compared to the sampling methods and is not included in any LCA software.

Another disadvantage of Bayesian approaches is that they are intrinsically subjective, as there is a risk of a lack of consistency or replicability, especially if the same study is conducted by various groups with different expert judgments [45]. A sensitivity analysis, on the other hand, can be used to determine if such variations have a major influence on the conclusions; if they do, it is helpful to identify discrepancies in order to enlighten the decision-maker or to design a study program to gather evidence on which such disagreements can be addressed. Despite its shortcomings, the Bayesian method is more responsive in dealing with circumstances when data is insufficient or missing, but the level of knowledge is sufficient to make judgments about prior distributions.

Fuzzy logic—In this method, the uncertainty is operationalized using fuzzy interval arithmetic by assigning possibility functions to uncertain parameters. To propagate the uncertainty through possibility functions, lower and upper limit intervals should be known and disseminated across the model concurrently [46]. This is performed by assigning a probability of one to the most likely value(s) and a probability of zero to the most implausible value(s) (outside the lower and upper bounds).

The fuzzy interval arithmetic method was first employed by Weckenmann and Schwan [47] in LCA contexts, using fuzzy membership functions for inventory data. Tan [48] formalized this approach for resolving LCA matrixes. This method requires the type of possibility function, the mean value, and the upper and lower bounds of each input variable. One of the key merits of the approach is that it requires less information to provide insight into the output uncertainty, hence it is not computationally intensive. However, the approach is not yet completely developed, and it has not yet been incorporated into LCA software. On the other hand, when paired with probability distribution sampling (i.e., hybrid approach), the dependability and information offered can be improved.

Sensitivity Analysis

A sensitivity analysis is carried out by altering input parameter(s) to analyze the effect on the output. Sensitivity analysis may be done in two ways: (1) local sensitivity analysis and (2) global sensitivity analysis. Analyzing the effect of altering one of the input parameters at a time on the outcomes is known as local sensitivity analysis (LSA). However, in cases of global sensitivity analysis (GSA), all input parameters change simultaneously to analyze sensitivity and variation in results. Furthermore, the contribution to the output variance may be estimated if the distribution functions of the parameters are known.

The local sensitivity analysis (also referred to as perturbation analysis) is the most basic approach in which the sensitivity of a parameter can be measured [49]. LSA can easily be implemented using LCA software as there are several options available for altering inputs. A particular arbitrary value (say $\pm$10% or 20%) can be employed for uncertain parameters, minimizing the need for extra data collection but causing biases in conclusions owing to varied uncertainty ranges among inputs. Rather than considering an arbitrary value for an uncertain parameter, the standard deviation can be a more appropriate option. In LSA, model linearity is presumed and it deals with a limited set of input domains. Furthermore, there is a possibility that the parameter correlation and interactions might be overlooked.

On the other hand, global sensitivity can be employed to analyze sensitivity and variation in results while changing all input parameters simultaneously [50]. A Monte Carlo sampling-based correlation analysis is a basic GSA method. The slope of the outcomes in response to the input variables is used to estimate the regression coefficients. The obtained regression coefficients help to analyze the contribution of uncertain parameter(s) to output variance. Another option is to use Spearman's rank correlation coefficients, which compute correlation coefficients based on the rank of values. This method, which has been employed in LCA before [51,52], may be used to find correlations in non-linear models. GSA is further classified as dependent and independent GSA. A standard independent GSA, such as Sobol indices, can be employed if all of the input parameters are independent. If the input parameters are correlated, the LCI data-induced correlation effects must be assessed using dependent GSA [50]. A decision tree to make the selection easy among sensitivity analysis is presented in Figure 3.

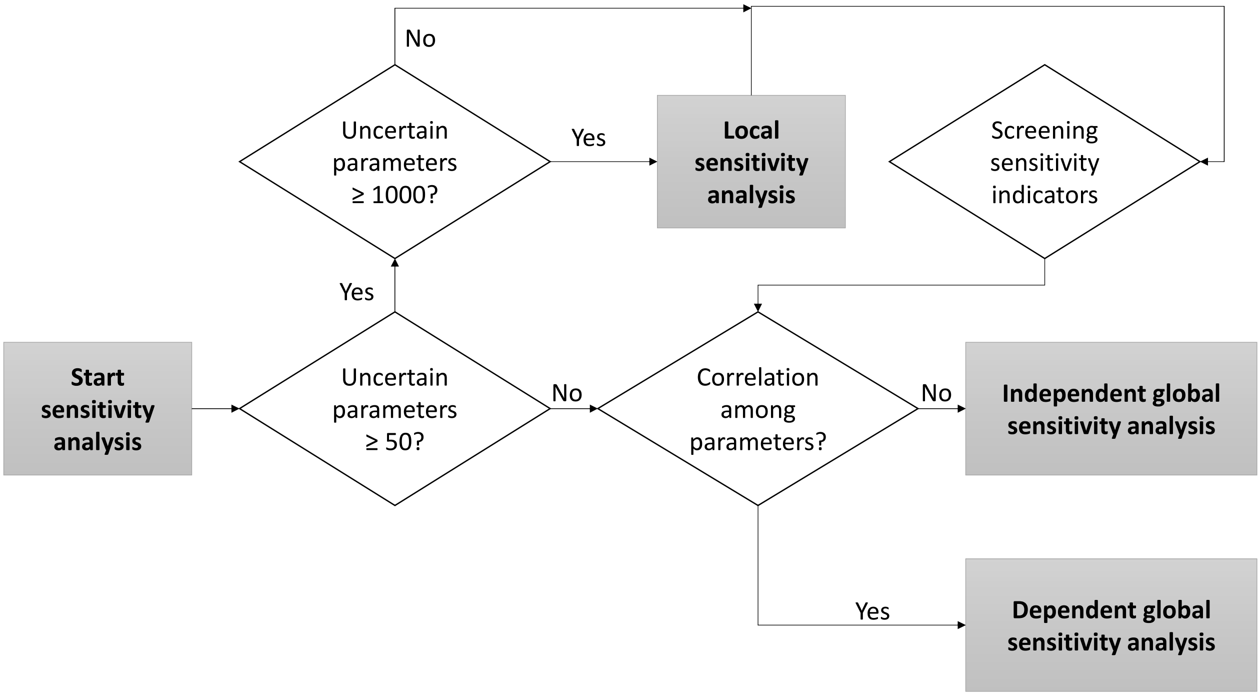

Figure 3. Decision tree for the selection of sensitivity analysis method (adopted from Wei et al. [50]).

In short, there are various approaches available to deal with parameter uncertainty in LCA; however, each method has its own pros and cons. A brief discussion has already been provided in the previous part. Here, a comparative discussion among these approaches is provided in Table 3.

3.2.2. Scenario Uncertainty

Scenario analysis is frequently employed in LCA to investigate uncertain decisions due to defining multiple scenarios. The sensitivity of the results is demonstrated by the extent of the variation among the findings of baseline and the alternative option(s) considered. Scenario uncertainty is influenced by the normative choices available to practitioners (e.g., geographical scales, functional units, allocation procedures, time horizons, weighting factors, waste-handling scenarios, etc.). Ylmén et al. [53], for example, conducted a study to emphasize choice uncertainty in LCA and to limit subjective interpretations of numerical data that lead to inappropriate judgments. Mendoza Beltran et al. [54] also adopted a strategy to propagate data uncertainty as well as uncertainty caused by methodological choices, especially due to the allocation methods used. In this study, Monte Carlo simulations were employed to analyze the data uncertainty and the different allocation methods were used as a scenario analysis. More representative outputs were obtained through this approach regarding the overall uncertainty. Furthermore, modeling of each adopted allocation approach as a separate scenario and simulating a Monte Carlo sampling on each of them also gave faster results.

Table 3. Merit and demerit-based consolidated discussion of identified approaches to treat parameter uncertainty.

Approaches	Pros	Cons
Sampling methods	The sampling methods produce more (directly) usable information than other methods (i.e., fuzzy interval or analytical approaches). Small and large uncertainty ranges can also be handled. If correlations exist between parameters, then it is technically easy to deal with.	It is time intensive as sometimes hours to days are required for simulations. More information related to the parameters (e.g., parameters/inputs and distribution type) is required. Advanced sampling methods (i.e., Latin Hypercube sampling, and Quasi-Monte Carlo sampling) are not available in LCA software.
Analytical methods	It may require complex mathematical equations, though uncertainty propagation is efficient and straightforward to apply with this approach. Computationally quick. Type of distribution and input parameters are not required. The correlation among the parameters can also be noted.	Fairly inflexible and confined to simple models. Less broadly applicable than Monte Carlo sampling method. It only works with small uncertainty ranges and provides lesser information than the sampling methods.
Statistical methods	This is preferable to sampling methods in terms of calculation time. It enables subjective uncertainty estimations to be addressed using normal statistical computing processes. When used with other approaches, it can provide more information.	This method is not yet fully functional in LCA and provides less information than analytical and sampling procedures.
Sensitivity analysis	Local sensitivity analysis is a promising approach for LCA practitioners just because of its simplicity and compatibility with LCA software. Global sensitivity analysis can provide a robust analysis regarding output sensitivity by studying the whole input space.	Local sensitivity analysis could be time extensive if there are many parameters. Global sensitivity analysis requires a large amount of data and a long computation time based on the probability distribution of inputs. Furthermore, it is not yet operational in LCA software.

Note: Conclusions are based on the information presented in Huijbregts [21], Lloyd and Ries [20], Rosenbaum et al. [15], Igos et al. [18], and Bamber et al. [19].

3.2.3. Model Uncertainty

In general, environmental interventions are often assumed to respond linearly to ecological systems in impact evaluations, and intervention thresholds are overlooked. The creation of characterization factors also contributes to model uncertainty. The choice and characteristics of the underlying models, as well as the list of substances for which characterization factors are derived, all contribute to the uncertainty in the impact assessment phase [55]. Model uncertainty cannot be reduced by LCA practitioners owing to the complexity of the mathematical connections which define the models (including models for creating emissions and characterization factors) [19], but it should be recognized and commented on wherever possible. For instance, the uncertainty in impact categories such as (eco)toxicity is substantially higher (measured in terms of error order of magnitude in characterization factor) than climate change or eutrophication. This is owing to a better knowledge of the underlying environmental processes as well as the modeling approaches that are used for climate change or eutrophication. Practitioners should be aware that (model, parameter) uncertainty fluctuates according to an indicator's position in the causation chain, which connects emissions to damage indicators through midpoints. Comparing the findings of midpoints and endpoints is a useful approach for a comprehensive study of model uncertainty, and if outcomes change, a more detailed inquiry must be conducted [15].

3.3. Uncertainty Characterization

Uncertainty can be characterized qualitatively and quantitatively. In the absence of sufficient uncertainty information, a pragmatic approach (i.e., the Pedigree method) can be used to characterize uncertainty. For instance, Yang et al. [31] applied it to characterize the uncertainty qualitatively. Parameter uncertainty can be dealt with qualitatively with the help of a pedigree matrix, but its application has also been questioned [7]. On the other hand, the model or scenario uncertainty cannot be addressed by this approach. Moreover, the pedigree approach is highly generic in nature and a sector-specific adaptation is required [31].

For characterization of the uncertainty quantitatively, the variability range can be specified according to the data representativeness and system stochasticity. There are several choices available that are commonly used to characterize uncertainty—probability distribution (random variable occurrence probability), fuzzy intervals or possibility distribution (depicting an imprecise set of probable values), variance (dispersion), and intervals (defined as lower and upper bond) [18]. In general, probability distributions have been used to characterize parameter and model uncertainty. On the other hand, the characterization of scenario uncertainty has been done in the literature through the development of unique scenarios.

Lognormal, normal, uniform, triangular, and gamma distributions are frequently encountered in literature [20]. However, the probability distribution provides rich information, and it also allows statistical treatment in terms of confidence interval or correlation [18]. Most of the studies have applied more than one distribution to avoid bias. For instance, Ullah et al. [13] applied multiple distributions (i.e., lognormal, Inverse Gaussian, and generalized extreme value). Henriksson et al. [7] proposed eight-data-point criteria for determining the kind of probability distribution. If there is not enough data to accurately explain the distribution, the practitioner could try a few other distributions, as done by Lacirignola et al. [56].

Qin and Suh [57] conducted a study to determine the best-fit distribution function for life cycle inventory. It was found that the lognormal distribution was generally used in ecoinvent for unit processes. Furthermore, from the obtained results, it was revealed that lognormal distribution is more reliable in terms of overlapping coefficients than the gamma or Weibull distributions. Qin and Suh [57] also urged the need for distribution of aggregate LCIs as unit process-based uncertainty analysis will be time-consuming and might not be necessary for most studies. However, Heijungs et al. [58] asserted that this results in an overestimation of the uncertainty in final outcomes. In another attempt, Suh and Qin [59] discovered that considering pre-calculated inventories and related geometric standard deviations results in a modest underestimate, not an overestimation. On the other hand, Muller et al. [60] claimed that the choice regarding the distribution types has no effect at all on comparisons of the product system. However, a default distribution should be selected for systems under consideration.

3.4. Uncertainty Reporting

In LCA, uncertainty reporting plays an imperative role in ensuring a robust and reliable analysis. The communication of uncertainty becomes more crucial in terms of unbiased interpretation from non-experts (such as decision-makers, marketing analysts, and the general public, etc.), as the LCA results are not limited just to the LCA community. In general, the uncertainty information can be presented in four different ways which include: qualitative, descriptive, graphical, and/or numerical. The qualitative method includes describing sources of uncertainty and their possible impact on outcomes, whereas the descriptive approach includes presenting central tendencies (i.e., mean, median, or mode) and variability (i.e., standard deviation) around the central tendency. The graphical method, on the other hand, is a graphical representation of the available uncertainty information. Reporting ranges (e.g., lower and upper bounds), probability distributions of outcomes, or statistical results are examples of numerical methods. The graphical method was the most common approach used to communicate information related to the uncertainty analysis. To present their findings, studies employed histograms, error bars, box-and-whisker plots, and cumulative distribution functions. The types of comparisons used in the selected studies to compare outcomes ranged from visual inspection to statistical testing. For instance, Ylmén et al. [53], opted for a visual approach with the help of confidence intervals to demonstrate the difference between judging deterministic and probabilistic study findings. Allegrini et al. [61], on the other hand, communicated uncertainty using error bars and histograms. Ullah et al. [13] used boxplots and distribution functions to demonstrate their findings. Statistical analysis results were communicated in tabular form and a descriptive approach was adopted to convey the effect size of the error in the outcomes. The advantages and disadvantages of the four methods are summarized in Table 4.

Table 4. Pros and cons of uncertainty communication approaches.

Approach	Pros	Cons
Qualitative	It enables quick integration of outcomes and drawn conclusions, particularly for non-quantitative data, and is easier to remember for most readers than numerical data.	Many of the terms used to characterize uncertainty qualitatively are erroneous and sensitive to human perception and interpretation.
Descriptive	It may also be easily coupled with the results and conclusions, which is particularly beneficial when dealing with quantitative data.	This approach is susceptible to several anomalies while defining the terms clearly, use them consistently, and link them to numerical data if available.
Graphical	This has the benefit of presenting a large dataset in a compact and organized manner, allowing us to report sufficient uncertainty information in a short time and on a single graph.	Graphical depictions of uncertainty can be deceptive, easily misinterpreted, or unnecessarily intricate at times.
Numerical	This method is particularly useful in inner layers of data, e.g., in a report appendix.	Communicating uncertainties with "false precision" displaying too many numbers is a typical error. This technique necessitates a highly precise quantification of uncertainty, which is unlikely to be justified in the context of an LCA.

3.5. Uncertainty Management Strategies

Many of the studies have highlighted uncertainty types and agree upon grouping them as parameter, scenario, and model uncertainties [18–20]. Various uncertainty analysis approaches have been developed and applied in LCA. However, the selection of approaches may be influenced by numerous aspects, which include the nature of the model, analysis needs, analyst expertise (in terms of software), and the resources available (particularly in terms of time and money). The available approaches for uncertainty treatment are mentioned under each class of uncertainty (i.e., parameter, scenario, and model) separately. Therefore, the uncertainty classification for the proposed framework is also considered as parameter, scenario, and model uncertainty. The three main steps (i.e., uncertainty propagation, characterization, and reporting) are highlighted in Figure 4; various toolboxes (i.e., methods and approaches) are listed under these steps for uncertainty propagation, characterization, and reporting. The highlighted boxes represent the uncertainty types (i.e., parameter, scenario, and model uncertainty) and their adaptation should be done according to the recommended approaches presented in the results and discussion section (see Figure 5) for uncertainty analysis. The red dashed line depicts the repetitive nature of various LCA phases (i.e., goal and scope definition, inventory analysis, impact assessment, and interpretation phase).

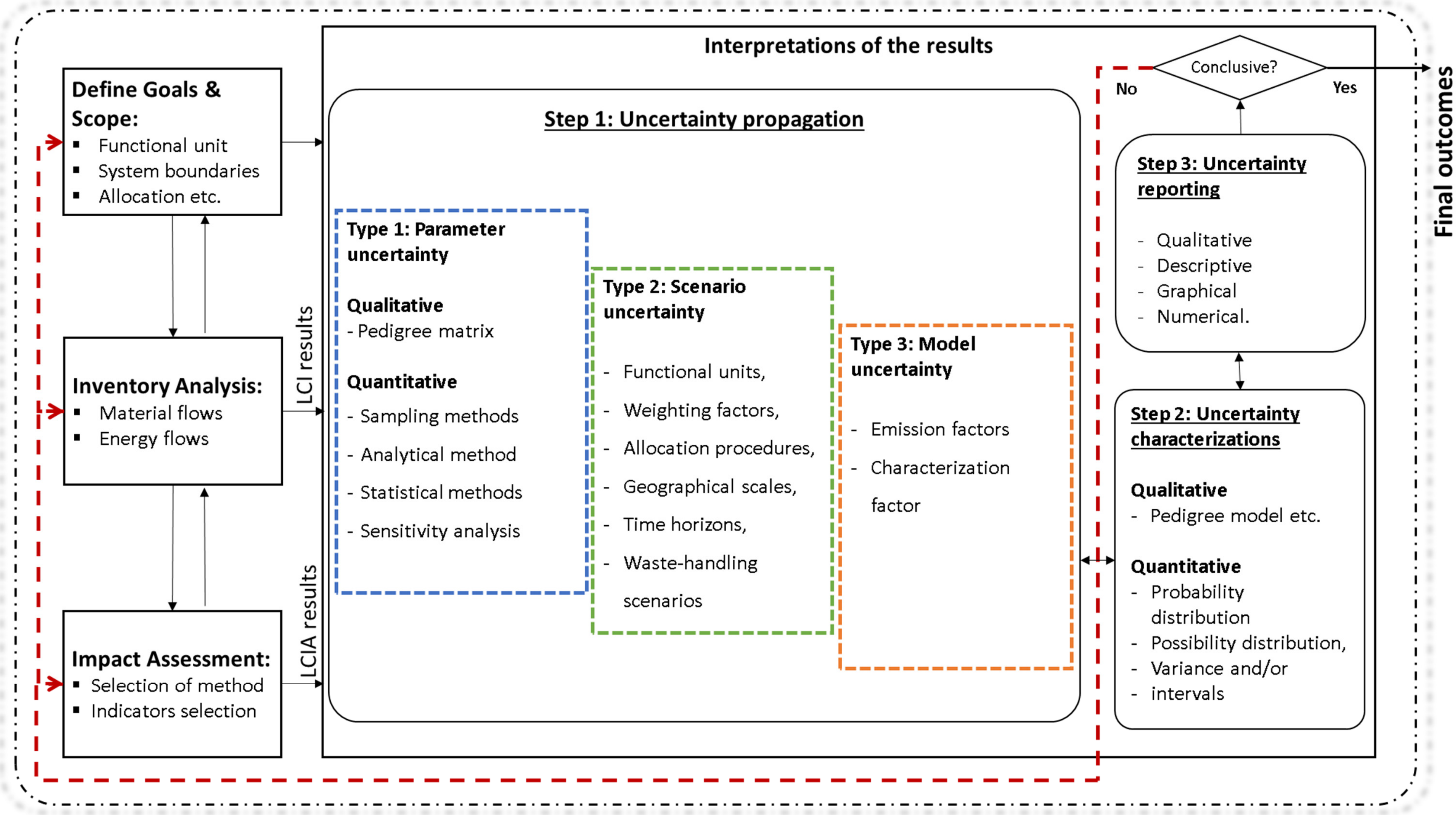

Figure 4. The proposed framework for uncertainty treatment in LCA.

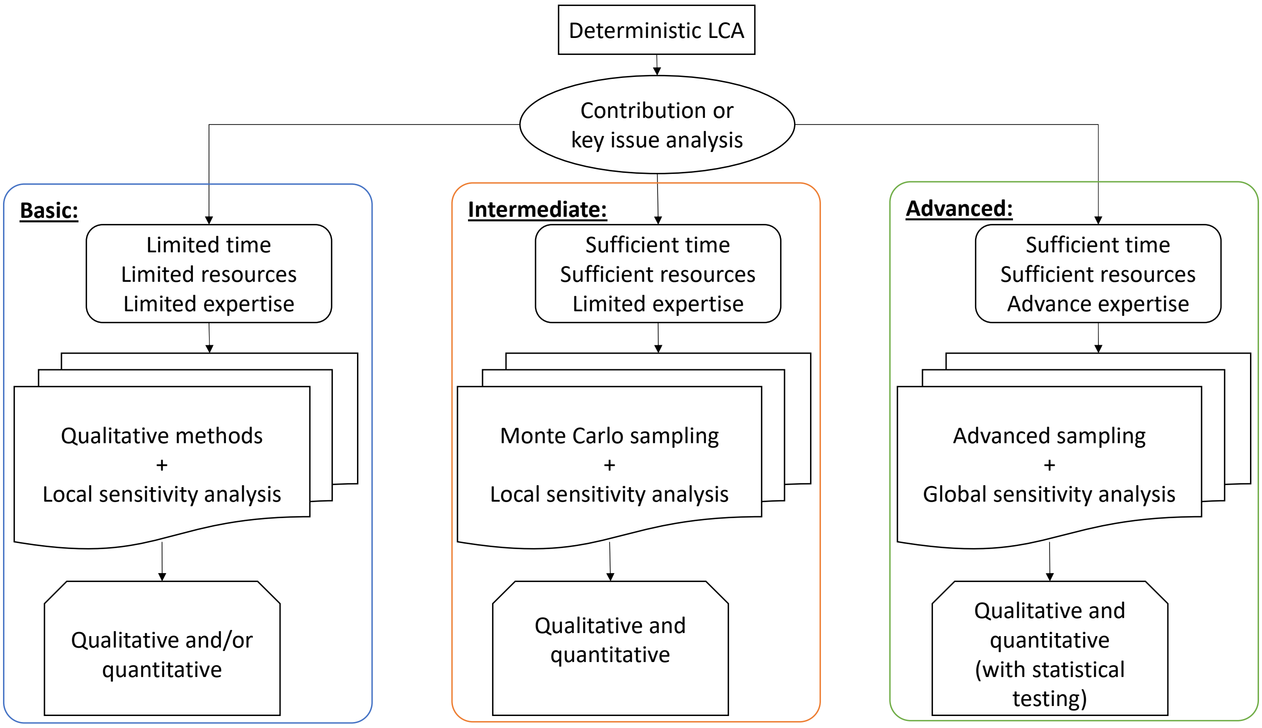

Figure 5. Recommended approaches considering level of expertise and resources.

The approach for managing (i.e., propagating, characterizing, and communicating) uncertainty in LCA research can be determined by considering the various circumstances (i.e., by identifying what is practicable). One of the key limitations to acquiring information in order to address the uncertainties associated with LCA outcomes is the availability of time, resources, and levels of expertise. In many scientific disciplines, uncertainty is managed while considering different tiers, in which complexity and demand for uncertainty assessment increase with each tier (or degree of information). This method has the advantage of permitting iterative progress and refinement of uncertainty outcomes as the study advances, from a preliminary estimation and screening to a sophisticated uncertainty analysis. This systematic selection allows the practitioner to tailor the scope of analysis according to the available resources, rather than selecting the most complicated method or disregarding all of them if resources are insufficient.

Rosenbaum et al. [15] presented a tiered approach drafted by the UNEP–SETAC working group on uncertainty management. The framework provided by Rosenbaum et al. [15] consists of five basic steps (which were generic in nature). Furthermore, Igos et al. [18] also recommended three levels for uncertainty treatment in LCA. However, at the advanced level, the selection of treatment approach was restricted to Latin Hypercube sampling. Therefore, drawing inspiration from these two frameworks, a tier-wise approach is recommended in Figure 5 considering three tiers, basic, intermediate, and advanced. The basic approach includes a qualitative method and local sensitivity analysis. LSA is being proposed in conjunction with the qualitative method as it may help to identify the critical input parameters. The intermediate level consists of a Monte Carlo sampling approach coupled with local sensitivity analysis, as both are available in LCA software. In conjunction with Monte Carlo, LSA is also being proposed so that probability distribution of significant parameters must be employed (if possible). The advanced treatment approach comprises of advanced sampling methods (i.e., Latin Hypercube or Quasi-Monte Carlo sampling) paired with global sensitivity analysis. The reason to place both sampling methods (i.e., Latin Hypercube or Quasi-Monte Carlo sampling) at the advanced level is that non-LCA software is required for both of them. Further statistical analysis should be performed in order to check the significance of the obtained results. In short, when developing a plan for uncertainty management, there might be various levels of sophistication that can be considered, and the most advanced one is not always required. Even a simple (e.g., qualitative or semi-quantitative) evaluation is a helpful and crucial first step in pinpointing sources of uncertainty in an LCA study conclusions when compared to completely disregarding uncertainty analysis. Ultimately, this process will help us be aware of potential issues and misconceptions while making an informed decision. It is also worth mentioning that a multilevel framework for uncertainty assessment can serve as a quick guide for individuals with distinct expertise. In each instance, there is always a basic minimum that may be performed without requiring considerable resources for uncertainty management.

4. Conclusions

The integration of uncertainty analysis and increased objectivity are pressing concerns in the field of LCA without which the credibility and scientific integrity of obtained results may be compromised. As various essential tools for incorporating uncertainty are now available, further efforts are required to operationalize these approaches while considering different levels of expertise and available resources. For this, a tier-wise framework has been proposed for uncertainty treatment in LCA, allowing practitioners to adopt the level of sophistication based on their needs and available resources. The lack of time, funding, and technical expertise were identified as the significant constraints, including uncertainty considerations which are especially important for robust decision-making. Parameter, scenario, and model, the well-acknowledged classes of uncertainty in LCA, were considered in the proposed framework. Among the considered classifications of uncertainty, model uncertainty was less reported than parameter and scenario uncertainty.

A brief review of the literature revealed that there are a wide number of approaches available to deal with such kind of uncertainties in LCA; however, there is no consensus yet on a preferred approach. Furthermore, there are various limitations of the current approaches considering both methodological and computational aspects. It was also revealed that only a few of the methods have been integrated into commercially or publicly available LCA software, which limits their broader use in LCA studies. An inclusive framework is provided in this study considering parameter, scenario, and model uncertainties, simultaneously. At the very basic level, a qualitative method (i.e., pedigree matrix), coupled with local sensitivity analysis was recommended; this method is already available in most standard LCA software. Local sensitivity analysis may help to analyze the sensitivity of results due to scenario and model uncertainty. However, in this approach, the uncertainty due to the system stochasticity will be overlooked while characterizing the uncertainty based on data quality. On the other hand, Monte Carlo sampling is frequently used for parameter uncertainty, it requires information regarding the input parameter and associated probability distribution. Furthermore, it is computationally intensive and may take several hours to days for simulations. Therefore, this approach was recommended at the intermediate level coupled with local sensitivity analysis. Local sensitivity analysis was recommended in conjunction with Monte Carlo as it may help to identify all the critical parameters so that their probability distributions could be considered in the analysis (if available). Furthermore, using this approach, scenario uncertainty can also be addressed along with parameter uncertainty when defining scenarios, and simulating Monte Carlo runs on each of them separately can give faster results. Advanced sampling methods (i.e., Latin Hypercube and Quasi-Monte Carlo) were proposed in conjunction with global sensitivity analysis at the advanced level as they are not yet available in LCA software, and an advanced level of expertise is required for implementation. However, advanced sampling has a faster convergence rate than the typical sampling method and global sensitivity analysis checks the sensitivity of the parameters over the entire input domain. Therefore, considering the benefits of both advanced sampling methods and global sensitivity analysis are recommended at the advanced level. The time-intensive nature could be a major limitation in the case of intermediate and advanced levels. Further considerations are provided below for the sake of a robust analysis:

- Both quantitative and qualitative characterization of uncertainty should be done by the LCA practitioners. Furthermore, parameter, scenario, and model uncertainties should also be reported in the LCA studies. When excluding any type of uncertainty, justification should be provided.
- Although model uncertainty cannot be propagated as parameter or scenario uncertainty, an assessment of model uncertainty may be commenced by comparing the outcomes of midpoint and endpoint indicators. If the results vary, a more extensive investigation should be conducted.
- LCA practitioners should not rely just on a single method (e.g., Monte Carlo sampling or Latin Hypercube sampling) and indicator (i.e., probability distribution, fuzzy intervals, variance, and intervals) for uncertainty propagation and characterization, respectively. Before making the final decision related to the methods or indicators, multiple options should be employed for the sake of unbiased interpretation.
- Usually, the advanced and reliable approaches are rarely applied by practitioners due to a lack of knowledge, time, data, or tools. LCA software should be improved and must include the new methods (not limited to Monte Carlo sampling).
- Various techniques such as histograms, error bars, distribution functions, etc. have been used for uncertainty communication. As LCA results are not limited only to the LCA community, uncertainty reporting must be done in a way that is easily understandable by non-experts as well.

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