GROWING UNCERTAINTY

Finding suitable methods of uncertainty propagation for agricultural Life Cycle Assessment in developing countries

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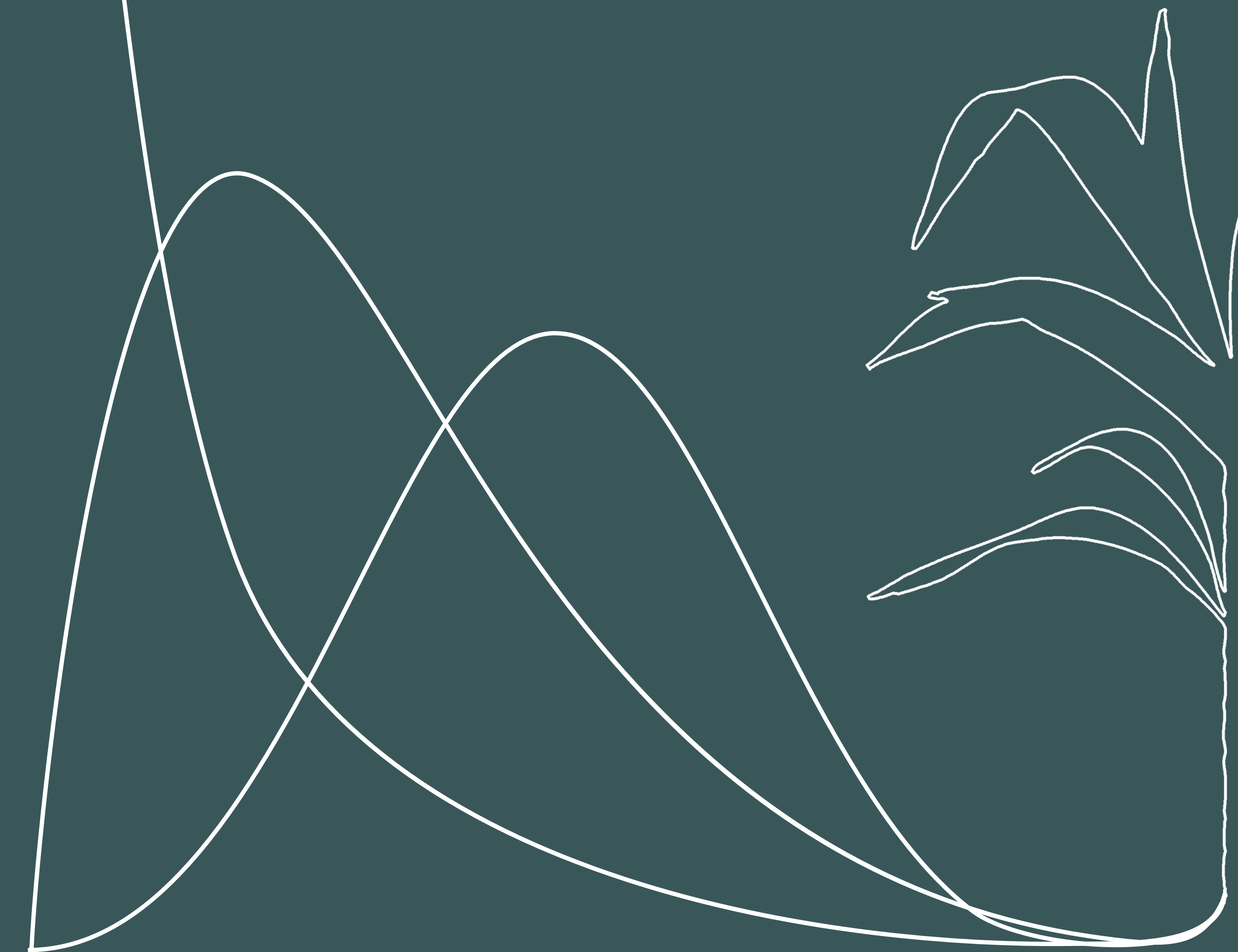

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Wisse ten Bosch

Master's thesis

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Doubt is not a pleasant condition, but certainty is absurd.

– VOLTAIRE, 1694-1778

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Abstract

Life cycle assessment (LCA) has been the primary tool for the quantification and comparison of the environmental impact of product systems. Despite ongoing development of the LCA methodology, uncertainties are often not adequately addressed in LCA research. The large variety of approaches to treat uncertainties and the lack of uniform guidelines prevent a widespread adoption of uncertainty analysis, while its importance is generally acknowledged. Especially in the agricultural sector, where LCA is often used as policy support, uncertainties are of great importance. This thesis aims to provide guidelines for practitioners of agricultural LCA in developing countries, as agriculture is often an important sector there. To this end four different method of uncertainty propagation are tested on a case study of sugarcane cultivation methods in Thailand. These methods are compared and evaluated on their suitability for agricultural LCA in developing countries, complemented by an expert survey in a Thai LCA research network. The results show that there is a general lack of knowledge among LCA practitioners on uncertainty analysis, while primary data is often abundant. Also, sampling methods can provide great insight into the output uncertainties, but are also complex and data intensive. Analytical or fuzzy interval methods could be a good alternative when knowledge or resources are lacking. LCA practitioners should be better guided in choosing and performing the most suitable propagation method for their situation. To this end, a decision tree for choosing the most suitable method depending on the user and the type of study closes this thesis.

Keywords: *life cycle assessment, uncertainty analysis, propagation, agriculture*

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Abbreviations

AUP	Analytical uncertainty propagation
CV	Coefficient of variation
EIA	Environmental impact assessment
FIA	Fuzzy interval arithmetic
GHG	Greenhouse gas
GOF	Goodness-of-fit
GSA	Global sensitivity analysis
GWP	Global warming potential
ISO	International Organisation for Standardisation
JGSEE	Joint Graduate School of Energy and Environment
KIA	Key issue analysis
KMUTT	King Mongkut University of Technology Thonburi
LCA	Life cycle assessment
LCI	Life cycle inventory
LCIA	Life cycle impact assessment
LSA	Local sensitivity analysis
MCS	Monte Carlo simulation
MEE	Method of elementary effects
OAT	One-at-a-time approach (sensitivity analysis)
pdf	Probability density function
SD	Standard deviation

1. Introduction

1.1 Background

In the light of climate change and environmental threats there has been a growing interest in sustainable development to improve environmental conditions for present and future generations. The challenges that this implies are arguably large, especially for developing countries as economic growth has been priority there, and climate change has only recently become a topic in policy development (Markandya & Halsnaes, 2002). At the same time developing countries often lack the scientific capacity and institutional support for tackling environmental problems (Kates et al., 2001). It has been argued that decision support tools for environmental policy, often developed in developed countries, can provide the basis for a shift towards sustainable development in developing countries (Cash et al., 2003). To this end, there has been growing interest from environmental scientists in tools to quantify and compare environmental impacts of products and services. The primary tool to do so is life cycle assessment (LCA), which aims to assess the environmental impacts and resources used throughout a product's life cycle (Finnveden et al., 2009). This comprehensive assessment enables, through its holistic approach, the comparison of product functions in terms of environmental impact (Guinée et al., 2002). LCA can therefore be used for a wide range of product types, including consumer products, industrial products and agricultural products (Bauman & Tillman, 2004). When considering environmental impacts in developing countries, agricultural products are especially important because the economies of many developing countries are largely dependent on agriculture (Tilman, 1999). LCA has proven to be a valuable tool to assess environmental impacts of agricultural products in developing countries, such as biofuels and renewable energy from biomass (Paolotti et al., 2017).

While early LCA studies, termed *ecobalances* or product environmental profiles, were conducted without a uniform methodology or harmonisation, standardisation efforts in the 1990s led to uniform guidelines for LCA practices (Klöpffer, 2006). The International Organisation for Standardisation (ISO) developed the first complete series of LCA standards with the ISO 14040 series (ISO, 2006). The ISO standard divides the LCA procedure into four phases (as described in Guinée et al., 2002):

1. *Goal and scope definition*; initial choices for the working plan are made, including definition of a research question, research scope and functional unit.
2. *Inventory analysis*; in this phase the product system is defined, including system boundaries, unit processes and data, allocations and final calculations. The main result is the inventory table presenting a list of quantified inputs and outputs.
3. *Impact assessmen*t; in this phase the results of the inventory analysis are interpreted in terms of environmental impact.
4. *Interpretation*; in this final phase the results from the impact assessment are evaluated in terms of completeness, consistency and robustness, and overall conclusions are formulated.

Over the last decade LCA methodology has seen an ongoing development and harmonisation, especially regarding consistency, data quality, and addressing uncertainty (Finnveden et al., 2009). Uncertainty of outcomes is one of the main issues recently discussed around LCA methodology (Finnveden et al., 2009). The acknowledgement that LCA research intrinsically includes a certain level of uncertainty is not new, and assessing these uncertainties has been named an essential part of LCA research (Ciroth, 2006). In an LCA context, uncertainty has been described by Finnveden et al. (2009, p. 14) as "the discrepancy between a measured or calculated quantity and the true value of that quantity''.

Existing LCA studies often do not address uncertainties, as is the case with many decision support tools (Finnveden et al., 2009). While the importance of addressing uncertainty has been acknowledged by many (e.g. Guo & Murphy (2012) and Payraudeau & Van Der Werf (2005)), uncertainties are often not properly addressed in LCA studies (Zamagni et al., 2009). Arguably this is a troublesome finding, especially when considering the potential impact of LCA studies in decision-making. As LCA can offer decision support aiming at sustainable development, uncertainties within LCA studies should not be neglected (Tillman, 2000).

The fact that many LCA studies do not address uncertainties properly has been ascribed by Geisler et al. (2005) to the lack of an 'integrative' approach, where uncertainties are transparently addressed according to uniform guidelines throughout LCA practices. Also, quantifying uncertainty through uncertainty analysis can be very time consuming, making it difficult to implement in LCA by default (Sonnemann et al., 2003). These issues are underlined by the large variety of approaches to treat uncertainty seen in LCA research. Many different quantitative methods are used to assess uncertainty in life cycle inventory (LCI) data. While generally only one of those methods is used, different methods might yield different outcomes (Lloyd & Ries, 2007). The suitability of different methods of uncertainty analysis for different types of LCA studies, and different ways of presenting their results has been subject of scientific debate in recent years. Henriksson et al. (2015a) state that the outcomes of uncertainty assessment need to fit the purpose of the study. For example, not all uncertainty analysis methods are suitable for comparative analysis of alternatives (Heijungs et al., 2017). The inappropriate use of uncertainty assessment methods for comparative purposes has been subject of recent debate, which has not yet led to a consensus among practitioners.

In the light of decision support for sustainable development in developing countries, agricultural LCA research can be very beneficial. For the purpose of assessing the environmental impact of e.g. biofuels and renewable energy, LCA has proven to be a valuable tool that enables the comparison of e.g. different functions of biomass (Paolotti et al., 2017). In terms of decision support, LCA outcomes can underline the significance of policy targets for environmental management. For example, LCA can be used to guide sustainable production of food products through comparison of different food products in terms of environmental impact (Mungkung & Gheewala, 2007). At the same time, it can be argued that uncertainty assessment in agricultural LCA is becoming increasingly important when LCA-based research on agricultural products is used in a comparative way as decision-making support. Nevertheless, scientific expertise and financial support for adequate LCA research is often lacking in developing countries, hindering adequate use of LCA studies for the benefit of sustainable development (Chiu & Yong, 2004). Moreover, the non-uniformity of uncertainty assessment approaches in LCA methodology does not promote an effective integration of LCA in national policies, especially considering the importance of uncertainty assessment in a decision-making context. Developing or adopting a uniform procedure for uncertainty assessment in agricultural LCA could improve the value of such research for sustainable development in developing countries.

1.2 Aim & research questions

Based on the issues discussed above, a twofold problem statement can be made:

1. The multiplicity of methods to assess uncertainty in LCA makes it difficult to treat uncertainties in an appropriate, uniform manner in a decision-making context, while consequences can be considerable. Research on the different outcomes that different methods might yield and their suitability for agricultural LCA purposes is yet to be conducted.
2. Developing countries can benefit significantly from agricultural LCA research to promote sustainable development, but the lack of a uniform procedure to assess uncertainties impedes appropriate use of such research.

The aim of this research is to address these two issues as follows: to provide guidelines for LCA practitioners in the field of agricultural LCA in developing countries on how to appropriately apply uncertainty assessment in their work. The research question is therefore:

> *What methods of uncertainty analysis are most suitable to use in agricultural life cycle assessment in developing countries in terms of procedure and outcomes?*

To answer the main research question, the following sub-questions will be answered:

1. What are the drivers and barriers for practitioners of agricultural LCAs in developing countries for applying uncertainty analysis?
2. What methods for assessing uncertainty in LCI data are available?
3. What are the differences in outcomes when applying different methods of uncertainty propagation on agricultural LCI data?
4. How can the results be used to guide practitioners of agricultural LCA to appropriately apply uncertainty assessment in their work?

1.3 Structure & case study

This thesis is structured as follows. First, the theoretical approach to this study will be presented in chapter two, as well as the theoretical framework in which the study is carried out. In the third chapter the methodology will be discussed. The fourth chapter will consist of the results of the methods used, and the sub-questions will be answered. The main research question can be answered based on the answers to the sub-questions. The final chapters will contain a discussion of this study and the final conclusions. To adequately address the problem statement, which is focussed on LCA research in developing countries, data from a real LCA research from the Thai King Mongkut's University of Technology Thonburi (KMUTT) in Bangkok will be used to compare different methods of uncertainty analysis by means of a case study. This LCA research, on different sugarcane cultivation practices, provides field data and an LCA model suitable for performing uncertainty analysis. The Thai LCA study is introduced here, the actual case study that will be performed as part of this thesis is explained in the methodology.

The LCA study was carried out in 2013-2014 by researchers from KMUTT's Joint Graduate School for Energy and Environment (JGSEE), in cooperation with partners from the sugarcane industry and different research institutions. The project was funded by the Thai National Science and Technology Development Agency and the Thailand Research Fund under the Royal Golden Jubilee

Ph.D. program (grant PHD/0101/2557). The LCA study discusses the environmental impacts of the sugarcane industry in Thailand, as part of a larger sustainability research project on the Thai sugar industry. Aside from the environmental impact assessment the project includes economic objectives regarding production efficiency and economic security, and social objectives regarding fair trading and safety and health issues.

The LCA study comprises the environmental impact the processes of cultivation of sugarcane and the refining of sugarcane into raw sugar, bio-ethanol and by-products. The goal of the study was to provide baseline environmental impact information of the Thai sugarcane industry, as well as providing recommendations for both competitive and sustainable practices in the sugarcane industry based on different scenarios. The main distinction between the scenarios was the cultivation practice (either conventional cultivation including pre-harvest field burning or 'green' cultivation with mechanical harvesting), and the production and use of different by-products from the sugar milling process (e.g. for electricity production and fertilizer). The results of the different scenarios were used to construct a roadmap to set targets for sustainable practices in the sugarcane industry. Publications resulting from the LCA study cover environmental impacts of different harvesting practices (Pongpat et al., 2017) and environmental sustainability of sugarcane biorefineries (Silalertruksa et al., 2017). For this thesis only the research on the cultivation of sugarcane will be used in the case study, thereby not considering the use of by-products in other processes. The main conclusions regarding the environmental impact of sugarcane cultivation practices include that green cultivation results in less greenhouse gas (GHG) emissions than conventional cultivation, because emissions from harvesting machinery are lower than from pre-harvest field burning. Also, most GHG emissions occur during the land treatment stage rather than during the harvesting stage (Pongpat et al., 2017).

Uncertainty analysis was not performed during the LCA study. The only information regarding data quality was given by the standard deviations of the input data of several parameters in the LCA model, but not all.

2. Theoretical approach

2.1 Theory

In order to assess the uncertainty propagation methods as mentioned in the research aim, it is necessary to elaborate on the theoretical background of uncertainty in LCA and types of methods that can be used to assess uncertainty. In this chapter, the state-of-the-art of scientific work on uncertainty analysis in LCA is presented. Subsequently a framework is presented within which this study is conducted.

2.1.1 Uncertainty in LCA

Before discussing uncertainty assessment it is essential to understand the concept of uncertainty in the context of LCA. As mentioned before, uncertainty describes the discrepancy between a measured value and a real value. Fundamentally, uncertainty is present in all stages of LCA, and is the result of data incompleteness due to a variety of causes (Heijungs & Lenzen, 2014). It is important here to make the distinction between *variability* and *uncertainty*. Variability is described by Huijbregts (1998, p. 273) as "stemming from inherent variations in the real world". Uncertainty, as stated by Björklund (2002, p. 64), is the result of "a lack of knowledge about the true value of a quantity". Uncertainty is connected to variability in the sense that inherent variability in e.g. input data leads to so-called *stochastic* uncertainty, while uncertainty due to imperfect knowledge and modelling choices is called *epistemic* uncertainty (Walker et al., 2003). Stochastic uncertainty is therefore always present in LCA research, because variability is always present in a real-world situation. Unfortunately this means that epistemic uncertainty is also unavoidable, as modelling a real-world situation requires a certain degree of generalisation to handle this variability. As for uncertainty in LCA, epistemic uncertainty is most interesting, because this type of uncertainty can be analysed with the aim of reducing it, whereas stochastic uncertainty cannot be reduced other than redefining the scope of the study.

Within epistemic uncertainty, three types of uncertainty can be discerned: parameter uncertainty, scenario uncertainty and model uncertainty. Huijbregts et al. (2003) describes those as follows. Parameter uncertainty is described as the lack of knowledge about the true value of a parameter, i.e. due to imprecise measurement and assumptions. Scenario uncertainty is caused by normative choices in LCA modelling, e.g. in choosing the functional unit, allocation methods or impact categories. Model uncertainty refers to the validity of the model in relation to the real-world situation, i.e. how simplifications and assumptions affect the validity of the model predictions. Although other classifications of epistemic uncertainty are possible, these three are the most widely used in LCA research and will therefore be adopted in this study (Lloyd & Ries, 2007). The relation between stochastic and epistemic uncertainty in LCA is depicted in Figure 1. Considering that the aim of this research is focussing on the life cycle assessment part of Figure 1 (the middle box), the focus of this research will be on epistemic uncertainty.

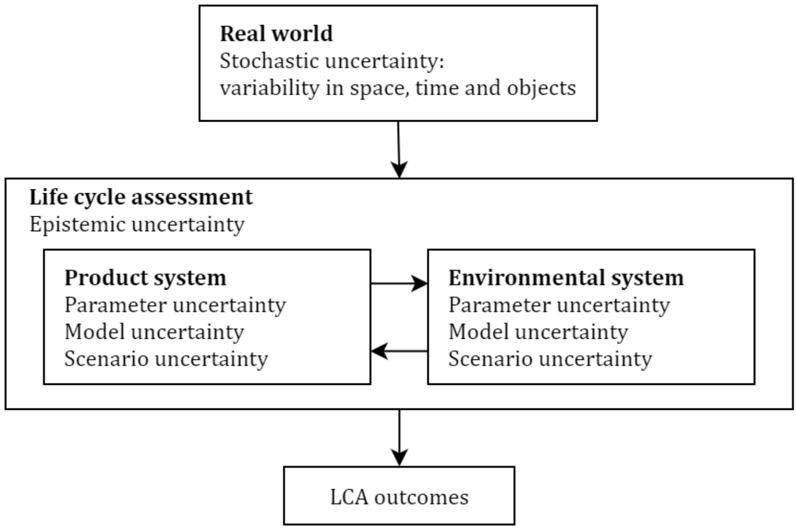


Figure 1: Uncertainty and variability in LCA. Adapted from: Huijbregts, 1998, p. 274

2.1.2 Uncertainty analysis

In general uncertainty analysis refers to the qualitative or quantitative assessment of the uncertainties in an LCA study. Different types of uncertainty ask for different assessment methods, although quantitative assessment is the preferred option when possible. Qualitative assessment generally requires little data (it usually includes expert judgement or data quality indicators), but this represents data quality rather than the amount of uncertainty (Lloyd & Ries, 2007, p. 170). Quantitative assessment is therefore more common in LCA studies (Lloyd & Ries, 2007). Parameter uncertainty can be quantified into an uncertainty distribution of the output variable, with the help of propagation methods. Uncertainty propagation can be seen as the quantitative part of uncertainty analysis, as it addresses the way uncertainties propagate into the output uncertainty of the LCA model (Heijungs & Lenzen, 2014, p. 1446). This is usually done through stochastic sampling, using Monte Carlo or Latin Hypercube simulations, or through analytical uncertainty calculation (Huijbregts, 1998). Stochastic sampling uses parameter distributions as input, making it widely applicable to life cycle inventory (LCI) data, while analytical methods require only uncertainty estimations. Scenario and model uncertainty are more difficult to quantify because they involve the assessment of normative choices, that are intrinsically not quantitative and therefore have no distributions. It was suggested by Huijbregts et al. (2003) that these uncertainties can be quantified by first explicitly naming all the normative choices in the different stages of the LCA, followed by a quantification of the resulting output uncertainty using nonparametric bootstrapping. This involves assigning probability values to each normative choice that is made concerning an alternative. A recent study by Mendoza Beltran et al. (2016) suggests a method that enables propagation of uncertainty due to allocation choices as well as uncertainty in unit process data. The authors call this a ‘pseudo-statistical’ method, because normative choices cannot be assessed in a truly statistical way. Considering the discussed difficulties of assessing scenario and model uncertainty, only parameter uncertainty will be considered in this study.

As shown by Lloyd and Ries (2007, p. 166), who conducted a survey of approaches to quantitative uncertainty analysis, parameter uncertainty was by far the most studied in the 24 LCA studies that the surveyed. The most used method to assess uncertainty was stochastic modelling, occurring in 67% of the studies (Lloyd & Ries, 2007, p. 167). Although most LCA studies use a purely stochastic method, yielding only absolute results, recent studies suggest using such quantitative propagation methods in a correlated way, yielding relative results that are necessary when comparing alternatives in LCA (Henriksson et al., 2015). Henriksson et al. (2015a) provide an example of this notion by comparing GHG emissions from the production of Pangasius fish in large or small farms, and expressing the uncertainty of each alternative's impact both in an absolute and a relative way. The absolute uncertainty, visually represented as a box-and-whisker plot, seem to indicate that the uncertainty around each alternative is too large to draw conclusions on the preferability of one alternative over the other. However, by subtracting the MCS output of one alternative from the other for each run the uncertainty around shared processes is disregarded, because MCS samples the same value for shared processes in the same run. This leaves the relative uncertainty, i.e. the uncertainty of the difference between two alternatives. In the example this showed that the relative uncertainty was in fact much smaller than the difference in GHG emissions from both alternatives, indicating that the impact of small Pangasius farms is indeed significantly larger than that of large farms. Also, it has been argued that possible correlations between among input parameters cannot be neglected (Bojacá & Schrevens, 2010). Studies on quantitative uncertainty propagation (Heijungs & Huijbregts, 2004; Lloyd & Ries, 2007) and comparing different quantitative methods (Benetto et al., 2008; Clavreul et al., 2013; Heijungs & Lenzen, 2014) are sometimes contradictory in their recommendations. For example: while Lloyd & Ries (2007) suggest focussing on qualitative uncertainty analysis when information on uncertainty is scarce, Clavreul et al. (2013) propose to draw 'optimistic' and 'pessimistic' scenarios and compute distributions in all cases. Based on such fundamental discussions, it can be stated that uncertainty propagation in LCA is a developing field of study.

2.1.3 Uncertainty propagation

As this study focusses on quantitative parameter uncertainty, only methods used to describe that are considered here. Within quantitative uncertainty analysis, the procedure where uncertainty information is analysed is called uncertainty propagation. Different methods for uncertainty propagation will be discussed here. Within the propagation phase of uncertainty analysis there are two main aspects to be considered. First there is the actual propagation method, or modelling technique. Several techniques are available, and as identified by Lloyd and Ries (2007) the most common techniques are stochastic modelling (e.g. with Monte Carlo simulation), analytical propagation (e.g. with Taylor series expansion) and fuzzy set-based techniques. Stochastic modelling was found by Lloyd & Ries (2007) to be most commonly used, although the reasons for choosing a specific technique in an LCA study often remain unclear. Stochastic modelling involves sampling a large number of times from a dataset to identify a range of possible outcomes for each parameter and thereby describe the output uncertainty. Monte Carlo (MC) sampling has been extensively covered in literature as an uncertainty propagation method in LCA, and adaptations and extensions of the method have been identified (e.g. Groen et al., 2014a; Heijungs & Huijbregts, 2004). Other MC-based methods include Latin hypercube sampling, metropolis sampling and quasi-MC sampling (Helton et al., 2006). The detailed differences between these methods will not be discussed here, for a detailed description the reader is referred to Groen et al. (2014a). Analytical uncertainty propagation is the technique of expressing output uncertainty as a function of the variances of all input parameters in an LCA model. This can be done using a first order Taylor series expansion of the LCA model, where only the variance of each parameter needs to be known (Groen et al., 2014a). Fuzzy set-based methods make use of a possibility function to describe the output uncertainty of an LCA model. By assigning a value of one to the most plausible value (i.e. the mean, or core value) and zero to the least plausible values, intervals for the output values can be created based on the likelihood of a value in the possibility function (Groen et al., 2014a). Larger intervals will therefore describe output values that are less likely to occur, while more plausible values will have small intervals. This method makes it possible to give insight in the distribution of the model output with limited uncertainty information, as only the boundaries of the possibility function need to be known.

The second important aspect is the uncertainty representation, or characterisation as referred to by Lloyd & Ries (2007). This involves describing the way parameters are distributed, for which there are several methods. Two main categories of uncertainty characterisation can be discerned (aside from analytical uncertainty propagation, for which no distribution type is needed): using a probability distribution (for sampling methods) or a possibility distribution (used in e.g. fuzzy interval methods). Simply put, probability distributions describe how probable the occurrence of different possible outcomes are, while possibility distributions give an estimation of the possibility that any given value will occur in the parameter based on intervals within the parameter (Clavreul et al., 2013). In LCA probability distributions have been the preferred option to represent uncertainty in input parameters, as they can give an accurate indication of uncertainty when many data points are available (Lloyd & Ries, 2007). The main disadvantage is that probability distributions become inaccurate when information is scarce, as is the case with e.g. expert judgement (Clavreul et al., 2013). Also, the preferable characterisation method can depend on the type of uncertainty: it has been argued that epistemic uncertainty is better described by possibility distributions, while for stochastic uncertainty probability distributions are preferred (Heijungs & Tan, 2010). The details of the different distributions will not be discussed here, but in Table 1 an overview of the most commonly used distributions relating to probability and possibility characterisation is given.

Table 1: Uncertainty characterisation types and relating distributions commonly used in LCA. Adapted from Lloyd & Ries (2007, p.168).

Uncertainty characterisation	Common distributions
Probability	Normal
	Lognormal
	Uniform
	Beta
	T-distribution
Possibility	Triangle
	Intervals
	Uniform

2.1.4 Sensitivity analysis

Parameter uncertainty in principle encompasses the uncertainty around all parameter values in the LCA model. However, due to the complexity of the systems that many LCA models aim to describe, a large number of input parameters is often included in the model. While it would be ideal to propagate uncertainties of all input parameters in a model, this would be very time consuming. Moreover, the output uncertainty of an LCA model can often be explained by the variance of just a few parameters (Groen, 2016; Koning et al., 2010). Therefore, the number of input parameters included can be limited to those that contribute most to the model output, both in terms of uncertainty and in terms of environmental impact. The assessment of the contribution of input parameters to the model output is done using sensitivity analysis, where the model output is tested on sensitivity to changes in the input parameters (Saltelli et al., 2006). In LCA modelling, sensitivity analysis has been acknowledged as being essential to the interpretation of the LCA results, because it can help identify priorities for data refinement and model simplifications – such as limiting the number of input parameters included in uncertainty propagation (Groen et al., 2014b; Saltelli et al., 2008).

Within sensitivity analysis three main types of analysis can be discerned: local sensitivity analysis (LSA), screening and global sensitivity analysis (GSA) (Groen et al., 2014b). Local sensitivity analysis refers to assessing the change in the model output when input parameters are changed. A common way to do this is via a one-at-a-time (OAT) approach, where parameter values are changed one at a time with a specific factor (Groen et al., 2014b). Screening involves identifying important contributors to the output *uncertainty* using basic sample information such as the range (Lloyd & Ries, 2007). In global sensitivity analysis, the contribution of the uncertainty around each input parameter to the output variance is assessed based on more specific uncertainty information, such as parameter distributions. GSA can be performed either before or after uncertainty propagation, respectively to find important parameters and to find additional information on the behaviour of the model (Anderson et al., 2014; Cucurachi et al., 2016).
From the above it follows that the most important parameters in a model are those that contribute to both the model output (in the case of LCA: environmental impact) and the output uncertainty. In literature such important parameters are also called 'key issues', described by Heijungs (1996) as model parameters that are strongly contributing to the outcomes *and* that are uncertain. A parameter that makes only little contribution to the outcomes and is fairly certain is considered not a key issue (Heijungs, 1996). This approach has been adopted by several authors, most notably by Saltelli et al. (2008). They describe importance in terms of contribution to the outcomes of the model as *influence*, and importance in terms of contribution of a parameter's uncertainty to the total output uncertainty as *importance*. Key issues are both influential and important (see Figure 2).

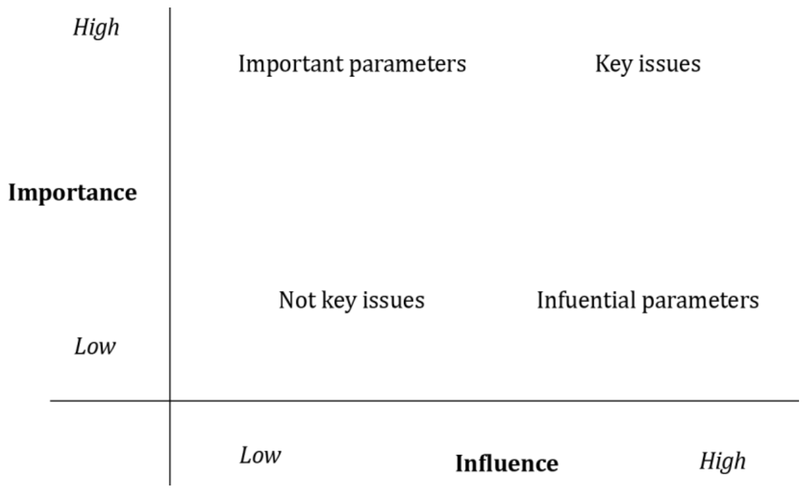


Figure 2: Identification of key issues based on influence and importance. Adapted from Groen (2016).

The analysis described above is referred to by Heijungs (1996) as key issue analysis (KIA), while the same analysis is called uncertainty importance analysis by Björklund (2002), and simply named 'sensitivity analysis' by Saltelli et al. (2008). For this research, the term sensitivity analysis is used to describe the procedure of assessing both influence and importance as described above.

2.2 Framework

While the theory discussed above provides a background of uncertainty analysis in LCA, it also shows that there is a large diversity of approaches to the assessment of uncertainties in LCA. In respect to the research questions of this study, it is necessary to combine several techniques that allow for a comparison of propagation methods that is feasible within time frame of this thesis. This means that from the multiplicity of techniques a selection needs to be made, and operationalised for this study. A procedure that incorporates the necessary elements for addressing the research question, and that serves as a framework for this study, is presented here. It is aimed at providing guidelines for the methodology presented in the next chapter.

As part of their research on uncertainty in product carbon footprints, Henriksson et al. (2015a) presented a procedure for analysing uncertainty in LCA data and presenting the results. This procedure starts with the collection of unit process data and distributions needed for sampling-based propagations methods (e.g. Monte Carlo simulation), followed by a propagation step and statistical testing of the results. The final step involves communication of the results for the aim of the LCA study. The procedure is applicable to this study in the sense that it provides a procedure for assessing uncertainties in LCA studies in general. Also, it allows for the comparison of outcomes of different methods, as steps two and three can be repeated with different methods. However, as discussed above, it might be necessary to select only those parameters in the LCA model of the case study that are key issues. Therefore an additional step in this procedure is needed before the uncertainty propagation, where the most important parameters are selected. Sensitivity analysis, as discussed above, can be used to do so.

An operationalisation of this framework for this study shows how the different steps can contribute to answering the research questions (depicted in Figure 3). Step one of the framework is data collection, essentially covering the life cycle inventory analysis. From the LCI data, sensitivity analysis can be used to select the key issues from the set of parameters. Of these parameters the distributions can be obtained with statistical analysis if the sample size is great enough, and if the propagation method requires that. These distributions are used in step two, where uncertainty propagation is done. Here the actual quantification of uncertainty takes place. In the case of this research, the propagation step can be repeated for each method that is being compared. The results of the propagation step can be tested statistically, e.g. to express the significance of the results. The outcomes of the different methods can be compared after this step. In the final step of the procedure the LCA outcomes are communicated to the target audience. Because the focus of this research is on methods for uncertainty propagation, the first and last step of this procedure are left out of the scope of this study (represented by the dashed line in Figure 3). The LCA research on which the case study is based provides the necessary data to continue with the sensitivity analysis. The communication step is excluded because it is not relevant for the purpose of this study.

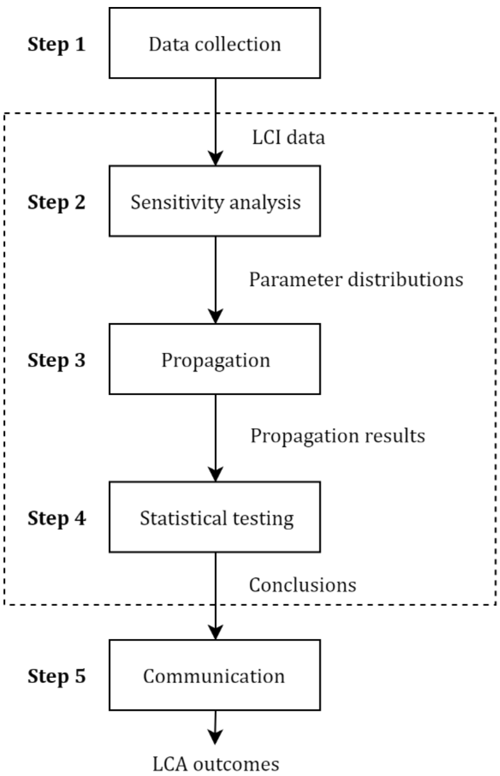


Figure 3: Procedure for propagating uncertainty in LCA data (adapted from: Henriksson et al., 2015a, p. 5). The dashed line indicates the scope of this study.

3. Methodology

The methodology of this study is divided into four phases:

1. Literature review
2. Expert survey
3. Case study
4. Evaluation

In this chapter the methodology for each phase will be presented in detail. For each phase, the outcome of the phase and how this contributes to answering the research questions is described.

3.1 Literature research

In the firsts phase of this research, a literature review will be done to provide input for answering the first two research questions, on drivers and barriers for uncertainty analysis and on the available methods. Where the previous chapter provided the elementary principles of uncertainty analysis in LCA, the literature review will explore what the arguments for and against uncertainty analysis are based on literature. Also, the available methods for uncertainty propagation are further explored.

3.1.1 Phase 1A: drivers and barriers from literature

To answer the first sub-question, it is necessary to understand the arguments from a scientific perspective for LCA practitioners in developing countries to include or exclude uncertainty analysis in their research, as well as their own motivations to do so. In this phase scientific literature will be reviewed to assess the arguments that can be found in literature.

Outcome phase 1A: an overview of drivers and barriers for uncertainty analysis found in literature.

3.1.2 Phase 1B: methods for uncertainty propagation

In order to perform and compare different analysis methods, a selection of methods needs to be made. Existing LCA studies and evaluation research on uncertainty analysis provide a large set of methods, some of which are commonly used (e.g. Monte Carlo analysis), while others are less commonly found in literature (e.g. fuzzy set methods and Taylor series expansion) (Benetto et al., 2008; Heijungs & Lenzen, 2014). In the literature review a selection of uncertainty propagation methods will be made to be used in the case study. The selection will be made based on applicability on parameter uncertainty and on the availability of documentation concerning the application of the method in LCA research.

Outcome phase 1B: a selection propagation methods to include in the case study. Considering the available time for this study, a minimum of three and a maximum of five different propagation methods will be included for comparison in the case study.

3.2 Expert survey

3.2.1 Phase 2: drivers and barriers from expert survey

In addition to the drivers and barriers for uncertainty analysis found in literature, experiences from practitioners in a developing country can contribute to a better understanding of their motivations to include or exclude uncertainty analysis in their work. To this end, LCA practitioners from Thailand – as an example of a developing country where LCA research is taking place – will be surveyed. The survey will be performed online and distributed to members of the Research Network on Food, Fuel, and Climate Change (FFCC) in Thailand. This research network includes LCA practitioners from five Thai universities and is financially supported by the Thailand National Science and Technology Development Agency's (NSTDA).

The survey consists of three sections: a general information part about the background and experience of the participant, a section with questions for those who have experience with uncertainty analysis and one for those who don't have experience with uncertainty analysis, and a final part with two finishing questions. The survey will be answered anonymously to gain the best results, as there are certain questions that participants could feel might harm their work or reputation (e.g. on research choices and knowledge). The questions of the survey can be found in Appendix II.

The processing of the survey results will be quantitatively, meaning that the results are summarised based on the number of times each answer was chosen. For open questions, the answers will either be grouped (if there are recurring answers) or included in the results in full (if they are unique). From this table of results, a qualitative assessment will be done to analyse the results in relation to the sub-question of drivers and barriers for uncertainty analysis.

Outcome phase 2: drivers and barriers from expert survey. The qualitative assessment of the survey results will lead to a number of conclusions that can be drawn concerning the first sub-question.

3.2.2 Evaluation criteria

To be able to compare the outcomes of different uncertainty propagation methods in the final phase of this study, criteria on which the outcomes are compared are needed. In the literature review an overview of driver and barriers for uncertainty analysis in LCA will be given. These can be complemented by the conclusions from the expert survey, to formulate criteria to which an appropriate uncertainty propagation method should comply. To operationalise these criteria for use in the final evaluation, a scoring method will be described for each criterion, based on three possible scores: scores of 1, 2 or 3, where 1 represents the least desirable situation in terms of suitability of the method for agricultural LCAs in developing countries, and 3 represents the ideal situation. For each criterion the requirements for all scores will be described. The scores of 1 to 3 indicate valuation on an ordinal scale, meaning that 3 is better than 1, but 3 is not three times better than 1. When the propagation methods included in the case study are evaluated in the final phase, this scoring method will help identify the strengths and weaknesses of each method.

Outcome phase 1 and 2: criteria for evaluation. The result of this step is a table with criteria in which the selected propagation methods will be scored. The scoring of the studied methods will be done after the propagation step.

3.3 Case study

To answer the third sub-question about different outcomes of different uncertainty propagation methods, a case study will be done. Following the framework described in chapter 2, the procedure to perform uncertainty analysis with several propagation methods includes two main parts: sensitivity analysis and uncertainty propagation. How these steps will be performed is explained in this chapter. For this case study the existing LCA research that was introduced in the theoretical approach will be used. However, considering the extensiveness of the original study, it is necessary to define a clear scope as to which parts of the original research will be subject of the case study. How the original research is translated to a case study to be used in this thesis is explained here. For the sake of clarity, the preparatory steps that are needed prior to performing sensitivity analysis and uncertainty propagation with the LCI data from the original study are discussed here as well.

3.3.1 Case study scope

As the original LCA research covers many different topics and can be seen as multiple LCA studies combined, a scope must be determined for the use of this project as a case study. In agreement with the project leader, prof. S.H. Gheewala, it was decided that the focus of this case study should be on the environmental impact occurring during the cultivation stage of sugarcane. The cultivation stage includes all product flows and processes that occur from the planting of the crop to the harvesting of sugarcane. This means that other subjects that were part of the original study, i.e. the processing of sugarcane into raw sugar, bio-ethanol and by-products, are excluded in this case study. The main distinction in the original LCA study for the cultivation stage was made between conventional cultivation and 'green' cultivation, identifying environmental issues related to pre-harvest field burning in conventional practices (Pongpat et al., 2017). Therefore, the scenarios from the original study can be adapted to this case study with a focus on these two cultivation practices. This distinction will be kept throughout the case study. Within sugarcane cultivation, four stages can be discerned: land preparation, crop planting, land treatment and harvesting. Land preparation covers ploughing the land to prepare it for the planting of the crop. The planting stage includes planting of cane stubbles ('setts') and fertilising the land. The treatment stage comprises application of fertiliser and pesticides and irrigation. The harvesting stage includes the harvesting of the sugarcane (either mechanically or manually) and transporting the harvested sugarcane stems to a central point at the farm. Conventional cultivation includes pre-harvest field burning, while green cultivation involves only mechanical harvesting. The main differences between the two scenarios are listed in Table 2.

Table 2: Main differences between the two cultivation practices per stage of cultivation.

Stage	Conventional cultivation	'Green' cultivation
Land preparation	Mechanical ploughing	Mechanical ploughing
Planting	Manual planting and application of fertiliser	Mechanical planting and application of fertiliser
Treatment	Manual application of fertilizer and pesticides	Mechanical application of fertilizer and pesticides
	Irrigation	Irrigation
Harvesting	Pre-harvest field burning	Mechanical harvesting
	Manual harvesting	
	On-site transporting of harvested cane by truck	On-site transporting of harvested cane by truck

3.3.2 Data preparation

For this case study two data types from the original LCA project are needed: the LCA model that contains the connections between goods, products and emissions, and the raw data as collected in the field. The LCA model is needed to perform the first analysis (i.e. a sensitivity analysis to find the most important parameters), while the raw data contains all the sample data which is needed to identify ranges and distributions for uncertainty propagation. The following section addresses first the data as it was used in the original study, followed by the preparatory steps that were needed to use this data in this case study.

Original data structure

Primary data was collected by researchers from KMUTT through questionnaires of sugarcane farmers and sugar milling companies in Thailand. A total of 1,652 farms and 20 sugar milling companies were surveyed in different regions of Thailand in 2013 and 2014. The raw data collected in the field was digitalised and saved in spreadsheets by the KMUTT researchers. These contain both qualitative data (e.g. harvesting method) and quantitative data (e.g. fertilizer input). To be able to use this data in an LCA model, the Thai researchers extracted average parameter values for all farms linked to one sugar milling company, followed by an average value for the 20 sugar milling companies. This averaging was done to obtain a single value to be used in the LCA model, but thereby the uncertainty information (i.e. the variance and distribution of the collected data points) was not incorporated in the model. Secondary data from the Thai national LCI database and the Ecoinvent v3 database was used for background processes in the model, which was constructed in the SimaPro LCA software. The distinction between conventional and green practices was maintained throughout the modelling process. This model structure is depicted in the flowcharts in

Figure 4 and Figure 5. The original model structure was maintained for the case study in order to obtain comparable results (and therefore useful for the KMUTT researchers). The stages of cultivation were structured in the original model as separate processes that deliver the input for the overall cultivation process. The output of each cultivation stage is then one hectare of cultivated land, so that the overall cultivation process delivers the amount of sugarcane produced on one hectare of land. The functional unit of the LCA study is 1 tonne of sugarcane output, which requires approximately 0.015 of a hectare to produce (the average yield of one hectare of sugarcane field is 68 tonnes of sugarcane). Input economic flows include different types of fertilizer, pesticide, diesel fuel, water for irrigation and transport of the harvested sugarcane to the factory. While different types and brands of fertilizer are used in sugarcane cultivation, for implementation in the model these were aggregated into N-fertilizer (ammonium sulphate), P-fertilizer (phosphate as P_2O_5), and K-fertilizer (potassium chloride), as well as urea fertilizer. Three types of pesticide were discerned: glyphosate, atrazine and unspecified pesticides. The process of cane trash burning, which is essentially the burning of pure biomass, leads to methane emissions in the model, while CO_2 emissions are omitted. The reason that CO_2 is omitted from the equation is that this is seen as biogenic CO_2, which has no (long-term) impact on climate change. Methane is included because biomass burning has been found to be an important source of atmospheric methane due to incomplete combustion. While CO_2 is mostly emitted during the flaming phase, methane is mostly emitted during the smoldering phase afterwards (Hao & Ward, 1993). In green cultivation, cane trash is not burned but disposed of as bio-waste. In Ecoinvent disposal is modelled as an input to the process where the waste is created (even though waste is actually an output of the harvesting process), which is why disposal is depicted as in input in Figure 5 as well.

Limitations of the original LCA model

While the original LCA model serves the purpose of this study well by providing LCI data on which uncertainty analysis can be performed, there are some limitations to the original model that need to be pointed out. As can be seen in the flowcharts of the LCA model, there are several processes that do not seem to adequately cover the chemical processes they represent. There seem to be no sulphur emissions from diesel combustion in Thai machinery, which is not expected (Bond et al., 2004). Also, methane (CH_4) emissions from diesel combustion are included, while methane is not one of the main components of emissions from diesel combustion (Hesterberg et al., 2008). However, because methane is a strong greenhouse gas (about 20 times stronger than CO_2), small emission quantities will still have a considerable impact, which explains why it is included in this model. There are also limitations related to modelling choices. Firstly, a distinction is made between urea and N-fertilizer, while ammonia is the main component of urea, and urea is therefore also an N-fertiliser. Secondly, the N-fertiliser product, ammonium sulphate was chosen from the database, but it remains unclear why this product was chosen over ammonium nitrate or calcium ammonium nitrate. A possible explanation is that ammonium sulphate is better suited for alkaline soil conditions (Bakker, 2012). Thirdly, the P-fertiliser product in the LCA model was wrongly chosen from the Ecoinvent database. For the phosphate fertiliser that is used on the land, the P_2O_5 content of di-ammonium phosphate was chosen. However, this product should never be chosen without the simultaneous use of di-ammonium phosphate as N-fertiliser, because they are physically the same product and only split for the purpose of energy allocation (Moreno Ruiz et al., 2013, p. 15). A possible implication of this error is an underestimation of the environmental impact related to P-fertiliser use, as only part of the impact related to di-ammonium phosphate production is allocated to P-fertiliser. Lastly, it can be argued that there is a negative feedback loop between cane trash burning and fertiliser use, because burned field will become more fertile, leading to a lower fertiliser demand. These are suspected to be human errors in the modelling process. Because the main goal of the case study is not to deliver a perfect LCA, but rather to use an existing agricultural LCA study for uncertainty analysis, the original LCA model is adopted in full, including the suspected errors.

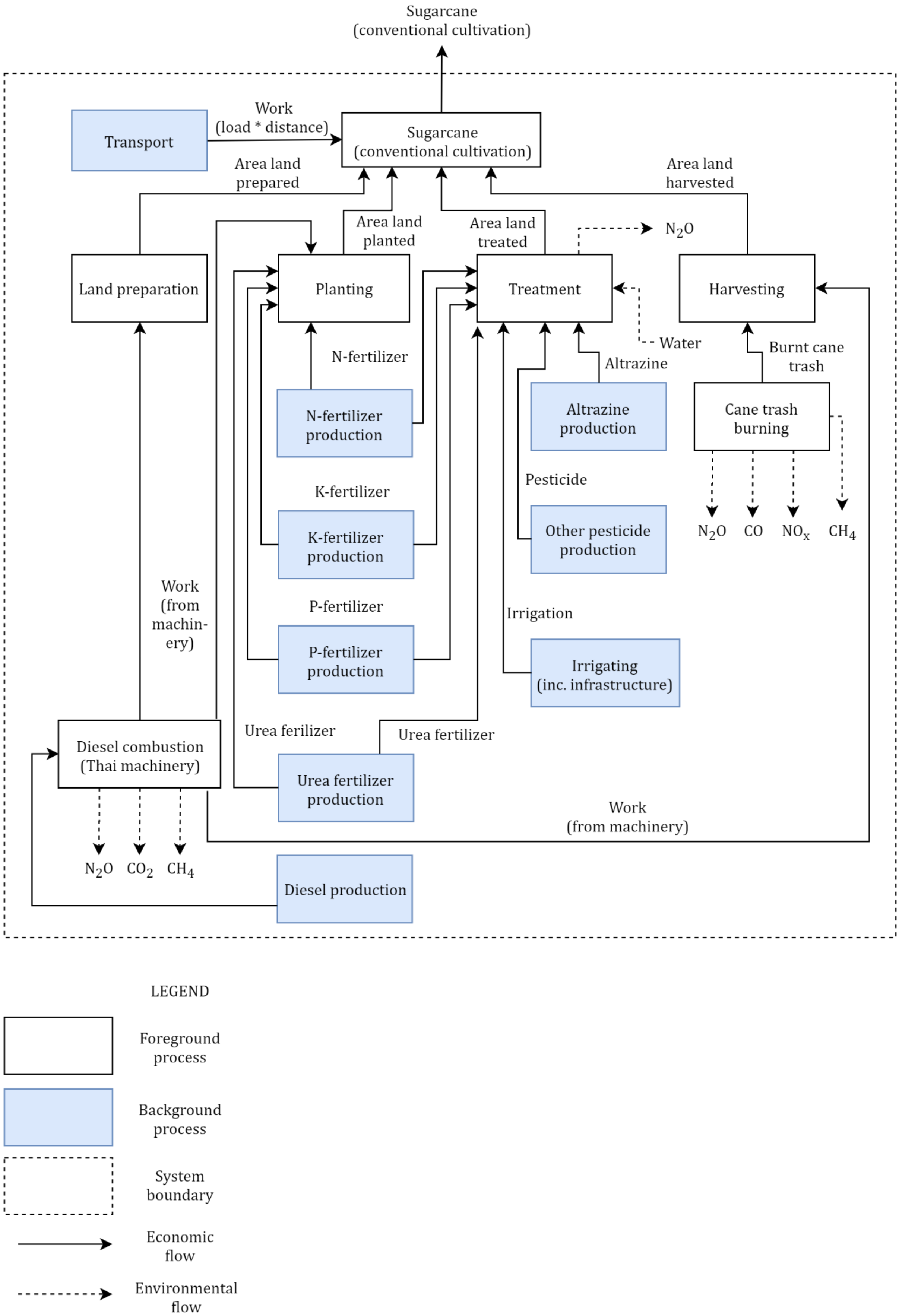


Figure 4: Flowchart of the conventional cultivation of sugarcane.

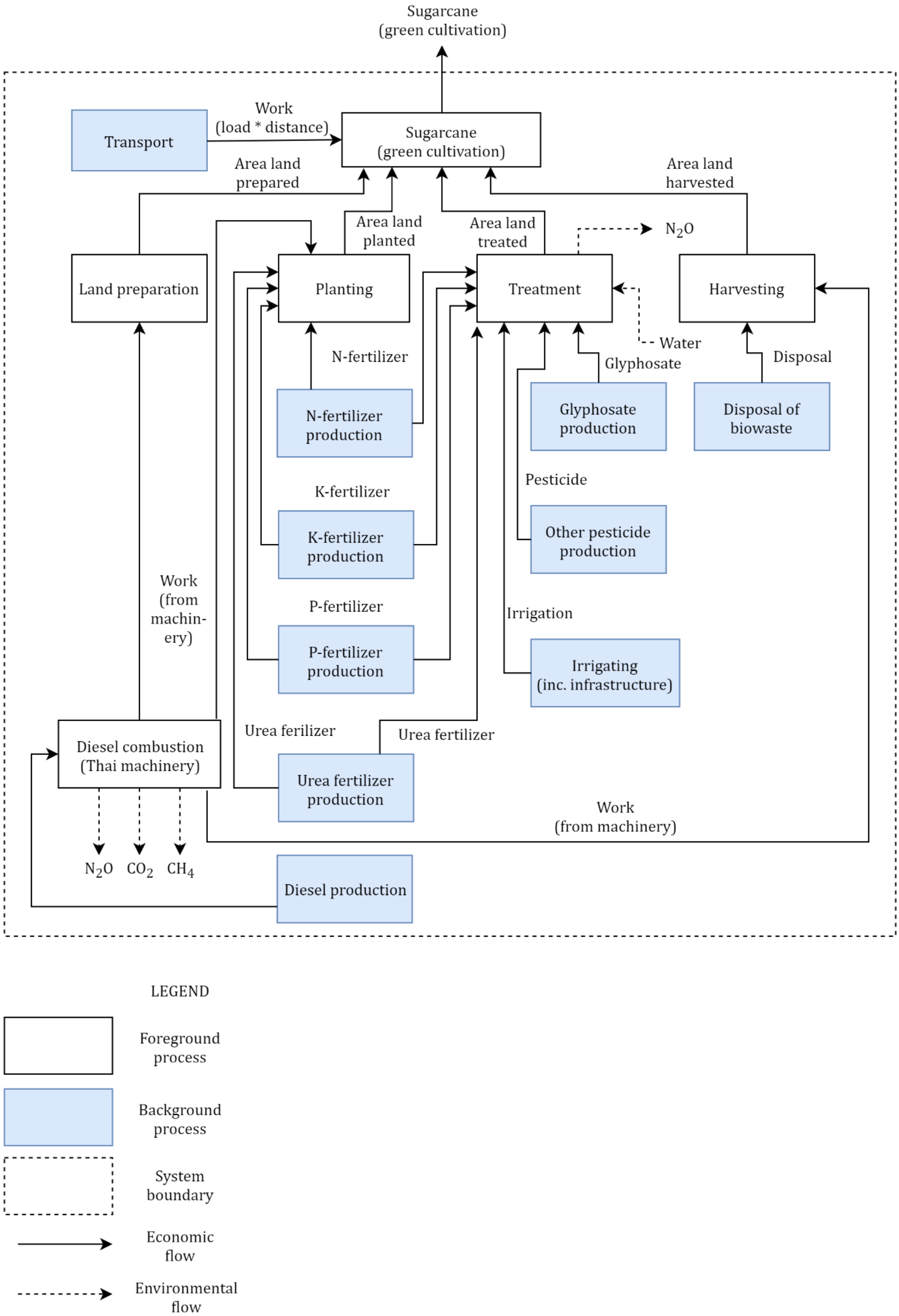


Figure 5: Flowchart of the green cultivation of sugarcane.

Data translation

In order to use the required data in this case study, several translation steps are required. Firstly, all qualitative data, including variable names, was written in Thai language and had to be (digitally) translated to English. The translated version has been checked with the Thai researcher concerned to prevent misinterpretations. Secondly, the original study was conducted with a set of 12 environmental impact categories from the ReCiPe v1.1 indicator set (at the midpoint level, from the hierarchical perspective). Due to time limitations for this thesis, only the ReCiPe climate change indicator of global warming potential (GWP100) will be used in this case study. Thirdly, the original model was built in the SimaPro software using the Ecoinvent v3 database, which has two main disadvantages. For one, SimaPro does not include extensive sensitivity analysis options, which means that the selected sensitivity analysis is not possible in this software. Another disadvantage is that the Ecoinvent v3 database contains two options in terms of modelling approach: either based on unit processes including uncertainty data, or based on system processes, using aggregated datasets and without uncertainty data. For the original LCA model the system-based approach was used, and because of the lack of uncertainty data any uncertainty-based analysis would be meaningless. Considering these disadvantages, the original LCA model had to be converted to alternative software.

As an alternative to the SimaPro software CMLCA was chosen because of the extensive options that it provides in terms of data handling, sensitivity analysis and uncertainty analysis. Because the Ecoinvent v3 database was not available in CMLCA, Ecoinvent v2.2 was used (which does not make the distinction between a unit-based and system-based approach, and therefore does include uncertainty data). The original model was manually copied to the CMLCA software and linked to corresponding goods and processes in the v2.2 database. The same impact categories that were used in the original model (ReCiPe v1.1) were available used in the CMLCA model. In all probability, this conversion step has consequences for the behaviour of the model, both in terms of outcomes and relative performance of the processes. To give a superficial indication of the way the two models compare, they were both run with the same functional unit (1 tonne of sugarcane output, conventional cultivation) and compared on impact for all 10 ReCiPe impact categories (see Table 3). It shows that for some categories the models are show a large difference (50-95%), while for others the models are relatively similar. For this case study however, the only indicator that will be used is climate change, GWP100. On this category the CMLCA model shows an 8.7% larger score than the SimaPro model, which was considered acceptable for the purpose of this study. The implications of this model conversion step will be further covered in the discussion.

Table 3: Comparison of impact scores for the two LCA models (ReCiPe v1.1). The impact category that is used in this study is highlighted.

Impact category	Unit	SimaPro model	CMLCA model	Difference
Natural land transformation, NLTP	m2	6.11E-03	1.19E-02	+94.8%
Particulate matter formation, PMFP	kg PM10-Eq	1.27E-01	1.35E-01	+6.3%
Marine ecotoxicity, METPinf	kg 1,4-DCB-Eq	4.31E-01	2.11E-01	-51.0%
Terrestrial acidification, TAP100	kg SO2-Eq	3.24E-01	3.76E-01	+16.0%
Terrestrial ecotoxicity, TETPinf	kg 1,4-DCB-Eq	4.71E-03	5.04E-03	+7.0%
Metal depletion, MDP	kg Fe-Eq	5.36E+00	2.02E+00	-62.3%
Fossil depletion, FDP	kg oil-Eq	1.22E+01	1.38E+01	+13.1%
Photochemical oxidant formation, POFP	kg NMVOC	7.95E-01	8.03E-01	+1.0%
Climate change, GWP100	**kg CO2-Eq**	**6.01E+01**	**6.53E+01**	**+8.7%**
Ionising radiation, IRP_HE	kg U235-Eq	3.33E+00	3.40E+00	+2.1%
Freshwater ecotoxicity, FETPinf	kg 1,4-DCB-Eq	4.55E-01	1.48E-01	-67.5%
Urban land occupation, ULO	m2a	7.72E-01	2.80E-01	-63.7%
Human toxicity, HTPinf	kg 1,4-DCB-Eq	9.93E+00	8.26E+00	-16.8%
Ozone depletion, ODPinf	kg CFC-11-Eq	6.11E-06	5.63E-06	-7.9%

3.3.3 Phase 3A: sensitivity analysis

For the first phase of the case study, specific methods of sensitivity analysis need to be selected. For the selection of the most essential parameters (key issues) in the case study LCA model two aspects are important: the influence and the importance of the parameters (as defined in chapter 2). The influence can be best assessed with a local sensitivity analysis, as the interest here is in the specific influence that a change in a parameter has in the model output. One widely used method for local sensitivity analysis in LCA is matrix perturbation (Groen et al., 2014b; Heijungs, 2010). This method, which is based on several matrix calculations, is also called perturbation analysis, operationalised for life cycle impact assessment by Heijungs (2010). Using first-order partial derivatives, the influence of each parameter in the model is estimated. The main equation can be formulated as (Heijungs, 2010, p. 513):

$$\Delta z = \frac{\partial z}{\partial x}\,\Delta x + \frac{\Delta z}{\Delta y}\,\Delta y$$

where the sensitivity is expressed, using the partial derivatives, as the change in the result (Δz), determined by a marginal change in parameter x (Δx) and in parameter y (Δy). The full calculations are covered in the paper by Heijungs (2010). The outcome of this perturbation analysis is a list of parameters and their sensitivity coefficients (multipliers). This method will be used to find the most essential parameters in terms of influence. Concerning importance of parameters, a screening method fits best, because an estimation of contributions to the output uncertainty can be obtained without first going through uncertainty propagation (Groen et al., 2014b). As in this case study this sensitivity analysis will be done before the uncertainty propagation, screening can provide the necessary information on importance. One screening method is the method of elementary effects (MEE), which uses the lower and upper boundaries of an input parameter's range to estimate the importance (Groen et al., 2014b). As this information will be available in the case study, MEE will be used to find the importance of input parameters. Contrary to perturbation analysis, which uses the default values of parameters, in MEE the ranges of parameters are used to measure the change of the model output based on changes in the input parameter (Groen, 2016). The elementary effect of a parameter is expressed as the change in the model outcome caused by changing a parameter within its range, defined by lower and upper values. By selecting random values within the parameter range the change compared to the default outcome can be determined. The outcome of the analysis is the measure of importance μ^*, which is the absolute mean of the average elementary effects of a parameter. This is expressed as (Groen, 2016, p. 33):

$$EE(A,i,j) = \frac{h\left(A_{ij} + \delta_{A,i,j}\right) - h(A_{ij})}{\Delta}$$

where A is a parameter in the model that is changed with predefined steps of 2/3 of the range (Δ) of that parameter, defined by boundaries i and j. The elementary effect EE is then calculated by dividing the output change by the step size Δ. By repeating this procedure R number of times, the measure of importance μ^* is found (Groen, 2016, p. 33):

$$\mu^*(A,i,j) = \frac{1}{R}\sum_{r}^{R}|EE(A,i,j)|$$

One of the benefits of this method is that it is not necessary to define distributions, and uncertainty propagation is not needed. This is also its main disadvantage, as a range is a very limited measure to describe the nature of a parameter. More extensive background on the MEE including the full mathematical formulations can be found in Groen (2016), Saltelli et al. (2008) and Campolongo et al. (2007).

Outcome phase 3A: selection of parameters. The perturbation analysis will result in a list of important parameters. Because key issues are both important and influential, the MEE can be limited to those parameters that have already been found in the perturbation analysis. To fit the parameter selection to the time constraints of this research, a maximum of ten parameters to be included in the propagation step will be kept as a guideline.

3.3.4 Phase 3B: uncertainty propagation

The second stage of the case study consists of the actual uncertainty propagation. With the methods that are selected from the literature study, the output uncertainty of the parameters selected in phase 3A will be propagated. The outcomes of the propagation step will be evaluated and compared in the next phase. Because the methods possibly require different types of input (e.g. parameter distributions or general uncertainty information), the required inputs will have to be determined from the available data. The model parameters selected in the previous phase will be used to run the uncertainty propagation.

Outcome phase 3B: uncertainty quantifications. Depending on the type of output from each propagation method, the results will be presented graphically and by means of statistical information. This includes at least the estimated mean value and the available expression of uncertainty (e.g. variance, standard deviation or confidence interval).

3.4 Evaluation

In this final phase the results from the literature study, uncertainty propagation and expert survey will be combined. The results of the uncertainty propagation will be evaluated based on the criteria for evaluation formulated after the second phase. Based on this evaluation, where the strengths and weaknesses of each method are identified, the most suitable method for assessing parameter uncertainty in agricultural LCAs in developing countries will be discussed. The full methodology is presented schematically in Figure 6. For each expected outcome (dashed boxes) is indicated how it is used in the process, either by serving as input for another phase or by directly answering a sub-question.

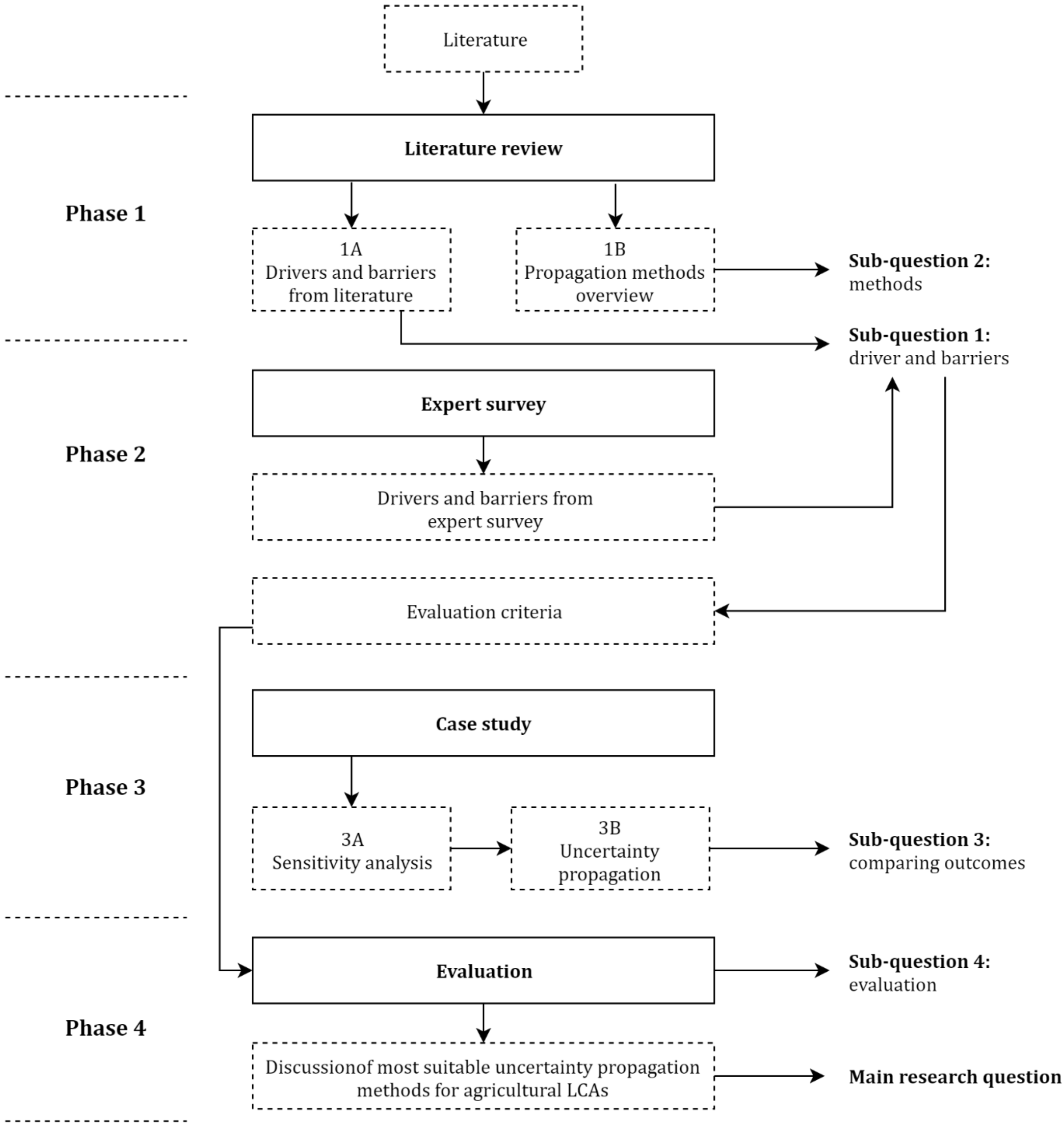


Figure 6: Research phases and expected outcomes (dashed boxes). Arrows indicate what information is used to answer each research question.

4. Results

4.1 Literature research

In this first phase of the study scientific on uncertainty analysis in LCA literature is reviewed. Drivers and barriers for uncertainty analysis are assessed in phase 1A to answer the first sub-question from a scientific perspective. An overview of the found drivers and barriers is given in Table 4. In phase 1B existing methods of uncertainty propagation are discussed in order to select a minimum of three and a maximum of five propagation methods to be used in the case study.

4.1.1 Phase 1A: drivers and barriers for uncertainty analysis

The importance of addressing the reliability of the outcomes of LCA research, especially in a decision-making context, has been stressed by many authors, most notably by Huijbregts (2002) and Geisler et al. (2005). Nevertheless, uncertainty analysis is far from common practice in LCA research. In order to understand the considerations of LCA practitioners whether or not to incorporate uncertainty analysis in their work (if they even deliberately make this choice), literature on this topic is reviewed and evaluated here.

Drivers

First of all, there are obvious arguments for performing uncertainty analysis related to scientific reliability. These arguments can be called scientific drivers, as they present a reason for LCA practitioners to include uncertainty analysis in their research to increase (or at least explain) the reliability of their work. Decisions, at least from a scientific perspective, are not supposed to be random, and should therefore be based on (scientific) data with credible sources. Regarding LCA studies, the outcomes can be significantly influenced by uncertainty, as discussed in chapter 1.1. LCA models are often based on single-point values, which can give a false sense of accuracy when the actual value can vary greatly (Koning et al., 2010). Considering this, as stated by Björklund (2002), the results of LCA studies must be accompanied by uncertainty analysis, otherwise the credibility can (and must) be questioned. The ISO 14040 guidelines for LCA mention the importance of uncertainty analysis to better explain and support the LCI conclusions (ISO, 2006). Scientific drivers for uncertainty analysis arguably become more important when LCA research is conducted in a decision-making context.

Secondly, there are drivers for uncertainty analysis related to the decision-making context in which LCA research is often conducted. When used to support decision-making, LCA is often comparative in nature, and not properly dealing with uncertainties may results in counterproductive decisions (Henriksson et al., 2015a). When comparing alternatives, the uncertainty of the outcomes may be larger than the difference between the alternatives, meaning that it is close to impossible to compare them in terms of environmental impact. An example of this issue was provided by Malça & Freire (2010), who performed a comparative LCA on rapeseed biofuel replacing fossil fuel. They found that while the outcomes suggest a significant advantage of the biofuel alternative, the high uncertainties in GHG emissions limit the conclusions to the point that appointing a preferred alternative becomes virtually impossible. Moreover the same authors state that decision-makers are often not qualified to judge comparative LCA results, and supporting information on uncertainty is required to guide them in the process (Malça & Freire, 2010). Uncertainty information can also contribute to a more informed discussion among stakeholders in a decision-making context (McManus et al., 2015).

Thirdly, there are regulatory drivers, referring to national or international requirements for scientific support of e.g. policy decisions. In the field of environmental impact assessment (EIA) in general, to which LCA is related, there is extensive national and international regulation and mandatory procedures that need to be followed. However, the specific field of LCA does not know such requirements (Jay et al., 2007). Nevertheless, there are countries where requirements concerning reliability of LCA research are explicitly formulated. In the United States for example, it is mandatory to communicate scientific uncertainty for important policy decisions based on LCA (Cohen, 2013). This requires at least some level of uncertainty analysis in LCA research. Still this seems to be an exception to the rule, while such legal requirements can be considered a powerful tool to encourage uncertainty analysis in LCA (Ross et al., 2002).

A fourth type of driver is related to practical availability of uncertainty analysis methods. It is easily argued that a prerequisite for LCA practitioners to perform uncertainty analysis in their work is that a way to do so needs to be available to them, preferably within their software of choice. All major LCA software tools, including SimaPro, CMLCA and OpenLCA, facilitate uncertainty analysis to some extent (at least provide the option of a Monte Carlo simulation) (Lloyd & Ries, 2007). This means that, apart from the question of data availability, the resources to perform at least some form of uncertainty analysis are readily available. This can be seen as a driver for uncertainty analysis.

Barriers

While the need for uncertainty analysis in LCA has been laid out above, there are many different reasons why it is not included in most LCA studies. Barriers for performing uncertainty analysis are related to different issues. First of all, barriers can relate to a lack of knowledge of the real-world phenomena that the LCA study is dealing with. Uncertainty analysis requires a certain amount of information on the uncertainty of input data, while this is often simply not available. According to Huijbregts et al. (2001) quantifying uncertainty can be 'extremely hard' when dealing with temporal or spatial variability in input data. This is underlined by Björklund (2002), who argues that deriving the necessary information for uncertainty analysis (e.g. parameter distributions) can be very difficult when insufficient data is available. Moreover, when considering qualitative assessment of data quality, LCA practitioners have to make a judgement on data accuracy while they often don't have this information (May & Brennan, 2003).

Secondly, there are methodological barriers related to uncertainty analysis. According to Heijungs & Lenzen (2014) there is a general lack of knowledge among LCA practitioners on the content of different types of uncertainty analysis, which is also a result of conflicting explanations of these methods in literature. Also, while standardisation efforts (e.g. ISO 14040) may have led to a commonly accepted framework for LCA research in general, these guidelines fail to provide an adequate framework for incorporation of uncertainty analysis in LCA studies (Heijungs & Huijbregts, 2004). Another methodological barrier exists in the quantification of uncertainty types other than stochastic uncertainty. Model and scenario uncertainty are much more difficult to assess and quantify, and methods to do so are less commonly known than e.g. Monte Carlo simulation (Mendoza Beltran et al., 2016). Including these types of uncertainty in uncertainty analysis requires a combination of methods, complicating the procedure significantly. A final barrier is related to available software to deal with uncertainties. Firstly, computation time can be significant for sampling techniques like Monte Carlo simulation when dealing with large LCA models (Heijungs & Lenzen, 2014). Secondly, as mentioned earlier, most LCA software tools include methods for uncertainty analysis, but these are generally still limited in terms of scientific validity, ignoring important aspects like correlation between parameters (for a more thorough investigation of this issue see recent studies by Henriksson et al. (2015b) and Heijungs et al. (2017)).

A third type of barrier for uncertainty analysis is related to interpretation of the results. Heijungs & Huijbregts (2004) argue that LCA research is already a complicated procedure, and both data collection and interpretation of the outcomes is even further complicated when uncertainty analysis is included. This poses a problem when the results have to be understood by decision-makers without the scientific background to understand them. Technical jargon and uncertainty results require a high level understanding, which complicates applicability in policy-related research (Cowell et al., 2002; Heijungs & Huijbregts, 2004). Outcomes of uncertainty analysis can also be wrongly interpreted when the methods used were incomplete (Björklund, 2002). This may give a false sense of credibility of the LCA results. Interpretation of uncertain results may also lead to pessimism. When LCA outcomes have a large uncertainty they may lead to a pessimistic view of the research, interpreting it as meaningless (Heijungs & Huijbregts, 2004). A final barrier related to interpretation is found in political use of LCA research. Political actors may tend to use the uncertainty of LCA results to their benefit, i.e. emphasising the uncertainty when the outcomes are not in line with their views (Bras-Klapwijk, 1998). This also goes for results that are in line with their views, when political actors may suppress or deny the uncertainty of the research.

Table 4: Drivers and barriers for uncertainty analysis found in literature

Drivers *Uncertainty analysis is included in LCA because…*	**Barriers** *Uncertainty analysis is excluded from LCA because…*
… it increases scientific reliability	… there is a lack of uncertainty information of input data
… a false sense of accuracy can be avoided	… there is a lack of knowledge among LCA practitioners of uncertainty analysis methods
… counterproductive decisions due to a lack of uncertainty information can be avoided	… there is a lack of an adequate framework for uncertainty analysis in international standards (e.g. ISO)
… it can guide decision-makers in the interpretation of LCA results	… it is complicated to assess model and scenario uncertainty
… it may be necessary in order to comply with (inter)national LCA requirements	… sampling methods require a significant computation time for large LCA models
… options for uncertainty analysis are available in all LCA software tools	… the options for uncertainty analysis in LCA software tools are limited in terms of available methods and scientific validity
	… the results of uncertainty analysis are too complex to interpret by decision-makers
	… the results of uncertainty analysis may lead to pessimism about the LCA outcomes
	… the results of uncertainty analysis may be used to the benefit of political actors

4.1.2 Phase 1B: selection of propagation methods

In this study uncertainty propagation methods are compared in terms of outcomes and their appropriateness for agricultural LCA in developing countries. Because many different propagation methods for parameter uncertainty propagation exist, and this study will focus on only a selection of propagation methods, an overview of existing methods will be given here. From this overview, a selection of three to five methods will be made based on availability (application examples should be available), input requirements (the case study should provide the necessary data) and technical feasibility (the method can be performed with the available time and resources).

As introduced in the theoretical approach, uncertainty propagation methods can be classified by modelling technique (stochastic, analytical or fuzzy techniques), while the characterisation of parameter uncertainty depends on the modelling technique and the type of data. For the sake of completeness, the commonly used modelling techniques should be represented in the selection of propagation methods used in this study. Comparing methods that are fundamentally different from each other also contributes to the aim of this study, as the most appropriate propagation method should be sought within the full spectrum of available method. The starting point is therefore to include one propagation method from each modelling technique that is most common: Monte Carlo simulation (MCS) for stochastic sampling, Taylor series expansion for analytical uncertainty propagation (AUP) and fuzzy interval arithmetic (FIA) for fuzzy techniques. In terms of the availability of examples in literature, all three modelling techniques have been covered in literature with multiple studies. While stochastic, or sampling methods are most common (especially MCS), analytical methods are included in numerous studies as well (Lloyd & Ries, 2007). Fuzzy techniques are less common, but recent studies have provided sufficient information on possible methods of this type (Clavreul et al., 2013; Groen, 2016).

Considering the recent discussion on uncertainty analysis in comparative LCA, and its implications for the procedure of sampling-based analyses (see Henriksson et al., 2015), two types of sampling techniques will be included. While the importance of dependent sampling has been acknowledged, the way the sampling results are analysed is still debated. Therefore, two sampling-based methods are included: one using independent analysis, and one using dependent analysis.

Depending on the type of propagation method, different inputs are required to quantify parameter uncertainty. Sampling-based methods require the distribution function of each parameter to be specified, together with a central value and a parameter of dispersion (e.g. the standard deviation) (Groen et al., 2014a). The specific expression of this parameter of dispersion depends on the distribution type. For analytical methods much less information is required, only the standard deviation is needed. Possibilistic methods require three values: a core value, the upper and lower bounds of the possibility function and the type of possibility function of each input parameter (Groen et al., 2014a). The input requirements for each method should be feasible for this study. As it is expected that the available data in the case study is sufficient to determine both probability and possibility distributions, no methods need to be excluded based on feasibility. The final selection of propagation methods is listed in Table 5.

Table 5: Selected uncertainty propagation methods. The input requirements are adapted from Groen et al. (2014a).

Modelling technique	Characterisation	Propagation method	Input requirements
Sampling	Probabilistic	Monte Carlo, *dependent analysis* Monte Carlo, *independent analysis*	1. Distribution function [*pdf*] 2. Central value [μ] 3. Parameter of dispersion [π]
Analytical	Probabilistic	First order Taylor approximation	1. Standard deviation [σ]
Fuzzy	Possibilistic	Fuzzy interval arithmetic	1. Core value [v_s] 2. Upper and lower bounds [δ+ and δ-] 3. Possibility function [S]

4.2 Expert survey

4.2.1 Phase 2: drivers and barriers from expert survey

A total of 21 members of the research network participated in the survey. Among them were three researchers, three PhD-students, two lecturers and a government official (twelve did not give their current occupation). Most of them had experience in more than six LCA projects. The full list of answers can be found in Appendix II. This section will be focussed on the conclusions that can be drawn from those answers.

1. *There is a general lack of knowledge among participants on how to perform uncertainty analysis.*

The answers show that one third of the participants is not familiar with the concept of uncertainty analysis, and more than half of the participants has no experience with performing uncertainty analysis. The most named reason for this was that they don't know how to perform uncertainty analysis. Consequently, more knowledge on the subject was named as the most important requirement for participants to include uncertainty analysis in their work.

2. *While parameter uncertainty is named as the most interesting uncertainty type, scenario analysis is the most used method.*

When asked which type of uncertainty is the most interesting for their work, most participants chose parameter uncertainty (although this does not mean that they have experience in assessing parameter uncertainty). However, this is not reflected by the answers to the question which methods they have used is their work. Scenario analysis was used the most (by eight participants), while five participants used sampling or analytical methods. One reason for the discrepancy between the most important uncertainty type and the methods that are being used could be that scenario analysis is less resource and knowledge intensive to perform.

3. *The importance of uncertainty analysis is generally acknowledged by participants*

Of all participants, two stated that uncertainty was not interesting for their work. This indicates that the importance of uncertainty analysis is generally acknowledged by participants. Moreover, the question if the participants wanted to learn more about uncertainty analysis if they had the opportunity was unanimously answered positively. Although this doesn't necessarily mean that they think uncertainty analysis is important, there seems to be a willingness to gain more knowledge on the subject, which is a necessary first step to tackle the lack of knowledge discussed above.

4. *Most researchers use SimaPro for scientific research, or only spreadsheet software.*

The SimaPro software by Pré Consultants shows to be the most used software tool for LCA research of the participants. SimaPro is one of the leading software tools in LCA, but there are limitations to its use (Herrmann & Moltesen, 2015). There are limited options for uncertainty analysis in SimaPro, and the tool is primarily aimed at business and education purposes (Pré-Consultants, 2017). This can be seen as a barrier for the further development of uncertainty analysis in the LCA research of practitioners in Thailand.

5. *Guidance and knowledge development would support an increase in application of uncertainty analysis*

Considering the suspected general lack of knowledge by LCA practitioners of uncertainty analysis, knowledge development would support an increase in application of uncertainty analysis. This is underlined by the answers to the question what the participants without experience un uncertainty analysis would need in order to include it in their work. There, knowledge is mentioned by 75% of the participants. Furthermore, the lack of consequent guidelines for uncertainty analysis is mentioned in the final question on suggestions for how LCA practitioners could be encouraged to include uncertainty analysis in their research. A step-by-step manual or international guidance would help practitioners to include uncertainty in their research, preferably from the start of the study. Finally, of all LCA studies by participants who performed uncertainty analysis, the results of uncertainty analysis were included in the final report or publication. This means that increasing the use of uncertainty analysis would indeed lead to an increase of application of uncertainty analysis in scientific reporting.

4.2.2 Evaluation criteria

From the literature overview given in the previous chapter, together with the findings from the expert survey, several observations can be made regarding the conditions to which an appropriate method for uncertainty analysis should comply. By translating these observations to concrete criteria of suitable methods uncertainty analysis in agricultural LCA, the results of the case study can be evaluated in the final phase of this study. In this section these criteria are formulated, and the scoring procedure for each criterion is explained. The final list of criteria and the scoring methods are depicted in Table 6.

From the results of the previous sections, the aspects of importance to a suitable method of uncertainty analysis can be categorised into three categories: resources (related to the required inputs and tools), procedure (related to the required activities during the analysis), and understanding (to what extent the analysis contributes to a better understanding of the LCA outcomes).

Resources

Although LCA studies tend to be data-intensive, uncertainty analysis may require large amounts of sample data that was initially not gathered. Sampling techniques require multiple data points, while an LCA study is sometimes based on single point estimates of parameter values (Björklund, 2002). The amount of primary data required for an uncertainty propagation method can be a limiting factor in the procedure of uncertainty analysis. When secondary data with uncertainty estimations suffice (like the pedigree matrix in Ecoinvent), or expert judgement can be used to quantify parameter uncertainty, this is seen as an advantage in terms of resource requirements. Therefore, the first criterion addresses the primary data requirement of the method.

> Criterion 1: *Primary data requirements*
> When many primary data points are required for uncertainty propagation, this is seen as a limiting factor. Conversely, when no primary data is needed this is an advantage in terms of suitability to all research types. Following the reasoning of Henriksson et al. (2014) that at least eight primary data points are needed to determine a distribution for an input parameter, the scoring for this criterion is as follows:
> 1. More than eight primary data points are required;
> 2. At least one, but less than eight primary data points are required;
> 3. No primary data points are required.

A second aspects related to resources refers to the time that is needed to complete the uncertainty propagation. As seen in the literature review, the available time to complete an uncertainty analysis (or an LCA study in whole) is sometimes limited. Therefore, it is seen as an advantage when uncertainty propagation is not very computationally demanding, and it can be completed fast.

Criterion 2: *Computation time*

The scoring of this criterion is based on how much time is required to complete the uncertainty propagation step for two alternatives in an LCA model. Computation time is considered 'short' when it takes less than ten minutes to complete, and it thereby doesn't influence the planning of the study and it can be repeated several times if needed. A maximum of three hours is set for the calculation time to be considered 'long', because the calculation can then be completed within half a day. If the calculation takes longer than three hours, it is considered 'very long', and it will influence the planning of the study.

1. Calculation time is more than three hours;
2. Calculation time is between ten minutes and three hours;
3. Calculation time is less than ten minutes.

The third aspect related to resources refers to the software that is required for the uncertainty propagation. The expert survey shows that most participants use only one software tool in their work, which may limit the possibilities for uncertainty propagation: when a method is not available in the preferred software tool (SimaPro, following the majority of participants in the survey), the practitioners has to use another tool, or even multiple tools. Therefore, the third criterion describes if, and if so how many software tools are required.

Criterion 3: *Software requirements*

If the full propagation step can be performed within the preferred software tool (SimaPro) this is seen as an advantage. When a different tool is required this is seen as a barrier, and the lowest score is given to methods that require multiple software tools.

1. Multiple software tools are required;
2. One software tool different from the preferred software is required;
3. The full uncertainty propagation can be performed within the preferred software tool.

Procedures

Due to the general lack of knowledge about uncertainty analysis that was found both from the literature review and the expert survey, uncertainty analysis is not widely used in LCA research. The question whether this knowledge should simply be increased, or if the methods should be simplified can be subject of further research, but for this study the focus is on the application of uncertainty analysis in the current environment of LCA research. In relation to the lack of knowledge of uncertainty analysis, the complexity of the procedures is important when discussing the suitability of propagation methods. While the core calculations of uncertainty propagation are generally made by software tools, additional procedures may be required, either in data preparation or after the main calculations. As stated in the literature review, the specification of distributions for input parameters may be required, depending on the method and available data. Because specifying distributions requires thorough understanding of statistical concepts related to uncertainty, it can be expected that LCA practitioners with limited knowledge of uncertainty analysis will have difficulties with this preparatory step. Therefore the fourth criterion describes the need to specify distributions for the input parameters in the LCA model.

Criterion 4: *Data preparation*

When no distributions need to be specified for the uncertainty propagation method, this is seen as an advantage. Because it is either necessary to do so or it isn't, this criterion can only be scored 1 or 3.

1. Specification of distributions is necessary
3. No distributions need to be specified

Another procedure that may be required in addition to the core calculations in the propagation stage is statistical testing of the outcome of the uncertainty propagation, or 'post-processing'. When a propagation method directly delivers uncertainty information, such as variance, no additional procedures are necessary. When a result is presented that is not directly interpretable however (e.g. a number of sampling results), statistical testing may be necessary to gain interpretable results. The fifth criterion therefore describes the need for post-processing.

Criterion 5: *Post-processing*
Because post-processing in the form of statistical testing requires additional knowledge, the need for post-processing operations is seen as a disadvantage. It is also possible that post-processing is not strictly necessary, but can be used for more insight (e.g. when sampling results are translated to a measure of variance by the software tool). Ideally post-processing is not necessary, so this case is assigned the highest score.

1. Statistical testing of the outcomes is crucial for interpretation
2. Statistical testing can be used for more insight, but not crucial for interpretation
3. Statistical testing of the outcomes is not necessary

Understanding
Uncertainty analysis methods should present results that lead to a better understanding of the LCA outcomes, both in terms of comparison and in terms of absolute significance of the results. In terms of comparison the outcomes should present insight in the actual extent to which one alternative is preferred over another in terms of environmental impact, considering the uncertainties. As shown in the literature reviews, comparing alternatives in a relative way is preferred over comparing in an absolute way, because it allows for the comparison of the specific uncertainty for each alternative by disregarding uncertainty around shared processes. However, this is only possible when the shared processes can be separated from the alternative-specific flows, which could be a problem a propagation method only provides a single uncertainty value. The results from the expert survey show that when uncertainty analysis is performed, the results are always incorporated in the reporting. This notion underlines the importance of this criterion, because if the results do not provide a better understanding of the results, but are presented anyway, this might give a false sense of accuracy (or at least a meaningless presentation of uncertainty). The sixth criterion describes whether relative comparison is possible: the comparative power.

Criterion 6: *Comparative power*
Because alternatives either can or cannot be compared in a relative way, only two scores are possible for this criterion. When relative comparison is possible this automatically means that absolute comparison is also possible, because relative comparison requires only a further specification of uncertainty information.

1. Alternatives can only be compared in an absolute way
3. The results allow for relative comparison of alternatives

In addition to the comparative power of the propagation method, practitioners should be able to understand and interpret the outcomes of uncertainty analysis. However, the interpretability of the results depends on the amount and type of uncertainty information that is presented. When more information on uncertainty is provided, a better interpretation of the output uncertainty is possible. When the presented uncertainty information is limited to single values (e.g. variance) or only graphs (e.g. a distribution of output uncertainty), this is seen as a disadvantage. The last criterion addresses the possibilities for interpretation, based on the type of uncertainty information that is presented through the propagation method.

Criterion 7: *Interpretation*
The highest score for this criterion is assigned when confidence intervals can be determined with the uncertainty information presented by the propagation method, because this is the most valuable uncertainty information when comparing alternatives. Single uncertainty values (e.g. variance values) are deemed less desirable, because it doesn't tell how the outcomes are distributed. When a graphical interpretation is necessary to understand the results (i.e. when no representative uncertainty values are given, but only an indication of the distribution of the outcomes) this is seen as a disadvantage.

1. Limited uncertainty information is presented, graphical interpretation is necessary
2. The results are presented as single uncertainty values (variance)
3. The results can be presented as confidence intervals

Table 6: Matrix for evaluating uncertainty analysis methods.

Category	Criterion	Scores 1	2	3
Resources	Primary data requirements	More than 8 primary data points	Less than 8 primary data points	No primary data required
	Computation time	Very long – calculation time is more than 3 hours	Long – calculation time between 10 minutes and 3 hours	Short – calculation time is less than 10 minutes
	Software requirements	Multiple software tools are required	One software tool – different from the software of choice – is required	Full analysis possible within LCA software of choice
Procedure	Data preparation	Specification of distributions is necessary		No distributions are required
	Post-processing	Statistical testing of the outcomes is crucial for interpretation	Statistical testing can be used for more insight, but not crucial for interpretation	Statistical testing of the outcomes is not necessary
Understanding	Comparative power	Alternatives can only be compared in an absolute way		The results allow for relative comparison of alternatives
	Interpretation	Limited uncertainty information is presented, graphical interpretation is necessary	The results are presented as single uncertainty values (variance)	The results can be presented as confidence intervals

Criteria weighting

While all seven criteria are important for the suitability of propagation methods for agricultural LCAs in developing countries, some are arguably more important than others. Because the aim of uncertainty analysis is to gain a better understanding of the uncertainty around LCA outcomes, it can be stated that the two criteria on comparative power and interpretation are of primary importance. Also, the abundancy of available primary data from the original LCA study suggests that primary data requirements will be of lesser importance in this type of LCA study. Assigning values to these criteria based on their relative importance can be done by weighting: more important criteria will be assigned higher values, making them count higher in the final evaluation. While this procedure is common practice for numerical variables that can be added and multiplied (e.g. impact categories in the normalisation phase of LCA), it is harder to implement for ordinal variables such as the evaluation criteria here. Because the scores of 1 to 3 are ordinal, meaning that 3 is not three times better than 1, the scores cannot be added or multiplied. Choosing a numerical scale for the scoring of the propagation methods would imply that the preferred option for each criterion would be 'three times better' than the least preferable option. Because of the qualitative nature of the criteria this numerical scale would not make sense. Quantitative weighting of the criteria is therefore not possible. Nevertheless, acknowledging that the two criteria on comparative power and interpretation are the most important criteria, and that primary data requirements are of lesser importance will steer the evaluation of the case study results in a way that reflects the importance of each criterion in the context of this study. This 'qualitative weighting' will be maintained throughout the final evaluation.

4.3 Case study

4.3.1 Sensitivity analysis

The first stage of the case study is dedicated to selecting a set of the most important parameters in the model in terms of contribution to the model outcomes and the uncertainty of these outcomes. First, a perturbation analysis is performed to find the sensitivity of the model outcomes to changes in the input parameters. Secondly, using the most influential parameters found in the previous analysis, an MEE is performed to find the importance of these parameters in terms of contribution to the model output uncertainty.

Perturbation analysis

In CMLCA, a perturbation analysis can be performed on the process level, elementary flow level, or the category level. As the focus of this study is on the ReCiPe climate change indicator (as explained in chapter 3), the perturbation analysis on the category level seems to be sufficient. However, by performing the analysis on the elementary flows that contribute to climate change, the individual contributions of the different GHGs to the multiplier value of each parameter can be discerned. This can provide additional insight in the specific role that each parameter plays in its contribution to the model outcome. Therefore, the perturbation analysis is repeated for the six elementary flows that contribute most to the resulting score on the climate change category (listed in Table 7). As 99% of the total impact score is explained by these six flows, it is justified to ignore other contributing flows. A general side note to the perturbation analysis in CMLCA is that elementary flows have to be converted to input products in the model in order to be included in the analysis. This does not affect the results, but it is contradictory to the main principles of the way CMLCA works.

Table 7: Elementary flows contributing to the climate change impact category (ReCiPe 1.1 climate change [GWP100]).

Elementary flow	**Value [kg CO_2-eq.]**	**Contribution [%]**
N_2O emissions to air	21.2	33
CO_2 emissions to air (high population density)	16.8	26
CO_2 emissions to air (low population density)	11.8	18
Methane emissions to air (unspecified)	7.59	12
CO_2 emissions to air (unspecified)	6.29	10
Methane emissions to air (low population density)	1.33	2
Explained by listed flows	65	99
Total impact score	65.3	100

The result of the perturbation analysis is a table of the most influential parameters in the model, i.e. with a multiplier value higher than the cut-off value of +0.01 (or below -0.01). The multiplier value indicates the magnitude of a change of 1% in the parameter on the output. For example, a multiplier value of +0.02 indicates that by increasing the parameter value with 1%, an increase in GWP of 0.02% will be observed. The multiplier value can also be negative, indicating a decrease in GWP when the parameter value is increased. A parameter can either be an input or an output flow, or an emission. Because the multiplier values represent the contribution to the climate change impact of the output flow of sugarcane, the sugarcane output flow has a multiplier value of -1.00 (as a 1% increase of the yield of sugarcane would lead to a 1% decrease of the climate change impact).

While a total of 386 parameters was found above the cut-off value, most of those are background processes with a fixed value and uncertainty data from the Ecoinvent database. Because the focus of this case study is on the parameters that are directly related to the cultivation of sugarcane (i.e. that were obtained in the field by KMUTT researchers), these background parameters will be excluded from further analysis. Table 8 lists the remaining parameters directly related to the model foreground processes (stages). Because the different parameters and their associated multiplier values may be hard to interpreted intuitively, an explanation of what each parameter means is added.

Table 8: Multipliers of the most influential parameters of conventional sugarcane cultivation.

Stage	Flow	Multiplier	Explanation
Sugarcane cultivation (total)	Sugarcane output [kg]	-1.000	Yield of sugarcane (kg/ha)
	Land preparation input [ha]	+0.040	Land preparation intensity (ha/kg output)
	Planting input [ha]	+0.032	Planting intensity
	Treatment input [ha]	+0.612	Treatment intensity
	Harvesting input [ha]	+0.215	Harvesting intensity
	Transport input [tkm]	+0.100	Transport (load * distance)
Land preparation	Diesel input [kg]	+0.040	Diesel use (kg/ha)
Planting	Diesel input [kg]	+0.024	Diesel use (kg/ha)
Treatment	N-fertilizer input [kg]	+0.112	N-fertilizer use (kg/ha)
	P-fertilizer input [kg]	+0.050	P-fertilizer use (kg/ha)
	Urea input [kg]	+0.139	Urea fertilizer use (kg/ha)
	N_2O emissions from treatment	+0.289	-
Harvesting	Cane trash burning [kg]	+0.152	Cane trash burning (kg/ha)
	CH_4 emissions from cane trash burning	+0.116	-
	N_2O emissions from cane trash burning	+0.036	-
	Diesel input [kg]	+0.063	Diesel use (kg/ha)
Transport	Transport output [tkm]	-0.183	Efficiency of transport (tkm/input)
Production of input materials (background processes)	Diesel output [kg]	-0.056	Efficiency of diesel production (kg/input)
	N-fertilizer output [kg]	-0.116	Efficiency of N-fertilizer production
	P-fertilizer output [kg]	-0.044	Efficiency of P-fertilizer production
	K-fertilizer output [kg]	-0.012	Efficiency of K-fertilizer production
	Urea output [kg]	-0.134	Efficiency of urea production

The multiplier table still shows several parameters that are not directly important to this study. The inputs to the total sugarcane cultivation can be interpreted as 'intensity' of cultivation practices, in hectare per kilogram of sugarcane produced. These are in fact the different stages in the cultivation process (aside from transport), and are therefore not relevant in the next step of this case study of uncertainty propagation. Also, the production of input materials is not relevant for the uncertainty analysis because these values are fixed in the database. Lastly, the parameter 'cane trash burning' constitutes of CH_4 and N_2O emissions, but as these parameters cannot be changed (as the chemical process of burning cane trash is fixed), only the total of the parameter 'cane trash burning' is of interest here. This leaves a total of nine parameters of potential relevance to uncertainty propagation in terms of influence, presented in Figure 7. The figure displays the parameters with the absolute multiplier value, because the relative magnitude of the multipliers is of interest here (i.e. how large the contribution of each parameter is compared to the others), and for visual interpretation this is best presented in an absolute way.

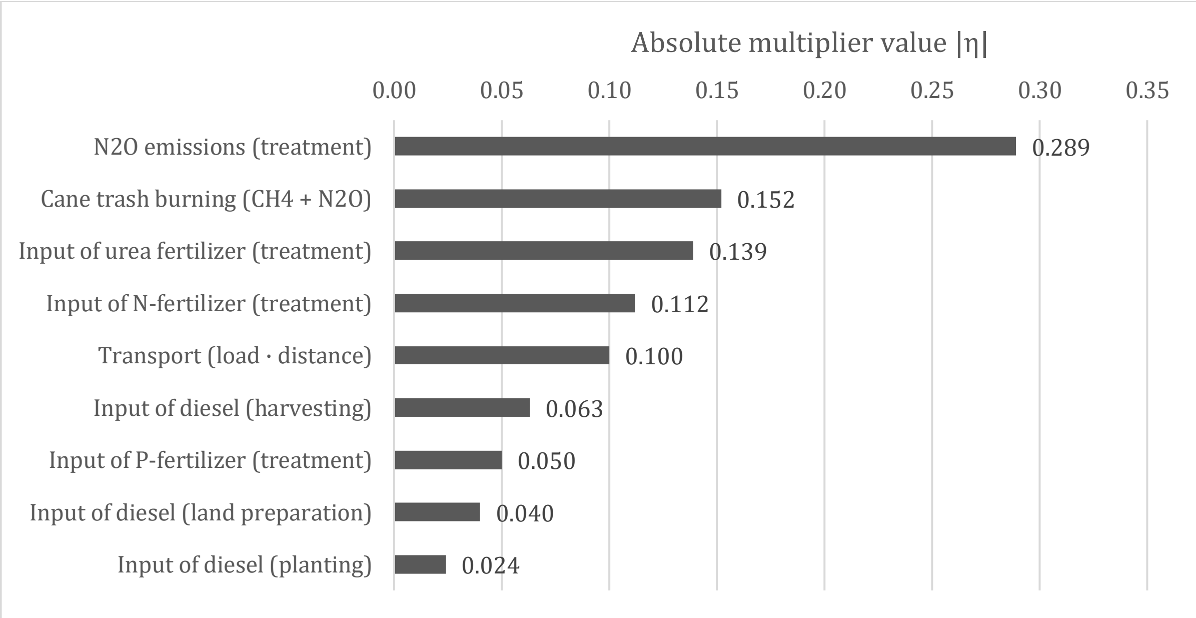


Figure 7: Selected relevant parameters and their corresponding multiplier values. For the sake of comparison of magnitude the absolute values are given.

Method of elementary effects

The MEE is performed for the nine parameters that were selected in the perturbation analysis in the previous section, in order to describe their importance in terms of their contribution to the output uncertainty. To perform an MEE, uncertainty information of the model parameters is needed in the form of ranges. As this case study is based on the sample data for one sugar mill, the ranges for each parameter are taken from this sample set (88 data points per parameter). While these ranges can be seen as indicative for the full dataset of 1,652 farms, the results may be different for other sugar mills due to a different geographical location, climate conditions and so on. Therefore, the results should be interpreted as only indicative. Also, for one parameter a range is not available (cane trash burning), as it was derived from literature. It was therefore excluded from the results.

The MEE analysis is performed with MatLab, using a script written by Groen (2016), who used MEE in her PhD thesis on uncertainty and sensitivity analysis in agricultural LCA. The required input data for an MEE are three matrices from the LCA model (technology matrix A, intervention matrix B and final demand matrix f), which are extracted from the CMLCA software. They are adapted to fit to the software, i.e. cut off at the foreground processes and aggregating impacts from background processes to foreground input parameters. The range of each parameter is defined in separate matrices (one for the upper values, one for the lower values). The MatLab script and the adapted matrices can be found in the electronic supplementary material.

The results of the MEE can be combined with the results from the perturbation analysis in a diagnostic diagram, as suggested in Figure 2. In Figure 8 the importance of the parameters is plotted on the y-axis, and the influence (as the absolute multiplier value) is plotted on the x-axis.

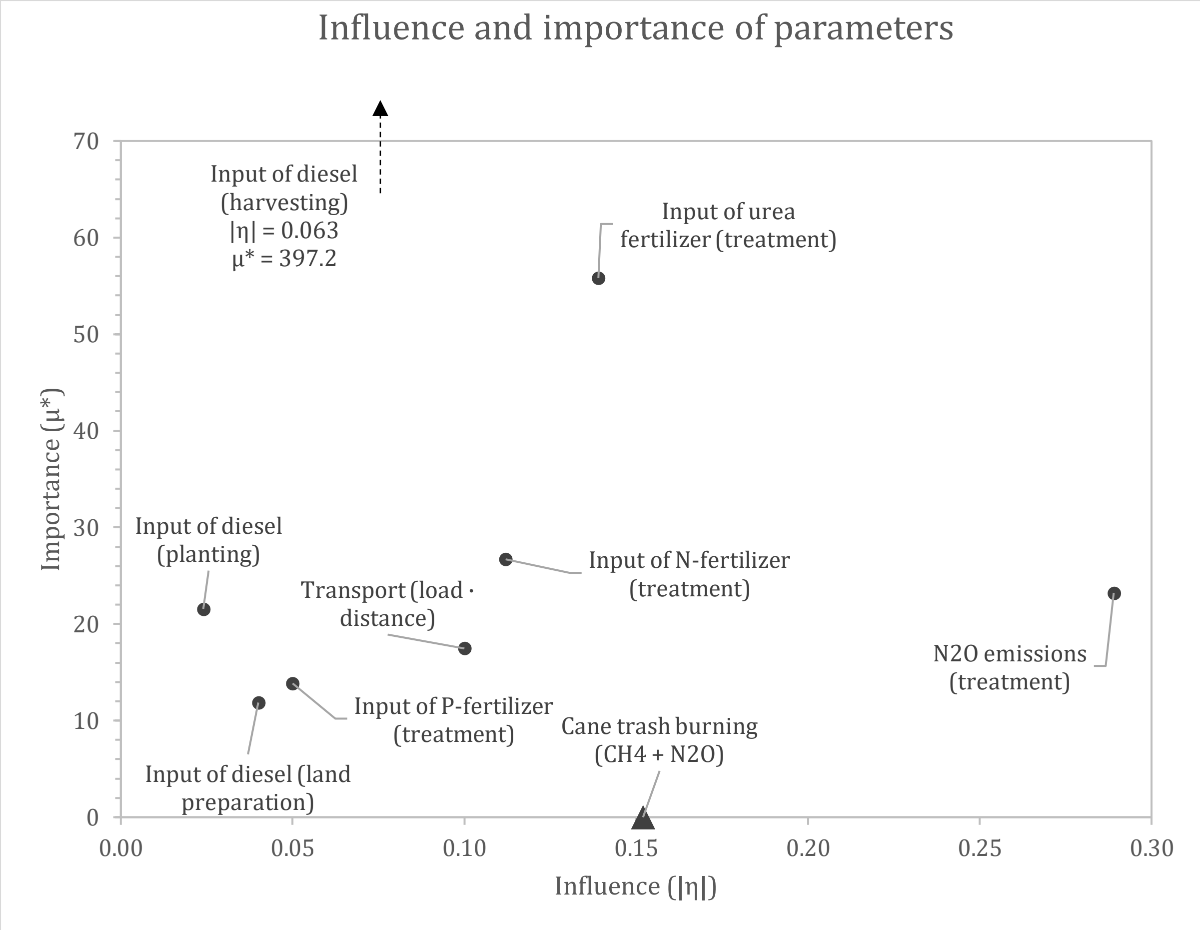


Figure 8: Combined results of the perturbation analysis and MEE analysis. Circles indicate parameters for which a range was available, triangles represent parameters for which the range is unknown. The parameter of diesel input in harvesting is indicated by an arrow, because its importance value is too high to fit on this scale.

The combined results of the perturbation analysis and MEE show that the diesel consumption during harvesting is by far the most important parameter in terms of uncertainty, but its influence on the model outcome is not exceptional. Also, urea and N-fertilizer use during treatment are significantly important while also scoring high on influence. N_2O emissions during the treatment stage are highly influential, but not exceptionally important in terms of uncertainty. Cane trash burning does not have a score on importance because a range was not available, but will be used in the propagation step because it is the second most influential parameter.

4.3.2 Phase 3B: uncertainty propagation

In this phase, the uncertainty of the nine parameter that were selected in the previous section is propagated using the methods selected in section 4.1. However, the data that is needed for the propagation step needs additional preparation. Errors in the full dataset (where in the previous phase only data from one sugar mill was used) need to be removed. Also, as described in the methodology, the required input for each propagation method needs to be obtained from the dataset. This is explained here.

Data errors

While preparing the raw data for the uncertainty propagation, it became apparent that the dataset contained several errors and missing values. This includes extremely high values (> 100 times the average value) and zero-values where zero is simply not possible. The parameters where zero-values are not allowed are transport (transport from the farm to the sugar mill is always necessary) and cane trash burning for conventional cultivation (assuming that conventional cultivation always includes cane trash burning). Also, some farms were listed with the cultivation method zero, which is considered an error as well. For the purpose of this study it is not necessary to remove all the farms containing errors from the dataset, but only the values containing errors are removed (except for the cultivation method errors).

The original dataset contained 1346 farms for conventional cultivation and 189 farms for green cultivation, adding up to a total of 13,815 data points for nine parameters. This excludes the farms containing an error for cultivation method. Table 9 lists the numbers of errors removed from the dataset for each error and alternative. A total of 606 data points were removed from the dataset, which corresponds with 4.3% of the data points values.

Table 9: Number of data errors removed from the dataset.

Error	**Number of errors**		
	Conventional cultivation	Green cultivation	Total
More than ten times the average value	20	3	23
Transport = 0	183	22	205
Cane trash burning = 0	46	-	46
Cultivation method = 0	42 farms		378
Total	249	25	606

Descriptive statistics

Several of the required inputs described in Table 5 can be easily generated from the available dataset. These descriptive statistics, including the mean, median and standard deviations can be obtained through simple calculations, without setting additional parameters. The bounds of the possibility functions are based on a pre-defined distance from the core value, for which the mean is taken. The upper and lower bounds are set to a distance of ±40% from the core value. This choice is further explained in the FIA results. The results of the descriptive statistics calculations, which were performed in R, are depicted in Table 10.

Table 10: Descriptive statistics of the parameters of conventional and green cultivation of 1 tonne of sugarcane.

Parameter	Unit	N	Mean	Median	SD	CV	Lower bound	Upper bound
Conventional cultivation								
Cane trash burning	t/ha	1300	70.72	65.91	18.04	0.26	49.50	91.94
Input of diesel in land preparation	kg/ha	1342	43.16	31.25	46.71	1.08	30.21	56.11
Input of diesel in planting	kg/ha	1336	14.33	6.25	17.57	1.23	10.03	18.63
Input of N-fertilizer in treatment	kg/ha	1345	174.81	150.00	137.90	0.79	122.37	227.25
Input of P-fertilizer in treatment	kg/ha	1345	99.39	93.75	79.24	0.80	69.57	129.21
Input of urea in treatment	kg/ha	1346	121.01	0.00	185.77	1.54	84.71	157.31
Input of diesel in harvesting	kg/ha	1344	14.55	0.00	49.15	3.38	10.19	18.92
Transport	tkm	1161	1096.03	700.0	1256.50	1.15	767.22	1424.84
N_2O emissions from treatment	kg/ha	1345	1.46	1.32	1.17	0.80	1.02	1.90
Green cultivation								
Input of diesel in land preparation	kg/ha	189	44.58	37.50	35.64	0.80	31.21	57.95
Input of diesel in planting	kg/ha	189	21.37	25.00	16.29	0.76	14.96	27.78
Input of N-fertilizer in treatment	kg/ha	189	168.54	148.44	124.59	0.74	117.98	219.10
Input of P-fertilizer in treatment	kg/ha	189	72.72	65.63	58.20	0.80	50.90	94.54
Input of urea in treatment	kg/ha	189	137.74	0.00	220.72	1.60	96.42	179.06
Input of diesel in harvesting	kg/ha	187	6.56	0.00	13.11	2.00	4.59	8.53
Transport	tkm	166	1051.84	875.00	846.32	0.80	736.29	1367.39
N_2O emissions from treatment	kg/ha	189	1.34	1.13	1.23	0.92	0.94	1.74

Distributions

One of the required inputs for uncertainty propagation with a sampling method is the distribution function that can be used to describe each parameter. In the sampling procedure, this function is used to estimate the probabilities of all values within the distribution function, and sample from this function according to these probabilities. When little data and time resources are limited, it is possible to assume a certain distribution (e.g. lognormal) for all parameters (Henriksson et al., 2014). When sufficient data is available (more than eight data points), Henriksson et al. (2014) argue that the best fitting distribution should be determined in order to avoid increasing data uncertainty by assuming one distribution. In this case study, because much primary data is available, the best fitting distribution will be determined for all parameters. However, the best fitting distribution must still present a truthful depiction of the way the parameter is distributed. This means that a normal distribution with the probability density function (pdf) stretching below zero is only possible for parameters where negative values can occur. In this case study, all nine parameters do not allow for negative values: negative fuel consumption, fertiliser use, transport or emissions are not possible in this system. This means that when the best fitting distribution implies a pdf that stretches below zero, it has to be adjusted to a distribution that does not allow for negative values (the lognormal distribution). Although this is arguably an assumption that affects the outcomes, it is necessary to avoid negative outcomes.

When determining the best fitting distribution for a parameter, the sample data is compared to theoretical fitted distribution functions, as where they perfectly following a distribution function. A goodness-of-fit (GOF) test determines the extent to which is does so, by testing the hypothesis that the sample data follows a certain distribution. If the null-hypothesis that the data does *not* follow a certain distribution is rejected, the data can be assumed to follow this distribution. Common GOF test methods that can be used to determine this information for several distributions include the Anderson-Darling (AD) test and the Kolmogorov-Smirnov (KS) test.

However, if the null-hypothesis is not rejected for any distribution, additional measures are needed to determine the best fitting distribution relative to the others. The AD and KS tests also give a specific value for each distribution when compared to the sample data. This information can be used to compare the fitting distributions in a relative way, when no conclusions can be drawn from the hypothesis-testing alone. This method may be required when using large sets of sample data, because it is not likely that primary data closely follows the theoretical distribution function. The GOF-tests are performed in R, and the results are listed in Table 11 and Table 12.

Table 11: Goodness-of-fit results for green cultivation parameters. The best fitting distributions for each parameter are highlighted. For the uniform distribution, the AD statistic and AIC criterion are not available.

Parameter	Distribution	AD statistic	KS statistic	AIC criterion	Explaining graphs
Input of diesel in land preparation	Normal	3.21	0.124	1890.1	CDFs P-P plot
	Lognormal	21.65	0.289	1898.2	
	Uniform		0.421		
Input of diesel in planting	Normal	10.27	0.197	1594.0	None
	Lognormal	24.53	0.273	1612.5	
	Uniform		0.352		
Input of N-fertilizer in treatment	Normal	5.74	0.154	2363.2	All
	Lognormal	20.36	0.271	2436.9	
	Uniform		0.474		
Input of P-fertilizer in treatment	Normal	2.95	0.110	2075.5	All
	Lognormal	20.47	0.273	2094.6	
	Uniform		0.487		
Input of urea in treatment	Normal	20.65	0.279	2579.4	None
	Lognormal	26.43	0.361	1869.8	
	Uniform		0.665		
Input of diesel in harvesting	Normal	33.72	0.387	1496.0	None
	Lognormal	33.26	0.430	980.0	
	Uniform		0.696		
Transport	Normal	8.80	0.165	2712.1	All
	Lognormal	1.23	0.091	2595.5	
	Uniform		0.681		
N_2O emissions from treatment	Normal	6.90	0.146	617.0	All
	Lognormal	2.02	0.095	527.1	
	Uniform		0.616		

Table 12: Goodness-of-fit results for conventional cultivation parameters. The best fitting distributions for each parameter are highlighted. For the uniform distribution, the AD statistic and AIC criterion are infinite and not available respectively.

Parameter	Distribution	AD statistic	KS statistic	AIC criterion	Explaining graphs
Cane trash burning	Normal	28.44	0.132	11212.3	All
	Lognormal	16.72	0.124	11080.3	
	Uniform		0.570		
Input of diesel in land preparation	Normal	57.43	0.178	14128.6	CDFs
	Lognormal	118.44	0.241	12714.9	
	Uniform		0.557		
Input of diesel in planting	Normal	100.65	0.291	11452.5	None
	Lognormal	167.20	0.336	9578.7	
	Uniform		0.668		
Input of N-fertilizer in treatment	Normal	37.20	0.146	17072.2	Histogram CDFs
	Lognormal	117.62	0.239	17348.3	
	Uniform		0.605		
Input of P-fertilizer in treatment	Normal	29.38	0.157	15582.0	All
	Lognormal	126.10	0.254	15802.8	
	Uniform		0.586		
Input of urea in treatment	Normal	139.30	0.302	17887.2	None
	Lognormal	197.82	0.370	12978.8	
	Uniform		0.683		
Input of diesel in harvesting	Normal		0.384	14286.7	CDFs
	Lognormal	218.71	0.409	7966.5	
	Uniform		0.885		
Transport	Normal		0.192	19867.8	P-P plot
	Lognormal	15.70	0.106	18724.0	
	Uniform		0.690		
N_2O emissions from treatment	Normal	32.41	0.130	4233.1	All
	Lognormal	7.32	0.082	3756.1	
	Uniform		0.578		

The information from the GOF-tests implies that most of the parameters in the model are normally distributed. However, when looking at the descriptive uncertainty information from Table 10, it becomes clear that all of these parameters will have a pdf that stretches below zero, implying the possibility of negative values. As this must be avoided, lognormal distributions are assumed for all parameters. It is acknowledged that the best procedure to handle the impossibility of negative values is by truncating the normal distributions at the zero value, thereby avoiding all values below zero. However, due to time restrictions the parameters were simply assumed to be lognormal. Still it is important to understand the best fitting distributions when interpreting the uncertainty propagation results, as the assumption of a different distribution influences the result. This will be discussed in the discussion chapter.

Using the information from this section, the CMLCA model can be supplemented with uncertainty information. In CMLCA parameter uncertainty for lognormally distributed parameters is expressed as the mean value and a parameter of dispersion *phi*. This parameter expresses the dispersion based on the coefficient of variation as follows (Heijungs & Frischknecht, 2005, p. 252):

$$phi = \sqrt{\ln(\mathrm{CV}^2) + 1}$$

where CV is the coefficient of variation. This formula is applied to the mean values and CVs from Table 10, and the resulting values that are put into CMLCA are listed in Table 13.

Table 13: Parameter uncertainty information as input in the CMLCA model.

Parameter	Distribution	Mean value	Parameter of dispersion (φ)
Conventional cultivation			Value
Cane trash burning	Lognormal	70.72	0.256
Input of diesel in land preparation	Lognormal	43.16	0.879
Input of diesel in planting	Lognormal	14.33	0.960
Input of N-fertiliser in treatment	Lognormal	174.81	0.696
Input of P-fertiliser in treatment	Lognormal	99.39	0.703
Input of urea in treatment	Lognormal	121.01	1.102
Input of diesel in harvesting	Lognormal	14.55	1.587
Transport	Lognormal	1096.03	0.918
N_2O emissions from treatment	Lognormal	1.46	0.703
Green cultivation			
Input of diesel in land preparation	Lognormal	44.58	0.703
Input of diesel in planting	Lognormal	21.37	0.675
Input of N-fertiliser in treatment	Lognormal	168.54	0.661
Input of P-fertiliser in treatment	Lognormal	72.72	0.703
Input of urea in treatment	Lognormal	137.74	1.127
Input of diesel in harvesting	Lognormal	6.56	1.269
Transport	Lognormal	1051.84	0.703
N_2O emissions from treatment	Lognormal	1.34	0.783

Correlations and common processes

One important aspect of assessing parameter uncertainty is the presence of correlations between parameters. The outcomes of comparative LCA studies often depend on both common and correlated parameters; *common* in the sense that alternatives often share part of the processes in the product system, and *correlated* in the sense that some parameters in the model may be fully or partly dependent on other parameters 'upstream' in the product chain (Lloyd & Ries, 2007). For example, in the sugarcane cultivation case study both alternatives include the production of fertiliser, which is therefore a shared process. Correlated parameters could be for example emissions (e.g. CO_2) directly related to another parameter (e.g. diesel combustion).

In the context of uncertainty, correlation between parameters is important because the results of uncertainty analysis can present wrong conclusions when correlation is ignored (Bojacá & Schrevens, 2010). Because the variance in a correlated parameter can be explained partly or fully by the variance in another parameter, including the variance of both parameters in uncertainty propagation would lead to an overestimation of the output uncertainty (Groen & Heijungs, 2017). In other words, this would be 'double counting' of parameter uncertainty, and should be accounted for during uncertainty propagation. Groen and Heijungs (2017) studied the effect of ignoring correlations between parameters, and found that the magnitude of over- or underestimation of uncertainty is determined by the variance in the parameter and by the correlation coefficient. Small parameter variance and a large correlation coefficient have a large effect on the output variance; depending on the type of correlation (technical parameter-emission, emission-emission or technical parameter-technical parameter), the output variance decreases or increases when correlations are ignored (Groen & Heijungs, 2017). Consequently, the importance of parameters in terms of their contribution to the output uncertainty (as can be quantified with a global sensitivity analysis) is *underestimated* when correlation is ignored.

Although correlations between input parameters can have a significant effect on the output uncertainty, incorporating them in uncertainty analysis in LCA is far from common practice (Lloyd & Ries, 2007). Groen and Heijungs (2017) name two main requirements that need to be met: the procedure for uncertainty propagation needs to be adapted, and knowledge about the correlation coefficients is needed. Most common LCA software tools do not provide for adapted procedures to handle such correlations within uncertainty propagation, and knowledge about this subject is not widespread. Because the focus of this research is on the comparison of uncertainty analysis methods, the application or even development of new methods for incorporating correlations in uncertainty analysis is beyond the scope of this study. However, understanding the correlations between parameters in the case study and interpreting the uncertainty propagation results accordingly (although limited to a qualitative assessment) is possible without the use of such new methods. Within the nine parameters under study for each alternative, considering the flowcharts of both product systems, three correlations are found. The emission of N_2O in the treatment phase is possibly directly linked with the application of N-fertiliser and urea fertiliser, as nitrogen is the main component of N-fertiliser and urea. Also, it is expected that N-fertiliser and urea are correlated, because both fertilisers are used nitrogen fertilisers providing the same service to the soil. When more N-fertiliser is used, less urea would be needed to provide the same amount of nitrogen to the soil. The correlation between parameters can be tested with Pearson's correlation coefficient *r*, found by

$$r = \frac{\sum(X_i - \bar{X})\,(Y_i - \bar{Y})}{[\sum(X_i - \bar{X})^2 \sum(Y_i - \bar{Y})^2]^{1/2}}$$

where *X* and *Y* are the parameters tested (Rodgers & Nicewander, 1988, p. 61). Although this measure does not say anything about causality, it gives an indication of the magnitude of correlation. A correlation coefficient of 1 indicates perfect correlation, while 0 means no correlation.

N-fertiliser and N_2O emissions have a correlation coefficient of 0.91, suggesting a strong correlation. An implication of this correlation is that in the uncertainty propagation, the outcome may be an overestimation of the actual uncertainty. This because the uncertainty stemming from the N-fertilizer and urea fertiliser use is also propagated in the uncertainty N_2O emissions. Urea fertiliser and N_2O emissions however have a correlation coefficient of only 0.04, suggesting a very weak or no correlation. Urea fertiliser and N-fertiliser also have a correlation coefficient of 0.04, and therefore don't suggest any correlation. Based on the chemical properties of urea fertiliser the lack of correlation with both N_2O emissions and N-fertiliser is not expected. A possible explanation is that the relationship between urea and N_2O emissions was not properly modelled in the original model (i.e. the emission factor of N_2O from urea fertiliser was not incorporated). The lack of correlation with N-fertiliser use suggests that either farmers don't take into account the chemical properties of the fertiliser products when applying them, or that the primary data on fertiliser use is incorrect. While this notion is important for the interpretation of the LCA results, it does not necessarily complicate matters for uncertainty propagation in this case study, because there is no correlation incorporated in the model.

Results: Monte Carlo simulation

The result of the MCS is a list of 3000 possible outcomes of the model for both alternatives. Regarding uncertainty, descriptive statistics can be given of this sample set. The mean and median values, CV, SD and the 95% confidence interval (as the lower and upper bounds) are listed in Table 14.

Table 14: Results of the Monte Carlo simulation (3000 runs).

Alternative	Mean	Median	SD	CV	2.5%	97.5%
Conventional cultivation	39.6	37.0	12.6	0.318	23.2	72.7
Green cultivation	32.8	30.5	11.7	0.357	17.7	61.6

Graphically the results are presented as histograms (Figure 9 and Figure 10), in a bar chart (Figure 12) and in box-whisker plots (Figure 11).

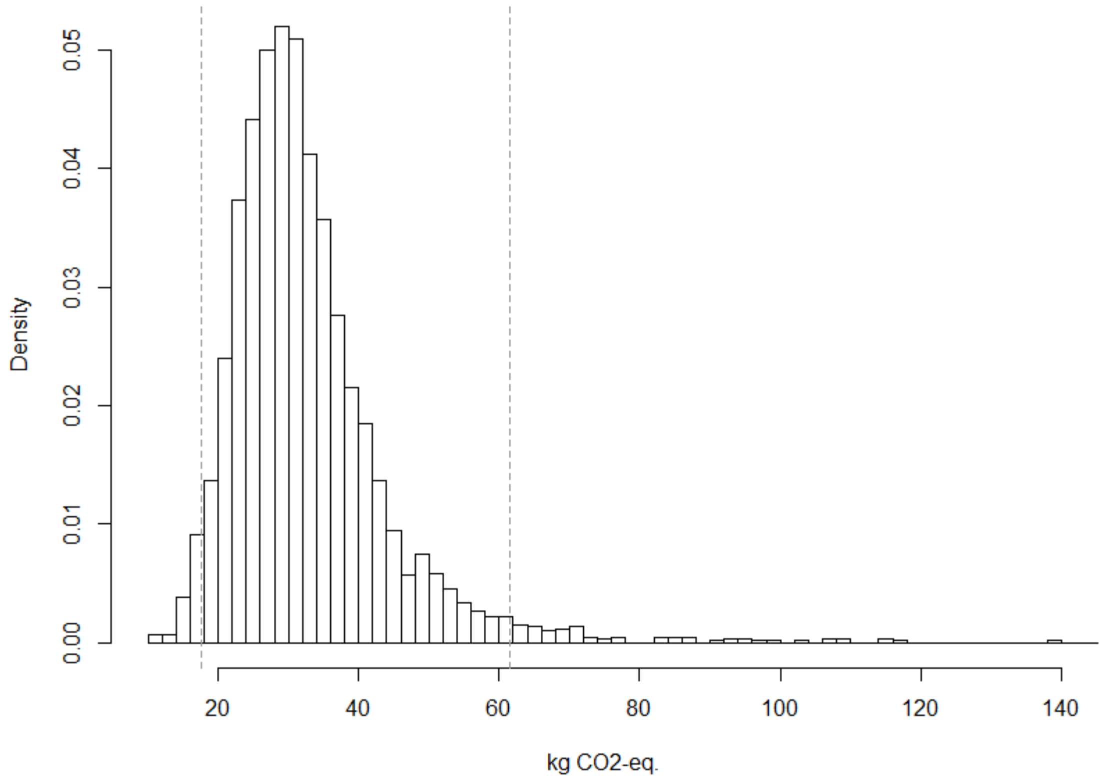


Figure 9: Histogram of the MCS results for green cultivation. The dashed lines represent the 2.5th and 97.5th percentile.

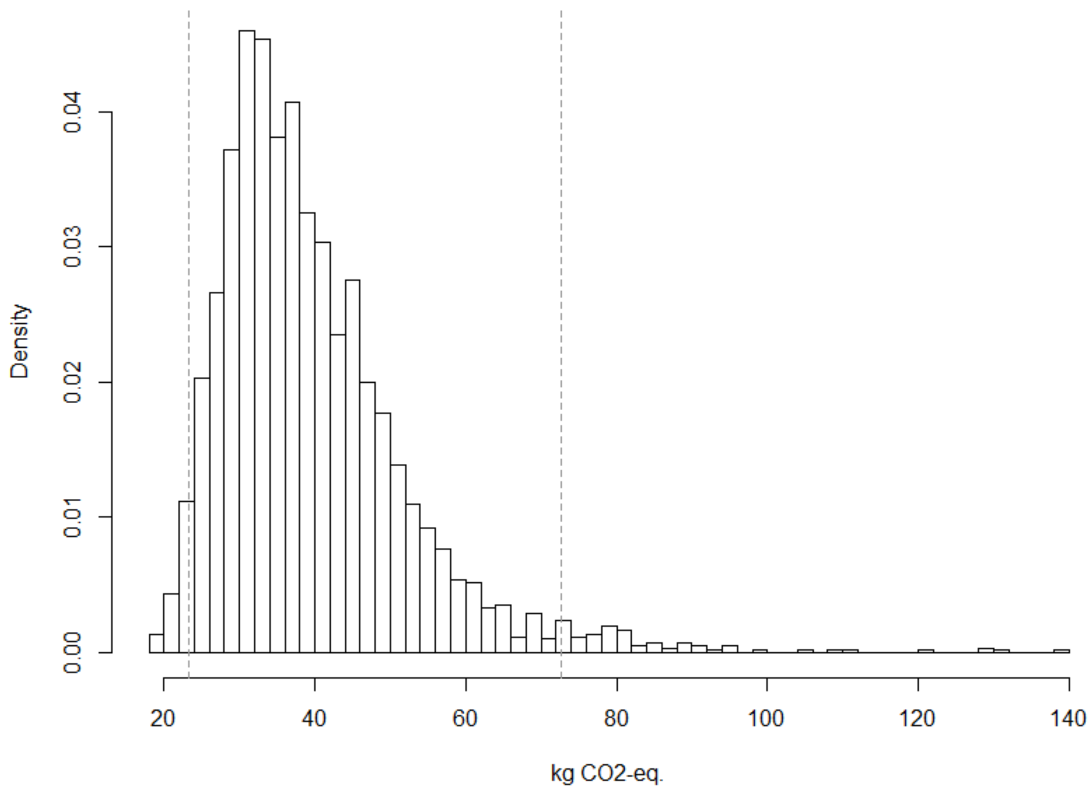


Figure 10: Histogram of the MCS results for conventional cultivation. The dashed lines represent the 2.5th and 97.5th percentile.

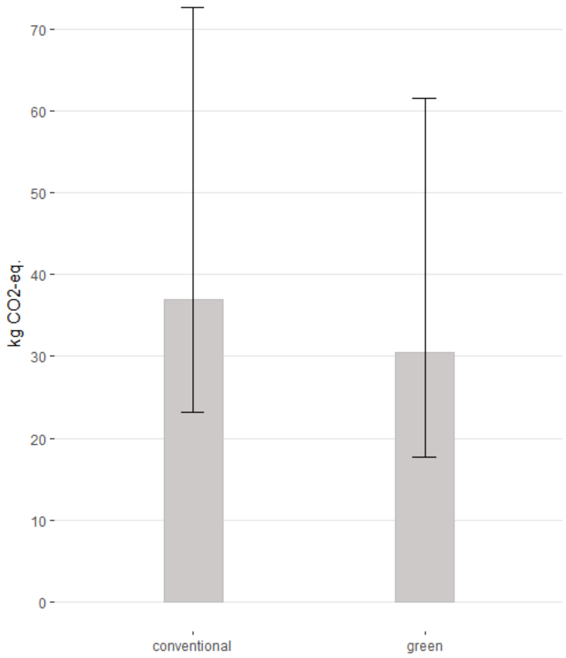


Figure 12: Bar chart of the MCS results for both alternatives. The error bars indicate the 95% confidence interval.

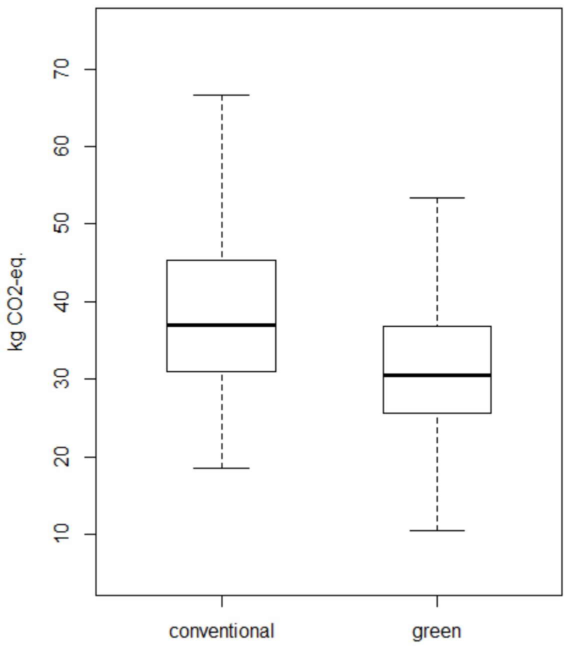


Figure 11: Box-and-whisker plot of the MCS results for both alternatives. The black line indicates the median, the box represents the 25th and 75th percentile, and the whiskers represent the 10th and 90th percentile.

The dependent analysis of the MCS is done using the method presented by Henriksson et al. (2015a). Because the resulting graphs for each alternative separately are the same for this method as for the independent analysis, this part will be focussed on the additional options that this method provides for the relative uncertainty of both alternatives. To assess the relative uncertainty (i.e. comparing the alternatives on uncertainty caused parameters specific to each alternative), the values for green cultivation obtained in the MCS are subtracted from those for conventional cultivation. The resulting sample set can be analysed in a similar way to the independent analysis. The descriptive statistics are given in Table 15.

Table 15: Results of the MCS dependent analysis.

Alternative	Mean	Median	SD	CV	2.5%	97.5%
Conventional – green cultivation	6.85	6.40	16.8	2.46	-25.4	41.4

Because of the negative values in the 95% confidence interval, this result is graphically best presented as a histogram (Figure 13) and a box-and-whisker plot (Figure 14).

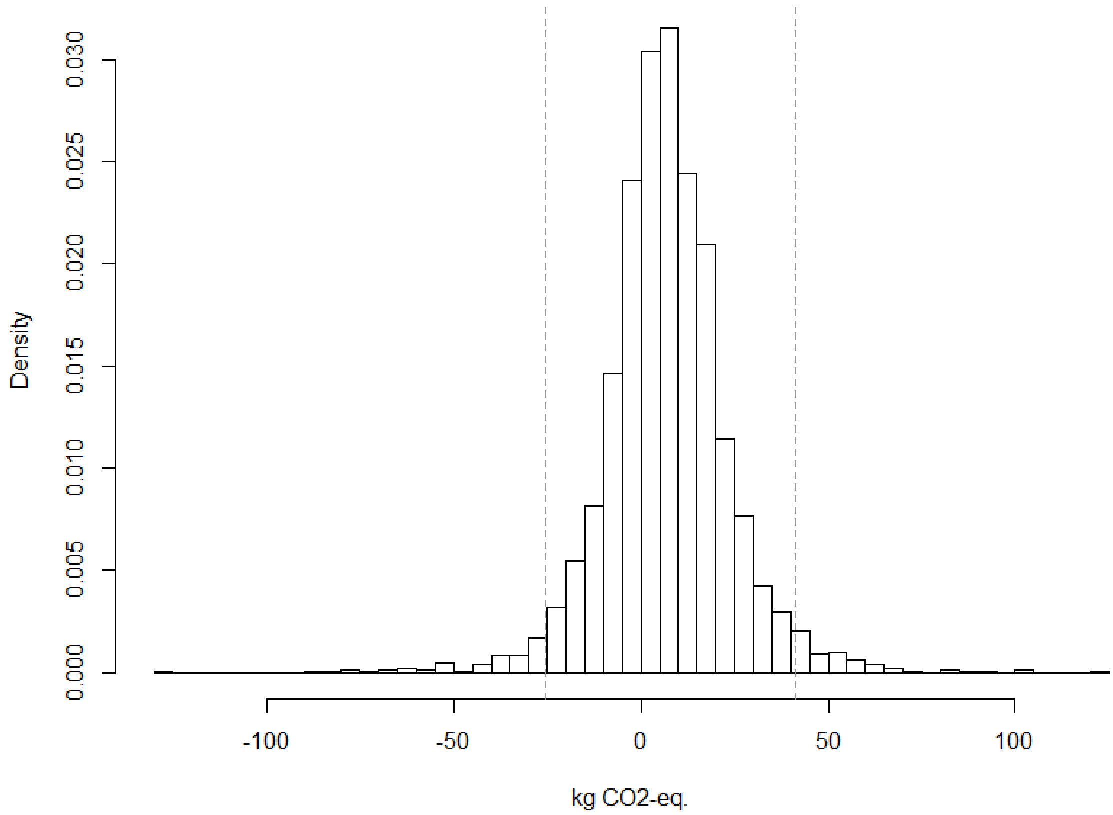


Figure 13: Histogram of the MCS dependent analysis results. The dashed lines represent the 2.5th and 97.5th percentile.

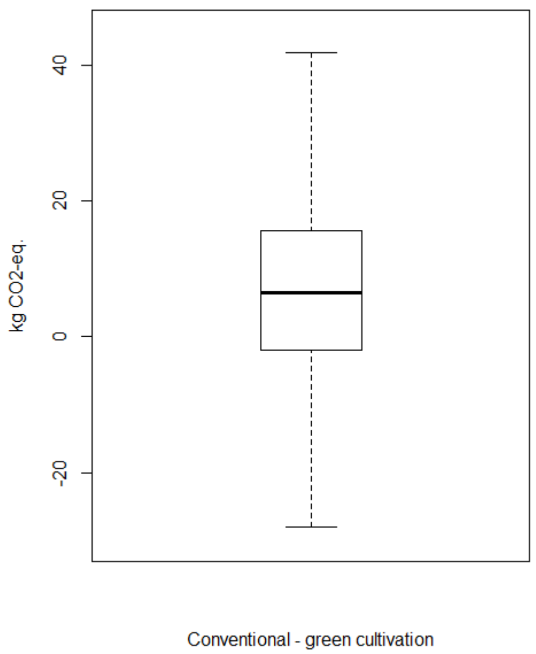


Figure 14: Box-and-whisker plot of the dependent analysis of the MCS results. The black line indicates the median, the box represents the 25th and 75th percentile, and the whiskers represent the 10th and 90th percentile.

Results: analytical method

The AUP was performed in CMLCA. The required inputs (standard deviations from the parameter mean) are not directly put into the model, but calculated on the background from the uncertainty information used in the MCS. As discussed earlier, a first order Taylor expansion was used to express the output uncertainty. The resulting output is given by the baseline and mean values (i.e. with and without including uncertainty information, which are the same for AUP), the standard deviation, variance and coefficient of variance. The results are listed in Table 16.

Table 16: Results of analytical uncertainty propagation.

Name	Baseline	Mean	SD	Variance (unit^2)	CV
Conventional cultivation	39.7	39.7	14.4	208	0.36
Green cultivation	33.1	33.1	12.9	166	0.39

Because this method is based on a single calculation, no distribution or confidence interval can be provided. Therefore, the results are presented in a bar chart with error bars representing the standard deviation (Figure 15).

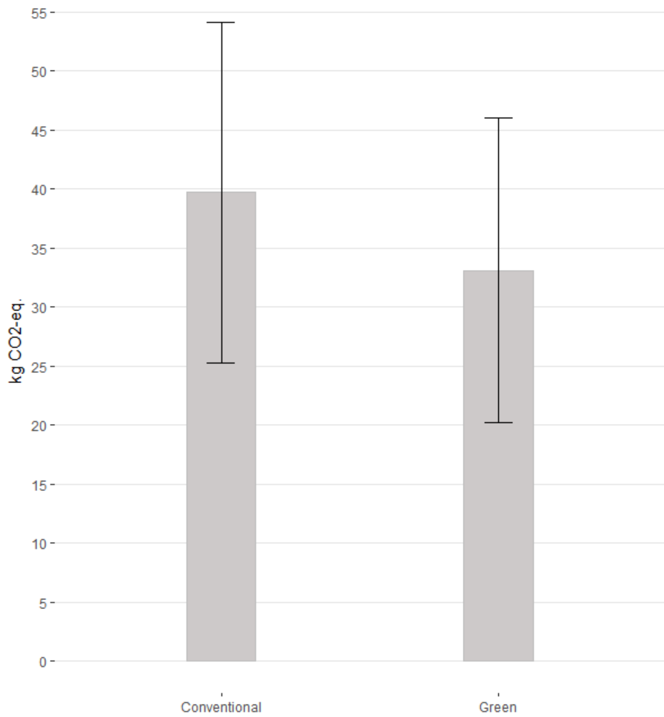


Figure 15: Bar chart of the results of the AUP method. The bars indicate the mean values, the error bars represent the standard deviation from the mean.

Results: fuzzy interval arithmetic method

The FIA was conducted in MatLab, using a script adapted from Evelyne Groen (2016) that can be found in the electronic supplementary material. This matrix-based approach (which is similar to the script used in the sensitivity analysis) requires the input of the mean values in the technology matrix, the intervention matrix and the final demand matrix. The script calculates a possibility function where the core value is set to one, and the lower and upper bounds are both zero. A number of alpha cuts is used to describe the levels of possibility between zero (least plausible value) and one (most plausible value). Here 11 alpha cuts are used, as this yields steps of 0.1. The interval between the lower and upper values at the alpha cuts give the range in which the values are estimated to be for a certain possibility. The result is a possibility function where the base represents the largest interval, and the top represents the most plausible value.

The intervals are described by the lower and upper bounds at ±40% from the core value, which is implemented in the model by setting the parameter range to 0.4. This range has to be chosen somewhat arbitrarily, as generally no expression of variance is known when only this method is used. An alternative is to use the actual ranges of the available data, but because of the very large data set these ranges will be very large, most likely resulting in an overestimation of the actual uncertainty. This is so because the possibility function does not allow for the specification of the probability that a given value will occur within the range, thereby assuming all values equally likely. Therefore, an estimation of the variance (in this case the rather arbitrary 40%) would give a better indication of the parameter uncertainty. Uncertainties around the intervention matrix are disregarded, as these are not subject of this study.

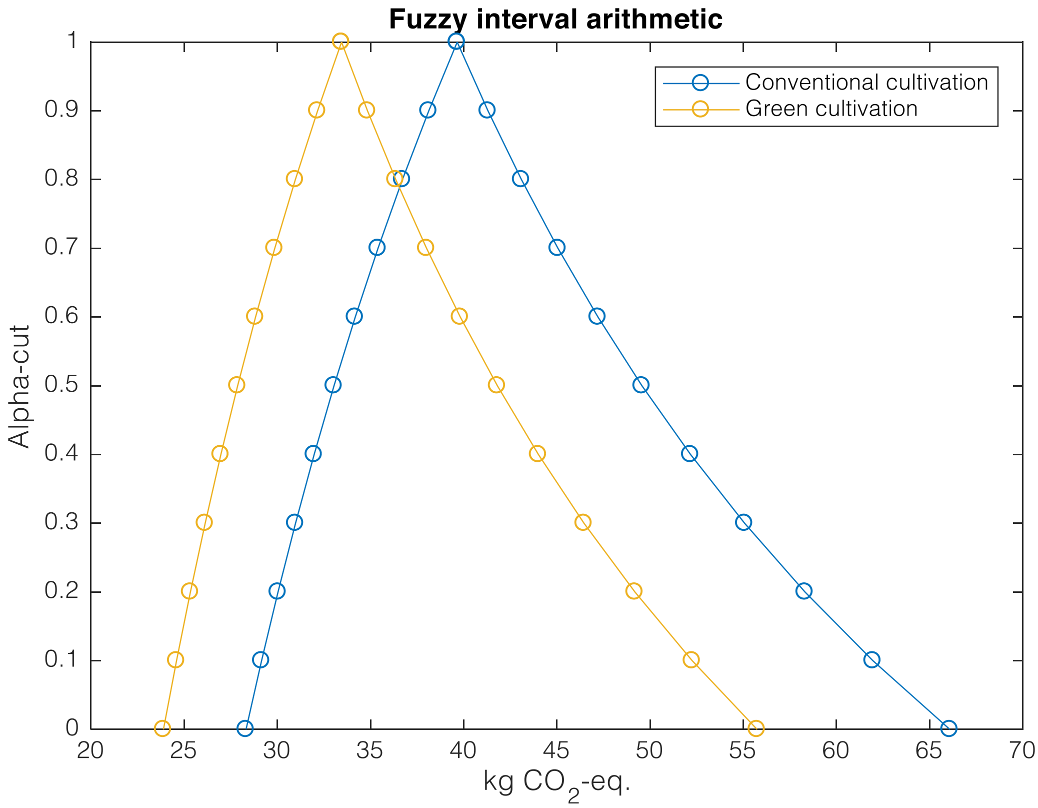


Figure 16: Results of the FIA method.

As it is not possible to determine a confidence interval or variance from the triangular fuzzy interval in Figure 16, the expression of uncertainty in this method is limited to the graphical interpretation and an estimated range around the core value (corresponding to the base of the triangle). This information is presented in

Table 17: Results of the FIA method.

Name	Baseline	Core value	Lower limit	Upper limit
Conventional cultivation	39.7	39.7	28.3	66.1
Green cultivation	33.1	33.1	23.9	55.7

4.4 Evaluation

In this final phase, the results from the uncertainty propagation are evaluated with the criteria selected earlier. The scoring guidelines formulated in section 4.2.2 are used to determine the score of each method per criterion. The final scores are listed in Table 17.

MCS – independent analysis

Primary data requirements:	Because a sampling method requires a significant amount of data points to be available, this method will not yield representative results when only a few data points are available. The score is therefore 1.
Computation time:	The computation time of this sampling method is very long (around 24 hours for 3000 runs). The score is therefore 1.
Software requirements:	Monte Carlo simulation with independent analysis is available in most LCA software tools, including SimaPro. No additional software is required, therefore the score is 3.
Data preparation:	For this method it is necessary to specify distributions for all parameters in the model. The score is therefore 1.
Post-processing:	Because the output of this method is given on a per-run basis, the essential uncertainty information can be easily determined within the software tool. However, additional testing can be done to find the confidence intervals for the alternatives, which provide more insight in the significance of the results. The score is therefore 2.
Comparative power:	Because the per-run output of this method is analysed independently, the output uncertainty can only be quantified in an absolute way. The score is therefore 1.
Interpretation:	Post-processing can be used to find confidence intervals, allowing for a better interpretation of the results. The score is therefore 3.

MCS – dependent analysis

Primary data requirements:	The data requirements for this method are the same as those for MCS with independent analysis, demanding enough data points to determine a distribution. The score is therefore 1.
Computation time:	The computation time for this method is the same as for MCS with independent analysis, taking around 24 hours for 3000 runs. The score is therefore 1.
Software requirements:	While the Monte Carlo sampling can be done within most LCA software tools, the procedure of dependent analysis requires the difference between both alternatives on a per-run basis to be known. This is not possible within SimaPro alone, the subtraction needs to be done in different software (e.g. spreadsheet software). The score is therefore 1.
Data preparation:	For this method it is necessary to specify distributions for all parameters in the model. The score is therefore 1.
Post-processing:	Other than with the MCS with independent analysis, post-processing is necessary for a dependent analysis. The outcomes of the MCS (3000 outcomes for each alternative) have to be subtracted and analysed (whereas in the independent analysis the

	basic uncertainty information can be presented by the LCA software). The score is therefore 1.
Comparative power:	Because the results of the MCS are analysed dependently, this method provides insight in the relative uncertainty of the LCA outcomes. This means that the comparative power of this method is high, as the specific uncertainty information for each alternative (i.e. not the shared processes) can be assessed. The score is therefore 3.
Interpretation:	Confidence intervals can be determined for the dependently analysed results because the output is again given on a per-run basis. The score is therefore 3.

Analytical uncertainty propagation

Primary data requirements:	The required input for this method is limited to a core value and standard deviation for each parameter. As the standard deviation can be determined with less than eight data points (although more would increase the reliability), the score on this criterion is 2.
Computation time:	The computation time for this method is very short: less than one minute. The score is therefore 3.
Software requirements:	Analytical uncertainty propagation can be performed within a single software tool, but not in SimaPro. Therefore another tool is needed (e.g. CMLCA), so the score for this criterion is 2.
Data preparation:	It is not necessary to define distributions for the model parameters for analytical uncertainty propagation. The score is therefore 3.
Post-processing:	The output of this method gives the essential uncertainty information, where post-processing is not necessary (nor possible). The score is therefore 3.
Comparative power:	Relative comparison of two alternatives is not possible, because the uncertainty around each alternative is calculated independently from each other. The score is therefore 1.
Interpretation:	As this method provides single uncertainty values (variance and standard deviation), confidence intervals cannot be determined. Graphical interpretation is possible in addition to the uncertainty information, but not required. The score is therefore 2.

Fuzzy interval arithmetic

Primary data requirements:	Only very limited uncertainty information is required to perform this method, as an estimation of the parameter uncertainty is sufficient. The score on this criterion is therefore 3.
Computation time:	The computation time for this method is very short, less than one minute. The score is therefore 3.
Software requirements:	FIA can currently not be performed within any LCA software tool. A different tool is therefore required (MatLab was used for this case study). The score is therefore 2.
Data preparation:	No distributions of input parameters are required for this method. The score is therefore 3.
Post-processing:	The output of this method gives the uncertainty information by means of a possibility distribution, where post-processing is would not lead to additional insights. The score is therefore 3.

Comparative power:	The uncertainty information that is presented by this method allows only for an absolute comparison of alternatives. The score is therefore 1.
Interpretation:	The possibility distribution that is presented as the outcome of this method provides only the upper and lower limits for each alternative. The uncertainty information is therefore limited, and graphical interpretation is necessary. The score is 1.

Table 18: The scores of each propagation method on the evaluation criteria.

Category	**Criterion**	**Monte Carlo simulation (independent analysis)**	**Monte Carlo simulation (dependent analysis)**	**Analytical uncertainty propagation**	**Fuzzy interval arithmetic**
Resources	Primary data requirements	1	1	2	3
	Computation time	1	1	3	3
	Software requirements	3	1	2	2
Procedure	Data preparation	1	1	3	3
	Post-processing	2	1	3	3
Understanding	Comparative power	1	3	1	1
	Interpretation	3	3	2	1

5. Discussion

5.1 Discussion of results

In this chapter, the insights from the case study evaluation are discussed in relation to the research questions and the situation of agricultural LCA research in developing countries. The research sub-questions are:

1. What are the drivers and barriers for practitioners of agricultural LCAs in developing countries for applying uncertainty analysis?
2. What methods for assessing uncertainty in LCI data are available?
3. What are the differences in outcomes when applying different methods of uncertainty propagation on agricultural LCI data?
4. How can the results be used to guide practitioners of agricultural LCA to appropriately apply uncertainty assessment in their work?

The literature review and expert survey show that the drivers for applying uncertainty analysis in LCA are related to increasing scientific reliability, better guiding decision-makers, and (to a lesser extent) compliance with international regulations. Especially when an LCA is comparative, uncertainty analysis is crucial to determine the significance of the difference in impact between alternatives, and to avoid counterproductive decisions. This underlines the importance of assessing the relative uncertainty of LCA alternatives, which has been subject of recent scientific debate. The most important barrier was found in the fact that there is a lack of knowledge among LCA practitioners of uncertainty analysis methods, which hampers a widespread and adequate implementation of uncertainty analysis in LCA practices. Scientific research on methods for uncertainty analysis to this date has been focussed on the scientific validity and adequacy of different propagation methods, thereby neglecting the fact that some methods are far too complex for LCA practitioners to perform. Further research is needed on the integration of adequate uncertainty propagation methods in LCA software tools, in such a way that users with limited knowledge of uncertainty analysis are able to perform them. Other barriers are related to the lack of an adequate framework and guidance for uncertainty analysis, and the need for sufficient uncertainty information of the input data.

Answering the second sub-question showed that there many different methods for uncertainty analysis in LCA. The methods for assessing parameter uncertainty are sampling methods, analytical methods or possibilistic methods, where sampling methods are by far used the most. This is in part due to the fact that Monte Carlo simulation is available in most LCA software tools, while other methods require additional tools. The fact that most propagation methods that have been studied in the context of LCA are rarely used in practice underlines the need for further implementation of such methods in LCA software tools.

The differences in outcomes of different uncertainty propagation methods, obtained in the case study of this thesis, were evaluated. This evaluation has provided insight in the advantages and disadvantages of the uncertainty propagation methods under study. The evaluation shows that the primary goal of uncertainty analysis – to gain a better understanding of the uncertainty around LCA outcomes – is best served using sampling methods. Including Monte Carlo-based uncertainty propagation in an LCA study allows the practitioner to draw reliable conclusions about the representativeness of the LCA results. Using MCS with dependent analysis allows for a comparison of two alternatives in a relative way, which is not possible with the other methods, and therefore has a high comparative power. However, the results also show that in terms of data requirements and knowledge of procedures, the sampling methods perform significantly worse than the analytical and fuzzy interval methods. For sampling methods to yield representative results, many primary data points are required. Less data is required for AUP (more than one data point) and FIA (no primary data required), but these methods contribute to a (far) lesser extent to a better understanding of the results. When FIA would be used for research where sufficient primary data is available, a considerable and 'unnecessary' simplification of the uncertainty information is needed. While the variance of each parameter could be used to estimate a representative range, there is no methodology available that allows for the implementation of such information in FIA. Using AUP would then be a 'second best' option in terms of quality of the results, because at least the variance of the alternatives is given.

The answer to the final sub-question, how the results can be used to guide LCA practitioners in developing countries in applying uncertainty analysis in their work, follows from the evaluation of the case study results. The evaluation has shown that data availability, knowledge of practitioners, and available time and software determine the most suitable method for uncertainty propagation in an agricultural LCA. However, the availability of primary data was not found to be an issue in Thai agricultural LCA research, where primary data was abundantly available. This implies that primary data requirements are of lesser concern for this type of LCA research in developing countries, where time investment in data collection is relatively large. Nevertheless, data availability may differ among developing countries regardless of the time investment by the LCA practitioners (e.g. due to limited data sources). Computation time and software requirements are still issues, depending on the resources available to the LCA practitioner. The specification of distributions and post-processing operations, which are required for the sampling methods, involve intricate procedures that complicate the uncertainty analysis as a whole. Because of the lack of knowledge of uncertainty analysis that was found in the expert survey, the required procedures for an adequate use of sampling-based uncertainty propagation is too complicated for most LCA practitioners to become common practice. The most suitable method of uncertainty propagation for agricultural LCA in developing countries should therefore be chosen based on the characteristics of study and the knowledge of the LCA practitioner.

5.2 Reflection

While the results presented in this study provide new insight into the suitability of different methods for uncertainty analysis for agricultural LCA in developing countries, there are some remarks that need to be made regarding the representativeness of the results for the situation it aims to describe. Or, to stay within this study's terminology: the uncertainty around this study. Several research choices and limitations have arguably influenced the result, and should therefore be discussed.

Firstly, choices regarding the case study LCA model have been made in order to fit the purpose of this study. While the original LCA model was constructed in the SimaPro software, the case study was performed based on an LCA model converted to CMCLA. While the implications of this conversion step have been discussed, it is still possible that the CMLCA model behaves differently than the SimaPro model. It is assumed that the two models are adequately corresponding, but it is not possible to rule out the possibility of discrepancy between the models, simply because the options required for this study are not available in SimaPro. This also emphasises that SimaPro does not provide enough options for adequate uncertainty analysis. Another point of discussion concerning the LCA model is the question whether the original model was an adequate representation of sugarcane cultivation in Thailand. While data was collected locally and the geographical spread of the data was preserved in the dataset, this information was not implemented in the LCA model. Several averaging steps were needed to provide an overall presentation of environmental impact in the sugarcane sector. This study has not addressed geographical differences because of time limitations, but the neglection of those is arguably a simplification that should be avoided. Also, the LCA model that was used in the case study of this thesis is rather imperfect and taken from a larger study that includes processes after the cultivation stage as well (see also section 3.3.1). While this model serves the purpose of this thesis well, no reliable conclusions can be drawn regarding the actual situation of Thai sugarcane cultivation practices.

Secondly, due to time limitations the extensiveness of the issues discussed in the case study is limited. This includes the selection of nine parameters for uncertainty propagation, the comparison of four methods, and the limited inclusion of the effect of correlation between parameters. Starting with the selection of parameters, the selection of parameters included in the uncertainty propagation can be seen as representative because they account for almost all uncertainty estimated in the LCA model. However, it must be acknowledged that all parameters in the model have some degree of uncertainty. Therefore the actual uncertainty around the model outcomes will be slightly larger. It should also be noted that the uncertainty of the background processes (i.e. the processes and flows from the Ecoinvent database) is included in the analyses performed in CMLCA. The discussion around the representativeness of these quantifications (stemming from data quality indicators) is not part of this study, but it should be noted that not all software tools allow for the convenient propagation of these 'background' uncertainties. Another issue that was encountered is that of assuming lognormal distributions to avoid negative values, while normal distributions fit some parameter data better. Although this is a recurring issue in all uncertainty propagation methods where distributions for input parameters need to be defined, there does not seem to be a uniform method to handle this problem. Also, while there are many methods for uncertainty analysis available, this study is limited to the comparison of four methods. Including more methods was not feasible in terms of available time, but it is recommended that other methods (e.g. other sampling or analytical techniques) are assessed similarly to this study to complement the results of this research. Lastly, the effect of correlation between parameters is only shortly discussed. Because the focus of this research was kept at the comparison of methods, the effect of including or excluding correlations was not studied here. However, this topic has been the subject of recent discussion in literature and is highly relevant for the way uncertainty analysis is performed. Therefore, the effect of correlation on the output uncertainty of different propagation methods should be part of further research, also, but not limited to the context of agricultural LCA in developing countries.

Thirdly, choices and limitations regarding the scope of this research need to be discussed. While choosing an adequate scope for this research is necessary, it also limits the extent to which the results can be generalised. This study aims at providing guidelines for LCA practitioners in developing countries on how uncertainty analysis is most appropriately applied. Because the case study was performed under the supervision of one of Thailand's leading LCA researchers, and 21 LCA practitioners across Thailand have been surveyed, the results can be considered as representative for the situation of LCA research in Thailand. However, it can be argued that one case study in Thailand is not sufficient to make general statements about developing countries. More research in other developing countries is needed to make such statements. A second discussion point regarding the scope of this research is the fact that only parameter uncertainty is discussed, while model uncertainty and scenario uncertainty are not necessarily of lesser importance. Especially considering the number of participants in the survey that have experience with the assessment of scenario uncertainty, it can be stated that more research on the suitability of uncertainty analysis methods for model and scenario uncertainty for LCA in developing countries would be valuable. Nevertheless, the availability of methods for assessing parameter uncertainty and large input datasets provide large potential for quantification of parameter uncertainty and its interpretation in LCA research in agricultural LCA.

Lastly, it can be stated that the LCA result of this case study, i.e. the environmental impact of sugarcane cultivation, is highly uncertain. Where the other methods give a strong suggestion that the output uncertainty is larger than the difference between both alternatives, the MCS with dependent analysis shows that this is indeed the case. The confidence interval of the difference between both alternatives stretches far below zero, indicating that the difference is not significant. Therefore, based solely on the cultivation stage, it cannot be concluded that green cultivation should be preferred over conventional cultivation. This underlines the need for uncertainty analysis to be included in this type of LCA research, as it may influence the conclusions drawn based on the LCA outcomes.

6. Conclusion

Considering the discussion above and the final evaluation, the main research question can be answered. The research question is:

> *What methods of uncertainty analysis are most suitable to use in agricultural life cycle assessment in developing countries in terms of procedure and outcomes?*

The comparison of methods in the case study has provided insight in the advantages and disadvantages of each method in terms of suitability for agricultural LCA in developing countries. Some elements of comparison are specifically important for developing countries, including data availability and application of the research in policy-making. Considering this and the final evaluation, the following conclusions can be drawn.

It can be argued that the extent to which each method provides a better understanding of the LCA results is the most important criterion, as that is the primary goal of uncertainty analysis. In situations where LCA research is used for policy support, as is often the case in Thailand, an understanding of the uncertainties around the LCA results is crucial. A dependent analysis of a Monte Carlo simulation has shown to meet this criterion best, as this is the only method that allows for a relative comparison of two alternatives. This advantage is only valid in a comparative context however, and limited to two alternatives. When not comparing alternatives, e.g. in a hotspot LCA, the independent analysis of an MCS performs only slightly better than other methods in terms of providing better understanding of the LCA results. The FIA however provides only limited understanding, as the uncertainty information it uses is very limited. In terms of resource requirements both sampling methods score low, while the AUP and FIA provide more possibilities. This is an advantage when limited time or data is available. However, in most agricultural LCA research much primary data is collected (as was the case in the case study), and data requirements are easily met. Therefore this issue becomes less important for such research, at least when sufficient time is available. In terms of difficulty of procedures, there are large differences between the studied methods. The AUP procedure is least complicated due to the single calculation that is used, and no post-processing is necessary. The independent analysis of the MCS and the FIA are more complicated, as several steps are needed to gain a result. Still, the final calculations can be performed within the LCA software. The dependent analysis of the MCS is most complicated, because several additional steps need to be performed manually, and in-depth understanding of the way this analysis works is needed. Considering the results from the expert survey concerning the found general lack of knowledge of uncertainty analysis among Thai LCA practitioners, this criterion is arguably very important. Lastly, the best interpretation of the uncertainty propagation results is possible with sampling methods, as this provides reliable information that can intuitively interpreted with confidence intervals. The outcomes of AUP are also easily interpreted with bar charts with error bars, but because the error bars are limited to variance-based information (standard deviations), the information is less valuable than confidence intervals. The FIA method is harder to interpret than the other methods, as a possibility distribution can be confusing for those without experience in possibilistic methods, and the outcomes are arguably less valuable when based on simply an estimation of uncertainty.

The conclusions above suggest that there is no single answer to the main research question, as all methods have advantages and disadvantages regarding suitability for agricultural LCA in developing countries. In any case, a first step towards a more widespread implementation of uncertainty analysis in LCA research would be to provide practitioners with extensive guidelines on how to perform uncertainty analysis, as well as the implementation of more methods in different LCA software tools. While such extensive guidelines can be subject of future research, based on the results of this study recommendations can be made regarding the choice for a specific method of uncertainty propagation. Based on the findings in this study, a decision tree is presented here for choosing the most suitable propagation method (see Figure 17).

Concludingly, it can be stated that ideally, in a comparative context MCS with dependent analysis of the alternatives in an LCA study should be used. However, there may be several reasons why this method is not preferred or possible. If the study is not comparative, MCS with independent analysis may suffice. Also, if the study includes more than two alternatives, dependent analysis is not possible (with the existing methodology), and independent analysis is best option. Other issues may be a lack of knowledge of uncertainty analysis, limited time available for the study, or that only few primary data points are available. In those cases, analytical uncertainty propagation is recommended. Only when no primary data points are available, FIA should be considered, because of the very limited contribution to better understanding the LCA outcomes it provides.

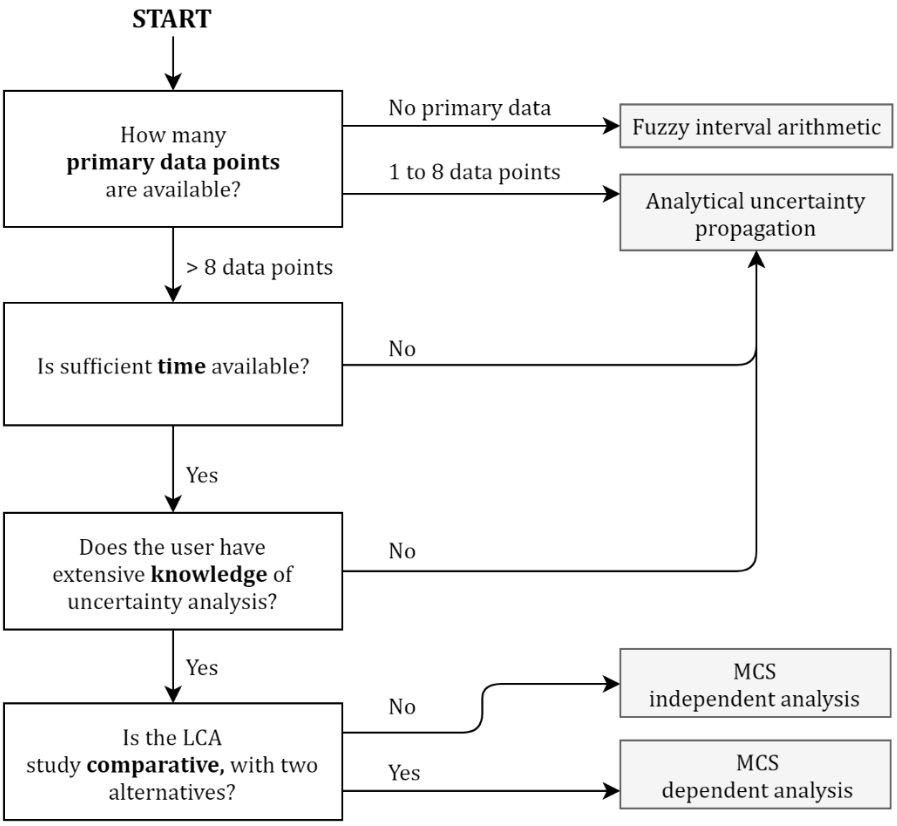


Figure 17: Decision tree for selecting the most suitable uncertainty analysis method.

This decision tree provides guidance for selecting the most suitable method depending on the user and the type of study. It is also clear however that both knowledge development among LCA practitioners and extensive step-by-step guidelines for uncertainty analysis would greatly support an increase of the use of uncertainty analysis in LCA research. This would allow for a greater contribution of the LCA method to sustainable development in both developing and developed countries.

References

Anderson, B., Borgonovo, E., Galeotti, M., & Roson, R. (2014). Uncertainty in Climate Change Modeling: Can Global Sensitivity Analysis Be of Help? *Risk Analysis*, *34*(2), 271–293.

Bakker, H. (2012). *Sugar Cane Cultivation and Management*. Dordrecht: Springer Science & Business Media.

Bauman, H., & Tillman, A. M. (2004). *The Hitch Hiker's Guide to LCA: An Orientation in Life Cycle Assessment Methodology and Application* (3rd ed., Vol. 13). Los Angeles, CA: Professional Publishing House.

Benetto, E., Dujet, C., & Rousseaux, P. (2008). Integrating fuzzy multicriteria analysis and uncertainty evaluation in life cycle assessment. *Environmental Modelling & Software*, *23*(12), 1461–1467.

Björklund, A. E. (2002). Survey of approaches to improve reliability in lca. *The International Journal of Life Cycle Assessment*, *7*(2), 64.

Bojacá, C. R., & Schrevens, E. (2010). Parameter uncertainty in LCA: stochastic sampling under correlation. *The International Journal of Life Cycle Assessment*, *15*(3), 238–246.

Bond, T. C., Streets, D. G., Yarber, K. F., Nelson, S. M., Woo, J., & Klimont, Z. (2004). A technology-based global inventory of black and organic carbon emissions from combustion. *Journal of Geophysical Research*, *109*(D14), D14203.

Bras-Klapwijk, R. M. (1998). Are life cycle assessments a threat to sound public policy making? *The International Journal of Life Cycle Assessment*, *3*(6), 333–342.

Cash, D. W., Clark, W. C., Alcock, F., Dickson, N. M., Eckley, N., Guston, D. H., … Mitchell, R. B. (2003). Knowledge systems for sustainable development. *Proceedings of the National Academy of Sciences of the United States of America*, *100*(14), 8086–8091.

Chiu, A. S. F., & Yong, G. (2004). On the industrial ecology potential in Asian developing countries. *Journal of Cleaner Production*, *12*(8–10), 1037–1045.

Ciroth, A. (2006). Validation – The Missing Link in Life Cycle Assessment. Towards pragmatic LCAs. *The International Journal of Life Cycle Assessment*, *11*(5), 295–297.

Clavreul, J., Guyonnet, D., Tonini, D., & Christensen, T. H. (2013). Stochastic and epistemic uncertainty propagation in LCA. *International Journal of Life Cycle Assessment*, *18*(7), 1393–1403.

Cohen, S. A. (2013). Emerging technologies: Socio-behavioral life cycle approaches. In N. F. Savage, M. E. Gorman, & A. Street (Eds.), *Emerging Technologies: Socio-Behavioral Life Cycle Approaches*. Boca Ranton, FL: CRC Press.

Cowell, S. J., Fairman, R., & Lofstedt, R. E. (2002). Use of Risk Assessment and Life Cycle Assessment in Decision Making: A Common Policy Research Agenda. *Risk Analysis*, *22*(5), 879–894.

Cucurachi, S., Borgonovo, E., & Heijungs, R. (2016). A Protocol for the Global Sensitivity Analysis of Impact Assessment Models in Life Cycle Assessment. *Risk Analysis*, *36*(2), 357–377.

Finnveden, G., Hauschild, M. Z., Ekvall, T., Guinée, J., Heijungs, R., Hellweg, S., … Suh, S. (2009). Recent developments in Life Cycle Assessment. *Journal of Environmental Management*, *91*(1), 1–21.

Geisler, G., Hellweg, S., & Hungerbühler, K. (2005). Uncertainties in LCA of Plant-Growth Regulators and Implications on Decision-Making. *The International Journal of Life Cycle Assessment*, *10*(3), 184–192.

Groen, E. A. (2016). *An Uncertain Climate - The value of uncertainty and sensitivity analysis in environmental impact assessment of food* (PhD thesis). Wageningen University, The Netherlands.

Groen, E. A., & Heijungs, R. (2017). Ignoring correlation in uncertainty and sensitivity analysis in life cycle assessment: what is the risk? *Environmental Impact Assessment Review*, *62*, 98–109.

Groen, E. A., Heijungs, R., Bokkers, E. A. M., & de Boer, I. J. M. (2014a). Methods for uncertainty propagation in life cycle assessment. *Environmental Modelling & Software*, *62*, 316–325.

Groen, E. A., Heijungs, R., Bokkers, E. a M., & Boer, I. J. M. De. (2014b). Sensitivity analysis in life cycle assessment. In *Proceedings of the 9th International Conference LCA of Food San Francisco, USA 8-10 October 2014* (pp. 482–488).

Guinée, J. B., Gorrée, M., Heijungs, R., Huppes, G., Kleijn, R., Koning, A. de, … Huijbregts, M. A. J. (2002).

Handbook on Life Cycle Assessment Operational Guide to the ISO Standards. I: LCA in Perspective. IIa: Guide. IIb: Operational Annex. III: Scientific Background. Dordrecht: Kluwer Academic Publishers.

Guo, M., & Murphy, R. J. (2012). LCA data quality: Sensitivity and uncertainty analysis. *Science of the Total Environment*, *435–436*, 230–243.

Hao, W. M., & Ward, D. E. (1993). Methane production from global biomass burning. *Journal of Geophysical Research*, *98*(D11), 20657.

Heijungs, R. (1996). Identification of key issues for further investigation in improving the reliability of life-cycle assessments. *Journal of Cleaner Production*, *4*(3–4), 159–166.

Heijungs, R. (2010). Sensitivity coefficients for matrix-based LCA. *The International Journal of Life Cycle Assessment*, *15*(5), 511–520.

Heijungs, R., & Frischknecht, R. (2005). Representing Statistical Distributions for Uncertain Parameters in LCA. Relationships between mathematical forms, their representation in EcoSpold, and their. *The International Journal of Life Cycle*.

Heijungs, R., Henriksson, P. J. ., & Guinée, J. B. (2017). Pre-calculated LCI systems with uncertainties cannot be used in comparative LCA. *International Journal of Life Cycle Assessment*, *22*(3), 461–461.

Heijungs, R., & Huijbregts, M. a J. (2004). A review of approaches to treat uncertainty in LCA. *iEMSs 2004 International Congress*, 8.

Heijungs, R., & Lenzen, M. (2014). Error propagation methods for LCA - A comparison. *International Journal of Life Cycle Assessment*, *19*(7), 1445–1461.

Heijungs, R., & Tan, R. R. (2010). Rigorous proof of fuzzy error propagation with matrix-based LCI. *The International Journal of Life Cycle Assessment*, *15*(9), 1014–1019.

Henriksson, P. J. G., Guinée, J. B., Heijungs, R., de Koning, A., & Green, D. M. (2014). A protocol for horizontal averaging of unit process data---including estimates for uncertainty. *The International Journal of Life Cycle Assessment*, *19*(2), 429–436.

Henriksson, P. J. G., Heijungs, R., Dao, H. M., Phan, L. T., De Snoo, G. R., & Guinée, J. B. (2015a). Product carbon footprints and their uncertainties in comparative decision contexts. *PLoS ONE*, *10*(3), 11.

Henriksson, P. J. G., Rico, A., Zhang, W., Ahmad-Al-Nahid, S., Newton, R., Phan, L. T., … Guinée, J. B. (2015b). Comparison of Asian Aquaculture Products by Use of Statistically Supported Life Cycle Assessment. *Environmental Science and Technology*, *49*(24), 14176–14183.

Herrmann, I., & Moltesen, A. (2015). Does it matter which Life Cycle Assessment (LCA) tool you choose? – a comparative assessment of SimaPro and GaBi. *Journal of Cleaner Production*, *86*, 163–169.

Hesterberg, T. W., Lapin, C. A., & Bunn, W. B. (2008). A Comparison of Emissions from Vehicles Fueled with Diesel or Compressed Natural Gas. *Environmental Science & Technology*, *42*(17), 6437–6445.

Huijbregts, M. (2002). Uncertainty and variability in environmental life-cycle assessment. *The International Journal of Life Cycle Assessment*, *7*(3), 173.

Huijbregts, M. A. J. (1998). Application of uncertainty and variability in LCA. *The International Journal of Life Cycle Assessment*, *3*(5), 273.

Huijbregts, M. A. J., Gilijamse, W., Ragas, A. M. J., & Reijnders, L. (2003). Evaluating Uncertainty in Environmental Life-Cycle Assessment. A Case Study Comparing Two Insulation Options for a Dutch One-Family Dwelling. *Environmental Science and Technology*, *37*(11), 2600–2608.

Huijbregts, M., Norris, G., Bretz, R., Ciroth, A., Maurice, B., von Bahr, B., … de Beaufort, A. S. H. (2001). Framework for modelling data uncertainty in life cycle inventories. *The International Journal of Life Cycle Assessment*, *6*(3), 127.

ISO. (2006). *ISO 14040: Environmental management — Life Cycle Assessment — Principles and Framework*. Geneva, Switzerland: Internation Organisation for Standardisation.

Jay, S., Jones, C., Slinn, P., & Wood, C. (2007). Environmental impact assessment: Retrospect and prospect. *Environmental Impact Assessment Review*, *27*(4), 287–300.

Kates, R. W., Clark, W. C., Corell, R., Hall, J. M., Jaeger, C. C., Lowe, I., … Svedin, U. (2001). Sustainability

Science. *Science*, *292*, 641–642.

Koning, A. de, Schowanek, D., Dewaele, J., Weisbrod, A., & Guinée, J. (2010). Uncertainties in a carbon footprint model for detergents; Quantifying the confidence in a comparative result. *International Journal of Life Cycle Assessment*, *15*(1), 79–89.

Lloyd, S. M., & Ries, R. (2007). Characterizing, Propagating, and Analyzing Uncertainty in Life-Cycle Assessment: A Survey of Quantitative Approaches. *Journal of Industrial Ecology*, *11*(1), 161–179.

Malça, J., & Freire, F. (2010). Uncertainty Analysis in Biofuel Systems. *Journal of Industrial Ecology*, *14*(2), 322–334.

Markandya, A., & Halsnaes, K. (Eds.). (2002). *Climate Change and Sustainable Development: Prospects for Developing Countries*. London, UK: Earthscan Publications.

May, J. R., & Brennan, D. J. (2003). Application of data quality assessment methods to an LCA of electricity generation. *The International Journal of Life Cycle Assessment*, *8*(4), 215–225.

McManus, M. C., Taylor, C. M., Mohr, A., Whittaker, C., Scown, C. D., Borrion, A. L., … Yin, Y. (2015). Challenge clusters facing LCA in environmental decision-making - what we can learn from biofuels. *International Journal of Life Cycle Assessment*, *20*(10), 1399–1414.

Mendoza Beltran, A., Heijungs, R., Guinée, J., & Tukker, A. (2016). A pseudo-statistical approach to treat choice uncertainty: the example of partitioning allocation methods. *International Journal of Life Cycle Assessment*, *21*(2), 252–264.

Moreno Ruiz, E., Weidema, B. P., Bauer, C., Nemecek, T., Vadenbo, C. O., Treyer, K., & Wernet, G. (2013). *Documentation of changes implemented in ecoinvent database 3.0. Ecoinvent report No. 5 (v4)*. St. Gallen.

Mungkung, R., & Gheewala, S. H. (2007). Use of life cycle assessment (LCA) to compare the environmental impacts of aquaculture and agri-food products. *FAO Fisheries Proceedings*, (10), 87–96.

Paolotti, L., Martino, G., Marchini, A., & Boggia, A. (2017). Economic and environmental assessment of agro-energy wood biomass supply chains. *Biomass and Bioenergy*, *97*, 172–185.

Payraudeau, S., & Werf, H. M. G. van der. (2005). Environmental impact assessment for a farming region: A review of methods. *Agriculture, Ecosystems and Environment*.

Pongpat, P., Gheewala, S. H., & Silalertruksa, T. (2017). An assessment of harvesting practices of sugarcane in the central region of Thailand. *Journal of Cleaner Production*, *142*, 1138–1147.

Pré-Consultants. (2017). About SimaPro. Retrieved from https://simapro.com/about/

Rodgers, J. L., & Nicewander, W. A. (1988). Thirteen Ways to Look at the Correlation Coefficient. *The American Statistician*, *42*(1), 59–66.

Ross, S., Evans, D., & Webber, M. (2002). How LCA studies deal with uncertainty. *The International Journal of Life Cycle Assessment*, *7*(1), 47–52.

Saltelli, A., Ratto, M., Andres, T., Campolongo, F., & Cariboni, J. (2008). *Global sensitivity analysis: the primer*. Hoboken, NJ: Wiley & Sons.

Saltelli, A., Ratto, M., Tarantola, S., & Campolongo, F. (2006). Sensitivity analysis practices: Strategies for model-based inference. *Reliability Engineering and System Safety*, *91*(10–11), 1109–1125.

Sonnemann, G. W., Schuhmacher, M., & Castells, F. (2003). Uncertainty assessment by a Monte Carlo simulation in a life cycle inventory of electricity produced by a waste incinerator. *Journal of Cleaner Production*, *11*(3), 279–292.

Tillman, A. M. (2000). Significance of decision-making for LCA methodology. *Environmental Impact Assessment Review*, *20*(1), 113–123.

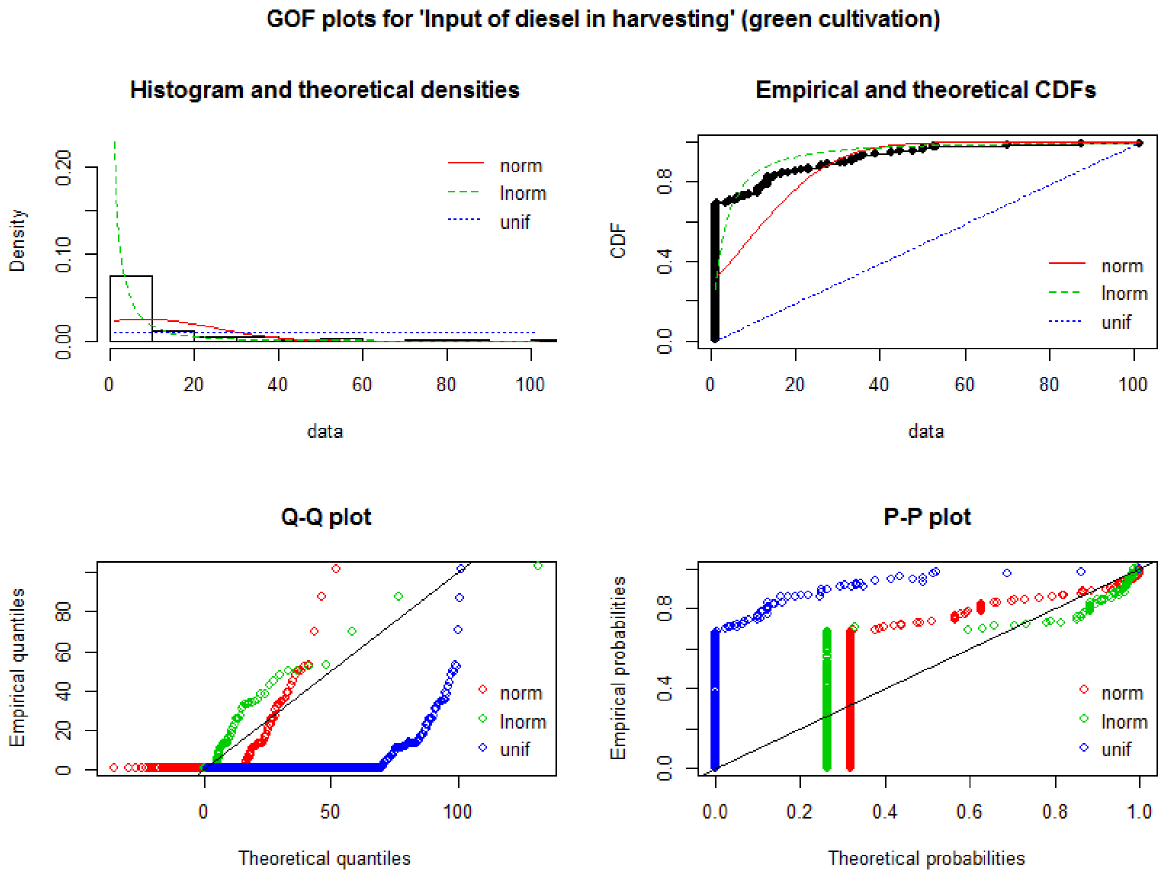
Tilman, D. (1999). Global environmental impacts of agricultural expansion: the need for sustainable and efficient practices. *Proceedings of the National Academy of Sciences of the United States of America*, *96*(11), 5995–6000.

Walker, W. E., Harremoes, P., Rotmans, J., van der Sluijs, J. P., van Asselt, M. B. A., Janssen, P., & von Krauss, M. P. K. (2003). Defining uncertainty: A conceptual basis for uncertainty management in model-based decision support. *Integrated Assessment*, *4*(1), 5–17.

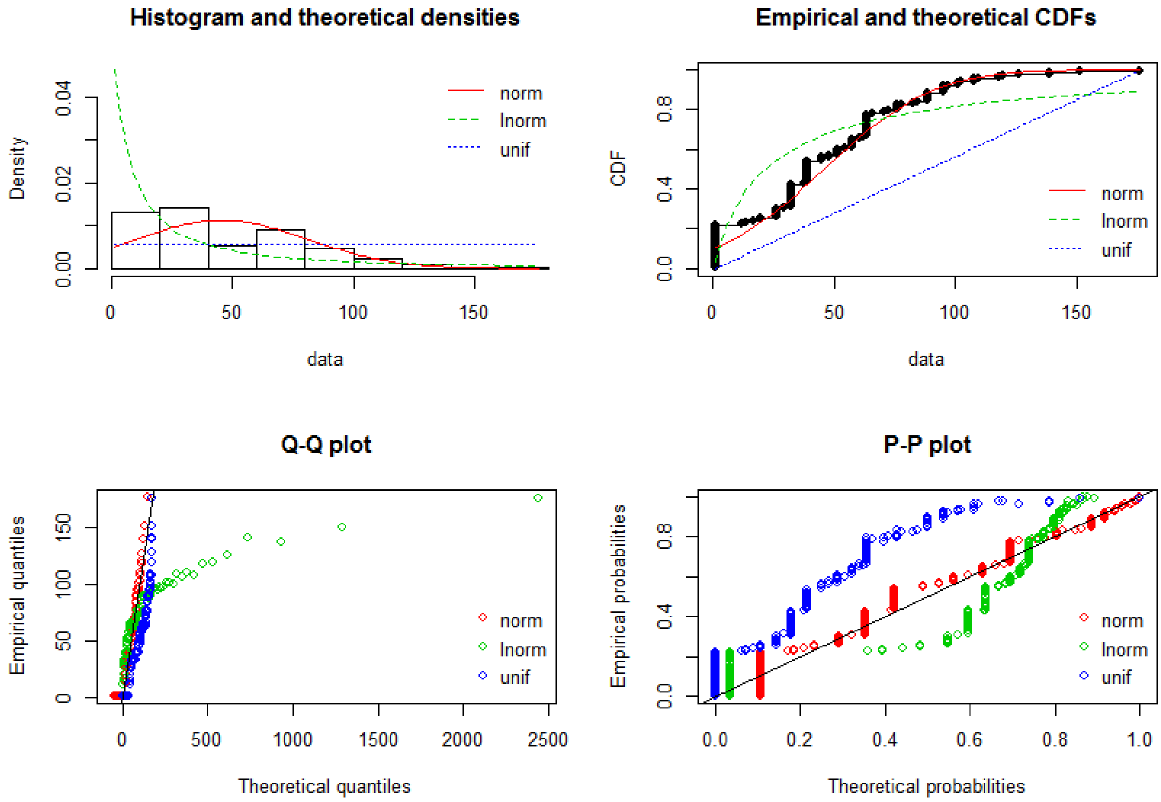
Zamagni, A., Buonamici, R., Buttol, P., Porta, P. L., & Masoni, P. (2009). *Main R&D lines to improve reliability, significance and usability of standardised LCA*. *Deliverable D14 of work package 5 of the CALCAS project*. Retrieved from https://www.researchgate.net/profile/Paolo_Masoni/publication/232770147_Main_RD_lines_to_improve_reliability_significance_and_usability_of_standardised_LCA/links/0fcfd509634d29b024000000.pdf

Appendix

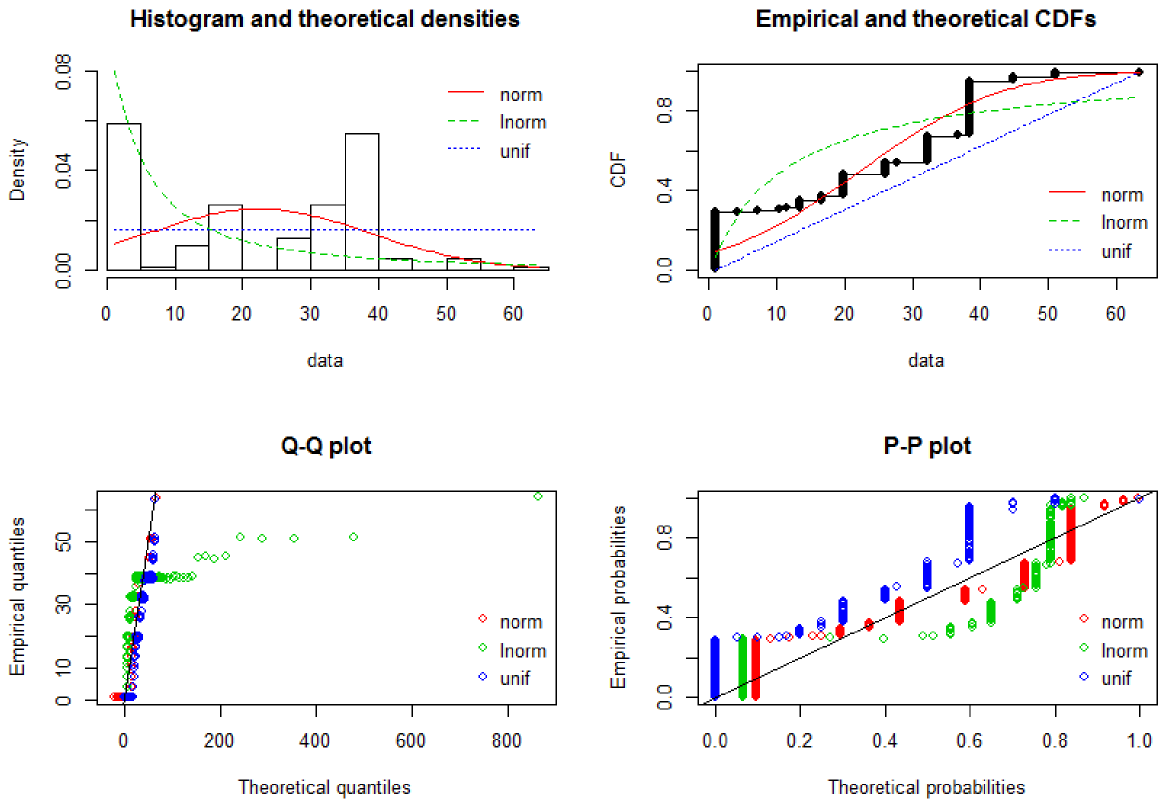
I. Goodness-of-fit plots



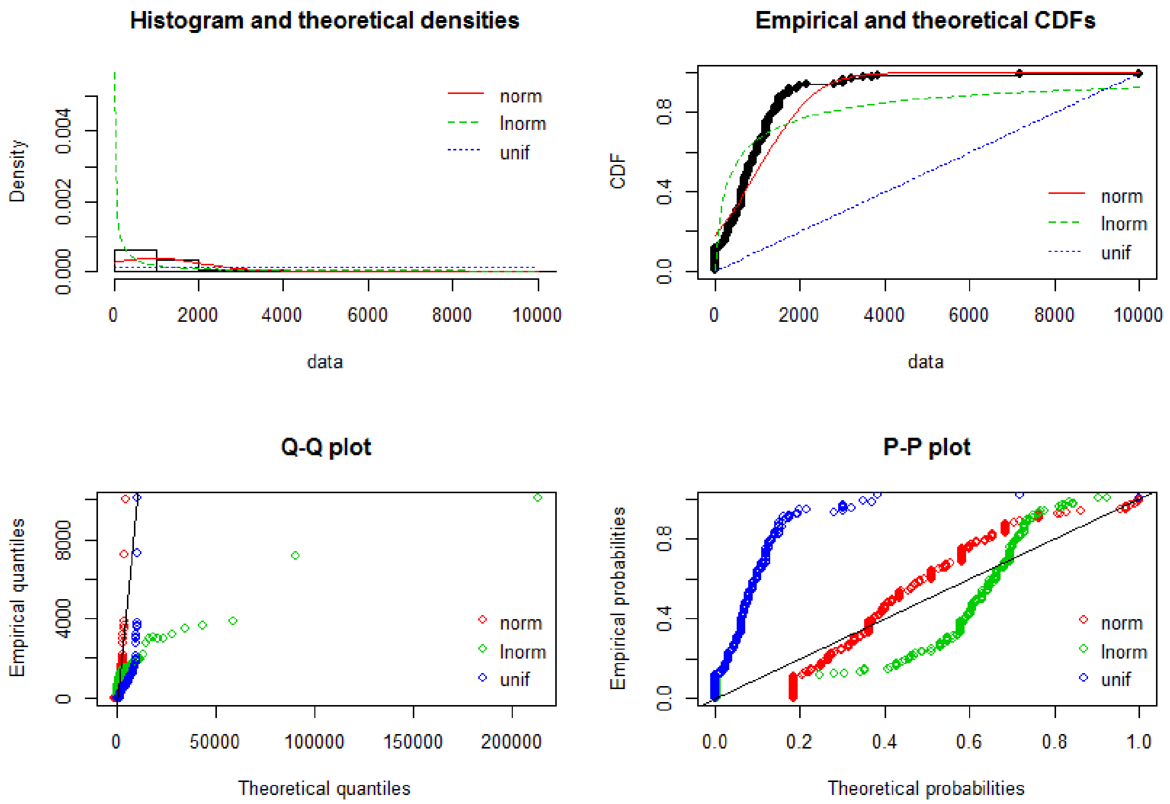
GOF plots for 'Input of diesel in land preparation' (green cultivation)



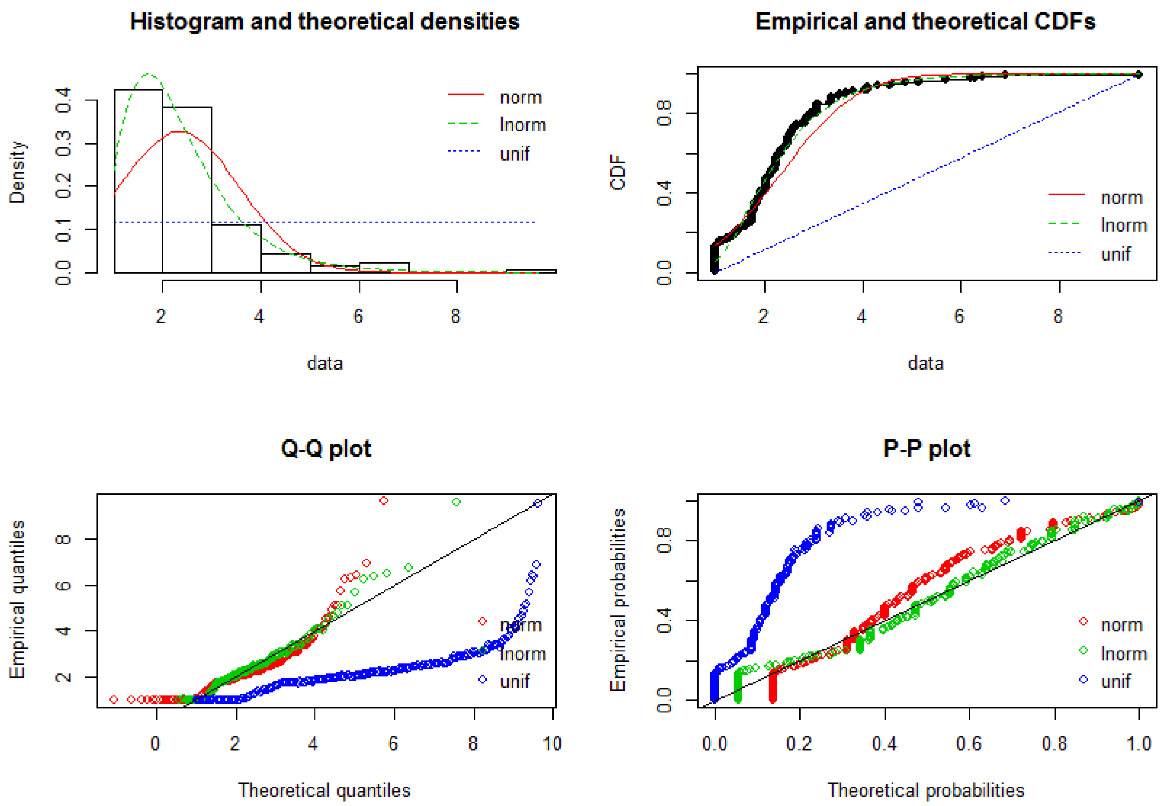
GOF plots for 'Input of diesel in planting' (green cultivation)

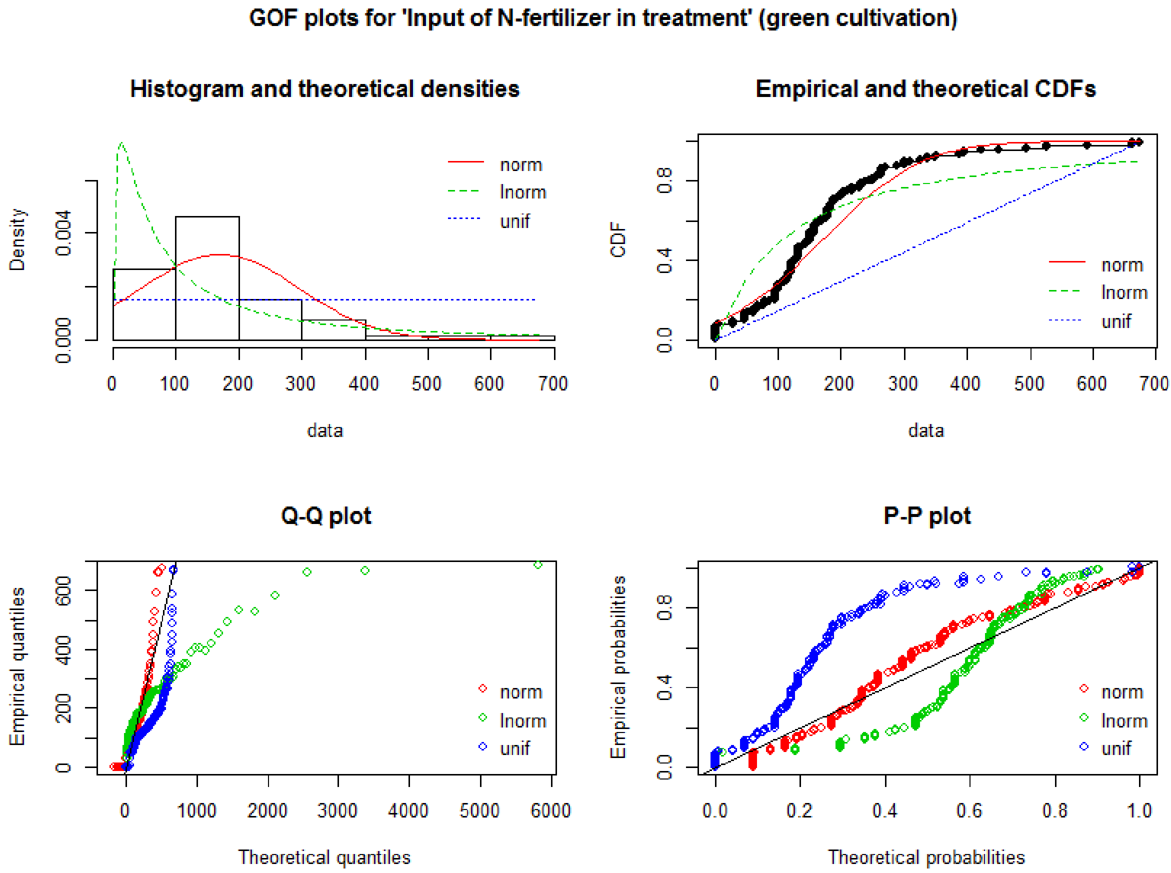


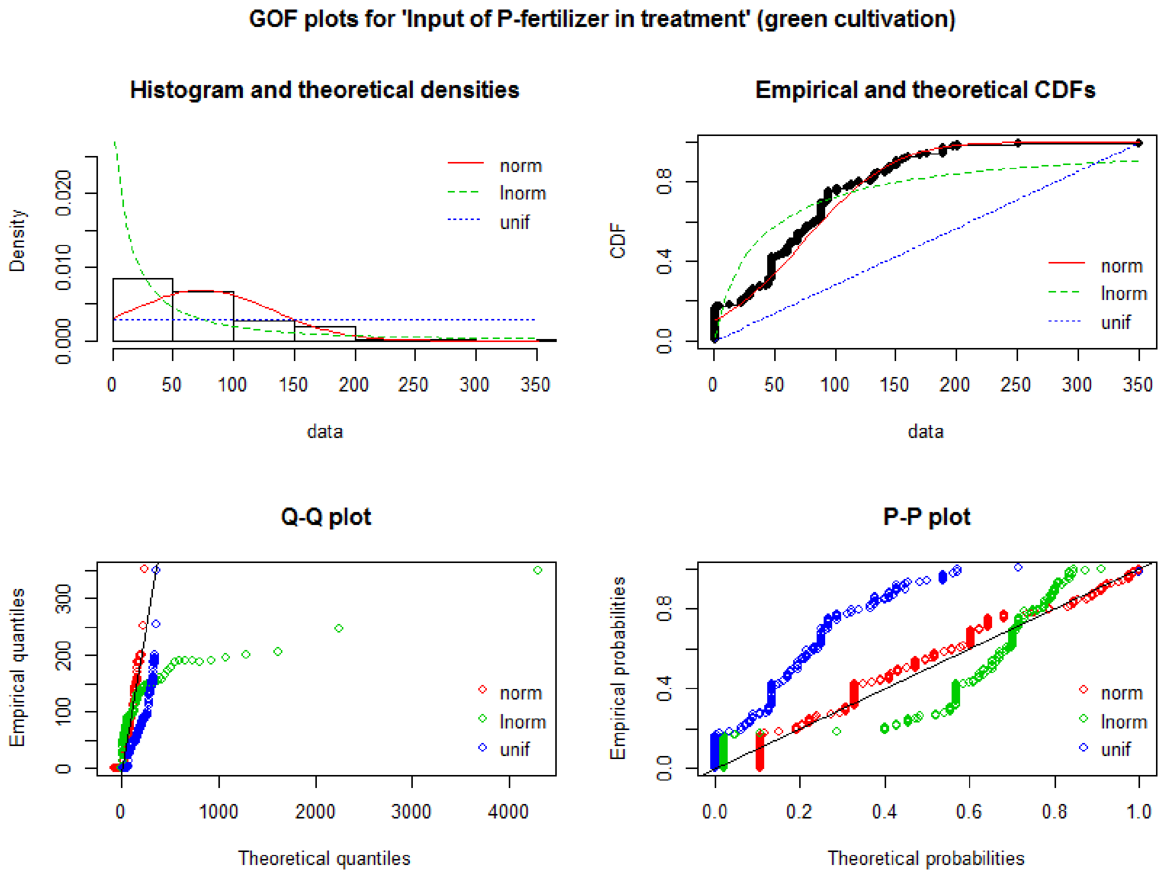
GOF plots for 'Transport' (green cultivation)

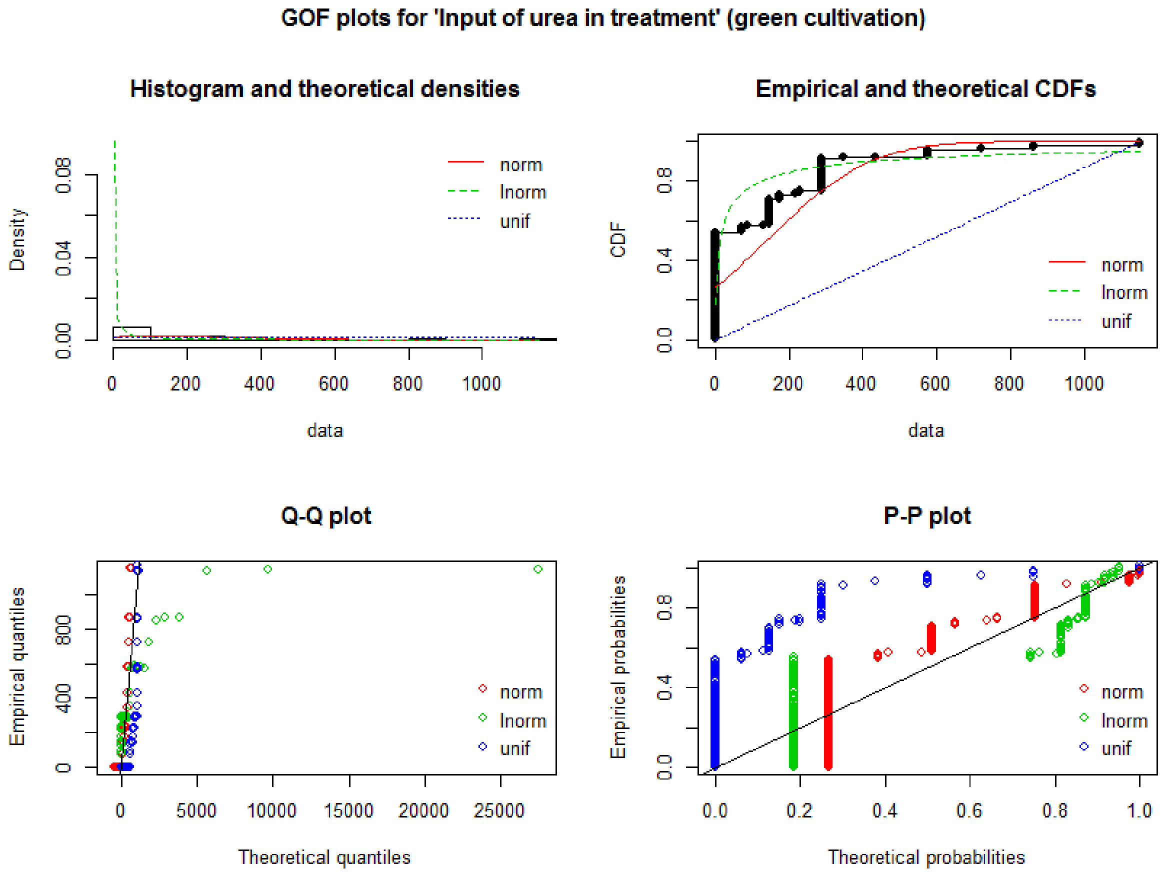


GOF plots for 'N2O emissions from treatment' (green cultivation)

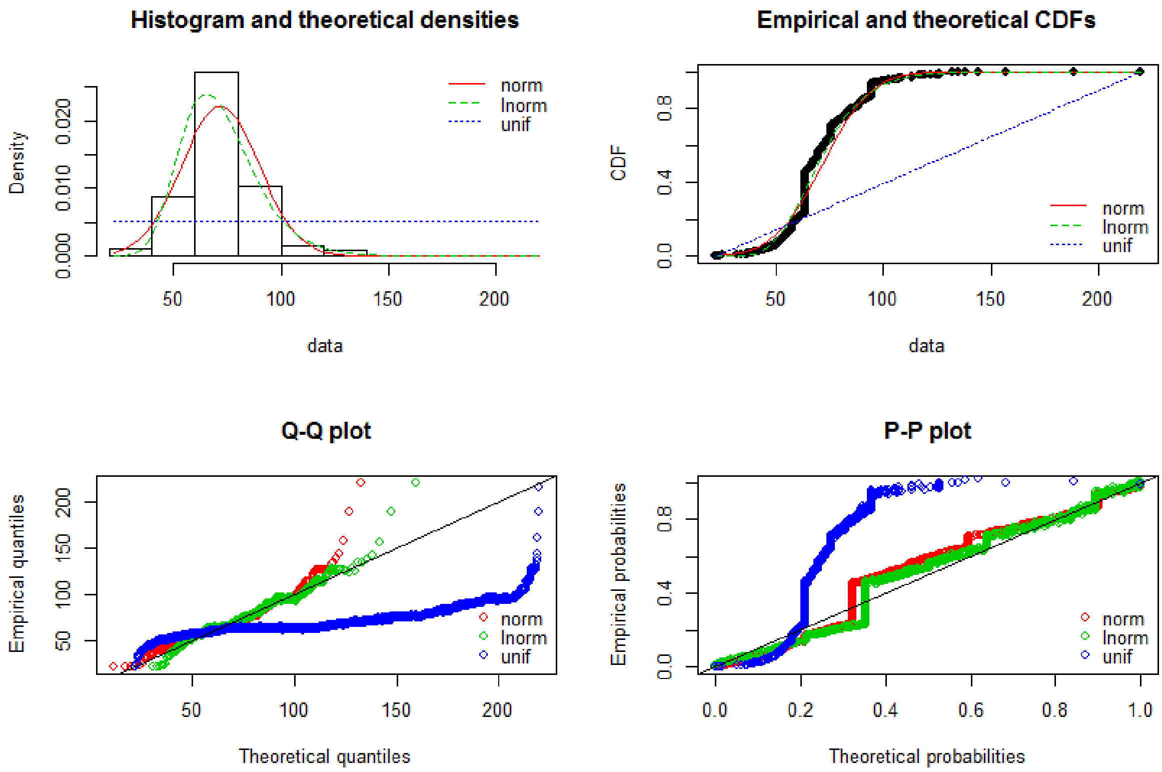



GOF plots for 'Input of N-fertilizer in treatment' (green cultivation)
Histogram and theoretical densities
Empirical and theoretical CDFs
Q-Q plot
P-P plot
norm
lnorm
unif
Density
CDF
data
Empirical quantiles
Theoretical quantiles
Empirical probabilities
Theoretical probabilities

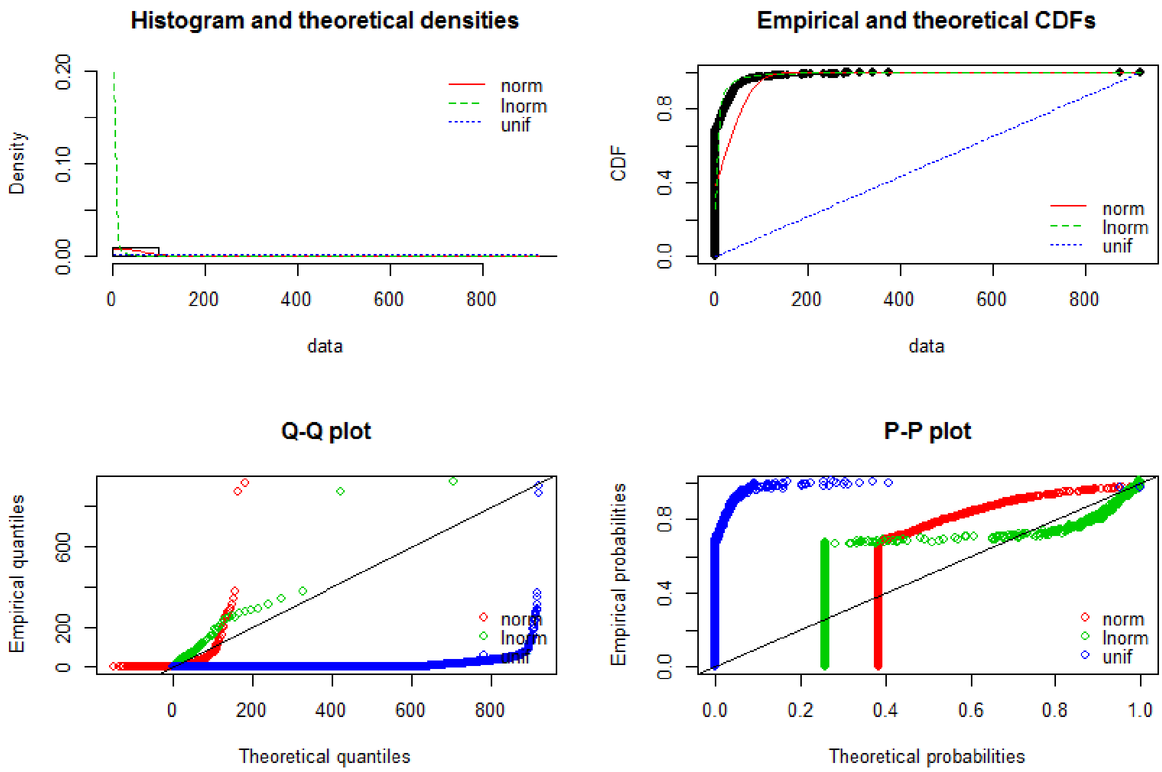

GOF plots for 'Input of P-fertilizer in treatment' (green cultivation)
Histogram and theoretical densities
Empirical and theoretical CDFs
Q-Q plot
P-P plot
norm
lnorm
unif
Density
CDF
data
Empirical quantiles
Theoretical quantiles
Empirical probabilities
Theoretical probabilities


GOF plots for 'Input of urea in treatment' (green cultivation)
Histogram and theoretical densities
Density
data
norm
lnorm
unif
Empirical and theoretical CDFs
CDF
Q-Q plot
Empirical quantiles
Theoretical quantiles
P-P plot
Empirical probabilities
Theoretical probabilities

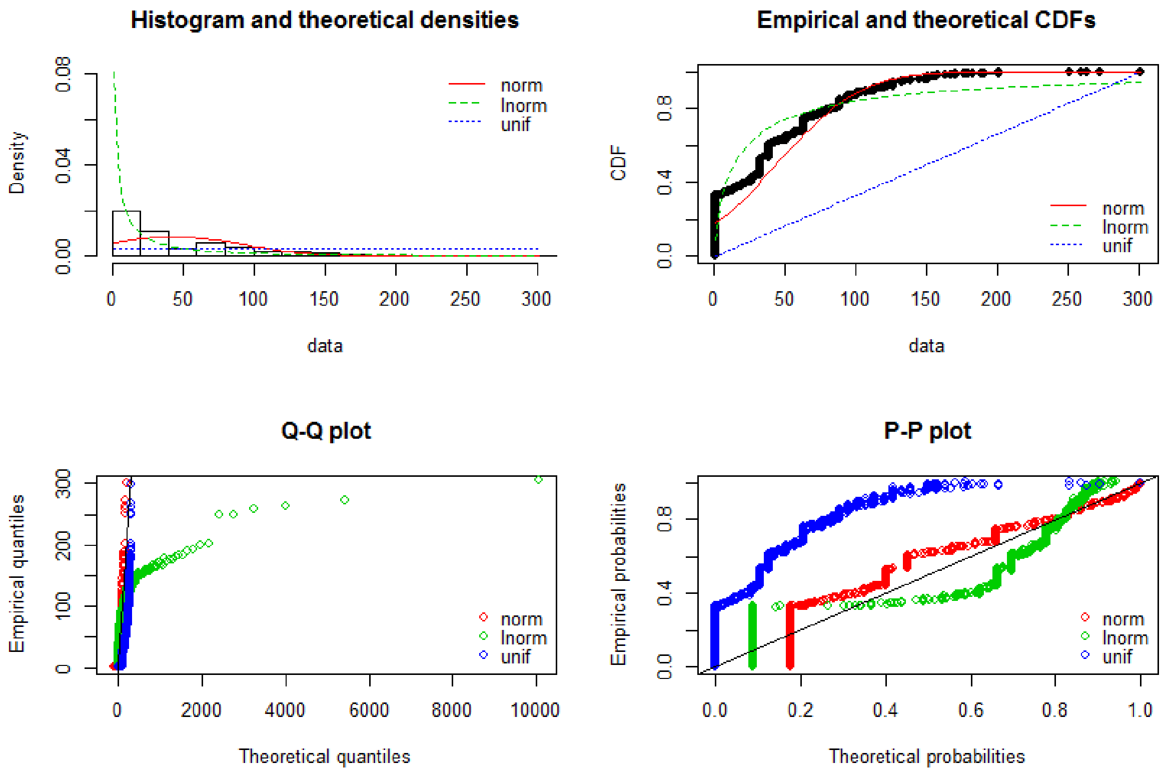
GOF plots for 'Cane trash burning' (conventional cultivation)



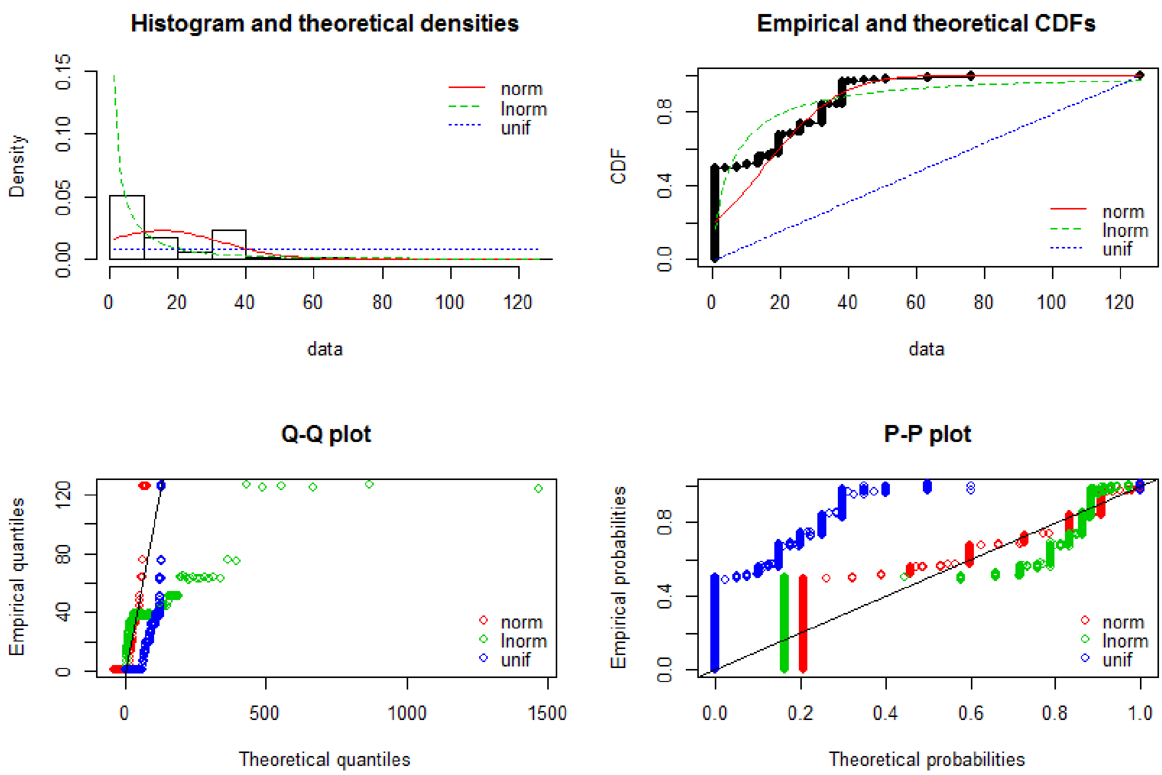
GOF plots for 'Input of diesel in harvesting' (conventional cultivation)



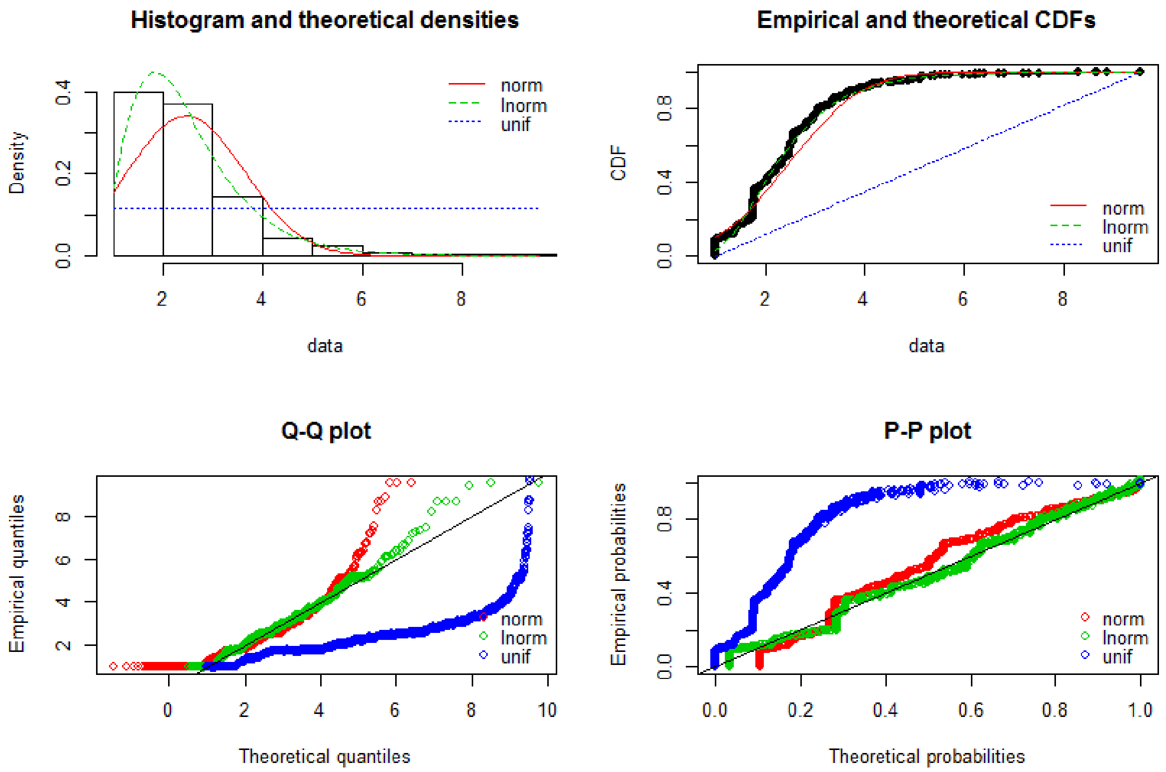
GOF plots for 'Input of diesel in land preparation' (conventional cultivation)



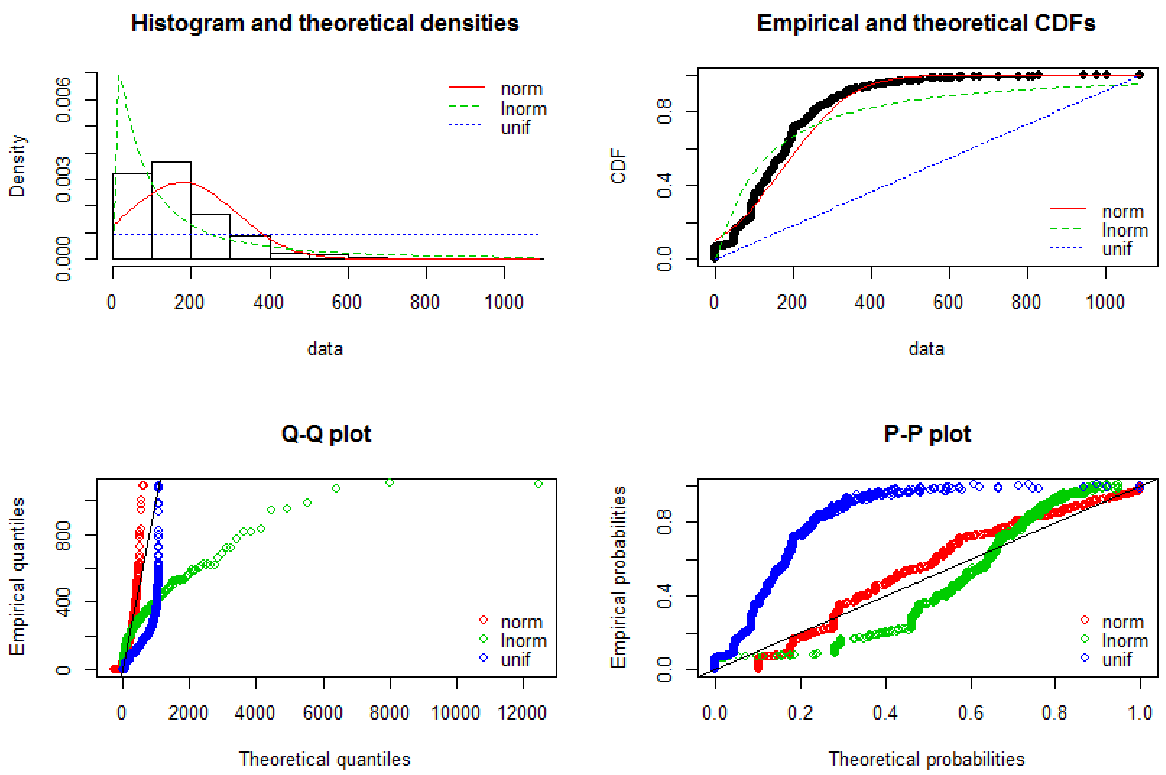
GOF plots for 'Input of diesel in planting' (conventional cultivation)



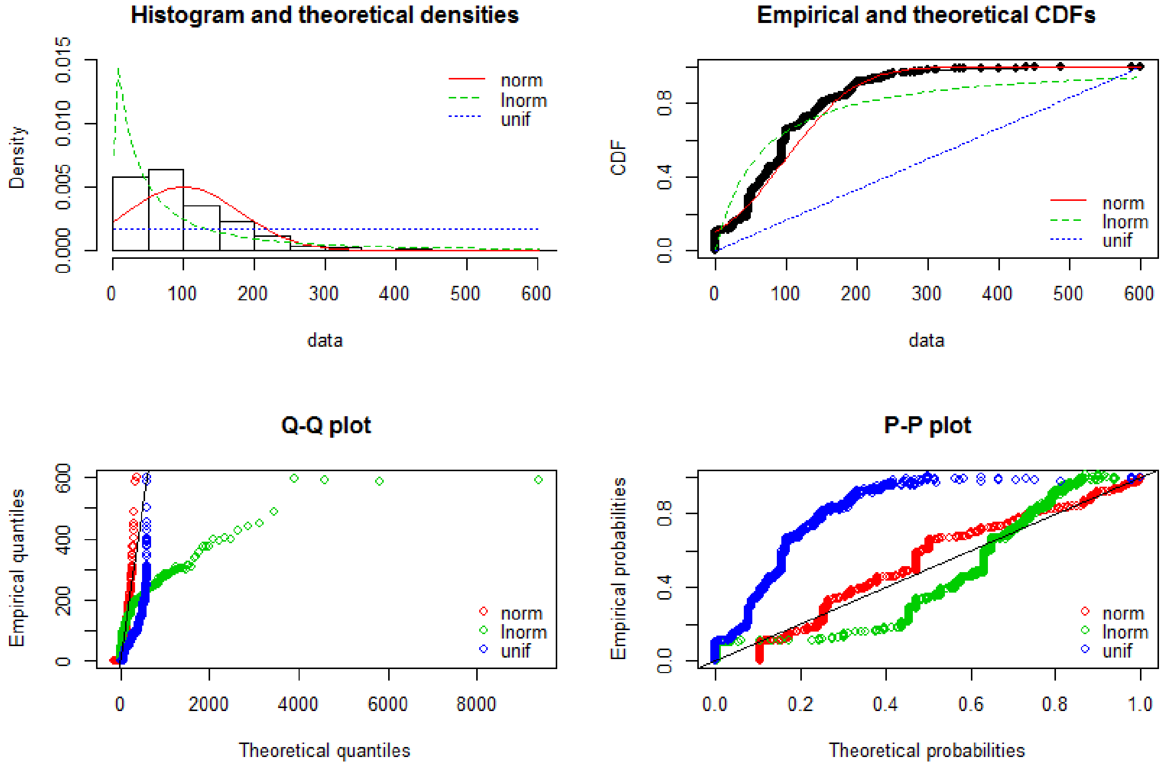
GOF plots for 'N2O emissions from treatment' (conventional cultivation)



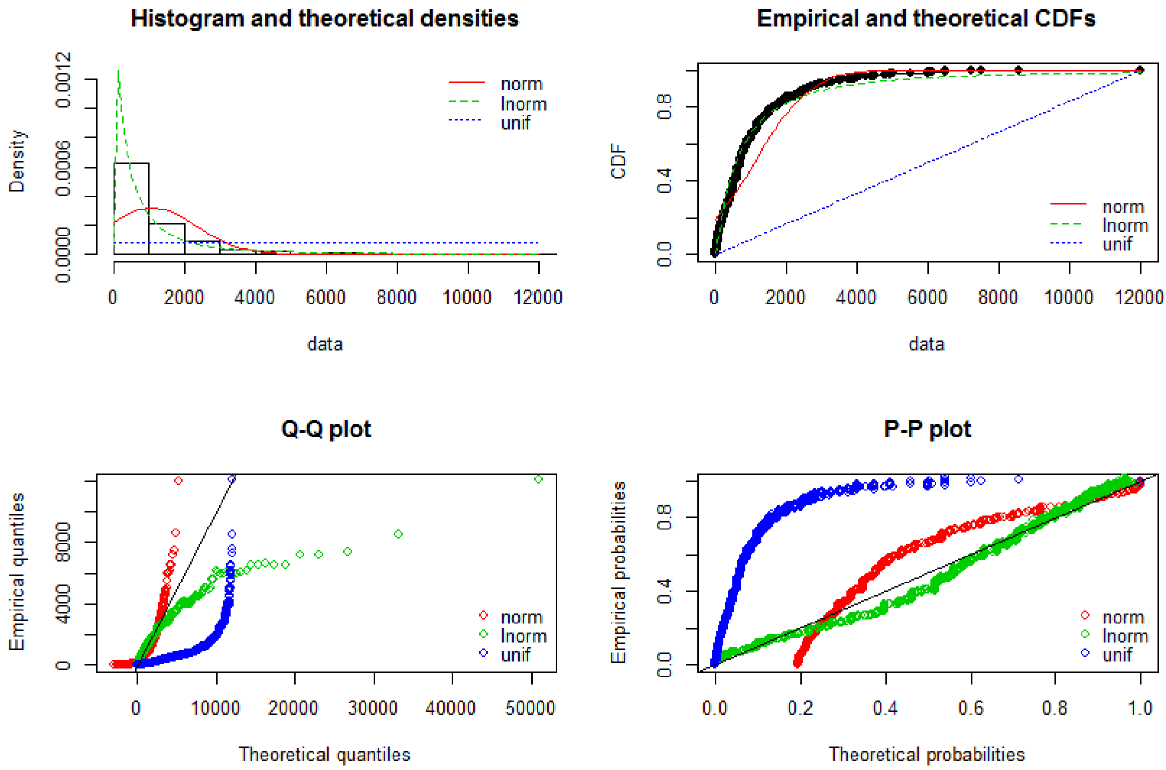
GOF plots for 'Input of N-fertilizer in treatment' (conventional cultivation)

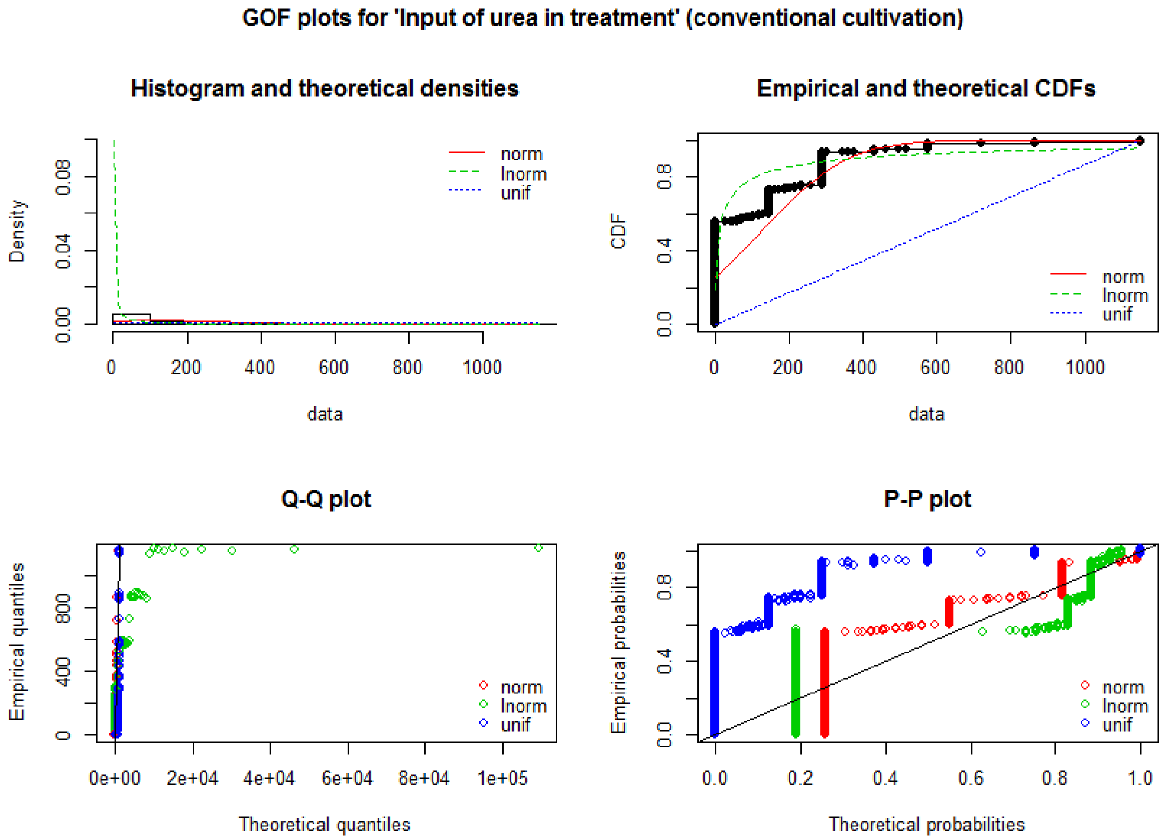


GOF plots for 'Input of P-fertilizer in treatment' (conventional cultivation)



GOF plots for 'Transport' (conventional cultivation)





GOF plots for 'Input of urea in treatment' (conventional cultivation)
Histogram and theoretical densities
Density
data
norm
lnorm
unif
Empirical and theoretical CDFs
CDF
data
Q-Q plot
Empirical quantiles
Theoretical quantiles
P-P plot
Empirical probabilities
Theoretical probabilities

II. Questionnaire for LCA practitioners

This questionnaire is part of a Master thesis research on uncertainty analysis in agricultural Life Cycle Assessment. One of the topics of interest is the way that LCA practitioners see uncertainty analysis, and why they do or do not incorporate uncertainty analysis in their research. The goal of this questionnaire is to gain understanding of the challenges for LCA practitioners related to uncertainty analysis, in order to give recommendations for methodological improvements.

Wisse ten Bosch
Graduate intern at King Mongkut's University of Technology Thonburi, Thailand
Master's student at Leiden University & Delft University of Technology, The Netherlands

1. What is your current occupation?
   Open question

2. What is your experience with LCA research (how many and what kind of projects were you involved in)?
   A. Less than 3 projects
   B. 3 to 6 projects
   C. 6 to 10 projects
   D. More than 10 projects

3. Are you familiar with the concept of uncertainty analysis in LCA?
   A. Yes
   B. No

4. What kind of LCA projects have you been you involved in?
   Open question

5. Which of the following LCA software tools have you used in your work?
   A. SimaPro
   B. GaBi
   C. CMLCA
   D. OpenLCA
   E. I don't use LCA software
   F. Other…

6. Are you familiar with the concept of uncertainty analysis?
   A. Yes
   B. No

7. Regarding uncertainty in LCA research, which type of uncertainty is most interesting for your work?
   A. Parameter uncertainty
   B. Scenario uncertainty
   C. Model uncertainty
   D. Uncertainty is not interesting for my work
   E. I don't know

8. Do you have any experience with performing uncertainty analysis?
   A. Yes
   B. No

   a. If so:

      Which of the following methods have you used in your work?
      A. Sampling methods
      B. Analytical methods
      C. Scenario analysis
      D. Fuzzy set methods
      E. I don't know

      Where did you learn how to perform uncertainty analysis?
      A. In a university course
      B. From a colleague
      C. Self-study
      D. From LCA software instructions
      E. Other…

      Did you encounter any challenges when performing uncertainty analysis?
      Open question

      In what way did you use the results from the uncertainty analysis in your research?
      A. Uncertainty was included in conclusions and recommendations
      B. Uncertainty was analysed, but not included in conclusions and recommendations
      C. *The results were not included in the final report/publications*

   b. If not:

      What were the main reasons for you not to perform uncertainty analysis in your LCA research?
      A. I don't know how to perform uncertainty analysis
      B. My LCA software does not support uncertainty analysis
      C. I didn't have enough data
      D. I didn't have enough time
      E. Uncertainty is not interesting for my work
      F. Uncertainty analysis is not mandatory
      G. Uncertainty analysis would undermine my results
      H. *Other…*

      What would you need in order to include uncertainty analysis in your future research (e.g. more time, resources, knowledge, etc.)?
      Open question

      Would you like to learn more about uncertainty analysis in LCA if you had the opportunity?
      A. Yes
      B. No

9. Regarding uncertainty analysis methods, how important are the following aspects to you (scale 1 to 5)?
    A. *The method is easy to use*
    B. *The method does not require many data points*
    C. *The method gives very accurate results*
    D. *The method is very fast in calculation*
    E. *The analysis can be performed within my LCA software*

10. Do you have any suggestions on how LCA practitioners could be encouraged to include uncertainty analysis in their research?
    Open question

Thank you for participating in this study. If you have any questions or comments regarding this questionnaire or my research, please contact me at w.s.tenbosch@tudelft.nl.

III. Result of the questionnaire for LCA practitioners

Question	Answers	N	%
General information (N = 21)			
What is your current occupation?	Lecturer Researcher Government official Student *Missing*	2 3 1 3 12	9.5% 14.3% 4.8% 14.3% 57.1%
What is your experience with LCA research?	Less than 3 projects 3 to 6 projects 6 to 10 projects More than 10 projects	3 7 6 5	14.3% 33.3% 28.6% 23.8%
What kind of LCA projects have you been you involved in?	Agriculture (Bio)energy Transport & fuels Raw materials Consumer products *Service* *LCA policy* *Water footprinting* *Waste management*	16 14 16 8 12 1 1 1 1	76.2% 66.7% 76.2% 38.1% 57.1% 4.8% 4.8% 4.8% 4.8%
Which of the following LCA software tools have you used in your work?	SimaPro GaBi CMLCA OpenLCA I don't use LCA software *Spreadsheet*	15 1 0 2 8 1	71.4% 4.8% 0.0% 9.5% 38.1% 4.8%
Are you familiar with the concept of uncertainty analysis?	Yes No	14 7	66.7% 33.3%
Regarding uncertainty in LCA research, which type of uncertainty is most interesting for your work?	Parameter uncertainty Scenario uncertainty Model uncertainty Uncertainty is not interesting for my work I don't know	8 6 4 2 1	38.1% 28.6% 19.0% 9.5% 4.8%
Do you have any experience with performing uncertainty analysis in your work?	Yes No	9 12	42.9% 57.1%
For those with experience in uncertainty analysis (N = 9):			
Which of the following methods have you used in your work?	Sampling methods Analytical methods Scenario analysis Fuzzy set methods I don't know	3 2 8 0 0	33.3% 22.2% 88.9% 0.0% 0.0%
Where did you learn how to perform uncertainty analysis?	In a university course From a colleague Self-study From LCA software instructions *From my advisors*	2 2 6 2 1	22.2% 22.2% 66.7% 22.2% 11.1%
Did you encounter any challenges when performing uncertainty analysis?	Yes Yes, the interpretation Yes, lack of data Yes, misleading data collected *Missing*	2 1 1 1 7	22.2% 11.1% 11.1% 11.1% 77.8%

In what way did you use the results from the uncertainty analysis in your research?	Uncertainty was included in conclusions and recommendations	8	88.9%
	Uncertainty was analysed, but not included in conclusions and recommendations	1	11.1%
	The results were not included in the final report/publications	0	-
For those without experience in uncertainty analysis (N = 12):			
What were the main reasons for you not to perform uncertainty analysis in your LCA research?	I don't know how to perform uncertainty analysis	6	50.0%
	My LCA software does not support uncertainty analysis	2	16.7%
	I didn't have enough data	3	25.0%
	I didn't have enough time	1	8.3%
	Uncertainty is not interesting for my work	1	8.3%
	Uncertainty analysis is not mandatory	2	16.7%
	Uncertainty analysis would undermine my results	0	-
	I asked someone else to do it	1	8.3%
What would you need in order to include uncertainty analysis in your future research (e.g. more time, resources, knowledge, etc.)?	Knowledge	9	75.0%
	Time	1	8.3%
	Resources	3	25.0%
	Guidelines	1	8.3%
Would you like to learn more about uncertainty analysis in LCA if you had the opportunity?	Yes	12	100%
	No	0	-
Final questions (N=21)			

		1	2	3	4	5	**Av.**
Regarding uncertainty analysis methods, how important are the following aspects to you (scale 1 to 5)?	The method is easy to use	1	2	7	2	8	**3.7**
	The method does not require many data points	1	3	8	5	3	**3.3**
	The method gives very accurate results	0	3	5	8	4	**3.6**
	The method is very fast in calculation	0	4	5	8	3	**3.4**
	The analysis can be performed within my LCA software	2	3	5	6	4	**3.4**

Do you have any suggestions on how LCA practitioners could be encouraged to include uncertainty analysis in their research?	An international guidance published by UNEP/SETAC or other well-known international institutions would encourage the research in this area.

	Results will be affected if not considering uncertainty issues Without uncertainty analysis, the results may alternate the fact and influence on decision making process, which will not support one of the reasons in doing LCA. The uncertainty and data analysis should be one of important topic for LCA since the beginning. Therefore the method and of uncertainty is necessary to apply along with the LCA steps. So the LCA practitioners can understand that where do they can apply uncertainty for their work and how can they analyse it. A methodology of uncertainty analysis need to be developed with a consistency of all aspect of sustainable data regarding environmental, economic and social aspects. Having a rigorous, step-by-step method on how it is to be done; a manual. So far, there seem only to be available only intellectual exercises performed sitting at a computer. Nothing really for real, field data.

Electronic supplementary material

E1

CMLCA model of sugarcane cultivation
File: E1_LCSAL.lca

E2

MatLab script for the method of elementary effects, adapted from Groen (2016).
File: E2_MEE_LCA.m

E3

Adapted matrices used in the MEE analysis

Files:	A-matrix (technology matrix):	E3_Amatrix.csv
	B-matrix (intervention matrix):	E3_Bmatrix.csv
	f-matrix (final demand matrix):	E3_fvector.csv

E4

Results of 3000 Monte Carlo runs
File: E4_results_MC3000.xlsx

E5

MatLab script for the fuzzy interval arithmetic method, adapted from Groen et al. (2016)
File: E5_FIA_LCA.m

Growing uncertainty

Finding suitable methods of uncertainty propagation for agricultural Life Cycle Assessment in developing countries

W.S. ten Bosch