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INTERPRETATION OF LCA STUDIES FOR DECISION SUPPORT

Prioritizing regionalization to enhance interpretation in consequential life cycle assessment: application to alternative transportation scenarios using partial equilibrium economic modeling

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Abstract

Purpose Consequential life cycle assessment (C-LCA) aims to assess the environmental consequences of a decision. It differs from traditional LCA because its inventory includes all the processes affected by the decision which are identified by accounting for causal links (physical, economic, etc.). However, C-LCA results could be quite uncertain which makes the interpretation phase harder. Therefore, strategies to assess and reduce uncertainty in C-LCA are needed. Part of uncertainty in C-LCA is due to spatial variability that can be reduced using regionalization. However, regionalization can be complex and time-consuming if straightforwardly applied to an entire LCA model.

Methods The main purpose of this article is to prioritize regionalization efforts to enhance interpretation in C-LCA by assessing the spatial uncertainty of a case study building on a partial equilibrium economic model. Three specific objectives are derived: (1) perform a C-LCA case study of alternative transportation scenarios to investigate the benefits of implementing a public policy for energy transition in France by 2050 with an uncertainty analysis to explore the strength of our conclusions, (2) perform global sensitivity analyses to identify and quantify the main sources of spatial uncertainty between foreground inventory model from partial equilibrium economic modeling, background inventory model and characterization factors, (3) propose a strategy to reduce the spatial uncertainty for our C-LCA case study by prioritizing regionalization.

Results and discussion Results show that the implementation of alternative transport scenarios in compliance with public policy for the energy transition in France is beneficial for some impact categories (ICs) (global warming, marine acidification, marine eutrophication, terrestrial acidification, thermally polluted water, photochemical oxidant formation, and particulate matter formation), with a confidence level of 95%. For other ICs, uncertainty reduction is required to determine conclusions with a similar level of confidence. Input variables with spatial variability from the partial equilibrium economic model are significant contributors to the C-LCA spatial uncertainty and should be prioritized for spatial uncertainty reduction. In addition, characterization factors are significant contributors to the spatial uncertainty results for all regionalized ICs (except land occupation IC).

Conclusions Ways to reduce the spatial uncertainty from economic modeling should be explored. Uncertainty reduction to enhance the interpretation phase and the decision-making should be prioritized depending on the goal and scope of the LCA study. In addition, using regionalized CFs in C-LCA seems to be relevant, and C-LCA calculation tools should be adapted accordingly.

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1 Introduction

Life cycle assessment (LCA) is an iterative methodology to assess the potential environmental impacts of products and services throughout their life cycle (International Organization for Standardization (ISO) 2006a, b). Two types of LCA may be distinguished depending on their objectives (Weidema 2003; Zamagni et al. 2012; Guiton and Benetto 2013): (i) attributional LCA (A-LCA) aims to assess the share of the overall environmental impacts that may be attributed to a product system in a status quo situation and (ii) consequential LCA (C-LCA) aims to assess the environmental consequences of a decision or a change (Weidema et al. 1999). ILCD (European Commission - Joint Research Centre - Institute for Environment and Sustainability 2010) and other authors (Dandres et al. 2011; Marvuglia et al. 2013; Plevin et al. 2014) recommend using the C-LCA approach to assess decisions with large-scale consequences (geographic and/or multi-sector scale), such as the implementation of a public policy.

The way the life cycle inventory (LCI) is built constitutes the main modeling difference between A-LCA and C-LCA. In theory, life cycle impact assessment (LCIA) methods should also be different between A-LCA and C-LCA. Indeed, it would be relevant to account for the consequences of the decision in the ecosphere by assessing the environmental feedbacks and the changes in the current state of the environment. However, the way C-LCA is now handled by LCA practitioners is by using the same models for LCIA in A-LCA and C-LCA. Consequential LCI (C-LCI) includes all the processes affected by the decision and are identified by accounting for causal links, which may be physical, economic, social, etc. (Zamagni et al. 2012). In practice, published C-LCAs often account for physical links and market mechanisms. Inventory data may be distinguished by foreground inventory data and background inventory data (Udo de Haes et al. 1997; Frischknecht 1998). Here, foreground inventory data refers to the inventory data of the case study that is specifically collected or modeled by the LCA practitioner. Background inventory data refers to generic data, often from LCI databases, used to model the supply chains linked to the foreground inventory. Foreground inventory data in C-LCA is obtained through a descriptive causal method (Weidema et al. 1999; Weidema 2005) or the use of models, often economic models that account for non-linearity, elastic substitution, or rebound effects (Earles et al. 2013). Using economic models is especially relevant when assessing prospective decisions with consequences on a large scale. Indeed, chains of market mechanisms are widely described in economic models and make it possible to also identify indirect consequences and account for technological progress (Dandres et al. 2011). In this study, we present a C-LCA case study to assess the potential environmental consequences (benefits or impacts) of the implementation of alternative transportation scenarios in France by 2050 through public policy for the energy transition. To perform the analysis, we applied a prospective economic partial equilibrium model, running from 2009 to 2050, to compute the foreground inventory data instead of just collecting data as traditionally done in LCA (Marvuglia et al. 2013). The background inventory data is obtained using an adapted version of the LCI database ecoinvent.

C-LCA and A-LCA deal with the same types of uncertainty: stochastic uncertainty (spatial, temporal, and technological variability) and epistemic uncertainty related to the lack of knowledge on reality (often named uncertainty in LCA) (Huijbregts 1998; Clavreul et al. 2013). However, a higher level of uncertainty is expected for C-LCA results compared with A-LCA (Whitefoot et al. 2011; Herrmann et al. 2014) which makes the interpretation phase harder. Indeed, C-LCA is complex and uncertain by nature as it aims at describing indirect consequences of a decision involving socio-economic links and is often prospective. Part of uncertainty sources in C-LCA is due to specificities to build the C-LCI (Whitefoot et al. 2011). More specifically, the use of economic modeling implies that uncertainty sources from those models are uncertainty sources in C-LCA. Three main sources of uncertainty in economic modeling can influence C-LCA: uncertainty due to the resolution mode of the model and related approximations (optimization, simulation, etc.), model uncertainty that simplifies reality (equations, linearity assumption, product in competition, partial equilibrium hypothesis, etc.), and input data uncertainty (prices, capacities, elasticities, etc.) (Dandres et al. 2014). Overall uncertainty assessment is rarely performed in C-LCA from economic models (Dandres et al. 2012, 2014). Strategies to assess and reduce uncertainty in C-LCA from economic models are needed. They should consider the goal and scope of the study; i.e., uncertainty reduction is required only if a conclusion cannot be drawn for the study or if the target level of uncertainty is not achieved to ultimately enhance decision making (Patouillard et al. 2018).

Spatial variability is part of the overall uncertainty in LCA, and thus in C-LCA. Using too generic information to represent data with spatial variability introduces an additional uncertainty, called *uncertainty due to spatial variability* in this article. This additional uncertainty may be reduced when regionalization is accounted for in LCA. Regionalization refers to the enhancement of the representativeness of the processes and environmental phenomena in a given region (Patouillard et al. 2016). To integrate regionalization into an LCA study, the LCA practitioner may perform an inventory regionalization and/or inventory spatialization (Patouillard et al. 2018). Inventory regionalization consists of collecting inventory data that is more representative of the spatial coverage for a given technology. Inventory spatialization consists of describing the spatial distribution of elementary flows to be able to use more regionalized characterization factors (CFs) from regionalized LCIA methods (Mutel et al. 2018). Efforts on inventory regionalization or spatialization must be prioritized depending on the impact category (IC) to guide the practitioner in reducing the uncertainty of the LCA (Patouillard et al. 2019). This may be achieved by performing a global sensitivity analysis (Patouillard et al. 2019). To our knowledge, the question of prioritizing regionalization in C-LCA has never been addressed in the literature. This article addresses regionalization efforts at the level of the inventory data, so it focuses on inventory regionalization and/or inventory spatialization only. Impact regionalization efforts, to develop spatially differentiated or regionalized characterization factors, are out of scope.

The main purpose of this article is to prioritize regionalization efforts to enhance interpretation in consequential LCA by assessing the spatial uncertainty of a case study building on a partial equilibrium economic model. This article is a case study based on the methodology developed by Patouillard et al. (2019) to prioritize regionalization efforts in LCA. To do so, we propose an adaptation of this methodology to prioritize regionalization efforts for the consequential LCA case study. Three specific objectives are derived: (1) perform a C-LCA case study of alternative transportation scenarios to investigate the benefits of implementing a public policy for energy transition in France with an uncertainty analysis to explore the strength of our conclusions; (2) perform global sensitivity analyses to identify and quantify the main sources of spatial uncertainty among foreground inventory data from partial equilibrium economic modeling, background inventory data, and CFs; (3) propose a strategy to reduce the spatial uncertainty for our C-LCA case study by prioritizing regionalization. This study aims to guide LCA practitioners and researchers to focus their efforts on the highest potential for uncertainty reduction in C-LCA based on the goal of the study.

2 Uncertainty analysis of C-LCA case study

2.1 Description of the C-LCA case study

2.1.1 Goal and scope definition

The goal of the study, used as C-LCA case study in this article, is to assess the consequences of implementing alternative transportation scenarios to meet the French law on the energy transition (LTE) targets and ultimately conclude if the consequences are potentially beneficial to the environment (more information on the context in SI). The functional unit is to "reach the LTE targets in the French transport sector by 2030 while meeting the French energy and mobility service demands from 2009 to 2050." Modeling the consequences of the decision involves identifying the affected processes by the decision (and their magnitude) in the economy. To do so, we isolate the consequences of the decision making the difference between the results of a scenario with the decision and a scenario without a decision (status-quo scenario) (Fig. 1).

2.1.2 Consequential life cycle inventory

Amounts of elementary flow (emission and resource consumption) generated by the processes included in the system boundaries are quantified. The system includes all the affected processes and their supply chain.

As proposed by Heijungs and Suh (2002), the LCI results are stored in the inventory vector $\boldsymbol{g}$ that describes the amount of each elementary flow generated to fulfill the functional unit and is calculated using Eq. 1.

$$\boldsymbol{g} = \boldsymbol{B}\boldsymbol{A}^{-1}\boldsymbol{f} \tag{1}$$

To calculate $\boldsymbol{g}$ for our case study, we used different tools to build an inventory model divided into two parts: the foreground inventory model based on a partial equilibrium economic model called MIRET (see Section 2.1.3 for more details) and the background inventory model mainly based on ecoinvent data (see Figs. 1 and 2). Here, we use the term *model* to encompass the data, associated equations, and principles leading to a result.

- The foreground inventory model is used to calculate $\boldsymbol{f} = [\boldsymbol{0}\ \ \boldsymbol{f}_{\text{affected}}]$, where and $\boldsymbol{f}_{\text{affected}}$ is the vector with element f_p represents the amount of output product as defined in MIRET for each directly affected process needed to fulfill the functional unit, or 0 for a product not defined in MIRET and thus considered non-directly affected processes, and $\boldsymbol{0}$ is the vector of zeros. Note that each directly affected process has only one output product (no multifunctionality). f_p is calculated based on optimization results from MIRET as described in Section 2.1.3. Notice that this deviates markedly from the traditional LCA model, in which vector $\boldsymbol{f}$ is set by the analyst and contains an amount for one product only. No elementary flow or unit process is modeled in the foreground inventory; they are all modeled in the background.
- The background inventory model corresponds to the technology matrix $\boldsymbol{A}$ and the environmental matrix $\boldsymbol{B}$. The background inventory refers to LCI datasets used to model (i) the direct emissions for each directly

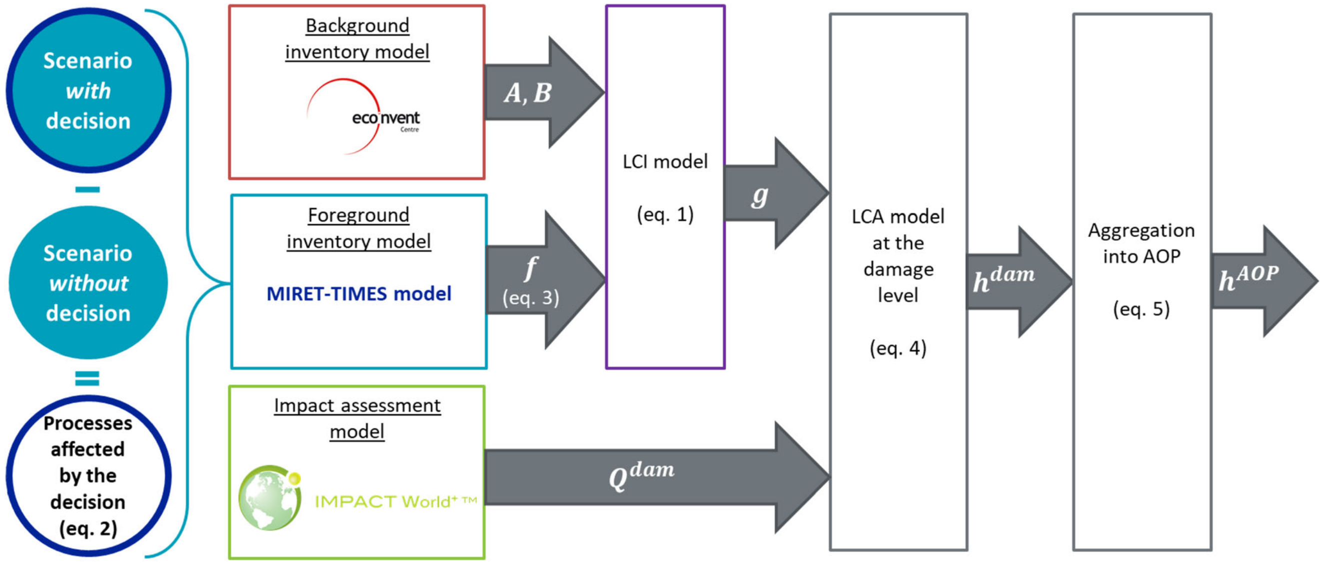

Fig. 1 Arrangement of the different models, tools, variables, and equations to build the C-LCA model

affected process and (ii) the part of the supply chain and associated indirect emissions for each affected process that is not described in MIRET. Note that all elementary flows and processes are modeled in the background inventory model and represent the overall life cycle. Most of those LCI datasets are adapted from the ecoinvent database. The mapping between directly affected processes from MIRET and the LCI datasets from ecoinvent is part of the background inventory model as described in Section 2.1.4. Note that the row order and column order match for $\boldsymbol{A}$ (e.g., if steel production is column 1, steel is row 1), all process output products are normalized to 1 and all processes have one single output. Here are the formats of the resulting $\boldsymbol{A}$ and $\boldsymbol{B}$ matrices (see Section 2.1.4 for more details) $\boldsymbol{A} = [\boldsymbol{A}_{\text{adapted\_ecoinvent}} \quad \boldsymbol{0} \quad \boldsymbol{A}_{\text{mapping}} \quad \boldsymbol{I}_{\text{affected}}]$ and $\boldsymbol{B} = [\boldsymbol{B}_{\text{adapted\_ecoinvent}} \quad \boldsymbol{0}]$ where $\boldsymbol{A}_{\text{adapted\_ecoinvent}}$ and $\boldsymbol{B}_{\text{adapted\_ecoinvent}}$ are the adapted versions of the technology and environmental matrices from ecoinvent; $\boldsymbol{A}_{\text{mapping}}$ is the matrix mapping each directly affected technology from MIRET to an adapted ecoinvent

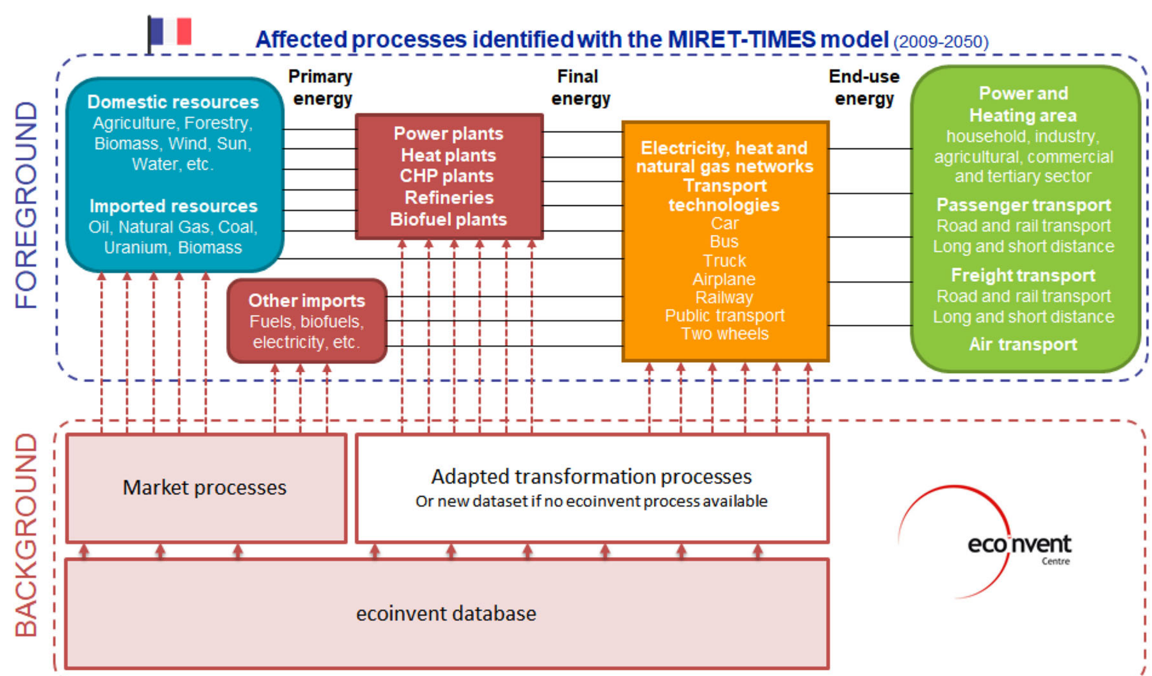

Fig. 2 Consequential inventory model. The foreground inventory model is the French MIRET-TIMES model used to identify directly affected processes. The background inventory model is based on an adapted version of the ecoinvent database

product, with element equal to − 1 if mapped or 0 otherwise; $\boldsymbol{I}_{\text{affected}}$ is the identity matrix with size $P \times P$ with P the number of affected processes from MIRET, and $\mathbf{0}$ are matrices of zeros.

2.1.3 Foreground inventory model based on a partial equilibrium economic model

A TIMES[1]-based prospective economic partial equilibrium model (Loulou et al. 2016), called MIRET and developed by IFP Énergies nouvelles (Menten et al. 2015), is used to identify the directly affected technologies in MIRET and quantify the associated amount of product reported in f. Direct and indirect elementary flows associated with those affected processes are modeled in the background inventory (see Section 2.1.4).

The MIRET model represents the energy and transport sectors in France and covers all the technologies occurring in France for the following steps: production and imports of resources for primary energy, production of final energy from primary energy, and production of end-use energy to meet the final energy demand in France. Based on input data, this dynamic model helps determine which technologies will be needed to meet the exogenous demands (mobility demand, energy demand, etc.) in each time slice t representing a specific year $Y_t \in \{2009; 2015; 2019; 2025; 2030; 2050\}$ by minimizing the total system cost under constraints (technological constraints, regulation constraints, etc.). Therefore, the identified technologies are cost-optimal and are limited by the structure of the model (technologies available, chosen granularity) and the nature of the partial equilibrium model where demands are exogenous. More details on the reference energy system of the MIRET model are available in SI. For more information on TIMES models and its use in LCA, see Lorne and Tchung-Ming (2012); Menten et al. (2015); Astudillo et al. (2017); and Albers et al. (2019). Running the MIRET model allows determining the optimal production volumes V (i.e., how much of the process is used in MIRET) for each process p existing in MIRET at year Y_t for a defined scenario. Please note the term production volume is used to qualify the output amount per year of a product from a technology existing in the MIRET model.

To identify the directly affected processes, we first built two scenarios with MIRET: (1) the scenario *without* decision which is business as usual scenario without the implementation of the LTE; (2) the scenario *with* decision that defines alternative transportation scenarios to be implemented with the LTE in France by 2050. Then, we calculated the difference of production volumes V for each technology p at year Y_t between the scenario *with* decision ($V_{p,t}^{\text{with}}$) and the one *without* decision ($V_{p,t}^{\text{without}}$). When $V_{p,t}^{\text{with}} - V_{p,t}^{\text{without}} \neq 0$, we considered the technology p at year Y_t as an affected process to be included in the C-LCA. The resulting production volume for each directly affected process $V_{p,t}^{\text{affected}}$ (Eq. 2) is then aggregated over time from 2009 to 2050 horizon with a linear interpolation between time slices to define f_p (Eq. 3). We identified $P = 97$ technologies in MIRET as directly affected processes (see SI for the complete list).

$$V_{p,t}^{\text{affected}} = V_{p,t}^{\text{with}} - V_{p,t}^{\text{without}} \tag{2}$$

$$f_p = \sum_{t=0}^{T-1} \left(V_{p,t}^{\text{affected}} + V_{p,t+1}^{\text{affected}} \right) \frac{(Y_{t+1} - Y_t)}{2} \tag{3}$$

Note that $f_p = 3V_{p,2009}^{\text{affected}} + 5V_{p,2015}^{\text{affected}} + 5V_{p,2019}^{\text{affected}} + \frac{11}{2} V_{p,2025}^{\text{affected}} + \frac{25}{2} V_{p,2030}^{\text{affected}} + 10V_{p,2050}^{\text{affected}}$ for our case study.

2.1.4 Adaptation for background inventory and mapping with the foreground

The background inventory model is mostly based on LCI datasets from the attributional LCI database ecoinvent version 3.3 cutoff (Wernet et al. 2016). Our choice of using the attributional version of ecoinvent 3.3 is discussed in Section 5.3. To model the direct elementary flows and supply chains of the directly affected processes, we mapped each MIRET process affected by the decision to a corresponding ecoinvent process that must be adapted for our case study (Yang 2016). All ecoinvent processes mapped with a MIRET process have been modified to (i) avoid double-counting by removing from the supply chain described in ecoinvent the consumption of products already modeled in MIRET (i.e., fuel production for car transportation is already modeled in MIRET and is considered an affected process, so it is removed from the supply chain of car transportation processes in ecoinvent), (ii) account for direct tailpipe emissions from biofuel blended fuels by adding those emissions in ecoinvent transportation processes according to the biofuel share within each vehicle that evolves dynamically based on the optimization result of the MIRET model, (iii) technological progress in energy efficiency for vehicle use processes. Mapping excel file between MIRET and ecoinvent and further details on adaptation are available in SI.

2.1.5 Life cycle impact assessment and LCA models

Elementary flows quantified in the LCI step are then characterized by an LCIA methodology to assess the potential environmental impacts of the affected processes' life cycle. To do

[1] TIMES: The Integrated Markal-Efom System. MARKAL (MARket ALlocation model, (Fishbone and Abilock 1981)) and EFOM (Van der Voort and Doni 1984) are two bottom-up energy models that inspired the structure of TIMES.

so, we used IMPACT World+, a regionalized LCIA methodology with global spatial coverage (Bulle et al. 2019). We chose impact indicators at the damage level which can be aggregated to assess the impacts on areas of protection (AOP). Hence, we will be able to prioritize the practitioner's efforts across damage ICs based on their contribution to the AOP. The implemented version of IMPACT World+ has two AOP ICs at the damage level: ecosystem quality (EQ) and human health (HH); and 16 and 11 damage ICs contributing to each AOP, respectively. ICs related to climate change contribute to both AOPs. The following ICs are spatially differentiated: freshwater acidification, terrestrial acidification, freshwater eutrophication, land occupation, and land transformation for EQ; and water availability for HH. Global CFs that represent the impact of an elementary flow emitted somewhere in the world were used to assess both spatially differentiated and generic ICs. For spatially differentiated ICs, global CFs are CFs spatially aggregated for the world, calculated as an average of native CFs weighted by the probability for each elementary flow to occur in each native region (Bulle et al. 2019).

Equations 4 and 5 describe the LCA calculation models to compute C-LCA impact scores which are performed with Brightway 2 LCA software (Mutel 2017) using traditional LCA calculation (not regionalized LCA calculation). $\boldsymbol{h^{dam}}$ represents the damage impact scores for damage ICs, for instance ionizing radiation contributing to ecosystem quality. It is a vector with a dimension $J = 27$ and with element h_j^{dam} for each damage IC j. $\boldsymbol{h^{dam}}$ is calculated using Eq. 4 where $\boldsymbol{Q^{dam}}$ is the matrix of CFs at damage level. $\boldsymbol{h^{AOP}}$ represents the total damage impact scores aggregated for AOP ICs, for instance ecosystem quality. It is a vector with a dimension $K = 2$ and with element h_k^{AOP} for each AOP IC k. $\boldsymbol{h^{AOP}}$ is calculated using Eq. 4 where $\boldsymbol{Q_{AOP}} = [1 \quad \cdots \quad 1\ 0\cdots0 \quad 0 \quad \cdots \quad 0\ 1\cdots1]$ is a matrix with dimensions $K \times J$ with element equals to 1 when the damage IC j contributes to the AOP IC k.

$$\boldsymbol{h^{dam}} = \boldsymbol{Q^{dam}} \boldsymbol{g} \tag{4}$$

$$\boldsymbol{h^{AOP}} = \boldsymbol{Q^{AOP}} \boldsymbol{h^{dam}} \tag{5}$$

In terms of interpretation of C-LCA impact scores, a negative impact score indicates that the alternative transportation scenario meeting the LTE targets (scenario *with*) is potentially more beneficial than the business-as-usual transportation scenario (scenario *with*). On the contrary, a positive impact score indicates that the consequences of implementing the LTE targets are potentially adverse to the environment.

2.2 Methods for uncertainty analysis

The uncertainty analysis makes it possible to determine the strength of the conclusion of our case study, i.e., whether the implementation of LTE in France would be potentially beneficial or not for the environment, by testing the significance of the conclusion regarding a chosen confidence level. This section describes the following: (i) the uncertainty sources estimation for our case study for the foreground and background inventory models and LCIA model, (ii) the general approach for uncertainty analysis of the C-LCA model for our case study, and (iii) the statistical tests applied. Then, the results of the statistical tests are used to identify the damage and AOP ICs to be prioritized for uncertainty reduction, as proposed by Patouillard et al. (2019).

We distinguish two types of decision-makers: decision-makers who draw conclusions on AOP and will analyze statistical tests for each AOP IC to identify for which one reducing uncertainty is necessary and decision-makers who draw conclusions on damage contributions who will analyze statistical tests for each damage IC or a selection of damage ICs that are of interest. Therefore, the priority and type of work for uncertainty reduction will depend on the type of decision-maker. That is why we apply the uncertainty analysis and statistical tests to both damage and AOP impact scores. We used the notation h_i to represent damage or AOP impact score (h_j^{dam} *or* h_k^{AOP}).

2.2.1 Estimation of uncertainty sources

As displayed in Fig. 1, the C-LCA model is an arrangement of several tools integrated or not with the LCA calculation model as described by Eqs. 1, 2, 3, 4, and 5. Each tool is a source of uncertainty for the overall C-LCA model. Since we are focused on spatial uncertainty, we aimed to select specifically spatial components of the different uncertainty sources when possible. We accounted for uncertainty sources from different input variables for the different parts of the C-LCA model: background inventory model, foreground inventory model, and LCIA data i.e. CFs.

- For the foreground inventory model, input variables of the MIRET model (i.e., prices of commodities, production capacities per year, yields) that may be subject to spatial variability were selected based on expert judgment. Finally, the prices of five different biomass commodities were considered based on their geographic origins. Further details on data sources and the calculation of relative extrema for spatial variability are available in SI.
- For the background inventory model, we accounted for uncertainty sources as defined in ecoinvent v3.3 that are estimated with the Pedigree approach using lognormal distributions (Muller et al. 2014). This uncertainty not only contains a spatial component but other uncertainty sources as well. Associated limitations for our case study are discussed in Section 5.3. We also accounted for the

correlation between input and output quantities from unit processes in an uncertainty analysis in background LCI for water and land transformation flows, as described in Patouillard et al. (2019).

- For the LCIA model, only the variability due to the spatial aggregation of global CFs for spatially differentiated ICs is considered the uncertainty source as done in Patouillard et al. (2019) (more information on the implementation is available in SI). Besides, during the uncertainty analysis, we accounted for the LCIA spatial correlations between elementary flows produced by the same unit process only for the land transformation IC and for certain elementary flows. Other types of spatial correlation are not taken into account in this case study due to the challenge of implementing them in a reasonable amount of time (see Patouillard et al. (2019) for more details). It is worth noting that uncertainty from CFs and spatial LCIA correlation is rarely implemented in available LCA software.

2.2.2 The general approach for uncertainty analysis

Table 1 summarizes the techniques used for the uncertainty analysis of the C-LCA case study. The background inventory model and the LCIA data are fully integrated with the LCA calculation tool. Therefore, to propagate the uncertainty from those sources to the C-LCA results, we used a random sampling from defined probability distributions for each source. On the other hand, the foreground inventory model (MIRET model) is not integrated with the rest of the model. Therefore, we propagate uncertainty sources in the MIRET model using a computer experimental design and bootstrapping resampling with a dependent sampling for the scenarios with and without decision (see details below). We used a Monte Carlo simulation with $R = 5000$ runs (r) to propagate all the uncertainty sources in the LCA calculation model and obtained the following set of impact scores $H_i = \{h_{i,r}\}_{r=0}^{R-1}$ for each IC i. Limitations of our uncertainty analysis are discussed in Section 5.3.

2.2.3 Uncertainty propagation in the foreground inventory model

The MIRET model version used here is relatively time-consuming (approximately 15 min/run) and there is no integration between the MIRET model and the rest of the C-LCA model. So, a substantial amount of time is required to extract and format the outputs of MIRET for each run. Therefore, performing a Monte Carlo analysis of 5000 runs to propagate the uncertainty within the MIRET model and linking it directly with the other part of the C-LCA model would have been very time-consuming. Consequently, we decided to use a computer experimental design (Santner et al. 2013; Aleisa and Heijungs 2020) to approximate the uncertainty propagation of the spatial variability of MIRET's inputs variables to its results. We chose a space-filling design that aims to spread sets of values evenly throughout the experimental region, thus exploring all the potential responses of the model (Pronzato and Müller 2012). For the case study, we used a Latin-Hypercube sampling design that provided 80 sets of values for the 5 random input variables considered uncorrelated variables with a uniform distribution (Damblin et al. 2013). A total of 80 sets are a good compromise to explore the space of 5 variables in minimum time. One set provides one random

Table 1 Techniques used for the uncertainty analysis of the C-LCA case study for the estimation of uncertainty sources, the uncertainty propagation, and the output format

Parts of the C-LCA model	Estimation of input uncertainty	Uncertainty propagation	Output format and integration with LCA model
Background inventory model = adapted ecoinvent database	Pedigree approach as defined in ecoinvent.		Fully integrated with the LCA model.
Foreground inventory model = MIRET model	Estimation of spatial variability based on historical data for 5 key parameters.	Computer experimental design (space-filling design with Latin-Hypercube sampling).	80 sets of MIRET results. Not integrated with the LCA model.
LCIA data = CFs from IMPACT World+	Spatial variability of global CFs for spatially differentiated ICs represented with four-parameter beta distributions		Fully integrated with the LCA model.
LCA calculation model	Resampling using bootstrapping for foreground inventory model. Random sampling from probability distributions for background inventory model and LCIA data.	Monte Carlo simulation with dependent sampling for the scenario with and without decision.	5 000 runs = C-LCA impact scores

value for each input variable. For each set s of input values, we run the MIRET model for the scenarios *with* and *without* and obtain new production volume values gathered in the following set $\left\{V_{p,t,s}^{\text{affected}}\right\}_{s=0}^{79} = \left\{V_{p,t,s}^{\text{with}} - V_{p,t,s}^{\text{without}}\right\}_{s=0}^{79}$ to ensure a dependent sampling between the scenarios *with* and *without*. During the Monte Carlo analysis for uncertainty analysis on the C-LCA model, we used the bootstrap resampling method (Efron 1994) that consists of randomly picking a set s of MIRET results $V_{p,t,s}^{\text{affected}}$ at each Monte Carlo iteration with replacement and recalculates $\boldsymbol{f}$ for every set using Eqs. 2 and 3.

2.2.4 Statistical tests and priority rules for uncertainty reduction

Statistical tests allow determining the strength of the conclusion depending on the goal of the LCA study. For our C-LCA case study, the goal is to investigate if the decision is beneficial for the environment. Positive C-LCA impact scores (h_i) are interpreted as adverse to the environment and negative ones as beneficial for the environment. Therefore, we want to compare the Monte Carlo output samples H_i for each IC i to a reference value. To do so, we can apply statistical tests based on the Null Hypothesis Significance Test (NHST). To avoid NHST limitations with a large sample size (our sample size is 5000), we used the modified NHST procedure proposed by Heijungs et al. (2016) and described in Mendoza Beltran et al. (2018). In our case study, tests for prioritization are one-tailed modified NHST for each IC i with the null hypothesis $H_0 : \delta_i \geq -\delta_0$; where $\delta_i = \frac{\mu_i}{} \sigma_i$ is the standardized mean of H_i, μ_i is the mean of impact scores H_i estimated with $\overline{H_i} = \frac{1}{R}\sum_{r=0}^{R-1} h_{i,r}$, σ_i is the standard deviation of H_i estimated with $s_i = \sqrt{\frac{1}{R-1}\sum_{r=0}^{R-1}\left(h_{i,r} - \overline{H_i}\right)}\ ^2$, δ_0 is a threshold value traditionally set at 0.2. The probability that we reject H_0 while being true is called the significance level (α) which should be set depending on the risk aversion of the decision-maker. In our case study, we conventionally set α to 0.05. If the p value of the test is lower than the chosen significance level (α), then H_0 is rejected and the alternative hypothesis $H_a : \delta_i < -\delta_0$ is considered statistically significant with a confidence level (1-α). If H_0 is rejected, the decision is beneficial for the IC. It means that the absolute distance between δ_i and zero is significantly more than δ_0, i.e. more than "0.2 standard deviation units" (Mendoza Beltran et al. 2018).

The priority for uncertainty reduction should set on actions with the potential to enhance the interpretation phase and the decision-making (Patouillard et al. 2019). In the case H_0 is rejected, there is no need to put efforts on reducing the uncertainty of C-LCA impact scores for related ICs as conclusions can already be drawn. However, if H_0 cannot be rejected for some ICs, it means that there is no statistical evidence that the decision is beneficial for these ICs. It can be that the decision is not beneficial or that the uncertainty level is still too high and prevents us from concluding. Therefore, we will prioritize our efforts to try to reduce the uncertainty of C-LCA impact scores for those ICs where H_0 cannot be rejected. The prioritization between ICs will depend on their relative contribution to the uncertainty, using the methodology described in Section 2.3. Different goals for this case study would have led to different statistical tests and the prioritization for uncertainty reduction would have been different.

2.3 Results of uncertainty analysis of the C-LCA case study

We performed a Monte Carlo analysis including all sources of identified uncertainty and displayed H_i the damage impact score distributions for each IC i (Fig. 3). Then, we identified ICs to be prioritized for uncertainty reduction based on the results of modified NHST statistical tests for sample size $R = 5000$, δ_0=0.2, and $\alpha = 0.05$. ICs where H_0 can be rejected with a confidence level of 95% are identified in Fig. 3 with the asterisk symbol. All detailed results for modified NHST statistical tests are available in SI.

Analysis for decision-makers focusing on AOP Even if the total impact score distribution for EQ contains both negative and positive values, the implementation of LTE in France from 2009 to 2050 would be beneficial for EQ with a confidence level of 95%, according to modified NHST statistical tests. The total impact scores for HH are evenly distributed between negative and positive values. Modified NHST statistical tests confirm that we cannot reject H_0 for HH with a confidence level of 95%, so no conclusion can be drawn. Therefore, attempting to reduce the uncertainty and increase the discriminating power for HH is relevant to our case study.

Analysis for decision-makers focusing on damage contributions Land transformation and water availability are the ICs that seem to dominate uncertainty in EQ and HH, respectively. The global sensitivity analysis ill test this intuition based on visual inspection. However, the impact score uncertainty for both ICs should be interpreted with caution since spatial correlation within IC between CFs has been partially addressed for these ICs and may affect the results (Patouillard et al. 2019). Beyond land transformation and water availability, modified NHST statistical tests confirm that the implementation of LTE in France is likely to have a beneficial impact on the following ICs with a confidence level of 95%: global warming (short-term and long-term altogether, for EQ and HH), marine acidification, marine eutrophication, terrestrial acidification, thermally polluted water, photochemical oxidant formation, and particulate matter formation. In this case, there

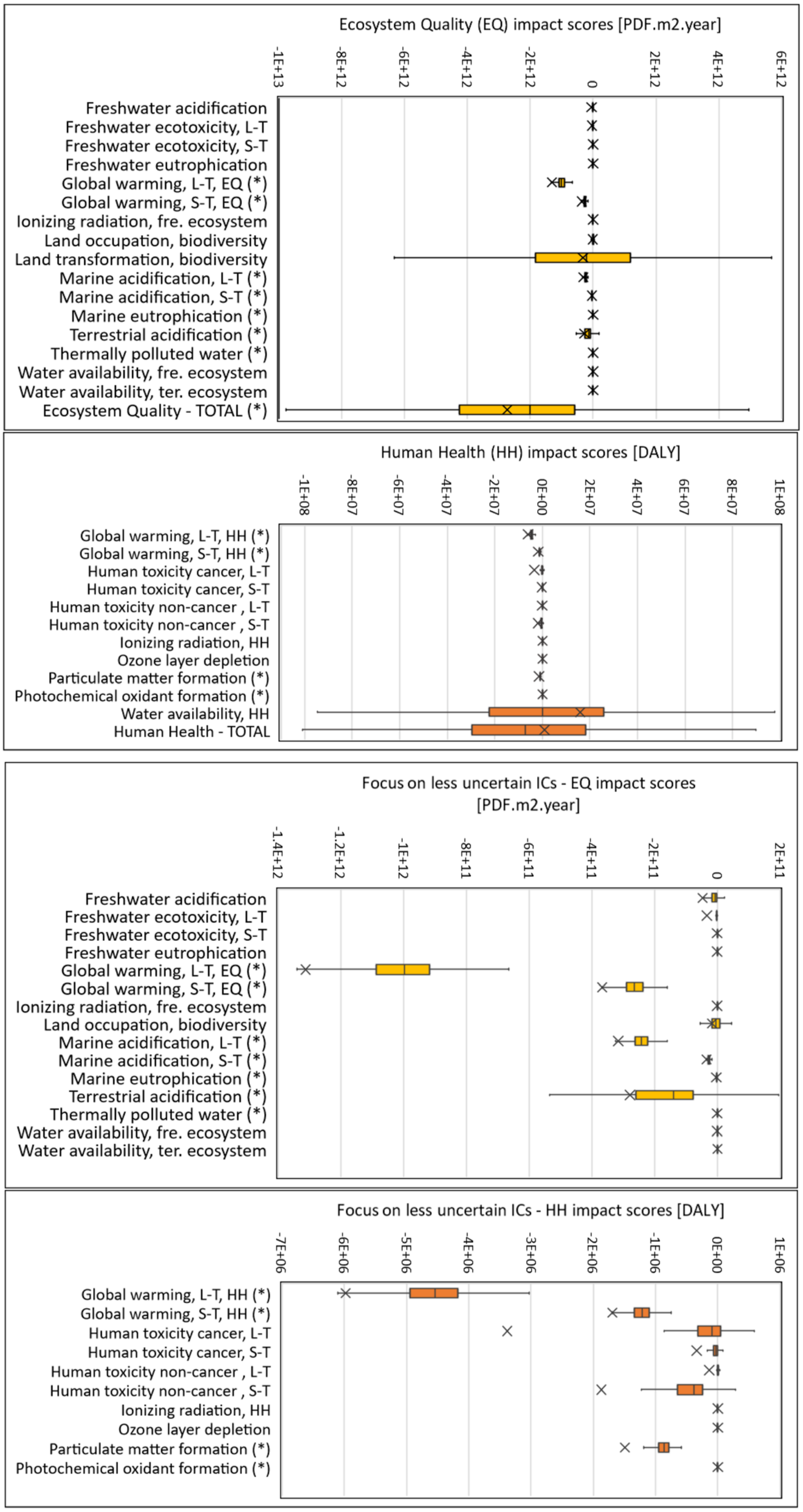

Fig. 3 Box and whisker charts representing the distribution of damage impact score $\boldsymbol{h_i}$ for each $\mathbf{IC}_i$ contributing to the ecosystem quality (EQ) AOP in PDF.m^2.year (left) and contributing to human health (HH) AOP in DALY (right). The whiskers represent the local minimum and local maximum. The bottom and top of each box represent the first and third quartiles. The bar inside the box represents the median, and the cross represents the mean value. Outliers are excluded following the Tukey standards (McGill et al. 1978). **p* value < 0.05 based on the results of modified NHST statistical tests. The charts on the top represent the distributions for $\boldsymbol{h_j^{dam}}$ for each damage IC and on the right of each graph for $\boldsymbol{h_k^{AOP}}$ for each AOP IC. The charts on the bottom focus on damage ICs that are less uncertain (excluding land transformation for EQ and water availability for HH). S-T, short-term; L-T, long-term

is no need to attempt to reduce the uncertainty for these ICs since we may already conclude on the benefits of implementing the LTE, which is the goal of our case study.

3 Global sensitivity analysis of the C-LCA case study

Once we identified ICs where uncertainty needs to be reduced, main sources of spatial uncertainty in the C-LCA model for each IC must be identified to adequately prioritize the data collection for regionalization. The objective of the global sensitivity analysis (GSA) is to identify the main sources of uncertainty in the C-LCA model (foreground inventory model based on economic modeling, background inventory model, CFs). In contrast to local sensitivity analysis, GSA provides a more representative sensitivity analysis by accounting for the overall variation range of inputs and accounts for interactions and correlations (Wei et al. 2015).

Here, we present the GSA indicators used in this study and the stepwise procedure to identify the key sensitive variables, also referred to as main uncertainty sources or main uncertainty contributors. The stepwise procedure allows to determine which impact categories and which parts of the LCA model should be prioritized for uncertainty reduction. This procedure is in line with the one proposed in Patouillard et al. (2019) and adapted for our C-LCA case study. Python scripts to perform GSA are available as supporting information in Patouillard et al. (2019) and accessible at https://doi.org/10.5281/zenodo.3597423.

3.1 GSA indicators definition

The first-order sensitivity index derived from the Sobol variance decomposition is designed for factor prioritization (Saltelli and Tarantola 2002; Saltelli 2017). This index is selected as our importance indicator for GSA to identify the main uncertainty sources in this study. For a model $Y = m(X_1, \ldots, X_l, \ldots, X_L)$ where X_l are the uncertain (or random) input variables of the model and Y is the output, the first-order sensitivity index $SI1_{X_l}$ measures the main influence or first-order effect of variable X_l on the results Y (Saltelli et al. 2010). We estimated $SI1_{X_l}$ using the procedure described in Patouillard et al. (2019). The total sensitivity index SIT_{X_l} also includes the second and higher-order effects of the variable X_l on the results (Saltelli et al. 2010). SIT_{X_l} is a sum of $SI1_{X_l}$ and all $SIk_{X_l \ldots X_k}$ (kth-order sensitivity index which represents the sensitivity due to interactions between variables $X_l \ldots X_k$). It provides additional information on the influence of X_l in the model, which could be useful. More information on the Sobol variance decomposition is available in SI.

3.2 A stepwise procedure to identify the main sources of uncertainty

As discussed in Patouillard et al. (2019), a straightforward approach to perform GSA on an LCA model would require more than 200 days of calculation to directly estimate the sensitivity of each variable. Therefore, we decomposed the LCA model into simpler models by grouping variables to prioritize the most sensitive part of the model step by step. The main reasons for grouping variables are as follows: (1) to reduce the computational complexity; (2) to drive the efforts with a practitioner's perspective. Indeed, the type of data, tools and expertise to improve the spatialization of elementary flows, the regionalization of foreground inventory model or the regionalization of background inventory model is very different; (3) to deal with correlation between variables (Jacques et al. 2006; Xu and Gertner 2008; Wei et al. 2015; Patouillard et al. 2019). Therefore, we created three uncorrelated groups of variables that are the different parts of the C-LCA model: background inventory model variables $X_{LCI_{bg}}$ from the ecoinvent database, foreground inventory model variables $X_{LCI_{fg}}$ from MIRET model, and LCIA variables X_{LCIA}, which are CFs from IMPACT World+ (Fig. 1). All inventory model variables can also be grouped in a single group of variables defined as $X_{LCI} = \{X_{LCI_{bg}}, X_{LCI_{fg}}\}$. This group choice will guide the efforts required since each part involves different efforts and skills for data and model improvements.

Here, we describe the stepwise procedure used to identify the main sources of h_i uncertainty for our case study. At each step, we performed a GSA on a specific model with the form $Y = m_x(X_1, \ldots, X_l, \ldots, X_L)$ as detailed in Table 2 and estimated sensitivity indices as described in Patouillard et al. (2019) (see the figure in SI).

The GSA interpretation to prioritize efforts for uncertainty reduction is explained at each step.

1. *IC ranking step:* Determine which damage IC is the main source of h_k^{AOP} uncertainty for each AOP IC. For each AOP IC, we ranked each damage IC based on its $SI1_{h_j^{dam}}$ value. Damage ICs with higher $SI1_{h_j^{dam}}$ are major contributors to the uncertainty of h_k^{AOP} and, therefore, should be prioritized for uncertainty reduction. This information is useful when the goal and scope of the LCA study focus on more than one damage IC.
2. *LCI vs. LCIA step*: Determine which group of variables between X_{LCI} and X_{LCIA} is the main source of h_j^{dam} uncertainty for each damage IC. Interpretation of sensitivity indices for this step makes it possible to prioritize efforts between inventory regionalization and inventory spatialization for the damage ICs selected during the *IC ranking* step. If $SI1_{X_{LCI}}$ is the highest sensitivity index, the

Table 2 Details on GSA models and sensitivity indices estimated at each step

Steps	Model on which the GSA is performed	Sensitivity indices estimated (details available in SI)
IC ranking	$\boldsymbol{h}^{AOP} = m_1\left(h_0^{dam}, \ldots, h_j^{dam}, \ldots, h_{J-1}^{dam}\right)$ based on equation 5.	$SI1_{h_j^{dam}}$ for each IC_k^{AOP}
LCI vs. LCIA	$\boldsymbol{h}^{dam} = m_2(X_{LCI}, X_{LCIA})$ based on equation 4.	$SI1_{X_{LCI}}, SI1_{X_{LCIA}}$ *and* $SI2_{X_{LCI},X_{LCIA}}$ for each IC_j^{dam}
Background vs. foreground LCI	$\boldsymbol{h}^{dam} = m_3\left(X_{LCI_{bg}}, X_{LCI_{fg}}, \mu_{X_{LCIA}}\right)$ which is a derived model from m_2 where X_{LCIA} are set to their mean deterministic values ($\mu_{X_{LCIA}}$).	$SI1_{X_{LCI_{bg}}}, SI1_{X_{LCI_{fg}}}$ *and* $SI2_{X_{LCI_{bg}},X_{LCI_{fg}}}$ for each IC_j^{dam}

h_j^{dam} uncertainty mainly comes from inventory model variables, and the inventory should, therefore, be investigated for regionalization. If $SI1_{X_{LCIA}}$ is the highest sensitivity index, the h_j^{dam} uncertainty is mainly coming from LCIA variables, and the inventory should, therefore, be investigated for spatialization to use more regionalized CFs. An $SI2_{X_{LCI},X_{LCIA}}$ (also referred to as interaction sensitivity index) higher than other sensitivity indices, which indicates that the h_j^{dam} uncertainty mainly comes from the interactions between both groups of variables. Therefore, no priority order may be drawn and both groups X_{LCI} and X_{LCIA} should be further studied.

3. *Background vs. foreground LCI step*: Determine which if $X_{LCI_{bg}}$ or $X_{LCI_{fg}}$ is the main source of h_j^{dam} uncertainty for each damage IC considering LCI uncertainty only. Interpretation of sensitivity indices for this step makes it possible to prioritize inventory regionalization efforts between background and foreground LCI for damage ICs selected during the *IC ranking* step and the *LCI vs. LCIA* step. Inventory regionalization efforts should be focused on (i) the background inventory model if $SI1_{X_{LCI_{bg}}}$ is higher than other sensitivity indices; (ii) the foreground inventory model, i.e., the MIRET model here, if $SI1_{X_{LCI_{fg}}}$ is higher.

3.3 Results of global sensitivity analysis of the C-LCA case study

3.3.1 IC ranking and LCI vs. LCIA steps

Figure 4 presents the results for GSA performed for the *IC ranking* step (length of each bar) and the *LCI vs. LCIA* step (divisions within each bar) by accounting for uncertainty from inventory model and LCIA variables.

Both groups of inventory model variables and LCIA variables are important contributors to total EQ impact score uncertainty. The total HH impact score uncertainty is driven by the interactions between both X_{LCI} and X_{LCIA} variable groups, meaning that no priority order may be drawn and that both groups should be further investigated. Therefore, inventory regionalization or inventory spatialization may be required depending on the damage IC. Land transformation and water availability have the highest first-order sensitivity indices for the *IC ranking* step for EQ and HH, respectively. Consequently, they are the most sensitive ICs. In the case of land transformation for EQ, the uncertainty mainly comes from the group of LCIA variables, highlighting the need for inventory spatialization. In the case of water availability for HH, the sensitivity is almost entirely due to the interactions between inventory model variables and LCIA variables. In this case, both groups of variables are sensitive and both inventory regionalization and spatialization should be enhanced. The spatial correlation within the IC between CFs has been partially addressed for land transformation but not for water availability. This limitation could partly explain the dominance of both ICs in the sensitivity in the *IC ranking* step (Patouillard et al. 2019).

Regarding other regionalized ICs, the group of LCIA variables dominates the resulting sensitivity for the freshwater eutrophication IC only, indicating that inventory spatialization should be a priority for this IC. The interaction sensitivity index dominates the resulting sensitivity for terrestrial and freshwater acidification ICs for EQ and water availability for HH. Consequently, inventory regionalization and spatialization should both be a priority. Land occupation and marine eutrophication are the only ICs for which the group of LCI variables is the most sensitive, indicating that inventory regionalization should be prioritized here for these ICs.

Finally, the group of inventory model variables necessarily dominates the resulting sensitivity for non-regionalized ICs since no uncertainty from LCIA is associated with those ICs. The next section analyzes the part of the C-LCI model (foreground or background inventory model) that must be prioritized to refine the regionalization strategy.

3.3.2 Digging deeper into inventory uncertainty

Figure 5 presents the results for the GSA performed for the *IC ranking* step (length of each bar) and the *background vs. foreground LCI* step (divisions within each bar). In both steps, only inventory model variables (background and foreground) are uncertain and LCIA variables are set to their mean

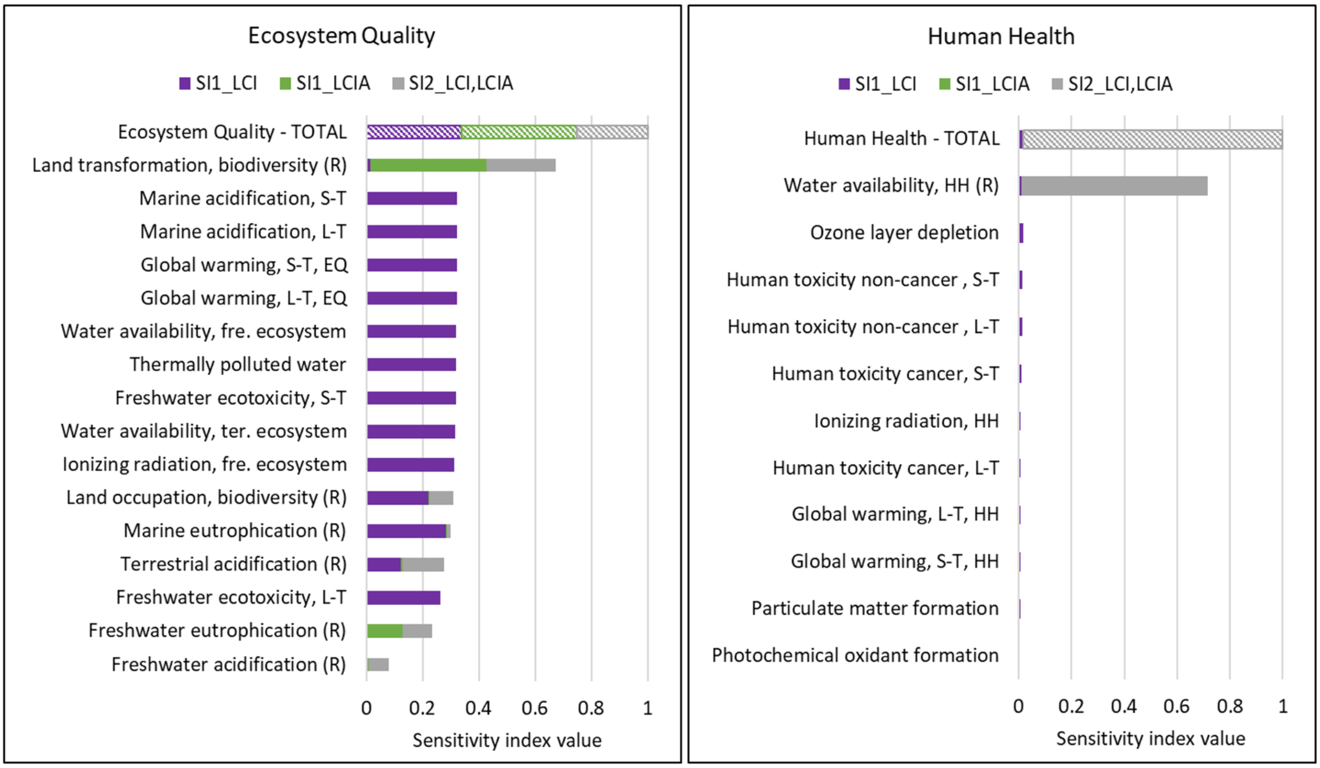

Fig. 4 GSA results for the *IC ranking* step (length of each bar) and the *LCI vs. LCIA* step (divisions within each bar). Values of first-order sensitivity indices for the *IC ranking* step for each damage IC contributing to the ecosystem quality (left) and human health AOPs (right). The divisions within each bar correspond to the contribution of sensitivity indices for the *LCI vs. LCIA* step with $SI1_{LCI}$: first-order sensitivity index for inventory model variables (purple);$SI1_{LCIA}$: first-order sensitivity index for LCIA variables (green); $SI2_{LCI,\ LCIA}$: second-order sensitivity index due to the interactions between LCI and LCIA variables (grey). The contribution of sensitivity indices for the *LCI vs. LCIA* step is also provided for each total AOP (hashed bar). Regionalized ICs are identified with the (R) symbol

deterministic values, thus making it possible to test the sensitivity of the inventory model variables only. As uncertainty for background variables does not only contain spatial uncertainty, their contribution to the overall spatial uncertainty might be overestimated.

For EQ, the contribution of ICs to the total damage impact score uncertainty from inventory model variables is similar, except for the land transformation IC where it is lower. So, a lower priority may be set on this latter IC for inventory regionalization, and other ICs are equally important. For HH, the water availability IC dominates the contribution of ICs to the total damage uncertainty from inventory model variables and therefore should become a study priority for inventory regionalization.

The group of background inventory model variables dominates the sensitivity of the inventory model variables for only two ICs: ionizing radiation IC for HH and land transformation IC for EQ. For other ICs, the sensitivity is mainly due to the group of foreground inventory model variables or the interaction between background and foreground inventory model variables. These results highlight the fact that efforts should be invested to reduce the uncertainty from the foreground inventory model with a more representative regionalization of this part of the inventory model. For ICs in which interactions dominate, uncertainty reduction should also focus on background inventory model, in addition to the foreground inventory model.

4 A proposed strategy for regionalization of the C-LCA case study

The proposed strategy for regionalization in LCA strongly depends on the goal of the study, study resources (time and financial resources), and available tools, skills, and experience of the team performing the study (Patouillard et al. 2018). Those factors affect the ICs that are selected for enhancement and the efforts invested to further study the sources of uncertainty within each group of variables.

This case study is performed in the context of the development and enhancement of the C-LCA practice with the MIRET-TIMES model at IFP Énergies nouvelles and case study conclusions are based on the performance of each damage IC (decision-makers focusing on damage contribution). The proposed strategy is divided into actions from very high

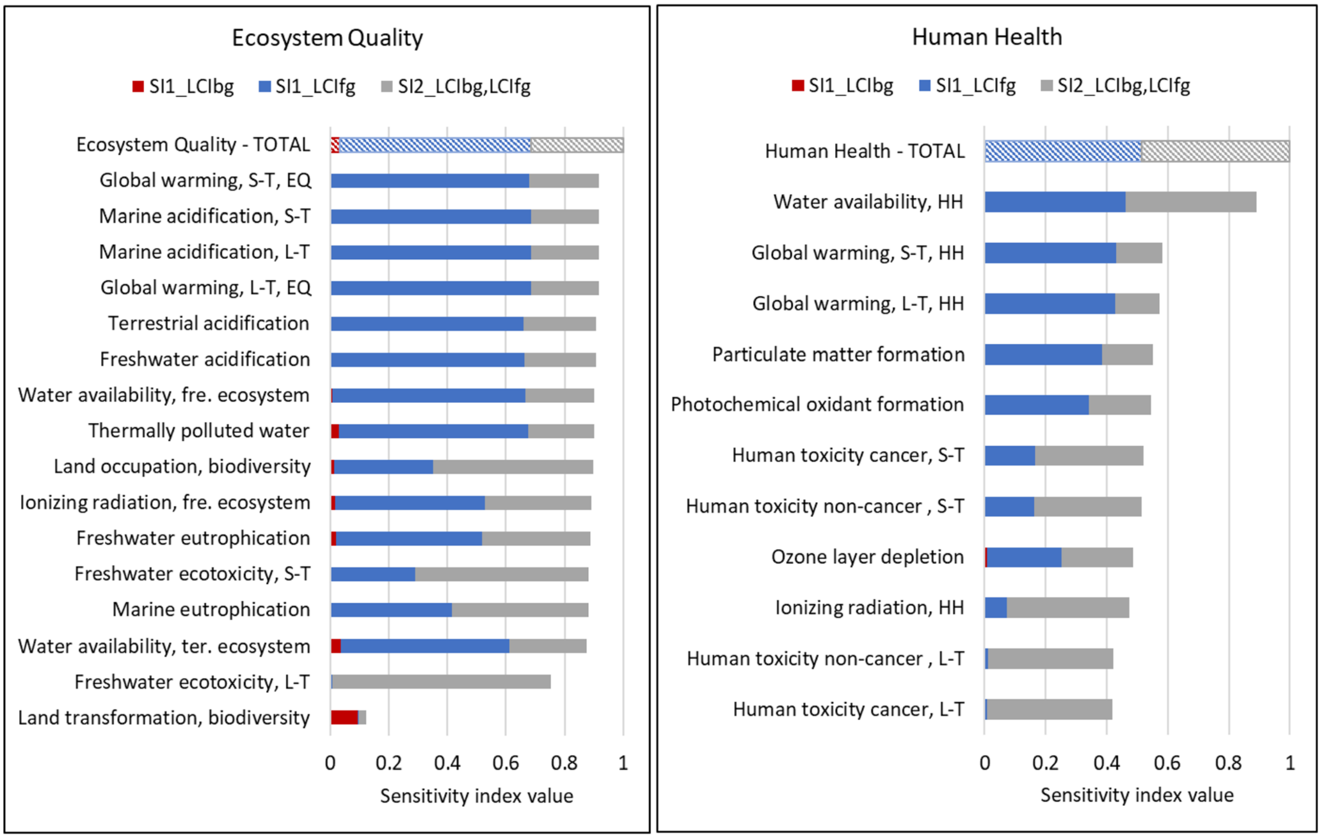

Fig. 5 GSA results for the *IC ranking* step considering only uncertainty from inventory model variables (length of each bar) and for the *background vs. foreground LCI* step (divisions within each bar). Values of first-order sensitivity indices for the *IC ranking* step considering only uncertainty from inventory model variables for each damage IC contributing to the ecosystem quality (left) and human health AOPs (right). The divisions within each bar correspond to the contribution of sensitivity indices for the *background vs. foreground LCI* step with $SI1_{LCI_{fg}}$: first-order sensitivity index for background LCI variables (red); $SI1_{LCI_{fg}}$: first-order sensitivity index for LCI_{fg} variables (blue); $SI2_{LCI_{bg},LCI_{fg}}$: second-order sensitivity index due to the interactions between $X_{LCI_{bg}}$ and $X_{LCI_{bg}}$ variables (grey). The contribution of sensitivity indices for the *background vs. foreground LCI* step is also provided for each total AOP (hashed bar)

to low priority depending on the importance of the sensitivity, available means, and confidence level about the study conclusions. In other words, actions with the highest potential for uncertainty reduction and which will help to draw study conclusions will be prioritized. Therefore, ICs for which we can already conclude with a confidence level of 95% (global warming, marine acidification, marine eutrophication, terrestrial acidification, thermally polluted water, photochemical oxidant formation, and particulate matter formation) are excluded from this strategy. Only damaged ICs in which uncertainty prevents us from concluding will be prioritized.

Here are the proposed actions per priority level for regionalization in C-LCA for our case study:

1. *Very-high-priority actions.* Those actions are focused on the most sensitive ICs (land transformation for EQ and water availability for HH) and the most sensitive part of their LCA model (LCIA data for both ICs and LCI data for water availability for HH).

- Investigate the influence of LCIA spatial correlation (spatial correlation within IC between CFs) on the impact score uncertainty for land transformation for EQ and water availability for HH, as it may highly influence the high sensitivity of both ICs (Patouillard et al. 2019).
- If the potential for uncertainty reduction with LCIA spatial correlation is high, implement the LCIA spatial correlation within IC between CFs for land transformation for EQ and water availability for HH and perform GSA as described in the methodology from the beginning.
- If the potential for uncertainty reduction with LCIA spatial correlation is low, spatialize elementary flows for land transformation for EQ and water availability for HH to use more regionalized CFs instead of global CFs. The first level of spatialization would be to use the available information from ecoinvent on the location of each process unit, which is often at the country

level. For water availability for HH, regionalize the inventory, especially the foreground LCI from the MIRET model.

2. *High-priority actions.* Those actions are focused on other high sensitive ICs in which sensitivity may be due to the foreground inventory model, i.e. the MIRET model (thermally polluted water, freshwater ecotoxicity, water availability, land occupation for EQ; ozone layer depletion, human toxicity for HH).

    - Perform a GSA to investigate the influence of each foreground LCI variable to identify which among them are more sensitive. Do it in priority for ICs where conclusions are more difficult to draw, i.e. when result distribution contains negative and positive values well spread around zero.
    - Enhance the description of the relative spatial variation of the most sensitive foreground inventory model variables. For instance, a more representative distribution may be defined to represent the relative spatial variation instead of the uniform distribution currently used. In this case, the space-filling experimental design should be adapted.

3. *Low-priority actions:* Those actions are focused on other parts of the LCA model for highly sensitive ICs.

    - Perform a GSA to investigate the influence of background LCI variables to identify the most sensitive ones. Enhance the regionalization for those variables by performing a more representative regional data collection. Do it for highly sensitive ICs where background inventory model variables may be sensitive (freshwater ecotoxicity, land occupation for EQ; ozone layer depletion, human toxicity, ionizing radiation for HH).
    - Spatialize elementary flows to use more regionalized CFs instead of global CFs. The first level of spatialization would be to use the available information from ecoinvent on the location of each process unit, which is often at the country level. Do it for highly sensitive ICs where LCIA data may be sensitive (land occupation and freshwater eutrophication for EQ).

5 Discussion

This article aims to prioritize regionalization efforts to enhance interpretation in C-LCA by assessing the spatial uncertainty of a case study building on a partial equilibrium economic model. The methodology used to prioritize regionalization efforts is an adaptation of the methodology proposed by Patouillard et al. (2019). The benefits and limits of this methodology are already discussed in Patouillard et al. (2019). Here, the discussion focuses on the limitations of its adaptation for our case study in C-LCA to avoid over-interpretation of the results.

5.1 Assessing uncertainty from partial equilibrium economic modeling

Assessing the spatial uncertainty of the foreground inventory model from the MIRET model was one of the challenges faced during this study. First, we relied on expert judgment to identify input variables of the MIRET model that may be subject to spatial variability. As it was not possible to assess the spatial variability of each MIRET model inputs, this approach helped us to focus our data collection to assess the spatial variability of the MIRET model in the context of our case study. However, by doing so, we excluded some inputs that might have been sensitive. As stated by Moret et al. (2017), this a priori exclusion should be avoided. Therefore, it would have been relevant to first identify the most sensitive inputs from the MIRET model and to assess the spatial variability of those inputs. Unfortunately, identifying the most sensitive inputs of the MIRET model was beyond the scope and the means of our case study. Nevertheless, future works on the MIRET model should focus on assessing the sensitivity of the model.

As the MIRET model was computationally intensive and not integrated with the background inventory model and LCA model, we used a computer experimental design to save time. We chose a standard design, known as space-filling, which consists of selecting sets of values for inputs uniformly spread across the experimental region. Still, we used the MIRET results for each experiment in our Monte Carlo analysis, using bootstrapping to randomly pick a MIRET result at each iteration. In doing so, we assumed a uniform distribution of the input variables of the MIRET model, which may lead to misestimating, and probably overestimating, the sensitivity of foreground inventory model variables (Muller et al. 2017). Indeed, input variables most likely have a value and distribution that are different from the uniform distribution. In our case study, input variables from the MIRET model are biomass prices. Their distribution should reflect prices from the different regions of origin weighted by the amount of biomass produced in each region. Their most likely value is the price in the region where most of the biomass originates (main import country or region). Alternative probability distributions to fit the spatial distribution of the biomass prices should be investigated to validate (or not) the choice for the uniform distribution.

An alternative way to account for input variable-specific distribution is to build a prediction model based on the computer experiment design results, for instance using response surface methodology (Draper 1997; Ba and Boyaci 2007).

The prediction model would be an estimation of the MIRET model, calculating MIRET result estimates from the input variable value defined by the user. Using this model, we may apply any distribution to the input variables and perform a Monte Carlo analysis directly on the prediction model to estimate MIRET uncertainty. However, the estimator to build the prediction model must be adapted to the MIRET model, especially because MIRET results are not linear and may have discontinuities regarding input variables. The existence of estimators adapted to the MIRET model, as well as computational time to build the prediction model, must be studied.

In our case study, we only investigated the spatial variability of the MIRET model. It involved a limited number of variables. Thus, the number of experiments, which depends on the number of variables, remains reasonable. If the purpose of the uncertainty analysis would have been to investigate all the MIRET uncertainty sources, and not only spatial variability, the number of variables would have been higher. Therefore, the number of experiments, and thus, the computational time to run them would have increased dramatically. In this case, an alternative to computer experimental design is required. The uncertainty of the TIMES model results can also be estimated with other approaches such as robust optimization (Nicolas et al. 2014). The associated computational time, as well as how uncertainty results can be used for C-LCA purposes, should be studied further.

5.2 LCIA spatial correlation in C-LCA

Once regionalized ICs have been dealt with, LCIA spatial correlations from different origins should be considered: the spatial correlation at the product system level, the spatial correlation between ICs (inter ICs) and the spatial correlation within IC between CFs (intra CFs) (Patouillard et al. 2019). There is an additional source of LCIA spatial correlation in C-LCA: LCIA spatial correlation between processes affected by the decision. Here, affected processes are identified by comparing two scenarios modeled using the economic model MIRET: one scenario with the decision and the other without. Only the difference between both scenarios is modeled in the C-LCA model. However, the spatial distribution of a process may be different between the scenario with and without the decision. For instance, biomass cultivation processes may occur in some regions in the scenario that implement the LTE and in other regions in the business-as-usual scenario. Here, since the MIRET version used in this exercise is not regionalized, we assumed that this spatial distribution is the same for both scenarios and thus also assumes that processes from the scenario with and without decision are perfectly spatially correlated. We, therefore, use regionalized CFs from the same region for both scenarios.

The effect of accounting (or not) for LCIA spatial correlation between affected processes may be studied by comparing C-LCA results from the current MIRET model (not regionalized) with a regionalized version of the MIRET model (GeoMIRET). With this version, we would be able to compare the spatial distribution of scenarios with and without the decision for each process and see if they match or not. If there is a difference between spatial distributions for each process that affects the C-LCA results, then not only should a set of affected processes be modeled in the C-LCA model but the LCA model of both scenarios, including affected and not affected processes, would have to be modeled. The difference between both LCA models must also be determined (Yang 2016).

5.3 Other main limitations of the case study

Even if we would have preferred to use a consequential version of an LCI database to fully represent the chain of consequences even in the background data, we decided not to assess the consequences of the decision in the background inventory model, by using the attributional version of ecoinvent 3.3 to model the background. Indeed, the consequential version of the ecoinvent 3.3 database has limitations to adequately represent the prospective consequences in the background inventory model. In this consequential version of the ecoinvent database, constrained productions and marginal supply mix shares are identified based on historical average data which limits the possibility to assess future consequences of a decision (Wernet et al. 2016; Vandepaer et al. 2018). Note that those shortcomings have been addressed in the most recent consequential version of ecoinvent and that consequential version of ecoinvent can surely be used in future consequential studies to model the background LCI.

Regarding uncertainty analysis, we accounted for the spatial uncertainty sources that we were able to quantify in the most comprehensive way as possible, i.e., trying to quantify the maximum sources of uncertainty in the case study. Nevertheless, quantifying all potential sources of spatial uncertainty in LCA was impossible because: (1) quantifying all quantitative sources would have required a very substantial amount of time that was beyond the time available for this study, (2) some qualitative uncertainty sources are difficult to translate into quantitative uncertainty, (3) we do not even know all potential sources in LCA, (4) the quantification of uncertainty is also uncertain. Interpretation of uncertainty analysis should keep in mind those limitations. More specifically, we do not account for the spatial component of the LCIA model uncertainty (i.e., spatial uncertainty from native resolution as opposed to the variability due to spatial aggregation) as this information is not yet provided by the LCIA method developers (Mutel et al. 2018). Regarding uncertainty for background LCI, we accounted for all components of the ecoinvent uncertainty data, not only the spatial component, as we only had access to the uncertainty information in that format. Therefore, if the main source of uncertainty comes from the background inventory model in our case study, the way to reduce it would be to collect more representative data, but not necessarily more regionalized ones. Besides, inventory model and LCIA correlations have been partially addressed in our case study, so uncertainty and GSA results should be interpreted with caution especially for land transformation and water availability impact indicators which are mainly affected (Patouillard et al. 2019).

6 Conclusion

The uncertainty analysis of this C-LCA case study including inventory model and LCIA input variables shows that the implementation of alternative transport scenarios in compliance with the LTE public policy is beneficial for some ICs, such as global warming, marine acidification, marine eutrophication, terrestrial acidification, thermally polluted water, photochemical oxidant formation, and particulate matter formation, with a confidence level of 95%. For other ICs, uncertainty reduction is required to determine conclusions with a similar level of confidence.

The GSA of our C-LCA case study highlights that input variables identified from the partial equilibrium economic model with spatial variability (foreground inventory model) are significant contributors to the spatial uncertainty results and should be prioritized for spatial uncertainty reduction. Indeed, ways to reduce the spatial uncertainty of the foreground inventory model from economic modeling should be explored. In this C-LCA case study, all regionalized ICs (except land occupation IC) require inventory spatialization, since the group of LCIA variables is the most sensitive. Therefore, using regionalized CFs in C-LCA is relevant, and C-LCA calculation tools should be adapted accordingly.

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