



**HAL**  
open science

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

Laure Patouillard, Daphné Lorne, Pierre Collet, Cécile Bulle, Manuele Margni

### ► **To cite this version:**

Laure Patouillard, Daphné Lorne, Pierre Collet, Cécile Bulle, Manuele Margni. Prioritizing regionalization to enhance interpretation in consequential life cycle assessment: Application to alternative transportation scenarios using partial equilibrium economic modeling. *International Journal of Life Cycle Assessment*, 2020, 25 (12), pp.2325-2341. 10.1007/s11367-020-01785-x . hal-03111911

**HAL Id: hal-03111911**

**<https://ifp.hal.science/hal-03111911>**

Submitted on 15 Jan 2021

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

[Click here to view linked References](#)

1  
2  
3  
4 Prioritizing regionalization to enhance interpretation in consequential life  
5  
6 cycle assessment: Application to alternative transportation scenarios using  
7  
8 partial equilibrium economic modeling  
9

10  
11  
12  
13  
14 Authors

15  
16 Laure Patouillard<sup>1,2,3</sup>, Daphné Lorne<sup>2</sup>, Pierre Collet<sup>2</sup>, Cécile Bulle<sup>4</sup>, Manuele Margni<sup>1</sup>

17  
18  
19 <sup>1</sup>CIRAIG, Polytechnique Montréal, P.O. Box 6079, Montréal, Québec H3C 3A7, Canada

20  
21 <sup>2</sup>IFP Energies nouvelles, 1-4 avenue de Bois-Préau, 92852 Rueil-Malmaison, France

22  
23  
24 <sup>3</sup>UMR 0210 INRA-AgroParisTech Economie publique, INRA, Thiverval-Grignon, France

25  
26 <sup>4</sup>CIRAIG, ESG UQAM, C.P.8888, succ. Centre ville, Montréal (QC), Canada H3C 3P8

27  
28  
29 E-mail contact: laure.patouillard@polymtl.ca  
30  
31  
32  
33

34 Journal

35  
36  
37 International Journal of Life Cycle Assessment

38  
39  
40 Special Issue: Interpretation of LCA Studies for Decision Support: State of the Art and Way Forward

41  
42 Key words

43  
44  
45 Life Cycle Assessment, interpretation, uncertainty, transport, public policy, regionalization, partial  
46  
47 equilibrium economic modelling, global sensitivity analysis  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

1  
2  
3  
4 Summary  
5  
6  
7  
8  
9

10 1. Introduction..... 4  
11 2. Uncertainty analysis of C-LCA case study..... 6  
12 2.1. Description of the C-LCA case study..... 6  
13 2.2. Methods for uncertainty analysis..... 11  
14 2.3. Results of uncertainty analysis of the C-LCA case study ..... 14  
15 3. Global sensitivity analysis of the C-LCA case study ..... 15  
16 3.1. GSA indicators definition ..... 15  
17 3.2. A stepwise procedure to identify the main sources of uncertainty ..... 16  
18 3.3. Results of global sensitivity analysis of the C-LCA case study ..... 17  
19 4. A proposed strategy for regionalization of the C-LCA case study ..... 19  
20 5. Discussion ..... 21  
21 5.1. Assessing uncertainty from partial equilibrium economic modelling..... 21  
22 5.2. LCIA spatial correlation in C-LCA ..... 22  
23 5.3. Other main limitations of the case study ..... 23  
24 6. Conclusion ..... 24  
25 Acknowledgements ..... 24  
26 Bibliography..... 25  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

## 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 modelling, background inventory model and characterisation 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, characterisation 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 modelling 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.

## 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 modelling 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 are specifically collected or modelled 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

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

33 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.

35 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 as compared to 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 modelling implies that uncertainty sources from those models are uncertainty sources in C-LCA. Three main sources of uncertainty in economic modelling 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).

52 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 in 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 in 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

1  
2  
3 65 never been addressed in the literature. This article addresses regionalization efforts at the level of the  
4  
5 66 inventory data, so focuses on inventory regionalization and/or inventory spatialization only. Impact  
6  
7 67 regionalization efforts, to develop spatially differentiated or regionalized characterization factors, is out of  
8  
9 68 scope.

10  
11 69 The main purpose of this article is to prioritize regionalization efforts to enhance interpretation in  
12  
13 70 consequential LCA by assessing the spatial uncertainty of a case study building on a partial equilibrium  
14  
15 71 economic model. This article is a case study based on the methodology developed by Patouillard et al. (2019)  
16  
17 72 to prioritize regionalization efforts in LCA. To do so, we propose an adaptation of this methodology to  
18  
19 73 prioritize regionalization efforts for the consequential LCA case study. Three specific objectives are derived:  
20  
21 74 (1) perform a C-LCA case study of alternative transportation scenarios to investigate the benefits of  
22  
23 75 implementing a public policy for energy transition in France with an uncertainty analysis to explore the  
24  
25 76 strength of our conclusions, (2) perform global sensitivity analyses to identify and quantify the main sources  
26  
27 77 of spatial uncertainty among foreground inventory data from partial equilibrium economic modelling,  
28  
29 78 background inventory data and CFs, (3) propose a strategy to reduce the spatial uncertainty for our C-LCA  
30  
31 79 case study by prioritizing regionalization. This study aims to guide LCA practitioners and researchers to focus  
32  
33 80 their efforts on the highest potential for uncertainty reduction in C-LCA based on the goal of the study.

## 33 81 2. Uncertainty analysis of C-LCA case study

### 34 35 82 2.1. Description of the C-LCA case study

#### 36 37 38 83 2.1.1. Goal and scope definition

39  
40 84 The goal of the study, used as C-LCA case study in this article, is to assess the consequences of implementing  
41  
42 85 alternative transportation scenarios to meet the French law on the energy transition (LTE) targets and  
43  
44 86 ultimately conclude if the consequences are potentially beneficial to the environment (more information on  
45  
46 87 the context in SI). The functional unit is to “reach the LTE targets in the French transport sector by 2030 while  
47  
48 88 meeting the French energy and mobility service demands from 2009 to 2050”. Modelling the consequences  
49  
50 89 of the decision involves identifying the affected processes by the decision (and their magnitude) in the  
51  
52 90 economy. To do so, we isolate the consequences of the decision making the difference between the results  
53  
54 91 of a scenario with the decision and a scenario without decision (status-quo scenario) (Figure 1).

#### 54 55 92 2.1.2. Consequential life cycle inventory

56  
57 93 Amounts of elementary flow (emission and resource consumption) generated by the processes included in  
58  
59 94 the system boundaries are quantified. The system includes all the affected processes and their supply chain.

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

95 As proposed by Heijungs and Suh (2002), the LCI results are stored in the inventory vector  $\mathbf{g}$  that describes  
96 the amount of each elementary flow generated to fulfill the functional unit and is calculated using equation  
97 1.

$$\mathbf{g} = \mathbf{B}\mathbf{A}^{-1}\mathbf{f} \quad (\text{equation 1})$$

99 To calculate  $\mathbf{g}$  for our case study, we used different tools to build an inventory model divided into two parts:  
100 the foreground inventory model based on a partial equilibrium economic model called MIRET (see section  
101 2.1.3 for more details) and the background inventory model mainly based on ecoinvent data (see Figure 1  
102 and Figure 2). Here, we use the term *model* to encompass the data, associated equations and principles  
103 leading to a result.

- The foreground inventory model is used to calculate  $\mathbf{f} = \begin{bmatrix} \mathbf{0} \\ \mathbf{f}_{affected} \end{bmatrix}$ , where  $\mathbf{f}_{affected}$  is the vector with element  $f_p$  represents the amount of output product as defined in MIRET for each directly affected process needed to fulfil the functional unit, or 0 for a product not defined in MIRET and thus considered as non-directly affected processes, and  $\mathbf{0}$  is the vector of zeros. Note that each directly affected process has only one output product (no multifunctionality).  $f_p$  are 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  $\mathbf{f}$  is set by the analyst and contains an amount for one product only. No elementary flow or unit process is modelled in the foreground inventory, they are all modelled in the background.
- The background inventory model corresponds to the technology matrix  $\mathbf{A}$  and the environmental matrix  $\mathbf{B}$ . The background inventory refers to LCI datasets used to model (i) the direct emissions for each directly 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 modelled 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  $\mathbf{A}$  (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  $\mathbf{A}$  and  $\mathbf{B}$  matrices (see section 2.1.4 for more details)  $\mathbf{A} = \begin{bmatrix} \mathbf{A}_{adapted\_ecoinvent} & \mathbf{A}_{mapping} \\ \mathbf{0} & \mathbf{I}_{affected} \end{bmatrix}$  and  $\mathbf{B} = [\mathbf{B}_{adapted\_ecoinvent} \quad \mathbf{0}]$  where  $\mathbf{A}_{adapted\_ecoinvent}$  and  $\mathbf{B}_{adapted\_ecoinvent}$  are the adapted versions



1  
2  
3  
4 125 of the technology and environmental matrices from ecoinvent;  $A_{mapping}$  is the matrix mapping each  
5 126 directly affected technology from MIRET to an adapted ecoinvent product, with element equal to -1  
6 if mapped or 0 otherwise;  $I_{affected}$  is the identity matrix with size  $P \times P$  with  $P$  the number of  
7 127 affected processes from MIRET, and  $\mathbf{0}$  are matrices of zeros.  
8  
9 128

10  
11 129 **Figure 1 – Arrangement of the different models, tools, variables and equations to build the C-LCA**  
12  
13 130 **model**

14  
15  
16 131 *2.1.3. Foreground inventory model based on a partial equilibrium economic model*

17 132 A TIMES<sup>1</sup>-based prospective economic partial equilibrium model (Loulou et al. 2016), called MIRET and  
18 developed by IFP Énergies nouvelles (Menten et al. 2015), is used to identify the directly affected  
19 133 technologies in MIRET and quantify the associated amount of product reported in  $f$ . Direct and indirect  
20 elementary flows associated with those affected processes are modelled in the background inventory (see  
21 134 section 2.1.4).  
22  
23 135

24  
25 136  
26  
27 137 The MIRET model represents the energy and transport sectors in France and covers all the technologies  
28 occurring in France for the following steps: production and imports of resources for primary energy,  
29 138 production of final energy from primary energy, production of end-use energy to meet the final energy  
30 demand in France. Based on input data, this dynamic model helps determine which technologies will be  
31 139 needed to meet the exogenous demands (mobility demand, energy demand, etc.) in each time slice  $t$   
32 140 representing a specific year  $Y_t \in \{2009; 2015; 2019; 2025; 2030; 2050\}$  by minimizing the total system  
33 cost under constraints (technological constraints, regulation constraints, etc.). Therefore, the identified  
34 141 technologies are cost-optimal and are limited by the structure of the model (technologies available, chosen  
35 granularity) and the nature of the partial equilibrium model where demands are exogenous. More details on  
36 142 the reference energy system of the MIRET model is available in SI. For more information on TIMES models  
37 and its use in LCA, see (Lorne and Tchung-Ming 2012; Menten et al. 2015; Astudillo et al. 2017; Albers et al.  
38 143 2019). Running the MIRET model allows determining the optimal production volumes  $V$  (i.e. how much of  
39 the process is used in MIRET) for each process  $p$  existing in MIRET at year  $Y_t$  for a defined scenario. Please  
40 144 note the term production volume is used to qualify the output amount per year of a product from a  
41 145 technology existing in the MIRET model.  
42  
43 146  
44  
45 147  
46  
47 148  
48  
49 149

50 150  
51  
52 151  
53  
54 152 To identify the directly affected processes, we first built two scenarios with MIRET: (1) the scenario *without*  
55 decision which is business as usual scenario without the implementation of the LTE; (2) the scenario *with*  
56 153  
57  
58  
59

---

60 <sup>1</sup> TIMES: The Integrated Markal-Efom System. MARKAL (MARKet ALlocation model, (Fishbone and Abilock 1981)) and  
61 EFOM (Van der Voort and Doni 1984) are two bottom-up energy models that inspired the structure of TIMES.  
62  
63  
64  
65

1  
2  
3 154 decision that defines alternative transportation scenarios to be implemented with the LTE in France by 2050.  
4  
5 155 Then, we calculated the difference of production volumes  $V$  for each technology  $p$  at year  $Y_t$  between the  
6  
7 156 scenario *with* decision ( $V_{p,t}^{with}$ ) and the one *without* decision ( $V_{p,t}^{without}$ ). When  $V_{p,t}^{with} - V_{p,t}^{without} \neq 0$ , we  
8  
9 157 considered the technology  $p$  at year  $Y_t$  as an affected process to be included in the C-LCA. The resulting  
10  
11 158 production volume for each directly affected process  $V_{p,t}^{affected}$  (equation 2) is then aggregated over time  
12  
13 159 from 2009 to 2050 horizon with a linear interpolation between time slices to define  $f_p$  (equation 3). We  
14  
15 160 identified  $P = 97$  technologies in MIRET as directly affected processes (see SI for the complete list).

$$161 \quad V_{p,t}^{affected} = V_{p,t}^{with} - V_{p,t}^{without} \quad (\text{equation 2})$$

$$162 \quad f_p = \sum_{t=0}^{T-1} (V_{p,t}^{affected} + V_{p,t+1}^{affected}) \frac{(Y_{t+1} - Y_t)}{2} \quad (\text{equation 3})$$

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

#### 165 *2.1.4. Adaptation for background inventory and mapping with the foreground*

166 The background inventory model is mostly based on LCI datasets from the attributional LCI database  
167 ecoinvent version 3.3 cut-off (Wernet et al. 2016). Our choice of using the attributional version of ecoinvent  
168 3.3 is discussed in section 4.3. To model the direct elementary flows and supply chains of the directly affected  
169 processes, we mapped each MIRET process affected by the decision to a corresponding ecoinvent process  
170 that must be adapted for our case study (Yang 2016). All ecoinvent processes mapped with a MIRET process  
171 have been modified to (i) avoid double-counting by removing from the supply chain described in ecoinvent  
172 the consumption of products already modelled in MIRET (i.e. fuel production for car transportation is already  
173 modelled in MIRET and is considered as an affected process, so it is removed from the supply chain of car  
174 transportation processes in ecoinvent), (ii) account for direct tailpipe emissions from biofuel blended fuels  
175 by adding those emissions in ecoinvent transportation processes according to the biofuel share within each  
176 vehicle that evolves dynamically based on the optimization result of the MIRET model, (iii) technological  
177 progress in energy efficiency for vehicle use processes. Mapping excel file between MIRET and ecoinvent and  
178 further details on adaptation are available in SI.

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

### 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 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 is performed with Brightway 2 LCA software (Mutel 2017) using traditional LCA calculation (not regionalized LCA calculation).  $\mathbf{h}^{dam}$  represents the damage impact scores for damage ICs, for instance ionizing radiation contributing to ecosystem quality. It's a vector with a dimension  $J = 27$  and with element  $h_j^{dam}$  for each damage IC  $j$ .  $\mathbf{h}^{dam}$  is calculated using equation 4 where  $\mathbf{Q}^{dam}$  is the matrix of CFs at damage level.  $\mathbf{h}^{AOP}$  represents the total damage impact scores aggregated for AOP ICs, for instance ecosystem quality. It's a vector with a dimension  $K = 2$  and with element  $h_k^{AOP}$  for each AOP IC  $k$ .  $\mathbf{h}^{AOP}$  is calculated using equation 4 where  $\mathbf{Q}_{AOP} = \begin{bmatrix} 1 & \dots & 1 & 0 & \dots & 0 \\ 0 & \dots & 0 & 1 & \dots & 1 \end{bmatrix}$  is a matrix with dimensions  $K \times J$  with element equals to 1 when the damage IC  $j$  contributes to the AOP IC  $k$ .

$$\mathbf{h}^{dam} = \mathbf{Q}^{dam} \mathbf{g} \quad (\text{equation 4})$$

$$\mathbf{h}^{AOP} = \mathbf{Q}^{AOP} \mathbf{h}^{dam} \quad (\text{equation 5})$$

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: (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's 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 Figure 1, the C-LCA model is an arrangement of several tools integrated or not with the LCA calculation model as described by equations 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, etc.) 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 4.3. We also accounted for the

1  
2  
3 242 correlation between input and output quantities from unit processes in an uncertainty analysis in  
4 background LCI for water and land transformation flows, as described in Patouillard et al (2019).

- 5 243  
6  
7 244 • For the LCIA model, only the variability due to the spatial aggregation of global CFs for spatially-  
8 differentiated ICs is considered as the uncertainty source as done in Patouillard et al (2019) (more  
9 245 information on the implementation is available in SI). Besides, during the uncertainty analysis, we  
10 246 accounted for the LCIA spatial correlations between elementary flows produced by the same unit  
11 247 process only for the land transformation IC and for certain elementary flows. Other types of spatial  
12 248 correlation are not taken into account in this case study due to the challenge of implementing them  
13 249 in a reasonable amount of time (see Patouillard et al (2019) for more details). It is worth noting that  
14 248 uncertainty from CFs and spatial LCIA correlation is rarely implemented in available LCA software.  
15  
16 249  
17  
18 250  
19  
20 251  
21

### 22 252 *2.2.1. The general approach for uncertainty analysis*

23 253 Table 1 summarizes the techniques used for the uncertainty analysis of the C-LCA case study. The background  
24 inventory model and the LCIA data are fully integrated with the LCA calculation tool. Therefore, to propagate  
25 254 the uncertainty from those sources to the C-LCA results, we used a random sampling from defined probability  
26 distributions for each source. On the other hand, the foreground inventory model (MIRET model) is not  
27 255 integrated with the rest of the model. Therefore, we propagate uncertainty sources in the MIRET model using  
28 a computer experimental design and bootstrapping resampling with a dependent sampling for the scenarios  
29 256 with and without decision (see details below). We used a Monte Carlo simulation with  $R = 5000$  runs ( $r$ ) to  
30 257 propagate all the uncertainty sources in the LCA calculation model and obtained the following set of impact  
31 scores  $H_i = \{h_{i,r}\}_{r=0}^{R-1}$  for each IC  $i$ . Limitations of our uncertainty analysis are discussed in section 4.3.  
32 258  
33  
34 259  
35  
36 260  
37

38 261 **Table 1 –Techniques used for the uncertainty analysis of the C-LCA case study for the estimation of**  
39 **uncertainty sources, the uncertainty propagation and the output format.**

### 40 262 *2.2.2. Uncertainty propagation in the foreground inventory model*

41 263 The MIRET model version used here is relatively time-consuming (approximately 15min/run) and there is no  
42 264 integration between the MIRET model and the rest of the C-LCA model. So, a substantial amount of time is  
43 required to extract and format the outputs of MIRET for each run. Therefore, performing a Monte Carlo  
44 265 analysis of 5 000 runs to propagate the uncertainty within the MIRET model and linking it directly with the  
45 other part of the C-LCA model would have been very time-consuming. Consequently, we decided to use a  
46 266 computer experimental design (Santner et al. 2013; Aleisa and Heijungs 2020) to approximate the  
47 uncertainty propagation of the spatial variability of MIRET’s inputs variables to its results. We chose a space-  
48 267 filling design that aims to spread sets of values evenly throughout the experimental region, thus exploring all  
49 268 the potential responses of the model (Pronzato and Müller 2012). For the case study, we used a Latin-  
50  
51 268  
52  
53 269  
54  
55 270  
56 271  
57  
58 272  
59  
60 273  
61

Hypercube sampling design that provided 80 sets of values for the 5 random input variables considered as 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 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  $\{V_{p,t,s}^{affected}\}_{s=0}^{79} = \{V_{p,t,s}^{with} - V_{p,t,s}^{without}\}_{s=0}^{79}$  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 in randomly picking a set  $s$  of MIRET results  $V_{p,t,s}^{affected}$  at each Monte Carlo iteration with replacement and recalculates  $f$  for every set using equations 2 and 3.

### 2.2.3. 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 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  $H_i$ ,  $\mu_i$  is the mean of impact scores  $H_i$  estimated with  $\bar{H}_i = \frac{1}{R} \sum_{r=0}^{R-1} h_{i,r}$ ,  $\sigma_i$  is the standard deviation of  $H_i$  estimated with  $s_i = \sqrt{\frac{1}{R-1} \sum_{r=0}^{R-1} (h_{i,r} - \bar{H}_i)^2}$ ,  $\delta_0$  is a threshold value traditionally set at 0.2. The probability that we reject  $H_0$  while being true is called the significance level ( $\alpha$ ) which should be set depending on the risk aversion of the decision-maker. In our case study, we conventionally set  $\alpha$  to 0.05. If the p-value of the test is lower than the chosen significance level ( $\alpha$ ), then  $H_0$  is rejected and the alternative hypothesis  $H_a : \delta_i < -\delta_0$  is considered as statistically significant with a confidence level  $(1-\alpha)$ . If  $H_0$  is rejected, the decision is beneficial for the IC. It means that the absolute distance between  $\delta_i$  and zero is significantly more than  $\delta_0$ , 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

1  
2  
3 304 drawn. However, if  $H_0$  cannot be rejected for some ICs, it means that there is no statistical evidence that the  
4  
5 305 decision is beneficial for these ICs. It can be that the decision is not beneficial or that the uncertainty level is  
6  
7 306 still too high and prevents us from concluding. Therefore, we will prioritize our efforts to try to reduce the  
8  
9 307 uncertainty of C-LCA impact scores for those ICs where  $H_0$  cannot be rejected. The prioritization between ICs  
10  
11 308 will depend on their relative contribution to the uncertainty, using the methodology described in section 2.3.  
12  
13 309 Different goals for this case study would have led to different statistical tests and the prioritization for  
14  
15 310 uncertainty reduction would have been different.

### 16 17 311 2.3. Results of uncertainty analysis of the C-LCA case study

18  
19 312 We performed a Monte Carlo analysis including all sources of identified uncertainty and displayed  $H_i$  the  
20  
21 313 damage impact score distributions for each IC  $i$  (Figure 3). Then we identified ICs to be prioritized for  
22  
23 314 uncertainty reduction based on the results of modified NHST statistical tests for sample size  $R = 5000$ ,  
24  
25 315  $\delta_0=0.2$  and  $\alpha=0.05$ . ICs where  $H_0$  can be rejected with a confidence level of 95% are identified in Figure 3  
26  
27 316 with the symbol (\*). All detailed results for modified NHST statistical tests are available in SI.

28  
29 317 **Analysis for decision-makers focusing on AOP:** Even if the total impact score distribution for EQ contains  
30  
31 318 both negative and positive values, the implementation of LTE in France from 2009 to 2050 would be  
32  
33 319 beneficial for EQ with a confidence level of 95%, according to modified NHST statistical tests. The total impact  
34  
35 320 scores for HH are evenly distributed between negative and positive values. Modified NHST statistical tests  
36  
37 321 confirm that we cannot reject  $H_0$  for HH with a confidence level of 95%, so no conclusion can be drawn.  
38  
39 322 Therefore, attempting to reduce the uncertainty and increase the discriminating power for HH is relevant to  
40  
41 323 our case study.

42  
43 324 **Analysis for decision-makers focusing on damage contributions:** Land transformation and water availability  
44  
45 325 are the ICs that seem to dominate uncertainty in EQ and HH, respectively. The global sensitivity analysis will  
46  
47 326 test this intuition based on visual inspection. However, the impact score uncertainty for both ICs should be  
48  
49 327 interpreted with caution since spatial correlation within IC between CFs has been partially addressed for  
50  
51 328 these ICs and may affect the results (Patouillard et al. 2019). Beyond land transformation and water  
52  
53 329 availability, modified NHST statistical tests confirm that the implementation of LTE in France is likely to have  
54  
55 330 a beneficial impact on the following ICs with a confidence level of 95%: global warming (short-term and long-  
56  
57 331 term altogether, for EQ and HH), marine acidification, marine eutrophication, terrestrial acidification,  
58  
59 332 thermally polluted water, photochemical oxidant formation and particulate matter formation. In this case,  
60  
61 333 there is no need to attempt to reduce the uncertainty for these ICs since we may already conclude on the  
62  
63 334 benefits of implementing the LTE, which is the goal of our case study.

1  
2  
3 335 **Figure 3 – Box and whisker charts representing the distribution of damage impact score  $h_i$  for each**  
4  
5 336 **IC<sub>i</sub> contributing to the ecosystem quality (EQ) AOP in PDF.m<sup>2</sup>.year (left) and contributing to human**  
6  
7 337 **health (HH) AOP in DALY (right). The whiskers represent the local minimum and local maximum. The**  
8 338 **bottom and top of each box represent the first and third quartiles. The bar inside the box represents**  
9  
10 339 **the median, and the cross represents the mean value. Outliers are excluded following the Tukey**  
11 340 **standards (McGill et al. 1978). (\*): p-value<0.05 based on the results of modified NHST statistical tests.**  
12  
13 341 **The charts on the top represent the distributions for  $h_j^{dam}$  for each damage IC and on the right of each**  
14  
15 342 **graph for  $h_k^{AOP}$  for each AOP IC. The charts on the bottom focus on damage ICs that are less uncertain**  
16 343 **(excluding land transformation for EQ and water availability for HH). S-T: short-term. L-T: long-term.**  
17  
18

### 19 344 3. Global sensitivity analysis of the C-LCA case study

20  
21 345 Once we identified ICs where uncertainty needs to be reduced, main sources of spatial uncertainty in the C-  
22  
23 346 LCA model for each IC must be identified to adequately prioritize the data collection for regionalization. The  
24  
25 347 objective of the global sensitivity analysis (GSA) is to identify the main sources of uncertainty in the C-LCA  
26 348 model (foreground inventory model based on economic modelling, background inventory model, CFs). In  
27  
28 349 contrast to local sensitivity analysis, GSA provides a more representative sensitivity analysis by accounting  
29  
30 350 for the overall variation range of inputs and accounts for interactions and correlations (Wei et al. 2015).  
31

32 351 Here, we present the GSA indicators used in this study and the stepwise procedure to identify the key  
33  
34 352 sensitive variables, also referred to as main uncertainty sources or main uncertainty contributors. The  
35  
36 353 stepwise procedure allows to determine which impact categories and which parts of the LCA model should  
37  
38 354 be prioritized for uncertainty reduction. This procedure is in line with the one proposed in Patouillard et al.  
39 355 (2019) and adapted for our C-LCA case study. Python scripts to perform GSA are available as supporting  
40  
41 356 information in Patouillard et al. (2019) and accessible at <https://doi.org/10.5281/zenodo.3597423>.  
42  
43

#### 44 357 3.1. GSA indicators definition

45 358 The first-order sensitivity index derived from the Sobol variance decomposition is designed for factor  
46  
47 359 prioritization (Saltelli and Tarantola 2002; Saltelli 2017). This index is selected as our importance indicator for  
48  
49 360 GSA to identify the main uncertainty sources in this study. For a model  $Y = m(X_1, \dots, X_l, \dots, X_L)$  where  $X_l$   
50  
51 361 are the uncertain (or random) input variables of the model and  $Y$  is the output, the first-order sensitivity  
52  
53 362 index  $SI1_{X_l}$  measures the main influence or first order effect of variable  $X_l$  on the results  $Y$  (Saltelli et al.  
54  
55 363 2010). We estimated  $SI1_{X_l}$  using the procedure described in Patouillard et al (2019). The total sensitivity  
56  
57 364 index  $SIT_{X_l}$  also includes the second and higher order effects of the variable  $X_l$  on the results (Saltelli et al.  
58 365 2010).  $SIT_{X_l}$  is a sum of  $SI1_{X_l}$  and all  $SIk_{X_l \dots X_k}$  ( $k^{\text{th}}$ -order sensitivity index which represent the sensitivity due  
59  
60  
61  
62  
63  
64  
65



1  
2  
3 366 to interactions between variables  $X_l \dots X_k$ ). It provides an additional information on the influence of  $X_l$  in the  
4  
5 367 model, which could be useful. More information on the Sobol variance decomposition is available in SI.

### 8 368 3.2. A stepwise procedure to identify the main sources of uncertainty

9  
10 369 As discussed in Patouillard et al. (2019), a straightforward approach to perform GSA on an LCA model would  
11  
12 370 require more than 200 days of calculation to directly estimate the sensitivity of each variable. Therefore, we  
13  
14 371 decomposed the LCA model into simpler models by grouping variables to prioritize the most sensitive part  
15  
16 372 of the model step by step. The main reasons for grouping variables are: (1) to reduce the computational  
17  
18 373 complexity; (2) to drive the efforts with a practitioner's perspective. Indeed, the type of data, tools and  
19  
20 374 expertise to improve the spatialization of elementary flows, the regionalization of foreground inventory  
21  
22 375 model or the regionalization of background inventory model is very different; (3) to deal with correlation  
23  
24 377 between variables (Jacques et al. 2006; Xu and Gertner 2008; Wei et al. 2015; Patouillard et al. 2019).  
25  
26 378 Therefore, we created three uncorrelated groups of variables that are the different parts of the C-LCA model:  
27  
28 379 background inventory model variables  $X_{LCI_{bg}}$  from the ecoinvent database, foreground inventory model  
29  
30 380 variables  $X_{LCI_{fg}}$  from MIRET model and LCIA variables  $X_{LCIA}$ , which are CFs from IMPACT World+ (Figure 1).  
31  
32 381 All inventory model variables can also be grouped in a single group of variables defined as  $X_{LCI} =$   
33  
34 382  $\{X_{LCI_{bg}}, X_{LCI_{fg}}\}$ . This group choice will guide the efforts required since each part involves different efforts  
35  
36 383 and skills for data and model improvements.

37  
38 384 Here, we describe the stepwise procedure used to identify the main sources of  $h_i$  uncertainty for our case  
39  
40 385 study. At each step, we performed a GSA on a specific model with the form  $Y = m_x(X_1, \dots, X_l, \dots, X_L)$  as  
41  
42 386 detailed in Table 2 and estimated sensitivity indices as described in Patouillard et al (2019) (see the figure in  
43  
44 387 SI).

45 388 **Table 2 – Details on GSA models and sensitivity indices estimated at each step**

46  
47 389 The GSA interpretation to prioritize efforts for uncertainty reduction is explained at each step.

- 48  
49  
50 390 1. IC ranking step: determine which damage IC is the main source of  $h_k^{AOP}$  uncertainty for each AOP IC.  
51  
52 391 For each AOP IC, we ranked each damage IC based on its  $SI1_{h_j^{dam}}$  value. Damage ICs with higher  
53  
54 392  $SI1_{h_j^{dam}}$  are major contributors to the uncertainty of  $h_k^{AOP}$  and, therefore, should be prioritized for  
55  
56 393 uncertainty reduction. This information is useful when the goal and scope of the LCA study focuses  
57  
58 394 on more than one damage IC.
- 59 395 2. LCI vs. LCIA step: determine which group of variables between  $X_{LCI}$  and  $X_{LCIA}$  is the main source of  
60  
61 396  $h_j^{dam}$  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  $h_j^{dam}$  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.

**Figure 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.**

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

1  
2  
3 429 the damage IC. Land transformation and water availability have the highest first-order sensitivity indices for  
4  
5 430 the *IC ranking* step for EQ and HH, respectively. Consequently, they are the most sensitive ICs. In the case of  
6  
7 431 land transformation for EQ, the uncertainty mainly comes from the group of LCIA variables, highlighting the  
8  
9 432 need for inventory spatialization. In the case of water availability for HH, the sensitivity is almost entirely due  
10  
11 433 to the interactions between inventory model variables and LCIA variables. In this case, both groups of  
12  
13 434 variables are sensitive and both inventory regionalization and spatialization should be enhanced. The spatial  
14  
15 435 correlation within the IC between CFs has been partially addressed for land transformation but not for water  
16  
17 436 availability. This limitation could partly explain the dominance of both ICs in the sensitivity in the *IC ranking*  
18  
19 437 step (Patouillard et al. 2019).

20 438 Regarding other regionalized ICs, the group of LCIA variables dominates the resulting sensitivity for the  
21  
22 439 freshwater eutrophication IC only, indicating that inventory spatialization should be a priority for this IC. The  
23  
24 440 interaction sensitivity index dominates the resulting sensitivity for terrestrial and freshwater acidification ICs  
25  
26 441 for EQ and water availability for HH. Consequently, inventory regionalization and spatialization should both  
27  
28 442 be a priority. Land occupation and marine eutrophication are the only ICs for which the group of LCI variables  
29  
30 443 is the most sensitive, indicating that inventory regionalization should be prioritized here for these ICs.

31  
32 444 Finally, the group of inventory model variables necessarily dominates the resulting sensitivity for non-  
33  
34 445 regionalized ICs since no uncertainty from LCIA is associated with those ICs. The next section analyzes the  
35  
36 446 part of the C-LCI model (foreground or background inventory model) that must be prioritized to refine the  
37  
38 447 regionalization strategy.

### 39 448 3.3.2. Digging deeper into inventory uncertainty

40  
41 449 Figure 5 presents the results for the GSA performed for the *IC ranking* step (length of each bar) and the  
42  
43 450 *background vs. foreground LCI* step (divisions within each bar). In both steps, only inventory model variables  
44  
45 451 (background and foreground) are uncertain and LCIA variables are set to their mean deterministic values,  
46  
47 452 thus making it possible to test the sensitivity of the inventory model variables only. As uncertainty for  
48  
49 453 background variables does not only contain spatial uncertainty, their contribution to the overall spatial  
50  
51 454 uncertainty might be overestimated.

52  
53 455 **Figure 5 - GSA results for the *IC ranking* step considering only uncertainty from inventory model  
54  
55 456 variables (length of each bar) and for the *background vs. foreground LCI* step (divisions within each  
56  
57 457 bar). Values of first-order sensitivity indices for the *IC ranking* step considering only uncertainty from  
58  
59 458 inventory model variables for each damage IC contributing to the ecosystem quality (left) and human  
60  
61 459 health AOPs (right). The divisions within each bar correspond to the contribution of sensitivity indices  
62  
63 460 for the *background vs. foreground LCI* step with  $SI1_{LCI_{fg}}$ : first-order sensitivity index for background**

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

**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  $X_{LCI_{fg}}$  variables (grey). The contribution of sensitivity indices for the *background vs. foreground LCI* step is also provided for each total AOP (hashed bar).**

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 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 damage ICs which uncertainty prevents us from concluding will be prioritized.

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

492 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 fromecoinvent 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 which sensitivity may be due to 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 variables 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 fromecoinvent on the location of each

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

525 process unit, which is often at the country level. Do it for highly sensitive ICs where LCIA data may be  
526 sensitive (land occupation and freshwater eutrophication for EQ).

## 5. Discussion

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

### 5.1. Assessing uncertainty from partial equilibrium economic modelling

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

544 As the MIRET model was computationally intensive and not integrated with the background inventory model  
545 and LCA model, we used a computer experimental design to save time. We chose a standard design, known  
546 as space-filling, which consists of selecting sets of values for inputs uniformly spread across the experimental  
547 region. Still, we used the MIRET results for each experiment in our Monte Carlo analysis, using bootstrapping  
548 to randomly pick a MIRET result at each iteration. In doing so, we assumed a uniform distribution of the input  
549 variables of the MIRET model, which may lead to misestimating, and probably overestimating, the sensitivity  
550 of foreground inventory model variables (Muller et al. 2017). Indeed, input variables most likely have a value  
551 and distribution that are different from the uniform distribution. In our case study, input variables from the  
552 MIRET model are biomass prices. Their distribution should reflect prices from the different region of origin  
553 weighted by the amount of biomass produced in each region. Their most likely value is the price in the region  
554 where most of the biomass originates (main import country or region). Alternative probability distributions  
555

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

556 to fit the spatial distribution of the biomass prices should be investigated to validate (or not) the choice for  
557 the uniform distribution.

558 An alternative way to account for input variable-specific distribution is to build a prediction model based on  
559 the computer experiment design results, for instance using response surface methodology (Draper 1997; Ba  
560 and Boyaci 2007). The prediction model would be an estimation of the MIRET model, calculating MIRET result  
561 estimates from the input variable value defined by the user. Using this model, we may apply any distribution  
562 to the input variables and perform a Monte Carlo analysis directly on the prediction model to estimate MIRET  
563 uncertainty. However, the estimator to build the prediction model must be adapted to the MIRET model,  
564 especially because MIRET results are not linear and may have discontinuities regarding input variables. The  
565 existence of estimators adapted to the MIRET model, as well as computational time to build the prediction  
566 model, must be studied.

567 In our case study, we only investigated the spatial variability of the MIRET model. It involved a limited number  
568 of variables. Thus, the number of experiments, which depends on the number of variables, remains  
569 reasonable. If the purpose of the uncertainty analysis would have been to investigate all the MIRET  
570 uncertainty sources, and not only spatial variability, the number of variables would have been higher.  
571 Therefore, the number of experiments and thus the computational time to run them would have increased  
572 dramatically. In this case, an alternative to computer experimental design is required. The uncertainty of the  
573 TIMES model results can also be estimated with other approaches such as robust optimization (Nicolas et al.  
574 2014). The associated computational time, as well as how uncertainty results can be used for C-LCA purposes,  
575 should be studied further.

## 5.2. LCIA spatial correlation in C-LCA

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

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

588 without decision are perfectly spatially correlated. We, therefore, use regionalized CFs from the same region  
589 for both scenarios.

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

598 [5.3. Other main limitations of the case study](#)

599 Even if we would have preferred to use a consequential version of an LCI database to fully represent the  
600 chain of consequences even in the background data, we decided not to assess the consequences of the  
601 decision in the background inventory model, by using the attributional version of ecoinvent 3.3 to model the  
602 background. Indeed, the consequential version of the ecoinvent 3.3 database has limitations to adequately  
603 represent the prospective consequences in the background inventory model. In this consequential version  
604 of the ecoinvent database, constrained productions and marginal supply mix shares are identified based on  
605 historical average data which limits the possibility to assess future consequences of a decision (Wernet et al.  
606 2016; Vandepaer et al. 2018). Note that those shortcomings have been addressed in the most recent  
607 consequential version of ecoinvent and that consequential version of ecoinvent can surely be used in future  
608 consequential studies to model the background LCI.

609 Regarding uncertainty analysis, we accounted for the spatial uncertainty sources that we were able to  
610 quantify in the most comprehensive way as possible, i.e. trying to quantify the maximum sources of  
611 uncertainty in the case study. Nevertheless, quantifying all potential sources of spatial uncertainty in LCA was  
612 impossible because: (1) quantifying all quantitative sources would have required a very substantial amount  
613 of time that was beyond the time available for this study, (2) some qualitative uncertainty sources are difficult  
614 to translate into quantitative uncertainty, (3) we do not even know all potential sources in LCA, (4) the  
615 quantification of uncertainty is also uncertain. Interpretation of uncertainty analysis should keep in mind  
616 those limitations. More specifically, we do not account for the spatial component of the LCIA model  
617 uncertainty (i.e. spatial uncertainty from native resolution as opposed to the variability due to spatial  
618 aggregation) as this information is not yet provided by LCIA method developers (Mutel et al. 2018). Regarding



1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

619 uncertainty for background LCI, we accounted for all components of theecoinvent uncertainty data, not only  
620 the spatial component, as we only had access to the uncertainty information in that format. Therefore, if the  
621 main source of uncertainty comes from background inventory model in our case study, the way to reduce it  
622 would be to collect more representative data, but not necessarily more regionalized ones. Besides, inventory  
623 model and LCIA correlations have been partially addressed in our case study, so uncertainty and GSA results  
624 should be interpreted with caution especially for land transformation and water availability impact indicators  
625 which are mainly affected (Patouillard et al. 2019).

## 6. Conclusion

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

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

## Acknowledgements

640 This work has been conducted with the financial and technical support of IFP Energies nouvelles and of the  
641 industrial partners of the International Chair in Life Cycle Assessment (a research unit of the CIRAI): Arcelor-  
642 Mittal, Hydro-Québec, LVMH, Michelin, Nestlé, Solvay, Optel Vision, Total, Umicore. The authors want to  
643 thank Reinout Heijungs for his very valuable inputs and as well as the anonymous reviewers whose remarks  
644 and good suggestions strongly improved this manuscript.

## Bibliography

- Albers A, Collet P, Lorne D, et al (2019) Coupling partial-equilibrium and dynamic biogenic carbon models to assess future transport scenarios in France. *Appl Energy* 239:316–330. doi: 10.1016/j.apenergy.2019.01.186
- Aleisa E, Heijungs R (2020) Leveraging life cycle assessment and simplex lattice design in optimizing fossil fuel blends for sustainable desalination. *Int J Life Cycle Assess* 25:744–759. doi: 10.1007/s11367-020-01738-4
- Astudillo MF, Vaillancourt K, Pineau P-O, Amor B (2017) Integrating energy system models in life cycle management. *Des Sustain Technol Prod policies from Sci to Innov*
- Ba D, Boyaci IH (2007) Modeling and optimization i: Usability of response surface methodology. *J Food Eng* 78:836–845. doi: 10.1016/j.jfoodeng.2005.11.024
- Bulle C, Margni M, Patouillard L, et al (2019) IMPACT World+: a globally regionalized life cycle impact assessment method. *Int J Life Cycle Assess* 24:1653–1674. doi: 10.1007/s11367-019-01583-0
- Clavreul J, Guyonnet D, Tonini D, Christensen TH (2013) Stochastic and epistemic uncertainty propagation in LCA. *Int J Life Cycle Assess* 18:1393–1403. doi: 10.1007/s11367-013-0572-6
- Damblin G, Couplet M, looss B (2013) Numerical studies of space-filling designs: Optimization of Latin Hypercube Samples and subprojection properties. *J Simul* 7:276–289. doi: 10.1057/jos.2013.16
- Dandres T, Gaudreault C, Tirado-Seco P, Samson R (2011) Assessing non-marginal variations with consequential LCA: Application to European energy sector. *Renew Sustain Energy Rev* 15:3121–3132. doi: 10.1016/j.rser.2011.04.004
- Dandres T, Gaudreault C, Tirado-Seco P, Samson R (2014) Uncertainty management in a macro life cycle assessment of a 2005–2025 European bioenergy policy. *Renew Sustain Energy Rev* 36:52–61. doi: 10.1016/j.rser.2014.04.042
- Dandres T, Gaudreault C, Tirado-Seco P, Samson R (2012) Macroanalysis of the economic and environmental impacts of a 2005–2025 European Union bioenergy policy using the GTAP model and life cycle assessment. *Renew Sustain Energy Rev* 16:1180–1192. doi:

1  
2  
3  
4 10.1016/j.rser.2011.11.003  
5

6 Draper NR (1997) Response surface methodology: Process and product optimization using  
7 designed experiments: RH Myers and DC Montgomery,(Wiley, New York, 1995, \$59.95,  
8 ISBN: 0471581003, pp. 714)  
9

10 Earles JM, Halog A, Ince P, Skog K (2013) Integrated Economic Equilibrium and Life Cycle  
11 Assessment Modeling for Policy-based Consequential LCA. J Ind Ecol 17:375–384. doi:  
12 10.1111/j.1530-9290.2012.00540.x  
13

14 Efron B (1994) Missing Data, Imputation, and the Bootstrap. J Am Stat Assoc 89:463–475. doi:  
15 10.1080/01621459.1994.10476768  
16

17 European Commission - Joint Research Centre - Institute for Environment and Sustainability  
18 (2010) International Reference Life Cycle Data System (ILCD) Handbook-Specific Guide for  
19 Life Cycle Inventory Data Sets  
20

21 Fishbone LG, Abilock H (1981) Markal, a linear-programming model for energy systems analysis:  
22 Technical description of the bnl version. Int J Energy Res 5:353–375. doi:  
23 10.1002/er.4440050406  
24

25 Frischknecht R (1998) Life cycle inventory analysis for decision-making. ETH Zurich  
26

27 Guiton M, Benetto E (2013) Analyse du cycle de vie conséquentielle : identification des  
28 conditions de mise en oeuvre et des bonnes pratiques. 1–109  
29

30 Heijungs R, Henriksson PJG, Guinée JB (2016) Measures of difference and significance in the era  
31 of computer simulations, meta-analysis, and big data. Entropy 18:1–11. doi:  
32 10.3390/e18100361  
33

34 Heijungs R, Suh S (2002) The computational structure of life cycle assessment. Kluwer Academic  
35 Publishers, Dordrecht  
36

37 Herrmann IT, Hauschild MZ, Sohn MD, McKone TE (2014) Confronting Uncertainty in Life Cycle  
38 Assessment Used for Decision Support. J Ind Ecol 18:366–379. doi: 10.1111/jiec.12085  
39

40 Huijbregts MAJ (1998) Uncertainty in LCA LCA Methodology Application of Uncertainty and  
41 Variability in LCA Part I : A General Framework for the Analysis of Uncertainty and  
42 Variability in Life Cycle Assessment. Int J Life Cycle Assess 3:273–280  
43

- 1  
2  
3  
4 International Organization for Standardization (ISO) (2006a) ISO14040:2006 Environmental  
5 management-life cycle assessment-principles and framework. 2006  
6  
7  
8 International Organization for Standardization (ISO) (2006b) ISO14044:2006 Environmental  
9 management - Life cycle assessment - Requirements and guidelines. 2006  
10  
11  
12 Jacques J, Lavergne C, Devictor N (2006) Sensitivity analysis in presence of model uncertainty  
13 and correlated inputs. *Reliab Eng Syst Saf* 91:1126–1134. doi: 10.1016/j.ress.2005.11.047  
14  
15  
16 Lorne D, Tchung-Ming S (2012) The French biofuels mandates under cost uncertainty - an  
17 assessment based on robust optimization. *Les Cah l'économie*  
18  
19  
20  
21 Loulou R, Remme U, Kanudia A, et al (2016) Documentation for the TIMES Model - Part II. IEA  
22 Energy Technol Syst Anal Program 1–78  
23  
24  
25 Marvuglia A, Benetto E, Rege S, Jury C (2013) Modelling approaches for consequential life-cycle  
26 assessment (C-LCA) of bioenergy: Critical review and proposed framework for biogas  
27 production. *Renew Sustain Energy Rev* 25:768–781. doi: 10.1016/j.rser.2013.04.031  
28  
29  
30  
31 McGill R, Tukey JW, Larsen WA (1978) Variations of box plots. *Am Stat* 32:12–16  
32  
33  
34 Mendoza Beltran A, Prado V, Font Vivanco D, et al (2018) Quantified Uncertainties in  
35 Comparative Life Cycle Assessment: What Can Be Concluded? *Environ Sci Technol*  
36 52:2152–2161. doi: 10.1021/acs.est.7b06365  
37  
38  
39  
40 Menten FM, Tchung-ming S, Lorne D, Bouvart F (2015) Lessons from the use of a long-term  
41 energy model for consequential life cycle assessment : the BTL case. *Renew Sustain Energy*  
42 *Rev* 43:942–960. doi: 10.1016/j.rser.2014.11.072  
43  
44  
45  
46 Moret S, Codina Gironès V, Bierlaire M, Maréchal F (2017) Characterization of input  
47 uncertainties in strategic energy planning models. *Appl Energy* 202:597–617. doi:  
48 10.1016/j.apenergy.2017.05.106  
49  
50  
51  
52 Muller S, Lesage P, Ciroth A, et al (2014) The application of the pedigree approach to the  
53 distributions foreseen in ecoinvent v3. *Int J Life Cycle Assess*. doi: 10.1007/s11367-014-  
54 0759-5  
55  
56  
57  
58 Muller S, Mutel C, Lesage P, Samson R (2017) Effects of Distribution Choice on the Modeling of  
59 Life Cycle Inventory Uncertainty: An Assessment on the Ecoinvent v2.2 Database. *J Ind Ecol*  
60  
61  
62  
63  
64  
65

- 1  
2  
3  
4 00: doi: 10.1111/jiec.12574  
5  
6  
7 Mutel C (2017) Brightway: An open source framework for Life Cycle Assessment. J Open Source  
8 Softw 2:. doi: 10.21105/joss.00236  
9  
10  
11 Mutel C, Liao X, Patouillard L, et al (2018) Overview and recommendations for regionalized life  
12 cycle impact assessment. Int J Life Cycle Assess 24:856–865. doi: 10.1007/s11367-018-  
13 1539-4  
14  
15  
16  
17 Nicolas C, Saint-Antonin V, Tchung-Ming S (2014) (How) does sectoral detail affect the  
18 robustness of policy insights from energy system models? The refining sector’s example.  
19 Econ Work Pap 0–23. doi: <https://ideas.repec.org/p/drm/wpaper/2014-56.html>  
20  
21  
22  
23 Patouillard L, Bulle C, Margni M (2016) Ready-to-use and advanced methodologies to prioritise  
24 the regionalisation effort in LCA. Matériaux Tech 104:105. doi: 10.1051/mattech/2016002  
25  
26  
27 Patouillard L, Bulle C, Querleu C, et al (2018) Critical review and practical recommendations to  
28 integrate the spatial dimension into life cycle assessment. J Clean Prod 177:398–412. doi:  
29 10.1016/j.jclepro.2017.12.192  
30  
31  
32  
33 Patouillard L, Collet P, Lesage P, et al (2019) Prioritizing regionalization efforts in life cycle  
34 assessment through global sensitivity analysis: a sector meta-analysis based on ecoinvent  
35 v3. Int J Life Cycle Assess 1–17. doi: 10.1007/s11367-019-01635-5  
36  
37  
38  
39 Plevin RJ, Delucchi MA, Creutzig F (2014) Using Attributional Life Cycle Assessment to Estimate  
40 Climate-Change Mitigation Benefits Misleads Policy Makers. J Ind Ecol 18:73–83. doi:  
41 10.1111/jiec.12074  
42  
43  
44  
45 Pronzato L, Müller WG (2012) Design of computer experiments: Space filling and beyond. Stat  
46 Comput 22:681–701. doi: 10.1007/s11222-011-9242-3  
47  
48  
49  
50 Saltelli A (2017) Sensitivity Analysis. In: Numbers for policy: Practical problems in quantification.  
51 [http://www.andreasaltelli.eu/file/repository/Bergen\\_Andrea\\_Thursday\\_SA.pdf](http://www.andreasaltelli.eu/file/repository/Bergen_Andrea_Thursday_SA.pdf)  
52  
53  
54 Saltelli A, Annoni P, Azzini I, et al (2010) Variance based sensitivity analysis of model output.  
55 Design and estimator for the total sensitivity index. Comput Phys Commun 181:259–270.  
56 doi: 10.1016/j.cpc.2009.09.018  
57  
58  
59  
60 Saltelli A, Tarantola S (2002) On the Relative Importance of Input Factors in Mathematical  
61

- 1  
2  
3  
4 Models. *J Am Stat Assoc* 97:702–709. doi: 10.1198/016214502388618447  
5  
6  
7 Santner TJ, Williams BJ, Notz WI (2013) *The design and analysis of computer experiments.*  
8  
9 Springer Science & Business Media
- 10  
11 Udo de Haes H a., Bensahel J-F, Clift R, et al (1997) Guidelines for the application of life cycle  
12  
13 assessment in the EU eco-label award scheme. European Commission
- 14  
15 Van der Voort E, Doni E (1984) EFOM-12C Mark I. Energy Supply Model Packag Math Descr Rapp  
16  
17
- 18 Vandepaer L, Treyer K, Mutel C, et al (2018) The integration of long-term marginal electricity  
19  
20 supply mixes in the ecoinvent consequential database version 3.4 and examination of  
21  
22 modeling choices. *Int J Life Cycle Assess* 1409–1428. doi: 10.1007/s11367-018-1571-4
- 23  
24 Wei W, Larrey-Lassalle P, Faure T, et al (2015) How to Conduct a Proper Sensitivity Analysis in  
25  
26 Life Cycle Assessment: Taking into Account Correlations within LCI Data and Interactions  
27  
28 within the LCA Calculation Model. *Environ Sci Technol* 49:377–385. doi:  
29  
30 10.1021/es502128k
- 31  
32 Weidema B (2005) Geographical, Technological and Temporal Delimitations in LCA. UMIP 2003  
33  
34 method. Danish Ministry of the Environment
- 35  
36 Weidema BP (2003) Market information in life cycle assessment. Environmental Project No 863.  
37  
38 Miljøstyrelsen
- 39  
40 Weidema BP, Frees N, Nielsen A-M (1999) Marginal production technologies for life cycle  
41  
42 inventories. *Int J Life Cycle Assess* 4:48–56. doi: 10.1007/BF02979395
- 43  
44 Wernet G, Bauer C, Steubing B, et al (2016) The ecoinvent database version 3 (part I): overview  
45  
46 and methodology. *Int J Life Cycle Assess* 21:1218–1230. doi: 10.1007/s11367-016-1087-8
- 47  
48 Whitefoot KS, Grimes-Casey HG, Girata CE, et al (2011) Consequential Life Cycle Assessment  
49  
50 With Market-Driven Design. *J Ind Ecol* 15:726–742. doi: 10.1111/j.1530-9290.2011.00367.x
- 51  
52  
53 Xu C, Gertner GZ (2008) Uncertainty and sensitivity analysis for models with correlated  
54  
55 parameters. *Reliab Eng Syst Saf* 93:1563–1573. doi: 10.1016/j.ress.2007.06.003
- 56  
57 Yang Y (2016) Two sides of the same coin: consequential life cycle assessment based on the  
58  
59 attributional framework. *J Clean Prod* 127:274–281. doi: 10.1016/j.jclepro.2016.03.089
- 60  
61  
62  
63  
64  
65

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

Zamagni A, Guinée J, Heijungs R, et al (2012) Lights and shadows in consequential LCA. Int J Life  
Cycle Assess 17:904–918. doi: 10.1007/s11367-012-0423-x

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

**Table 1.**

<b>Parts of the C-LCA model</b>	<b>Estimation of input uncertainty</b>	<b>Uncertainty propagation</b>	<b>Output format and integration with LCA model</b>
<b>Background inventory model = adapted ecoinvent database</b>	Pedigree approach as defined in ecoinvent.		Fully integrated with the LCA model.
<b>Foreground inventory model = MIRET model</b>	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.
<b>LCIA data = CFs from IMPACT World+</b>	Spatial variability of global CFs for spatially-differentiated ICs represented with four-parameter beta distributions		Fully integrated with the LCA model.
<b>LCA calculation model</b>	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



1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

**Table 2**

Steps	Model on which the GSA is performed	Sensitivity indices estimated (details available in SI)
<b>IC ranking</b>	$h^{AOP} = m_1(h_0^{dam}, \dots, h_j^{dam}, \dots, h_{j-1}^{dam})$ based on equation 5.	$SI1_{h_j^{dam}}$ for each $IC_k^{AOP}$
<b>LCI vs. LCIA</b>	$h^{dam} = m_2(X_{LCI}, X_{LCIA})$ based on equation 4.	$SI1_{X_{LCI}}, SI1_{X_{LCIA}}$ and $SI2_{X_{LCI}, X_{LCIA}}$ for each $IC_j^{dam}$
<b>background vs. foreground LCI</b>	$h^{dam} = m_3(X_{LCI_{bg}}, X_{LCI_{fg}}, \mu_{X_{LCIA}})$ 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 $IC_j^{dam}$

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

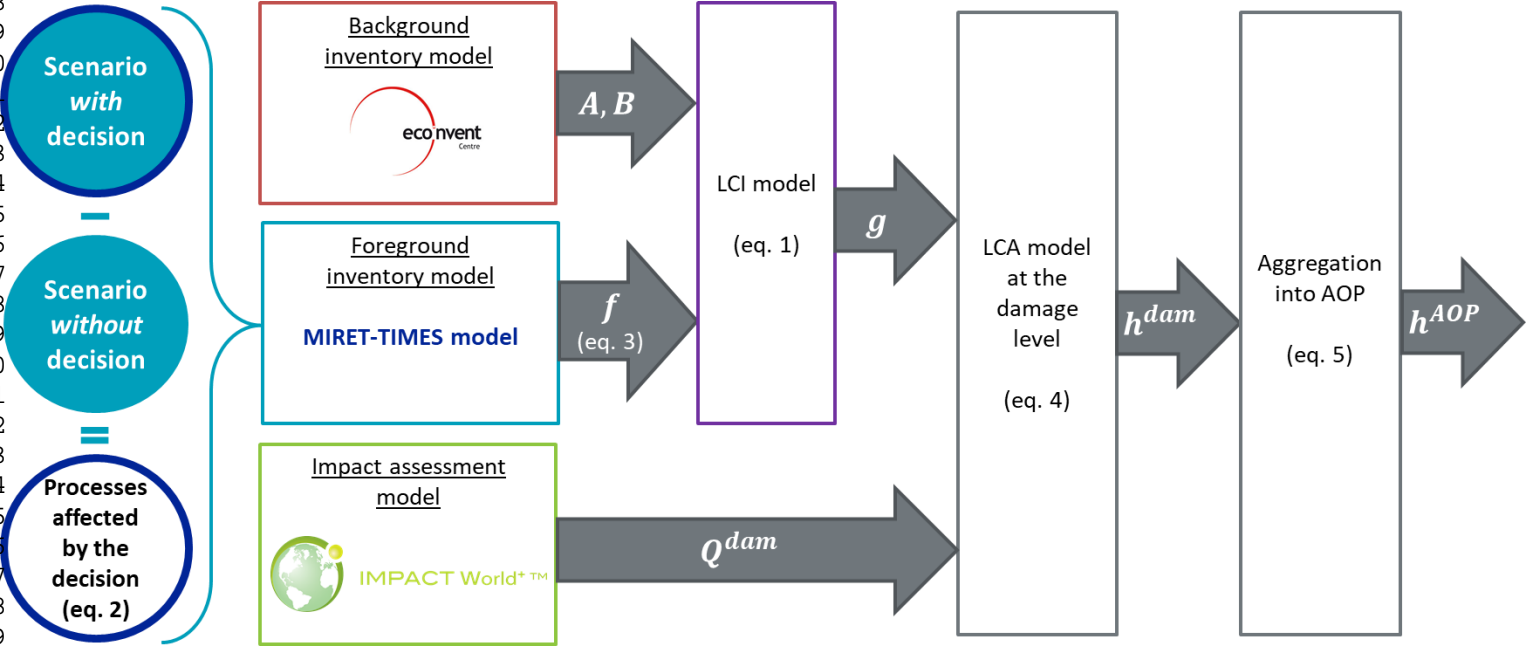


Figure 1

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

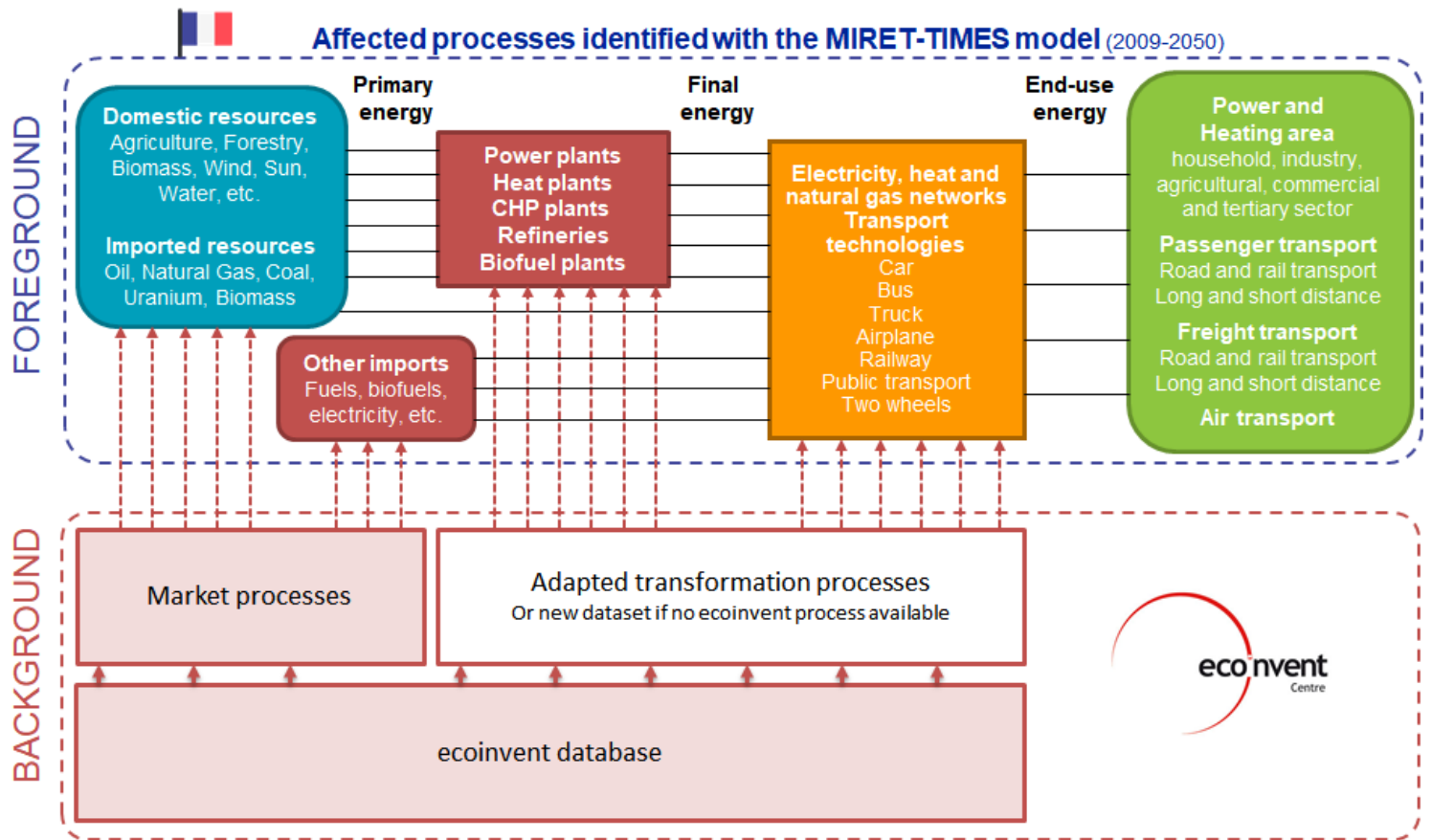


Figure 2.

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

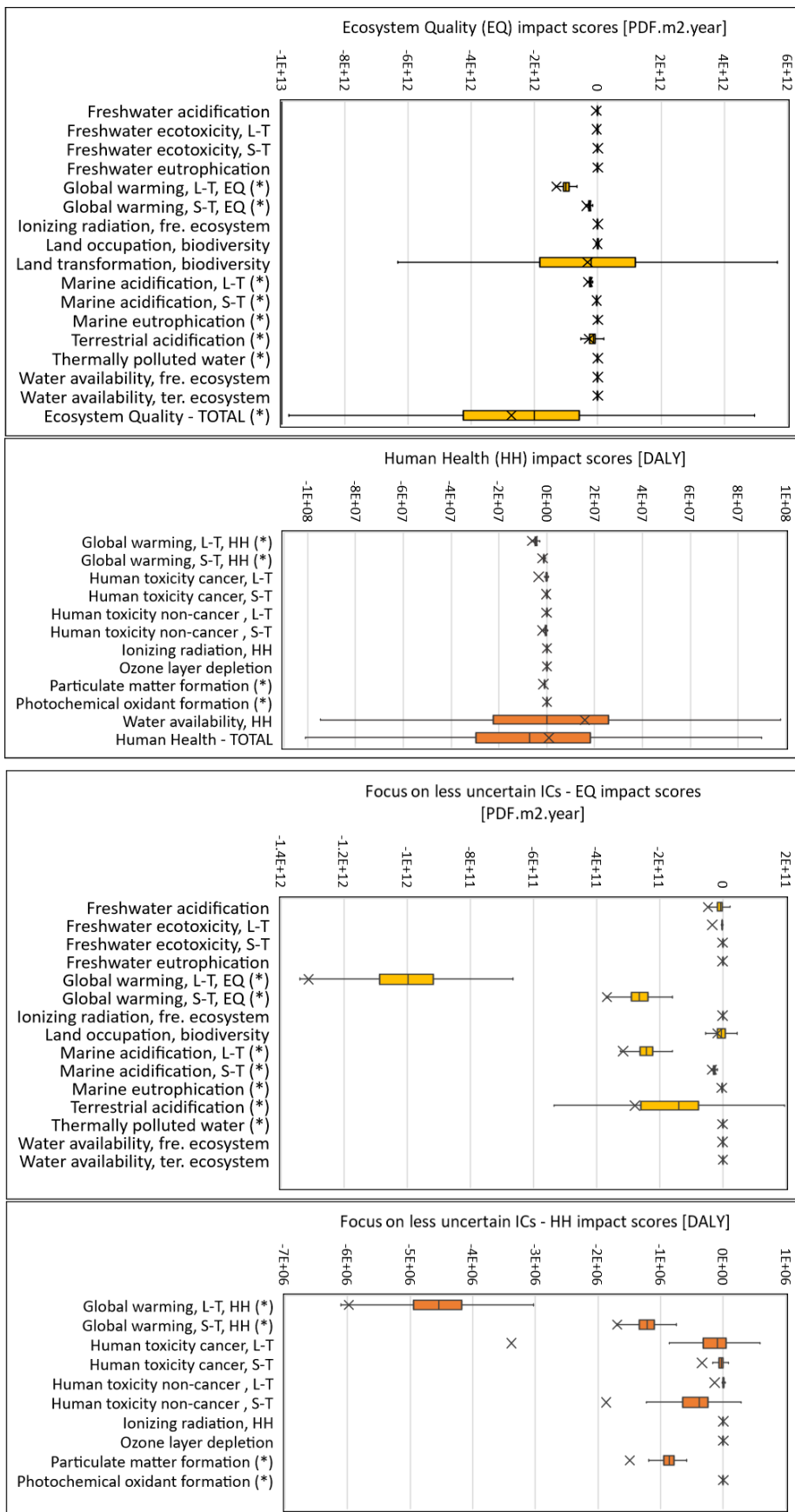


Figure 3.

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

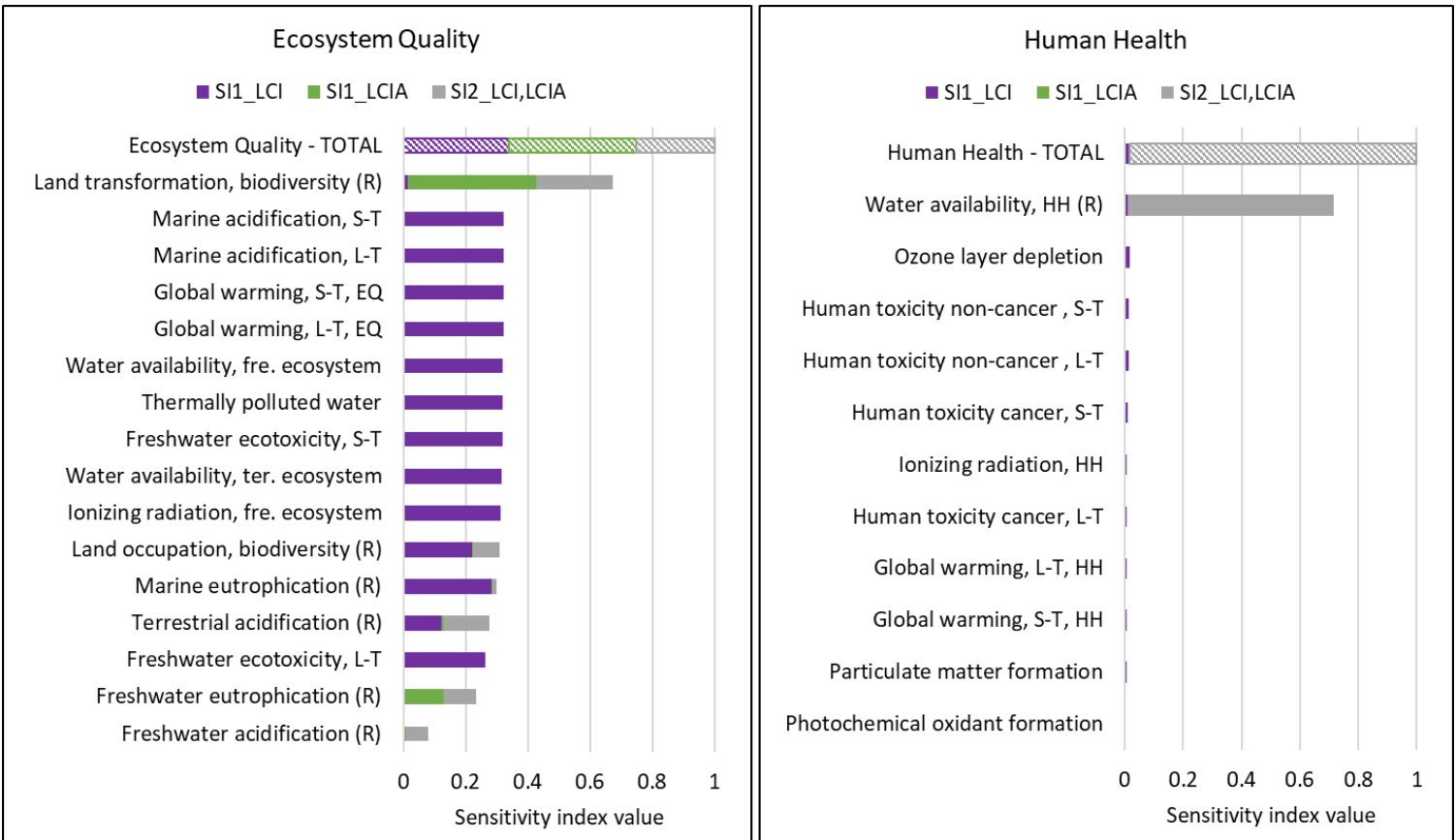


Figure 4.

1  
2  
3  
4  
5  
6  
7  
8  
9  
10  
11  
12  
13  
14  
15  
16  
17  
18  
19  
20  
21  
22  
23  
24  
25  
26  
27  
28  
29  
30  
31  
32  
33  
34  
35  
36  
37  
38  
39  
40  
41  
42  
43  
44  
45  
46  
47  
48  
49  
50  
51  
52  
53  
54  
55  
56  
57  
58  
59  
60  
61  
62  
63  
64  
65

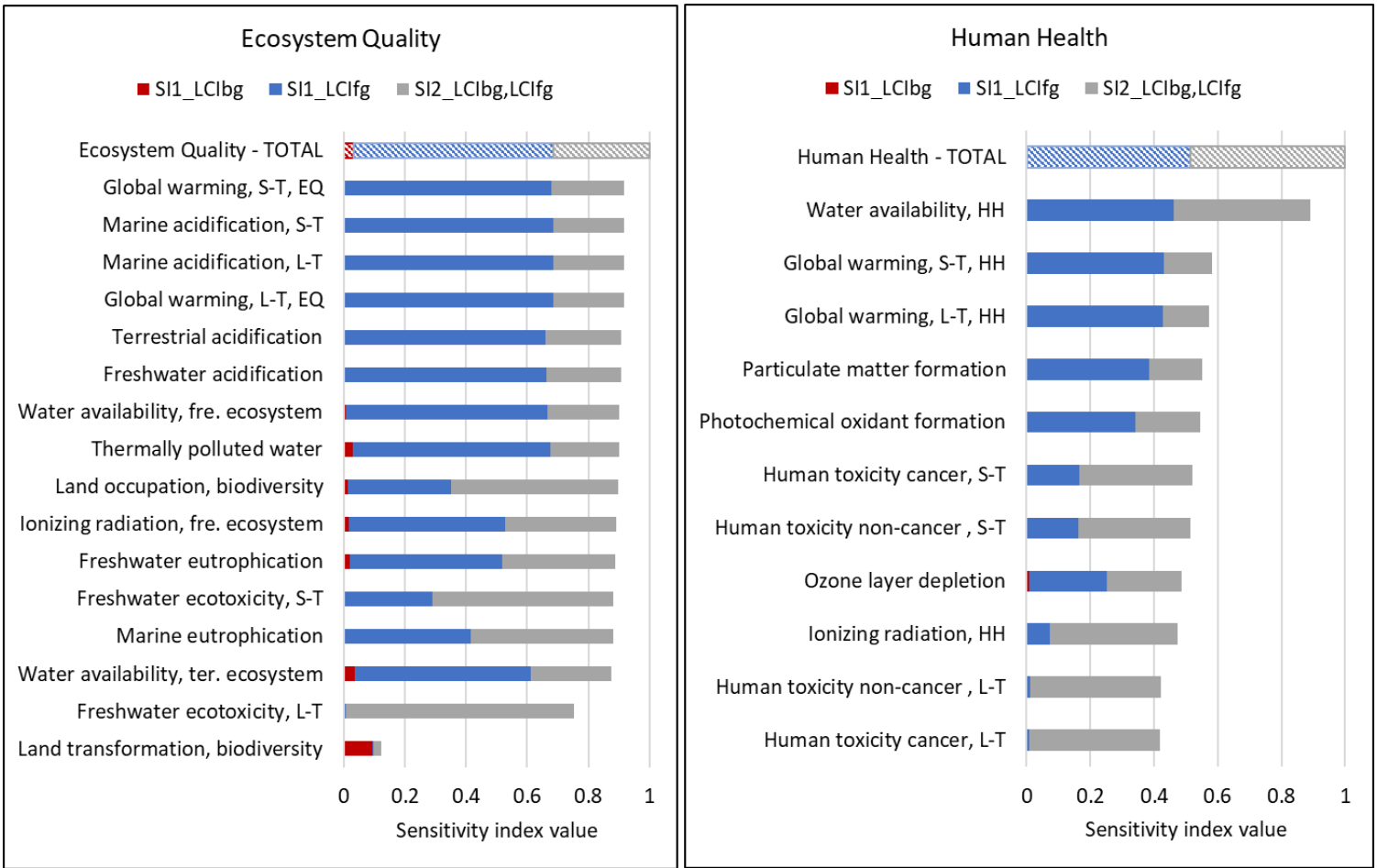
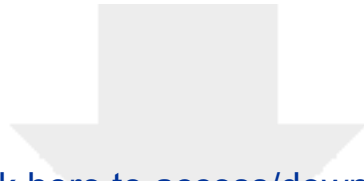
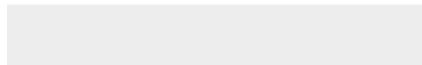


Figure 5



Click here to access/download  
**Supplementary Material**  
SI\_Patouillard et al.pdf





Click here to access/download  
**Supplementary Material**  
SI\_Patouillard et al.xlsx

