Evaluating Uncertainty in Environmental Life-Cycle Assessment. A Case Study Comparing Two Insulation Options for a Dutch One-Family Dwelling

MARK A. J. HUIJBREGTS,*·‡
WIM GILIJAMSE,[§] AD M. J. RAGAS,[‡] AND
LUCAS REIJNDERS[†]

Department of Environmental Studies, University of Nijmegen, P.O. Box 9010, NL-6500 GL Nijmegen, The Netherlands, Institute for Biodiversity and Ecosystem Dynamics, University of Amsterdam, Nieuwe Achtergracht 166, NL-1018 WV, Amsterdam, The Netherlands, and Netherlands Energy Research Foundation ECN, P.O. Box 1, NL-1755 ZG, Petten, The Netherlands

The evaluation of uncertainty is relatively new in environmental life-cycle assessment (LCA). It provides useful information to assess the reliability of LCA-based decisions and to guide future research toward reducing uncertainty. Most uncertainty studies in LCA quantify only one type of uncertainty, i.e., uncertainty due to input data (parameter uncertainty). However, LCA outcomes can also be uncertain due to normative choices (scenario uncertainty) and the mathematical models involved (model uncertainty). The present paper outlines a new methodology that quantifies parameter, scenario, and model uncertainty simultaneously in environmental life-cycle assessment. The procedure is illustrated in a case study that compares two insulation options for a Dutch one-family dwelling. Parameter uncertainty was quantified by means of Monte Carlo simulation. Scenario and model uncertainty were quantified by resampling different decision scenarios and model formulations, respectively. Although scenario and model uncertainty were not quantified comprehensively, the results indicate that both types of uncertainty influence the case study outcomes. This stresses the importance of quantifying parameter, scenario, and model uncertainty simultaneously. The two insulation options studied were found to have significantly different impact scores for global warming, stratospheric ozone depletion, and eutrophication. The thickest insulation option has the lowest impact on global warming and eutrophication, and the highest impact on stratospheric ozone depletion.

Introduction

Environmental life-cycle assessment (LCA) is a tool for the analysis and comparison of environmental impacts from product systems (*I*). It considers the full life-cycle of a product from resource extraction to waste disposal. The basis of every

LCA is the "functional unit"; e.g., "the printing of 100 pages of text" with the aim to compare the environmental impacts of different types of printers. Matrix calculus can be used to obtain the vector **r** of environmental impact scores related to the functional unit of the product system under study (2, 3):

$$\mathbf{r} = \mathbf{Q} \times \mathbf{H} \times \mathbf{G}^{-1} \times \mathbf{u} \tag{1}$$

where \mathbf{Q} is the matrix of characterization factors, representing the relative importance of the emissions per impact category, \mathbf{H} is the environmental intervention matrix representing the emissions per unit process of the product system, \mathbf{G} is the technology matrix representing the inter-process flows needed for the functioning of the product system, and \mathbf{u} is the external supply vector, related to the functional unit.

It is evident that there are considerable uncertainties involved in the calculation of the environmental impact vector **r**. If these uncertainties are not accounted for, LCAs may give rise to incorrect decisions: apparent differences between product systems may turn out statistically insignificant if uncertainties are included in the analysis.

LCA outcomes can be uncertain for several reasons (4). A general distinction can be made between parameter, scenario, and model uncertainty (5,6). Parameter uncertainty is introduced by measurement errors in input data. Scenario uncertainty reflects that LCA outcomes inherently depend on normative choices in the modeling procedure, e.g., concerning the relevant time horizon or geographical scale. Model uncertainty is introduced by disregarding potentially relevant aspects of the real world within the LCA modeling structure. A simultaneous assessment of these sources of uncertainty is necessary to quantify the combined effect and the relative importance of the different types of uncertainty in LCA. However, most uncertainty studies in LCA concentrate on one specific type of uncertainty (7-11) or quantify the combined uncertainty in a simplified manner (12).

The aim of the present paper is to outline a methodology for quantification of the combined effects of parameter, scenario, and model uncertainty in LCA outcomes. The methodology is illustrated in a case study that compares two insulation options for a Dutch one-family dwelling. Although the results of the case study are not generalizable to other problems and applications, they do illustrate the relevance of quantifying parameter, scenario, and model uncertainty simultaneously. Uncertainties included in this case study are (a) parameter uncertainty in the functional unit, inventory data, and characterization factors; (b) scenario uncertainty caused by normative choices concerning the allocation of environmental burdens in recycling processes, future waste scenarios, and the timing, geographical scale, and definition of environmental impacts; and (c) model uncertainty due to the lack of spatial differentiation and the lack of suitable characterization factors for sum emissions, such as metals. Other sources of uncertainty were left out for reasons of feasibility.

Methodology

Parameter Uncertainty. Parameter uncertainty reflects our incomplete knowledge about the true value of a parameter, e.g., due to imprecise measurements, (expert) estimations, and assumptions (6). Monte Carlo simulation is a technique to quantify parameter uncertainty. It propagates known parameter uncertainties into an uncertainty distribution of the output variable (13). To perform Monte Carlo simulation, each uncertain input parameter has to be specified as an

^{*} Corresponding author phone: $+31\,24\,365\,28\,35$; fax: $+31\,24\,365\,30\,30$; e-mail: m.huijbregts@sci.kun.nl.

[†] University of Amsterdam.

[‡] University of Nijmegen.

 $[\]S$ Netherlands Energy Research Foundation ECN.

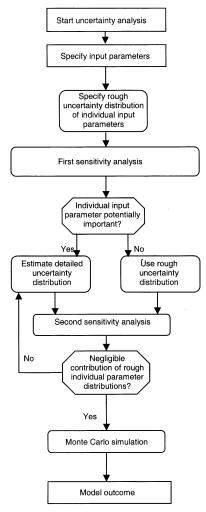


FIGURE 1. Scheme for the analysis of parameter uncertainty in environmental life-cycle assessment, derived from Huijbregts et al. (13).

uncertainty distribution. However, LCA studies involve an enormous amount of parameters (generally > 10 000) and it is unfeasible to characterize the uncertainty ranges for all these parameters in detail. This problem can be overcome with the stratified procedure illustrated in Figure 1. First, all uncertain input parameters are assigned a distribution with the widest range that can be regarded as realistic, as based on measured data or expert judgment. Next, a sensitivity analysis (e.g., Monte Carlo simulation in combination with Spearman Rank correlation) is performed to identify the parameters that contribute most to the output uncertainty. These important parameters are specified in more detail and their importance is confirmed in a second sensitivity analysis. This second analysis is necessary because defining parameters in more detail may affect their uncertainty importance. Finally, when all important input parameters have been specified in detail, a Monte Carlo simulation can be performed to quantify the output uncertainty (14-17).

Scenario Uncertainty. Normative choices are unavoidable in LCA studies. These normative choices lead to uncertainty because different choices may generate different LCA outcomes. Quantification of this scenario uncertainty involves two steps. First, an overview has to be made of the normative choices involved in the LCA study. Second, a procedure has to be developed to quantify the consequences of normative choices in terms of output uncertainty.

Table 1 provides an overview of the scenario uncertainties generally encountered in LCA studies. Important normative

choices in the inventory analysis are the choice of the procedure to allocate environmental impacts for multioutput processes, multiwaste processes, and open-loop recycling, and the choice of how to assess future situations, such as the disposal of long-life products (18). In the impact assessment, the choice of a particular environmental endpoint should be made explicit. For instance, inclusion or exclusion of "below threshold" impact changes may result in considerably different characterization factors (19, 20). The choice for a particular time horizon should also be considered. For instance, the toxic impact of metals may differ more than six orders of magnitude depending on the time horizon chosen (21). Finally, a potentially important choice is the decision whether to include potential impacts linked to pollutants exported from the emitting region (22). Exposure that occurs outside this region may fully dominate the potential impacts, obscuring those in the emitting region itself (21).

Once potentially important scenario uncertainties have been identified, a nonparametric bootstrapping procedure (23) is proposed to quantify the resulting output uncertainty. First, for each normative choice two or more alternatives are formulated. Second, a probability is assigned to each alternative, reflecting the preference of the decision-maker for this alternative. For each normative choice, the sum of probabilities assigned to the various alternatives must equal 1. Finally, per bootstrap iteration, an alternative is chosen randomly for each normative choice, based on the defined probabilities for the various alternatives. The resulting output distribution reflects the uncertainty of the decision-maker regarding the normative choices involved.

Model Uncertainty. Many aspects of the real world cannot be modeled within the present LCA structure (6, 24). Assumptions and simplifications are made that lead to uncertainty regarding the validity of the model predictions for the real world situation. Quantification of this model uncertainty is comparable with that of scenario uncertainty. First, an overview has to be made of the relevant assumptions made in the LCA study. Second, a procedure has to be developed to quantify the consequences of model choices in terms of output uncertainty.

Table 1 provides an overview of the model uncertainties generally encountered in LCA studies. Important model uncertainties are that spatial and temporal characteristics are generally lost by the aggregation of emissions in the inventory analysis. Furthermore, nonlinearities in economic and ecological processes are completely ignored (24). Characterization factors are computed with the help of simplified environmental models that suffer from model uncertainties. For instance, the sensitivity of the receiving environment is not taken into account in the computation of characterization factors for pollutants causing aquatic eutrophication (25). Finally, the lack of characterization factors for toxicologically important substances, such as PCBs, or important sum emissions, such as metals, may cause substantial model uncertainty in LCA outcomes.

Model uncertainty can be quantified with the same bootstrapping procedure as proposed for scenario uncertainty. For each uncertain model formulation, two or more alternatives are formulated. Subsequently, the modeler assigns a probability to each alternative identified. This probability can be interpreted as the faith of the modeler in a particular model formulation. The resulting output distribution reflects the uncertainty of the modeler regarding the alternative model formulations.

Output Variable. The following output variable is used to compare the environmental impacts of two production systems:

TABLE 1. List of Scenario and Model Uncertainties in Environmental Life-Cycle Assessment (5, 6)

LCA phase	Scenario uncertainty	Model uncertainty
goal and scope	functional unit system boundaries	
inventory analysis	allocation waste handling of long-life products	ignoring nonlinear processes complete lack of process data no spatial details on emissions no temporal details on emissions sum emissions
impact assessment	number of impact categories impact definition time horizon of impacts spatial horizon of impacts	ignoring nonlinear processes no information on substance properties no interactions with other pollutants no modeling of metabolites no information on the sensitivity of the receiving environment steady-state assumption uniform mixing of compartments

$$CI_u = \frac{r_{u,A}}{r_{u,B}} \tag{2}$$

where CI_u is the comparison indicator for impact category u (dimensionless) and $r_{u,A}$ and $r_{u,B}$ are the environmental impact scores of impact category u related to product systems A and B, respectively (expressed in kg impact equivalents, such as kg CO_2 equivalents). The environmental impact scores of the product systems compared can be considered to be significantly different, if, for instance, 95% of the iterations lay above or beneath 1. Correlations between both product systems are accounted for through simultaneous variation of parameters that occur in both product systems (12, 26).

Case Study

Goal and Scope. The Dutch government has drawn up plans for the construction of over 1.2 million new houses by the year 2015. At the same time, the Dutch government has signed the Kyoto protocol that aims at a 5% reduction in the emission of greenhouse gases. One way to reconcile these apparently conflicting policy goals is the application of efficient and environmentally sound insulation options. The case study compares two of these insulation options for a standard one-family dwelling in The Netherlands. The basis of comparison (functional unit) is "the provision of heat comfort during the lifetime of the reference Dutch one-family dwelling". The dimensions of the dwelling and the determination method of the energy demand for heat provision to maintain a comfortable indoor temperature are given by the Dutch Normalization Institute (27, 28).

Both insulation options involve the application of expanded polystyrene (EP) in walls, roof, and floor. Option A considers an insulation thickness commonly applied in Dutch new dwellings (95 mm of EP in walls and 150 mm in roofs and ground floors), whereas option B considers the current maximum thickness (185 mm of EP in walls and 200 mm in roofs and ground floors) (29). Figure 2A and B show the main operation steps of the two insulation options. Although the same insulation material is applied in both options, there are considerable differences in the resources used. For instance, a substantial increase in wall insulation thickness is only possible when, instead of using sand lime bricks for the inner wall, a wooden inner wall with insulation material inside is applied. Table 2 provides an overview of the differences in materials and energy used per functional unit between both insulation options.

In the inventory analysis, data were gathered for all the relevant processes involved in the life-cycle of both insulation options. The outcome of the inventory analysis is a comprehensive list of emissions per functional unit (see Table A1 of the Supplementary Information for an overview of the

emissions considered). The inventory outcomes were used to calculate impact scores for ten impact categories: (1) global warming, (2) stratospheric ozone depletion, (3) photochemical ozone creation, (4) acidification, (5) terrestrial eutrophication, (6) aquatic eutrophication, (7) terrestrial ecotoxicity, (8) freshwater ecotoxicity, (9) marine ecotoxicity, and (10) human toxicity. The Supplementary Information provides detailed information about the data sources used to convert the material and energy use related to the functional unit into impact scores. Other potentially relevant impact categories (i.e., radiation, land use, and abiotic depletion) were not considered because of a lack of information on characterization factors or inventory data.

Parameter Uncertainty. Table A2 in the Supporting Information shows the conservative uncertainty ranges used in the initial sensitivity analysis for inter-process flows, environmental interventions, and characterization factors. A parameter was considered important if it contributed more than 1% to the output uncertainty. Table A3 of the Supplementary Information shows the detailed uncertainty distributions subsequently used in the final Monte Carlo simulation. In all cases, a log-normal uncertainty distribution was chosen to represent uncertainty in parameter values because it avoids negative values, it captures a large value range, and the uncertainty in many processes and parameters follows a skewed distribution (30-38).

Scenario Uncertainty. The case study included the following scenario uncertainties.

- (a) Two different methods that reflect two extreme visions on how to allocate environmental burdens in open-loop recycling processes were considered in the inventory analysis (39). The "cutoff method" allocates the environmental interventions caused by the waste recycling process to the product systems that convert the waste of the insulation options into useful products (40). The "avoided-impacts method" allocates the environmental interventions caused by the waste recycling process to the two insulation options under study, but also credits the insulation options by subtracting the avoided environmental interventions from the original inventory table (41).
- (b) Two future waste handling scenarios were defined, assuming current and high recycling rates of the materials considered, respectively (Table A4 of the Supplementary Information).
- (c) The influence of including or excluding potential impact changes below assumed environmental thresholds was assessed for the impact categories acidification and terrestrial eutrophication, resulting in two scenarios: (i) potential impact changes in all ecosystems considered, and (ii) potential impact changes in ecosystems where the noeffect level is actually exceeded (19).

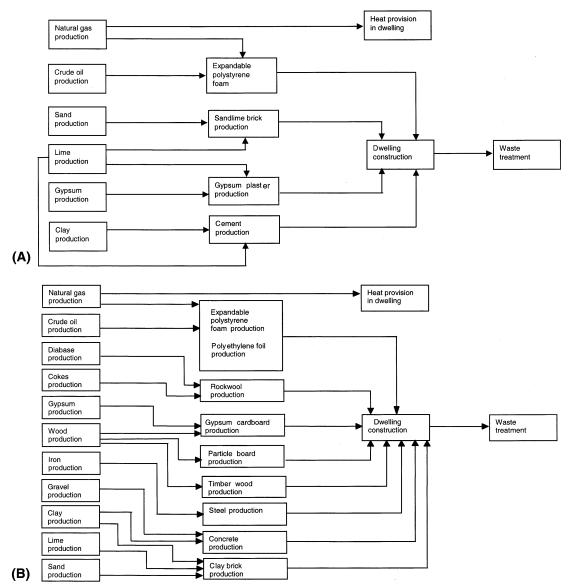


FIGURE 2. (A) Summary of operation steps in insulation option A. Transport, electricity, and heat are required in all operation steps. (B) Summary of operation steps in insulation option B. Transport, electricity, and heat are required in all operation steps.

TABLE 2. Typical Amounts of Materials and Energy Used Per Function Unit for the Common (A) and Maximum Insulation (B) Scenarios (27-29, 53-55)

input	unit	option A	option B
natural gas	m^3	44,000	39,000
expanded polystyrene	kg	330	470
sandlime brick	kg	6,200	
mortar cement	kg	1,250	25
gypsum plaster	kg	150	
rock wool	kg		10
gypsum cardboard	kg		450
polyethylene foil	kg		20
timber wood	kg		500
stainless steel	kg		100
clay brick	kg		50
particle board	kg		10
concrete	kg		75

(d) Time horizon dependent differences in the impact of greenhouse gases were included in the analysis. Characterization factors representative for time horizons of 20, 100, and 500 years were applied (42).

- (e) For toxic substances, characterization factors for an infinite time horizon and a time horizon of 20 years were included (21, 43).
- (f) Impact scores for the toxicity categories were calculated by including and excluding potential toxic impacts outside the Western European region of emission (21, 43).

Other sources of scenario uncertainty were left out of the analysis for reasons of feasibility. To determine the potential impact of the identified alternatives on the case study outcome, all alternatives per normative choice were given equal probability. To illustrate the consequences of ignoring or reducing scenario uncertainty, the results of this "equal-probability simulation" will be compared with the outcomes that would have resulted if one specific alternative had been chosen.

Model Uncertainty. In the case study, the following model uncertainties were quantified.

(a) Model uncertainty due to the lack of spatial variability was assessed for the impact categories terrestrial eutrophication and acidification. Region-specific characterization factors of 44 European regions were available for NO_x , NH_3 , and SO_2 air emissions (19). For the emission data lacking spatial information, a characterization factor was randomly

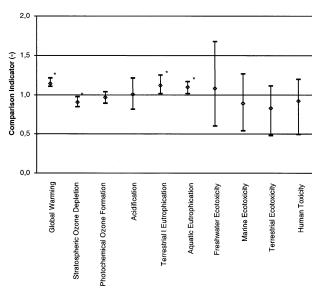


FIGURE 3. Intervals of the comparison indicators for the ten impact categories, including parameter uncertainty, model uncertainty, and scenario uncertainty. The top of the line is the 95th percentile, the mark is the median, and the bottom of the line is the 5th percentile. An asterisk (*) indicates that the comparison indicator deviates significantly from 1 (one-sided $\alpha=0.05$).

drawn with replacement from all of the characterization factors of the 44 regions available.

(b) The second type of model uncertainty taken into account was the lack of suitable characterization factors for the toxic impacts of sum emissions of "metals" and for the photochemical ozone formation impacts of "nonmethane volatile organic carbons (NMVOCs)". In this case, characterization factors of 19 metals and 114 individual volatile organic substances (21, 44, 45) were applied in the bootstrap procedure.

Other sources of model uncertainty were left out of the analysis for reasons of feasibility. To determine the potential impact of the model uncertainties on the LCA outcome, all alternative model formulations were given equal probability. To illustrate the consequences of ignoring or reducing model uncertainty, the results of this "equal-probability simulation" will be compared with the outcomes of three different scenarios. Average, low, and high characterization factors were used, respectively, in these scenarios to weigh sum emissions and acidifying emissions lacking spatial information (see Table A5 of the Supplementary Information).

Calculations. Sensitivity analyses, Monte Carlo simulations, and bootstrapping were performed in Crystal Ball 4.0e (46). Each simulation consisted of 10 000 iterations, which generally produces a representative picture of the complete uncertainty distribution of the model outcome (4).

Results

Figure 3 shows the overall uncertainty in the comparison indicators due to the combination of parameter, scenario, and model uncertainty. If the comparison indicator is higher than 1, insulation option A has an impact score higher than that of insulation option B, and vice versa for a comparison indicator score lower than 1. The two insulation options have significantly different impacts on the impact categories global warming, terrestrial eutrophication, aquatic eutrophication, and stratospheric ozone depletion. The building with the thickest insulation (option B) shows the smallest contribution to the impact categories global warming, terrestrial eutrophication, and aquatic eutrophication and the highest contribution to stratospheric ozone depletion. All other comparison indicators do not differ significantly.

As noted before, an LCA outcome may give rise to incorrect decisions if apparent differences between product systems turn out statistically insignificant after inclusion of all uncertainties. This raises the question whether the comparison indicators that do not differ significantly in Figure 3 would have differed significantly had model or scenario uncertainty not been accounted for. For this purpose, Figure 4 shows the comparison indicators that would have resulted if one specific scenario had been chosen. Although some uncertainty ranges show considerable differences between the scenarios chosen (i.e., for freshwater and marine ecotoxicity), none of the comparison indicators differ significantly from 1. Figure 5 shows the influence of the model uncertainties considered, i.e., disregarding the lack of spatial variation in the assessment of emissions causing acidification and the lack of detailed information on metal and NMVOC emissions for the impact categories photochemical ozone formation, freshwater ecotoxicity, marine ecotoxicity, terrestrial ecotoxicity, and human toxicity. The lack of spatial differentiation may significantly affect the comparison indicator for acidification, but the lack of detailed metal and NMVOC emissions data did not have a large influence on the other impact categories. This indicates that ignoring the uncertainty in the spatial differentiation of acidifying emissions could have resulted in the unjustified conclusion that the thickest insulation option B has a significantly lower impact on acidification.

Discussion

Methodology. In this article, a new methodology was presented for the simultaneous quantification of parameter, scenario, and model uncertainty in environmental life-cycle assessment. It was illustrated in a case study that compares two insulation options for a Dutch one-family dwelling. The methodology helped to structure the uncertainty analysis, to aggregate the different types of uncertainty, and to identify the most important sources of uncertainty. However, problems were also encountered. For example, the gathering of detailed information on parameter uncertainty was a timeconsuming task. Particularly, a detailed description of uncertainty ranges of environmental interventions per unit process was generally lacking. This problem could be overcome with the introduction of a common database format in which uncertainty ranges and corresponding distribution types for life-cycle inventory data are listed (47).

What do the case study results tell us about the usefulness of the proposed methodology and the importance of parameter, scenario, and model uncertainty in LCA? Comparing the results in Figures 3, 4, and 5, it seems that parameter uncertainty is the main type of uncertainty, and that model and scenario uncertainty are only of minor importance. However, it should be kept in mind that the case study results strongly depend on the case study setting. If this setting changes (i.e., comparing different insulation materials or changing the dimensions of the dwelling), the case study outcome, including the importance of the different types of uncertainty, might change. It is also important to notice that the present case study compares two insulation options that are quite similar, i.e., both options use expanded polystyrene as an insulation material. This may affect the case study outcomes in two ways. First, the use of different insulation materials is likely to result in larger differences between both insulation options, i.e., the median value of the comparison indicators in Figure 3 will deviate more from unity. Second, the correlation between both insulation options will decrease when different insulation materials are used. This correlation was accounted for through simultaneous variation of parameters that occur in both product systems (see Methodology section). A decrease in correlation is likely to result in wider confidence intervals. As a result,

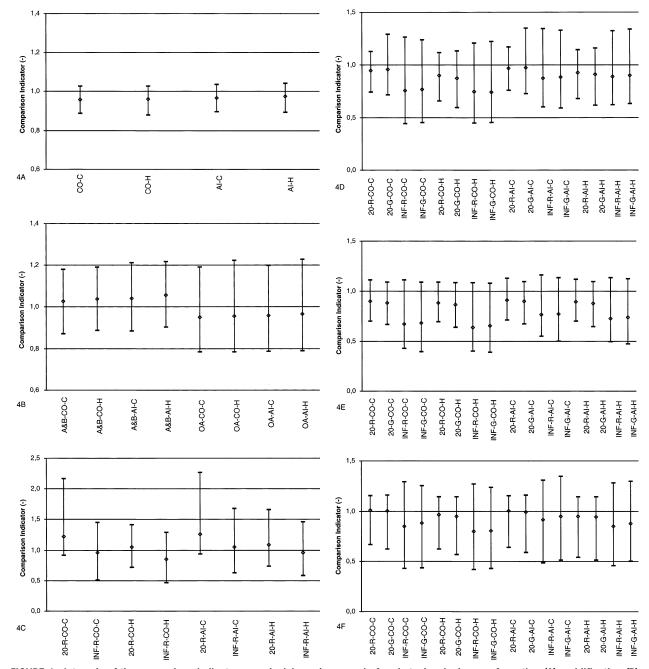


FIGURE 4. Intervals of the comparison indicators per decision rule scenario for photochemical ozone formation (A), acidification (B), freshwater ecotoxicity (C), marine ecotoxicity (D), terrestrial ecotoxicity (E), and human toxicity (F). The top of the line is the 95th percentile, the mark is the median, and the bottom of the line is the 5th percentile. CO = Cutoff allocation; AI = AVOIDE =

significant differences between comparison indicators in Figures 3, 4, and 5 may become insignificant.

Another factor to keep in mind when interpreting the results in Figures 3, 4, and 5 is that the analysis of scenario and model uncertainty was only preliminary in our case study. It was unfeasible to assess the impact of all scenario and model uncertainties. Examples of scenario uncertainties not included are (1) the choice of the functional unit, (2) the time horizon considered for the impact category stratospheric ozone depletion, and (3) the exclusion of below-threshold impacts for toxic substances (48). Examples of model uncertainties not included are (1) the spatial differentiation for toxic substances (21), aquatic eutrophication (49), and photochemical ozone formation (50); (2) model uncertainties

due to the steady-state assumption in multimedia fate models (51); and (3) the exclusion of the fate and effects of toxic transformation products (52). A further and more systematic analysis of these scenario and model uncertainties is certainly required within an LCA context. The overall uncertainty as indicated by the confidence intervals shown in Figure 3 will increase when all model and scenario uncertainties are included. This may result in significant differences turning into insignificant differences, particularly if the upper or lower bound of the confidence interval is close to unity as is the case for the impact categories stratospheric ozone depletion and eutrophication.

Notwithstanding the facts that the overall uncertainty in Figure 3 is underestimated and not representative for other

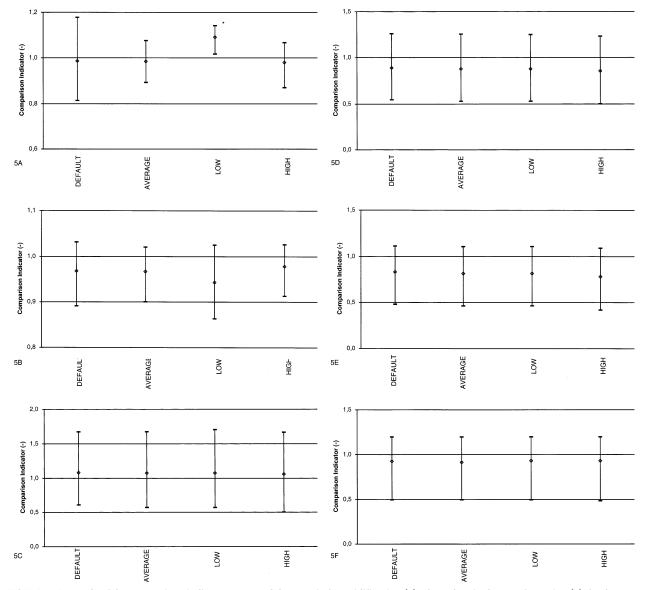


FIGURE 5. Intervals of the comparison indicators per model scenario for acidification (A), photochemical ozone formation (B), freshwater ecotoxicity (C), marine ecotoxicity (D), terrestrial ecotoxicity (E), and human toxicity (F). The top of the line is the 95th percentile, the mark is the median, and the bottom of the line is the 5th percentile. An asterisk (*) indicates that the comparison indicator deviates significantly from 1 (one-sided $\alpha=0.05$). Default = scenario including model uncertainty; average = scenario using average characterization factors for processes lacking specific emission estimates; low = scenario using low characterization factors for processes lacking specific emission estimates.

case studies, the case study results clearly demonstrate that not only parameter uncertainty, but also scenario and model uncertainty can influence LCA outcomes. For scenario uncertainties this is most apparent for the impact categories freshwater and marine ecotoxicity (Figure 4C and D), although none of the considered scenarios would give rise to incorrect decisions because the comparison indicators do not deviate significantly from unity. The impact of model uncertainties is most apparent for the impact category acidification (Figure 5A). Indeed, if low characterization factors would be adopted for processes lacking specific spatial emission estimates, this could give rise to the unjustified conclusion that the thickest insulation option has a significantly lower impact on acidification. This proves that it is important to include scenario and model uncertainty in an uncertainty analysis of LCA studies.

Case Study. The insulation options compared did not differ significantly from each other, except for the impact categories global warming, terrestrial eutrophication, aquatic eutrophication, and stratospheric ozone depletion. With due

consideration of the aforesaid limitations in the application of the methodology, this situation is most effectively improved by reducing uncertainties introducing the largest spread in the model outcomes.

Uncertainty in the comparison of photochemical ozone formation and toxic impacts was mainly caused by parameter uncertainty in our case study. The difficulty of weighing sum emissions was not found important (see Figure 5B-D), as specific emission estimates were available for the majority of the unit processes. Table A3 of the Supplementary Information gives a detailed overview of the parameters found important in the sensitivity analysis. Gathering more reliable estimates for the pentane air emission due to foaming of expanded polystyrene, ethane air emission due to gas leakage, and the amount of gas leakage in low-pressure grids will most effectively improve the reliability of the comparison of photochemical ozone formation impacts. Reducing parameter uncertainty in the comparison of toxic impacts on ecosystems requires additional information on substancespecific input parameters that describe no-effect concentrations of heavy metals. The comparison of toxic impacts on humans will benefit from additional information on substance-specific input parameters that describe the fate and human exposure of carcinogenic polycyclic aromatic hydrocarbons (PAHs) emitted to air, the acceptable daily intake of arsenic, and the PAHs air emission by a gas-fired heating boiler.

Uncertainty in the comparison of acidifying impacts was caused by a combination of parameter uncertainty and model uncertainty in our case study. In the context of the present case study, increasing the reliability of SO_2 air emission due to crude oil refining, NO_x air emission by a gas-fired heating boiler, and the acidification factor of NO_x emitted in The Netherlands should have priority (see also Table A3 of the Supplementary Information). Furthermore, although an important portion of the emissions is defined regionally (i.e., all emissions in the use phase occur in The Netherlands), the unknown location of the emissions occurring in other unit processes may still significantly affect the product comparison (see Figure 5A). Therefore, additional research toward the location of acidifying emissions may also improve the reliability of the current case study results.

Concluding Remarks. We have shown how parameter, scenario, and model uncertainty can be assessed and combined in environmental life-cycle assessment. The case study results indicate that, depending on the impact category, parameter, scenario, and model uncertainty can influence LCA outcomes, stressing the importance of a simultaneous assessment of the various sources of uncertainty. Further improvements in the application of the methodology should be realized, including the development of a life-cycle inventory database with spatial and uncertainty information, and the further development of spatial and temporal explicit impact assessment models for a more systematic analysis of scenario and model uncertainty.

Acknowledgments

We thank three anonymous referees for their helpful comments. This work was part of a Ph.D. project, financed by the University of Amsterdam and the Dutch Organization for Scientific Research.

Supporting Information Available

Description of the inventory data, the selection of parameter ranges, and the selection of scenarios (15 pages). This material is available free of charge via the Internet at http://pubs.acs.org.

Literature Cited

- (1) Consoli, F.; Allen, D.; Boustead, I.; Fava, J.; Franklin, W.; Jensen, A. A.; De Oude, N.; Parrish, R.; Perriman, R.; Postlethwaite, D.; Quay, B.; Séguin, J.; Vigon, B. Guidelines for Life-Cycle Assessment: A 'Code of Practice'; Society of Environmental Toxicology and Chemistry: Pensacola, FL, 1993.
- (2) Heijungs, R. Ecol. Econ. 1994, 10, 69-81.
- (3) Hendrickson, C.; Horvath, A.; Joshi, S.; Lave, L. Environ. Sci. Technol. 1998, 32, A184-A191.
- (4) Morgan, M. G.; Henrion, M. A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis; Cambridge University Press: New York, 1990.
- (5) Hertwich, E. G.; McKone, T. E.; Pease, W. S. Risk Anal. 2000, 20, 439–454.
- (6) Huijbregts, M. A. J. Int. J. LCA 1998, 3, 273-280.
- (7) Heijungs, R. J. Clean. Prod. 1996, 4, 159-166.
- (8) Weidema, B.; Wesnaes, M. S. J. Clean. Prod. 1996, 4, 167-174.
- (9) Steen, B. J. Clean. Prod. 1997, 5, 255-262.
- (10) Chevalier, J.-L.; Le Téno, J.-F. Int. J. Life Cycle Assess. 1996, 1, 90–96.
- (11) Maurice, B.; Frischknecht, R.; Coelho-Schwirtz, V.; Hungerbühler, K. *J. Clean. Prod.* **2000**, *8*, 95–108.
- (12) Huijbregts, M. A. J. Int. J. Life Cycle Assess. 1998, 3, 343-351.

- (13) Huijbregts, M. A. J.; Norris, G.; Bretz, R.; Ciroth, A.; Maurice, B.; Von Bahr, B.; Weidema, B.; De Beaufort, A. S. H. Int. J. Life Cycle Assess. 2001, 6, 127–132.
- (14) Burmaster, D. E.; Anderson, P. D. Risk Anal. 1994, 14, 477-481.
- (15) Janssen, P. H. M.; Slob, W.; Rotmans, J. Sensitivity analysis and uncertainty analysis: an overview of ideas, methods and techniques. Report 958805001. National Institute of Public Health and the Environment: Bilthoven, The Netherlands, 1990.
- (16) Ragas, A. M. J.; Etienne, R. S.; Willemsen, F. H.; Van de Meent, D. Environ. Toxicol. Chem. 1999, 18, 1856–1867.
- (17) McKay, M. D.; Beckman, R. J.; Conover, W. J. Technometrics 1979, 21, 239–245.
- (18) Personen, H.-L.; Ekvall, T.; Fleischer, G.; Huppes, G.; Jahn, C.; Klos, Z. S.; Rebitzer, G.; Sonnemann, G. W.; Tintinelli, A.; Weidema, B. P.; Wenzel, H. *Int. J. Life Cycle Assess.* 2000, 5, 21–30
- (19) Huijbregts, M. A. J.; Schöpp, W.; Verkuijlen, E.; Heijungs, R.; Reijnders, L. J. Ind. Ecol. 2000, 4, 115–142.
- (20) Potting, J.; Schöpp, W.; Blok, K.; Hauschild, M. J. Ind. Ecol. 2000, 2, 63–87.
- (21) Huijbregts, M. A. J.; Guinée, J. B.; Reijnders, L. Chemosphere 2001, 44, 59–65.
- (22) Hertwich, E. G.; Pease, W. S.; McKone, T. E. Environ. Sci. Technol. 1998, 32, A138–A144.
- (23) Efron, B.; Tibshirani, R. Science 1991, 253, 390-395.
- (24) Guinée, J. B.; Huppes, G.; Heijungs, R. *Environ. Manag. Health* **2001**, *12*, 301–311.
- (25) Huijbregts, M. A. J.; Seppälä, J. Int. J. Life Cycle Assess. 2001, 6, 339–343.
- (26) Cano-Ruiz, J. A. Decision support tools for environmentally conscious chemical process design. Thesis, MIT, Cambridge, MA, 2000; pp 150–156.
- (27) Dutch Normalisation Institute. Energy performance of dwellings and residential buildings – determination method (in Dutch). Dutch Normalisation Institute: Delft, 1994.
- (28) Dutch Normalisation Institute. Energy performance of dwellings and residential buildings – examples (in Dutch). Dutch Normalisation Institute: Delft, 1995.
- (29) Mak, J. P.; Anink, D. A.; Kortman, L. G. M.; Ewijk, H. A. L. Ecoquantum — final report (in Dutch). W/E Adviseurs: Gouda, 1996.
- (30) Bennett, D. H.; Scheringer, M.; McKone, T. E.; Hungelbühler, K. Environ. Sci. Technol. 2001, 35, 1181–1189.
- (31) Slob, W. Risk Anal. 1994, 14, 571-576.
- (32) MacLeod, M.; Fraser, A. J.; Mackay, D. Environ. Toxicol. Chem. 2002, 21, 700-709.
- (33) Hertwich, E. G.; McKone, T. E.; Pease, W. S. Risk Anal. 1999, 19, 1193–1204.
- (34) McKone, T. E. Relat. Eng. Syst. Saf. 1996, 54, 165-181.
- (35) McKone, T. E.; Ryan, P. B. Environ. Sci. Technol. 1989, 23, 1154– 1163.
- (36) Rabl, A.; Spadaro, J. V. Environ. Int. 1999, 25, 29-46.
- (37) Jager, T.; Vermeire, T. G.; Rikken, M. G. J.; Van der Poel, P. Chemosphere 2001, 43, 257–264.
- (38) Wayne, R. O. J. Air Waste Manage. Assoc. 1990, 40, 1378-1383.
- (39) Kortman, J. G. M.; Eggels, P. G.; Huppes, G.; Van Oers, L.; Lindeijer, E. W.; Van der Ven, E. L.; Guinée, J. B. Assessment of the Environmental Impacts of Recycling of Long Life Products at the End-of-Life Stage (in Dutch). Report 96.155x; RIZA: Lelystad, 1996.
- (40) Ekvall, T.; Tillman, A.-M. *Int. J. Life Cycle Assess.* **1997**, *2*, 155–162.
- (41) Finnveden, G. Resour. Conserv. Recycl. 1999, 26, 173–187.
- (42) Ramaswamy, V.; Boucher, O.; Haigh, J.; Hauglustaine, D.; Haywood, J.; Myhre, G.; Nakajima, T.; Shi, G. Y.; Solomon, S. Radiative forcing of climate change. In *Climate Change 2001: The Scientific Basis*; Houghton, J. T., et al., Eds.; Cambridge University Press: New York, 2001.
- (43) Huijbregts, M. A. J.; Thissen, U.; Guinée, J. B.; Jager, T.; Kalf, D.; Van de Meent, D.; Ragas, A. M. J.; Wegener Sleeswijk, A.; Reijnders, L. Chemosphere 2000, 41, 541–573.
- (44) Derwent, R. G.; Jenkin, M. E.; Saunders, S. M. Atmos. Environ. 1996, 30, 181–199.
- (45) Derwent, R. G.; Jenkin, M. E.; Saunders, S. M.; Pilling, M. J. Atmos. Environ. 1998, 32, 2429–2441.
- (46) Crystal Ball version 4.0e. Forecasting and risk analysis for spreadsheet users. Decisioneering: Denver, 1998.
- (47) Weidema, B P. The SPOLD file format '99. http://www.spold.org/publ/.
- (48) Guinée, J. B., Ed. Handbook on Life Cycle Assessment; Kluwer: Dordrecht, The Netherlands, 2002; pp 525–633.

- (49) Huijbregts, M. A. J.; Seppälä, J. Int. J. Life Cycle Assess. 2000, 5,
- (50) Andersson-Sköld, A.; Holmberg, L. Atmos. Environ. 2000, 34, 3159 - 3169.
- (51) Hertwich, E. G. Environ. Sci. Technol. 2001, 35, 936-940.
 (52) Fenner, K.; Scheringer, M.; Hungelbühler, K. Environ. Sci. Technol. 2000, 34, 3809-3817.
 (53) Adan, O. C. G. Properties of Building and Insulation Materials
- (in Dutch); SBR: Rotterdam, The Netherlands, 1994.
- (54) Huffmeijer, F. J. M. Lifetime of Building Products Values in

Practice (in Dutch); SBR: Rotterdam, The Netherlands, 1995. (55) DHV-AIB. Environmental Profiles of Insulation Materials in their Application (in Dutch); DHV-AIB: Amersfoort, The Netherlands, 1995.

Received for review October 7, 2002. Revised manuscript received February 26, 2003. Accepted March 3, 2003.

ES020971+