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Diagnosis of uncertainty treatment in neighbourhood life cycle assessments

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Abstract. Urban areas are complex, multifunctional, long-lasting dynamic systems responsible for impressive resource consumption and environmental impacts. Assessments at the neighbourhood scale offers an important complexity compromise. This paper scrutinizes approaches for handling uncertainty analysis (UA) and sensitivity analysis (SA) in LCAs at the neighbourhood scale, aiming at identifying inconsistencies, limitations and challenges, and supporting the development of assessment guidelines. A systematic literature review was performed. Results from the final 35-paper sample show that only one-third of the papers actually performed some calculation. Two of the most recent ones used Monte Carlo (MC) simulations, whilst SA was mainly carried out through scenarios. Despite no clear trend is shown, this may indicate attempts to also apply MC at the neighbourhood scale. The basic quest in UA and SA, particularly global sensitivity analysis, is to balance quality and completeness of output information and computational force needed. Automating calculations, using lighter sampling methods and fast calculators should be further investigated. Finally, future studies could also focus on defining a minimum group of parameters to investigate and on which strategy to follow in specific data availability circumstances. Fuzzy sets seem better for environmental assessments with high degree of uncertainties and probabilistic distributions give results that are more precise. Dynamic models, future scenario uncertainty and spatial uncertainties propagation should also be further explored once the basic challenges for uncertainty assessment are overcome.

1. Introduction

A true sustainable future can only be achieved if urban settlements are diagnosed and treated at the core of the problem as they converge most economic, social and environmentally damaging activities. On the environmental front, traditional urban planning and city management seems to be struggling to deal with the multifunctionality, longevity and dynamism of urban systems, longing for powerful conceptual methodologies that can comprehensively handle its complexity, such as Urban Metabolism and Life Cycle Assessment (LCA).

Neighbourhoods, on the other hand, represent a city's primary cell and characterize the minimal scale for addressing urban spaces socio-economic aspects and the typical scale for urban development projects. Assessments at this scale, consequently, offer an important complexity compromise. Nevertheless, the intricacy inherent to the scale still culminates in an enormous amount of data management and, seeing as LCAs involve numerous calculations, its use to support decision-making can be hampered by the various uncertainties embedded in them [1]. Therefore, addressing uncertainty issues [2–7] is fundamental for improving data quality and the reliability and credibility of LCA studies.



This paper scrutinizes approaches for handling uncertainty analysis (UA) and sensitivity analysis (SA) in LCAs at the neighbourhood scale, aiming at identifying inconsistencies, limitations and challenges, and supporting the development of assessment guidelines. To do so, a systematic literature review was carried out aspiring to answer the following research question: *‘How are neighbourhood LCA researcher/practitioner dealing with uncertainty issues?’*.

2. Method

A previous systematic mapping analysis (SMA) [8] was updated. From its 101-paper final sample, 41 articles specifically dealt with neighbourhood LCA, and were scrutinized to understand how uncertainty issues are being dealt with in LCA at that scale. Through an adaptation of systematic literature review (SLR) guidelines [9] and systematic mapping process [10,11], the research was developed following eight main steps:

- i. Definition of main research questions driving the research;
- ii. Search process;
- iii. Relevance screening using exclusion criteria;
- iv. Paper classification through a keywording process;
- v. Data extraction and mapping;
- vi. Comprehensiveness ranking regarding uncertainty issues;
- vii. Synthesis of findings in descriptive or statistical manner;
- viii. Discussion and analysis of the information extracted from the most relevant papers.

3. Results and Discussion

3.1. Definition of main research questions

Besides the main research question propelling this study, for each paper reviewed, additional sub-questions were also outlined to drive the research process: (a) *Was an uncertainty and/or a sensitivity analysis conducted?* (b) *Which types of uncertainties were analysed?* (c) *Were the uncertainty sources explained?* (d) *Were different types of uncertainties analysed simultaneously?* (e) *Were quantitative or qualitative uncertainty importance analysis performed on parameters?* (f) *Was the correlation between parameters acknowledged, discussed or explicitly accounted for?* (g) *Was the uncertainty methodological framework explained?* (h) *Were temporal and spatial variabilities considered?* (i) *How was the uncertainty distribution expressed and why?* (j) *Which mathematical calculation method was used?* (k) *Was mass and energy conservation discussed?*

The first research sub-question (a) aimed at determining if UA and SA are being tackled in the studied scale and with which frequency. The second, third and fourth sub-questions (b, c and d) intended to find if researchers at this scale investigate different types and sources of uncertainties in their studies and if/how they handle simultaneity effects. The fifth and sixth sub-question (e and f) envisioned to explore if researchers consider correlations and interactions between parameters and their individual contribution to total result uncertainty. The seventh sub-question (g) targeted at verifying if the UA presented by each work followed a determined framework and if that was transparently described. The eighth sub-question (h) aimed at finding if/how geographical and temporal variability were considered. Lastly, the final three sub-questions (i, j, and k) sought to understand the mathematically approach regarding UA and SA.

3.2. Search conduction

The search for primary papers to be analysed in this SLR begun by selecting only the researches classified as ‘neighbourhood LCA’ or ‘neighbourhood hybrid LCA’ at the second level keywording process of the previous SMA [8]. Subsequently, the following search terms and string formulation were applied to the 41 resulting papers: ‘uncertainit*’ OR ‘sensitivit*’ OR ‘variabilit*’ OR ‘distribution’ OR ‘scenario’.

3.3. Screening of relevant papers

Seeing as these 41 articles had already been screened in regards to database provenance, peer reviewing, English language and being field or scale related, the main criterion that guided the inclusion of a paper on the final sample was that it should acknowledge at least once one of the search terms mentioned above: uncertainty, sensitivity, variability, scenario or distribution. After this process, 35 (85%) papers formed the final SLR sample.

3.4. Keywording

Each paper was then assigned to a keyword that best described its approach regarding uncertainty, sensitivity or scenario assessment (Figure 1). Nine papers (26%) regarded only scenario evaluation; 10 papers (29%) dealt superficially with uncertainty and sensitivity issues, usually by simply acknowledging its importance but not performing calculations; 4 articles (11%) regarded the three aspects simultaneously but only for reviewing purposes, not performing calculations. Twelve papers (34%) actually developed some calculation regarding either uncertainty (7 paper / 20%) and/or sensitivity analysis (5 papers / 14%), but in different detail levels.

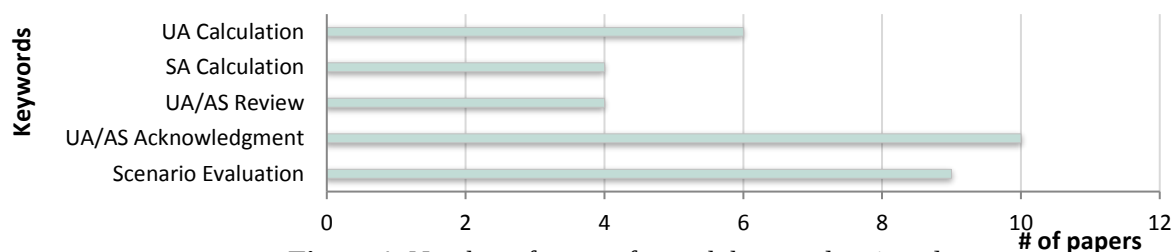


Figure 1. Number of papers for each keyword assigned

3.5. Data extraction and mapping

Besides the 14 categories presented in the previous SMA [8], the information collected from the 35-paper SLR sample was further categorized concerning: (i) uncertainty analysis performance; (ii) sensitivity analysis performance; (iii) scenario evaluation performance; (iv) uncertainty location; (v) uncertainty nature; (vi) uncertainty level; (vii) simultaneity; (viii) uncertainty importance analysis; (ix) correlation between parameters; (x) uncertainty framework; (xi) temporal variability; (xii) spatial variability; (xiii) uncertainty distribution form; (xiv) calculation method; (xv) conservation of mass and energy; (xvi) keyword; (xvii) ranking; (xviii) main findings.

3.6. Ranking assessment

The sample was categorized from A to E to describe how uncertainty, sensitivity or scenario issues were dealt with. Papers that actually performed some sort of UA calculation were rated as 'A'; those that performed SA calculation, as 'B'; review papers, as 'C'; articles that only acknowledged UA or SA, as 'D'; and papers that only performed scenario evaluation were rated as 'E'. Finally, the papers were also assigned marks - (+++), (++) and (+) - according with the number of aspects (UA, SA or scenario) undertook simultaneously, until configuring a 10-class relevance ranking shown in Figure 2.

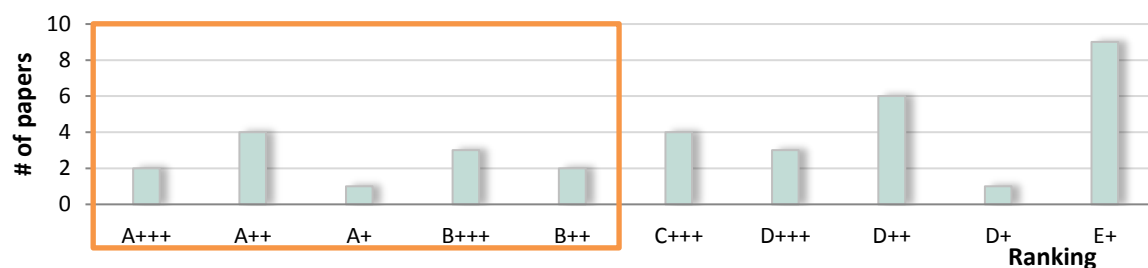


Figure 2. Paper relevance ranking categories

3.7. *Synthesis of findings and Discussion*

3.7.1. Uncertainty and sensitivity analysis performance. From the overall SLR sampled papers, 22 papers (63%) referenced uncertainty or sensitivity issues in some way. As mentioned above, 10 of the papers (29%) simply acknowledged the existence [12,13] and importance [14,15] of UA and/or SA, but did not calculate them. For instance, Fan et al. [16] highlighted the existence of uncertainty and subjective information as one of their study's limitations. Peuportier and Roux [17] recognized that their neighbourhood LCA results would be more robust if a sensitivity analysis was performed in buildings life span and occupants' behaviour. Huang et al. [18] stated that further research should be done to validate their new integrated life-cycle model for carbon footprint evaluation of districts results, and that a sensitivity analysis should be applied when using different data method and sources.

The empirical nature of the LCA performed by Norman et al. [19] removed some of the inherent uncertainty about the real world environmental effects of urban form and confirmed the validity to adopt widely acknowledged strategies such as automobile transportation reduction, public transit use increase, land use focused on higher density development near employment area, use of renewable energy and alternative fuels. Authors also recognized that their relative results' sensitivity to the choice of functional unit demanded a meticulous consideration given the repercussion that functional unit assumptions may have on urban land use policy.

While still not showing any uncertainty or sensitivity calculation, Heinonen et al. [20] acknowledged them in different aspects of their study. First, those authors opted to use a 25-year lifespan in their residential development LCA indicating that a longer perspective would only considerably increase the use phase assessment uncertainties and would not help to explain the major findings. Subsequently, they approached future uncertainties, stating that, although they accounted for emissions temporal allocation, they did not consider fluctuation on their intensities and consumption volumes over time, which would be very difficult to predict. Finally, while those authors recognized that a number of uncertainties present in their assessments could decrease results accuracy, they affirmed that those uncertainties were detailed in previous studies and should not compromise the general findings, as long as the average residents' aggregate level is maintained in the analyses. Lastly, while exploring perspectives to build a contextualized urban typo-morphologies library to facilitate LCA scaling up from building to territory scale, Sibiude et al. [21], proposed the characterization of representative city cells (qualitatively and quantitatively) that could be aggregated to create higher scale data. Authors, however, acknowledged the need for sensitivity studies to determine cell dimension and system's components data granularity issues, and the need for the evaluation of results uncertainty due to interactions between cells.

In another front and with more analytical depth, the four review papers (11%) also tackled UA and SA on neighbourhood LCA. Through a systematic mapping, Skaar et al. [22] investigated how algorithms and parametric LCA have been used to contribute to decision making for material, buildings and neighbourhoods. Among the 16,209 papers mapped, authors found that, the methods most used were simulation (14.7%), sensitivity analysis (9.4%), multicriteria (7.6%) and propagation (7.1%). Uncertainty analysis was performed in only 3.7% of the papers and statistical procedures such as Monte Carlo (2.1%) and Fuzzy sets (4.5%) had similar lower frequency.

Lotteau et al. [23], on the other hand, reviewed the UA performed by Stephan et al. [24] and the SA performed by Nichols and Kockelman [25], and highlighted the fact that the evaluation of scenarios performed by the other seven case studies on their sample could also be considered as sensitivity analysis. Additionally, authors emphasized that, considering that neighbourhoods are long-lasting complex objects, systematically including UA related to long-term temporal evolution of key parameters is an important challenge to be conquered.

Castaldo and Pisello [26], while reviewing different building dynamic approaches and tools for simulation of realistic dense urban environments, identified grey models as a good 'bottom up' method to be used when a system is lacking information or when a huge input data uncertainty is detected. Those authors also recognized UA and SA as important procedural extensions analytical tools to calibrate dynamic simulation methods, and that key parameters selection, model uncertainty ranges

determination, improper model assumptions, simulation code errors and the lack of robust numerical algorithms must all be accounted for.

Mastrucci et al. [27] tackled UA and SA in different fronts in a review of bottom-up building stocks LCA studies analysed according to aggregation model (archetypes or building-by-building), energy analysis (statistical or engineering-based) and LCA performance. Authors highlighted the high uncertainty level of background inventory data adaptation for defining future energy mix scenarios; the higher uncertainty of end-point LCIA methods (relatively to mid-point) due to less consensual physical and social aspects, which introduce subjective value choices; and that while normalization and weighting steps should be addressed more often to enable comparability across studies, they represent an additional uncertainty source. Similarly to Lotteau et al. [23], Mastrucci et al. [27] concluded that few studies quantitatively evaluated input data uncertainty and variability and their propagation throughout the LCA, and that SA was mainly carried out through scenarios describing the evaluation of the stock, policy effects and refurbishment strategies.

The 12 studies (34%) that actually performed some sort of UA and/or SA calculations (highlighted in Figure 2) will be discussed in section 3.7.6.

3.7.2. Uncertainty types, sources and simultaneity. The type and source (location, nature and level [1,5]) of uncertainty was almost never specified in detail by authors. In the few cases it was, authors referred to parameter uncertainty [2], such as lack of representative inventory data or lack of knowledge of uncertainty distribution and, to a lesser extent, model uncertainty, such as temporal and spatial characteristics lost by aggregation, and the need for performing dynamic modelling.

For that matter, Mastrucci et al. [27] emphasized that uncertainty of model inputs, model parameters and modes structure is currently a major issue in LCAs of large building stocks due to the amount of missing information and assumptions to be made, suggesting that input parameter uncertainty characterization and modelling should be carefully addressed in this scale. Moreover, simultaneous analysis of different uncertainty types was seldom performed and, as Skaar et al. [22] have highlighted in their review, despite some advances regarding global sensitivity analysis application, simultaneous accounting for varying parameters and involved uncertainties is yet another under-researched method.

3.7.3. Uncertainty importance analysis and correlations. The lack of emphasis of the sampled papers on the contribution that individual parameter uncertainties might have on the total result uncertainty shows that uncertainty importance analysis [3] is under-researched in neighbourhood LCA studies. Correlation between parameters, although more expressive, are also rarely characterized and quantified. Resch and Andresen [28], while developing a relational database tool focused on systematizing and storing result data and study design for building LCAs, were among the few authors who acknowledged the importance of investigating the relationship between variables.

3.7.4. Uncertainty methodological framework. Due to the variety of types and sources of LCA uncertainty, UA should be guided by a framework [3], however, reviewed papers in general did not reference or present a precise uncertainty framework to be followed, making comparability between studies even harder. Uncertainty characterization phase [1] was almost never discussed in depth by authors and each followed their own process and calculation method. These facts are corroborated by Mastrucci et al. [27], who recommended the development of an uncertainty propagation framework supported by global sensitivity analysis and fast calculators, such as surrogate models, to overcome the limitations of lack of uncertainty propagation and stochastic sensitivity analysis in engineering-based models commonly applied to assess energy demand of buildings stock LCAs.

Although it did not constitute an uncertainty framework per se, Skaar et al. [22] suggested that, to account for LCA uncertainty, first a sensitivity analysis should be carried out to recognize the dominant parameters of the overall considered system, enabling a simplified LCA model while permitting a sharper overview of the multiperformance criteria and multiobjective optimisation decisions variance. Those researchers also recommended expanding the system of interest in terms of scales (from

component to neighbourhood) and LCA stages (from A1 to C4 [29]) whenever possible and to use algorithms to manage the complexity and nonlinearity enhanced in the scale transition process. Such algorithms would help to reduce the risk of designing buildings that are suboptimal in the neighbourhood context; to address the key challenges of time and resource use; and to explore consequences, among others.

3.7.5. Temporal and spatial variability. Accounting for spatial characteristics and temporal evolution is very important to ensure that urban assessments effectively support decision-making. For more robust results, temporal evolution, dynamic models, future scenario uncertainty, spatial uncertainties propagation and scaling errors should be properly tackled [27]. Although static approaches are still majority, these aspects were fairly acknowledged by the studies reviewed. Stephan et al. [24], for instance, recognized the great uncertainty embedded in potential technological breakthroughs and the increased renewable energy's market share, and investigated the changes in key parameters over time, testing the effect of the parameter evolution on all scenarios studied. The first step of the methodology proposed by Walker et al. [30] is the recognition of area-specific measures, who also acknowledged the importance of having hourly energy consumption to identify accurate energy performance. Finally, the study presented by Sibiude et al. [21], as mentioned in section 3.7.1, focused on enhancement perspectives to simplify scaling up from building to territory.

3.7.6. Uncertainty distribution and statistical calculation method. Most of the twelve papers (34%) that actually performed some sort of UA and/or SA calculations did not detail the calculation process and methods used, but rather highlighted main assumptions made. From those, five papers (14%) focused on SA and, while some were more superficial [31,32], others went deeper into the subject. For instance, Lausset et al. [33] proposed a LCA model for neighbourhood and performed a sensitivity analysis based on Sensitivity Ratio to investigate critical parameters, finding that the travel distance per inhabitant and the building's energy load were the two most influential parameters on the total emissions.

Nichols and Kockelman [25] developed a system of statistical models, energy equations, and estimates to account for a life cycle energy assessment (LCEA) of four different neighbourhoods in Austin, Texas. Those authors used Elasticities to estimate the relative sensitivity of neighbourhood energy consumption in response to changes in the built environment or user behaviour, concluding that, from the several urban design variables used in calculations, changes in population density and residential unit size could trigger the greatest per capita energy savings. Nichols and Kockelman [25] also suggested caution with their initial estimates due to the amount of uncertainty involved, and recommended the expansion of the built environment variables and household behaviours for future research.

Last but not least, while comparing LCEA and life cycle cost (LCC) of two social housing neighbourhoods in Mexico city – one compact design near the centre area and one sprawled layout located in the city outskirts – Ochoa-Sosa et al. [34] performed three sensitivity analysis to understand how commuting data influenced overall results. The first two SA consisted in modifying, respectively, the total commuting time and transportation spending ranges, and the data source for average speed for all trips and for public transportation. These aspects affected the overall results but did not change the relative results between neighbourhood cells (NC). Finally, 100,000-iteration Monte Carlo simulations (assuming normality in all data sources and unknown standard deviations as 5% of mean values) were carried out using R language and environment to iteratively change all data inputs and register the differences in CED and LCC. Those authors then concluded that the compact NC would have an overall better performance for CED (64%) and LCC (69%).

Analogously, some of the seven studies (20%) that performed UA calculations were more superficial regarding calculation processes and methods used [28,35–37] and others were more thorough. Stephan et al. [24] acknowledged the considerable amount of uncertainty that infringed their low-density neighbourhood LCA study in Melbourne, Australia, and used an interval analysis to account for data uncertainty and variability by determining suitable literature based ranges around the nominal values of

embodied energy and operational and transport requirements. Those authors assumed symmetrical uncertainty boundaries to simplify the assessment, and stated that parameter uncertainty was very likely overestimated (due to the many parameters having a normal rather than a flat distribution), but that it should not affect findings, since the parameter deviation would occur similarly in both scenarios compared. Stephan et al. [24] also alleged that a probabilistic uncertainty model was not produced due to insufficient information for all the parameters assumed in the study.

Using an Urban Building Energy Model (UBEM) tool called the “Urban Modelling Interface”, De Wolf et al. [38] performed energy and carbon simulations on a residential neighbourhood block in Al-Qadisiyyah, Kuwait, to determine the embodied and operational carbon life cycle impact of current and 3 future scenarios situations (Upgraded envelope performance; Low carbon materials; and PV + Low Carbon). Simulation input parameter uncertainty was tackled by defining archetype descriptions as probability distribution and subsequently updating these to posterior joint multivariate distribution by Bayesian calibration using measured energy data points. De Wolf et al. [38] also acknowledged that a sensitivity analysis of the different building geometries could be performed due to the diversity of results.

Finally, Walker et al. [30] proposed a new decision support assessment methodology based on life cycle performance design (LCPD) and key performance indicators (KPIs) focused on the transition towards energy neutral neighbourhoods. The method followed four main steps and included a probabilistic sensitivity analysis at the end. First, the neighbourhood boundaries defined by stakeholder’s inputs are combined with local knowledge and area-specific resources and measures, to identify the realizable scenarios intrinsic to the geographical area. Subsequently, the annual energy performance of each scenario is estimated through simulation models based on the current energy consumption and the building’s demand profile. The authors emphasized the importance of having smaller resolution data at this point, such as hourly energy consumption, to identify the accurate energy performance. Then, a performance assessment of the energy consumption, CO₂ emissions and associated costs of energy infrastructural components is done considering all life cycle stages and using LCPD-based KPIs. In this step, a knowledge-based deterministic approach is used to predict the operational stage energy demand variation of the buildings until 2050 and results are represented in a performance matrix. Lastly, the performance matrix is converted into an opportunity-loss matrix using the minimax regret method, and decision makers decide on the best development scenario. Afterwards, this chosen scenario is further inspected through a 10,000-iteration Monte Carlo simulation of the KPIs parameters uncertainties to find the deviation of the results and the most influential uncertainty parameter. Finally, a multi-criteria decision-making matrix is used to assess the threats, risks and barriers to realize the chosen scenario via a weighting process.

4. Conclusions and final remarks

The SLR made very clear that uncertainty and sensitivity analysis are not being sufficiently performed nor detailed. None of the neighbourhood LCA studies reviewed presented a UA and/or SA comprehensive enough to satisfy all of the uncertainty facets proposed in the data extraction and mapping phase of this SLR. Few studies quantitatively evaluated input data uncertainty and variability and their propagation throughout the LCA, and SA was mainly carried out through scenarios describing the evaluation of the stock, policy effects and refurbishment strategies. These scarce quantitative results say little about the magnitude of uncertainties involved, beyond the general acknowledgement that they are certainly high. Indeed, neighbourhood LCAs are embedded with high uncertainty level due to urban settlements multifunctional characteristics. The large scale and complexity facilitates measurement imprecisions, lack of representative inventory data due to the high number of parameters, potential correlations and lack of knowledge about probability distribution. The dynamism and intricacy of its systems enhance temporal variability and non-linearity issues (Table 1).

Table 1. Neighbourhood LCA Uncertainty Examples

	Type/Source	Goal and Scope	LCI	LCIA
Location	Parameter Uncertainty		Data aggregation / extrapolation Building stock embodied energy Lack of knowledge of uncertainty distribution	Foreground unit process data representativeness and variability
	Model Uncertainty		Extrapolation from similar processes Variability in process relationships Static/linear modelling	Modelling structure representativeness
	Scenario Uncertainty	Functional unit Neighbourhood boundaries Modelling framework	Building stock lifespan Allocation methods Waste handling	Impact categories selection Time horizon of impacts Spatial horizon of impacts
Nature	Epistemic Uncertainty	Geographical representativeness Temporal representativeness Technological representativeness	Energy consumption (annual/hourly) Commuting distance/time Foreground and background data representativeness	Indicators representativeness Indoor vs outdoor emissions Regional environmental sensitivity
	Ontic Uncertainty	Variability of performance characteristics	Occupants' behaviour variability Societal and institutional variability Technological breakthroughs	Indicators' relationships variability CF variability

The type and source of uncertainties was almost never specified in detail by authors. Also, simultaneous analysis of different uncertainty types was seldom performed, despite some advances regarding global sensitivity analysis application. That is possibly related to the computational requirements, which are added to the high amount of missing information and assumptions to be made when assessing large building stocks. In this regard, uncertainty propagation frameworks, supported by e.g. global sensitivity analysis and fast calculators, such as surrogate models, may help to overcome the limitations of lack of uncertainty propagation and stochastic sensitivity analysis.

Authors generally do not detail their uncertainty assessment framework, do not state or detail the uncertainty characterization phase (location, nature and level of uncertainty) and follow their own process and calculation methods. Furthermore, important aspects regarding UA and SA are not being significantly considered, such as uncertainty importance analysis, correlations between parameter, temporal and spatial variability and conservation of mass and energy. A protocol for declaring the methodological framework and uncertainty assessment steps would be very helpful for comparing studies and advancing the body of knowledge in the field.

Two – but among the most recent - papers used Monte Carlo simulations, but with great disparity in the number of iterations used. The basic quest in UA and SA, particularly global sensitivity analysis, is to balance quality and completeness (i.e. number of parameters simultaneously analyzed) of output information and computational force needed. In terms of computational capacity, shifting from 10,000 to 100,000 makes a big difference. In other scales it seems to have some consensus on using 10,000 iterations and it is not clear if 100,000 would be really needed to reach convergence.

In UA carried out in other scales, MC support seems dominant. Although the reviewed literature does not indicate a similar clear trend, this may be an indication of attempts to apply sampling techniques also at the neighborhood scale. For buildings, for example, a robust assessment procedure can be to define, for each uncertainty source investigated, data points to describe at least a triangular probability distribution as input for MC simulations, which in turn supports global sensitivity analysis. An undisputable limitation is the high number of scenarios needed (at least three per uncertainty source). This number grows progressively as the number of parameters considered increases, meaning that several LCAs must be carried out to feed the simulations, which will also increase computational demand. If this part can be somehow automated, its application might become more frequent in the near future. Also, sampling methods with less computational requirements, like the Latin hypercube sampling, or the already mentioned use of fast calculators and surrogate models.

Finally, future studies could also focus on defining a minimum group of parameters to investigate in LCAs at this scale, and on which strategy to follow in specific data availability circumstances. Fuzzy

sets seem better for environmental assessments with high degree of uncertainties and probabilistic distributions give results that are more precise. Static approaches are still majority in the specific literature, but dynamic models, future scenario uncertainty and spatial uncertainties propagation should be further explored once the basic challenges for uncertainty assessment are overcome.

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