Data granularity for life cycle modelling at an urban scale

Matan Mayer[a]* and Martin Bechthold[b]

[a]*IE School of Architecture and Design, IE University, Madrid and Segovia, Spain;*
[b]*Harvard Graduate School of Design, Harvard University, Cambridge, MA, USA*

Calle Cardenal Zúñiga, 12, 40003 Segovia, Spain, email: mmayer@faculty.ie.edu, matan@post.harvard.edu

Calculating emissions and related environmental impacts for buildings is typically a data-heavy and labour intensive task. Widely used life cycle assessment (LCA) standards require meticulous modelling of a wide range of processes for each part within a product or a subassembly. This level of detailing demands time-consuming manual modelling and essentially renders full LCA of entire city blocks unrealistic. In order to facilitate greater automation in the modelling and analysis of building clusters, the effects of automatically collected input data on LCA results should be studied. Within this context, this paper investigates how LCA results of modelling processes which involve a range of automated input data sources compare to those resulting from a highly detailed base case model based on complete spatial and material information. Findings show that models generated from data gathered from Google Street View and the U.S. Census produce the closest results to the base case model, displaying median deviation rates of 19.6% and 15.4% respectively, with the lowest deviations occurring in embodied energy (0.06%-6.0%) and global warming potential (0.7%-4.8%) results. These findings imply that data with lower granularity can lead to precise LCA results in some instances, depending on the inventory and impact categories considered.

Keywords: life cycle assessment; urban districts; data quality; building information modelling; data mining; life cycle modelling

1. Introduction

Since its introduction in the early 1990s, life cycle assessment (LCA) has been globally recognized as an established method for quantifying environmental footprints of products, services and processes (Curran, 2006) - earning official standardization under the International Organization for Standardization's 14040 series in 1997 (ISO, 1997). Environmental impact assessment in the built environment is primarily based on LCA methods as well (Crawford, 2011). An application of LCA, life cycle modelling (LCM) can be defined as an instrument for recognizing and quantifying possible environmental and economic impacts of production, use, and disposal of products or building assemblies (Züst, Caduff and Schumacher 1997). Due to their methodological structure, LCA and LCM studies rely heavily on highly specific data in order to achieve an accurate impact estimation. Depending on its system boundary definition, a LCA study of even a simple product can require detailed information regarding a large amount of extraction, transportation, processing, manufacturing, packaging, and delivery operations across a range of geographic locations.

In terms of data quality, this high level of detail is not always available, and depending on the scale of the analysed specimen – not always realistic. This is particularly the case when a LCA study focuses on large aggregations of buildings or infrastructure. Urban scale LCA studies, therefore, might require a different approach to data granularity – one that accepts incomplete or low-resolution data sets to a certain degree. In order to determine the exact level of granularity that might be acceptable in urban scale studies, research should be conducted to quantify - based on experimentation - the effects of data granularity on the accuracy of LCA results. Within this context, this paper presents a comparative study of five sources of publically available modelling data and their influence on LCA accuracy. An important distinction to note is that the presented study does not focus on input data for life cycle assessment (i.e. information regarding the environmental footprint of industrial processes), but rather focuses on input data for 3D digital building models that are then used to conduct LCA studies.

2. Literature review

Approaches to life cycle assessment methodology have generated diverse discourse and a wide range of investigation domains throughout the years – work that is too broad to survey in its entirety here. Given that this paper focuses narrowly on urban scale LCA, this review centres on that specific domain within LCA research and on two supporting areas: data acquisition and granularity, and building information modelling (BIM) in the context of LCA.

2.1. Environmental impact assessment of urban districts

As a growing share of the world's population moves into cities (Johnson and Munshi-South 2017), there is increased interest in quantifying material and energy consumption of entire urban districts. Also, research shows that environmental decisions that are made at the district level such as orientation, compactness and urban density greatly affect single-building energy demands due to heating/cooling loads and the degree of natural ventilation or lack thereof (Lotteau et al. 2015; Oliver-Solà et al. 2011). Traditionally, district scale assessment relied mostly on a tally of the consumptive metabolic inputs and outputs of the system as a whole. Baynes and Wiedmann (2012) identify three categories of city-scale environmental footprint analysis: [a] consumption based approaches (CBA), which focus on assessing environmental impacts based on economy-wide consumption patterns of energy, materials and water. The most notable method in this category is environmentally extended input-output analysis (EE-IOA); [b] metabolism-based approaches (MBA), which quantify material, water, waste, and energy flows through urban districts. The most recognized MBA method is urban material and energy flow analysis (MEFA); and [c] complex systems approaches, where the assessment is based on the study of relationships and feedbacks within urban systems. Although LCA research joined this field relatively recently, its methodological foundations are fully compatible with those of both CBA and MBA (Anderson, Wulfhorst and Lang 2015). Furthermore, Loiseau et al. (2012) note that among a range of methods and tools to assess the environmental impact of large scale developments, LCA is the only method that allows a clear distinction between different life cycle stages, environmental impacts, and discrete parts of the studied specimen. In doing so, LCA can prevent skewed results due to burden sharing – a situation that is common in methods that analyse inputs and outputs of the entire system at once. Conducting LCA studies at an urban scale poses two major challenges. The first is methodological and has to do with the difficult task of establishing a clear functional unit and a consistent system boundary when analysing a complex, multifunctional and dynamic network as a city (Mirabella, Allacker, and Sala 2018). The second challenge has to do with data collection. While process input data for LCA calculations is widely accessible through established databases, obtaining detailed information regarding the physical composition of multiple buildings and infrastructure elements in an urban district is a highly laborious task. The next subsections focus on this aspect and its implications.

2.2. Data acquisition and granularity for LCA/LCM

Data quality characterization and impact is a central topic of investigation within LCA research (Guo and Murphy 2012; Wang and Shen 2013; Bicalho et al. 2017; Yu, Liu and Gu 2018). However, as the scale of the subject of a LCA or a LCM study increases, so does the amount of components and subcomponents that need to be analysed. At scales larger than that of a single building, data acquisition becomes as much of a challenge as data quality. With specific regards to material use, some published studies of neighbourhood and district scale analysis rely solely on floorplans in order to obtain building data. This is the case for example in Norman et al. (2006), Stephan, Crawford and De Myttenaere (2013), and Nichols and Kockelman (2014), where large neighbourhood developments are studied based on detailed floorplans of a few representative buildings. More challenging cases are those where the use of floorplans is not feasible due to a high degree of diversity in the studied urban district. This is the case for existing districts, where buildings were built in different periods by various developers or institutions. Analysing such cases using floorplans alone requires a painstaking process of manually modelling each building in the district. Often, such an investment of time and resources might not be realistic. A number of studies explore alternative data acquisition and characterization methods to address this issue. Davila and Reinhart (2013) propose to utilize a combination of footprint outline data and user input with regards to basic parameters such as building height, materiality and age;

Filchakova, Wilke, and Robinson (2009) propose to rely on comprehensive resident surveys to obtain model input data; Sarralde, Quinn, and Wiesmann (2011) propose to use publically available census data in order to characterize built mass in the studied area; and Stephan and Aristide (2017, 2018) propose a bottom-up city-wide mapping of building material quantities and associated embodied emissions using a combination of GIS and census data. Data granularity, which relates to the level of detail in input data, is found to influence LCA results as well, however it has been far less studied than other related topics. As far as the authors can tell, Ross and Cheah (2018) has been the only published study to date to explore the connection between the two. Their study concludes that in the context of domestic cooling system energy consumption, higher data granularity obtained through sensing can reduce uncertainty in LCA.

2.3. BIM and LCA/LCM

Building information modelling (BIM) is essentially an object oriented approach to three dimensional digital modelling in the building industry (Barlish and Sullivan 2012). While traditional 3D modelling software packages use lines and surfaces to define a geometry in space – a geometry that may or may not amount to building components such as columns, beams, windows or doors - BIM software packages recognize building components as discrete elements that can be associated with a range of product attributes such as assembly properties, cost, construction schedule and materiality. This high level of specificity for each component within the model generates a comprehensive data inventory that can then be queried for various purposes. In this sense, the use of BIM allows to significantly ease the typically labour intensive task of collecting component data for building-scale LCA studies (Soust-Verdaguer, Llatas, and García-Martínez 2017). The potential advantages of integrating BIM and LCA are recognized in literature. Ajayi et al. (2015) use a building information model in order to extract material quantities which are then manually entered into a stand-alone LCA solver called Athena, with the aim of evaluating the effect of building material specifications on life cycle performance; Basbagill et al. (2013) combine BIM and LCA in order to investigate how design decisions made in the early stages of a project influence embodied energy levels and associated carbon emissions; Gantner et al. (2014) and Jrade and Jalaei (2013) connect a building information model to a material environmental impact database that is based on LCA findings as well as a cost estimation module in order to assist practitioners in identifying opportunities for affordable impact reduction early in the design process. In these and other instances, workflow is identified as a major barrier on a path to full BIM-LCA integration (Antón and Díaz 2014; Häkkinen and Kiviniemi 2008). For the most part, this challenge is a result of ambiguity in the manner in which components are defined in BIM software in relation to the high degree of specificity that is required in order to assign LCA database entries to them. For example, in BIM software, a timber frame wall could be defined as consisting of timber studs, glass fibre batt insulation, OSB sheathing, and PVC siding. In order to match these definitions with actual materials in a LCA database, a user would need to choose a specific wood species, an origin, define specific drying and planing processes and so forth for each material in the assembly. This lengthy process significantly diminishes the labour-associated advantages that the integration of LCA and BIM is meant to provide. Rist (2011) attempts to address this challenge by proposing a detailed manual for smooth interoperability between BIM models and LCA software. To conclude, despite the existence of prior literature regarding the integration of BIM and LCA on one hand and the impact of data quality and granularity on LCA on the other, there seems to be a clear lack of investigation into the influence of BIM data granularity on LCA. This paper explores the relationship between the two.

3. Hypothesis

In addition to the contribution space that has been identified in the literature review, it is important to observe that the results obtained in the featured studies lack calibration and validation against a control case. In the absence of a control group for comparison - which in the context of life cycle modelling would be a fully detailed model, study results cannot be validated for relative accuracy and are therefore essentially unreliable. To address this problem, this paper presents a comparative methodology for assessing the influence of data source type and quality on LCA results. The underlying hypothesis is that data granularity of the sources for the components depicted in a 3D input model plays a prominent role in the level of accuracy of LCA results. Two assumptions guide this hypothesis as it is translated into an experiment: (a) a LCA study based on a 3D model that is constructed using a full set of design documents (floorplans, sections, elevations and photos) is likely to produce the most accurate results, and thus can be used as a control case against which other cases can be evaluated; and (b) the influence of data granularity on LCA is scalable, meaning that a contained experiment could indicate trends that occur at larger scales as well.

4. Research methodology

The developed methodology aims to evaluate various mined data sources for life cycle modelling information in relation to their influence on analysis results. In order to produce clear and reproducible results, the methodology is demonstrated on a relatively contained case study with the intension of increasing its complexity in future research.

4.1. Workflow

In terms of methodological workflow, this study follows a sequence of five major steps (see Figure 1): (1) Data acquisition and characterization – this step features five sources of publically available data regarding the dimensions, geometry and materiality of the studied case. The sources can be mined or scraped in an automated manner with the exception of the base case data source. The base case is the most complete data source in the study - the results of the other sources are measured against it in a comparative manner. (2) Modelling – a building information model is constructed based on the input data obtained from each data source. The software used for this purpose in the study is Autodesk Revit (Khemlani 2004). (3) Analysis – each of the 3D models is broken down into individual components that are then analyzed for LCA results using the Thinkstep (formerly GaBi) database (Thinkstep 2016) and the Tally plug-in (KT Innovations 2014). Extracting a comprehensive bill of material quantities from the Revit model, Tally pairs Revit's material definitions with material entries in the Thinkstep database and returns LCI and LCIA results for the entire model (see Figure 3). (4) Results - Life cycle inventory (LCI) and life cycle impact assessment (LCIA) results are retrieved for each of the models. The evaluated LCI output in this study is embodied energy (EE). The LCIA outputs are global warming potential (GWP), ozone depletion potential (ODP), acidification, eutrophication, and smog formation. In an effort to focus on material use, the study considers embodied impacts only. The analyzed service lifespan is 60 years as is common in published built environment studies (Azari 2014; Bribián, Valero Capilla, and Usón 2011). The scope of all studies in this paper is cradle-to-grave, accounting for all material manufacturing, maintenance and replacement, and eventual end-of-life (disposal, incineration, and/or recycling), including the materials and energy used across all life cycle stages. System boundaries include primary materials and all additional materials required for the product's manufacturing and use including hardware, sealants, adhesives, coatings and finishing. The functional unit is 1 square metre of building floor area. (5) Comparative assessment - the last step in this sequence includes a comparative evaluation of the five data cases where the result sets of the first four sources are measured in terms of deviation from the result set of the fifth – the base case.

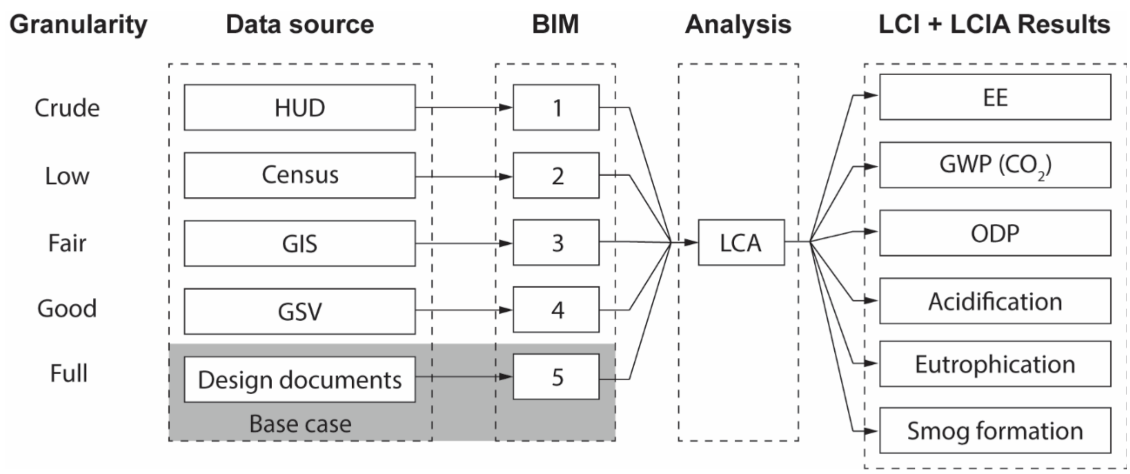


Figure 1. Methodological workflow

4.2. Data sources

All data sources used in this study are available for public use online, meaning that they could be gathered at large scales by automated data scraping. The geographical context of the study is New England, and so some of the resources are unique to the U.S., however similar equivalents could be found in other contexts as well. The sources are ranked in the following list based on the perceived level of data specificity they provide:

A. Department of Housing and Urban Development (HUD) – HUD releases the American Housing Survey on a biannual basis (USDHUD 2017). The survey includes national averages with regards to building area, median age, number of stories, structure type, and foundation type. In the context of this study, this source is assumed to provide crude data specificity as it includes only national averages.

B. U.S. Census – The United States Census Bureau releases data regarding new and existing construction on an annual basis (U.S. Census Bureau 2018). In addition to the number of buildings constructed regionally, the data includes building characteristics such as area, median age, primary and secondary envelope materials, number of stories, structure type, construction method, and foundation type. The data is divided into four geographical regions: Northeast, Midwest, South, and West. In the context of this study, this source is assumed to provide a low degree of data specificity as it includes only regional averages.

C. Geographic Information System (GIS) - City-level GIS provide a range of regularly updated information regarding spatial qualities of the built environment (Star and Estes 1990). In the case of this study, the data used was from the local GIS of the municipality of Cambridge, Massachusetts. The data included information regarding building area, physical footprint, roof configuration, height, number of stories, and orientation. Unlike the HUD and census data, the information provided by GIS is building specific and not based on regional or national averages. In the context of this study, this source is assumed to provide data specificity in the range of 25% deviation from the base case as it includes detailed local information.

D. Google Street View (GSV) – Google periodically captures façade images of buildings in various locations globally. In combination with aerial images from Google Maps and Google Earth, it is possible to construct a relatively comprehensive description of multiple building envelopes in a studied urban block. Seiferling et al. (2017) and Li and Ratti (2018) for example, use automated GSV data scraping in order to evaluate tree coverage in urban areas. Law et al. (2018) use computer vision in combination with a deep neural network model to automatically extract visual features such as surface material information from GSV images in order to estimate and predict house prices. In the context of this study, this source is assumed to provide a high degree of data specificity as it includes detailed footprint and material information.

E. Full design documentation – This source is used in the study as a base case for comparison. It includes permit (for new construction) or as-built documentation (for existing buildings). This documentation includes floorplan, section, and elevation data, as well as external and internal footage of the building. Unlike the other sources, this source also provides information on internal components such as partitions, doors and flooring. This source is considered to provide the most comprehensive information and therefore is assumed to produce the most accurate LCA result. Each of the sources above was used in order to construct a building information model of the case study.

4.3. Case study

The case study for the implementation and testing of the described methodology is a 384m^2 timber frame single family home in Cambridge, Massachusetts built in the 1920's. The floor area and materiality of the house is typical to the neighbourhood within which it is located. As mentioned earlier, the authors selected a single house case for this study because it is a relatively contained specimen. The intention is to expand the subject of study to a larger part of an urban district in future research.

Figure 2. View of the case study building from north-west (left) and a BIM representation of its components.

Table 1 describes the five models that have been constructed using data retrieved from the five data sources explained in section 4.2. Material compositions of these models are based as much as possible on information provided in the data sources. At points where this information needed to be supplemented, any additional assumptions are based on the geographical context of the case study (north-eastern U.S.). For example, given the case study, structural systems are assumed to be based on a timber balloon frame, which is typical to 20th century residential construction in this region (Peterson 2000). In this context, it is important to note that fenestration in all models is based solely on information available in the data sources. For example, Google Street View provides images of only three of the four facades of the case study; therefore, in the GSV model the fourth façade is left non-fenestrated. For a full bill of material quantities for each model, please see: https://figshare.com/articles/Bill_of_material_quantities_-_Data_granularity_for_life_cycle_modelling_at_an_urban_scale/9917831.

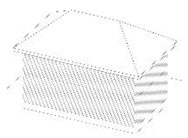
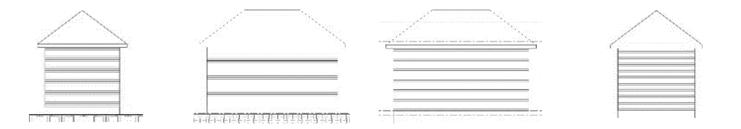
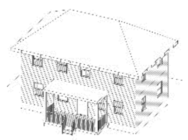
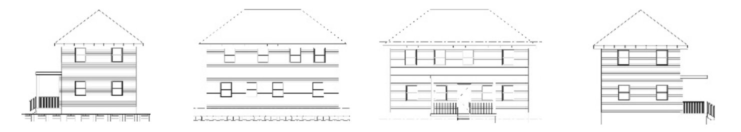
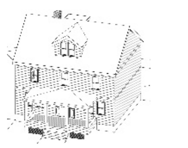
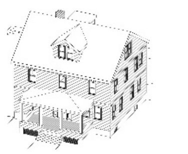
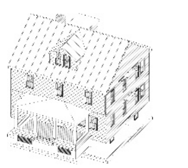
Data	Axonometric	Elevations
HUD		
Census		
GIS		
GSV		
Base case		

Table 1. Axonometric and elevation views of the models used in the study.

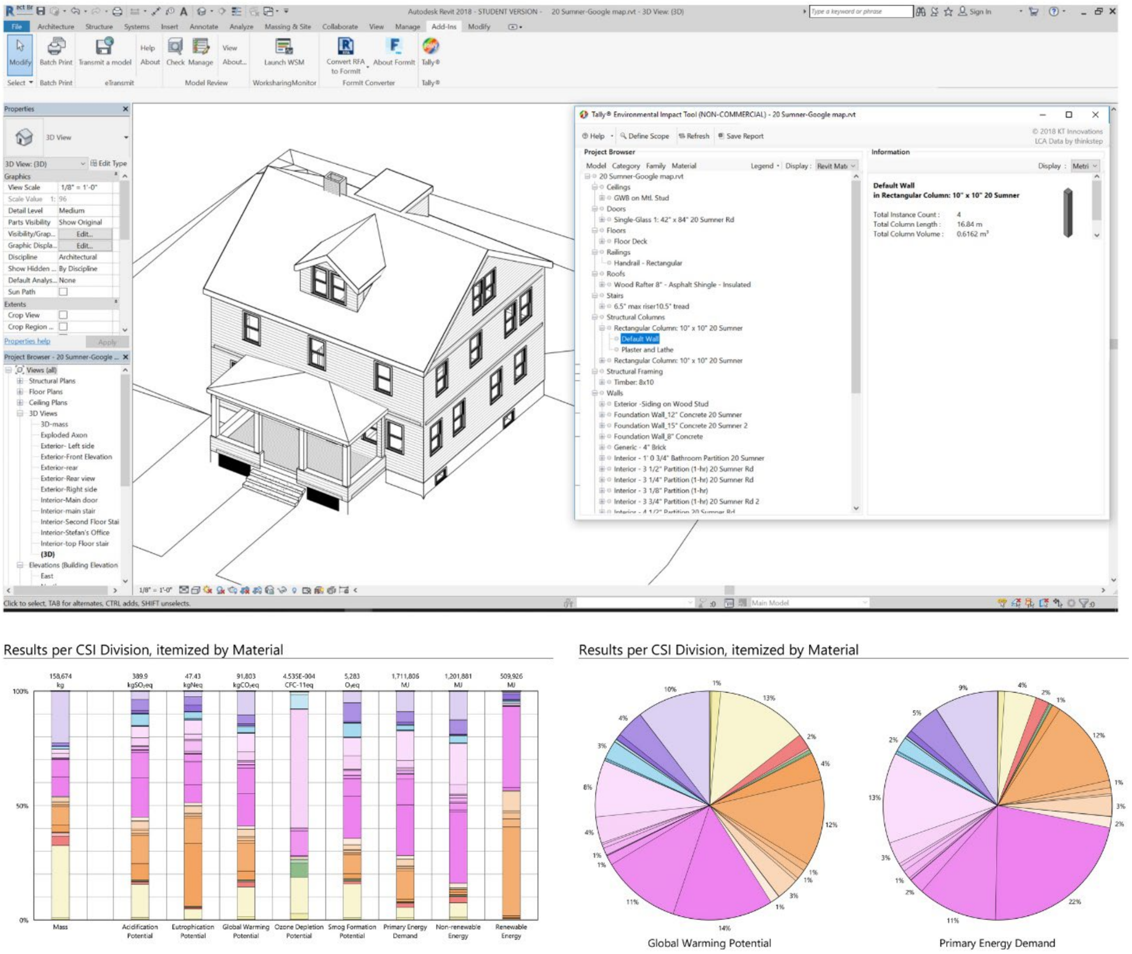
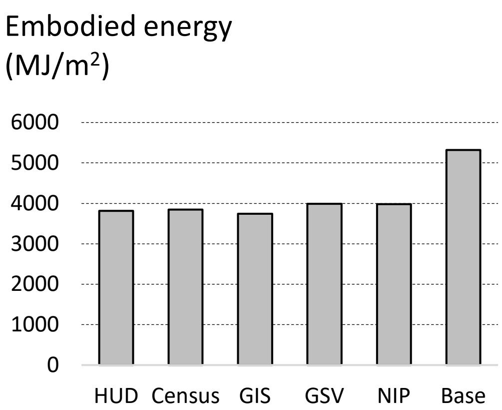
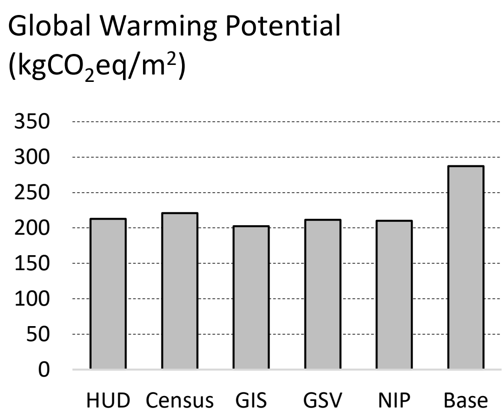


Figure 3. Conducting a LCA study of the GSV case in the Revit-Tally environment.

5. Results

Findings are presented in the following section in two general parts, with a separate analysis for each. The first part focuses on comparative results in absolute values for each LCI or LCIA category. The second part looks comparatively at the deviation from the result set of the base case.





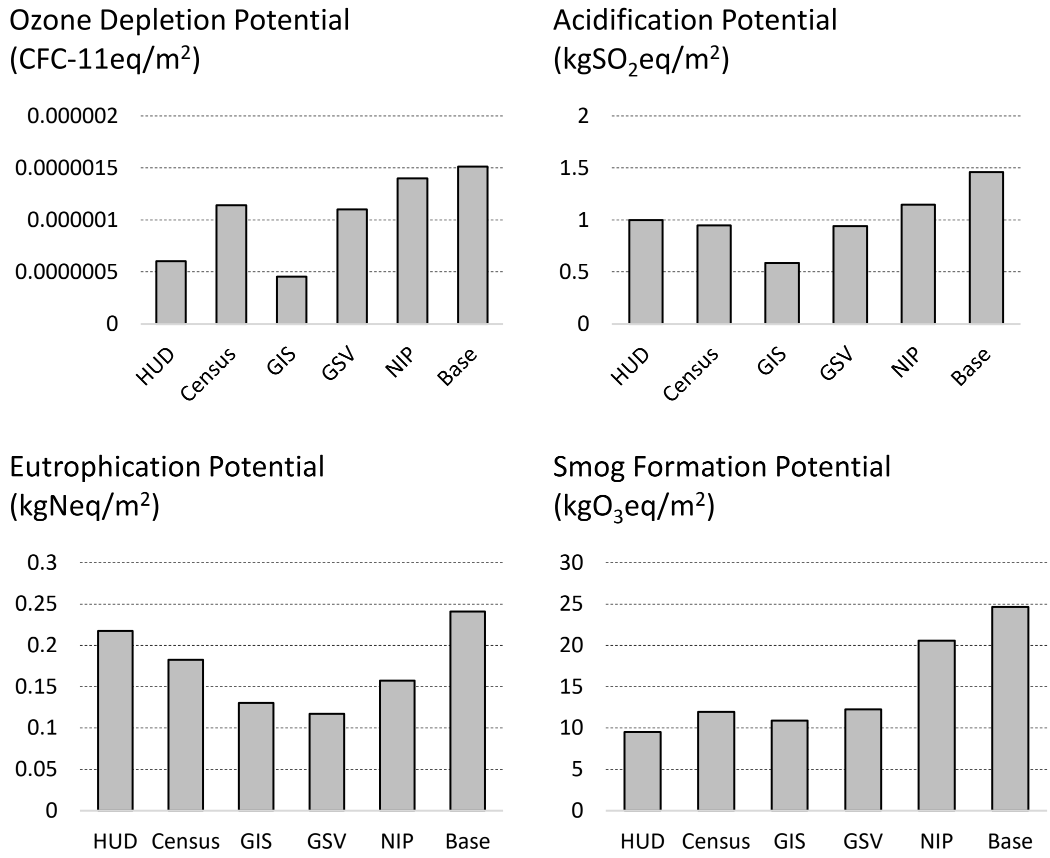


Figure 4. Comparative LCA results per functional unit ($1m^2$) in absolute values. NIP - base case with no internal partitions.

As can be observed in Figure 4, the base case consistently produces the highest result in terms of consumption and impact. This is mainly due to the fact that as the base case model is based on full design documentation, it is the only specimen in the study with internal partitions. Those extra components generate a higher impact than the one produced by the other specimens - which are based mostly on envelope information. In order to negate the skewing influence of internal partitions in the base model, findings in Figure 4 also contain a NIP category, which is essentially the base case with no internal partitions. In the embodied energy and global warming potential categories the results of the study closely follow the assumptions described earlier in the study, where the Google Street View and GIS models come close to capturing the actual impacts generated by the project, and the HUD and census models are proven to be less reliable in terms of actual impact prediction. In the other impact categories, the situation is slightly less expectable. In particular, the eutrophication potential category presents surprising results, where the HUD model impact not only comes closest to the impact generated by the base case, but surpasses the NIP model. The GSV model generates the least accurate result in this category. In part, this and other instances where the HUD and census models rank higher than expected may have to do with the relative lack of fenestration in these models. All data sources except for the full design documentation fail to provide full fenestration information. The HUD data source doesn’t contain any information regarding fenestration and even the more complete data sources like Google Street View provide fenestration information only regarding street-facing facades. In the case of eutrophication, which is largely generated by nitrogen and phosphorus (Conley et al. 2009), the use of glass in envelope openings might reduce impact and therefore models such as the HUD come closer to the impact that is generated when internal partitions are considered in the base case model.

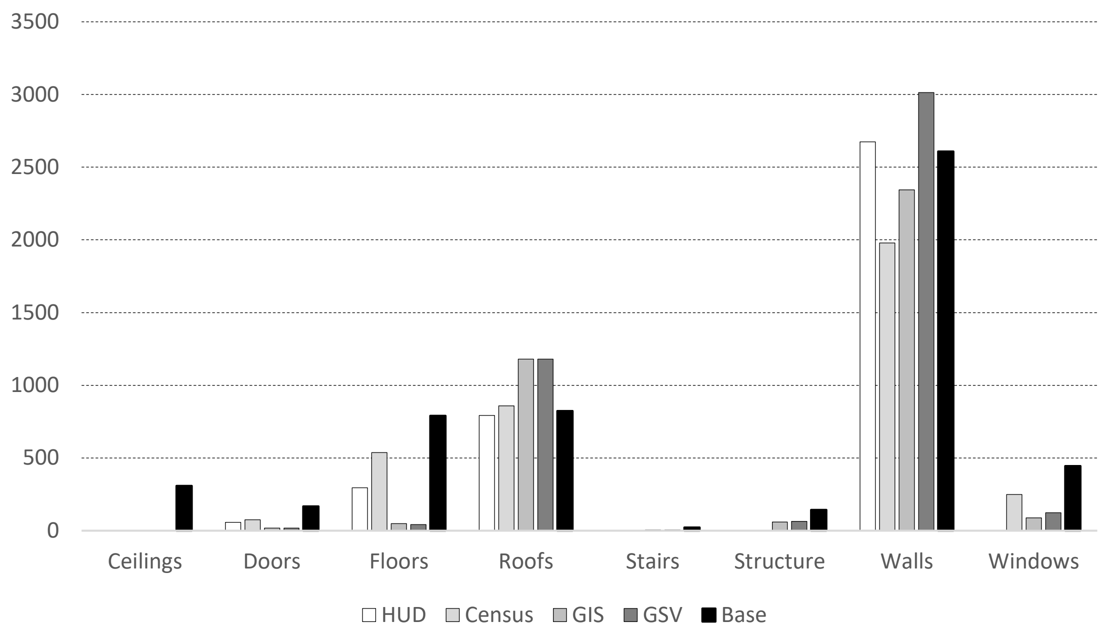


Figure 5. Embodied energy (MJ) by Revit assembly group per m^2.

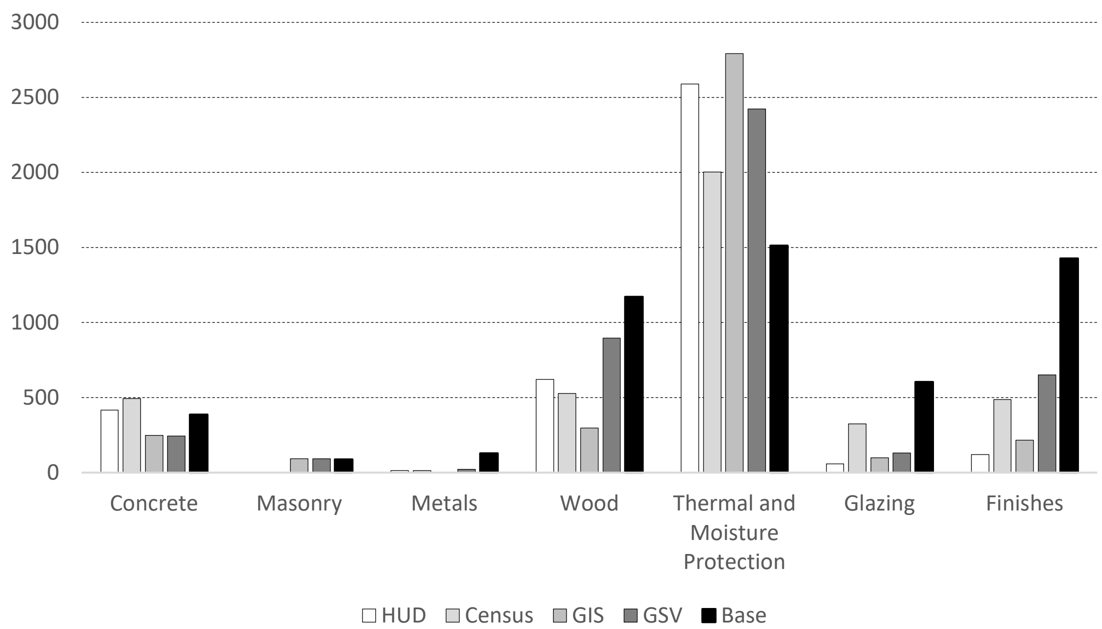


Figure 6. Embodied energy (MJ) by construction material per m^2.

A further breakdown of the results for embodied energy by assembly group and construction material are shown in Figures 5 and 6. This breakdown suggests that in terms of assembly groups, the added embodied energy consumption that generally characterizes the base case can be attributed more specifically to additional windows, floor slabs, and doors in comparison to the other models. In terms of construction materials, this added consumption can be attributed to metals, glazing and surface finishes. In all models, most of the consumed energy is concentrated in wall and roof assemblies, specifically in thermal and moisture protection.

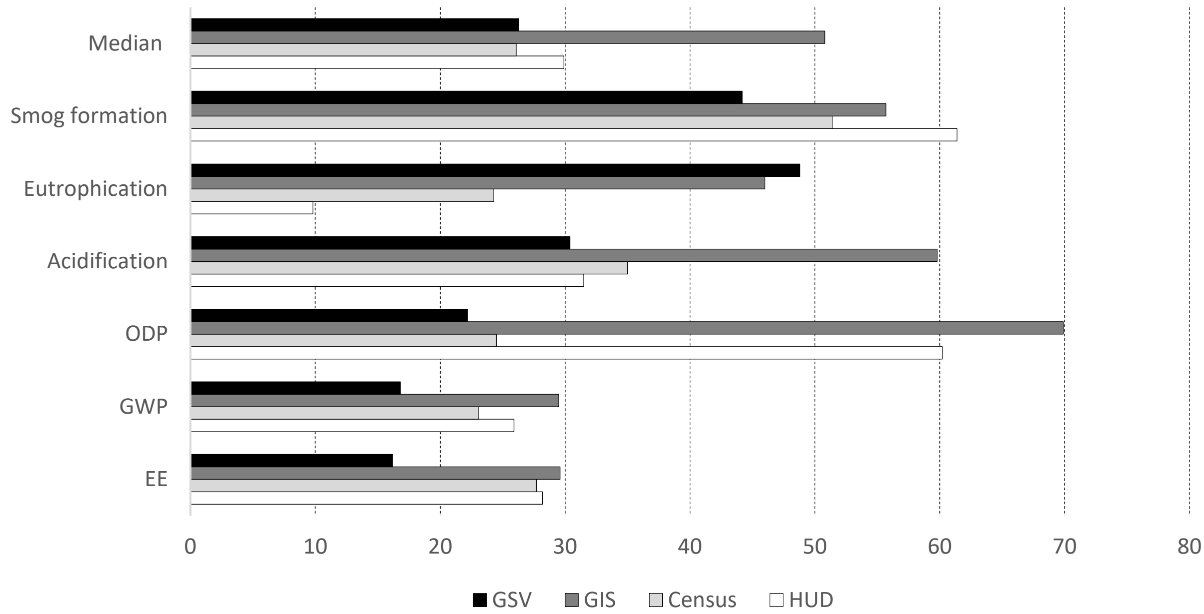


Figure 7. Deviation from base case (%).

	HUD	Census	GIS	GSV
Embodied energy (EE)	4.1	3.4	6.0	0.06
Global warming potential (GWP)	1.3	4.8	3.6	0.7
Ozone depletion potential (ODP)	56.9	18.3	67.4	21.3
Acidification	12.7	17.2	48.9	17.9
Eutrophication	27.6	13.7	17.1	25.4
Smog formation	53.7	41.8	46.9	40.5
Median	**20.2**	**15.4**	**32.0**	**19.6**

Table 2. Deviation from base case with no internal partitions (NIP). Results in %.

When the findings focus on deviation from the base case with no internal partitions results (Table 2), a number of observations can be made. First, in general, the deviations in the embodied energy and global warming potential categories are low for all data sources – 0.06%-6%. This point is meaningful as it implies that in a LCA study of a large development focusing on EE and GWP (carbon footprint) outputs, mined data sources can be used with relative confidence. Second, although as expected, the GSV model generates impact levels that are consistently close to the impacts generated by the base case (NIP) model, the census model achieves a lower deviation median at 15.4%. In fact, with the exception of the smog formation category, the census model performs consistently better than most other models in the study. This observation is important as the census model is based on regional averages – a data type that can be obtained quite easily and without a need for complex automated mining. Lastly, it is worth noting that in terms of deviation from the base case (NIP), the GIS model is found to be the least reliable with a median deviation of 32.0%. One of the probable reasons for this is the lack of documentation of the building's facades in this data source in relation to other data sources, particularly to the GSV source - which offers almost full façade documentation. Although the GIS model performs relatively well in the EE and GWP categories, for all other categories it is imprecise to a degree that renders its use in this context as not advantageous.

6. Discussion

The study aims to contribute to knowledge with regards to the prospects of using automated data acquisition in order to conduct LCA studies at an urban scale – particularly as it relates to the reliability of results that are based on incomplete or crude modelling data. In this context, some of the main limitations of the study should be discussed. First, the results of the study are based on one case study. Precedents for LCA-related studies that have been based on a single building case do exist (Zabalza et al. 2013; Collinge et al. 2012; Wu et al. 2018), and given the labour-intensive nature of producing five full BIM specimens for each case study, the amount of cases that can be analysed in one project are limited, however the authors acknowledge the clear difficulties in demonstrating the viability of a methodology based on a single case. With this study, the authors intend to establish a workflow that could be followed for analyzing further cases of multiple building and infrastructure types in future research. Second, the authors acknowledge the limitations of the life cycle inventory method that has been used in the study. The study used LCI results that have been generated by the Tally Revit plug-in through process analysis – a bottom-up method for compiling inputs and outputs based on a breakdown of the studied product into a series of single production processes. A major limitation of process analysis is what is known as 'truncation errors' (Lenzen 2000; Majeau-Bettez et al. 2011; Crawford et al. 2018). Due to the compartmentalized nature of process analysis, where each process is considered independently, even if a system boundary is clearly defined, it is inevitable that some intermediate processes would be omitted from the analysis, resulting in a truncation error. Research shows that as a result of truncation errors, process analysis can underestimate embodied energy values by up to 87% (Crawford 2008). These inaccuracies can typically be reduced by implementing input-output analysis - which relies on financial transactions in order to establish the energy intensity of local economic sectors - to fill in the gaps and create a hybrid analysis (Crawford and

Stephan 2013). However, in this study data regarding the financial cost of materials is limited, and therefore LCI results generated from the models should be considered with this limitation in mind.

7. Conclusions

This paper presented a methodology for assessing the influence of 3D model input data granularity on LCA study results. The methodology is demonstrated on a case study of a single family house with the intention of expanding the knowledge that the study generates to an urban scale. Findings of the study show that data mining of publically available sources for 3D modelling produce LCA results that are precise up to a 0.06% deviation rate from results based on a full data set. On average, depending on the type of data source that is used, results exhibit a 21.8% deviation from the full data base case (with no internal partitions). When looking specifically at the key impact categories of embodied energy and carbon footprint (GWP), results across the board are closer to the base case. These findings suggest that mined data could be used for urban scale life cycle modelling while taking into consideration a median error range of 20.2% for HUD-based models, 15.4% for census-based models, 32% for GIS-based models, and 19.6% GSV-based models. Future research trajectories include expanding this study to examine further case studies of other building types as well as infrastructure.

Disclosure statement

This is to acknowledge that no financial interest or benefit has arisen from the direct applications of this research.

References

Ajayi, Saheed O., Lukumon O. Oyedele, Boris Ceranic, Mike Gallanagh, and Kabir O. Kadiri. "Life cycle environmental performance of material specification: a BIM-enhanced comparative assessment." International Journal of Sustainable Building Technology and Urban Development 6, no. 1 (2015): 14-24.

Anderson, John E., Gebhard Wulfhorst, and Werner Lang. "Energy analysis of the built environment—A review and outlook." Renewable and Sustainable Energy Reviews 44 (2015): 149-158.

Antón, Laura Álvarez, and Joaquín Díaz. "Integration of LCA and BIM for Sustainable Construction." International Journal of Social, Behavioral, Educational, Economic, Business and Industrial Engineering 8, no. 5 (2014): 1378-1382.

Azari, Rahman. "Integrated energy and environmental life cycle assessment of office building envelopes." Energy and Buildings 82 (2014): 156-162.

Barlish, Kristen, and Kenneth Sullivan. "How to measure the benefits of BIM—A case study approach." Automation in construction 24 (2012): 149-159.

Basbagill, J., F. Flager, M. Lepech, and M. Fischer. "Application of life-cycle assessment to early stage building design for reduced embodied environmental impacts." Building and Environment 60 (2013): 81-92.

Baynes, Timothy M., and Thomas Wiedmann. "General approaches for assessing urban environmental sustainability." Current Opinion in Environmental Sustainability 4, no. 4 (2012): 458-464.

Bicalho, Tereza, Ildo Sauer, Alexandre Rambaud, and Yulia Altukhova. "LCA data quality: A management science perspective." Journal of Cleaner Production 156 (2017): 888-898.

Bribián, Ignacio Zabalza, Antonio Valero Capilla, and Alfonso Aranda Usón. "Life cycle assessment of building materials: Comparative analysis of energy and environmental impacts and evaluation of the eco-efficiency improvement potential." Building and environment 46, no. 5 (2011): 1133-1140.

Collinge, William O., J. C. DeBlois, M. E. Sweriduk, A. E. Landis, A. K. Jones, L. A. Schaefer, and M. M. Bilec. "Measuring Whole-Building Performance with Dynamic LCA: A Case Study of a Green University Building'." In International Symposium on Life Cycle Assessment and Construction, pp. 309-17. 2012..

Conley, Daniel J., Hans W. Paerl, Robert W. Howarth, Donald F. Boesch, Sybil P. Seitzinger, Karl E. Havens, Christiane Lancelot, and Gene E. Likens. "Controlling eutrophication: nitrogen and phosphorus." Science (2009): 1014-1015.

Crawford, Robert H. "Validation of a hybrid life-cycle inventory analysis method." Journal of environmental management 88, no. 3 (2008): 496-506.

Crawford, Robert H. Life cycle assessment in the built environment. Routledge, 2011.

Crawford, Robert H., and André Stephan. "The significance of embodied energy in certified passive houses." In Proceedings of World Academy of Science, Engineering and Technology, no. 78, p. 453. World Academy of Science, Engineering and Technology (WASET), 2013.

Crawford, Robert H., Paul-Antoine Bontinck, André Stephan, Thomas Wiedmann, and Man Yu. "Hybrid life cycle inventory methods–a review." Journal of Cleaner Production 172 (2018): 1273-1288.

Curran, M. A. "A Brief History of Life-Cycle Assessment." Life Cycle Assessment: Principles and Practice (2006).

Davila, Carlos Cerezo, and Christoph Reinhart. "Urban energy lifecycle: an analytical framework to evaluate the embodied energy use of urban developments." In Proceedings of BS2013: 13th Conference of International Building Performance Simulation Association, Chambéry, France, August, pp. 26-28. 2013.

Filchakova, Natalia, Urs Wilke, and Darren Robinson. "Energy modelling of city housing stock and its temporal evolution." iji 2, no. 4 (2009): 0-1.

Gantner, J., S. Schneider, M. Fischer, A. Lozanovski, and F. Gehring. "BIM as a data source for LCA and building certification schemes Certification schemes and BIM as a possible solution German research project BIMiD." In New Zel. LIfe Cycle Assess. Conf, pp. 116-119. 2014.

Guo, M., and R. J. Murphy. "LCA data quality: sensitivity and uncertainty analysis." Science of the total environment 435 (2012): 230-243.

Häkkinen, Tarja, and A. Kiviniemi. "Sustainable building and BIM." In Proceedings of SB08 Conference Melbourne, pp. 21-25. 2008.

International Standard Organization. ISO 14040: Environmental Management-Life Cycle Assessment-Principles and framework. 1997.

Johnson, Marc TJ, and Jason Munshi-South. "Evolution of life in urban environments." Science 358, no. 6363 (2017): eaam8327.

Jrade, Ahmad, and Farzad Jalaei. "Integrating building information modelling with sustainability to design building projects at the conceptual stage." In Building Simulation, vol. 6, no. 4, pp. 429-444. Springer Berlin Heidelberg, 2013.

Khemlani, Lachmi. "Autodesk Revit: implementation in practice." White paper, Autodesk (2004).

KT Innovations, Autodesk, Tally-Autodesk, (2014). http://choosetally.com/.

Law, Stephen, Brooks Paige, and Chris Russell. "Take a look around: using street view and satellite images to estimate house prices." arXiv preprint arXiv:1807.07155 (2018).

Lenzen, Manfred. "Errors in conventional and Input-Output—based Life—Cycle inventories." Journal of industrial ecology 4, no. 4 (2000): 127-148.

Li, Xiaojiang, and Carlo Ratti. "Mapping the spatial distribution of shade provision of street trees in Boston using Google Street View panoramas." Urban Forestry & Urban Greening 31 (2018): 109-119.

Loiseau, Eléonore, Guillaume Junqua, Philippe Roux, and Véronique Bellon-Maurel. "Environmental assessment of a territory: An overview of existing tools and methods." Journal of environmental management 112 (2012): 213-225.

Lotteau, Marc, Philippe Loubet, Maxime Pousse, Emmanuel Dufrasnes, and Guido Sonnemann. "Critical review of life cycle assessment (LCA) for the built environment at the neighborhood scale." Building and Environment 93 (2015): 165-178.

Majeau-Bettez, Guillaume, Anders Hammer Strømman, and Edgar G. Hertwich. "Evaluation of process-and input–output-based life cycle inventory data with regard to truncation and aggregation issues." Environmental science & technology 45, no. 23 (2011): 10170-10177.

Mirabella, Nadia, Karen Allacker, and Serenella Sala. "Current trends and limitations of life cycle assessment applied to the urban scale: critical analysis and review of selected literature." The International Journal of Life Cycle Assessment (2018): 1-20.

Nichols, Brice G., and Kara M. Kockelman. "Life-cycle energy implications of different residential settings: recognizing buildings, travel, and public infrastructure." Energy Policy 68 (2014): 232-242.

Norman, Jonathan, Heather L. MacLean, and Christopher A. Kennedy. "Comparing high and low residential density: life-cycle analysis of energy use and greenhouse gas emissions." Journal of urban planning and development 132, no. 1 (2006): 10-21.

Oliver-Solà, Jordi, Alejandro Josa, Alejandro P. Arena, Xavier Gabarrell, and Joan Rieradevall. "The GWP-Chart: An environmental tool for guiding urban planning processes. Application to concrete sidewalks." Cities 28, no. 3 (2011): 245-250.

Peterson, Fred W. "Anglo-American wooden frame farmhouses in the Midwest, 1830-1900: Origins of balloon frame construction." Perspectives in vernacular architecture 8 (2000): 3-16.

Rist, Tobin. "A path to BIM-based LCA for whole-buildings." Master's thesis, Norges teknisk-naturvitenskapelige universitet, Fakultet for ingeniørvitenskap og teknologi, Institutt for bygg, anlegg og transport, 2011.

Ross, Stephen A., and Lynette Cheah. "Uncertainty quantification in life cycle assessments: exploring distribution choice and greater data granularity to characterize product use." Journal of Industrial Ecology (2018).

Sarralde, Juan José, David Quinn, and Daniel Wiesmann. "Urban modelling for resource performance analysis: estimating cities' renewable energy potential." In Proceedings of Building Simulation, pp. 1370-1377. 2011.

Seiferling, Ian, Nikhil Naik, Carlo Ratti, and Raphäel Proulx. "Green streets− Quantifying and mapping urban trees with street-level imagery and computer vision." Landscape and Urban Planning 165 (2017): 93-101.

Soust-Verdaguer, Bernardette, Carmen Llatas, and Antonio García-Martínez. "Critical review of BIM-based LCA method to buildings." Energy and Buildings 136 (2017): 110-120.

Star, Jeffrey, and John E. Estes. Geographic information systems: an introduction. Vol. 303. Englewood Cliffs, NJ: Prentice Hall, 1990.

Stephan, André, and Aristide Athanassiadis. "Quantifying and mapping embodied environmental requirements of urban building stocks." Building and environment 114 (2017): 187-202.

Stephan, André, and Aristide Athanassiadis. "Towards a more circular construction sector: Estimating and spatialising current and future non-structural material replacement flows to maintain urban building stocks." Resources, conservation and recycling 129 (2018): 248-262.

Stephan, André, Robert H. Crawford, and Kristel De Myttenaere. "Multi-scale life cycle energy analysis of a low-density suburban neighbourhood in Melbourne, Australia." Building and Environment 68 (2013): 35-49.

Thinkstep. "Gabi LCA Software and Database." (2016).

United States Census Bureau, Characteristics of New Single-Family Houses Completed, (2018). https://www.census.gov/construction/chars/completed.html.

United States Department of Housing and Urban Development, American Housing Survey, (2017). https://www.huduser.gov/portal/datasets/ahs.html.

Wang, Endong, and Zhigang Shen. "A hybrid Data Quality Indicator and statistical method for improving uncertainty analysis in LCA of complex system–application to the whole-building embodied energy analysis." Journal of cleaner production 43 (2013): 166-173.

Wu, Yun-Wu, Ming-Hui D. Wen, Li-Ming Young, and I-Ting Hsu. "LCA-based economic benefit analysis for building integrated photovoltaic (BIPV) Façades: A case study in Taiwan." International Journal of Green Energy 15, no. 1 (2018): 8-12.

Yu, Bin, Qiang Liu, and Xingyu Gu. "Data quality and uncertainty assessment methodology for pavement LCA." International Journal of Pavement Engineering 19, no. 6 (2018): 519-525.

Zabalza, Ignacio, Sabina Scarpellini, Alfonso Aranda, Eva Llera, and Alberto Jáñez. "Use of LCA as a tool for building ecodesign. A case study of a low energy building in Spain." Energies 6, no. 8 (2013): 3901-3921.

Züst, R., G. Caduff, and B. Schumacher. "Life-cycle modelling as an instrument for life-cycle engineering." CIRP Annals-Manufacturing Technology 46, no. 1 (1997): 351-354.