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Reprint of: Uncertainty analysis for measuring greenhouse gas emissions in the building construction phase: a case study in China

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ABSTRACT

Uncertainty analysis is useful in determining whether the results of life cycle assessment are sufficiently reliable and valid when making optimal decisions. However, only a few studies have measured carbon emissions by considering the inherent uncertainty during building construction phase that may result in the misinterpretation of critical parameters. To address such weakness, a multi-method-based uncertainty analysis framework was developed in view of the basic characteristics of the construction practice. This framework integrated the deterministic and probabilistic approaches to facilitate the uncertainty assessment in quantifying carbon emissions and to provide insights into the sensitive construction activities from the uncertainty perspective. The developed framework was examined through a mix-use project in Guangzhou China. Results showed that the uncertainties in the measurement method and geographic representativeness are the major uncertainty sources for the building construction phase. The total greenhouse gas emission for the target building was 8791.5 tonnes of carbon dioxide equivalent with a 9.8% coefficient of variation, which was in line with the result calculated by the deterministic method and with the result extrapolated based on the data collected from China. The results of the scenario analysis showed that the proportion of 1% in contribution analysis and the coefficient of variation of 18% in uncertainty analysis can be regarded as the baseline for determining the critical input parameters. This study lends a useful tool for monitoring the uncertainty of LCA studies in the construction practice. In addition, this framework can facilitate to avoid the misinterpretation of the final results during the decision-making process. Although this study focuses on Chinese construction industry, it also provides good references for measuring uncertainty of greenhouse gas emissions of construction industries around the world.

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1. Introduction

The carbon dioxide (CO_2) emissions related to the residential and commercial building sector have been a global concern. As the primary contributor of global greenhouse gas (GHG) emissions, the construction industry plays a significant role in global warming. The Intergovernmental Panel on Climate Change asserts that the building sector contributed 40% to the total energy consumption and 25% to the global total CO_2 emissions (IEA, 2007; Metz et al., 2007). In China, the situation is significantly urgent owing to its accelerated urbanization. According to the 12th Five-Year Plan, the urbanization rate in China will reach a historic high of 51.5% in 2015. As the result of such extensive construction, the growth rate of energy consumption in buildings is more than 10% in past decades (Chang et al., 2014), producing large amount of CO_2 emissions. Therefore, the negative effects of extensive building constructions on China's environmental sustainability should be evaluated. In fact, the carbon emissions generated from building construction activities have been extensively studied in China. At the national level, the GHG emissions from the construction sector have been quantified using a series of macro-level analysis techniques, such as input–output (I–O) analysis and structural path analysis (Chang et al., 2014; Chen and Zhang, 2010; Liu et al., 2012). At the project level, numerous studies have investigated the carbon emissions

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from different types of buildings. As the major building type, residential buildings play a significant role in GHG emissions. Gao (2012) measured the embodied carbon footprint of residential buildings by conducting an empirical study of 17 buildings in Jiangsu province. Liu et al. (2009) quantified the life cycle CO_2 emissions of residential communities in China. Regarding office buildings, Wang et al. (2016) employed two case studies to illustrate the current GHG emission reduction performance of Chinese green buildings. Yao (2013) developed a benchmark for the carbon emissions from office buildings based on life cycle assessment theory. The current research hotspot for GHG emission quantification lies in investigating the influence of innovative construction techniques such as precast construction (Aye et al., 2012; Mao et al., 2013). In sum, previous research provides relevant insights into the current GHG emission status of the construction sector from the industrial and project perspectives. Nonetheless, the uncertainties generated during modeling are yet to be extensively looked into.

As an effective tool in the decision-making process for saving energy and reducing emissions, life cycle assessment (LCA) is widely used in the construction industry for environmental quantification. Theoretically, the outcome of an LCA analysis should be reliable and valid for decision makers to make optimal decisions. However, in the construction practice, the uncertainty of the inherent data affects the accuracy of LCA results. As such, the importance of uncertainty analysis behind the LCA results has been emphasized in recent years (Ciroth et al., 2002; Geisler et al., 2005; Sonnemann et al., 2003; Sugiyama et al., 2005). Therefore, the present study establishes a multi-method-based analytical framework to simulate the uncertainty that emanates from the computational process in the construction industry. This study aims to accurately assess the GHG emissions from buildings and to contribute to the literature from three aspects. First, this paper develops a multi-method-based analytical framework that can systematically identify the uncertainty sources and that can quantify the uncertainty bundled in construction activities. This framework can reinforce the importance of measuring uncertainties in LCA studies and can avoid the misinterpretation of the final results during the decision-making process. Second, the integration of qualitative and quantitative assessment methods provides a possible solution for assessing the uncertainty of LCA studies in the construction practice. This method also provides a sufficient understanding on the uncertainty related to building construction. Third, this paper identifies the critical parameters that influence the GHG emissions during building construction in the context of China.

The remainder of this paper is organized into six sections. Following the Introduction, Section 2 presents an overview of the recent uncertainty analysis in LCA studies. Section 3 establishes a multi-method-based uncertainty analytical framework by considering the basic characteristics of building construction. To overcome the data gap in traditional construction projects, this study collected input data based on an extended system boundary, considering onsite miscellaneous works and construction-related human activities. The focus was directed toward data inaccuracy analysis rather than the lack of data. The study mainly focused on the parameter uncertainty given that it is most sensitive to the final result. Section 4 applies the uncertainty analysis framework for measuring GHG emissions to a real building case. Section 5 discusses the proposed approach along with policy implications, and Section 6 presents the conclusions.

2. Overview of uncertainty analysis in LCA studies

Various researchers have investigated the sources of uncertainty based on LCA analysis. Weidema and Wesnæs identified five indicators, including data reliability, completeness, temporal correlation, geographical correlation, and technological correlation, to evaluate the additional uncertainty caused by data availability and quality (Weidema, 1998; Weidema and Wesnæs, 1996). Huijbregts et al. (2001) classified these indicators into two groups, namely, data inaccuracy and lack of data. With the development of LCA methodology, recent studies have determined that uncertainty not only comes from input parameters but also from the initial assumptions and the selected methodology. Geisler et al. (2004) identified uncertainty sources according to the different phases of LCA. These researchers regarded the measurements of elementary flows, temporal and spatial correlations, and production process as the uncertainty sources in life cycle inventory analysis (LCIA) phases. Huijbregts et al. (2003) emphasized that in addition to the uncertainties from input data, LCA outcomes can also be influenced by selected scenarios and mathematical models. Basset-Mens et al. (2004) quantified uncertainty by considering the variability in the LCA in pig farming systems. The uncertainty sources included technical performance, emission factors, and the functional unit. After reviewing 24 LCA studies focusing on quantitative uncertainty analysis, Lloyd and Ries (2007) concluded that uncertainty and variability come from three LCA modeling components, namely, input data, normative choice, and model, whereas Cellura et al. (2011) categorized the uncertainty sources in LCA analysis as methodological choices, initial assumptions, and quality of data. Williams et al. (2009) divided uncertainty types into data, cutoff, aggregation, temporal, and geographic uncertainty to conduct uncertainty analysis for a hybrid LCA model. Gavankar et al. (2015) focused on the communication of uncertainty in LCAs than on the technical aspects and summarized five criteria to facilitate uncertainty communication. In sum, previous works addressed three different uncertainty sources significant in LCA-related studies. These sources are parameter, model, and scenario uncertainties in which the parameter uncertainty is the most sensitive to the final LCA outcome (Huijbregts et al., 2003).

Assessment tools vary in terms of uncertainty types, and they can generally be divided into qualitative and quantitative approaches. The data quality index (DQI) is the most commonly used qualitative assessment method because of its high applicability and feasibility. The data quality evaluation matrix (Weidema, 1998) and the transformation matrix (Kennedy et al., 1996) are the two most efficient tools used in DQI assessment. However, DQI remains limited in terms of its assessment accuracy due to the subjective determination of data quality. Although the quantitative analysis techniques are complemented for the current qualitative uncertainty assessment methods to minimize variations, the results still tend to be underestimated as specified by Coulon et al. (1997). Considering the aforementioned limitations in the application of qualitative approaches in uncertainty analysis, quantitative approaches have been introduced based on data availability. Basson and Petrie (2004) adopted a set of statistical methods to differentiate and identify both the technical and valuation uncertainties in the LCA analysis of a coal-based power station. Canter et al. (2002) conducted uncertainty analysis in LCA for four beverage delivery systems. The group applied DQI to evaluate the uncertainty of target input data, which were first selected according to their individual contributions, and used Monte Carlo simulation (MCS) to obtain the overall uncertainty and model variance. May and Brennan (2003) performed uncertainty analysis by implementing three steps: gravity analysis to determine data contribution, uncertainty analysis, and sensitivity analysis. Imbeault-Tétreault et al. (2013) outlined an analytical approach for uncertainty analysis to mitigate the resource intensity in MCS and validated this quantitative method in a real case to reveal its importance in uncertainty calculation. Herrmann et al. (2014) established an LCA classification

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matrix to summarize the inherent uncertainty scale under each LCA model; this matrix provided an index map for LCA analysts and decision makers. In general, fuzzy logic analysis, interval theory, and possibility uncertainty analysis are commonly used for LCA uncertainty evaluation given that the data are insufficient for further processing (Chevalier and Le Téno, 1996; Tan et al., 2002, 2007). By contrast, stochastic methods such as MCS can be adopted if a large amount of actual data can be observed and collected (Geisler et al., 2004; Lo et al., 2005; Venkatesh et al., 2010). In particular, stochastic methods are superior to other methods due to their inherent advantages in capturing the variability and uncertainty in LCA. Tan et al. (2002) applied possibility theory to assess the uncertainties in LCIA and clarified that possibilistic methods have advantages in computational efficiency when compared with probabilistic approaches. André and Lopes (2012) held the same view by comparing possibilistic and probabilistic approaches and identified that the latter is limited by a relatively slow computational process but can provide sufficient uncertainty information. Lloyd and Ries (2007) asserted that stochastic methods were mostly used (67%) in previous research, followed by scenario analysis (29%) and fuzzy data sets (17%). This study summarizes the typical uncertainty sources and their corresponding assessment methods as shown in Table 1.

The estimation of uncertainty in LCA analysis is not only associated with uncertainty sources and assessment methods, but also with the research scope and objectives. Given that this study aims to establish an uncertainty analysis framework for LCA in building construction, it considers some basic characteristics relevant to the construction industry, especially for building construction. First, a specific building is distinctive due to its characterized building profile such as design parameters and construction structure. Therefore, elementary flows may vary among different buildings. This specificity determines that all input parameters involved in a certain building are unique. In this case, sufficient data can hardly be collected to describe the probability distribution of the elementary flows of buildings. However, such procedure can be partially mitigated by improving the data collection quality and by enhancing the measurement method during the building construction phase. Second, unlike the manufacturing industry that is characterized by reproducibility and mass production, the inventory data of environmental emission, energy input, and resource use during building construction are rarely reported from private and public sources. The probable reason behind this condition is the confidentiality requirement between the client and the contractor. This case verifies that the uncertainty analysis in LCA is insufficiently applied to real building cases in the construction industry.

This study aims to explore how the uncertainty analysis in LCA can be conducted and how a multi-method-based analytical framework can be established for the construction industry. This study also intends to reveal the uncertainty sources bundled in construction activities and the key parameters involved in construction processes in the context of China.

3. Research methods

Parameter uncertainties stem from the lack of knowledge about the true value of a parameter (Huijbregts et al., 2003). A probabilistic approach can be used to reflect the most probable value of the objective. Traditionally, the goodness of fit between data samples and probability distributions can be examined to identify the most appropriate probability distribution for parameters based on a certain number of observations. However, the basic features of building products result in a limited amount of actual data. In this case, expert judgment is used as a substitute for the lack of knowledge to estimate uncertainty ranges. In this case, DQI should be used as the supplement for uncertainty evaluation. However, pure DQI method has weakness in subjective evaluation, but the latest improvements in uncertainty analysis can facilitate the comprehensive assessment of the parameter uncertainty. Therefore, both DQI and probabilistic method are used in this study to address the lack of actual data in the construction industry. The data categorization system first introduced by Heijungs (1996) is used to identify the key parameters according to their uncertainty and contribution in the final output. The important parameters with high uncertainty and contribution are then selected for further analysis in the context of the construction industry.

3.1. DQI assessment method

DQI is a semi-quantitative method comprising a series of indicators that aim to describe the parameter uncertainty from different aspects. The DQI system is established based on experts' subjective judgment as well as on objective mathematical calculations. Given the characteristic of building construction, the data quality is mainly influenced by three aspects. First, the accuracy and validity of the available data is determined by the data measurement method. A consistent measurement of material flows in the construction site can improve data precision and avoid the possibility of uncertainty. However, regular investigation and subjective evaluation are frequently adopted in the construction industry owing to the restrictions in the data measurement technology. Second, the computational framework in LCA analysis implies that the calculated results may vary due to the changes in geographic climate, manufacturing technology, and data age. Third, the data sources in the construction practice are complicated because of its multitude of activities and long-term duration. Therefore, a priority system should be established to reflect the reliability by ranking different data sources. Comprehensively considering the conclusions of previous research (Wang and Shen, 2013; Weidema and

Table 1
Typical uncertainty sources and their corresponding assessment methods.

Uncertainty sources	Typical uncertainties	Assessment method
Assumption	System boundary	Scenarios analysis
	Functional unit	
	Allocation method	
Parameter	Material flow	DQI
	Energy flow	Fuzzy theory
	Other input data	Analytical uncertainty propagation
		Bayesian statistics
		Possibilistic approach
		Probabilistic approach
Model	Transformation factor	Probabilistic approach
	Modeling process of the product system	Sensitive analysis

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Wesnæs, 1996), five types of data quality indicators are identified in this study, namely, data measurement method, source of data, geographic representativeness, technical representativeness, and temporal representativeness. The score for each indicator ranges from one to five. The value represents the uncertainty of each category from low to high. In consideration of the basic characteristics of the construction industry, a DQI matrix was established (see Table 2) by Weidema and Wesnæs (1996) and Wang and Shen (2013). Table 3 shows the difference of data sources from the general situation and building construction.

3.2. Contribution analysis

This section determines the contribution of each construction activity to the final cumulative results. The use of original process-based inventory data enables the calculation of the deterministic contributions for each construction activity. However, the result of the deterministic analysis is relatively imprecise because the uncertainty of all coefficients contributes to the overall uncertainty value. Such deterministic contribution can be regarded as the basic reference and cornerstone for identifying the important parameters, which substantially contribute to the final output. Maurice et al. (2000) emphasized that the percentage of data contributions may vary from one model to another. Therefore, the scenario analysis is conducted to verify and validate the reliability of the selected key parameters.

3.3. MCS

MCS is a numerical method used to sample a probability distribution for the concerned factors to produce thousands of possible outcomes. The results of MCS are further analyzed to obtain the probabilities of different occurring outcomes (Xu, 1985; Shen et al., 2011). MCS is a useful tool for measuring the total uncertainty aggregated by various uncertainty factors with non-linear relationship. In this study, the total carbon emission is the aggregation of carbon emission in various activities in the construction phase. If the carbon emission in each activity is taken as a stochastic factor considering the uncertainty of parameters, then the total carbon emission should also be a stochastic factor. The statistical features of the total carbon emission can be determined through its probability distribution obtained by MCS. MCS first determines the corresponding probability distribution for each input factor. The probability distribution for the concerned factor can be obtained either by fitting a large number of existing data or by experts view. Based on the established relationship between the observed and input factors, MCS can be run with Crystal Ball software to obtain the probability distribution of the observed factor. To identify the extent in which uncertainty can be considered, the coefficient of variation (CV) is used to describe the degree of uncertainty based on the MCS results. Considering the constraints and deficiencies of data availability in the construction industry, β distribution is assumed to describe the possible value for each construction activity. Canter et al. (2002) and Wang and Shen (2013) thoroughly explored the reasons and rationale for applying Beta function in uncertainty analysis. Kennedy et al. (1996) established a transformation matrix to define four unknown parameters involved in β distribution, namely, α, β, lower point, and upper point. MCS is conducted in Crystal Ball software with 10,000 iterations. The number of iterations directly determines the stability of the final output. The result will be convergent with the increasing numbers of simulations, and the excessive iterations are regarded as a less efficient means to run MCS. Therefore, the examination of convergence is a valid method to confirm the appropriate number of iterations (Cowles and Carlin, 1996; Shen et al., 2011). Numerous mean values and standard deviations derived from simulations with different iterations are then generated to examine the trend of convergence.

3.4. Parameter categorization system

The parameter categorization coordinate comprehensively reflects the importance of input parameters in the dimension of uncertainty and contribution. With the CV and the percentage of contribution represented in the horizontal and vertical axes, respectively, all coordinates can be classified into four quadrants according to the degree of their importance. These quadrants are divided into highly concerned data in the upper right part, concerned data in the upper left and lower right parts, and general data in the lower left part. The parameters in the upper right quadrant have high percentage in contribution and uncertainty, critical to the accuracy of the accumulative results and therefore require detailed analysis.

3.5. Basic procedure of uncertainty analysis

Fig. 1 shows the fundamental procedure of parameter uncertainty analysis. Contribution analysis and DQI assessment can be conducted simultaneously to determine the importance of input data based on the compilation of the original inventory. Parameter categorization, combined with scenario analysis, further verifies the critical input parameters with particular concerns. Finally, according to the assumed probability distribution for each construction activity, the overall CV and the final cumulative results are calculated with MCS.

4. Case study

The case project refers to the study by Hong et al. (2015), who

Table 2
Data Quality Index (DQI) evaluation system.

Quality score	Data quality indicators				
	Measurement method	Data source	Geographic factor	Technical factor	Temporal factor
5	Consistently measured data	Verified data from independent source	Field survey/measure data	Data from process studied of the enterprise with same technology	Less than 3 years
4	Regularly measured data	Verified data from interested party	Data from an area with similar production condition	Data from process studied of the enterprise with similar technology	Less than 6 years
3	Data estimated based on measurements	Unverified data from independent source	Regional data	Data from enterprises with different technology	Less than 10 years
2	Data estimated partly based on assumptions	Unverified data from irrelevant enterprise	National data	Data from process related of enterprises with similar technology	Less than 15 years
1	Subjective estimated data	Unverified data from interested party	International data	Data from process related of enterprises with different technology	More than 15 years or unknown

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Table 3
Different data source in the construction industry.

Quality score	General data source	Specific in construction industry
5	Verified data from independent source	Accounting receipt
4	Verified data from interested party	Stakeholder's report
3	Unverified data from independent source	Bill of quantity
2	Unverified data from irrelevant enterprise	Material use application record
1	Unverified data from interested party	Secondary data from the procurement agency

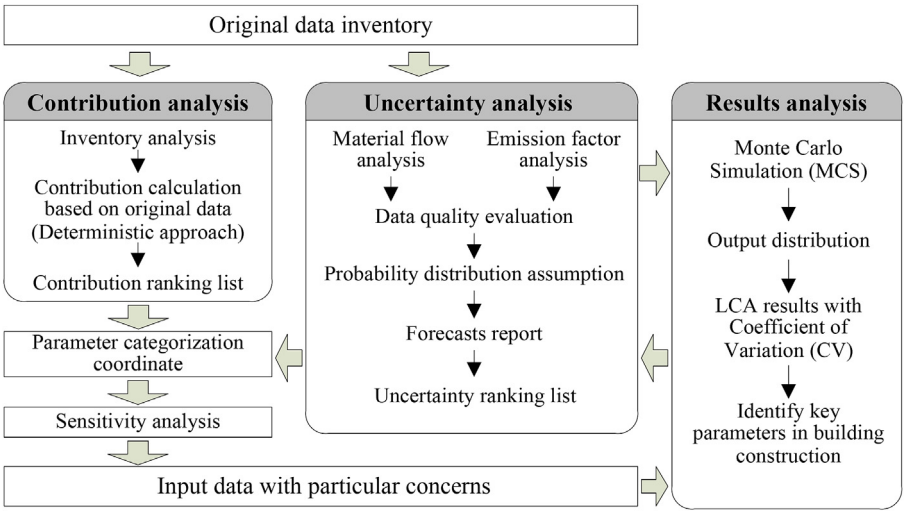


Fig. 1. A multi-method based uncertainty analysis framework.

examined a residential complex with a reinforced concrete framework in Guangdong Province, China. The gross floor area investigated in this study is 11,508 m^2 that comprises a clubhouse and retail outlets. The construction period was more than two years from April 1, 2008 to August 31, 2010. The system boundary covers the carbon impacts of all involved construction activities, which can be summarized in the following six categories:

- Fuels used by construction equipment (Direct emissions)
- Electricity consumption (Direct and indirect emissions)
- Onsite assembly and miscellaneous works (Direct emissions)
- Building material production (Indirect emissions)
- Transportation (Direct and indirect emissions)
- Construction-related human activities (Direct and indirect emissions)

All data collected in this study are based on field survey and face-to-face interview with clients, contractors, prefabrication suppliers, and other stakeholders involved in the target project. The detailed process data are collected from multiple sources, including accounting receipt, stakeholder's report, bill of quantity, material use application record, and secondary data from the procurement agencies. The deterministic GHG emissions are quantified based on ISO 14064-1:2006 (ISO, 2006) used as the reference for contribution evaluation.

During the CO_2 emission quantification, 122 construction activities are involved in the emission factor collection and have been subjected to DQI analysis (see Table 4). The analysis result shows that the DQI scores vary among different construction activities. The emission factors are uncertain in terms of the measurement method, geographic representativeness, and technical representativeness. This condition may have arisen from the fact that this study engaged proxy data available on the international LCA software Ecoinvent v2.0 database. Most of these data were developed for Switzerland and Europe, and a few were established for global use. By contrast, the elementary flow data in the entire project are decomposed into 331 construction activities. Table 5 demonstrates the result of the DQI analysis. The construction inventory data have weaknesses in measurement method and data source mainly because most material flow data are collected based on the bill of quantity, which is compiled under various assumptions. In addition, given that the major data collection method used in this study is field survey and face-to-face interview, the indicator of the temporal correlation represents less uncertainty.

5. Results

Table 6 illustrates the ranking list of the construction activities in terms of their contribution and uncertainty.

As two of the most important and frequently used materials for construction, steel and concrete represented the highest relative contribution with proportions of 49% and 13%, respectively, cumulatively accounting for approximately 2/3 of the total carbon emissions. The transportation of construction equipment and building materials played a major role in the uncertainty analysis with CVs of 24% and 20%, respectively.

Fig. 2 shows the distribution of all construction activities in the parameter categorization coordinate. Each point in the figure represents one certain construction activity. Most construction activities converged on the area with an uncertainty interval of 15%–20% and a contribution of 0%–1%. To comprehensively investigate the effect of changes in uncertainty and contribution on the determination of critical construction activities, this study identified the key parameters by considering the different levels of contribution and uncertainty. Given the aforementioned converged area and the results obtained in Table 6, we established 12 scenarios. The

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Table 4
Result of DQI analysis for emission factor parameters.[a]

GHG emissions related construction activities	Number of emission factors	Measurement method	Data source	Geographic representativeness	Technical representativeness	Temporal representativeness
Fuels use in construction equipment	6	Data estimated based on measurements (3)	China Energy Statistical Yearbook 2007 (5)	National data (2)	Data from process related of enterprises with similar technology (2)	Less than 6 years (4)
Onsite welding and cutting	1		Chemical formula (5)	Field survey/measure data (5)	Data from process studied of the enterprise with same technology (5)	Less than 3 years (5)
Temporary septic-tank	1	Data estimated partly based on assumptions (2)	IPCC 2006 (5)	International data (1)	Data from process related of enterprises with similar technology (2)	Less than 6 years (4)
Office electricity use	1		2009 NDRC Report[b] (5)	Data from an area with similar production condition (4)	Data from process studied of the enterprise with similar technology (4)	Less than 3 years (5)
Construction electricity use	1					
Building materials production	79		Ecoinvent v2.0 database (5)	International data (1)	Data from process related of enterprises with similar technology (2)	Less than 6 years (4)
Building materials transportation	12					
Construction equipment transportation	9					
Fuels used in staff transportation	3					
Construction water production	1	Data estimated based on measurements (3)	Guidelines 2010[c] (5)			Less than 3 years (5)
Office water production	1					
Office cooking oil use	3		China Energy Statistical Yearbook 2007 (5)	National data (2)		Less than 6 years (4)
Onsite cooking oil use	3					
Offsite septic-tank	1	Data estimated partly based on assumptions (2)	IPCC 2006 (5)	International data (1)		

[a] The number list in "()" is the DQI score.
[b] 2009 NDRC Report of Emission Factors for Chinese Regional Power Grid.
[c] Guidelines to Account for and Report on GHG Emissions and Removals for Buildings in Hong Kong 2010.

minimum value for each scenario in terms of their contribution and uncertainty is listed in the first two columns of Table 7.

Table 7 shows the results of the scenario analysis (10,000 runs MCS). Scenarios 1, 2, and 3 revealed that the number of key parameters decreased dramatically when the uncertainty increased. Electricity use and a number of building materials were defined as key parameters at above the 0.1% level of contribution. Considering that several building materials, such as aluminum and polyamide safety netting, have a relatively small weight (<0.1%) while a significant quantity of GHG (2%–3%) is released during the construction phase, alternatives with low carbon intensity should be selected. When the frequency of occurrence for each key parameter

Table 5
Result of DQI analysis for elementary flow data.[a]

GHG emissions related construction activities	Number of activities	Measurement method	Data source	Geographic representativeness	Technical representativeness	Temporal representativeness
Fuels use in construction equipment	7	Data estimated partly based on assumptions (2)	Contractor's report (4)	Field survey/measure data (5)	Data from process studied of the enterprise with same technology (5)	Less than 3 years (5)
Onsite welding and cutting	17	Data estimated based on measurements (3)				
Temporary septic-tank	8	Data estimated partly based on assumptions (2)				
Office electricity use	29	Consistently measured data (5)	Accounting receipt (5)			
Construction electricity use	29					
Building materials production	79	Data estimated partly based on assumptions (2)	Bill of quantity (3)		Data from process studied of the enterprise with similar technology (4)	
Building materials transportation	24			Data from an area with similar production condition (4)		
Construction equipment transportation	19		Secondary data from the procurement agency (1)			
Fuels used in staff transportation	15					
Construction water production	15	Consistently measured data (5)	Accounting receipt (5)	Field survey/measure data (5)	Data from process studied of the enterprise with same technology (5)	
Office water production	29					
Office cooking oil use	29	Regularly measured data (4)				
Onsite cooking oil use	29					
Offsite septic-tank	2	Regularly measured data (4)	Accounting receipt (5)			

[a] The number list in "()" is the DQI score.

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Table 6
Results of contribution analysis and uncertainty analysis.

	Construction activities	Contribution	Construction activities	Uncertainty
1	Steel	48.95%	Construction equipment transportation (7.5 ~ 16t)	24.77%
2	Concrete	13.24%	Company cars	24.73%
3	Talcum powder	8.79%	Construction equipment transportation (16 ~ 32t)	24.65%
4	U. F. foamed plastic	5.26%	Construction equipment transportation (3.5 ~ 7.5t)	24.64%
5	Polyamides safety net	2.79%	Building materials production (>32t)	20.82%
6	Onsite electricity use	2.42%	Building materials transportation 16 ~ 32t	20.72%
7	Cement	2.12%	Building materials transportation 3.5 ~ 7.5t	20.63%
8	Aluminum	2.00%	Building materials transportation 7.5 ~ 16t	20.61%
9	Offsite electricity use	1.52%	Concrete block	19.21%
10	Glass	1.07%	Timber	19.21%

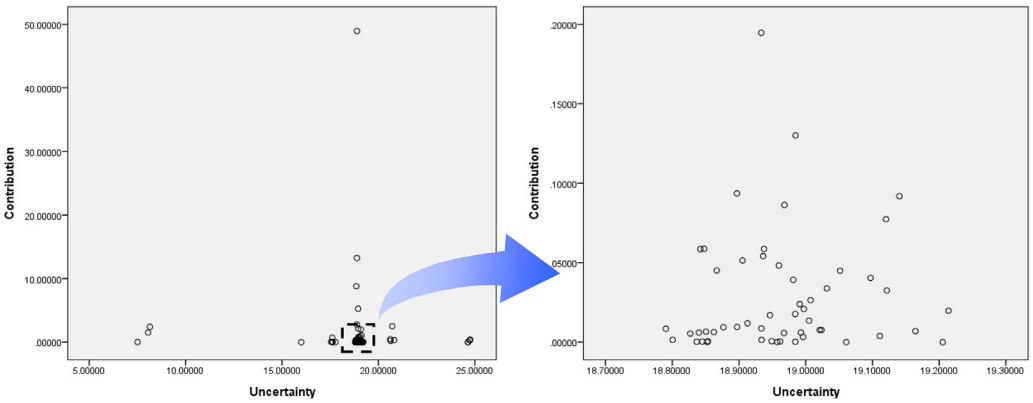


Fig. 2. Distribution of construction activities in parameter categorization coordinate.

was considered (see Fig. 3), steel was regarded as the key parameter in eight scenarios, followed by concrete, aluminum, and glass in six scenarios. The result further demonstrated the important status of these four types of building materials in CO_2 emissions during building construction. Two scenarios did not display any result under the assumption that the contribution proportion is more than 10% and the CV is more than 19%. This condition verifies that because of great efforts in data collection and consolidation, this study can improve the data quality and minimize the possible uncertainties. Considering the change trends of key parameters in 12 scenarios, the proportion of 1% in contribution analysis and a CV of 18% in uncertainty analysis can be selected as the basic value to determine the input parameters that need special attention and careful processing. Therefore, eight building materials not only generated large amount of GHG emissions but also represented a high level of uncertainty in the final output. These materials are steel, concrete, talcum powder, U. F. foamed plastic, polyamide safety netting, cement, aluminum, and glass.

Fig. 4 shows the results of MCS in terms of the total GHG emissions. The mean value of MCS was 8791.5 tonnes of carbon dioxide equivalent (CO_2e), which was in line with the deterministic result of 8779.4 tonnes of CO_2e. The standard deviation and CV for the total emissions were 863.1 and 9.8% respectively, revealing that the uncertainties from the input parameters in this study were acceptable. According to the uncertainty results, a confidence interval within a 90% certainty was estimated from 7422.3 tonnes of CO_2e to 10,202.7 tonnes of CO_2e with the range width of 2780.4 tonnes of CO_2e.

Table 8 shows the GHG emission intensity of different buildings in China. Given the geographic and structural similarities of these buildings, the estimated GHG emission intensity was highly consistent with the findings summarized in Table 8, especially with the building cases analyzed in Shenzhen and Hong Kong. Chang et al. (2016) conducted a disaggregated I–O analysis to quantify the GHG emission for different types of buildings at the national average level. Such benchmark provides a macro-level perspective to examine the reliability of results obtained in present study. Given the emission intensity provided by Chang et al. (2016) for the category of urban residential and office buildings, the result obtained from the uncertainty analysis framework in this study was also acceptable and reasonable.

Fig. 5 shows the trend of convergence for the total GHG emissions with the increasing number of iterations. The mean value of the total amount of emissions became stable after 4500 simulations were run, whereas the standard deviation converged significantly from 5500 iterations. Therefore, the result of MCS with 10,000 runs can be considered effective and valid to reflect the real amount of GHG emissions from the building construction phase.

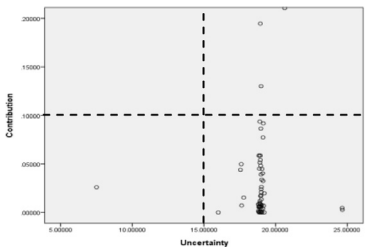
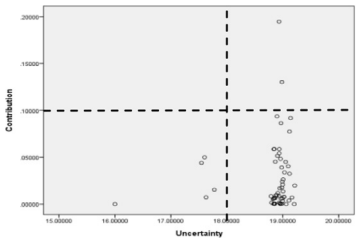
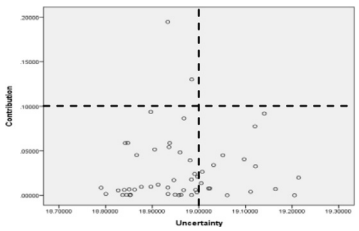
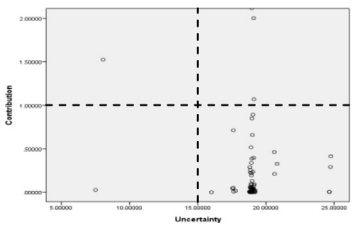
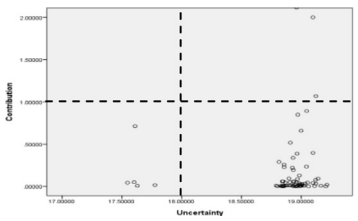
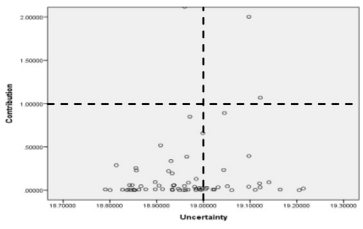
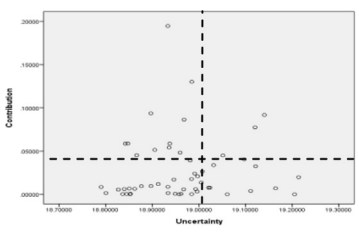
6. Discussions and policy implications

The uncertainty analysis for LCA is scarcely conducted in the construction industry because the actual process data for building products are often irreproducible and unavailable. As such, the related data and results are limited. This study mitigates such problem by developing an uncertainty assessment framework with the combination of qualitative and quantitative approaches. The framework switches the focus of concern from the contribution-oriented analysis in traditional GHG assessment toward the uncertainty effect examination. The results obtained in this study further emphasize the importance of identifying the uncertainty factors in GHG emission assessment.

In addition to the exploration of typical carbon-intensive construction activities according to their significant emission contributions, this study also provides evidence for the uncertainty-related sensitive factors for assessing GHG emissions.

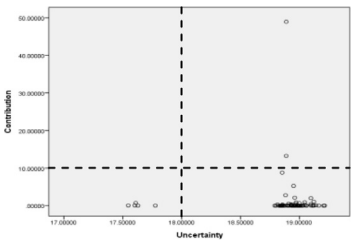
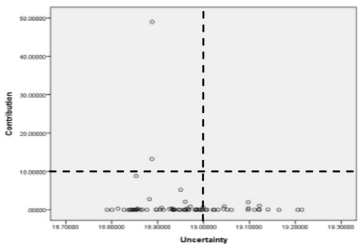
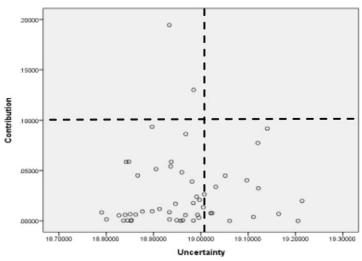
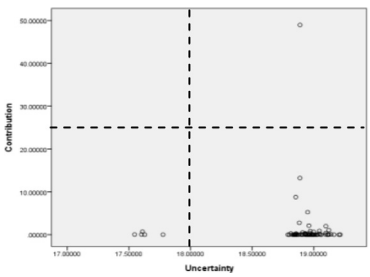
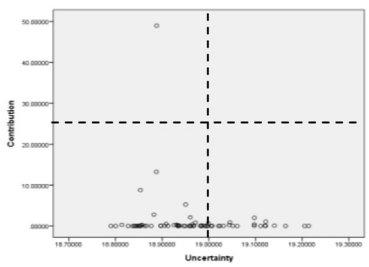
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Table 7
Result of scenario analysis.

	Contribution	Uncertainty	Key parameters	Distribution
1	>0.1%	>15%	Onsite electricity use; Offsite electricity use; Steel; Concrete; Talcum powder; U. F. foamed plastic; Polyamides safety net; Cement; Aluminum; Glass; Slag; Clay haydite; Welding rod; Polyurethane; Perlite; Timber plates; Wire entanglement; Formwork; UPVC pipe; Marble; Gravel; Ceramic;	
2	>0.1%	>18%	Steel; Concrete; Talcum powder; U. F. foamed plastic; Polyamides safety net; Cement; Aluminum; Glass; Slag; Clay haydite; Welding rod; Polyurethane; Perlite; Timber plates; Wire entanglement; Formwork; UPVC pipe; Marble; Gravel; Ceramic;	
3	>0.1%	>19%	Aluminum; Glass; Slag; Timber plates; Gravel;	
4	>1%	>15%	Steel; Concrete; Talcum powder; U. F. foamed plastic; Polyamides safety net; Cement; Aluminum; Glass;	
5	>1%	>18%	Steel; Concrete; Talcum powder; U. F. foamed plastic; Polyamides safety net; Cement; Aluminum; Glass;	
6	>1%	>19%	Aluminum; Glass;	
7	>10%	>15%	Steel; Concrete;	

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Table 7 (*continued*)

	Contribution	Uncertainty	Key parameters	Distribution
8	>10%	>18%	Steel; Concrete;	
9	>10%	>19%	NULL	
10	>25%	>15%	Steel	
11	>25%	>18%	Steel	
12	>25%	>19%	Null	

Traditionally, steel and concrete are regarded as the major CO_2 contributors owing to their carbon-intensive manufacturing process. The result of the scenario analysis indicated that aluminum, glass, slag, timber, and gravel are also important, especially considering the effect of their uncertainty (>19%). Given the basic characteristics of building construction, the data measurement for inventory analysis is a significant uncertainty source that influences emission evaluation. Most material flow data are collected or calculated based on the bill of quantities, originally compiled and pre-estimated under numerous assumptions. The quantity changes in the adopted materials and fuels due to wastage, reconstruction, and unexpected events in the construction site may suffer from a high level of uncertainty, thereby underestimating the actual GHG emissions. Furthermore, the emission factors lack the consideration of regional diversity and case-specificity, which has weakness in technical and geographical representativeness to reflect the current GHG emission status in China. Although the carbon emissions generated from the construction practice have been extensively studied in China, no uniform, authoritative, and official emission factor database applicable for such context has been established. The major barriers for regional specific data measurement include the complexity of geographical conditions, the variation in climate zones, and the differences in manufacturing technologies. Therefore, the corresponding strategies that can holistically mitigate the

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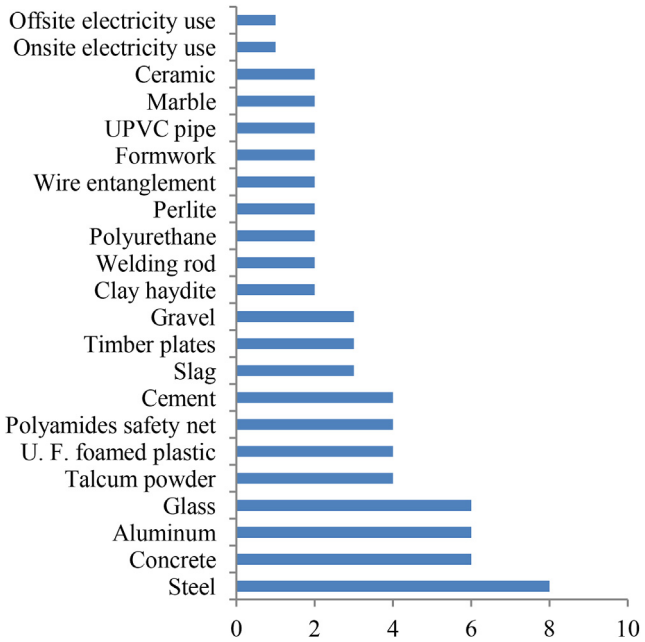


Fig. 3. Frequency of occurrence for key construction activities in 12 scenarios.

international emission factors to extrapolate GHG emissions generated from the target building to establish a general situation to examine the effect of data geographic representativeness on the accuracy of final results. However, the overdependence of international data has a disadvantage in reflecting the real situation of GHG emission status in China's construction industry. Therefore, to reflect the real transition of China's building emission patterns, this study collected emission factors for primary construction activities based on the data measured and estimated in the context of China (see Table 9). The results show that the target building generated 8962.3 tonnes of CO_2e to 9491.3 tonnes of CO_2e according to different data sources collected in Table 9 that is 2.1%–8.1% higher than the deterministic result and 1.9%–8.0% higher than the mean value of MCS. Such fluctuation of value is still consistent with the CV (9.8%), demonstrating the validity of the uncertainty analysis framework developed in this study. Most importantly, the total amount of emissions estimated according to China's construction practice is higher than the international level, implying the importance of using localized emission factors.

Third, besides the geographic uncertainty at the international level, intra-national difference has also been emphasized in previous studies (Williams et al., 2009). Such variation is exaggerated in China owing to its imbalanced regional economic development. A promising solution is to identify the major material supply regions according to the material flows in the upstream supply chain of China's construction industry (Hong et al., 2016b). Therefore, the focus of concern can be narrowed into only several typical resource-supply regions, allowing the leading authority to establish an emission factor database by only investigating the resource-abundant suppliers.

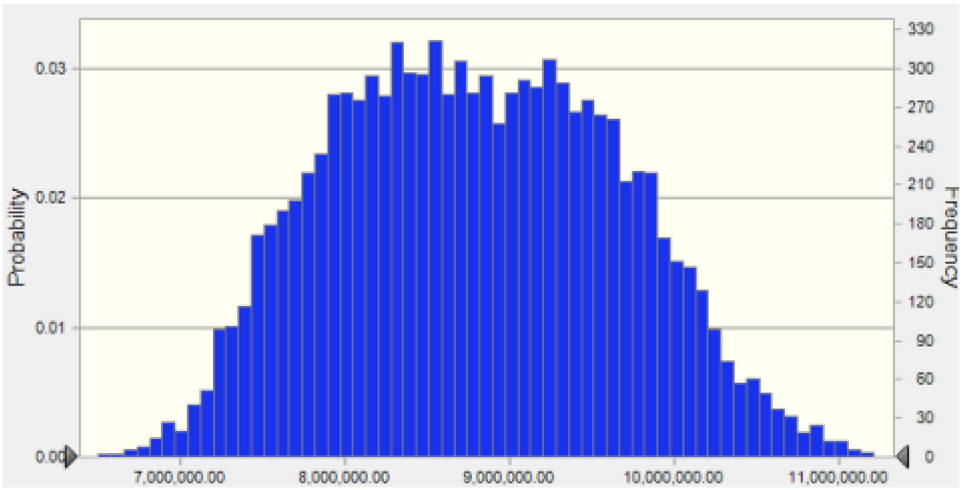


Fig. 4. Monte Carlo simulation result for total GHG emissions.

uncertainty that emanates from building construction should be developed and implemented.

First, to address the temporal uncertainty during assessment, the validity of time period applicable for the corresponding analysis should be indicated. The length of valid time is critical because the assessment result with a short temporal validity reinforces the accuracy level under the current production technology but restrains the future use of such study. Therefore, one compromise for such dilemma is to integrate the national average data from I–O analysis into a process-based model. In this situation, the result can include the case-specific information on actual material inputs and the emission outputs of unit primary process, and it can also reflect the national technology progress in a fixed period.

Second, the national level variations during production may be caused by the different levels of technology and economic development. Therefore, such discrepancy can be reduced by using region-specific production data. For instance, this study utilizes the

Fourth, given a high level of uncertainties generated from data measurement, adopting a precast construction or an industrialization building system is an effective means to improve data accuracy. Compared with conventional construction technologies, prefabrication provides a standard, resource-efficient, and modular construction process that can not only minimize the waste and resource depletion during manufacturing but also reduce reconstruction and unexpected events in the construction site (Hong et al., 2016a). As such, the preliminary estimation of the material inventory flow through the bill of quantity can relatively reflect the actual materials used during building construction.

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Table 8
GHG emission intensity obtained in previous research.

Source	Location	Building type	Structure	Gross floor area (m^2)	Assessment model	GHG emissions (tCO2e/m2)
Xing et al. (2008)	Shanghai	Office	RC	34,620	Process-based	0.606
			SF	46,240		0.315
Wu et al. (2012)	Dalian	Office	RC	36,500	Process-based	0.803
Wang et al. (2016)	Shenzhen	Office	RC	25,023.9	Process-based	1.183
Yan et al. (2010)	Hong Kong	Commercial	RC	43,210	Process-based	0.525
Mao et al. (2013)	Shenzhen	Residential	FSS	216,000	Process-based	0.348
Liu et al. (2009)	Beijing	Residential	FSS	35,356	Process-based	0.374
	Beijing	Residential	FSS	33,290		0.49
	Beijing	Office	RC	91,371		0.541
Gao (2012)	Jiangsu	Residential	FSS	5644–28032	Process-based	0.326
	Jiangsu	Residential	RC	1176–8809		0.273
Yao (2013)	Wuhan	Office	RC	5712–41260	Process-based	0.271–0.48
Chang et al. (2016)	China	Urban Residential	–	–	I–O based	0.260
		Office				0.320
Present study	Guangzhou	Residential+ commercial	RC	11,508	Process-based	0.645–0.887*

Note: "RC" represents the reinforced concrete frame; "SF" represents the steel-framed structure "FSS" represents the frame-shear wall structure; "*" represents that this result was obtained with the confidence interval of 90%.

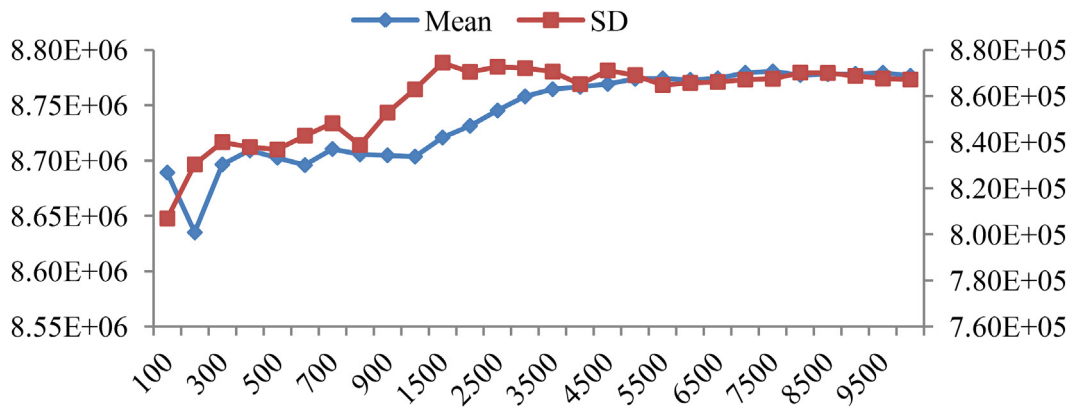


Fig. 5. The trend of convergence of mean and SD for the total GHG emissions.

Table 9
Emission factors collected in the context of China.

	Unit	Emission factor	Data source
Onsite construction equipment use			
Diesel	kgCO2/kg	2.17–3.78	[1]–[7]
Onsite electricity use			
Electricity	kgCO2/KWh	0.700–0.953	[1]–[7]
Onsite water use			
Water	$kgCO2/m^3$	0.259–0.414	[3]–[5], [7]
Transportation			
Road transportation	kgCO2/tkm	0.159–0.227	[1], [3], [5], [6]
Materials production			
Steel	kgCO2/kg	1.33–2.60	[1]–[7]
Concrete	$kgCO2/m^3$	251–425	[1]–[7]
Cement	kgCO2/kg	0.698–1.035	[1]-[7]
Aluminum	kgCO2/kg	26.0–29.8	[1]–[5]
Glass	kgCO2/kg	1.10–2.82	[1]–[7]
UPVC pipe	kgCO2/kg	4.65–4.70	[1], [3], [5]
Gravel	kgCO2/kg	0.002	[4], [5]
Ceramic	kgCO2/kg	0.740	[1], [3]–[5]

Source: [1] Liu et al. (2009); [2] Li (2010); [3] Gao (2012); [4] Yao (2013); [5] Wang et al. (2016); [6] Yan et al. (2010); [7] Mao et al. (2013).

7. Conclusions

This study develops a multi-method-based uncertainty analysis framework and quantifies the uncertainty associated with GHG inventories in building construction in China. This framework integrates the deterministic and probabilistic approaches to facilitate the uncertainty assessment in quantifying carbon emissions and to provide insights into the sensitive construction activities from the uncertainty perspective. Based on the uncertainty analysis framework and case study, four important findings of this study are listed as follows:

(1) The uncertainty in measurement method and geographic representativeness is considered the major uncertainty source for elementary flow estimation and emission factor collection during building construction.
(2) The total GHG emissions obtained from the analytical framework for the target building was 8791.5 tonnes of CO_2e with a CV of 9.8%, which was in line with the result calculated by the deterministic method and the result extrapolated based on the data collected from China.
(3) Apart from the sensitive parameters explored in the traditional uncertainty analysis, the result of the scenario analysis showed that aluminum, glass, slag, timber, and gravel are also important, especially considering the effect of their uncertainty (>19%).
(4) According to the parameter coordinate in the scenario analysis, the proportion of 1% in contribution analysis and the CV of 18% in uncertainty analysis can be regarded as the baseline for determining the critical input parameters. Under this assumption, steel, concrete, talcum powder, U. F. foamed

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plastic, polyamide safety netting, cement, aluminum, and glass are the key parameters that should be given due attention.

This study can reinforce the importance of measuring uncertainties in LCA studies and can avoid the misinterpretation of the final results during the decision-making process. In addition, the integration of qualitative and quantitative assessment methods provides a possible solution for assessing the uncertainty of LCA studies in the construction practice. This method also provides a sufficient understanding on the uncertainty related to building construction. Moreover, this study identifies the critical parameters that influence the GHG emissions during building construction in the context of China. However, it should be noticed that insufficient number of construction projects was investigated in this study. Future studies should be conducted to validate the developed uncertainty analysis framework through investigating various types of construction projects around the world.

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