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The Impact of Life Cycle Assessment Database Selection on Embodied Carbon Estimation of Buildings

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Abstract

Reliable and accurate carbon assessment of a building is becoming more important along with carbon neutrality goals. Although various life cycle assessment (LCA) databases have been adopted for assessing buildings' embodied carbon emissions, the results displayed inconsistent and the reasons behind the differences were not well revealed. This study aims to identify the main factors contributing to the inconsistencies by systematically analyzing 20 databases, and to explore their numerical influences at the three levels of buildings' products, i.e., materials, components and flats. Through a comprehensive evaluation using a four-principle framework, the results showed that ecoinvent, AuLCI, and Global Digital EPD performed well in flexibility, comprehensiveness, transparency, and uniformity. The quantitative results at the three levels of the cases indicated that the influences of different databases would be greater for evaluating a material compared with a more comprehensive building product (e.g. component or flat). It also concluded that the emission factors of steel should be selected carefully compared with other materials. Further, the analysis of the qualitative causes based on the four-step LCA framework emphasized the importance of clarifying the background information and selecting the proper database at the initial step of conducting carbon assessment. By developing a systematic construct including both qualitative and quantitative approaches revisiting the reasons causing inconsistencies by LCA databases, this study facilitated a better way for both professional and non-

professional users to select a more suitable carbon assessment database according to their purpose.

Keywords

Embodied Carbon, Life Cycle Assessment (LCA), Database Selection, Prefabrication

1. Introduction

Embodied carbon (EC) generated from material production, transportation and construction phases of buildings has drawn increasing attention in recent years [1], since EC exerts intensive and considerable impacts in a short period of time, which is regarded as a new spotlight for research [2]. In addition, buildings are to blame for over 37% of global energy use in IPCC AR6 report, suggesting predominant influences on climate change [3]. To better evaluate the EC of buildings' materials and products, many life cycle assessment (LCA) databases have been developed. Compared with other products, buildings' construction consists of different types of materials and consumes many fuels, which are more sensitive to background data selection. The reliability of the selected databases is, therefore extremely vital to ensure accurate EC results.

Although more than 20 databases can be applied to the construction industry, several challenges still exist. LCA databases are usually developed by an organization located in a specific country or region, and the modeled carbon emissions are based on their manufacturing and construction industry structures [4]. Each database has different features in its functionality, assumptions, life cycle stages, data quality, and modeling principles [5–7]. Therefore, it may result in a failure in carbon assessment if an unsuitable database or an incorrect dataset is selected. For example, a study conducted by Brogaard et al. [8] indicated that the highest and lowest estimated carbon emissions from the primary production of steel could be as high as 1761% by using different datasets. In addition, some databases (e.g., ICE and Korea LCI) only focus on the cradle-to-gate scope, thus omitting the analysis of other stages of a building.

To better reflect the influences of different LCA databases, some studies have been conducted to compare them using specific case buildings [9,10]. Their results commonly indicated significant inconsistent assessment results when more than one database was used. For example, Mohebbi et al. [11] proposed that 35.2% deviations in carbon assessment results could be caused using ICE and UK EFDB. Takano et al. [12] compared the assessed carbon emissions and methods of three buildings using GaBi and ecoinvent 3.0 databases. The results identified that up to 183% differences could be caused among these databases regarding wood fiber board. However, a direct comparison of the calculated results is debatable, as it failed to reveal the real reasons leading to the inconsistencies. Different databases consist of data collected from various sources and are based on different calculation methodologies, thus affecting the calculated results from different aspects [13].

Some studies have thus explored the reasons behind the inconsistent results by different databases through a comprehensive literature review [14–16]. They proposed that factors such as geographical and technological representativeness, documentation transparency, data completeness, system boundaries, and allocation methodologies may be affectable. However, these factors were usually identified randomly, and the numerical influences were ignored. Pure qualitative examination thus may fail to reflect how and the extent of different factors affect the final carbon results. In addition, different databases usually cover different numbers of datasets for a specific type of material. For example, Probas provides more than 300 emission factors for different types of metal materials, whereas ICE has a wide range of datasets of cement and concrete, which is more suitable to be used for assessing concrete buildings. It thus affects the end-users behaviors to select a more suitable database according to the purposes, scopes, and objects of a study. However, current studies seldom provide such guidance.

Therefore, this paper aims to identify the main factors contributing to the inconsistencies of 20 LCA databases for buildings in a systems manner and to explore their numerical influences on the carbon emission values at the three levels of buildings' products, i.e., materials, components, and flats. Based on a document analysis, databases and their corresponding datasets that could be used for assessing buildings' carbon were collected. The differences among these LCA databases were clearly identified through a comprehensive literature review and analyzed using a systematic framework integrating four principles of flexibility, comprehensiveness, transparency, and uniformity. Numerical influences of these factors on the carbon values of typical high-rise public residential buildings' products were calculated. The reasons behind the variations in results were investigated following the typical four-step LCA process. The paper finally discussed the results and provided practical suggestions to assist end-users in the selection of a suitable LCA database in accordance with their needs.

2. Literature review

In the past decades, over 100 LCA databases have been adopted by different industries, and more than 20 of them have been applied to the building industry. A few studies thoroughly reexamined the existing LCA software, offering readers an overall and informative introduction of these tools for readers' reference [2,17,18]. Some of these studies have thus been developed to compare the carbon evaluated from different databases. Most studies have taken the Gabi and ecoinvent databases as examples due to their wide applicability and flexibility, as well as the abundant datasets [19]. Other databases, such as Gabi, ecoinvent, IBO, CFP, and Synergia database [20], ICE, CLCD, Japan CFP, and Korea LCI database [21], the product-specific database, i.e., EPD [22], Excel-based environmental assessment tool ELP-s [23], Umberto and openLCA [24], UK EFDB and ICE [25], USDA LCA Digital Commons, Carnegie Mellon, BEES (NIST), and Embodied Carbon Calculator for Construction (EC3) [26] have been thoroughly examined. Their results indicated significant inconsistencies existed in the assessed carbon results.

Many studies thus called for action to examine the reasons for the variations. The most widely used method is to compare materials' carbon evaluated by a number of databases and then discuss their differences. The main reasons summarized in these previous studies can be seen in Table 1. Many of them were blamed on the inconsistent energy mix and material production processes or technologies in different databases, as these databases were developed under the background of different industry structures and construction environments in a nation or region [12,22]. For example, databases in a reference country using more renewable energy (e.g., natural gas and biomass) for electricity generation would display a lower carbon emission factor. The study conducted by Brogaard et al. [27] demonstrated that the raw materials used, recycled content, and processes were the main determinants of the variations in carbon emission factors. For example, using the electric arc furnace for steel production could generate less carbon compared with adopting the basic oxygen furnace. Therefore, the technical and geographical representativeness determined the need for a local database in every nation [28]. A more flexible and transparent database thus can have higher applicability since the end-users can adjust the LCI datasets (e.g. the electricity mix, transportation distance, and raw materials used) according to their situations [29]. In addition, the scarcity of specific datasets in some databases also led to variations in results as substitution by similar ones is needed [12]. For example, there is only one dataset of general concrete without specifying the strength class; thus, it is the only choice when calculating the emissions of concrete. Some databases lack regular updating, transparent scope definition, and clear rules and standards, which show less reliability compared with others [24]. Among a bundle of factors, the misuse of database due to lack of expertise knowledge is also a main concern, and even skilled users can overlook the potential errors while estimation [30]. As the third step of conducting LCA, a number of studies also proposed that different life cycle impact assessment (LCIA) methods could bring deviations in results, thus might lead to different evaluations for the same product. In the study of Hauschild et al. [31], extant 91 models belonging to 12 LCIA methods were evaluated using criteria from both scientific quality and stakeholder acceptance aspects. Their findings demonstrated that there were uniform characteristic models and factors for LCIA. Similar conclusions have also been proposed by Chen et al. [32], who compared the LCI dataset of 1 kg of aluminum in the USLCI database and emphasized that the coverage and values of substances also varied significantly in different LCIA methods. To further examine how different LCIA methods affect climate change, Bueno et al. [33] conducted a sensitivity analysis of four LCI datasets using EDIP 97/2003, CML 2001, Impact 2002+, ReCiPe, and the ILCD methods. Their results demonstrated that although slight differences were observed in some datasets, most of them presented consistency in assessing the global warming potential (GWP) caused by a product's activities. The authors suggested that the latest version of LCIA was always the most appropriate for LCA studies. As for LCA tools integrating several different databases, Herrmann and Moltesen [9] compared Simapro and Gabi from three levels, i.e., inventory level, LCIA method level, and unit process level. The results show that elementary flow, the LCIA method used, and the characteristic factors on the same substance between Gabi and Simapro are the major causes of inconsistencies.

Some indicators are also proposed to further examine the extent of the inconsistencies. For example, Silva et al. compared the deviations of four LCA software using the relative dispersion indicator [24]. Takano et al. [20] applied both relative standard deviation (RSD) and percentage relative differences (PRD) to indicate the inconsistency of results in a numerical way, while Silva et al. [24] used RSD to show the extent of differences. In addition, in terms of comparison with a benchmark database, the relative difference was also considered a proper indicator [25]. The results indicated that the difference in background datasets, characteristic factors, and lack of rules and standards are the primary reasons leading to the discrepancies between different databases.

Although these studies paid an important foundation for recognizing the main reasons for the inconsistent results evaluated by different databases, many of factors were identified randomly. There is still a lack of systematic understanding of the reasons and their numerical influences on the final results.

Table 1. Main factors explaining the inconsistency of LCA databases

No.	Factor	Sources
1	Data amount/ data scarcity/substitution of generic datasets	[20,34]
2	Characterization model/LCIA method	[9,30]
3	Allocation rules	[35]
4	Data documentation	[36]
5	Data sources/traceability	[37,38]
6	Location for case data/nation of data/different industry structures in different nations	[34,37,39]
7	Technical scope/assessment scope differences/whether transportation is included	[34,37]
8	Regular updating	[37]
9	Contextualization/flexible adjustment/customizable	[37,38]
10	Accuracy/verification procedure for data	[37]
11	The energy mix for electricity generation	[39]
12	The different mix of raw materials	[30,34]
13	Application of different equipment or machines	[40]

14	Utilization of different types of fuels	[41]
15	Recycled or secondary content or material	[36]
16	Background database	[34,37]

3. Methodology

The overall analysis framework for achieving the research objectives includes typical three steps of research design proposed by Creswell [42], namely data collection and processing, data analysis, and case study. Through detailed document analysis, databases that could be applied to the construction industry and the major construction materials were collected. Normalization of the materials' composites, units of measure, and the included gases was conducted for more efficient comparisons. In the second step, with the reasons causing the inconsistency of different databases identified in section 2, an overall analysis was conducted using a four-principle framework. Followed by a three-level comparative analysis, the numerical influences of these reasons were figured out. In the third step, along with the typical four-step LCA process, the typical high-rise public residential buildings' products in Hong Kong were taken as case studies to examine how different factors affect the final results at different levels in practice. The methodology this study adopted can be seen in Figure 1.

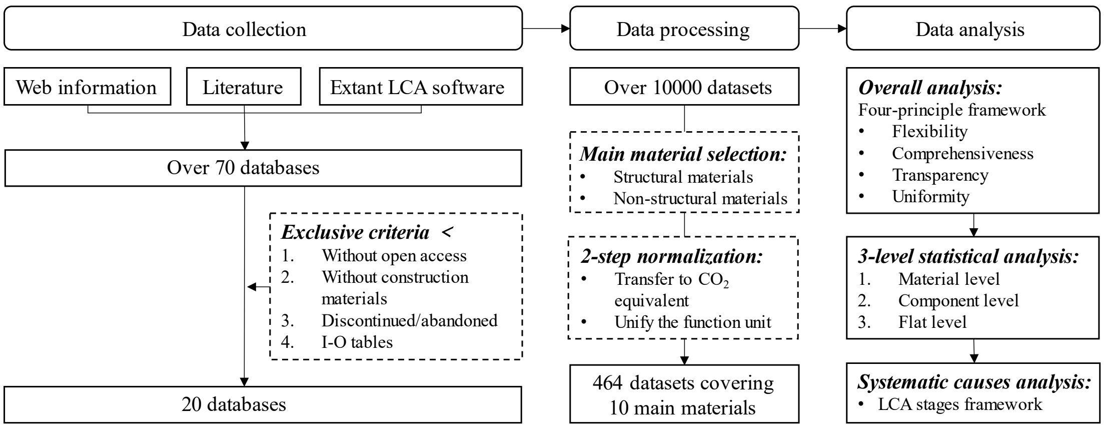


Figure 1. A framework of the methodology

3.1 Data collection and data processing

Starting from collecting the 53 databases provided by Greenhouse Gas Protocol (ghgprotocol.org), more databases were included through a comprehensive literature review, web searching as well as extant LCA software such as openLCA and Simapro. To better analyze the carbon from the construction industry, databases under the following criteria were excluded: 1) databases without open access (except for Simpro, since the authors have a paid license); 2) databases without providing construction materials; 3) discontinued or abandoned databases; 4) databases only adopting the input-output method that focuses on economic indicators. As a result, a total of 20 databases were collected as samples, which are presented in Table 2. Each of the databases embeds a number of datasets and can be modeled by different LCIA methods (e.g., IPCC 2013 GWP100a, CML 2001) according to the end-user's purposes. These datasets are calculated based on material production activities or collected from industry reports, journal papers, and conference papers. Taking the ICE database as an example, the emission factors of steel products were collected from reports of World Steel, while concrete emission factors were modeled from journal articles. Similarly, China PCF, CPM database, and Probas collect data from academic papers. Further, databases including Korea LCI, USLCI, milieudatabase (Netherlands), ÖKOBAUDAT (Germany), and GB/T 51366-2019 (China) encompass national emission factors from governmental sources.

To better compare the influences of different databases on construction materials, ten types of materials were selected for detailed comparison. Both structural materials (e.g., cement, aggregates, concrete, steel, bricks, and blocks) and non-structural materials (e.g., paint, insulation, glass, wood, and aluminum) were included. Materials with alternatives were considered as different ones. For example, ordinary portland cement (OPC) should be compared separately with CEM II-A-S - 13% GGBs. To enhance the comparisons, a two-step normalization process was conducted. First, the different functional units of the same material were normalized to the most commonly used ones. Second, the pure gas emission of datasets from IPCC EFDB was transferred into into CO_2 equivalent based on the equation provided by the IPCC AR5 report [43]. Finally, a total of 464 datasets covering ten materials were collected for further comparison. Table 3 shows the specific materials selected, the normalized units, the density, and the numbers of normalized datasets.

Table 2. Overview of LCA databases on construction materials

No.	Database	Region	Organization	Method	Latest update year	Access	Sources	Technical scope for construction materials
1	AusLCI (Australian National Life Cycle Inventory Database)	Australia	Australian Life Cycle Assessment Society (ALCAS)	Best Practice Guide for Mid-Point Life Cycle Impact Assessment in Australia ALCAS Impact Assessment Committee	-2022	Embedded in Simapro/ Free download of data from homepage	Process-based model	A1-A3, D [d]
2	CIC.CAT (CIC Carbon Assessment tool)	Hong Kong of China	Construction Industry Council	-	-	Online calculation tool	-	A1-A3, D [b]
3	CPM LCA Database	Sweden	the Swedish Life Cycle Center	EDIP 1997	-	Online calculation tool	Industry reports, journal papers and conference paper	A1-A3, A4 [d]
4	Digital Environmental Hub for Global Construction Products	International	UKCoMDat ESCoMDat ITCoMDat TurCoMDat NordCoMDat EUCoMDat GloCoMDat	-	-2022	Free browsing at website	EPD supplier	A1-A3, A4, C1-C3, D [d]
5	ecoinvent database	International	Ecoinvent Association	IPCC 2021 GWP100	-2022	Embedded in Simapro	Process-based model	A1-A3, A4, D [a]

6	Environmental Footprint (EF) database	International	European Commission	Environmental Footprint (Mid-point indicator)	2019	Free download of data from openLCA	Process-based model	A1-A3, A4, D [b]
7	EPD (Environmental Product Declaration)	International	EPD International AB	EN 15804+A2 (2019)	-	Free browsing at website	EPD supplier	A1-A3, A4, C1-C3, D [d]
8	ETH-ESU 96	-	Environmental Consultancy for Business and Authorities	IPCC 2021 GWP100	-2010	Embedded in Simapro	Process-based model	A1-A3 [b]
9	GB/T 51366-2019 Standard for calculating building carbon emissions	China	the Ministry of Housing and Urban-Rural Development of China	-	2019	Free download of data from homepage	Governmental standard	A1-A3 [a]
10	ICE (The Inventory of Carbon and Energy)	UK	University of Bath	Meta	-2019	Free download of data from homepage	industry reports, journal papers and conference paper	A1-A3 [a]
11	IDEMAT (Industrial Design & Engineering Materials database)	Netherlands	the Sustainable Impact Metrics Foundation, SIMF of the Delft University of Technology	IPCC 2021 GWP 100	-2020	Embedded in Simapro	Industrial reports (Plastic Europe), Journal papers, process-based model	A1-A3 [a]

12	IPCC EFDB (Database on Greenhouse Gas Emission Factors)	International	Intergovernmental Panel on Climate Change	Pure gas emission	-2020	Free download of data from homepage	industry reports, journal papers and conference paper	A1-A3, A4 [d]
13	Korea LCI DB	Korea	The Korea Environmental Industry & Technology Institute (KEITI)	-	2002	Free browsing at website	-	A1-A3 [d]
14	milieudatabase		Environmental Policy Committee (MBG) & Technical-Content Committee (TIC)		-2022	Free browsing at website (when collecting)	-	A1-A3 [b]
15	ÖKOBAUDAT (OBD)	Germany	German Federal Ministry of the Interior, Building and Community (BMI)	EN 15804+A2 (2019)	2021	Free download of data from homepage	Governmental reports	A1-A3 [b]
16	OzLCI (Evah OzLCI2019 Free Database)	Australia	The Evah Institute	IPCC 2013 GWP 100a	2019	Free download of data from openLCA	-	A1-A3, D [d]
17	Probas (Process-oriented basic data for environmental	Germany	The Federal Environment Agency and the International	-	-	Free browsing at website	Industry reports, journal papers and conference	A1-A3, D [d]

	management systems)		Institute for Sustainability Analyses and Strategies (IINAS)				paper	
18	UK EFDB (UK Government GHG Conversion Factors for Company Reporting)	UK	Department for Business, Energy & Industrial Strategy Department for Environment Food & Rural Affairs	IPCC 2013 GWP 100a	2022	Free download of data from homepage	Governmental reports	A1-A3, D [a]
19	USLCI (U.S. Life Cycle Inventory Database)	US	National Renewable Energy Laboratory (NREL)	IPCC 2021 GWP 100	-2022	Embedded in Simapro	Governmental reports; Process-based model	A1-A3, A4, D [a]
20	China Products Carbon Footprint Factors Database	China	China Urban Greenhouse Gas Working Group	IPCC 2021 GWP 100	2022	Free download of data from homepage	Journal papers and conference paper	A1-A3, D [a]

Notes: the source of the technical scope of the focal database is: a. the systematic documentation of the database in question; b. literature; c. the introduction of GHG protocol website; d. the knowledge of the authors based on dataset documentation.

Table 3. The units, densities and sources, and numbers of normalized datasets

Material	Specific product	Unit	Density	Sources of density	Numbers of normalized datasets
Aggregates	Aggregate and sand [i]	$kgCO_{2e}/t$	$1680kg/m^3$	[44]	50

	Limestone [iii]				
Aluminum	Primary aluminum Secondary aluminum Aluminum alloy	$kgCO_{2e}/kg$	Only mass units conversed	-	15
Bricks and blocks	Clay bricks Concrete blocks	$kgCO_{2e}/kg$	$950kg/m^3$ $1680kg/m^3$	[45,46]	13 for bricks 18 for blocks
Cement	Ordinary Portland Cement (OPC) Cement [ii]	$kgCO_{2e}/kg$	Only mass units conversed	-	24
Concrete	C30 concrete C50 concrete Normal concrete [iii]	$kgCO_{2e}/m^3$	$2380kg/m^3$	[47]	10
Glass	Flat glass Tempered glass Glass [ii]	$kgCO_{2e}/kg$	Square measures were all excluded and only mass units conversed	-	12
Insulation	Mineral wool Polystyrene Insulation [ii]	$kgCO_{2e}/kg$	Square measures were all excluded	-	0
Paint	Paint	$kgCO_{2e}/kg$	Square measures were all excluded	-	0
Steel	Rebar Steel [ii]	$kgCO_{2e}/kg$	Only mass units conversed	-	27
Wood	Plywood Wood [ii]	$kgCO_{2e}/kg$	620 kg/m3	[47]	14

Note: i. Aggregate and sand cover products of sand, aggregates, and aggregate and sand.
ii. If a database only contains the normal product, such as cement, glass, insulation, steel and wood, these products were selected to be the substitute for the specific product.

iii. As no aggregates were included in ecoinvent, limestone, gravel, and sand were selected as a substitution.

3.2 Data analysis

3.2.1 Overview of databases

To further evaluate and compare the databases, a four-principle evaluation framework which included flexibility, comprehensiveness, transparency, and uniformity was adopted. This framework was established based on the principles of LCA in ISO 14040 [48] and ecoinvent data quality guidelines [49]. The flexibility of a database determines its wide applicability of the databases to different cases and regions [37]. The comprehensiveness explains the abundant materials covered to meet the requirements of more end-users [20]. De Wolf et al. [34] also highlighted the importance of data coverage by criticizing the potential hinder that data scarcity and wide ranges cause. In addition, the transparency of datasets in a specific database improves its comparability and functionality. Moreover, the uniformity of a database indicates the consistency of datasets, providing users with stable emission factors for carbon calculations [49]. We grouped the 16 factors in section 2 into the four principles, to explore the data quality of each database. The principles, factors, and detailed evaluation rules are presented in Table 4.

Table 4. Evaluation rules of LCA databases

Evaluation principle	No.	Factors affecting emission factors	Evaluation rules
Flexibility	(1)	Flexible adjustment/ contextualization	0: fixed emission factor/pure gas
	(2)	LCIA method selection	1: partly flexible 2: totally flexible
Comprehensiveness	(3)	Alternative raw materials	0: less than the lower quartile of average amount
	(4)	Recycled materials	2: more than the upper quartile
	(5)	Alternative Equipment	1: others
	(6)	Regular updating	0: stop updating 1: update irregularly 2: update regularly
	(7)	Data amount	0: less than the lower quartile
	(8)	Nation(s) of data	of average amount 2: more than the upper quartile 1: others
Transparency	(9)	Fuel types	0: unable to see 1: partly traceable 2: all the fuels used can be

			traced
	(10)	Data documentation	0: no attached document 1: simple explanation of the dataset 2: detailed documentation
	(11)	Data accuracy (verification)	0: unknown 1: peer or industry reviewed 2: EPD or verified LCI datasets
	(12)	Characteristic factors	0: fixed emission factor/pure gas emission 1: only suitable for specific LCIA method 2: transparent characteristic factor suitable for multiple LCIA methods
Uniformity	(13)	Background database	0: unknown 1: no unified background data 2: unified background database
	(14)	Energy mix for electricity generation	0: unknown 1: no unified energy mix 2: unified energy mix
	(15)	Data sources	0: unknown 1: no unified data sources 2: unified data sources
	(16)	Technical scope	0: unknown 1: no unified technical scope 2: unified technical scope

3.2.2 A three-level comparative analysis for examining the numerical differences

To identify the reasons leading to the inconsistent carbon results among different databases and quantify their numerical differences, a three-level comparative analysis (i.e., materials, components, and flats) was conducted. The comparison at the material level initially presents the statistical characteristics, providing an overall observation on the data range of different products of the same material. Then, the carbon of selected components and flats would be calculated using the databases collected. Therefore, their influences on LCA results should be different under varied spatial levels. To better reflect their numerical influences on the carbon results at the three levels. The percentage of relative differences (PRD) (Equation (1)) is selected as the indicator to quantify the deviations between results from various databases.

$$PRD = \frac{Carbon_x - Carbon_{ref}}{Carbon_{ref}} \times 100\% \quad (1)$$

where $Carbon_x$ is the carbon emissions calculated by the database in question ($kgCO_{2e}$), while $Carbon_{ref}$ is the carbon emissions calculated by the reference database ($kgCO_{2e}$). In this paper, the ecoinvent database was selected as the reference database for its comprehensiveness in material types and wide applications in various nations [26,50]. Among these databases, ecoinvent, ICE, EF Database, and GB/T 51366-2019 provide generic datasets, while EPD and Global Digital EPD encompass product-specific datasets. Therefore, their influences on LCA results should be different under varied spatial levels, because flats aggregate several components and combines more materials than components and a single kind of material.

3.2.3 A systematic qualitative investigation of causes leading to the inconsistencies

Considering the randomness and incompleteness of analysis in previous research, this study adopted a framework of a typical four-step LCA process provided by ISO 14040 series, guides and instructions [51–53] to investigate the causes leading to inconsistencies of carbon results. The typical LCA process consists of four steps, including goal and scope definition, inventory analysis, impact assessment, and interpretation, along with the three other steps simultaneously [54]. In the first step, the initial information, such as audience, impact categories and process and production information, was clarified [55]. Then in the second step, according to the requirements of process and production, data were collected and gathered. In the third step, classification based on the specific impact categories defined in the first step was conducted, followed by normalization and weighting processes [54]. The final step was the elaboration of the conclusions, limitations, recommendations, etc.

3.3 Case study

Typical public residential prefabricated building products in Hong Kong were selected for conducting the case study. From July 2013, four types of Modular Flat Design (MFD) for public housing developments (i.e., 1P/2P, 2P/3P, 1- Bedroom (1B), and 2-Bedroom (2B) flats) have been adopted in all public rental housing (PRH) developed by Hong Kong Housing Authority (HKHA). Each flat consists of a range of standardized precast components (e.g., Precast Façade, Staircase, Panel Wall, Semi-precast Slab) and a series of materials that stand for the status quo of the main products used in high-rise public residential housings in Hong Kong. The selected products can therefore be seen in Figure 2. They were selected due to their representativeness, accessibility, and informativeness.

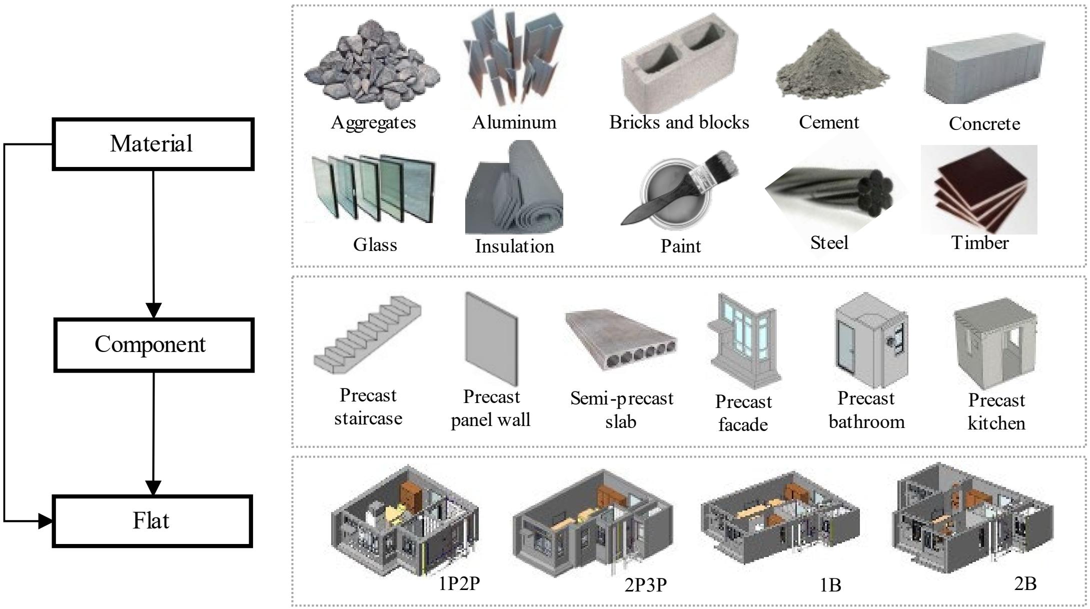


Figure 2. The three-level prefabricated building products selected for the case study

4. Results and analysis

4.1 Overview of databases

The selected 20 databases displayed different levels of detail even for the same materials, as shown in Figure 3. The number of datasets provided by a database indicates the precision of the database. For instance, ecoinvent provides both crushed and round gravel, while EF database only includes gravel of production mix. The higher data density of the specific materials shows a wider range of choices while calculating a component with special designs. Ecoinvent provides more selection of insulation, concrete and aggregates from different locations and is supplied by different manufacturers. In contrast, some databases only have one or two alternative emission factors of a material, such as China PCF, EF database and GB/T 51366-2019. What is also noteworthy is that AusLCI and Global Digital EPD cover almost all of the main materials in construction activities, while CIC.CAT, milieudatabase and OBD simply have one or two types of materials. Especially, USLCI does not provide datasets of steel and concrete.

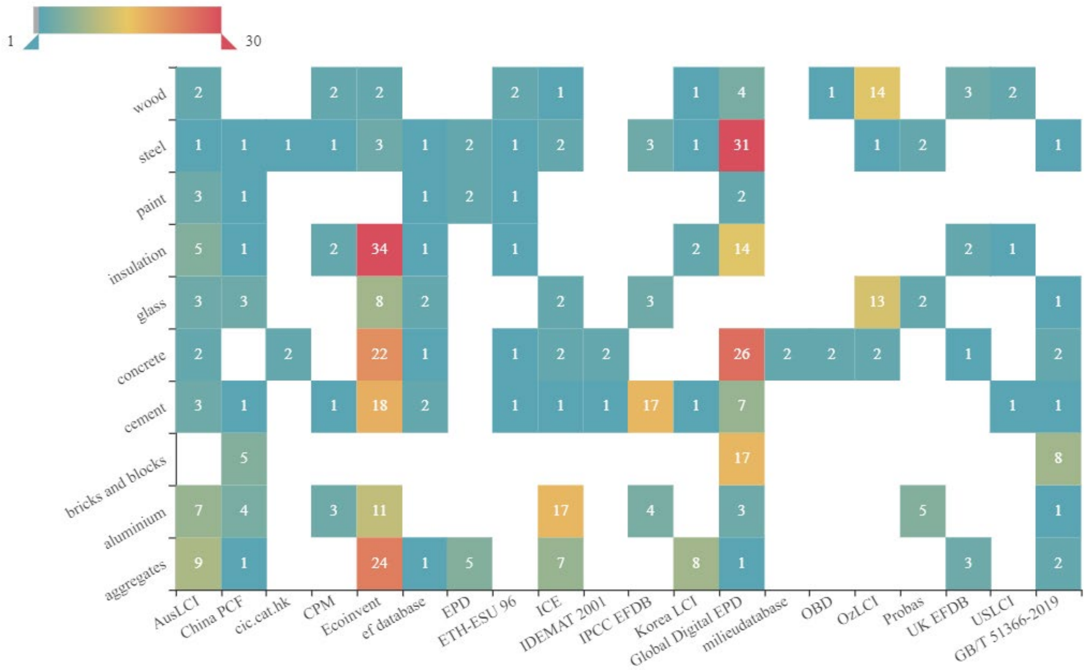


Figure 3. Heatmap of the materials in the 20 databases

The evaluation based on the four-principle evaluation framework is shown in Figure 4. In general, most databases show drawbacks in one or two dimensions (basically completeness and flexibility), except 6 databases got low scores in all four perspectives due to the lack of data. Among all the databases, ecoinvent gets the highest score in all of the four aspects, displaying excellent performance in flexibility, comprehensiveness, transparency, and uniformity. Following are AusLCI and OzLCI, with both slightly weaker in comprehensiveness and uniformity. Databases including CPM, EF database, and Global Digital EPD show a balanced performance, without either a specifically excellent or an especially terrible performance in any aspect. Taking EF database as an example, it achieves flexible and transparent but fails to have unified data documentation. Several databases have displayed weakness in flexibility, such as China PCF, EPD, IPCC EFDB, Korea LCI, milieudatabase, OBD, UK EFDB, and GB/T 51366-2019. Those databases provide unchangeable emission factors, lacking flexible alternations to different LCIA methods and contextualization. In addition, the lack of transparency for unknown dataset sources is the main weakness for the ICE database. Some databases, such as USLCI and IDEMAT, provide a small number of alternative datasets for the same kind of materials, therefore, get a lower score in comprehensiveness. Notably, a range of databases presents a very low score in total, such as CIC.CAT, Korea LCI, milieudatabse, OBD, UK EFDB, and GB/T 51366-2019, with at least 10 items to be 0. These databases are easy for a non-professional user, but not suitable for a comprehensive carbon assessment.

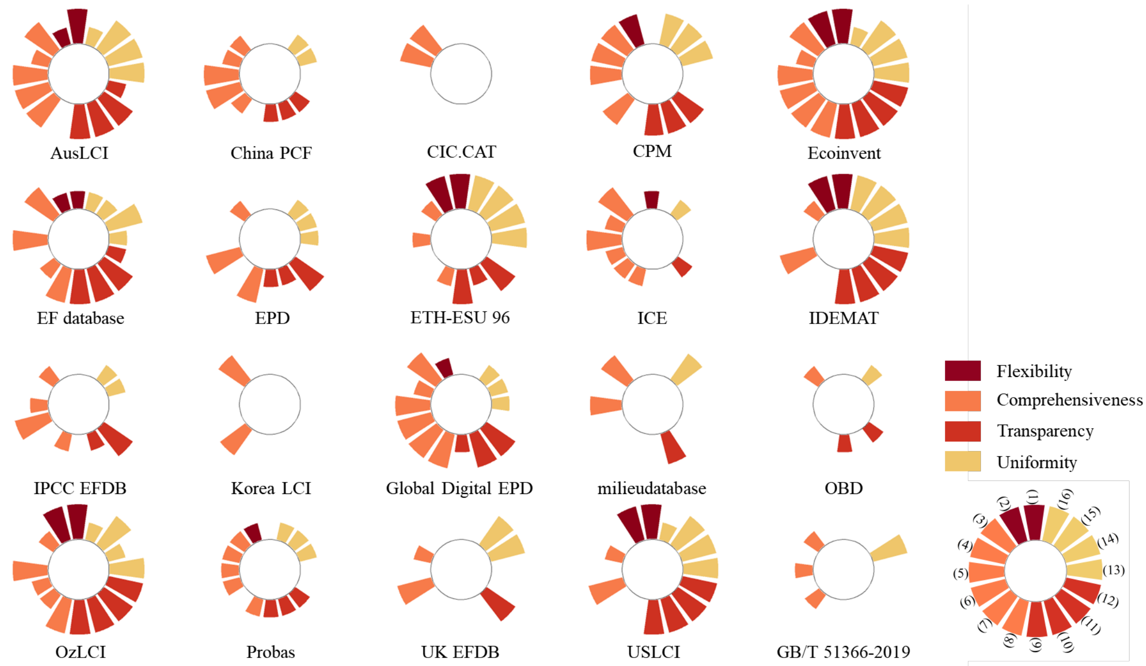


Figure 4. Results of overall analysis based on the four-principle framework

Note: each of the columns represents an evaluation rule according to the serial number

4.2 Material-level comparison

The selected 20 databases were compared by calculating 1 unit of the construction materials. The descriptive statistics of the selected sample datasets including min, max, mean, and standard deviation, can be seen in Table 5. Figure 5 shows the range and outliers in each kind of material by box graphs and the colors of the scatter indicate the database that a dataset belongs to.

Table 5. Descriptive statistics of datasets (Unit: $kgCO_{2e}/kg$)

Material	Min	Max	Mean	Std.	Number of datasets
Aggregates	0.0149	39.2413	6.0109	9.3200	61
Aluminum	0.4556	23.1226	11.2588	6.7560	53
Bricks	0.0127	0.6200	0.2727	0.1442	28
Concrete blocks	0.0065	0.5415	0.2005	0.1759	39
Cement	0.3764	1.3714	0.7806	0.2050	55
Concrete	123.5220	666.9826	336.1004	98.8090	68
Glass	0.0542	2.3255	0.8828	0.4122	32
Insulation	0.1900	37.1000	4.0108	6.5864	65
Paint	1.0500	2.7749	1.8436	0.6674	9
Steel	0.2820	4.0800	1.6296	1.0680	49
Wood	0.0385	1.9227	0.8050	0.5600	24

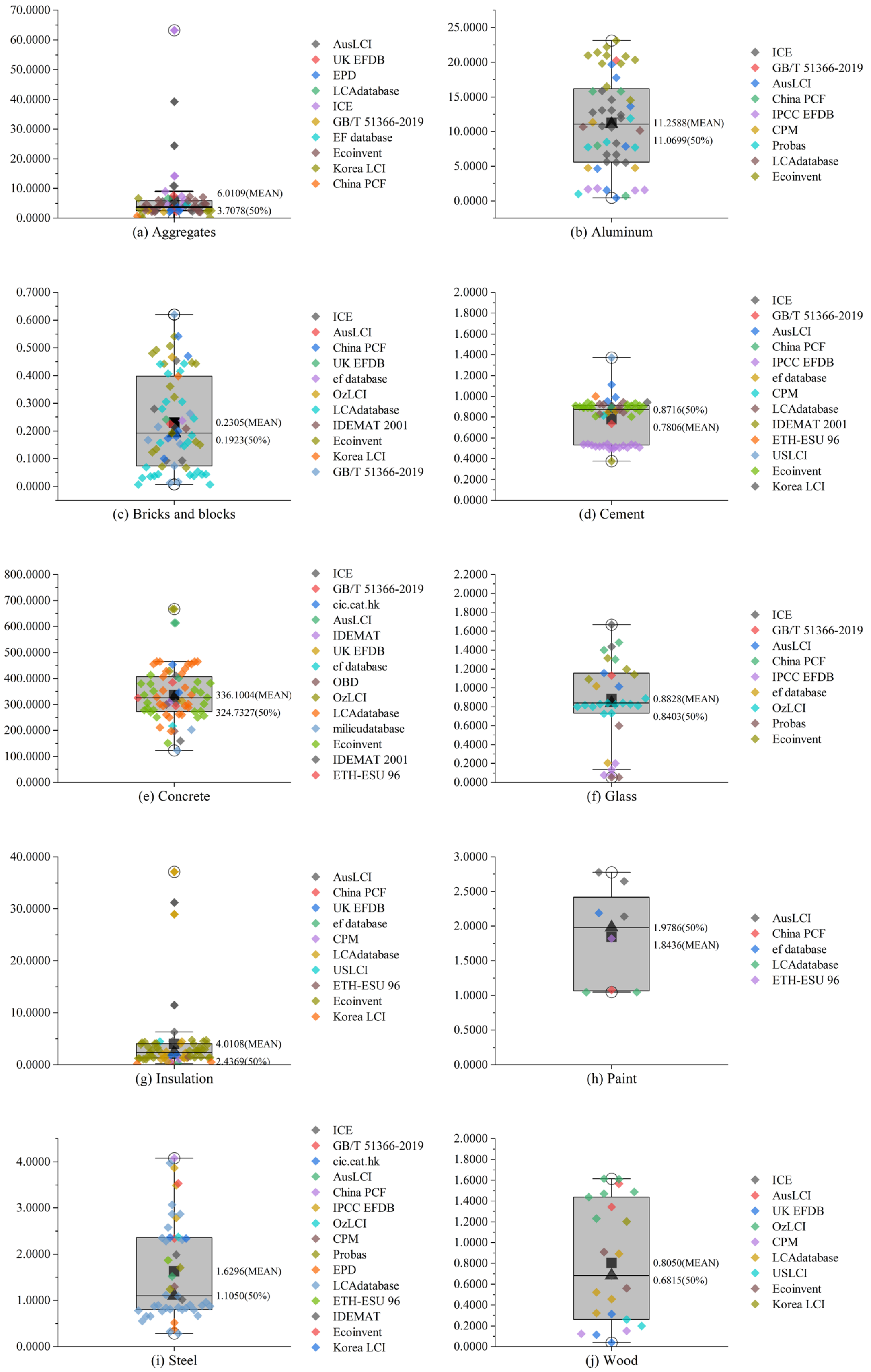


Figure 5. Box graphs of the emission factors of 10 main materials

Generally, the emission factors of the majority of materials stay in a reasonable range without outliers, except for aggregates and glass, which indicates that even not the same products, the emission factors of the same material can be close in statistics. Among all the materials, insulation and concrete show fewer inconsistencies in emission factors since a tight distribution is presented. Additionally, the results also show that different databases have different concentrations. For example, the majority of the concrete blocks, concrete, and steel datasets are from Global Digital EPD, whereas IPCC EFDB and provides more datasets for cement.

Aggregates include sand, crushed or broken stones, gravel, and so on [56], and are commonly extracted from three sources (i.e. natural, recycled, and secondary aggregates). Recycled aggregates come from reprocessing materials that previously have been used in construction and demolition waste. The higher the recycled content rate, the lower the emission factor will be achieved [57]. The secondary aggregates refer to the byproducts of other industrial processes that have not been used in construction. As can be seen in Figure 5 (a), emission factors of aggregates have high inconsistencies among 61 datasets collected from the 20 databases, ranging from 0.0149 to 39.2413 $kgCO_{2e}/kg$. In particular, two datasets from ICE and two from AusLCI are excessively high. The reason for the abnormal data in AusLCI can be explained as the consideration of the milling and crushing process of limestone. However, due to the lack of background data in the ICE database, no explanation can be reasonably examined for the extremely high dataset.

Aluminum in these databases, including aluminum, aluminum sheet, and aluminum alloy is usually utilized for window frames in building construction [36]. The emission factors of aluminum vary from 0.4560 to 23.5000 $kgCO_{2e}/kg$, due to the fluctuating rate of recycling content, the fuel used, and the various final products. The recycling rate is the main factor influencing the embodied carbon of aluminum, reducing the emission factor up to more than 90% [41]. Taking aluminum data in AusLCI as an example, primary aluminum produces 19.6701 $kgCO_{2e}/kg$, while aluminum made of old scrap emits 0.4556 $kgCO_{2e}/kg$. The emission factors of aluminum alloy in AusLCI and Probas are lower than those in other datasets due to the use of renewable energy. Even for the same primary aluminum production, there are huge differences in emission factors. For instance, the emission factor of the primary aluminum (11.3300 $kgCO_{2e}/kg$) is more than twice that of virgin aluminum (4.7570 $kgCO_{2e}/kg$) in the CPM database. Due to the high-temperature burning treatment, the production of bricks is a carbon-intensive process. The energy types, kilns applied, and the raw materials are the key factors affecting the carbon emissions of bricks. Oztas and Yuksek [40] proposed that continuous kilns including Hoffman, tunnel, fixed chimney Bull's trench (BTK), and zigzag are more energy efficient for taking advantage of waste heat. Moreover, according to the IPCC AR6 report [58], renewable energy including natural gas and biomass helps decrease carbon emissions for its high embodied energy per unit. Further, the raw materials of bricks are mainly clay, gangue, and fly ash [59,60]. With the admixtures like fly ash and gangue increasing, the carbon emission decreases accordingly. For example, the carbon emissions of coal gangue solid bricks (with 90% gangue) are less than 5% of that of clay bricks.

Emission factors for OPC stay in the range of 0.7350-1.1110 kg CO_{2e}/kg excluding the extreme values from USLCI, IDEMAT, and IPCC EFDB, as presented in Figure 5 (d). As indicated by Zhang et al. [21], the main factors influencing the carbon emissions of cement include low-carbon fuel, the electricity consumption by equipment, and the location of raw materials. The emission factor of OPC in USLCI exceeds others for its energy source of bituminous coal (80.7000 kg CO_2/GJ, IPCC 2006 [61]), while EF database applied the mix of crude oil (73.3000 CO_2/GJ, IPCC 2006 [61]) and natural gas (56.1000 CO_2/GJ, IPCC 2006 [61]) as the main fuels. The OPC in IDEMAT2001 has the lowest emission factor due to the utilization of cement clinker as raw material, not taking emissions including limestone decomposition and heat release into consideration [62]. Moreover, OPC datasets in IPCC EFDB have lower emission factors, since they considered the mix of all kinds of raw materials, including clinker, cement, coal, CKD, limestone, etc.

The major contributor to carbon emissions from concrete is the production of cement [63]. Therefore, alternative constituents could result in a high reduction of carbon emissions [64,65]. Transportation distance and consumed energy are also key determinants of the carbon emission of concrete. Taking the datasets of C50 concrete from OzLCI and AusLCI as examples, they both use coal and crude oil as the main fuels for transportation, resulting in high emission factors of concrete compared with other datasets. In addition, the general concrete dataset "concrete not reinforced ETH

U” in ETH-ESU96 (324.7324 $kgCO_{2e}$/kg) considers a 100 km distance for the transportation of raw materials of concrete, while IDEMAT 2001 only calculates 10 km (160.0318 $kgCO_{2e}$/kg).

Emission data for glass are presented in Figure 5 (f). Carbon emissions of glass including flat glass, tempered glass, and general glass, range from 0.0542 to 1.6672 $kgCO_{2e}$/kg. The heating treatment during glass production is an energy-intensive process and generates about three-fourths of the total emission [66,67]. For example, the dataset “glass-flat-CZ” in the Probas database applying hydro, sun, and wind as energy sources generates low carbon emissions. Further, different technologies used in glass production can affect carbon emissions. For instance, the emission factor of “flat glass (tempering)” in the EF database (0.2063 $kgCO_{2e}$/kg) is much lower than “flat glass (uncoated)” (1.0191$kgCO_{2e}$/kg) in the same database. In addition, the recycled content can reduce the heating temperature and thus decrease carbon emissions. However, the supply of recycled glass remains limited, due to a lack of global legislation on glass recycling and stock dynamics limiting the availability of discarded flat glass [68]. Thus, recycled glass is rarely to be considered in these databases. As for datasets in the IPCC EFDB, the interestingly low emissions may be caused by the optimized raw material mix of sand (56.2%), feldspar (5.3 %), dolomite (9.8%), limestone (8.6%), soda ash (20.0 %) and others (0.1%).

The most used insulation materials include foam insulation (e.g., foam glass, EPS, XPS) and mineral wool (e.g., rock wool, glass wool). As shown in Figure 5 (g), carbon emission factors of insulation materials vary in a wide range. The blowing agent is the main determinant of carbon emission during foam insulation production. Compared with HFC-125a (1010.0000 $kgCO_{2e}$/kg), insulation with HFC-134a (1370.0000 $kgCO_{2e}$/kg) has higher carbon emissions [69]. The recycled content is also a main factor affecting the carbon emission of insulation materials.

Steel production consists of primary steel and secondary steel. The former route adopts iron ore as raw material and furnaces with fuels (blast furnace (BF), basic oxygen furnace (BOF) and open hearth furnace (OHF), etc.) as burning furnaces; whereas the latter route utilized steel scrap and Electric arc furnace (EAF) [70]. The burning of steel scrap and electricity use by machines require high energy consumption, resulting in a high and diverse carbon emission generated by steel production. Notably, the datasets provided by IPCC EFDB only cover the steel production process, excluding raw material extraction, transportation, and sintering, thus presenting exclusively low values.

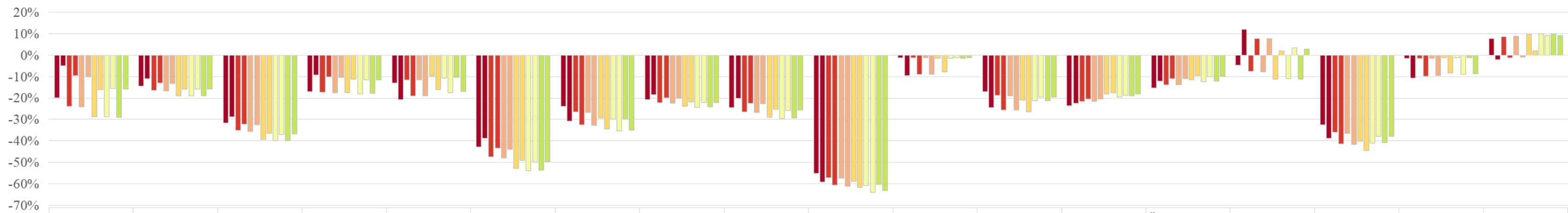
Emission factors of wood can be shown in Figure 5 (j), ranging from 0.0385 to 1.6144 $kgCO_{2e}/kg$. Wood production for construction usually only considers the timber industry subsystem, excluding the forestry subsystem [71]. As the most commonly used material, the production of plywood involves a series of mechanical treatments, such as peeling and clipping, sawing and trimming, and sanding [72]. Besides the energy consumed by machines, heat treatment including veneer drying and hot pressing also account for the energy use. Therefore, fuels applied for energy are the key determinants of the carbon emissions generated by plywood production [71]. Datasets of the "Plywood, at plywood plant, US PNW/kg/US" and "Plywood, at plywood plant, US SE/kg/US" in the USLCI (0.1996 and 0.2601 $kgCO_{2e}/kg$; electricity) and "Plywood production" in the CPM database (0.1527 $kgCO_{2e}/kg$; crude oil and recyclable energy) can be convincing evidence of energy saving from fuel types, compared with datasets in OzLCI (1.4380-1.6144 $kgCO_{2e}/kg$; crude oil, natural gas, and coal). Additionally, recycled materials can also significantly reduce the carbon emissions of wood [73]. For instance, UK EFDB reports low emission factors on datasets with recycled material (0.0385 and 0.1130 $kgCO_{2e}/kg$), which explains the sharp variance between them and other datasets.

4.3 Component-level comparison

Following the steps and equation (1), the results of PRDs of these standardized prefabricated components were calculated as Figure 6 shows. A total of 18 databases were compared with ecoinvent as the reference database, and USLCI was excluded for lack of steel and concrete emission factors. In general, the average value of PRDs is -21.20%, and the median value is -19.06%. Databases including CIC.CAT, IPCC EFDB, OBD, and UK EFDB have low and stable differences based on the average and median value, while the PRDs of Global Digital EPD and EF database display fluctuating trends. EPD, ETH-ESU 96, ICE, IDEMAT, milieudatabase, Probas, and CPM present relatively high and fluctuating deviations. The rest (AUSLCI, GB/T 51366-2019, Korea

LCI, and OzLCI) present average PRDs close to the total average. What is noteworthy is that only PRDs of China PCF with ecoinvent are positive. This is because the relative differences of emission factors of steel (short for $\frac{\Delta EF_s}{EF_s}$) account for the majority of the PRDs, and only $\frac{\Delta EF_s}{EF_s}$ for China PCF is positive (also indicating the steel emission factor of China PCF is the only one bigger than that of ecoinvent). For example, the PRD of Kitchen (C30) of AusLCI is -28.93%, with concrete contributing 6.98% and steel contributing --35.91%. More specifically, the emission factors of steel are diverse, whereas those of concrete are close to each other, leading to major differences when calculating the PRDs of components.

In terms of the differences in PRDs between the same components with different grades of concrete, the higher PRD is determined by, the higher differences in concrete emission factors ($\frac{\Delta EF_{C30}}{EF_{C30}}$ and $\frac{\Delta EF_{C50}}{EF_{C50}}$) (see Table 6). For example, when $\frac{\Delta EF_{C30}}{EF_{C30}} < \frac{\Delta EF_{C50}}{EF_{C50}} < 0$ and $\frac{\Delta EF_s}{EF_s} < 0$ (e.g., Global Digital EPD, GB/T 51366-2019, ICE, milieudatabase, ÖKOBAUDAT) or $\frac{\Delta EF_{C50}}{EF_{C50}} > \frac{\Delta EF_{C30}}{EF_{C30}} > 0$ and $\frac{\Delta EF_s}{EF_s} < 0$ (e.g., AusLCI, CIC.CAT, OzLCI), the deviation of C30 concrete is higher than that of C50 concrete. The major differences are from steel, and ΔEF_S of all the databases except China PCF are less than 0, thus higher $\frac{\Delta EF_{C50}}{EF_{C50}}$ can cause fewer negative deviations or offset more of the negative parts than C30. More specifically, taking precast staircase (C30) and precast staircase (C50) in CIC.CAT for example, $\frac{\Delta EF_{C30}}{EF_{C30}}$ between CIC.CAT and ecoinvent is 0.0565, and $\frac{\Delta EF_{C50}}{EF_{C50}}$ is 0.0954, leading to a higher difference of C30 (PRD: -19.86%) than C50 (PRD: -4.78%) by less offset. The opposite trend happens in the PRD of C30 and C50 in the EF database. $\frac{\Delta EF_{C30}}{EF_{C30}}$ (-0.3374) of EF database with ecoinvent is higher than $\frac{\Delta EF_{C50}}{EF_{C50}}$ (-0.4755), and the PRD of C30 (-12.85%) is higher than C50 (-20.79%), indicating the deviation by C50 is bigger (more negative increment). In short, the differences between concrete emission factors of different strength grades from the same database can cause considerable influences on the same building component.



	AusLCI	CIC.CAT	CPM	Global Digital EPD	EF database	EPD	ETH-ESU 96	GB/T 51366-2019	ICE	IDEMAT	IPCC EFDB	Korea LCI DB	milieudatabase	ÖKOBAUDAT	OzLCI	Probas	UK EFDB	China PCF
Precast staircase (C30) (%)	-19.86	-14.42	-31.74	-17.04	-12.85	-42.84	-23.86	-20.63	-24.33	-55.12	-0.49	-16.89	-23.70	-15.15	-4.70	-32.54	-1.58	7.87
Precast staircase (C50) (%)	-4.78	-10.89	-28.85	-9.20	-20.79	-38.94	-30.80	-18.34	-20.22	-59.21	-9.56	-24.47	-22.29	-11.98	11.90	-38.69	-10.55	-1.97
Precast panel wall (C30) (%)	-23.76	-16.41	-35.18	-17.34	-11.65	-47.47	-26.38	-22.11	-26.46	-57.17	-0.55	-18.72	-21.50	-13.74	-7.56	-36.06	-1.43	8.72
Precast panel wall (C50) (%)	-9.63	-13.02	-32.24	-10.14	-19.02	-43.52	-32.52	-19.89	-22.52	-60.74	-8.84	-25.49	-20.40	-10.96	7.86	-41.39	-9.65	-0.35
Semi-precast slab (C30) (%)	-24.13	-16.62	-35.58	-17.45	-11.64	-48.01	-26.68	-22.32	-26.74	-57.60	-0.55	-18.93	-21.48	-13.73	-7.78	-36.47	-1.43	8.82
Semi-precast slab (C50) (%)	-9.98	-13.21	-32.61	-10.25	-19.01	-44.01	-32.79	-20.09	-22.78	-61.14	-8.84	-25.68	-20.38	-10.95	7.65	-41.76	-9.64	-0.25
Precast facade (C30) (%)	-28.66	-18.85	-39.25	-17.44	-9.82	-52.97	-29.37	-23.74	-28.92	-58.97	-0.61	-20.88	-18.12	-11.58	-11.34	-40.23	-1.21	9.73
Precast facade (C50) (%)	-16.25	-15.77	-36.45	-11.29	-16.24	-49.20	-34.40	-21.73	-25.38	-61.89	-7.69	-26.52	-17.42	-9.36	2.10	-44.49	-8.24	1.91
Bathroom (C30) (%)	-28.85	-19.12	-40.03	-18.13	-10.59	-54.02	-29.96	-24.38	-29.60	-61.00	-0.62	-21.30	-19.53	-12.48	-11.05	-41.03	-1.30	9.92
Bathroom (C50) (%)	-15.53	-15.81	-36.97	-11.48	-17.41	-49.90	-35.31	-22.18	-25.76	-63.98	-0.57	-19.67	-18.67	-10.03	3.34	-37.90	-8.83	9.16
Kitchen (C30) (%)	-28.93	-19.10	-39.89	-17.91	-10.29	-53.84	-29.86	-24.22	-29.45	-60.41	-0.62	-21.23	-18.99	-12.13	-11.25	-40.90	-1.26	9.89
Kitchen (C50) (%)	-15.95	-15.88	-36.93	-11.45	-16.96	-49.84	-35.08	-22.09	-25.72	-63.35	-0.57	-19.65	-18.19	-9.78	2.78	-37.85	-8.61	9.15

Figure 6. Results of PRDs at the component level

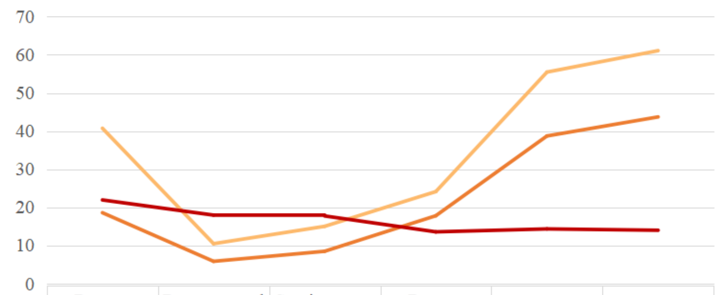
Table 6. The relative difference of concrete and steel emission factors of other 18 databases with ecoinvent

		$\frac{\Delta EF_{C30}}{EF_{C30}}$	$\frac{\Delta EF_{C50}}{EF_{C50}}$	$\frac{\Delta EF_{S}}{EF_{S}}$
1	AusLCI	0.2288	0.4847	-0.5694
2	CIC.CAT	0.0565	0.0954	-0.3303
3	CPM	-	-	-0.6326
4	Global Digital EPD	-0.2021	-0.0161	-0.1863
5	EF database	-0.3374	-0.4755	-
6	EPD	-	-	-0.8537
7	ETH-ESU 96	-0.0073	-0.2142	-0.47
8	GB/T 51366-2019	-0.0982	-0.0684	-0.3366
9	ICE	-0.0645	-0.0078	-0.4358
10	IDEMAT	-0.5108	-0.6128	-0.7108
11	IPCC EFDB	-	-	-0.0098
12	Korea LCI DB	-	-	-0.3366
13	milieudatabase	-0.6224	-0.5099	-
14	ÖKOBAUDAT	-0.3978	-0.2741	-
15	OzLCI	0.3084	0.6139	-0.3275
16	Probas	-	-	-0.6484
17	UK EFDB	-0.0414	-0.2412	-
18	China PCF	-	-	0.1568

For different components, the ratio of concrete to steel ($\frac{W_C}{W_S}$) is the main factor bringing about the differences. Figure 7 presents $\frac{W_C}{W_S}$ of the components in question. As carbon emissions generated from steel account for the major differences, the PRDs calculated by databases without steel datasets (including EF database, milieudatabase, ÖKOBAUDAT, and UK EFDB) show the same trend as that of $\frac{W_C}{W_S}$. For instance, when figuring out the PRDs of milieudatabase, steel dataset in ecoinvent as substitution, and the equation (2) is as follows:

$$PRD=\frac{(C_x+S_x)\text{-}(C_{ref}+S_{ref})}{(C_{ref}+S_{ref})}=\frac{(EF_{Cx}\text{-}EF_{Cx})\times W_C}{EF_{Cref}\times W_C+EF_{Sref}\times W_s}=\frac{EF_{Cx}\text{-}EF_{Cref}}{EF_{Cref}+EF_{Sref}\times\frac{W_S}{W_C}} \tag{2}$$

where C_x is the carbon emissions of concrete calculated by the target database (e.g., milieudatabase), C_{ref} is the carbon emissions of concrete calculated by the reference database (ecoinvent), S_x and S_{ref} are the carbon emissions of steel calculated by the target database and ecoinvent respectively. In this example, $S_x = S_{ref}$. The equation reveals that as $\frac{W_C}{W_S}$ gets higher, the minus PRDs get lower, indicating higher deviations. This equation explains the trend of PRDs by EF database, milieudatabase, ÖKOBAUDAT, and UK EFDB. In line with this logic, databases containing steel datasets present the opposite trend with $\frac{W_C}{W_S}$, since steel mainly determines the components' emissions.



	Precast staircase	Precast panel wall	Semi-precast slab	Precast facade	Bathroom	Kitchen
Concrete (×10² kg)	40.74	10.45	15.01	24.12	55.48	61.10
Steel (×10 kg)	18.58	5.82	8.46	17.79	38.72	43.72
Wc/Wc (kg/kg)	21.93	17.95	17.73	13.56	14.33	13.98

Figure 7. The weight of concrete, the weight of steel, and the ratio of concrete to steel for the selected components

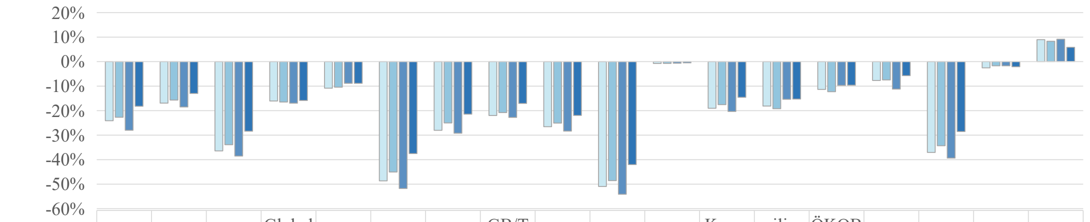
It can be concluded that even for the same component, the wide range of steel emission factors in different databases determine the differential PRDs. The emission factors of steel in theses 20 databases are both high and diverse, and the $\frac{\Delta EF_s}{EF_s}$ are diverse (see Table 6), which explains the large differences of PRDs of the same component calculated by different databases. For instance, the PRDs of semi-precast slab (C30) calculated by CPM (-35.58%) and Probas (-36.47%) are close since and the deviations are mainly from the slight differences of steel (-0.6326 for CPM, and 0.6484 for Probas) when both of their $\frac{\Delta EF_C}{EF_C}$ are 0 for lack of concrete data.

4.4 Flat-level comparison

The results at the flat level remain more stable but higher differences. As Figure 8 shows, the PRDs at the flat level are stable, and the results of different flats by the same database are close. The average value of PRDs is -19.41%, and the median value is -17.71% for all databases, both of which indicate lower deviations than those at the component level.

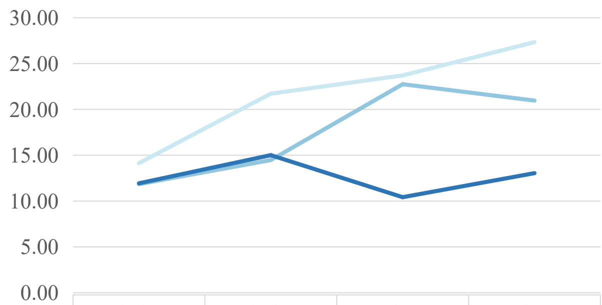
Similar to the analysis at the component level, the major deviations are brought by $\frac{\Delta EF_s}{EF_s}$. As presented in Table 6, EPD and IDEMAT have the highest $\frac{\Delta EF_s}{EF_s}$ (-0.8537 and -

0.7108), therefore, the deviations at the flat level calculated by them are the highest, while IPCC EFDB has the lowest $\frac{\Delta EF_s}{EF_s}$ (-0.0098), contributing the lowest deviations at the flat level. In addition, the varied differences of the same flat by different databases are affected by $\frac{W_C}{W_S}$. Databases not providing steel datasets, such as EF database, milieudatabase, ÖKOBAUDAT, UK EFDB, present the same trend with $\frac{W_C}{W_S}$, showing that concrete determines the carbon emissions when steel emission factors are the same (see Figure 9).



	AusLCI	CIC.CAT	CPM	Global Digital EPD	EF database	EPD	ETH-ESU 96	GB/T 51366-2019	ICE	IDEMAT	IPCC EFDB	Korea LCI DB	milieu database	ÖKOBAUDAT	OzLCI	Probas	UK EFDB	China PCF
1P2P (%)	-24.11	-16.93	-36.42	-16.06	-10.84	-48.64	-28.02	-21.98	-26.55	-50.95	-0.74	-19.03	-18.13	-11.33	-7.68	-37.05	-2.53	8.97
2P3P (%)	-22.70	-15.68	-33.90	-16.48	-10.43	-45.04	-25.02	-20.79	-25.08	-48.56	-0.72	-17.55	-19.20	-12.27	-7.46	-34.32	-1.69	8.32
1B (%)	-28.01	-18.50	-38.53	-16.96	-8.85	-51.76	-29.21	-22.76	-28.35	-54.12	-0.65	-20.34	-15.37	-9.69	-11.20	-39.35	-1.70	9.15
2B (%)	-18.21	-12.98	-28.39	-15.85	-8.86	-37.52	-21.43	-17.06	-21.95	-42.01	-0.49	-14.56	-15.27	-9.61	-5.71	-28.52	-2.08	5.83

Figure 8. Results of PRDs at the flat level

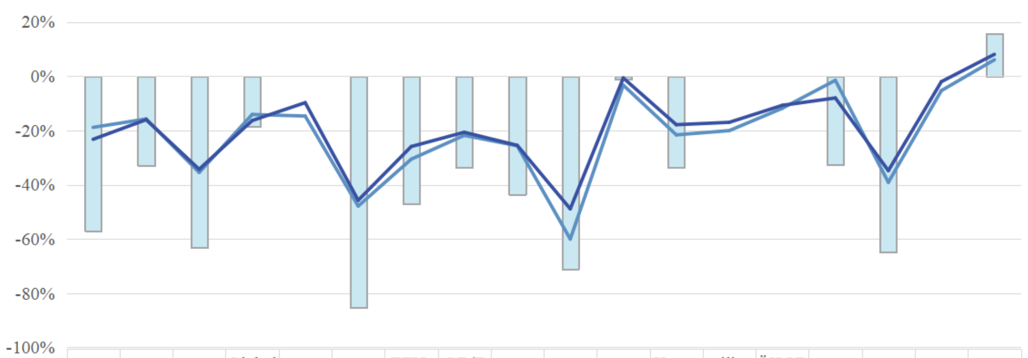


	1P2P	2P3P	1B	2B
Concrete (×10³ kg)	14.14	21.71	23.70	27.33
Steel (×10² kg)	11.85	14.47	22.75	20.96
Wc/Ws (×10²)	11.93	15.01	10.42	13.04

Figure 9. The weight of concrete, the weight of steel, and the ratio of concrete on steel for the selected flats

In general, the main reasons causing differences in carbon emission estimation are the different emission factors of steel and the ratio of steel. Since steel accounts for the majority of carbon emissions from construction production, the higher emission factor and steel ratio make the carbon emissions higher, and even little differences in emission factors would result in rather large deviations in emissions. Figure 10 concludes the

$\frac{\Delta EF_s}{EF_s}$, and the average PRDs by each database at the component level and the flat level. The figure further confirms that both the differences at the component and flat level correspond to the differences of steel emission factors, indicating the crucialness of steel emission factors. Noteworthily, though $\frac{\Delta EF_s}{EF_s}$ of ETH-ESU 96 is higher than IDEMAT, the latter one calculated higher average PRDs for much higher $\frac{\Delta EF_c}{EF_c}$.



	AusLCI	CIC.CAT	CPM	Global Digital EPD	EF database	EPD	ETH-ESU 96	GB/T 51366-2019	ICE	IDEMAT	IPCC EFDB	Korea LCI DB	milieu database	ÖKOBAUDAT	OzLCI	Probas	UK EFDB	China PCF
△EFs/EFs	-56.94	-33.03	-63.26	-18.63	0.00	-85.37	-47.00	-33.66	-43.58	-71.08	-0.98	-33.66	0.00	0.00	-32.75	-64.84	0.00	15.68
component	-18.86	-15.76	-35.48	-14.09	-14.69	-47.88	-30.59	-21.81	-25.66	-60.05	-3.29	-21.62	-20.05	-11.82	-1.50	-39.11	-5.31	6.05
flat	-23.26	-16.02	-34.31	-16.34	-9.74	-45.74	-25.92	-20.65	-25.48	-48.91	-0.65	-17.87	-16.99	-10.72	-8.02	-34.81	-2.00	8.07

Figure 10. The $\frac{\Delta EF_s}{EF_s}$ of each database, and the average PRD of components and flats

4.5 A systematic qualitative investigation of causes leading to the inconsistencies

4.5.1 Goal and scope definition

In the first step, the basic information of the building project should be defined, such as geographic and site characteristics, duration, year of construction, system boundary, and environmental impact categories assessed [74]. In this step, factors including the background database, nations of data, whether the data are regularly updated, the impact categories, and system boundary should be taken into consideration in the choice of database. According to the features and requirements of the project, a proper database for carbon estimation can be selected. In addition, varied data amount, documentation details, and contextualization also change the decision of the estimator for their expertise knowledge [75]. For instance, Global Digital EPD collects a considerable number of product-specific datasets provided by EPD suppliers, which is suitable for a comprehensive and accurate evaluation conducted by experts, while GB/T 51366-2019 offers rather simple instructions and emission factors for nonexpert users and audiences.

4.5.2 Inventory Analysis

ISO defines life cycle inventory analysis (LCI) as the "phase of life cycle assessment involving the compilation and quantification of inputs and outputs for a product throughout its life cycle" [54]. Clarifying the information helps choose the correct emission factors and make adjustments accordingly. Inventory information includes material flow, energy requirements, and the scenarios in each process [74]. The raw materials, energy mix, fuel types, waste disposal or recycled content as data input [76], and cut-off rules, allocation approaches and the harmonization of flats during data gathering determine the accuracy of estimation to a large extent [34].

4.5.3 Impact Assessment

In this step, the collected inventory data undergo classification and characterization procedures, during which impact categories and LCIA methods can cause differences. Though the discrepancies of characteristic factors embedded in different LCIA methods and different versions, the total effects are examined to be slight and insignificant to the whole case [33]. For example, the characteristic factors of IPCC GWP 2021 are generally higher than those of IPCC GWP 2013a. Cherubini et al. [35] proposed that the uncertainty caused by using different LCIA methods could be significantly large, through the one-by-one comparison of 37 LCIA methods. However, the gaps in characteristic factors and the covered substances can only exert tiny influences on the whole, and the total differences are slight.

4.5.4 Interpretation

Interpretation of a life cycle involves critical review, determination of data sensitivity, and result presentation [77]. In this step, users should consider the completeness, consistency, and accuracy of the results presented to the audience. The sensitivity analysis assessment of data quality should also be carried out, based on which the limitations of the LCA study should be identified. At last, Conclusions, limitations, and recommendations are to be presented in accordance with the requirements of the LCA study and the audience [76].

5. Discussion

This paper analyzed the gaps between databases by a systematic four-principle framework based on the comprehensive literature review. Based on the factors from the literatures, quantitative research on the inconsistencies among different emission factors evolved in various databases was conducted with a typical Hong Kong high-rise building case. The samples are 464 datasets from 20 databases providing construction materials. Last, the underlying reasons leading to the gaps and inconsistencies were investigated along with the four-step LCA process framework.

First, although there exists a range of databases for calculating carbon emissions in the construction industry, they display large variations in flexibility, comprehensiveness, transparency, and uniformity, affecting the validity and reliability of calculated results. As the most used database, ecoinvent has covered almost all the types of 10 materials, and performs well in the four aspects, which is in line with Martinez-Ferrero et al. [41]. However, the other 19 databases have defects in either material coverage or information incompleteness. Among them, CIC.CAT, EPD, IPCC EFDB, millieudatabase, OBD, UK EFDB displayed incomplete data information and coverage, providing less than five types of materials and got low scores in the four-principle framework. The deficiency of datasets covering different techniques and geographical regions can lead to unpredictable inconsistencies, while the non-uniformity of system boundaries, technical scopes, and data sources are affective. Although some databases, such as USLCI and OzLCI, cover very few types of materials, their data display good performance in all four aspects. Therefore, they may perform well in evaluating specifical materials (e.g., glass and wood) instead of the entire concrete or steel structure buildings. In contrast, Global Digital EPD lacks flexibility and unity in terms of data, although it has covered nine materials. This is to say, most of the datasets lacks documentation, and cannot be adjusted according to the energy-mix, recycled contents, LCIA methods, etc. The users thus need to well balance the four aspects when choosing databases.

Second, reduced inconsistencies using different databases were identified if a more comprehensive concrete product was assessed. The average differences among different flats (around 5%) reduce to a certain degree than those among different components (around 10%), due to the reduced differences in steel ratio. This is also in line with the study conducted by Takano et al. (2014), who showed that the inconsistencies became more balanced for a whole building compared with a building product. In addition, the prevailing proportion of steel in the building was highlighted, which explained the huge discrepancies between steel emission factors and the ratio of steel mass [78]. For instance, the selection of steel emission factor can cause up to 50% deviation. Therefore, it should take high notice of selecting the emission factor of steel products [32]. The influences of using different databases may be greater for steel buildings compared with other types. Interesting still, the significant variations at the material level can become tiny when it is used in estimations of components and flats, due to the minor volume or mass of the materials (e.g., insulation, paint, and glass).

Third, the major factors causing inconsistencies between carbon results were identified as alternative raw materials, technical scope, energy mix, fuels, etc. As [34] highlighted, the data scarcity and wide ranges hindered the accurate choice of emission factors and the estimation results. For a non-professional, a simple and easy database (e.g., GB/T 51366-2019, Korea LCI, IPCC EFDB, and CIC.CAT) may be a better choice. These databases offer only one or two alternative emission factors for the same material, which is more convenient for amateurs. While for a comprehensive and elaborate case, databases providing detailed documentation and flexible adjustment must be suitable, such as AusLCI, ecoinvent and Global Digital EPD. Further, a series of factors were discussed separately by previous studies, such as data amount, data documentation [36], data age [37], the nation of data [39], system boundaries [79], technical scope, and data sources, etc. Therefore, to well define the goal and scope is crucial for LCA studies, which sets a good start for choosing a suitable database. To improve the reliability of LCA databases and tools, we recommend that these databases and tools should (1) cover the main materials, even without much options; (2) offer documentation in details (i.e., the techniques, allocation rules, system boundaries, fuel types, etc.), in order to provide references and guidance for users, (3) ensure the uniformity of datasets in energy-mix, technical scopes, data sources, and background databases.

6. Conclusion

Considering the inconsistencies of carbon results brought by various LCA databases, this paper compared 20 databases containing construction materials by conducting a systematic perspective including overall evaluation, three-level quantitative comparison with a building case, and a qualitative causes analysis based on the LCA four-step framework. The results offered scientific and integral evidence on the selection of databases.

First, the 20 databases were thoroughly evaluated and compared using an established four-principle framework in flexibility, comprehensiveness, transparency, and uniformity. The framework adapted from Weidema quality index and ISO standard provides a reliable and scientific reference for evaluating the quality of datasets. Additionally, it integrated the factors influencing the accuracy of emission factors, and provided an objective tool to select suitable databases for end-users.

Second, the quantitative case analysis deconstructed the inconsistent results at the material, component, and flat levels, respectively, providing numerical explanations and comparisons of how the selection of different databases affected the carbon emission of buildings' products. The results figured out that the major contributors to deviations among different levels were the emission factor and ratio of steel. Moreover, this study enriched the comparative studies with a larger number of sample databases, enhancing the robustness of the case study by providing more references to the unpopular databases.

Third, by applying a typical four-step LCA framework, the qualitative causes of discrepancies in carbon results by different databases were systematically explained, facilitating a new perspective to decompose the underlying factors causing deviations. The framework not only provides further guidance to examine the factors step by step, but also offers a tool for users to select the corresponding datasets matching with the specific characteristics of the construction project.

There are a few limitations in this study. First, under the limitation of availability, some databases requiring paid license were not included in this study, and were still left unexplored. Second, this study only discussed databases adopting the process-based method as it was more used for the carbon assessment of a single building project. Future studies can therefore include more databases that adopt the input-output and hybrid methods.

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