Techniques and Tools for Integrating Building Material Stock Analysis and Life Cycle Assessment at the Urban Scale: A Systematic Literature Review

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Abstract

The urban building stock has a high demand for materials and energy, exerting tremendous pressure on natural resources. A current research trend is to integrate Building Material Stock (BMS) analysis with Life Cycle Assessment (LCA) to evaluate energy use, material stock/flows, and related environmental performance associated with the life cycle of building stocks. Compared with urban building energy modelling (UBEM), material-related analysis is a relatively new topic. Some studies applied new techniques and tools to improve the modelling and the dynamic evolution of the BMS system. However, there is a lack of comprehensive review studies summarising the recent publications on these applications. Therefore, this study conducts a comprehensive literature review, primarily focusing on examining the tools and techniques employed for integrating "BMS-LCA" at the urban scale. This review includes 99 articles chosen from a pool of 557 related papers (in the recent decade), systematically retrieved from *Scopus* and *Web of Science*, along with additional manual searches. Through a comprehensive bibliometric and content-based synthesis analysis of selected literature, this paper synthesises the techniques/tools used for effectively completing various analysis phases of "BMS-LCA", including data collection and processing, stock modelling and analysis, and result evaluations. Key findings highlight the significance of integrating artificial intelligence and geospatial technology in optimising data collection, machine learning and data-driven models in enhancing building stock aggregation and classification, and innovative application of relevant LCA software and databases in facilitating BMS's LCA, etc. This review provides a valuable reference for researchers in future investigations, as it identifies novel ways of applying techniques/tools and opportunities for methodology improvement in the urban-level "BMS-LCA" study.

1. Introduction

According to UN-Habitat, cities consume more than 60% of resources and are responsible for 70% of global greenhouse gas (GHG) emissions. The buildings and their construction are significant consumers regarding energy and materials [1]. Building stock refers to all the buildings belonging to the urban building sector. Building Stock Modelling (BSM) is a commonly used tool to analyse energy demand and material inventory for parts or the entire building stock in a specified area [2]. In contrast to Urban Building Energy Modelling (UBEM), which has a long research history and more established applications, research on Building Material Stock (BMS) is relatively newer and has progressed steadily, which is the field focused on in this paper.

In recent years, there has been great attention on exploring the environmental performance associated with the entire life cycle, from raw material extraction and manufacturing through construction, occupancy, maintenance, and eventual demolition or recycling of construction materials stored in urban building stock [3]. However, BMS modelling usually uses mass as a proxy for environmental performance, which can not accurately analyse and quantify the Environmental Impact (EI) caused by the building stock and related environmental/economic factors [4]. Life Cycle Assessment (LCA), as a comprehensive environmental assessment approach [5, 6], has been widely applied at the scale of buildings [7] to investigate the environmental performance of buildings at all life cycle stages, including design, construction, use, operation, and disposal [8].

Merely assessing individual buildings' environmental performance isn't enough to understand the urban context fully. Recently, a new research trend has been to extend LCA to the urban scale [1]. To gain a comprehensive understanding, the analysis should extend to the city, district, or neighbourhood scale for some complex and high-resolution investigation [9]. Hence, this review paper concentrates on studies conducted at the "urban level," a term not characterised by a straightforward meaning but encompassing investigations ranging from the neighbourhood to district and on a global scale. Besides, we

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mainly focused on the embodied EI related to the building material stock [10] at large spatial scales, which is a sunk cost spent before the building is used and is more critical to sustainable planning and policy decisions [11]. According to the new vision proposed by the World Green Building Council (WorldGBC) [12], with new buildings striving for net-zero operational carbon by 2030, the focus is shifting to embodied carbon, which will become a critical factor in the impact assessment of buildings' life cycle in the coming 20 years.

Different from the building level, applying LCA at the urban scale aims to take a snapshot of the general trends in a city's environmental loading by analysing the BMS's material aggregation, energy demands, and EI over a period [13]. As Österbring et al. [14] said, the BMS model can not only be used to describe the EI of the existing but also future building stock when combined with an LCA model, considering various lifecycle scenarios for refurbishment, densification, and replacement. Additionally, scholars have proposed enhancing urban sustainability by integrating resource stocks and flows with environmental impacts, thereby integrating urban metabolism with LCA [15, 16]. Hence, "BMS-LCA" would be a useful composite approach to help decision-makers understand their region's metabolism by systematically linking the embodied impacts, related construction activities, and material inflows and outflows.

The "BMS-LCA" mainly consists of three elements: 1) building stock aggregation model, 2) building stock-related analysis such as Material Flow Analysis (MFA), and 3) LCA model. A building stock aggregation model describes the entire urban building stock, including modelling individual stock components (buildings, materials, or technologies) and extrapolating results at a larger level. The main approaches for building stock aggregation modelling are "archetype" and "building by building". The stock aggregation model forms the basis through providing inputs for stock-related analysis and LCA. Meanwhile, stock-related analysis and LCA results are fed back to the stock aggregation model, extrapolated to the desired scale, and utilised for result visualisation and reporting.

The building stock-related analysis employs various assessment approaches/models to encompass multiple aspects such as energy use, material composition/mass, and material flows. To clearly define the scope of this review, we summarise the categories and steps of each stage for urban-level BMS aggregation, related analysis, and LCA modelling (see Figure 1) based on existing literature [17, 18, 11, 19, 20]. This research reviews the papers related to BMS-related analysis, corresponding material stock aggregation, and LCA modelling (blue rectangles in Figure 1).

Due to the complexity of the urban construction system, conducting "BMS-LCA" at the urban scale presents challenges, having pushed the application of innovative methodology and tools [21], including more efficient use of digital technologies. In recent years, automation and digitalisation have offered opportunities to improve the accuracy and performance of "BMS-LCA" models. Hence, this research provides an overview of the existing techniques and tools employed to support and enhance the "BMS-LCA" process. The "tools" reviewed in this research refer to digital tools, including software applications or platforms that aid in conducting "BMS-LCA", such as statistical analysis software, data visualisation tools, Geographic Information System (GIS) software, and data collection/survey tools. The "techniques" include computational techniques referring to methods or approaches used in computational processes, often involving algorithms, mathematical models, and data analysis to solve problems or perform tasks.

This review paper conducts a Systematic Literature Review (SLR) on tools and techniques used in existing research papers and summarises how these can support different stages/steps of the "BMS-LCA" process. The primary objectives of this study are 1) to integrate bibliometric and content-based analysis to categorise and organise the related published articles, 2) to identify gaps and future research trends, 3) to highlight the methodological innovation, and 4) to summarise the application of technologies and tools. This paper is organised into six sections: section 2 illustrates the methodology of conducting SLR, section 3 explains the bibliometric analysis results, and section 4 summarises the content-based synthesis analysis result. The discussion on future research trends and limitations is provided in section 5. In section 6, the conclusion is presented.

2. Methodology

SLR is recommended for critically evaluating pertinent research to gather and investigate paper information [22]. SLR adopts a transparent, replicable, and scientific method, minimising bias and providing an audit trail for readers [23]. This study follows the steps of SLR outlined by Tawfik et al. [24]:

2.1. Identifying Research Questions

This research focuses on: "How can techniques and tools improve the existing analysis workflow of 'BMS-LCA' for urban building systems?". In our initial investigation, we found that currently, there is no comprehensive SLR specifically addressing this particular question (see section 2.2).

2.2. Preliminary Search and Idea Validation

We first conducted preliminary research to search the existing review papers related to "BMS-LCA" to identify the current knowledge and gaps in the field. The first category of review papers aims to provide a summary and assessment of the material stock and flow analysis methodologies. For instance, Mohammadiziazi and Bilec [25] reviewed 62 articles, evaluated the

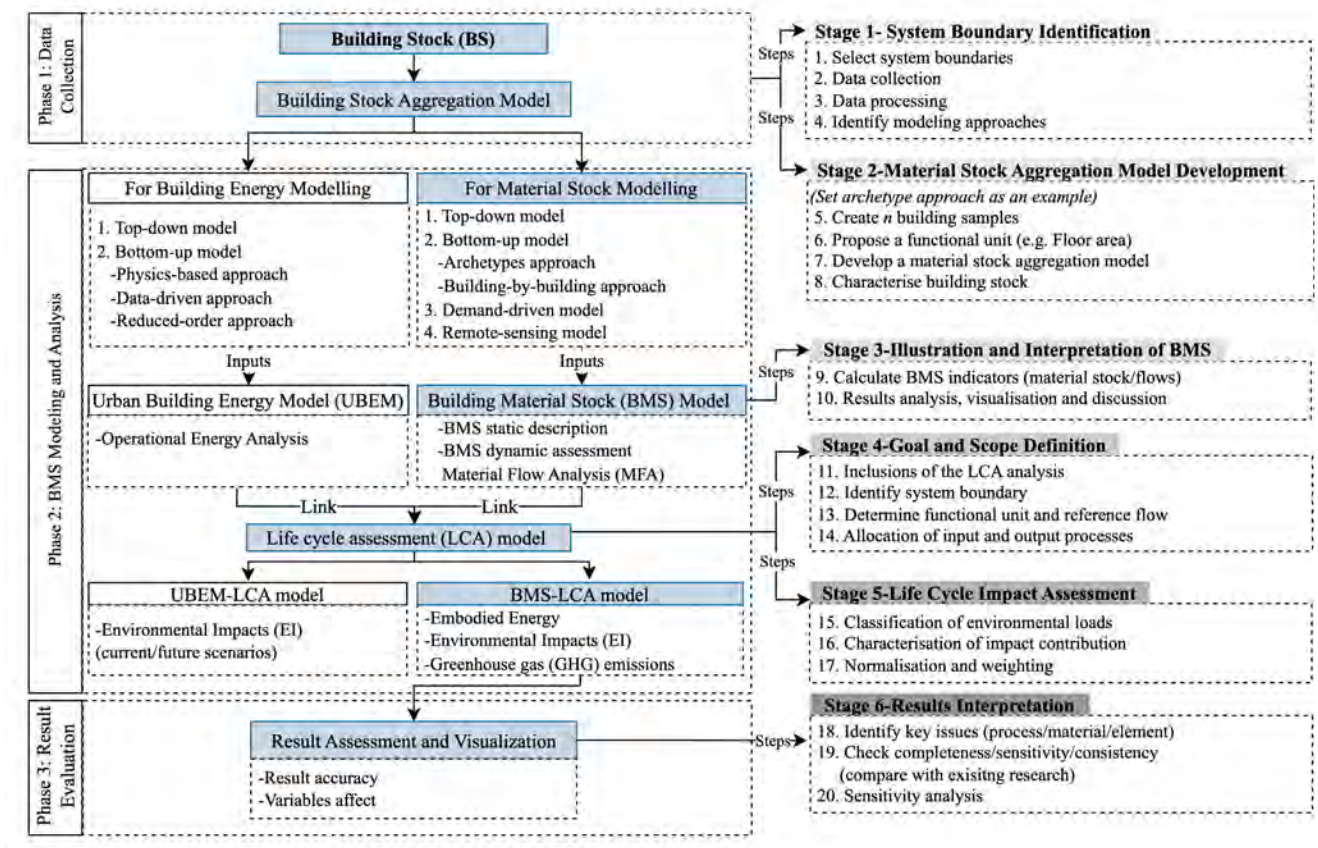

Figure 1: Categories of building stock models and steps of integrating building material stock and life cycle assessment.

approaches including “bottom-up”, “top-down”, and “remote sensing”, applied for quantifying and spatialising BMS, and summarised the advantages and shortcomings of each approach. Similarly, Nasir et al. [26] reviewed 38 papers to identify common approaches in estimating material stocks, primarily focusing on the “bottom-up”, “top-down”, and “demand-driven” methodologies. Besides evaluating the approaches, this paper also summarises the procedure for calculating BMS and provides suggestions on approach selection for different sizes of the study area. Rajaratnam et al. [27] provided a comprehensive overview of 52 papers to summarise the approaches using GIS and remote sensing for data collection and preparation approaches phases when conducting building stock data mining.

Some other review papers focused on the dynamic analysis of BMS. For instance, Göswein et al. [28] reviewed 28 articles, summarised three kinds of dynamic assessment of BMS, including “spatial”, “evolutionary temporal”, and “spatial-cohort” dynamics, and provided a framework for choosing appropriate dynamic BMS assessment tools (MFA, LCA or GIS) when adapting various BMS accounting methods. Besides, Augiseau and Barles [29] reviewed nonmetallic construction material stock and flow analysis papers and proposed a conceptual framework, emphasising the pivotal role of buildings as subjects of research in understanding material stocks within the built environment. Lanau et al. [30] reviewed 249 available publications on built environment stocks, including the materials stocked in buildings and infrastructures (roads, rail, etc.), and provided an overview of built environment stocks research through a bibliometrics analysis and methodological approaches review.

The second category of papers focuses on applying LCA at the urban scale. For example, Mastrucci et al. [11] reviewed the application of LCA on “bottom-up” building stock from the urban to the transnational scale. The analysis of LCA in related papers is based on LCA’s four steps, including goal and scope definition, life cycle inventory, life cycle impact assessment and interpretation, and the highlighted performing LCA instead of only energy analysis and concluded that future research should include geolocalisation and sensitivity analysis for potential technology changes. Seyedabadi et al. [31] reviewed 150 papers and divided the scope and methodology analysis of LCA into process-based, input-output, and hybrid ways, according to the research scales: building, urban object, and urban scale.

Through preliminary research of existing review papers, this research noticed that 1) most review papers focus on the methods for stock quantification and lack attention to summary and discussing the techniques/tools applied in various phases of integrating BMS analysis and LCA at the urban scale; 2) while prior reviews highlight limitations at the urban level, such as data limitation, method lacking universality, high labour/time cost, etc., few offer insights into methodology improvement. Hence, this study systematically examines the gaps in existing research by integrating domain knowledge of industrial ecology, architecture, and computer science and technology. Our focus is specifically on a detailed analysis of the application of computational techniques and digital tools. By scrutinising how these technologies have contributed to the solution of current challenges and identifying their potential for addressing them, we aim to propel advancements in this interdisciplinary domain.

2.3. Inclusion and Exclusion Criteria

To set search and review boundaries, inclusion criteria are 1) papers from 2013-2023 (recent three years for conference papers), 2) in English, 3) peer-reviewed originals, 4) BMS analysis focus (with or without LCA), 5) building-related, 6) (part of) at a large scale (country/urban), 7) quantitative, objective measures and analysis, 8) sufficient data analysis detail.

2.4. Search Strategy and String

This study conducted a comprehensive literature search in June 2023 using *Scopus* and *WoS* databases and a manual search in July 2023, including tracing the citations from selected articles.

The search strategy involved “subject index” and “free-text” terms [32], such as “material stock (flows)”, “building”, and “urban”, along with their synonyms and abbreviations to form a search string. For instance, “housing” and “house” can be combined using “hous*”. Papers without the LCA stage were also included to encompass various BMS modelling approaches. We refined our search terms through a trial search to balance broad and specific searching, identifying pertinent terms within each retrieved paper. The search string was developed using Boolean operators “*AND*” and “*OR*” to connect the keywords and string expressions. An example of the search string used in *Scopus*:

> TITLE-ABS-KEY ((“material stock*” *OR* “material inventory” *OR* “material flow*” *OR* “BMS” *OR* “MSA” *OR* “MFA”) *AND* (“building” *OR* “housing”) *AND* (“country” *OR* “urban*” *OR* “city” *OR* “region”)).

Following the database search with specific criteria, the constraints on the publication year, type, language, etc., 439 papers were collected from *Scopus* and 259 from *WoS*. A total of 698 search records with complete information were combined and exported for screening. After removing duplicates, 557 original articles remained.

2.5. Paper Title and Abstract Screening

Based on several articles’ comparison results of different SLR tools, this study used *Rayyan* as a support tool [33, 34] to highlight the keywords, add label references with reasons for inclusion or exclusion, and intelligent sort references based on likely relevance. Each article’s title and abstract were reviewed, and the reasons for collecting 86 papers that met the criteria and scope were added.

2.6. Full-Text Screening and Data Extraction

Furthermore, we conducted full-text screening and quality assessment. We excluded papers that focused on 1) water, electrical waste and electronic equipment, and food waste instead of buildings, 2) building, product, and process level but not the urban (country) level; 3) review literature, etc. Additionally, we identified 13 additional papers by manually screening the references of selected papers. Ninety-nine papers were included for the next analysis phase, with six from *Scopus*, 92 from *WoS*, and one manually added from other databases. A flow diagram (Figure 2) summarises the paper selection process. A standardised extraction form (refer to Supporting Information A) was created to collect data from the selected studies.

2.7. Bibliometric Analysis and Content-Based Synthesis Analysis

This study initially conducted a bibliometric analysis, examining selected articles’ bibliographic parameters (e.g., publication year, citations, countries, etc.) as outlined in Supporting Information B. The bibliometric analysis covered 1) basic information, 2) modelling approach, related techniques, and tools, 3) technical development and publication trend, and 4) geographical distribution. Following this, content-based synthesis was employed within this SLR to identify, analyse, and synthesise information from the collected literature based on its content. Specifically, content-based synthesis analysis was utilised to review the method and research cases in the included papers, summarising the tools and techniques used to enhance the “BMS-LCA” workflow.

3. Bibliometric Analysis Result

The bibliometric analysis deals with the articles based on their bibliographic parameters from online databases. The bibliographic parameters include the publications, keywords, articles, authors, institutions, journals, countries, and most searched areas.

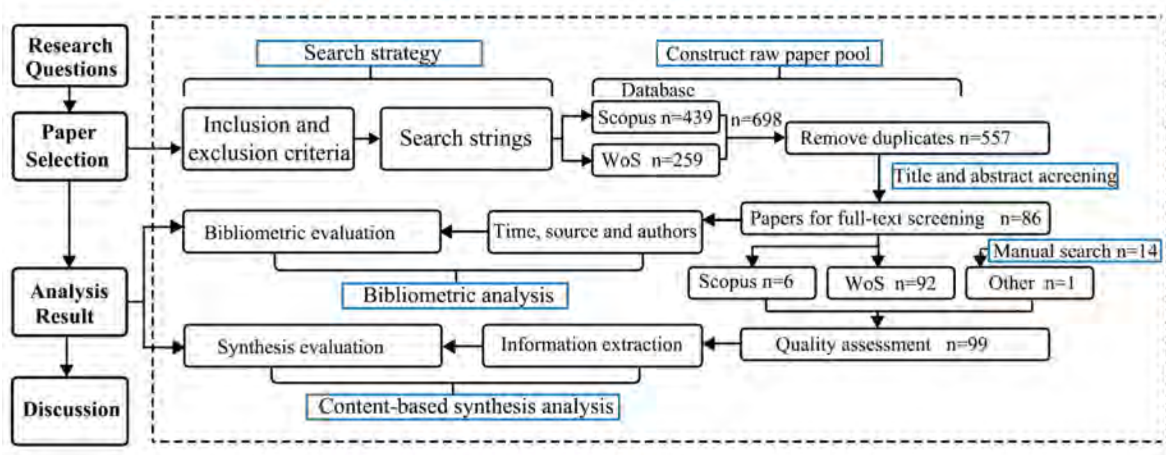

Figure 2: Flow diagram of the paper screening process.

3.1. Overview of the Included Papers

First of all, we summarised the primary information of all 99 selected articles (Table 1), showing an increase in publications from 2016-2017 (Figure 3) and a high average of citations per year in 2018 (7.73), indicating a topic of great academic interest with an average citation per article of 23. In the past five years, this research field has gradually received more attention from researchers.

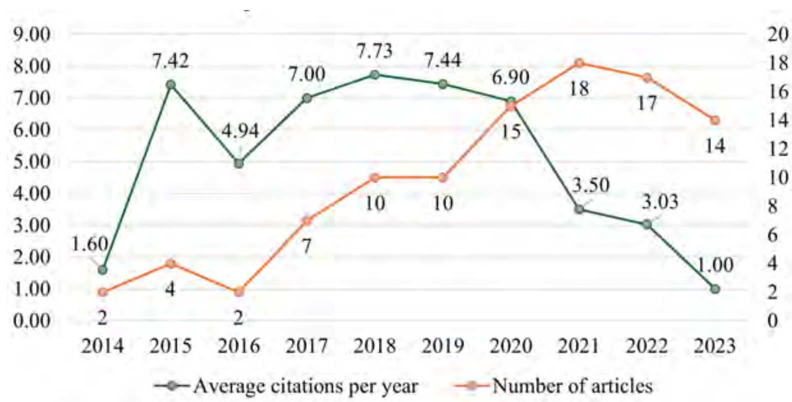

Figure 3: Average production and citation per year.

3.2. Trends of Tools and Techniques Application

For the detailed discussion, this research established the categories of techniques/tools referencing their specific roles during the "BMS-LCA" process. The research trend, depicted in Figure 4, highlights the increasing use of 4D-GIS and the growing interest in dynamic assessment of BMS combined with LCA since 2019. It should be explained that although 4D-GIS can be part of GIS, we set it as a separate tool category, considering it is specifically used to support the dynamic assessment of BMS at time dimensions. Furthermore, GIS has played a crucial role in the "BMS-LCA" process of managing, analysing, and visualising geospatial data. In recent years, ML models, including deep learning incorporated therein, have been increasingly employed for data mining and processing, with their support for "data-driven" BMS modelling representing an emerging approach. We also summarised the trend of applying various BMS modelling approaches and noticed that the "bottom-up" is the most widely used in selected papers. Besides, since 2021, some studies have innovated using "remote-sensing" methods, such as correlating building volumes to provide input for "bottom-up" modelling.

3.3. Geographical Distribution

This study also developed a Sankey diagram to summarise the main factors for the reviewed studies (Figure 5) and to show the geographical distribution (based on the location of research cases) of various tools/techniques and BMS model application situations. Building materials lists are usually private in many urban areas, especially in the U.S., which may also be why a lack of research exists, as access to detailed data on the types and quantities of materials used in buildings

Table 1
The primary information of all included papers.

Description		Explanation	Indicators
Main information	Timespan	Years of publication.	2013-2023
	Sources	Journals, books, etc.	33
	Documents	Total the number of documents.	99
	Average citations per doc.	Average number of citations in each article.	23
	Annual Growth Rate %	-	24.14
	Document Average Age	-	2.97
	References	-	3636
Document types	Article	-	90
	Conference Paper	-	5
	Early access/processing paper	-	4
Document contents	Keywords plus (ID)	Number of keywords designated by WoS/Scopus.	230
	Author's keywords (DE)	Keywords defined by the authors.	361
Authors	Authors	Total the number of authors.	325
	Co-Authors per Doc	Average number of co-authors per document.	4.31

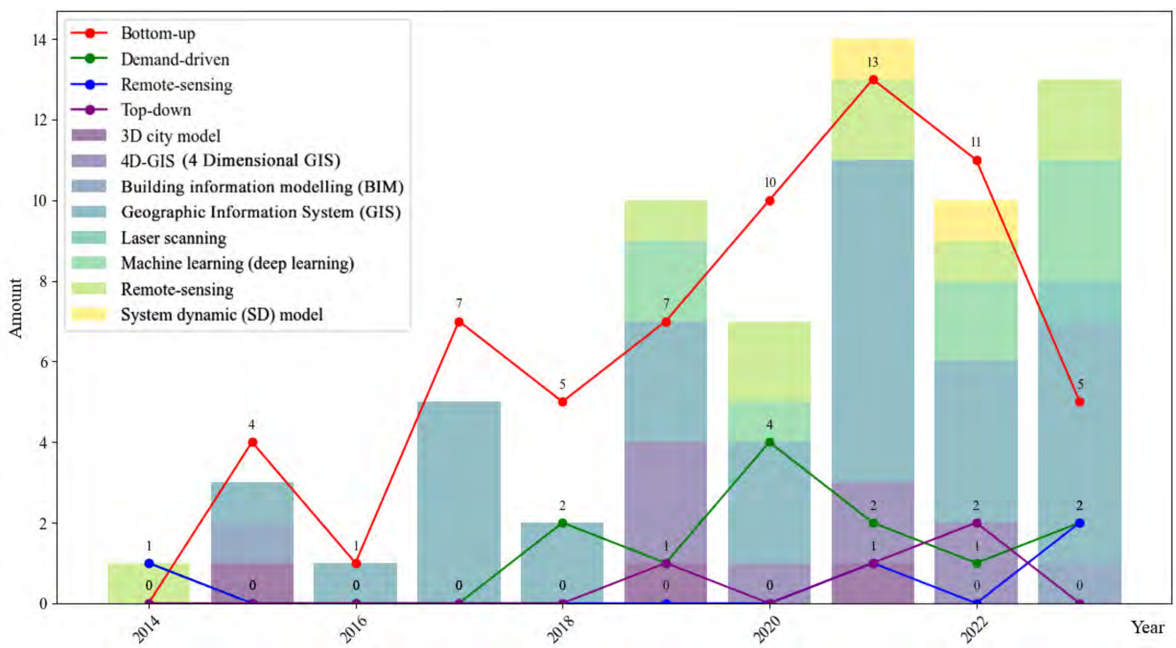

Figure 4: Application trend of building material stock modelling approaches and tools/techniques over the years.

is crucial for accurate assessments of environmental impacts. The abundance of "BMS-LCA" research in Europe is driven by the region's strong commitment to sustainability, notably exemplified by initiatives like the *European Green Deal* [35]. Additionally, Europe's emphasis on resource efficiency, seen in policies like the *Circular Economy Action Plan* [36], and available maintained national databases for many European countries, contribute to the prominence of "BMS-LCA" research in the region.

Figure 5 also summarises the levels of study. The research in European countries is highly diverse, encompassing large-scale "BMS-LCA" studies across various levels, ranging from the "neighbourhood level" to the "global level". Most of the research was conducted at the city level in some regions outside Europe. Building data for "BMS-LCA" at the city level is more detailed, comprehensive, and accessible. While data at more minor geographical scales might be limited, the granularity of data might be insufficient for in-depth building material life cycle studies at larger scales. Each scale of "BMS-LCA" studies serves different purposes and requires specific tools and techniques adapted to the data resolution and granularity needed at that level. For instance, neighbourhood-level "BMS-LCA" studies require highly granular building data for detailed analysis of building materials and construction practices for assessing material stock and recycling potential within neighbourhoods. Figure 5 shows that Building Information Modelling (BIM), which provides detailed digital representations of building projects, can be combined with 3D city models to support neighbourhood-level "BMS-LCA" studies. These 3D city models, developed using remote sensing data such as high-resolution satellite imagery and LiDAR, offer detailed

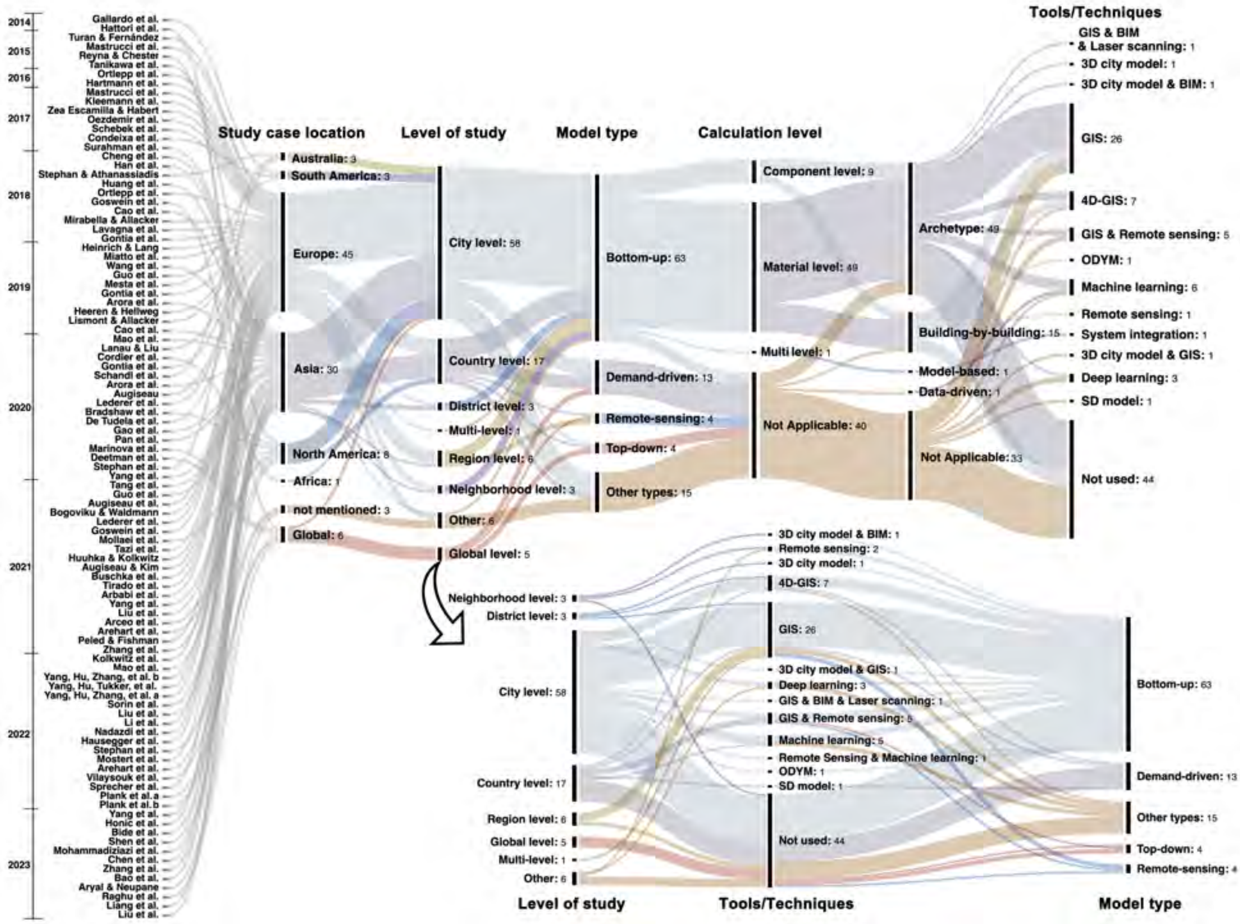

Figure 5: Sankey diagram of geographical distribution (*ODYM: Open Dynamic Material Systems Model; SD: System Dynamics*).

representations of buildings and infrastructure within a neighbourhood. For broader "BMS-LCA" studies at the regional, city or country level, it becomes challenging to collect BIM models for each building or to create semantically rich 3D city models. Hence, GIS is used to manage large amounts of building data and understand material stock dynamics and their spatial distribution. Additionally, city-level BMS modelling, especially bottom-up approaches, requires data collection for a large number of buildings, and some building data may be missing. Therefore, integrating some tools and techniques, such as remote sensing deep learning and machine learning, can fill data gaps at a broader scale. At the regional and global levels, "BMS-LCA" studies focus on global sustainability assessments and resource management, which typically rely on statistical analysis and mathematical models to handle and analyze large datasets from diverse sources.

The selected papers widely employ the "bottom-up" approach conducted at the material (material intensity) level. This methodology provides more granular and detailed information on the material stored by analysing individual buildings and processes compared with other model types. As element data of buildings is more scarce, most of the "bottom-up" BMS modelling was conducted at the material level. The "other types" refer to some papers that focus on subtopics related to BMS modelling such as "data-driven" BMS modelling, material intensity (MI) database development, etc.

3.4. Knowledge Graph of Tools/Techniques

The tools and techniques employed in selected papers are synthesised with the phases and steps associated with "BMS-LCA", as shown in Figure 6's knowledge graph summarization. This knowledge graph defines the four phases: data collection, BMS analysis, LCA modelling, and result evaluation. For each phase, we noticed various techniques/tools are used to support them in the selected papers. Some techniques and tools such as 3D city modelling, Machine Learning (ML) or deep learning models, remote sensing (e.g., LiDAR), and GIS (including 4G GIS) are used in more than one phase. In the following section 4, we will analyse these techniques/tools and their function, pros, and cons when applied in the "BMS-LCA" process.

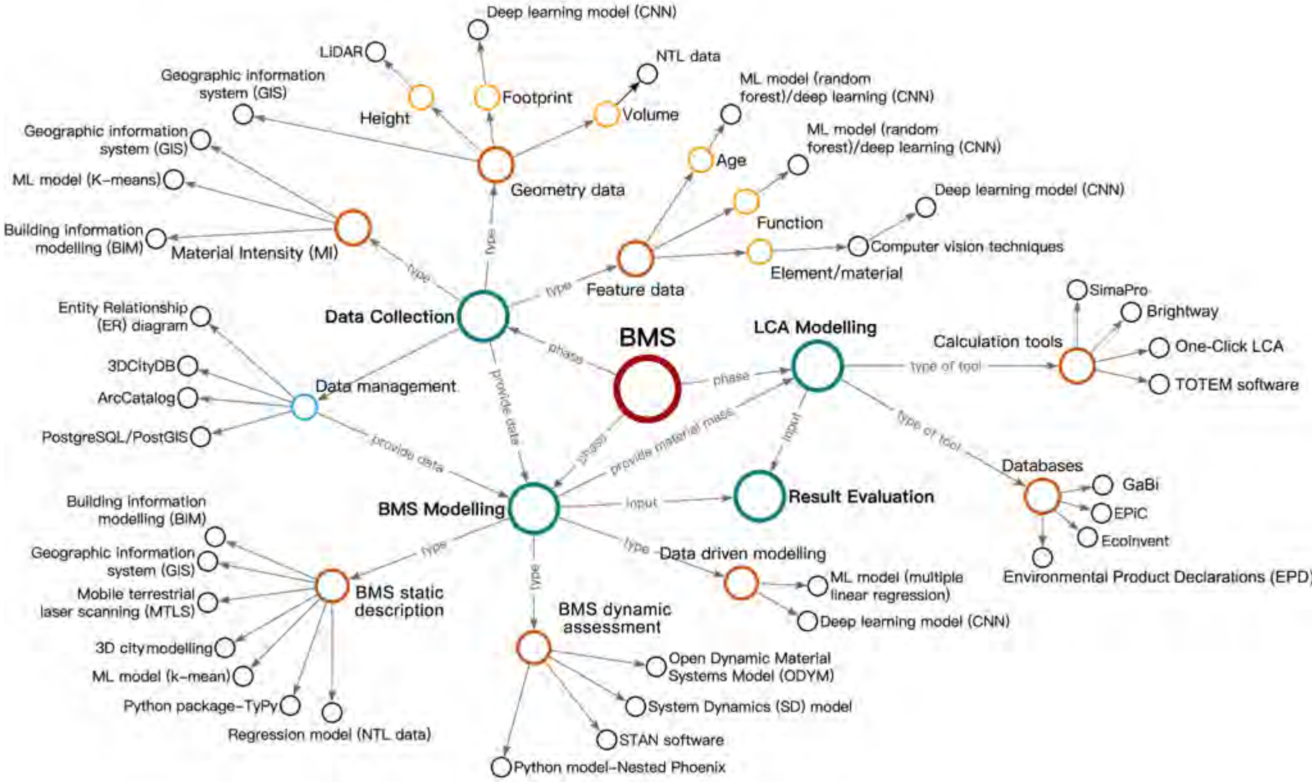

Figure 6: Knowledge graph presenting the tools and techniques applied in the selected papers (*BMS: building material stock; LCA: life cycle assessment*).

4. Content-Based Synthesis Analysis Result

Four approaches, "bottom-up", "top-down", "demand-driven", or "remote-sensing", are used for BMS modelling, adapting the data availability in different research cases. The "bottom-up" approach investigates end-use buildings at a point in time and extrapolates the results at the stock level for a defined area. Consequently, while the "bottom-up" approach is often adopted for static description of BMS, it can also contribute to pointing out BMS changes over time when a temporally dense series of "snapshots" is compiled. To address data limitations, the "remote-sensing" approach is proposed to estimate the mass/volume of BMS in a given area. Hence, the "remote-sensing" approach can also supplement "bottom-up" modelling.

The "top-down" is based on the mass-balance principle, which relies on materials' economic and trade data entering a defined geographical location [29]. To determine the in-stock materials in the given years, the researchers calculated the use of materials in those years by adding the domestic extraction and imports while subtracting exports and factoring in the materials saved from previous years. Hence, the "top-down" approach can provide an overview of the BMS dynamics over long time periods. The "demand-driven" approach utilises the correlation between driving forces indicators (population, lifestyle, gross domestic product, etc.) and the demand for building materials [37] to conduct BMS modelling.

By analysing the features of various BMS modelling approaches, we noticed that the existing research mainly focuses on two aspects when modelling BMS: 1) static description of stored materials and 2) dynamic assessment such as MFA. Hence, we divide the content-based analysis into two parts: "static description" and "dynamic assessment" of BMS.

4.1. Data Collection and Processing Phase

Data collection is the first crucial step closely linked to choosing a methodology and output quality. Because there is no exhaustive survey of buildings in most countries, various data sources and data generation tools/approaches are used in selected papers.

4.1.1. Data for Static Description

Static description can be conducted through the "bottom-up" approach, further divided into "material-level" and "component-level" descriptions. Moreover, the "bottom-up" approach can be integrated with "remote-sensing" approaches. Based on the different BMS modelling approaches, the data types required can be categorised into 1) material feature data such as MI coefficients (kg/m^2 or kg/m^3), and material density, 2) geometric data of the building and elements such as building height, area of building footprints, building volume, surface area of element, element thickness, etc., 3) feature data

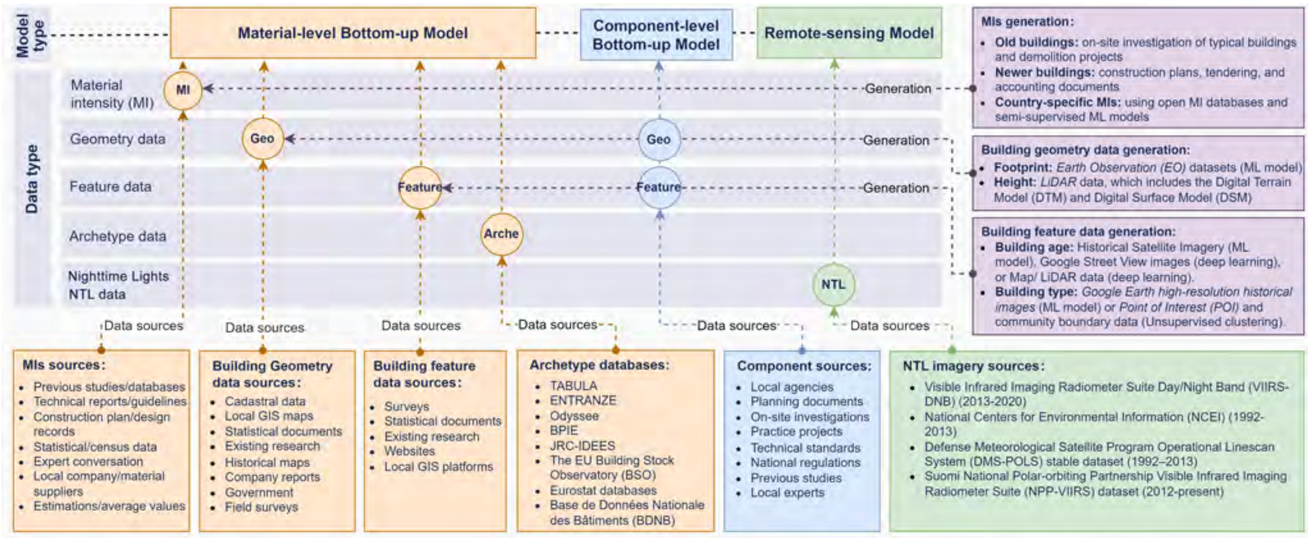

Figure 7: The data sources for static description of building material stock.

of buildings and elements such as building age, building function, element types, etc., 4) archetype data, 5) *Nighttime Light (NTL)* imagery data.

Figure 7 summarises all data sources and some data generation methods of the BMS static description mentioned by existing papers. As the data sources cited in existing studies are already summarised in figure 7, we will mainly explain the data generation approaches in the following paragraphs that can fill the data gap of conducting urban-level "BMS-LCA".

4.1.1.1. Data for "material-level" BMS modelling : The "material-level" bottom-up BMS modelling requires building Gross Floor Area (GFA) or Gross Volume (GV) and MIs to identify material mass/volume stored in the building stock. Equation 1 illustrates how the total stock S_m^t of material m at time i can be calculated by multiplying building total floor area GFA^t by the material intensity coefficient MI_m^t.

$$S_m^t = GFA^t \times MI_m^t \quad (1)$$

• **Material Intensities (MIs)** are varied with construction styles and are typically estimated according to building ages and functions [38] and can be obtained in different ways. First, the open-source global database developed by the research community [39] currently has over 900 MI data points for 32 material categories of various types of buildings covering 21 countries. It is important to note that when utilising MI values from such databases, consideration should be given to the specific building type information [40]. MIs can also be calculated through on-site investigation of typical buildings [41, 42] and demolition projects [43] or from tendering documents, construction plans, and accounting documents for newer buildings. Last, we noticed that MIs of a building can also be generated in a floor-by-floor way by combining *GIS* and *BIM*, which was created from the point cloud (geometry) [44].

• **Building physical attributes data:** The building features such as footprint and height (number of floors) are essential for GFA or GV calculations and 3D representation. The GFA of buildings can be calculated by multiplying the area of building footprints $A_{footprint}$ by the number of stories $N_{stories}$ (see equation 2).

$$GFA = A_{footprint} \times N_{stories} \quad (2)$$

Apart from directly collecting such building data from available data sources, it can also be collected based on remote sensing and data acquisition techniques. The remote sensing techniques applied for building stock data collection mainly include the following aspects (see Figure 8): 1) high-resolution satellite imagery, which is used for building footprint areas/cover areas extraction; 2) LiDAR data, which provides building height information; 3) NTL images which contain radiance values to identify and extract the building stock; 4) aerial building images to generate detailed building information such as windows and doors.

Building footprint areas can be generated from satellite or aerial imagery combined with building extraction algorithms. ML or deep learning models, such as Convolutional Neural Networks (CNN) and Generative Adversarial Networks (GAN), are used in existing research for data acquisition. [45, 46]. Point cloud data such as LiDAR [47] can capture the Earth's 3D scenes for building height generation. For example, the Digital Terrain Model (DTM) and Digital Surface Model (DSM) are

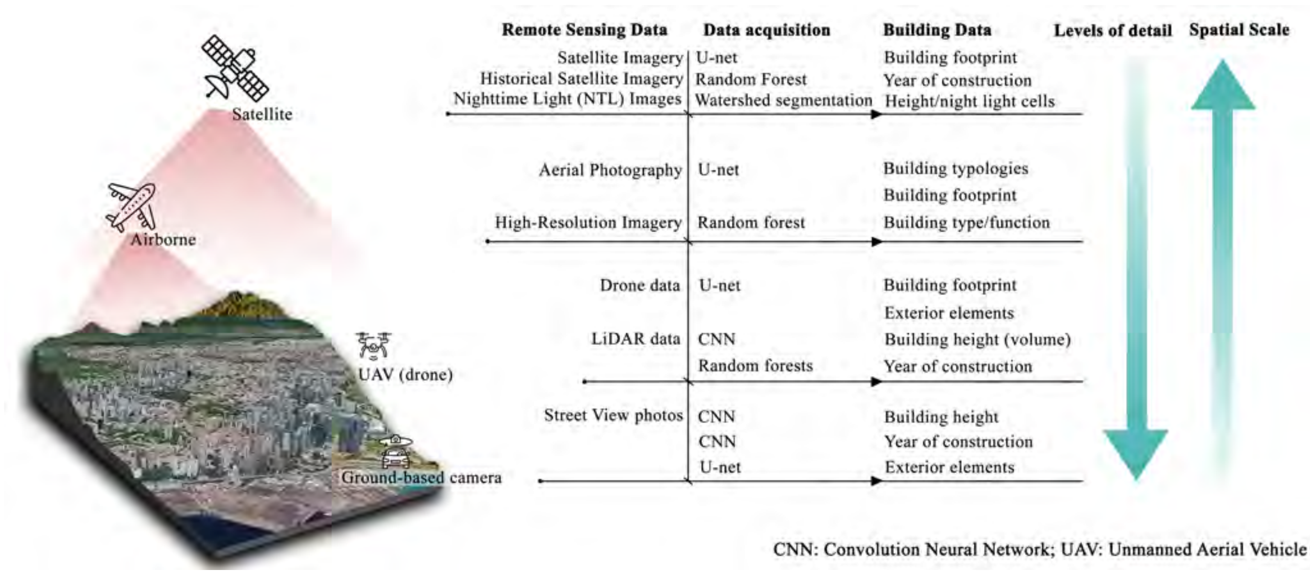

Figure 8: The remote sensing techniques applied for building data collection (the urban image at the bottom left is from *Google Earth Pro*).

adopted to retrieve building height by modelling the terrain's height and elevation features [48]. Besides, the NTL images can be combined with LiDAR data to support the "bottom-up" approach by calculating built-up volume [49].

4.1.1.2. Data for "component-level" BMS modelling: "Component-level" bottom-up modelling can provide more information for secondary resource recovery, requiring more detailed building component data, such as 1) size and geometry, 2) type, 3) number, 4) material composition, and 5) wear condition. Such component data can be generated by adapting drone-based fly and street view images to cover the entire building envelope and gathering information about the exterior elements, combining with deep learning and computer vision techniques [50, 51]. The other approach uses *3D Laser Scanning* and *BIM* to capture detailed data of buildings using a laser beam [44], which is better suited for small areas and a limited number of archetypes' high-resolution modelling because of the high cost.

• **Building typology and archetype:** The building typology process aims to form the virtual representations (archetypes) of several buildings that share similar characteristics in the BMS by clustering large amounts of urban buildings into building usage categories (office, commercial, residential, and industry, etc.), building ages and specific building properties (e.g., building construction materials used, and typical building geometries, etc.). The archetype approach can deliver a relatively high level of accuracy with lower computational effort [52]. While some regions already have existing databases, many research initiatives focus on creating archetypes based on the unique building situations, materials, and practices of the area under study. When developing archetypes for "bottom-up" modelling and MIs identification, the building age and function are two crucial parameters when classifying a building stock into archetypes.

• **Building age:** Building age is a critical indicator that provides valuable insights into the historical context, construction methods, and materials used in a particular structure. The year of construction can be generated using ML/deep learning models based on building attributes extracted from map data [53], *Google* Street View images [54], LiDAR data [55], or historical satellite imagery [56].

• **Building type:** The design of buildings, both architecturally and structurally, is intricately linked to their intended functions, significantly shaping the material selection and quantity. Various methodologies have been employed in existing research to generate building-type data. For instance, one approach involves utilising aerial images and deep learning techniques (U-net model) to segment German building types [57]. Deng and Chen [56] utilised ML models, specifically random forest, in conjunction with GIS data to discern building functions based on geometric characteristics extracted from *Google Earth* images. Additionally, Bradshaw et al. [38] integrated image interpretation techniques with a scale factor to identify and classify building functions.

4.1.1.3 Data for remote-sensing BMS modelling: Because of insufficient and available data sources and inaccessible cadastral records in some cities, especially in developing countries, six studies adopted NTL imagery to develop BMS models. Using statistical methods like regression analysis, researchers assess the correlation between the radiance values extracted from NTL imagery and the socio-economic indicators [58].

4.1.2. Data for Dynamic Assessment

The dynamic assessment involves modelling the BMS in both temporal and spatial dimensions. There are 62 papers containing dynamic assessments of BMS, which can be conducted in "stock-driven" and "flow-driven" ways, requiring different kinds of data. The data needed for the dynamic BMS evaluation are summarised in Table 2. The dynamic assessments of BMS can be divided into "stock-driven" and "flow-driven" methods:

- **Stock-driven** analyses the change of stock based on a temporally dense series of stocks (snapshots) of study areas. Such a series of stocks can be calculated based on "bottom-up", "remote-sensing", and "demand-driven" approaches. In the "bottom-up" modelling approach, the change of stock (ΔS) is next year's stock (S^t) minus the previous year's stock (S^{t-1}). The researcher can determine next year's stock (S_t) by adding last year's stock (S_{t-1}) to the materials in the newly constructed stock and then subtracting the materials removed due to demolitions. The quantity of materials from new constructions and demolitions is calculated by multiplying the difference in total floor areas between new constructions (N_t) and demolitions (D_t) by the material intensity (MI) (see Equation 3).

  $$\begin{cases} \Delta S = S^t - S^{t-1}, \\ S^t = S^{t-1} + \sum (N^t \times MI) - \sum (D^t \times MI) \end{cases} \tag{3}$$

  The spatial dynamic of BMS, such as material inflow and outflow across defined area/city boundaries, can be calculated based on current BMS (S^t). The material inflow (I^t) in the year(t) is determined by subtracting the net growth, expressed as the sum ($\sum_n^{i=1}$), multiplied by the residual percentage ($L^t_{lifespan}$), from the total material stock (S^t) (see Equation 4).

  $$\begin{cases} I^t = S^t - \sum_n^{i=1} \times L^t_{lifespan}, \\ O^t = I^t - (S^t - S^{t-1}) \end{cases} \tag{4}$$

  If using the "remote sensing" approach, the in-use stock per capita (t/person) (y^i) can be calculated by multiplying λ by nighttime light per capita (unit/person) (x^i). β is the coefficient of the ratio of nighttime lights to building stock regression model (see Equation 5).

  $$\begin{cases} y^t = \beta \times x^t, \\ \Delta S = S^t - S^{t-1} = y^t \times POP^t - y^{t-1} \times POP^{t-1} \end{cases} \tag{5}$$

  To compute the change in stock (ΔS), using a "demand-driven" approach, researchers can obtain this value by multiplying the population change (POP) between these two years by the per capita floor area ($PCFA$)(see Equation 6).

  $$\Delta S = S^t - S^{t-1} = PCFA^t \times (POP^t - POP^{t-1}) \tag{6}$$

- **Flow-driven** commences by computing the material flows (inflow and outflow) within the system boundary. This methodology proves beneficial for conducting comprehensive BMS analyses at a larger scale, such as the global or country level. For instance, the outflow of materials, also called waste material flow (O^t), can be determined by aggregating the waste generated from construction and demolition activities (see Equation 7), which can be calculated by multiplying the material used for construction (NS^t) or demolition activities (DS^t) by construction waste production rate (I^c) or demolition waste production rate (I^D).

  $$O^t = NS^t \times I^c + DS^t \times I^D \tag{7}$$

  The "flow-driven" dynamic assessment of BMS can also be conducted in a top-down way, relying on import (S^t_{import}) and export (S^t_{export}) data (see Equation 8). The current year's building stock (S^t) can be calculated by subtracting the local sum of export and waste material (SW^t) mass from the sum of import and newly produced material (P^t) mass.

  $$\begin{cases} \Delta S = S^t - S^{t-1}, \\ S^t = (S^t_{import} + P^t) - (S^t_{export} + SW^t) \end{cases} \tag{8}$$

4.1.3. Data for LCA

LCA combined with BMS/MFA analysis in existing papers mainly includes two types (see Figure 9): 1) resource use: embodied energy, water; 2) environmental emissions, GHG emissions, and EI, caused by several/whole buildings' lifetime stages.

Table 2
The data required for various dynamic assessments of building material stock.

Model types	Approach	Calculation rules	Data required	Data sources	Papers
Stock-driven	Bottom-up	$\Delta S = S^t - S^{t-1}$	Footprint change Building age	• Satellite maps/Aerial photography • Footprint land cover maps	[59] [60]
		$S^t = S^{t-1} + \sum(N^t \times MI) - \sum(D^t \times MI)$	Annual constructed floor area Annual demolished floor area	• Statistical yearbooks	[61]
		$I^t = S^t - \sum_n^{i=1} \times L^t_{lifespan}$ $O^t = I^t - (S^t - S^{t-1})$	Building average lifespan	• Calculated by Weibull distribution	[62]
	Remote-sensing	$y^t = \beta \times x^t$ $\Delta S = S^t - S^{t-1} = y^t \times POP^t - y^{t-1} \times POP^{t-1}$	Urban night-time light (*NTL*)	• Night-time light images • Regression models	[49]
	Demand-driven	$S^t - S^{t-1} = PCFA^t \times (POP^t - POP^{t-1})$	Population (*POP*) Per capita floor area (*PCFA*)	• Historical data • Statistical yearbooks	[63]
Flow-driven	Top-down	$O^t = NS^t \times I^c + DS^t \times I^D$	Construction waste production rate (I^c) Demolition waste production rate (I^D)	• Technical guideline • Previous survey • Statistics (e.g., SitraM database)	[64] [65]
		$S^t = (S^t_{import} + P^t) - (S^t_{export} + SW^t)$	Material import (S^t_{import}) Material production (P) Material export (S^t_{export}) Material waste (SW^t)	• Literature review • UN Comtrade database	[66]

** Where S is in-use stock of certain materials; N is new construction floor areas at time t; D is demolitions floor areas at time t; MI is material intensity; I stands for the yearly net addition to stock; $L_{lifespan}$ represents the residual percentage of buildings estimated through a Weibull distribution; O^t is the yearly outflows; y^t is in-use stock per capita (t/person), x^t is nighttime light per capita (unit/person), β is a coefficient of the ratio of nighttime lights to building stock which got form regression models; NS^t is the material used for construction; DS^t is the material released from demolition activities.*

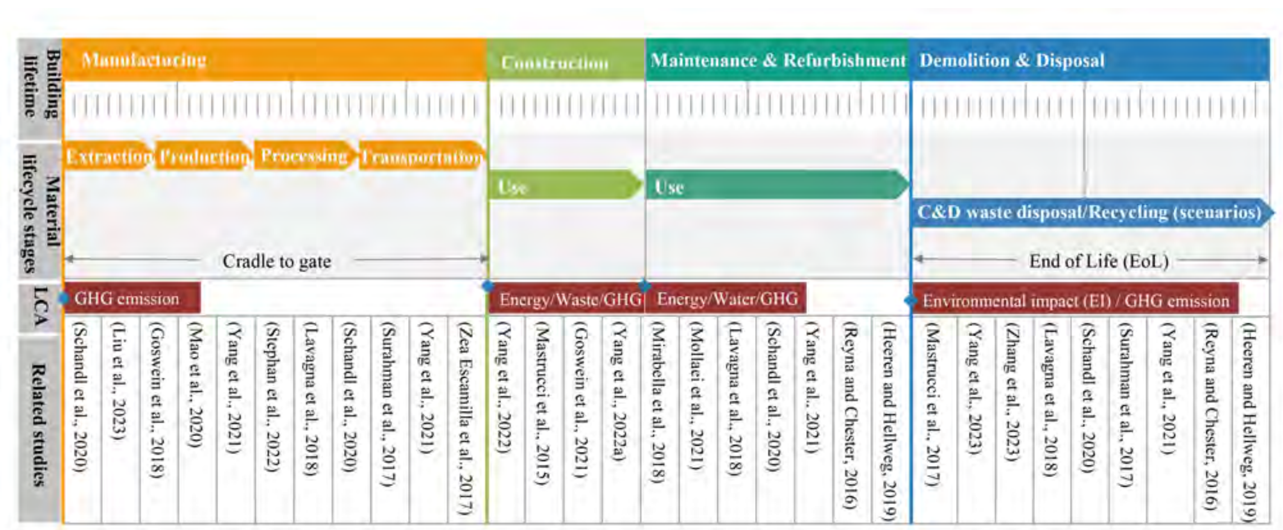

Figure 9: Types of life cycle assessment combined with building material stock analysis in existing studies (*GHG: Greenhouse Gas*).

For the resource consumption-related analysis, the data required are energy-related and water-related indicators, which can be collected from existing research [67], national publications [68], related databases and industries [69]. The GHG (CO_2, CH_2, N_4O, etc.) emission-related analysis requires combining "mass of materials (kg)" and "Carbon Emission Factor (GEF)", which can be collected from literature, related databases (e.g., Inventory of Carbon and Energy (ICE), *Ecoinvent*, *EPiC*, etc.) and statistic documents. The EI assessment is based on different indicators, such as Global Warming Potential (GWP), Abiotic Depletion Potential (ADP), and human toxicity, etc., which were gathered from standards [38].

4.1.4. Data Management

Following the acquisition process of intricate data essential for BMS, our attention is directed toward the tools/techniques available for data management, such as filling data gaps and storing data. Many included papers mentioned that conducting "BMS-LCA" at the urban level requires a large amount of data. In contrast, data limitations are prevalent in many countries, and very few datahubs can cover all the required information. To address data limitation issues, some approaches are

Table 3
Comparison of data management tools for building material stock modelling.

Tools	Property	With other tools	Functions	Support data	Skill required	Features
PostgreSQL/ PostGIS	Object-relational database/plug-in	GIS applications	Store, manage, and analyze data	Relational data/ spatial data	Programming language (SQL)	• Open-source • Flexibility and cost efficiency • Spatial analysis
ArcCatalog	Component of Esri's ArcGIS	ArcGIS	Manage, organise, catalogue, and search data in ArcGIS	GIS geographic data	Data cataloguing and ArcGIS tools	• Use with Esri software with licenses • Customization options limited • No spatial analysis (need ArcGIS) • User-friendly interface
3DCityDB	Open-source spatial database system	3D Modelling applications	Manage and query 3D city models and related geospatial data	CityGML and KML formats for 3D modelling	3D Modelling 3DCityDB tools and plugins	• Handle complex 3D city models • Open standards
ER diagrams	Data model visual representation	Database design	Model the structure and organisation of data	Common data types	Database design, data modelling	• Visualization • Difficult to handle complex database • Limited to the static structure

**3DCityDB: 3D City Database; KML: Keyhole Markup Language; ER: Entity Relationship; 3D modelling applications can be Blender, Unity, and Unreal Engine, etc.*

proposed: 1) combining various data sources and processing heterogeneous information [70], 2) making several assumptions (using average values) based on statistical, national standards, and study data, 3) using the data from another period or nearest geographical areas data (K-nearest neighbour algorithm) [71].

For data storage, developing structural databases for BMS modelling can support 1) data merging, combining geometry, feature, and different-scales data; 2) data delivery: inputting data for modelling and analysis at the targeted level; 3) data updating: update when new data becomes available; 4) data connection: associate material/components properties with buildings [72]. Some papers [11, 73] have developed data models that implemented spatiotemporal structured databases to store data in a standardised format, facilitating improved data management. Several tools can support various steps of database development (see Table 3), including Entity Relationship (ER) diagrams, *PostgreSQL* and its extension-*PostGIS* [74], *ArcCatalog10.2* [75], and *3DCityDB* [76]. In summary, *PostgreSQL* with *PostGIS* is versatile, supporting relational and spatial data management. *ArcCatalog (ArcGIS)* is tailored for managing and organising GIS geographic data, with a user-friendly interface but limited to an extensive set of spatial analysis functions. Instead, it relies on other components of the *ArcGIS* suite for more advanced spatial analysis tasks. *3D CityDB* specialises in handling complex 3D city models and related geospatial data, making it suitable for 3D urban modelling applications for BMS. In the context of "BMS-LCA", ER diagrams help model the relationships between different entities (such as buildings, elements, or materials), their attributes (including quantity, location, material composition, and any other relevant characteristics), and how they interact. In this way, ER diagrams are a valuable tool for designing the data model for the "BMS-LCA" study.

4.2. Modelling and Analysis Phase

Following BMS's various modelling approaches, we summarised the techniques and tools applied during the "BMS-LCA" modelling and analysis phase.

4.2.1. Static description of BMS

The static description of BMS refers to the representation of the materials stock present within a geographical area at a specific point in time. As introduced in section 4.1.1, the static description of BMS can be conducted at "material-level" and "component-level", according to the level of details of available building data.

4.2.1.1 Material-level modelling: Two material-level "bottom-up" approaches are "archetype" and "building-by-building". The "building-by-building" approach requires a large amount of data to quantify the mass/composition of materials used in buildings one by one, which is typically applied at the neighbourhood/district level. Most of the studies applied the "archetype" approach, which clusters large numbers of urban buildings into groups with similar material characteristics, using a typical building to stand for others to reduce the total data requirements. Through reviewing all related papers, we summarise all tools and techniques mentioned and employed to support the urban-scale "bottom-up" description of BMS:

- **3D city modelling:** Some studies start by developing a 3D city model, a digital representation of the Earth's surface and buildings, to provide a realistic and detailed view of the city. Visualisation aids in understanding the spatial distribution of buildings, which is crucial for assessing material usage patterns. Besides, 3D city modelling allows for spatial analysis of building footprints, volumes, and material characteristics, automatically supporting BMS analysis through code-driven analysis. The methods for 3D city modelling used in previous research follow these steps:

Table 4
Archetype definition using machine learning model.

Machine learning	Inputs	Process	Describe	Algorithms applied	Publications
Supervised learning	Pre-categorized Building data	Classification	Buildings are classified based on the training dataset.	Rule-based algorithm	[59]
Unsupervised learning	Unlabelled Building data	Clustering	Assigning properties of given building data to classify it.	K-means Artificial neural network (ANN)	[88]

– Processing LiDAR data with *LAStools* [77] to create bare earth surfaces and building polygons [59];
– Using Python scripting module in *Rhinoceros* to access the freely reusable data [78] from *OpenStreetMap (OSM)*;
– Collecting and integrating building footprint and height data in a GIS platform through the "*Join Attributes by Location*" function [79, 80].

- **Geographic Information System (GIS):** A total of 27 papers used GIS software (e.g., *ArcGIS*, *QGIS*, *SAGA GIS*, *GRASS GIS*, etc.) in their studies to assist "bottom-up" modelling. As a system that can manage, analyse, and display geographically referenced information, GIS supports various crucial steps in this process, including location-specific data extraction (especially for the "building-by-building" model), data management and integration, data processing, building geometry calculation, and result visualisation. Some studies utilised existing GIS databases from government urban planning offices to extract geometric features and incorporate a spatial dimension [56, 81]. For areas lacking polygon GIS layers, GIS software can integrate building attribute data with MIs data through location information [82, 69].

  Additionally, GIS played a crucial role in processing and calculating data layers for tasks such as estimating distances between buildings [21], calculating external façade areas [83], and determining shared wall areas among multiple buildings [84]. In remote sensing, GIS software, specifically Watershed Segmentation algorithms, processed NTL data to detect built-up areas, cut, mask, and extract nighttime brightness [85].

  GIS is also employed for data generation, enabling tasks such as comparing maps over time to track building changes (e.g., construction and demolition) [62]. Some studies use 4D-GIS to explore building stock and material trends over time [86]. GIS can also aid in data visualisation, mapping BMS modelling results, and material distribution. For instance, Shen et al. [87] used *GETIS OrdGi** in *ArcGIS 10.2* to map out hotspots of residential building materials across six specific periods, aiding in the identification of distribution patterns.

- **Regression model:** Regression analysis aids large-scale "remote-sensing" modelling (country/global). Studies by Liu et al. [85] and Peled and Fishman [49] used NTL and building volume data to train a regression model, obtaining a correlation coefficient (β) that predicts building volumes in different areas based on NTL data.

For archetype-based BMS models, classification is crucial. To introduce criteria to the analysed BMS and split the buildings into several categories, the classification process is conducted to define building archetypes as representative of buildings with similar properties. Typically, the conventional classification approach involves dividing the building stock into distinct groups based on indicators chosen by modellers. The commonly used indicators include building age and function, which inherit material-related properties of the buildings. However, while using this approach to identify the indicators is straightforward, it heavily depends on the subjective judgment of researchers. Two techniques are adopted to overcome the subjectivity of the classification process: supervised learning and unsupervised learning techniques (see Table 4).

- **Supervised learning technique:** Supervised learning techniques aim to enhance the accuracy and efficiency of the building classification process by training a model from labelled data and learning the types and number of archetypes from the training set. Here are some examples of applying supervised learning techniques for building classification from review papers. In the work by Schandl et al. [59], a rule-based algorithm was devised to categorise buildings based on land-use zoning regulations and polygons. In this way, the classification process is not solely based on building characteristics but also considers the surrounding land-use context and geographical features represented by polygons. Furthermore, Bradshaw et al. [38] introduced a scale factor and developed a classification system to class buildings based on their footprints. Incorporating a scale factor implies that the model considers the size or scale of buildings, allowing for a more nuanced understanding of their characteristics.

- **Unsupervised learning technique:** Unsupervised learning is an option when the amount of archetypes is unknown. Unsupervised learning, such as clustering, can discover concealed patterns in building characteristic data sets through similarities and exemplary elements, enabling the examination of diverse indicators. For instance, Lismont and Allacker [88] adopted k-means algorithms for standard indicators and clustering. However, a limitation lies in the impact of data completeness on the quality of clustering algorithm outputs. To enhance unsupervised learning algorithms, it is essential to balance the number and representativeness of archetypes, aiming to describe the building stock as comprehensively as possible with fewer archetype buildings.

Moreover, the archetype can also be developed in a parametric manner by first defining the base material compositions according to the building typologies [89, 74], which are identified based on regulations, standards, expert knowledge, and other criteria. By analyzing the typical construction systems of various building typologies, the associated construction assemblies can be detailed in terms of their material composition. Parametrizing building elements and linking them to geometric variables allows for the calculation of material quantities. The geometric variables of buildings and elements can be derived and processed from GIS databases. The parametric process can be achieved by developing a computational engine using the programming language. Such an archetype approach can achieve a "building-by-building" BMS modelling if it can be integrated with the available geospatial data from GIS.

4.2.1.2 Component-level modelling: Some studies developed the "bottom-up" model at the building component level to describe BMS in more detail. To address more detailed component data, existing papers use several tools/techniques:

- **Building Information Modelling (BIM):** In BMS studies, the BIM software, such as *Revit*, is used for building-level information models, representing buildings' physical and functional characteristics. In one way, it can model each archetype based on structural systems and dimensions, incorporating material data to accurately quantify the material composition of each archetype [90]. In another way, Honic et al. [44] used BIM to calculate MIs for archetype buildings more accurately by considering various building floors. BIM is often paired with higher Level of Detail (LOD) GIS models to improve data collection for new buildings and neighbourhood-level BMS models. However, its implementation is limited and mainly used for new buildings or neighborhood-level BMS models. The various BIM initiatives proposed by the government will improve the data quality of the building stock, but access to BIM models is limited in some countries [91].

- **TyPy:** TyPy is a Python package developed by CSTB in 2023, used to create building typologies and component information from a macro-components database. Tirado et al. [92] employed TyPy to model buildings, utilising a catalogue of macro-components to describe building element details.

- **Deep learning and computer vision techniques:** In cases of missing component data, computer vision models extract material information from *Google* street view images. For example, Arbabi et al. [50] adopted U-Net-based CNN to segment images and count doors and windows on building façades. Raghu et al. [93] fine-tuned CNN and Transformer image classification models to identify external façade materials. Deep learning techniques show great potential to enrich the BMS database through open-source image data processing.

- **Mobile Terrestrial Laser Scanning (MTLS):** Deep learning models excel at generating exterior wall information, but collecting indoor components and related materials data necessitates other methods. Laser scanning, performed with handheld devices, can obtain the actual geometry data of buildings [44]. However, as MTLS involves a manual data collection approach, resulting in high time and labour costs, it is better suited for supplementing missing data from a limited number of representative buildings.

4.2.1.3 Data-driven modelling: Some researchers have also employed a data-driven approach to improve the quantification of BMS modelling. Data-driven BMS modelling utilises empirical data and advanced models, such as deep learning, which can result in a more accurate and precise model of BMS. For instance, Bao et al. [94] introduced a CNN-based deep learning model that accurately estimates building stock using multi-source remote sensing data, encompassing ground-detail features from Optical Remote Sensing (ORS) and spatiotemporal features from NTL data. This model reliably predicts building stock based on ORS features. Additionally, Yuan et al. [95] established an ML model by analysing data from 71 demolished building projects to predict BMS when the six basic building features (building type, building year, height, perimeter, total floor area, and total floor number) are available. However, it should be noted that the success of data-driven models heavily depends on the quality and completeness of the available data. Inadequate or biased data may affect the reliability of the models. Also, the data-driven BMS modelling can be challenging to interpret because the outputs are generated directly from data.

4.2.2. Dynamic assessment of BMS

Dynamic BMS modelling involves complex system concepts and computational rules, necessitating specific tools to support the analysis phase. We summarise the tools used in the reviewed papers for dynamic assessment of BMS:

- **Open Dynamic Material Systems Model (ODYM):** ODYM is an open-source framework programmed in Python for material flow analysis [96]. It is applied to assist in modelling stock-flow relations in material systems, providing a lifetime model to calculate building material outflow in stock-driven dynamic assessment of BMS [97]. ODYM has been recently employed to predict stocks of residential and commercial construction materials on a global scale [98, 99].

- **Software for System Dynamics (SD) model:** SD is a method and mathematical modelling technique for understanding the long-term behaviour of complex systems by simulating complex social-economic urban system behaviour in a quantitative way[100]. Some tools for SD have been applied in reviewed papers. For instance, Yang et al. [67] used software *Vensim Version 7.0* and *Stella Architect Version 1.9* to develop a causal loop diagram and an SD model for dynamic assessment of BMS. The *Vensim* and *Stella* are widely used software packages for SD model development. Both tools offer user-friendly environments for constructing, simulating, and analysing SD models of complex systems. The graphical representation and simulation capabilities of *Vensim* and *Stella* facilitate the creation of causal loop diagrams, stock-and-flow diagrams, and other visualisations, supporting understanding of BMS's dynamic behaviour.

- **STAN software:** STAN is a tool to perform MFA under consideration of data uncertainties by visualising and mapping the material flows using a graphical model [101]. As a general MFA tool, it is also used by a reviewed paper for the dynamic analysis of BMS [102]. Through linking to databases and conducting uncertainty analysis, the data uncertainties, statistical tools, and error propagation can be considered by developing the graphical model.

- **Computational engine development:** Proposed by Stephen et al. [103], a Python-based model named *Nested Phoenix* is developed to quantify material stocks and flows at multi-scale, as well as urban BMS's life cycle environmental performance. The *Nested Phoenix* has a comprehensive architecture that can extract data from a complex network of tables to a structural database and can link with other tools such as *GIS* and *PostgreSQL*. By integrating these tools, *Nested Phoenix* can visually represent complex BMS systems and identify the uncertainties that impact dynamic analysis accuracy.

4.2.3. LCA modelling

In this subsection, we summarise the "calculation tools" and "databases" used for LCA modelling, specifically for EI evaluation of the BMS, by the selected papers. This subsection defines commonly utilised tools for developing LCA models integrated with BMS analysis. While many general software tools are available for LCA modelling, we will only introduce those adopted in the papers reviewed.

4.2.3.1 Calculation tools: Numerous calculation tools are available for LCA (see table 5), facilitating comprehensive EI cased by BMS. Some mentioned tools include:

- **SimaPro:** *SimaPro*, a widely utilised LCA tool, has been employed by five studies to calculate impact factors and analyse related environmental performance, such as Global Warming Potential (GWP), Embodied Energy (EE), GHG emission, etc., by using life cycle inventory data. For instance, Mastrucci et al. [21] concentrate on the retrofitting of the urban building stock, utilising *SimaPro 7.3.3* to predict the EI resulting from the implementation of diverse building retrofitting measures. This application of *SimaPro* underscores its role in facilitating detailed analyses of environmental performance metrics in retrofitting different building elements in building stock. Additionally, Lavagna et al. [104] first identified the representation of housing by dividing the building stock into several clusters. They conducted comprehensive LCA modelling for each lifecycle stage of every representative dwelling, employing *SimaPro 8.3*. *SimaPro* allowed for a detailed analysis of the EI associated with different housing types, facilitating LCA investigations of archetypes and preparing to extend the results to the urban level. Moreover, Zea Escamilla and Habert [75] also used *SimaPro 7.3* combined with GIS technologies in their paper to calculate the EI of houses considering the LCA of construction materials and transportation of these materials. The integration of *SimaPro* with GIS technologies highlights its adaptability in accommodating various aspects of LCA studies, including the spatial dimension of material-related environmental assessments.

- **Brightway:** *Activity Browser* is the graphical interface to *Brightway* [105], an LCA software written in Python, which plays a crucial role in supporting data selection and model setup for LCA studies, particularly in the context of future scenarios modelling. For instance, Zhong et al. [106] used *Brightway* software to calculate EI (GHG emissions) of the cradle-to-gate production of one kg of each type of construction material.

- **One-Click LCA:** *One-Click LCA* is a user-friendly software supporting the LCA process, making it easier to assess and optimise the EI of buildings and construction materials during their life cycle. This software can be installed as a plugin in *Revit*. For example, Al-Obaidy et al. [107] used *One-Click LCA* to evaluate building materials' environmental impact, treating reused content as recycled materials and including reuse content into the overall calculation of GHG emissions results. Hence, *One-Click LCA* guides how to model LCA for recycled material, indicating that it considers using recycled materials in its calculations.

Table 5
The life cycle assessment tools used for building material stock analysis.

Name of LCA tool	Features of tools	Application in BMS analysis	References
SimaPro	A widely used LCA tool for detailed analysis of environmental metrics	1. LCA for urban building stock retrofitting 2. Comprehensive LCA for representation housing (each lifecycle stage) 3. Integrate with GIS for spatial assessments (material transportation)	[104, 21, 75]
Brightway	An open-source software package for LCA	1. Future scenarios modelling 2. Can work with large datasets	[105, 106]
One-Click LCA	A user-friendly plug-in for Revit	Perform LCA for recycled materials	[107]
TOTEM software	An online tool to optimise EI of building materials	Support optimisation at the building design stage	[108]

- **TOTEM software:** *TOTEM* is another tool to analyse the EI of building materials, optimise the design to reduce environmental impact, and support decision-making in the design stage [108]. However, it does not refer to a database specific to reused and reclaimed materials and does not consider the impact of the production stage for the reclaimed materials or components.

4.2.3.2 Databases The research of LCA relies not only on the establishment of standards but also on the accumulation of assessment data and results. Therefore, continually accumulating assessment data and organising these data into a database format is a crucial aspect of LCA research.

- **Ecoinvent:** *Ecoinvent* is a standalone database that can be used in most LCA software and contains background inventory data related to the EIs associated with the entire life cycle of materials [109], including extraction, production, and transportation, making it valuable for evaluating building materials' EIs from a "cradle-to-grave" perspective. However, researchers should check for the availability of specific urban-related building material data points, as the database covers many industries.

- **Environmental Product Declarations (EPD):** The EPD is a standardised document that provides information about the environmental performance over the entire life cycle of construction products and buildings [110].

- **GaBi:** *GaBi* is an LCA software that includes its database, which is one of the most widely used databases, providing a comprehensive collection of life cycle inventory data, including information on the resource inputs, energy use, and emissions associated with various materials and processes.

- **EPiC database:** *EPiC* is an open-access database providing a vast collection of life cycle inventory (LCI) data related to various construction processes and building materials, which is essential for assessing resource consumption, emissions, and other environmental impacts in LCA studies [111]. The *EPiC* database relies on a hybrid LCI approach, a feature that sets it apart from other global databases of embodied environmental flow coefficients for construction materials. The *EPiC* database based on hybrid analysis combines both process-based and economic input-output (EIO) LCI data.

  Process-based LCI offers detailed data on specific processes within the supply chain but often suffers from truncation errors due to its limited system boundaries. These errors occur when certain upstream or downstream processes are omitted, leading to incomplete environmental assessments. EIO LCI encompasses a broader economic scope by using national economic data to estimate environmental flows, thereby minimizing truncation errors. By integrating these two approaches, the hybrid LCI method used in the *EPiC* database ensures extensive coverage of the entire supply chain while maintaining detailed process-specific information. Hence, *EPiC* is particularly relevant for assessing the EIs of building materials in urban settings because urban-scale LCA requires accounting for the complex interplay of numerous materials and processes over extensive supply chains. Truncation errors in this context can compound, leading to gross underestimations of embodied environmental flows.

4.3. Result Evaluation Phase

The accuracy of urban-level models would be constrained due to their reliance on statistical and reference data for inferring or forecasting building stocks' material and component composition, as articulated by Mastrucci et al. [11]. Hence, exploring input factors' uncertainties and quantifying the ultimate results' precision is necessary. A total of 52 papers included the result evaluation phase. The applied approaches were as follows:

- **Comparison analysis:** Some research compared their model outputs with 1) existing studies' results [60]; 2) manual count results from checking imagery, Google Street View, real estate, or observation on the ground [59]; 3) actual historical data

[67], questionnaires [71], and official statistical data [64]. Such comparison analysis allows for validating and calibrating the modelling result against real-world observations. However, such comparison analysis assumes that the existing studies or data used for comparison are accurate and reliable, which may not capture nuances or changes in the BMS system that occurred after the reference data was collected. Also, the reference data is not always available.

- **Discussion error data:** Other research reflected on and analysed the potential resources of errors [112] and tried to quantify the uncertainty of data sources [113]. The advantage of such a result evaluation approach is that it can promote transparency by acknowledging potential sources of errors and fostering a better understanding of the "BMS-LCA" limitations. At the same time, the discussion of error data sets the stage for an iterative model refinement process. Researchers can use the insights from error analysis to update the "BMS-LCA" process, refine input parameters, or seek more accurate data sources, improving the model's predictive capabilities over time. However, identifying and quantifying all sources of error can be challenging, while offering a straightforward solution to mitigate all identified errors proves to be a complex task.

- **Sensitivity and scenario analysis:** Some papers mentioned that, because of data limitations, they have to use average values or make assumptions based on experts' knowledge [102]. Five studies performed a sensitivity analysis to discern the apportionment of output uncertainty among different sources of variability in the input parameters. Hence, the sensitivity analysis can help identify which input parameters impact model outputs most, informing model improvement priorities. However, sensitivity and scenario analysis are typically static and may not capture the dynamic nature of BMS systems. Both sensitivity and scenario analysis rely on assumptions about the relationships and interactions among variables. If these assumptions change over time, the results of the analysis may not accurately reflect reality.

- **Uncertainty analysis:** uncertainty analysis is widely used by 16 papers to model and quantify the inherent uncertainties in input data and parameters to provide a probabilistic view of potential outcomes. Monte Carlo (MC) simulation, which is a statistical method for modelling complex systems while accounting for the inherent uncertainties, was used to achieve this goal [114], and *Crystal Ball* software was used as a tool [65] to provide a user-friendly interface for implementing MC simulation and visualisation of probability distributions and results. Using uncertainty analysis, researchers attempt to describe the entire set of possible outcomes and their associated probabilities of occurrence. In the context of "BMS-LCA", this uncertainty analysis is typically employed to generate and evaluate specific parameters integral to the "BMS-LCA" study. For instance, Bradshaw et al. [38] assigned the MIs data from statistics census reports by MC simulation coded in *R*, conducting multiple simulations to assess the extent of uncertainty.

5. Discussion

This section reviews the literature on "BMS-LCA" studies and summarises the proposed limitations and future research trends in this field.

5.1. Limitations, challenges, and opportunities

Reviewing the related papers, we found some limitations and challenges to applying "BMS-LCA" to urban areas. Hence, this section will provide a detailed discussion on 1) which approaches (based on techniques and tools) have already been attempted or envisioned in existing reviewed papers to overcome these limitations, 2) which limitations have not been solved, and what approaches have potential to overcome them.

(1) **Data limitation:** Data limitations are the most frequently mentioned research gaps in existing research. They are evident in factors like availability, amount, recency, and quality, particularly in building materials properties, MIs, state of renovation, building usage, and residual service life. For example, the real building lifespan data is essential but always missing in some research cases, which is usually calculated from the proportion of building stock registered as demolished. Many existing studies have to rely on simplistic assumptions about building lifespan [115]. For instance, A review paper [116] summarised that the lifespan assumptions across the reviewed studies varied between 50 and 100 years, with the most frequently employed assumption being a lifespan of 50 years. To enhance the validity of the assumption, lifespan assumptions can also be modelled using probability distributions such as standard (the Gaussian distribution), Weibull, log-normal, etc.

    Similarly, the granularity of material transportation data, often recorded daily or monthly, presents challenges when attempting to reconcile it with annual or decadal scales. A potential approach is using statistical techniques such as interpolation and extrapolation to estimate transportation volumes for annual or decadal periods to help fill missing gaps and extend data to longer time scales.

(2) **Uncertainties in broader applications:** There are inherent uncertainties when applying "BMS-LCA" at a broader scale, especially regarding selecting MIs, archetypes, and forward-looking scenario assumptions. For instance, as Buffat et al.

[117] mentioned, various life cycle inventory databases, LCA methods, and the material scopes of existing studies could all bring variability for broader applications. Moreover, some prospective scenario assumptions of LCA analysis entail large uncertainties [39]. To address such uncertainties, a sensitivity analysis has been conducted by existing studies to assess the impact of different input indicators for "BMS-LCA" on the results and provide insights into the reliability of the findings. It would be helpful to develop common structural databases, protocols, and guidelines to address this limitation.

(3) **Incomplete views:** There are some incomplete views in selected studies, reflected in the following aspects: 1) exclusion of non-residential buildings due to data limitations, 2) focus on structural systems while overlooking other building systems, resulting in underestimation of specific building components, 3) not considering all life cycle stages in most LCAs. This limitation is mainly caused by the missing data required for "BMS-LCA" in some regions. For instance, new construction and refurbishment scenarios are challenging to include in modelling for evaluation when lifespan data is unavailable [59].

(4) **Lack of accuracy evaluation:** Even though some selected papers tested the accuracy of outputs, more articles did not evaluate the accuracy and performance of "BMS-LCA" results. An intuitive way to evaluate the model's accuracy is to compare the output result with actual measurement data. However, the data limitation at city scales makes implementing this method challenging [118]. While direct measurement data may be scarce, the available proxy data could be a reasonable substitute, including data from similar cities, regions, or industries where measurements have been conducted. Besides, domain experts can be engaged for result evaluation based on their knowledge of the urban BMS system and identify potential sources of error or uncertainty.

(5) **Lack of interpretability:** "BMS-LCA" results in a lack of interpretability, particularly in "data-driven" BMS modelling, which can appear as a "black box" to users despite its potential to address data limitations [119]. One research gap is to make such a "data-driven" model interpretable when representing, quantifying, and analysing BMS, offering more strategies for material recycling. To improve the interpretability of the "data-driven" BMS model, researchers can utilise various methods to look at the interpretability of such models, such as feature selection and engineering, visualisation tools, and some model-specific interpretation techniques [120].

(6) **Limited transferability of models:** Current models suffer from limited transferability as they predominantly depend on local data, constraining their applicability across diverse regions. For instance, archetype-based "bottom-up" BMS models prove inadequate for global modelling owing to architectural variations, leading to impractical results when employing a solitary archetype to depict a range of buildings. A viable solution lies in developing and utilising extensive datasets incorporating diverse buildings, climates, and usage patterns to train models for "data-driven" BMS modelling, thus enabling better generalisation across regions.

5.2. Future Research Agenda

Many reviewed papers also proposed significant future research trends of "BMS-LCA" analysis at the urban level.

(1) **Improving spatial-temporal resolution:** The first research trend is improving the resolution of the spatial-temporal dimension to "BMS-LCA" by adopting data mining techniques [60]. While 4D-GIS can provide a geographical platform for constructing and overseeing spatiotemporal building stocks, their efficacy is limited by data integrity and resolution issues. Geospatial Artificial Intelligence (GeoAI) has recently received widespread attention, which merges AI with GIS. Using AI methods, researchers can achieve more precise identification of urban spatial features and elements by employing algorithms designed for remote sensing image target detection, semantic segmentation, and multi-temporal change detection. Moreover, integrating LCA with GIS analysis of material road transportation has been used to enhance LCA's spatial resolution. In future research, applying GeoAI, which can utilise information from various data sources such as GPS and road sensors, to aid in identifying traffic on roads, tracking material products, and mapping supply chains, etc., will be a promising research direction for improving the spatial resolution of "BMS-LCA" studies.

In the temporal dimension, addressing this limitation requires developing high-resolution real-time data from autonomous satellites and integrating relevant research databases operating on annual or decadal scales [85]. Besides, combining GeoAI with sensors, monitoring devices, etc., enables real-time monitoring and data analysis of urban environments, public facilities, and buildings. When satellite images and street view images are insufficient for collecting high-resolution building material data in a timely manner, mobile sensing could be employed to accurately detect building materials by combining them with deep learning-based image segmentation techniques. For instance, Arbabi et al. [50] recommended a mobile sensing platform to identify wall construction and used thermal and hyperspectral imaging to assess heat loss patterns and component material quality in future studies.

(2) **Investigating building inside materials:** Collecting information on material compositions inside buildings is the next frontier and a critical research topic for improving the BMS quantification. While envelope materials are important, such as concrete and steel, each of them only accounts for around 25% of the global embodied environmental flows [61] and even less in terms of total construction material mass. Hence, beyond the envelope materials, it is essential to consider the materials used in other inside building systems, such as heating, ventilation, and air conditioning (HVAC) systems, plumbing, and electrical systems. For instance, HVAC systems contain materials like metals (copper, aluminium), plastics, etc., each with its environmental footprint. Plumbing systems primarily use materials such as copper, polyvinyl chloride (PVC), and cross-linked polyethylene (PEX), while electrical systems include copper wiring, plastic insulation, and various metals in circuit components. Incorporating data from these systems into a centralized database would provide a more complete picture of a building and the whole BMS's material composition, which can also enhance impact assessment regarding renovations, retrofits, and demolitions during the whole life cycle of the buildings.

However, developing complete databases for inside building materials at the urban-level BMS modelling is challenging. There are some approaches worth attention to collecting inside building material information. First, implementing regulations that require property owners to disclose a comprehensive, third-party-certified list of materials used in buildings during selling, lending, or renovation processes can significantly improve data availability. Besides, a centralised database can be developed to host such information for property owners and developers to submit material data electronically. The material passports, which document the lifecycle of inside building systems' materials, can be linked to the centralized database, allowing easy retrieval of such material information. Moreover, some studies [121, 122, 74] attempt to develop parametric models based on expert knowledge and rules of thumb to assume and quantify building elements' materials. This includes understanding the construction methods and how they influence material quantities. Such models use predefined parameters captured from the relationships between building components and the building's geometry and spatial features to simulate internal material stocks. When detailed data collection is impractical, parametric models are efficient and can provide reasonable estimates without the need for extensive physical inspections at a large scale.

(3) **Developing shared data space:** A shared data space can support information exchange, which is specifically essential for "BMS-LCA" studies. Such data space can harmonise the available data on building materials, facilitating the comparison of BMS studies and their data across various countries. The resources and energy availability vary significantly across different countries and regions, and their respective levels of construction technological advancement are also uneven. These differences manifest strongly in LCA data, highlighting the regional features of LCA databases. Hence, almost every country and region requires the establishment of localised EI databases. Since the inception of LCA, numerous related databases have been developed worldwide. LCA necessitates a shared data platform that can be utilised across multiple databases to facilitate the search for required information [123].

Some existing global data hubs, such as *Metabolism of Cities* [124], include libraries of available datasets and documents for various regions (currently 69 cities) that could be used to exchange information in future research. The researcher can first identify and choose the cities they are interested in on the *Metabolism of Cities* website and explore the datasets, publications, maps, and multimedia materials on urban material flow, stocks, consumption, etc. It should be noted that *Metabolism of Cities* contains not only building material information but also other resources such as water and electricity consumption. Meier-Dotzler et al. [125] suggested that the environmental and energetic values of the building components should be released for other related studies, perhaps in conjunction with BIM. To enhance the digital urban mining platform, one can consider using material passports to reuse and recycle building components based on existing data easily [92].

(4) **Crowdsourced and user-friendly modelling platform:** Achieving circularity in construction materials is a global wide participation subject, which necessitates collective efforts from various sectors of society, including government, industries, businesses, and individuals. It is a research trend to develop a user-friendly modelling platform for "BMS-LCA" [65], which can be expected to fill data limitations by collecting crowdsourced data as a web-based and open platform. Building occupants contribute material data through crowdsourcing platforms, which are then integrated into databases and transferred to user-friendly modelling platforms, processing modelling and simulation tasks. This involves exporting the simulation results back to the city model and achieving data integration. As such, the results can be easily visualised using tools such as *3DCityDB* Web Map Client.

(5) **Enhance model evaluation:** Considering the uncertainties and assumptions within the "BMS-LCA" models, it is crucial to devise policy mechanisms and evaluation metrics in future research to explore and compare the performances of various types of BMS and LCA models [126]. Besides, developing an open-source standard dataset containing relevant data inputs, parameters, and performance indicators for "BMS-LCA" modelling can validate and verify the model's outputs.

(6) **Improving modelling approaches:** The existing BMS models are typically specific to research cases and regions. It is imperative to enhance modelling approaches to account for varying data availability [127]. This can be achieved through coding actual assemblies, implementing parameterised models for tracking material flows during construction, and exploring innovative modelling techniques as crucial research avenues for the future. Future advancements in "BMS-LCA" modelling require an approach that achieves a harmonious equilibrium between expert knowledge and "data-driven" components. A "data-driven" approach for modelling BMS can only uncover hidden patterns within the data. Introducing expert knowledge can effectively mitigate the data requirements of traditional, purely "data-driven" modelling approaches. For urban-level BMS analysis and LCA domains, data scarcity is a limiting factor for developing deep learning models. Introducing expert knowledge can enhance the model's performance and explanatory capabilities.

Besides, it is worth exploring combining techniques and tools efficiently to improve the "BMS-LCA" modelling matching different scales. For instance, at the neighbourhood level, integrating BIM models, which provide detailed information about building components and materials, with 3D city models that offer a broader spatial context by representing the surrounding environment can support tracking material stocks and flows within a neighbourhood in space dimension. Besides, at the city level, the synergy of 3D city models and GIS can enhance visualization and spatial analysis as 3D city models provide a 3D view of urban environments, and GIS adds the capability to analyze spatial relationships and patterns of BMS within this 3D context. Additionally, combining GIS, BIM, and Laser scanning can assess accurate measurements of some topical buildings (archetypes) when modelling BMS at the city level. Moreover, combining GIS, remote sensing, and machine learning can support automated and up-to-date building information collection in large geographic areas. The feasibility of applying and combining these tools and techniques depends on the availability of materials, such as BIM models, GIS databases, satellite imagery, and the professional expertise of researchers.

Despite the comprehensive nature of this review, several limitations should be acknowledged. First, the review includes only papers published in English. This language bias may exclude relevant studies and advancements published in other languages, potentially overlooking important contributions from non-English-speaking researchers. Additionally, the temporal scope of the review is limited to the past 10 years, which might omit older yet still significant studies. Research conducted outside this timeframe could offer valuable insights not captured in this review. Moreover, the rapid pace of technological advancements and contextual shifts can affect the relevance of findings from the early part of the review period, potentially limiting the applicability of some conclusions to current tools, technologies, or recent developments.

Also, this review paper currently mainly focused on the embodied impacts related to building materials and didn't discuss the tradeoff between embodied and operational impacts, such as energy consumption and maintenance, during the evolution of the BMS. This omission is critical as the balance between embodied and operational impacts can shift significantly over time, influencing the overall sustainability of the BMS. For instance, a building designed with high-efficiency materials may have a higher initial embodied impact but lower operational costs, leading to long-term environmental benefits. Conversely, focusing solely on minimizing embodied impacts without considering operational efficiency may not reduce the overall emissions and resource use. Hence, it is worth more attention to integrating the LCA studies that tradeoffs between embodied and operational impacts to BMS analysis. By integrating both types of impacts into "BMS-LCA" studies, future research can better understand the long-term environmental performance of BMS and provide a holistic evaluation of building sustainability.

6. Conclusion

This review examined 99 papers on integrating "BMS-LCA" in urban building systems over the past decade, summarising the techniques and tools employed. The SLR commenced with a rigorous database search and bibliometric and content-based synthesis analyses. The "bibliometric analysis" section offers a comprehensive summary of tools and BMS models utilised in selected "BMS-LCA" papers and insights into their temporal and spatial distribution. In particular, applying ML and data mining techniques has the potential to revolutionise the BMS modelling approach and support BMS modelling in a "data-driven way". The "content-based synthesis analysis" section discussed and compared the tools/methods used in data collection, static description/dynamic assessment of BMS, LCA model, and result evaluation phases. Applying strategic tools and techniques within the "BMS-LCA" workflow is crucial for enhancing the accuracy and precision of urban building stock analysis in the future. For instance, integrating GIS and real-time high-precision data would be essential to achieve high-precision spatial and temporal analysis in BMS. Moreover, the application of data science emerges as a promising approach to address data scarcity issues in "BMS-LCA" studies. In conclusion, This study offers guidance on applying techniques and tools while identifying potential avenues for enhancing "BMS-LCA" processes at the urban scale. It underscores critical research gaps that researchers should prioritise for further investigation.

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A. Appendix A

- Supporting Information S1: Data Extraction Form

B. Appendix B

- Supporting Information S2: Information Extraction of Selected Papers

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