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# Searching for new Urban Metabolism techniques: A review towards future development for a city-scale Urban Metabolism Digital Twin

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ABSTRACT

This review delves into the integration prospects of Urban Metabolism (UM) with industry 4.0 technologies, particularly digital twin (DT), to bolster sustainable urban development. Embracing a DT framework can enable the visualization of interdependencies within civil systems, facilitating the prediction of interventions to mitigate future climate change impacts. Therefore, the scope of this review was to determine how UM results are represented to end users, such as architects, and engineers and evaluate if these methods align with industry practices. Initially, we analyzed 70 UM studies to investigate the methods and visualization techniques employed. Trends revealed minimal integration of UM with Industry 4.0 technologies or DTs. The findings underscored a lack of dynamic and geographically oriented visualization in UM, with static representation methods like bar charts and Sankey diagrams prevailing, and mostly disconnected from the geographical location of the flows represented. Consequently, the research was further expanded to explicitly review the use of emerging technologies from Industry 4.0, including DTs, using targeted words. An extended review showed a gap in the integration of the UM framework with DT technologies, although an increased use in mapping was depicted. There was inconsistency in the adoption of specific technologies or visualization methods, highlighting ongoing research in this area. The increased use of geographic information system (GIS) and light detection and ranging (LiDAR) marked a pivotal change for more elaborate mapping of UM outcomes. Limited application of dynamic visualizations in UM persists, with MFA diagrams, Sankey diagrams, and bar charts being commonly used methods, despite the need to develop such type of visualizations in the sustainability field. There is an obvious lack of interoperability of these methods with Computer-Aided Design (CAD) software as well as Building Information Model (BIM) software, which are standard tools in urban planning and design. This limitation is particularly significant in environments where the ability to modify planning scenarios and work with precise spatial representations is crucial. We argue that UM can be more effective if integrated with technologies such as DT, which can resolve the spatial issue and describe UM contextualizing it and potentially depicting it in real-time. Additionally, DTs can offer promising solution by integrating UM analysis results and facilitating modifications to the 3-dimensional environment based on this information. This capability empowers planners and designers to conduct simulations, update UM analyses, and iterate the design process, aligning with contemporary practices in planning and design. Given the interdisciplinary nature of UM, which includes various concepts such as urban flows, city flows, system of systems, and urban networks, our study deliberately focuses solely on UM and its associated frameworks. This targeted approach may limit the breadth of concepts explored, but it ensures depth and coherence in our analysis of UM for this study.

## 1. Introduction

463 million people are currently living in 29 urban areas larger than 10 million people. By 2035, this number is projected to grow to 862 million in 48 urban areas. Thus, we are at an inflection point (Kennedy et al., 2015; Stewart et al., 2020). Design and engineering methods at the system level have not fundamentally changed in the last decades. For instance, little research on urban planning and urban metabolism (UM) integration was conducted (Galan & Perrotti, 2019; Oliveira & Vaz, 2021). Moreover, existing planning tools are not equipped to integrate the results of either UM models or urban dynamics models used to forecast land use change, urban growth or shrinkage, or impacts of urban expansion on the environment (Kennedy et al., 2011; Koenig, 2018), as the ability to understand a complex sustainability

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analysis or urban simulation model becomes more complex the more parameters are considered. It can be complicated and time-demanding for the planner to quantify unintended impacts on the environment or on citizens' well-being when designing for new development. There is, therefore, the need to quickly integrate urban modeling theories with sustainability scenarios and input from shareholders (Beloin-Saint-Pierre et al., 2017; Broto et al., 2012; D'Amico et al., 2022; Elliot et al., 2019; Musango et al., 2017). Additionally, traditional UM models do not provide a dynamic picture of the flows circulating into a city, offering instead a static glimpse of inputs and related outputs.

A digital twin (DT) is one technology that is emerging from Industry 4.0; however, Industry 4.0 includes but is not limited to Internet of Things (IoT), Artificial Intelligence (AI), Big Data, and cloud computing. DTs and other Industry 4.0 technologies have the potential to unlock a wide array of opportunities to support and improve sustainability decision-making due to their power of visualization, interoperability, short development periods, real-time data collection, enhanced flexibility, and decentralization of information (Ghobakhloo, 2020; Lasi et al., 2014; Xu et al., 2018). For instance, a DT can facilitate collaboration in complex projects and enable predictive maintenance in urban infrastructure.

In this context, urban planners, developers, and policymakers may find it advantageous to navigate complex decisions within a high-fidelity simulation environment. This simulation environment not only aids in decision-making, but also fosters much-needed citizen engagement and input, especially sustainable development decisions. Through an integrated process that harnesses advanced tools, urban development can thrive in a dynamic modeling environment. Community discussions can be facilitated, allowing for exploration of future developments before their physical realization (White et al., 2021), and proposals and designs can be fine-tuned through meaningful community engagement and advanced e-participation (Le Blanc, 2020).

The relationship between UM and DTs is complementary, as they serve distinct yet interrelated roles in understanding and optimizing urban systems. UM encompasses a range of established methods for analyzing the flows of materials, energy, and resources within cities, providing insights into resource usage, waste generation, and environmental impacts (Beloin-Saint-Pierre et al., 2017; D'Amico et al., 2022; Kennedy et al., 2007, 2011; Li, 2018; Zhang, 2013; Zhang et al., 2015). On the other hand, DTs offer virtual representations of physical assets, processes, and systems, leveraging real-time data, simulations, and predictive analytics to monitor, simulate, and optimize complex systems. In the urban context, DTs can model infrastructure, transportation networks, energy grids, and environmental conditions (Cugurullo et al., 2023; IBM, 2020; Lu et al., 2020; Semenyuk et al., 2023; Tagliabue et al., 2021; White et al., 2021).

Integrating UM and DTs enables cities to achieve sustainable development by providing a comprehensive understanding of urban dynamics and facilitating data-driven decision-making. This integration allows end-users to assess environmental impacts, identify inefficiencies, and design more sustainable urban systems. Incorporating UM into a DT environment enhances planning and management capabilities, enabling city planners, policymakers, and shareholders to test scenarios, optimize resource allocation, and develop strategies for enhancing urban sustainability.

In summary, UM provides the conceptual framework for understanding urban systems, while DTs offer the technological platform for modeling, simulating, and optimizing urban processes towards sustainability (D'Amico et al., 2022; Musango et al., 2017).

The overarching aim of this research is to elegantly merge sustainability assessments into the collaborative urban design process through meaningful and system-level visualizations. Specifically, the research aims to bridge the existing gap between UM and emerging technologies, with a particular focus on DTs, to advance sustainable urban development. With this paper, we aimed to address three key questions. First, what is the current state of UM in terms of industrial ecology methods and visualization techniques? Second, what is the current status of UM in the context of emerging technologies, particularly DTs? Given the answers to the first two questions, how can we merge sustainability assessments into meaningful and system-level visualizations?

To explore these questions, the paper is structured in the following manner: (1) a background on UM, Industry 4.0 and DT technologies, (2) a methods section a where systematic literature review of recent UM research focusing on methods and visualizations, is compared with a second systematic and refined literature review of UM investigating Industry 4.0 technologies, considering methods advancements and improved visualizations techniques (i.e, DTs). (3) Results, (4) discussion and (5) conclusions.

## 2. Background

In this section, we will delve into the concept of Digital Twin (DT) and their evolving role in urban development. Since the introduction of DTs this technology have rapidly advanced as a transformative tool. This novelty can be leveraged in the context of Urban Metabolism (UM) studies, where diverse data structures and traditional visualizations often hinder assimilation of this studies in urban planning. The synergy between UM and DTs presents a compelling opportunity to bridge these gaps and enhance the sustainability of urban environments.

What is a Digital Twin? A DT was first introduced in manufacturing processes in 2002 (IBM, 2020). The first publication, by NASA, can be traced back to 2011 (Davila Delgado & Oyedele, 2021). A DT is a non-static tool, a replica of its original counterpart used to virtualize a physical asset, process, or system that exists in the real world. The main difference between a DT and a Building Information Model (BIM) is the real-time data component. A DT is a high-fidelity replica that can also give feedback to the sensors from which the data is exchanged (Batty, 2018; Davila Delgado & Oyedele, 2021; Digital Twin Consortium, 2021; Fuller et al., 2020). As Fuller et al. (2020) highlight, this feedback is a crucial aspect of the definition of a DT. When this two-way data exchange does not exist, a DT is a mere digital shadow (Fuller et al., 2020).

The DT industry was valued at 30 billion USD in 2019, is projected to grow to 35 billion USD by 2025 (Evans et al., 2022). Nevertheless, this technology's adoption remains challenging for small cities and municipalities due to its high computational requirements and the need for skilled personnel to manage and store data (Lu et al., 2020).

DTs are often mentioned as one of the key factors of the fourth industrial revolution or Industry 4.0, which has the characteristic of merging different technologies between the physical, digital, and biological spheres. A fundamental concept of Industry 4.0 is a renewed emphasis on meeting human needs, in contrast to a traditional productivity-centric manufacturing systems. These fundamental concepts converge around cyber and physical systems into a unified whole (Lasi et al., 2014).

By embracing a DT framework, the visualization of interdependencies within civil systems can be enabled and facilitate the prediction of interventions to address future climate change impacts (Allam & Newman, 2023). While still relatively under-explored, the widespread adoption of DT models holds significant promise for various civil engineering applications (Adade & de Vries, 2023; Charitonidou, 2022), climate adaptation initiatives (Bauer et al., 2021; Ye et al., 2023), and community development efforts (Bagaria et al., 2020).

Cities have emerged as an important platform for realizing the potential for DTs (Angelidou, 2014). A recent example is New York City's hybrid twin for urban transportation, which integrates real-time transit and planning (American Society of Civil Engineers, 2022). Additionally, DTs has been instrumental in creating replicas of cities such as Singapore, Shanghai, Auckland, Glasgow, Boston, and Amaravati (Digital Twin Consortium, 2021; Unreal Engine, 2022). These DTs were crafted by integrating data from diverse sources, including city sensors, satellites, and drones, enabling the comprehensive monitoring and representation of physical assets. Another example of a DT is for Dublin, where researchers from Trinity College have developed an open-source DT that is accessible for use by citizens (White et al., 2021). Even though cities are at the forefront of DTs, cities could face challenges in reconciling older technologies and their workforce (Allam & Newman, 2018; Deren et al., 2021).

The concept of Urban Metabolism (UM) traces its origins back to A. Wolman in 1965 (Wolman, 1965). In UM studies, the city is compared to a living organism. The term 'metabolism' finds its roots in Greek, signifying 'conversion' or 'transformation'. While originally used to describe physiological processes within individual organisms, the concept of metabolism has found application in fields such as biology, ecosystems, architecture and even cultural systems (Baccini & Brunner, 2012; Newman, 1999; Rogers, 2008). Due to the term "metabolism", literature reviews are often vast because this word has been used across disciplines.

In 2007, Kennedy and colleagues proposed a revised definition of UM as "the sum total of technical and socioeconomic processes occurring in cities, resulting in growth, energy production, and waste elimination" (Kennedy et al., 2007). This definition remains foundational in the field. UM studies scrutinize the sourcing of resources, the pathways through which resources enter a system, and their circulation within it, including eventual elimination (Zhang, 2013). Notable reviews of UM literature include studies by Beloin-Saint-Pierre et al. (2017), Holmes and Pincetl (2012), Kennedy et al. (2007), Kennedy and Hoornweg (2012), Kennedy et al. (2011), Li (2018), Zhang (2013) and Zhang et al. (2015).

Urban designers have embraced UM to explore community issues, leading to the implementation of several models in a bottom-up participatory fashion in recent years (Chini & Stillwell, 2020; Ecocity Builders, 2022; Khalil & Al-Ahwal, 2021; Papageorgiou et al., 2020; Smit et al., 2019; Stelwagen et al., 2021; Suzuki et al., 2010; Wang et al., 2020).

In a broader context, the framework proposed by Allam and Newman (2018) includes three essential pillars. First, Urban Metabolism, this involves understanding the accumulation of materials and energy stocks and flows within cities. Second, Governance, the framework emphasizes the importance of forecasting unintended consequences of urban management programs, infrastructure developments, policies, and expansion plans. The goal is to enhance the city's sustainability through effective governance. Third, Culture, often overlooked in discussions of smart cities, as the cultural aspect plays a crucial role. It involves promoting two-way communication between citizens and government, considering urban cultural heritage, inclusivity, and livability. Therefore, as we endeavor to create sustainable cities, it becomes imperative to shift our conceptualization and approach, which is rooted in an older paradigm, reflecting a different era when the first modern cities emerged (Allam & Newman, 2018; Bettencourt, 2014).

To navigate the complexities of urban development, it has been proposed that urban modeling theories be integrated with UM and leveraged through the use of industry 4.0 technologies (Bibri, 2022; D'Amico et al., 2022; Stephan et al., 2022a), such as DTs (Beloin-Saint-Pierre et al., 2017; Broto et al., 2012; Elliot et al., 2019; Musango et al., 2017).

However, the interdisciplinary adoption of UM has resulted in diverse data structures, contingent on distinct methodologies employed (e.g., material flow analysis, life cycle assessment, input–output). Consequently, data sets are not easily exchanged among researchers, particularly when novel methods are introduced. This issue has been previously addressed by authors such as Broto et al. (2012), Holmes and Pincetl (2012), Kennedy and Hoornweg (2012), and more recently by Pauliuk et al. (2019). Several authors touch on the general lack of city-wide data that impairs the potential of these methods, highlighting the need for policies to facilitate data collection specifically in the United States (Caputo et al., 2019; Chini & Stillwell, 2020; Creutzig et al., 2019; Galan & Perrotti, 2019; González-García & Dias, 2019). Moreover, the visualization techniques utilized have not progressed significantly from the type of presentation that Wolman proposed in its first publication on UM in 1965. Non-geolocated and conceptual diagrams, along with charts and matrices, are currently employed to illustrate flows and stocks within a city or a system. These visualizations often fail to align with the daily tools used by urban planners, who stand to benefit greatly from UM studies.

As we delve deeper into specific examples of UM studies, it becomes evident how DTs have the potential to revolutionize UM, particularly by enriching UM outcome analysis through real-time data visualization, simulation capabilities, and predictive analytics (D'Amico et al., 2022). Comprehensive maps illustrating material, goods, substance, people, waste, and food flows are rare and typically require laborious data analysis and computer programming (Bahers et al., 2022). For instance, the Municipality of Rotterdam collaborated with the International Architecture Biennale of Rotterdam (IABR) to explore urban-nature relationships during the 6th IABR (International Architecture Biennale Rotterdam, 2014). Utilizing the concept of UM, this initiative depicted Rotterdam's urban system through its flows, offering insights crucial for design, planning, and governance of urban landscapes. Despite their static nature, these maps synthesized complex urban dynamics, suggesting strategies for resource optimization, energy by-product utilization, and flow optimization. However, such maps represent specific snapshots, like the year 2013 for Rotterdam. DTs present a solution by dynamically visualizing flows and contextualizing analyses in real-world scenarios.

Another example lies in the work of Metabolic (2018), advising governments, businesses, and NGOs on adapting to a rapidly changing global context. Leveraging UM, circular economy, and systems thinking, Metabolic translates these concepts into actionable strategies for urban and regional economic development, as evidenced in projects for Rotterdam and Charlotte. Yet, Metabolic's endeavors remain private, underscoring the potential of a UM digital twin for public accessibility and development.

In summary, DTs, despite their sophistication, have yet to incorporate sustainability data streams and visualizations. These aspects, crucial for designing sustainably and proactively addressing emerging challenges (Ferrão & Fernández, 2013), are often missing. At the same time, UM studies lack robust graphical output and dynamic data visualization. Therefore, integration of UM with DTs is critical now to leverage their potential.

## 3. Methods

To explore these concepts further, we conducted two sequential literature reviews (see Fig. 1). In the first review, we focused on UM in the context of case studies, methods, and visualization of results (review 1).

The initial UM review underscored the prevalent use of static visualization methods in presenting UM analysis outcomes. These graphical depictions primarily consist of diagrams that lack geographic contextualization for the analyzed flows. Furthermore, minimal utilization of geolocation techniques like light detection and ranging (LIDAR) or geographic information system (GIS), or machine learning for managing extensive datasets inherent in analytical methods, was observed. In summary, Review 1 elucidated the absence of Industry 4.0 technologies and dynamic visualization approaches within UM analytical studies.

Consequently, recognizing the potential for integrating such technologies to enhance UM practices we then conducted a second review (review 2), that combined UM and Industry 4.0 technologies (such as the Internet of Things, Artificial Intelligence, Digital Twins, GIS, and System Dynamics). In both reviews, we classified papers in categories based on the system analyzed and the objective of the study (see Figs. 2 and 3), and we also conducted a detailed analysis of methods (see Figs. 4 and 5), and visualization techniques used (see Figs. 6, 7, 8, and 9).

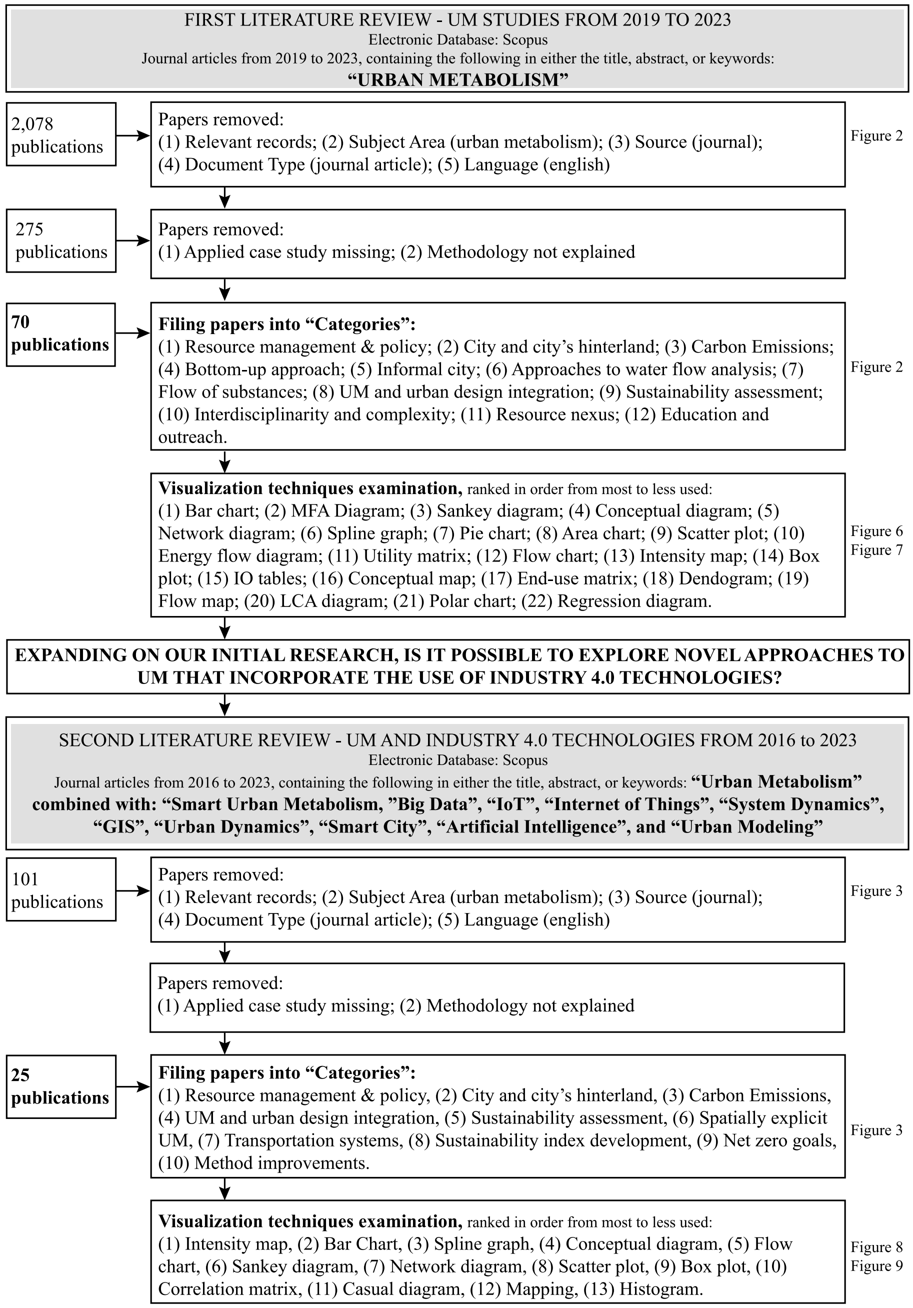


**Fig. 1.** Literature review methodology.

While review 2 did not yield specific results in the intersection of DT and UM, it underscored researchers' robust endeavors in exploring novel methodologies like system dynamics and machine learning to enhance UM analysis.

In light of the interdisciplinary nature of UM, which encompasses diverse concepts such as urban flows, flows of materials, city flows, system of systems, and urban networks, we deliberately chose to focus our study specifically on UM and its associated frameworks only, to provide a targeted analysis of its interaction with Industry 4.0 technologies, particularly digital twins, understanding that this focused approach may present a limitation in the breadth of concepts explored. For the purpose of this study, we maintained a focused approach to ensure depth and coherence in our analysis of UM. Furthermore, such concepts have been explored in literature in relation to a UM framework by Bi and Little (2022) and Kasai et al. (2015).

### 3.1. Review 1

For the first review, the time period was 2019 to 2023. This time period was selected because there was a gap in prior reviews between 2019 and 2023, along with a significant increase in publications. For the second review, we expanded the period from 2016 to 2023 as Industry 4.0 developed earlier than 2019.

In review 1, we used the key phrase "Urban Metabolism" as the search criterion, using the Scopus database. This review aimed to provide both a comprehensive view of UM for the most recent years while providing adequate information on the case studies, methods, and visualizations. This process is detailed in Fig. 1. Initially, we retrieved a total of 2078 papers. These papers were then filtered based on subject area (urban metabolism), source (journal), document type (journal article), research area (i.e., environmental science and ecology, or urban studies) and language (English).

| FIRST LITERATURE REVIEW **Urban Metabolism Studies** | **KEYWORDS SELECTED** | **RESULTS ANALYZED** | **PAPERS SELECTED** |
|---|---|---|---|
| | Urban Metabolism | **275** | **70** |

| **CATEGORY** | **PAPERS** | **N of Studies** | **% of Total** |
|---|---|---|---|
| Resource Management & Policy | (Andreoni, 2022; Cunha and Ferrao, 2023; Dextre et al., 2022; Emamjomehzadeh et al., 2023; Fan & Fang, 2019; Fu et al. 2022; Galychyn et al., 2022; González-García et al., 2021; Guo et al. 2023; Ipsen, 2019, 2019; Kissinger & Stossel, 2019, 2021; Kolkwitz et al., 2023; Lanau et al., 2021; Y. Li, Zhang, Hao, et al., 2019; J. Liu et al., 2021; N. Liu et al., 2021; Yang et al. (2023b,c); Mohareb and Perrotti 2023; Pérez-Sánchez et al., 2019; Roy & Thangaraj, 2021; Stelwagen et al., 2021; Stephan et al., 2022; Sun et al., 2023; Wu et al., 2023; Xia et al., 2019; Zhai et al., 2019; Zhang et al,. 2022; Zhang et al., 2019; Zhi et al., 2023) | 26 | 37% |
| City and City's Hinterland | (Bahers et al., 2020; Chini & Stillwell, 2019; Chiu et al., 2019; Cui et al., 2019; Deng et al. 2022; Derrible et al., 2021; Gan et al., 2023; González-García & Dias, 2019; Islam et al., 2021; Y. Li, Zhang, Hao, et al., 2019; Maranghi et al., 2020; Mohareb and Perrotti, 2023; Pianegonda et al. 2022; Strydom et al., 2019; Tanguy et al., 2020; Wang et al., 2019; Wassenaar et al., 2023; Whetstone et al., 2020; L. Xu et al., 2021) | 17 | 24% |
| Bottom-Up Approach | (Chini & Stillwell, 2020; Khalil & Al-Ahwal, 2021; Papageorgiou et al., 2020; Smit et al., 2019; Stelwagen et al., 2021; Wang et al., 2020) | 5 | 6% |
| Resource Nexus | (I.-C. Chen et al., 2020; ; Dextre et al. 2022; Zhang et al. 2022; Emamjomehzadeh et al., 2023; Sun et al., 2023) | 4 | 5% |
| Carbon Emissions | (S. Chen et al., 2020; L. Zhang et al., 2020; Q. Zhang et al., 2019) | 3 | 4% |
| Flow of Substances | (Guo et al., 2023; Tasmeea et al., 2021; X. Xu et al., 2020) | 3 | 3% |
| Informal City | (Kovacic et al., 2019; Smit et al., 2019) | 2 | 4% |
| Approaches to Water Flow Analysis | (Arora et al. 2022; Chini & Stillwell, 2020; Hastie et al., 2020) | 3 | 2% |
| Regional Metabolism | (Talandier and Donsimoni, 2022; Wang et al. 2022); | 1 | 3% |
| UM & Urban Design Integration | (Galan & Perrotti, 2019) | 2 | 1% |
| Sustainability Assessment | (Ohms et al., 2019) | 1 | 1% |
| Interdisciplinarity & Complexity | (Bortolotti et al., 2020) | 1 | 1% |
| Education & Outreach | (Taleghani et al., 2020) | 1 | 1% |
| Transportation Systems | (L. Zhang et al., 2020;) | 1 | 1% |
| Sustainability Index development | (J. Liu et al., 2021) | 1 | 1% |
| University Metabolism | (Kumdokrub et al., 2023) | 1 | 1% |
| Method Improvement | (Kolkwitz et al., 2023) | 1 | 1% |

N.B. : Papers may be catalogued in two different categories. Weight was assigned proportionally to both categories.

**Fig. 2.** Urban metabolism studies from 2019 to 2021 (Review 1) results and categories.

We down-selected the 2078 papers based on several considerations. First, manuscript not written in English were excluded, and those from unrelated fields like anthropology, arts and humanities, or agriculture were also disregarded, even if they included 'metabolism' as a keyword. Second, we narrowed the number by reviewing the abstracts of the chosen papers, focusing on references to applied case studies, new frameworks, or enhancements to the current state of UM research. This ensured that the methodologies were analyzable, and results could also be included in the paper. We considered case studies an essential aspect for contextualizing the study results. Thus, the final number was 275 papers.

We conducted a detailed review of these 275 papers to filter out those lacking applied case study, therefore not employing any method or using data to calculate UM. The scrutiny methodology employed is particularly relevant for UM studies as it ensures that the selected papers provide actionable insights into UM analysis outcomes, guaranteeing the availability of methodological approaches and data-driven calculations necessary for meaningful analysis and visualization. Specifically, we focused on the analysis of methods described within the single papers, which allows for the analysis of results and types of visualizations used, deemed fundamental to understanding UM and its usefulness for decision-making in policy or design. Papers with methodologies and results based on case studies were retained and subjected to further scrutiny. As a result of this process, we included 70 papers in our first review.

Of the 70, we then performed an extensive analysis on each paper, systematically categorizing the visual representations used to present case study findings. The result of this analysis is a comprehensive inventory of visualization methods commonly employed in UM research for illustrating case study outcomes. Papers were classified based on categories representative of the UM system analyzed and the objective of the study (e.g., city and city's hinterland), method employed, and visualization techniques.

### 3.2. Review 2

A second literature review, based on the findings of the first literature review, was conducted. We, expanding on the initial research,

| SECOND LITERATURE REVIEW **UM and INDUSTRY 4.0** | **KEYWORDS SELECTED** | **RESULTS ANALYZED** | **PAPERS SELECTED** |
|---|---|---|---|
| | UM + [ Smart UM; Big Data; IOT; Digital Twin; Internet of Things; System Dynamics; GIS; Urban Dynamics; Smart City; Artificial Intelligence; Urban Modelling ] | **101** | **25** |

| CATEGORY | PAPERS | N of Studies | % of Total |
|---|---|---|---|
| Resource management & Policy | (Cui, 2022; Elliot and Levasseur, 2022; Elliot et al., 2022; Elshaboury and Almetwaly, 2023; Hu, 2019; Mohammadiziazi et al., 2021; Mao et al. 2022; Pena et al., 2022; Yang et al. (2023a); Younan et al., 2023; Xia et al., 2022) | 9 | 37% |
| City & City's Hinterland | (Farzinmoghadam, 2019; Gopal, 2016; Koenig, 2018) | 3 | 12% |
| Method Improvement | (Huang et al., 2018; Mao et al. 2022; Peponi et al. 2022; Xia et al., 2022) | 3 | 11% |
| Spatially Explicit UM | (Schandl, 2020; Yeow, 2019; Xia et al., 2022) | 2 | 8% |
| Carbon Emissions | (Carpio, 2021; Elliot et al., 2022) | 2 | 7% |
| Net Zero Goals | (Procter, 2016) | 1 | 4% |
| Resource Nexus | (Tang et al., 2022) | 1 | 4% |
| Sustainability Index | (Caputo, 2019) | 1 | 4% |
| Transportation Systems | (Amiri, 2021) | 1 | 4% |
| UM & Urban Design Integration | (Elliot, 2018) | 1 | 4% |
| Sustainability Assessment | (Ai et al., 2019) | 1 | 4% |
| University Metabolism | (Ai et al., 2019) | 1 | 4% |

N.B. : Papers may be catalogued in two different categories. Weight was assigned proportionally to both categories.

**Fig. 3.** Urban metabolism and industry 4.0 technology (Review 2) results and categories.

investigated novel approaches to UM that incorporate the use of Industry 4.0 technologies. Review two is from 2016 to 2023. This time frame aligns with the emergence of the Industry 4.0. Analyzing this extended duration offers insights into the evolution and impact of Industry 4.0 technologies in UM research.

Like the first review, the Scopus database was used to perform the search. This review was performed using the key phrase "Urban Metabolism" and: "Digital Twin", "Big Data", "IoT", "Internet of Things", "System Dynamics", "GIS", "Urban Dynamics", "Smart City", "Artificial Intelligence", "Smart Urban Metabolism", and "Urban Modeling". 101 papers were retrieved; using the same criteria from the first review (i.e., case study and method), a total of 25 papers were selected and analyzed in depth (see Figs. 1 and 5). For Review 2, we followed the same criteria and methodology used in Review 1 to ensure consistency and comparability in the selection of papers, thereby maintaining continuity between the two reviews. Also for the second review, papers were classified based on categories indicative of the UM system analyzed and the objective of the study (e.g., transportation systems), method employed, and visualization techniques.

## 4. Results

This section presents the findings from both review 1 and review 2. The selected papers are analyzed based on the methods employed (see Figs. 4 and 5) and the visualization techniques used (refer to Figs. 6, 7, 8, and 9). Some papers may employ a combination of methods to assess UM in their case studies, using various visualization techniques to effectively convey different aspects of their results. The papers are further classified in broad categories representative of the UM system analyzed and the objective of the study, as identified and described in Fig. 1 and illustrated in Fig. 2 for review 1 and in Fig. 3 for review 2.

### *4.1. Categories*

With respect to review 1, the category of "resource management and policy" is the most prevalent (37%) (Andreoni, 2022; Cunha & Ferrao, 2023; Galychyn et al., 2022; Ipsen et al., 2019; Liu, Goel et al., 2021; Liu, Zhang et al., 2021; Mohareb & Perrotti, 2023; Stephan et al., 2022a; Xia et al., 2019) with "city and city's hinterland" following (at 24%) (Bahers et al., 2020; Cui et al., 2019; Deng et al., 2022; Derrible et al., 2021; Gan et al., 2023; Islam et al., 2021; Pianegonda et al., 2022; Strydom et al., 2019; Tanguy et al., 2020; Wassenaar et al., 2023). Combined these two categories represent 61% of the results of this first review. These categories appear to prioritize the assessment of existing conditions and management practices, with less emphasis on exploring new technologies or alternative approaches. Such research remains important as it provides a foundation for future work on the development of innovative and sustainable urban resource management strategies.

In review 2, we saw that limited research integrated UM with Industry 4.0 technologies. Further, UM and digital twin (DT)technologies yielded no results. It becomes evident that there is significant untapped potential for further exploration and integration. There is a pressing need for technological integration, particularly leveraging DT technology, the Internet of Things (IoT), and big data, to handle larger volumes of data more effectively.

Firstly, DT technology offers a powerful platform for simulating and visualizing complex urban systems, enabling researchers and designers to model and analyze UM processes in real-time. Through the integration of IoT devices and sensor networks, DTs can capture real-world data streams, providing valuable insights into urban resource flows, energy consumption patterns, and environmental impacts. Furthermore, UM and DT integration holds the potential to address the challenge

| FIRST LITERATURE REVIEW **Urban Metabolism Studies** | **KEYWORDS SELECTED** | **RESULTS ANALYZED** | **PAPERS SELECTED** |
|---|---|---|---|
| | Urban Metabolism | **275** | **70** |

| METHOD USED | PAPERS | N of Studies | % of Total |
|---|---|---|---|
| MFA or EFA | (Arora et al., 2022; Bahers et al., 2020; I.-C. Chen et al., 2020; Chini & Stillwell, 2019; Cui et al., 2019; Deng et al., 2022; Derrible et al., 2021; Fu et al., 2022; Hastie et al., 2020; Khalil & Al-Ahwal, 2021; Kissinger & Stossel, 2019, 2021; Kumdokrub et al., 2023; Lanau et al., 2021; Mohareb and Perrotti, 2023; Pianegonda et al., 2022; Strydom et al., 2019; Tanguy et al., 2020; Wang et al., 2020; Q. Zhang et al., 2019; Zhi et al., 2023) | 23 | 33% |
| MFA / LCA | (S. Chen et al., 2020; Dextre et al., 2022; González-García et al., 2021; González-García & Dias, 2019; Ipsen, 2019; Maranghi et al., 2020; Ohms et al., 2019; Stelwagen et al., 2021) | 7 | 10% |
| MuSIASEM | (Andreoni, 2022; Kovacic et al., 2019; Pérez-Sánchez et al., 2019; Smit et al., 2019) | 5 | 7% |
| ENA | (Fan & Fang, 2019; Li et al., 2023; Wang et al., 2019; Xia et al., 2019) | 4 | 6% |
| IO / ENA | (X. Xu et al., 2020; Zhai et al., 2019; G. Zhang et al., 2019) | 3 | 4% |
| MFA / ENA | (Galan & Perrotti, 2019; Papageorgiou et al., 2020; Y. Li, Zhang, Hao, et al., 2019) | 3 | 4% |
| MFA / AGM | (Yang et al., 2023b,c) | 2 | 3% |
| Economy-Wide MFA | (N. Liu et al., 2021; Taleghani et al., 2020) | 2 | 3% |
| IO | (Islam et al., 2021; Zhang et al., 2022) | 2 | 3% |
| SFA | (Guo et al., 2023; Tasmeea et al., 2021) | 2 | 3% |
| MFA / EBM | (Talandier and Donsimoni, 2022) | 1 | 1% |
| CEPA | (L. Zhang et al., 2020) | 1 | 1% |
| DEA | (Gan et al., 2023); | 1 | 1% |
| Emergy | (Chiu et al., 2019) | 1 | 1% |
| Exergy | (J. Liu et al., 2021) | 1 | 1% |
| IO / Emergy | (Galychyn et al., 2022) | 1 | 1% |
| IUMAT | (Roy & Thangaraj, 2021) | 1 | 1% |
| LCA | (Whetstone et al., 2020) | 1 | 1% |
| LCA / NST | (Stephan et al., 2022) | 1 | 1% |
| Metabolic Network | (Wang et al., 2022) | 1 | 1% |
| MFA / CART | (L. Xu et al., 2021) | 1 | 1% |
| MFA / ML | (Emamjomehzadeh et al., 2023) | 1 | 1% |
| MFA / PIOT | (Cunha and Ferrao, 2023) | 1 | 1% |
| MFA / SFA / EIA / LCA | (Bortolotti et al., 2020) | 1 | 1% |
| PFA | (Wassenaar et al., 2023); | 1 | 1% |
| RM | (Wu et al., 2023) | 1 | 1% |
| RM / AoV | (Chini & Stillwell, 2020) | 1 | 1% |

N.B. : "MFA" = material flow analysis; "LCA" = life cycle assessment; "ENA" = ecological network analysis, "MuSIASEM"= multi-scale integrated analysis of societal and ecosystem metabolism; "IO" = input-output; "IUMAT" = integrated urban metabolism analysis tool; "SFA" = substance flow analysis; "CEPA" = carbon emission pinch analysis; "EIA" = environmental impact assessment; "RM" = Regression Model; "AoV" = Analysis of Variance; "AGM" = allometric growth model; "NST" = nested system theory; "EBM" = economic base model; "PFA" = pragmatic flow assessment; "RM" = regression model

**Fig. 4.** Commonly used methods from literature Review 1 (Urban metabolism studies from 2019 to 2021).

of limited real-time data availability (Neves et al., 2023), thereby catalyzing research and investment efforts towards more comprehensive and timely data collection for UM studies. Given that the predominant category identified in review 2 was "resource management and policy", embracing the UM and DT integrative approach has the potential to foster evidence-based decision-making in urban design and infrastructure development.

A few categories that were not a part of review 1 were identified such as "spatially explicit UM" and "method improvement" (Huang, 2018; Mao et al., 2022; Peponi et al., 2022; Schandl et al., 2020; Xia et al., 2022; Yeow & Cheah, 2019). Of the 25 papers, the prevalent categories were "resource management and policy" (Cui, 2022; Elshaboury & Almetwaly, 2023; Hu et al., 2019; Mohammadiziazi et al., 2021; Pena et al., 2022; Younan et al., 2023), followed by "city and city's hinterland" (12%) (Farzinmoghadam, 2019; Gopal, 2016; Koenig, 2018) and "method improvement" (Schandl et al., 2020; Xia et al., 2022; Yeow & Cheah, 2019) (11%) (Fig. 3) with the three categories accounting for more than half (61%) of the papers analyzed. To summarize, these papers explore resource use and material flow. The "city and city's hinterland" (12%) and "method improvement" articles (11%) introduced the use of machine learning (ML) to support material flow analysis (MFA) (Mao et al., 2022; Peponi et al., 2022) or system dynamics (SD) for emergy analysis (Huang, 2018). Despite the prevalence of studies with some form of data geo-localization in these categories, the primary visualization methods remained bar charts and spline graphs.

It is also interesting that despite fewer categories were identified in the second review, the prevalent categories align closely with those discovered in the first review, indicating a consistent pattern across both analyses, and suggesting robustness in the identified themes. Additionally, the absence of the 'informal city' category in the second review may be attributed to potential resource limitations.

### 4.2. Methods

Regarding review 1, in terms of methods used, material flow analysis (MFA) and MFA in conjunction with life cycle assessment (LCA) have emerged as the most used, respectively the 33% and 10% (Fig. 4). MFA, being the most prevalent, models the flow of materials entering and exiting a city, calculating the stocks of materials and the point at which such accumulation occurs within the system. MFA's integration

| SECOND LITERATURE REVIEW **UM and INDUSTRY 4.0** | **KEYWORDS SELECTED** | **RESULTS ANALYZED** | **PAPERS SELECTED** |
|---|---|---|---|
| | UM + [ Smart UM; Big Data; IOT; Digital Twin; Internet of Things; System Dynamics; GIS; Urban Dynamics; Smart City; Artificial Intelligence; Urban Modelling ] | **101** | **25** |

| **METHOD USED** | **PAPERS** | **N of Studies** | **% of Total** |
|---|---|---|---|
| SD | (Elliot and Levasseur, 2022; Hu, 2019; Koenig, 2018; Procter, 2016; Tang et al., 2022) | 5 | 20% |
| ML | (Caputo, 2019; Elshaboury and Almetwaly, 2023; Gopal, 2016) | 3 | 12% |
| IUMAT / AI | (Amiri, 2021; Farzinmoghadam, 2019) | 2 | 8% |
| MFA or EFA | (Cui, 2022) | 2 | 8% |
| MFA / ML | (Mao et al., 2022; Peponi et al., 2022) | 1 | 4% |
| ENA | (Xia et al., 2022) | 1 | 4% |
| Carbon Accounting / Satellite Image Analysis / GIS | (Carpio, 2021) | 1 | 4% |
| IO / SD | (Elliot, 2018) | 1 | 4% |
| SD / Emergy | (Huang et al., 2018) | 1 | 4% |
| MFA / GIS | (Yeow, 2019) | 1 | 4% |
| Carbon Accounting / AI / LIDAR | (Schandl, 2020) | 1 | 4% |
| Fisher Information / DEA | (Ai et al., 2019) | 1 | 4% |
| GIS / LIDAR | (Mohammadiziazi et al., 2021) | 1 | 4% |
| SD / ESTIMUM | (Elliot et al., 2022) | 1 | 4% |
| GIS | (Pena et al., 2022) | 1 | 4% |
| MFA / 4D-GIS | (Yang et al., 2023a) | 1 | 4% |
| MFA / Casual Loop Diagram | (Younan et al., 2023) | 1 | 4% |

N.B. : “SD” = system dynamics; “IUMAT” = integrated urban metabolism analysis tool; ”IO” = input-output; “MFA” = material flow analysis; “EFA” = energy flow analysis; “GIS” = geographic information system; “AI” = artificial intelligence; “LIDAR” = light detection and ranging; “DEA” = data envelopment analysis; “CA” = carbon accounting; “ESTIMUM” = ecosystem service toolbox for integrated multi-scale modelling of urban metabolism; “ENA” = ecological network analysis; “ML” = machine learning.

**Fig. 5.** Commonly used methods from literature Review 2 (Urban metabolism and industry 4.0 technologies).

with LCA facilitates the identification and quantification of environmental impacts. Combined MFA and LCA represent nearly the 50% of the methods used in review 1 (Fig. 4). The remainder 50% of the papers utilized a scattered variety of methods as it can be observed in Fig. 4, spanning from Input-Output analysis (Galychyn et al., 2022; Islam et al., 2021; Zhang et al., 2022), to Exergy Accounting (Liu, Goel et al., 2021), to the use of specific UM tools such as the Integrated Urban Metabolism Analysis Tool (IUMAT) (González-García et al., 2021; Liu, Goel et al., 2021) and Multi-Scale Integrated Analysis of Societal and Ecosystem Metabolism (MuSIASEM) (Andreoni, 2022; Dextre et al., 2022). While ecological network analysis (ENA), which aims to assess the structure, function, and dynamics of industrial ecosystems, was employed independently in a limited number of cases (6%) (Li et al., 2023), it is frequently integrated with input–output models or MFA (Galan & Perrotti, 2019; Li et al., 2019; Xu et al., 2020; Zhai et al., 2019), resulting in its overall utilization in 13% of the papers analyzed. This method is predominantly featured in the “resource management and policy” category, (Fig. 10).

As system dynamics (SD) emerged as the prevalent method (20%) in review 2 (Elliot & Levasseur, 2022; Elliot et al., 2022; Hu et al., 2019; Koenig, 2018; Procter, 2016; Tang et al., 2022) (Fig. 5), the integration of DTs as a next step appears logical. The adoption of SD approaches within DT frameworks allows for the dynamic modeling of feedback loops and causal relationships within urban systems, facilitating a deeper understanding of system behaviors and emergent phenomena. Nonetheless, DTs have the capacity to provide an ideal environment for visualizing and analyzing results generated by SD. Ultimately, researchers will be able explore various scenarios and interventions to optimize UM processes, enhance resource efficiency, and promote sustainable urban development.

In some cases, SD was combined with the use of an input–output model or emergy to calculate the variables of the metabolic system used in the SD environment (Huang, 2018). MFA do not reveal the mechanisms within the system analyzed (Beloin-Saint-Pierre et al., 2017; Zhang, 2013); therefore, the development of hybrid methods has helped researchers unveil relations and dependencies between different flows in the system analyzed. Ultimately, hybrid approaches can also help end-users facilitate planning and policy decision-making (Elliot, 2018).

### 4.3. Visualization techniques

Regarding visualization techniques, we carefully reviewed each paper, identifying and classifying all graphical outputs utilized to depict the outcomes of the case studies. This enabled the creation of a comprehensive list of the visualization techniques commonly utilized in UM research.

With respect to review 1 and visualizations a not significant variation was observed in the choice of visualization techniques corresponding to each of the methods employed (see Fig. 6). When MFA was

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METHOD USED (Immediately below method frequency among the selected papers, See Figure 4)

| VISUALIZATION TECHNIQUE | CEPA | DEA | Economy-Wide MFA | Emergy | ENA | Exergy | IO | IO / Emergy | IO / ENA | IUMAT | LCA | LCA / Nested System Theory | Metabolic Network | MFA or EFA | MFA / Allometric Growth Model | MFA / CART | MFA / Economic Base Model | MFA / ENA | MFA / LCA | MFA / ML | MFA / PIOT | MFA / SFA / EIA / LCA | MuSIASEM | Pragmatic Flow Assessment | Regression Model | Regression Models / Analysis of Variance | SFA | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1% | 1% | 3% | 1% | 6% | 1% | 3% | 1% | 4% | 1% | 1% | 1% | 1% | 33% | 3% | 1% | 1% | 4% | 10% | 1% | 1% | 1% | 7% | 1% | 1% | 1% | 3% | |
| Area Chart | | | | | 1 | | | | | | | | | 4 | | | | 1 | 2 | | | | | | | | | 8 |
| Bar Chart | 1 | 1 | 1 | | 2 | 1 | 2 | | 2 | | 1 | | 1 | 12 | | 1 | | 1 | 3 | 1 | 1 | | 3 | | | | 2 | 36 |
| Box Plot | | | | | | | | | | | | | | 1 | | 1 | | | | | | | | | | 1 | | 3 |
| Chord Diagram | | | | | | | | | | | | | | 1 | | | | | | | 1 | | | | | | | 2 |
| Conceptual Diagram | | | | | | | | | 1 | 1 | | | 1 | 3 | | | 1 | 1 | 3 | | | 1 | 1 | | | | | 13 |
| Conceptual Map | | | | | | | | | | | | | | 1 | | | 1 | | | | | | | | | | | 2 |
| Dendogram | | | | | | | | | | | | | | | | | | | | | | | 1 | | | | | 1 |
| Direct &/or Integral Utility Matrix | | | | | 1 | | | | 1 | | | | | | | | | | | | | | | | | | | 2 |
| End-use Matrix | | | | | | | | | | | | | | | | | | | | | | | 1 | | | | | 1 |
| Energy Flow Diagram | | | | 1 | | | | | | | | | | | | | | | | | | | | | | | | 1 |
| Flow Map | | | | | | | 1 | | | | | | | 1 | | | | | | | | | | | | | 1 | 3 |
| Heat Map | | 1 | | | 1 | | | | | | | | | | | | | | | | | | | | | | | 2 |
| Intensity Map | | | | | 1 | | | | | | | | | 2 | 1 | 1 | | | | | | | | | | | | 5 |
| IO Tables | | | | | | | | | | | | | | | | | | | | | 1 | | | | | | | 1 |
| LCA Diagram | | | | | | | | | | | | | | | | | | | 1 | | | | | | | | | 1 |
| MFA Diagram | | | 2 | | 1 | | | | | | 1 | | | 9 | | | | 1 | 4 | | 1 | | 1 | 1 | 1 | | 1 | 23 |
| Network Diagram | | | | | 2 | | | | 2 | | | | | | | | 1 | 1 | 1 | | | | | | | | | 7 |
| Pie Chart | | | | | | 1 | | | | | | | 1 | 2 | | | | | 1 | | | | | | | | 2 | 7 |
| Polar Chart | | | | | | | | | | | | | | | | 1 | | | | | | | | | | | | 1 |
| Radar Chart | | 1 | | | | | | | | | | | | | | | | | | | | | | | | | | 1 |
| Regression Diagram | | | | | | | | | | | | | | | | | | | | | | | | | | 1 | | 1 |
| Sankey Diagram | | | | | | 1 | 1 | | | | | 1 | | 10 | | | | 2 | 2 | | | | 1 | | | | | 18 |
| Scatter Plot | | | 1 | | | | 1 | | | | | | | | | 1 | | | | | | | | | | | | 3 |
| Spline Graph | 1 | 1 | | | 1 | | 1 | | 1 | | | 1 | | 4 | 2 | | | | | 1 | | | 1 | | 1 | | | 15 |
| Table | | | | | | | | 1 | | | | | | | | | | | | | | | | | | | | 1 |
| Three Chart | | | | | | | | | | | | 1 | | | | | | | | | | | | | | | | 1 |

N.B. : "MFA" = material flow analysis; "LCA" = life cycle assessment; "ENA" = ecological network analysis; "EFA" = energy flow analysis; "MuSIASEM"= multi-scale integrated analysis of societal and ecosystem metabolism; "IO" = input-output; "IUMAT" = integrated urban metabolism analysis tool; "SFA" = substance flow analysis; "CEPA" = carbon emission pinch analysis; "EIA" = environmental impact assessment; "DEA" = data envelopment analysis; "PIOT" = physical input output table
The total numbr of papers anlyzed is 70.

**Fig. 6.** Review 1 heat map to compare visualization techniques against method used.

used, as expected, MFA diagrams or Sankey diagrams were presented. MFA diagrams, while effectively illustrating material flows, are not the most suitable tool for pinpointing flows on a specific geographic territory being primarily designed to offer a systemic overview of flows and relationships among processes, sectors, or nodes. Despite being predominantly used in two of the observed categories ("city and city hinterland" and "resource management and policy"), this visualization method accounts for 14% of instances across different methodologies (Arora et al., 2022; Chen, Wang et al., 2020; Cui et al., 2019; Derrible et al., 2021; González-García et al., 2021; Ipsen et al., 2019; Kissinger & Stossel, 2019; Lanau et al., 2021; Ohms et al., 2019; Papageorgiou et al., 2020; Stelwagen et al., 2021; Stephan et al., 2022b; Taleghani et al., 2020; Wang et al., 2020; Whetstone et al., 2020; Wu et al., 2023; Xia et al., 2019; Zhang, Liu et al., 2019). Our analysis shows how Sankey diagrams are also widely used in the two of the main observed categories (12%) (Bahers et al., 2020; Chen, Chen et al., 2020; Chen, Wang et al., 2020; Chini & Stillwell, 2019; Derrible et al., 2021; Galan & Perrotti, 2019; Hastie et al., 2020; Islam et al., 2021; Khalil & Al-Ahwal, 2021; Kumdokrub et al., 2023; Li et al., 2019; Liu, Goel et al., 2021; Stelwagen et al., 2021; Strydom et al., 2019; Tanguy et al., 2020) (Fig. 7). Primarily to visualize the magnitude and direction of flows within a system, Sankey diagrams do not provide precise geographic localization information on their own. However, they can be adapted or supplemented with geographic information to represent flows on the territory (Evans, 2016). Bar charts were employed across nearly all of methods (24%) (Fig. 6), and they were used to convey quantitative data to compare and contrast different variables, categories, or metrics (Chen, Chen et al., 2020; Fu et al., 2022; González-García et al., 2021; González-García & Dias, 2019; Ipsen et al., 2019; Islam et al., 2021; Kissinger & Stossel, 2019, 2021; Kovacic et al., 2019; Lanau et al., 2021; Li et al., 2019; Liu, Goel et al., 2021; Liu, Zhang et al., 2021; Ohms et al., 2019; Smit et al., 2019; Strydom et al., 2019; Tanguy et al., 2020; Tasmeea et al., 2021; Wang et al., 2019; Whetstone et al., 2020; Xu et al., 2021; Zhai et al., 2019; Zhang, Huang et al., 2019; Zhang et al., 2020; Zhang, Liu et al., 2019; Zhi et al., 2023).

These graphical representations are decontextualized from the actual geographic locations of the analyzed elements and do not convey the intensity of these metrics, impacts, or flows at different territorial scales. This is a fundamental aspect of urban planning practice, as analyzing the context in which development will be carried out is crucial.

Review 1 revealed that in 2019, only one paper attempted to spatially describe UM (Xia et al., 2019), while there were no such cases in 2020. However, there was a notable increase in 2022 and 2023, with papers employing conceptual maps and diagrams, and intensity maps to depict the geographical distribution of flows analyzed for a fixed period, typically one year (Kolkwitz et al., 2023; Pianegonda et al., 2022; Stephan et al., 2022b; Talandier & Donsimoni, 2022; Wang et al., 2022; Yang, Liu, Li et al., 2023; Yang, Liu, Wang et al., 2023).

Galan and Perrotti (2019) incorporated UM analysis into spatial planning decision-making by using MFA and ecological footprint analysis contemporarily, to provide a means for planners and decision-makers to easily understand the results of the study. A regional model to integrate UM to spatial planning was developed with the aim of optimizing the material and energy flows in the region (Galan & Perrotti, 2019). However, the volume of data to be processed was an obstacle forcing the authors to limit the quantity of data to be processed to a reasonable amount. Ultimately, the authors did not incorporate the use of technologies such as DT, IoT, and SD, which would allow them to handle a higher volume of data more easily and start a framework to technologically advance the concept of UM.

Spatial graphics are pivotal in infrastructure design, facilitating the analysis of interrelations between new or revised infrastructure in a

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CATEGORY

(Immediately below Total number of papers in the category and category frequency among the selected papers, See Figure 2)

| VISUALIZATION TECHNIQUE | Approaches to Water Flow Analysis | Bottom-Up Approach | Carbon Emissions | City & City's Hinterland | Education & Outreach | Flows of Substances | Informal City | Interdisciplinarity & Complexity | Method Improvement | Regional Metabolism | Resource Management & Policy | Resource Nexus | Sustainability Assessment | Sustainability Index | Transportation Systems | UM & Urban Design Integration | University Metabolism | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 3 | 5 | 3 | 17 | 1 | 3 | 2 | 1 | 1 | 2 | 26 | 4 | 1 | 1 | 1 | 1 | 1 | |
| | 4% | 6% | 5% | 24% | 1% | 4% | 3% | 1% | 1% | 3% | 37% | 5% | 1% | 1% | 1% | 1% | 1% | |
| Area Chart | | | | 3 | | | | | 1 | | 2 | 1 | | | | | | 6 |
| Bar Chart | | 2 | 3 | 9 | | 2 | 2 | | | 1 | 15 | 2 | 1 | 1 | 1 | | 1 | 37 |
| Box Plot | 1 | 1 | | 1 | | | | | | | 1 | | | | | | | 3 |
| Chord Diagram | | | | | | | | | | | 1 | | | | | | | 1 |
| Conceptual Diagram | 1 | 1 | 1 | 3 | | 1 | | 1 | | 1 | 3 | | | | | 1 | | 12 |
| Conceptual Map | | | | 1 | | | | | | 2 | | | | | | | 1 | 4 |
| Dendogram | | | | | | | | | | | 1 | | | | | | | 1 |
| End-use Matrix | | | | | | | | | | | 1 | | | | | | | 1 |
| Energy Flow Diagram | | | | 1 | | | | | | | | | | | | | | 1 |
| Flow Chart | | 1 | | 1 | | | 1 | | | | | | | | | | | 2 |
| Flow Map | | | | 2 | | 1 | | | | | 1 | | | | | | | 3 |
| Heat Map | | | | 1 | | | | | | | | 1 | | | | | | 2 |
| Intensity Map | | | 1 | 2 | | | | | | | 3 | | | | | | | 5 |
| IO Tables | | 1 | | | | | | | | | | | | | | | | 1 |
| LCA Diagram | | 1 | | | | | | | | | 1 | | | | | | | 1 |
| MFA Diagram | | 3 | 2 | 5 | 1 | 1 | | | | | 7 | 1 | 1 | | | 1 | | 21 |
| Network Diagram | | | | 3 | | | | | | 1 | 3 | 1 | | | | | | 7 |
| Pie Chart | | 1 | | 2 | | 2 | 1 | | | 1 | 3 | | | 1 | | | | 8 |
| Polar Chart | | | | 1 | | | | | | | | | | | | | | 1 |
| Radar Chart | | | | 1 | | | | | | | | | | | | | | 1 |
| Regression Diagram | 1 | 1 | | | | | | | | | | | | | | | | 1 |
| Sankey Diagram | 2 | 2 | 1 | 6 | | | 1 | | | | 3 | 1 | | 1 | | 1 | 1 | 17 |
| Scatter Plot | | | | 3 | | | | | | | 1 | | | | | | | 4 |
| Spline Graph | | | 2 | 1 | | | | | | | 8 | 2 | | | 1 | | | 14 |
| Tables | | | | | | | | | | | 1 | | | | | | | 1 |
| Three Chart | | | | | | | | | | | 1 | | | | | | | 1 |
| Utility Matrix | | | | | | | | | | | 2 | | | | | | | 2 |

N.B. : The same journal paper may fall under more than one "category" therefore the same paper may be classified under two different categories. The same journal paper may use more than one visualization technique.
Total Number of papers analyzed is 70.

**Fig. 7.** Review 1 heat map to compare visualization techniques against category.

comprehensive manner. Galan and Perrotti (2019) employs sankey and conceptual diagrams to illustrate water, waste, and electricity flows, effectively identifying targets. However, these visualizations lack geographical context, making it challenging to envision flows and stocks within the real-world environment, which is crucial for informed decision-making. Integration of geographical context in visualization techniques is essential to immediately recognize the impact of specific flows or stocks on particular locations and assess their potential reuse. Therefore, advancements in spatial analysis technologies, such as advanced GIS applications, remote sensing technologies, and interactive mapping tools, are indispensable for enhancing UM studies.

In contrast to review 1, review 2 revealed a significant effort by researchers to evaluate the spatial aspects of UM, as evidenced by a substantial increase in studies introducing new spatial visualization methods such as correlation matrices (Elliot, 2018) and mapping (Pena et al., 2022) (Figs. 8 and 9).

However, the results indicate that the use of bar charts (26%) (Cui, 2022; Elliot et al., 2022; Younan et al., 2023) and spline graphs (21%) (Elliot et al., 2022; Farzinmoghadam, 2019; Peponi et al., 2022) remains predominant, accounting for 47% of the papers examined.

As illustrated in Fig. 9, review 2 highlighted a narrower variety of visualization methods when analyzing works in the convergence between UM and Industry 4.0. Few new visualization methods were identified, including correlation matrices (Elliot, 2018), histograms (Mohammadiziazi et al., 2021), violin plots (Yang, Dang et al., 2023), and mapping (Pena et al., 2022). It can be summarized that a dynamic visual representation of UM has not yet been established. Furthermore, no trends among methods have been identified; for instance, bar charts, intensity maps, and spline graphs were the most used even when methods such as SD and ML were employed (Fig. 8).

Fig. 9 also indicates that the predominant category in review 2 is "resource management and policy". Researchers' efforts in exploring new visualization methods and techniques within this category suggest the need to find better, improved, and more direct ways to communicate results to policymakers and designers for decision-making

| UM and Industry 4.0 Technologies | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| METHOD USED (Immediately below method frequency among the selected papers, See Figure 3) | | | | | | | | | | | | | | | | | | |
| | 4% | 4% | 4% | 4% | 4% | 4% | 4% | 8% | 4% | 4% | 4% | 4% | 8% | 12% | 20% | 4% | 4% | |
| VISUALIZATION TECHNIQUE | CA / AI / LIDAR | CA / Satellite Image Analysis / GIS | ENA | Fisher Information / DEA | GIS | GIS / LIDAR | IO / SD | IUMAT / AI | MFA / 4D-GIS | MFA / Casual Loop Diagram | MFA or EFA | MFA / GIS | MFA / ML | ML | SD | SD / Emergy | SD / ESTIMUM | |
| Area Chart | | | | | | | | | | | | | 1 | | 1 | | | 2 |
| Bar Chart | 1 | | | 1 | | | 1 | | | 1 | 1 | | 2 | 3 | 1 | | 1 | 12 |
| Box Plot | | 1 | | | | | | | 1 | | | | | | | | | 2 |
| Casual Diagram | | | | 1 | | | | | | | | | | | | | | 1 |
| Chord Diagram | | | | | | | | | | | 1 | | | | | | | 1 |
| Conceptual Diagram | | | | | | | | | | | | | | | 1 | 1 | | 2 |
| Correlation Matrix | | | | | | | 1 | | | | | | | | | | | 1 |
| Flow Map | | | 1 | 1 | | | | 1 | | | | | | | | | | 3 |
| Heat Map | | | | | | | | | | | | | 1 | | | | 1 | 2 |
| Histogram | | | | | | 1 | | | 1 | | | | | | | | | 2 |
| Intensity Map | | | | | | 1 | 1 | 1 | | 1 | | 1 | 1 | 2 | 2 | | | 10 |
| Mapping | 1 | | | | 1 | | | | | | | | | | | | | 2 |
| Network Diagram | | | | | | | | | | | | | | | 1 | | | 1 |
| Sankey Diagram | 1 | | | | | | | | | | | | | | | | | 1 |
| Scatter Plot | | | | | | | | | | | | | | | 1 | | | 1 |
| Spline Graph | | 1 | | 1 | | | | 1 | | 1 | 1 | | 1 | 1 | 4 | | 1 | 12 |
| Violin Plot | | | | | | | | | 1 | | | | | | | | | 1 |

N.B. : "SD" = system dynamics; "IUMAT" = integrated urban metabolism analysis tool; "IO" = input-output; "MFA" = material flow analysis; "EFA" = energy flow analysis; "GPS" = global positioning system; "AI" = artificial intelligence; "LIDAR" = Light detection and ranging; "CA" = carbon accounting; "ENA" = ecological network analysis
Total number of papers analyzed is 25.

**Fig. 8.** Review 2 heat map to compare visualization techniques against method used.

purposes. DTs can address this issue by offering an immersive gaming environment where end-users can better understand specific concepts and characteristics of new developments, or how solutions can be applied in real case studies.

### 4.4. Results summary

In reviewing the literature on UM and UM use of Industry 4.0 technologies distinct trends emerged across all categories, methods and visualization techniques analyzed. This section aims to provide a concise summary of the key findings derived from the two comprehensive reviews.

In review 1, combining Figs. 6 and 7, the two main categories of "city and city's hinterland" and "resource management and policy", largely used sankey diagrams, MFA diagram, and bar diagram. While the remaining categories tended to use a limited number of techniques, often tied to their chosen research methodologies (Bortolotti et al., 2020; Chini & Stillwell, 2020; Chiu et al., 2019; Fan & Fang, 2019; Maranghi et al., 2020; Pérez-Sánchez et al., 2019; Roy & Thangaraj, 2021; Xu et al., 2020). The larger number of articles in this field indicated a significant emphasis on investigating the best strategies for managing and optimizing urban resources. These studies were primarily focused on analyzing the socio-economic conditions of urban areas (Bahers et al., 2020; Bortolotti et al., 2020; Cui et al., 2019; Guo et al., 2023; Liu, Goel et al., 2021; Stelwagen et al., 2021; Xu et al., 2021), such as patterns of consumption and urbanization, to better understand their environmental impact; this understanding can then inform resource management and policy decisions aimed at optimizing resource usage and planning for future resource management (Emamjomehzadeh et al., 2023; Islam et al., 2021; Kissinger & Stossel, 2021; Lanau et al., 2021; Li et al., 2019; Roy & Thangaraj, 2021; Sun et al., 2023).

Summarizing review 2, Figs. 8, and 9 show that spatial variables were not predominant despite their usefulness being widely recognized (Elliot, 2018; Gopal, 2016; Koenig, 2018; Oliveira & Vaz, 2021). Visualization techniques such as bar charts, sankey diagrams, MFA diagrams, and spline graphs were widely used in UM analyses.

In review 1, the analysis of 70 papers revealed a predominant focus on Chinese cities, accounting for 36% of the studies, followed by European regions at 24%. This distribution underscores China's leadership in analytical UM studies conducted between 2019 and 2023. The primary objective of these studies was to create evidence for policy-making or resource management, with the category of "resource management and policy" emerging as the most prominent. Notably, a diverse array of methods and visualization techniques were employed, indicating ongoing experimentation and exploration within the field, as depicted in Fig. 10.

On the contrary, review 2 showcased a more balanced distribution of research efforts among Europe (20%), China (24%), and the United States (Fig. 11). Among the 25 papers scrutinized, spanning from 2016

| UM and Industry 4.0 Technologies | Carbon Emissions | City & City's Hinterland | Method Improvement | Net Zero Goals | Resource management & Policy | Resource Nexus | Spatially Explicit UM | Sustainability Assessment | Sustainability Index | Transportation Systems | UM & Urban Design Integration | University Metabolism | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| CATEGORY (Immediately below category frequency among the selected papers, See Figure 3) | 2 | 3 | 3 | 1 | 9 | 1 | 2 | 1 | 1 | 1 | 1 | 1 | |
| | 7% | 12% | 11% | 4% | 37% | 4% | 8% | 2% | 4% | 4% | 4% | 2% | |
| **VISUALIZATION TECHNIQUE** | | | | | | | | | | | | | |
| Area Chart | 1 | | 1 | | 1 | | | | | | | | 2 |
| Bar Chart | | 1 | 2 | | 5 | 1 | 1 | 1 | 1 | | 1 | 1 | 13 |
| Box Plot | 1 | | | | 1 | | | | | | | | 2 |
| Casual Diagram | | | | | | | | 1 | | | | 1 | 1 |
| Chord Diagram | | | | | 1 | | | | | | | | 1 |
| Conceptual Diagram | | | 1 | 1 | | | | | | | | | 2 |
| Correlation Matrix | | | | | | | | | | | 1 | | 1 |
| Flow Map | 0.3 | 1 | 0.3 | | 0.3 | | | 1 | | | | 1 | 3 |
| Heat Map | | | 1 | | 2 | | | | | | | | 2 |
| Histogram | | | | | 2 | | | | | | | | 2 |
| Intensity Map | | 1 | 1 | 1 | 3 | | 1 | | 1 | 1 | 1 | | 10 |
| Mapping | | | | | 1 | | 1 | | | | | | 2 |
| Network Diagram | | | | | 1 | | | | | | | | 1 |
| Sankey Diagram | | | | | | | 1 | | | | | | 1 |
| Scatter Plot | | | | 1 | | | | | | | | | 1 |
| Spline Graph | 2 | 2 | 1 | 1 | 5 | 1 | | 1 | | | | 1 | 12 |
| Violin Plot | | | | | 1 | | | | | | | | 1 |

N.B. : The same journal paper may fall under more than one "category" therefore the same paper may be classified under two different categories. The same journal paper may use more than one visualization technique. Total number of papers analyzed is 25.

**Fig. 9.** Review 2 heat map to compare visualization techniques against categories.

to 2023, the United States took the lead with 28% of the papers focusing on the integration of Industry 4.0 technologies into UM analysis. The exploration of various frameworks, ranging from machine learning to GIS and LIDAR usage, to SD and IUMAT, reflects the diverse research scopes within this domain.

Review 2 also revealed that, despite the primary focus on informing policy-making and resource management, in Europe and China, a similar array of methods was employed across these regions, highlighting the universality of the challenges and objectives in UM research.

However, it is noteworthy that regions with limited resources, particularly in developing countries, were not as prominent in review 2. This observation can be attributed to the intricate nature of UM studies, which often encounter challenges related to interdisciplinary collaboration, data limitations, and insufficient financial, technical, and digital infrastructure required for advanced technology solutions.

For example, regions in Africa accounted for 7% of the papers analyzed in review 1, employing analytical methodologies, such as combining MFA with LCA. Data collection approaches were predominantly bottom-up due to the scarcity of top-down data availability. These findings underscore the imperative of addressing resource constraints and enhancing data accessibility to facilitate UM studies in developing regions, thereby promoting equitable and inclusive urban development initiatives.

## 5. Discussion

This study investigated UM and UM integration with Industry 4.0 technologies; we also explored sustainability methods and visualizations at a system-level. The findings from both review 1 and review 2 (summarized in Fig. 12) highlight trends and gaps in UM methods.

The dominance of "resource management and policy" and "city and city's hinterland" categories in review 1 signify a foundation for understanding and optimizing urban resource usage and their distribution on the territory. However, the limited integration of advanced technologies, such as DTs and Industry 4.0, raises questions about the potential uncharted benefits of DTs in enhancing UM studies. The prevalence of MFA and MFA combined with LCA in review 1 indicates

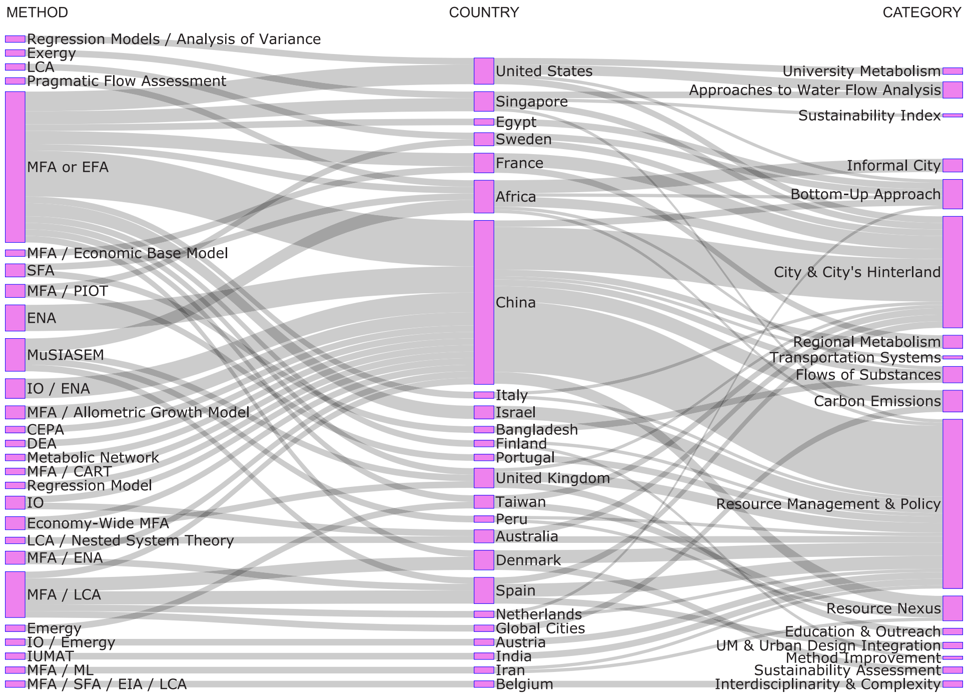


**Fig. 10.** Review 1: Sankey diagram showing connections across countries (Center), methods employed (Left), and categories (Right). N.B. : "MFA" = material flow analysis; "LCA" = life cycle assessment; "ENA" = ecological network analysis; "EFA" = energy flow analysis; "MuSIASEM"= multi-scale integrated analysis of societal and ecosystem metabolism; "IO" = input–output; "IUMAT" = integrated urban metabolism analysis tool; "SFA" = substance flow analysis; "CEPA" = carbon emission pinch analysis; "EIA" = environmental impact assessment; "DEA" = data envelopment analysis; "PIOT" = physical input output table. The total number of papers analyzed is 70.

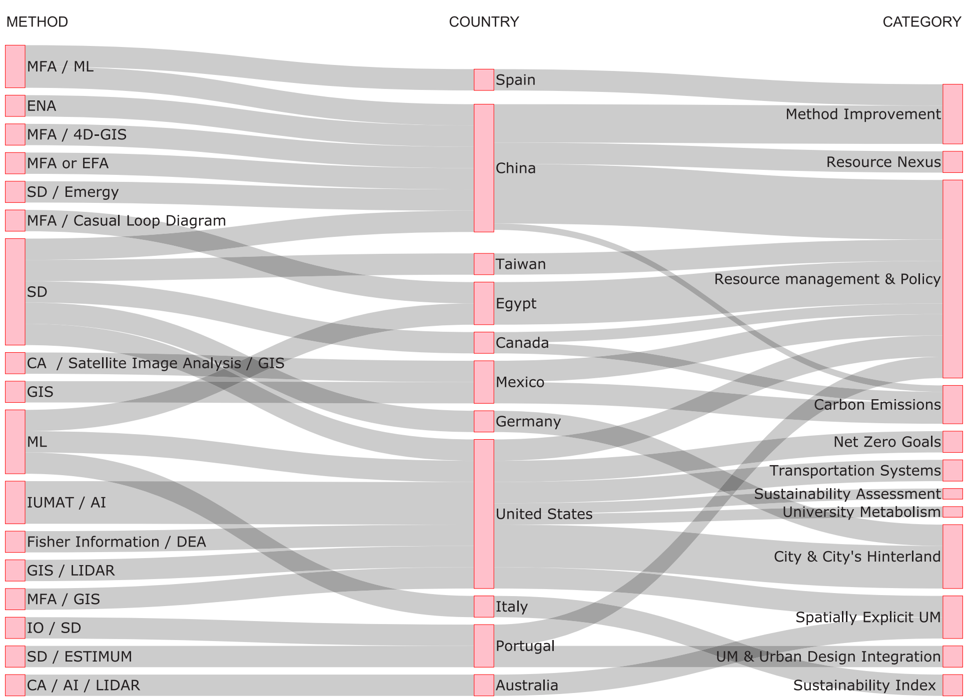


**Fig. 11.** Review 2: Sankey diagram showing connections across countries (Center), methods employed (Left), and categories (Right). N.B. : "SD" = system dynamics; "IUMAT" = integrated urban metabolism analysis tool; "IO" = input–output; "MFA" = material flow analysis; "EFA" = energy flow analysis; "GPS" = global positioning system; "AI" = artificial intelligence; "LIDAR" = Light detection and ranging; "CA" = carbon accounting; "ENA" = ecological network analysis. Total number of papers analyzed is 25.

a favored analytical approach but also emphasizes a need for methodological diversification. We found that leveraging DT technologies due to their capacity for dynamic and interactive representations could be the bridge to usher in a new generation of comprehensive and insightful UM studies.

On average, the papers analyzed utilized two to three different visualization types (mainly sankey diagrams, bar charts and MFA diagrams), with some employing four or five graphical representations (additionally spline graphs, conceptual diagrams, and area charts were used). This diversity in visualization methods reflects the necessity to

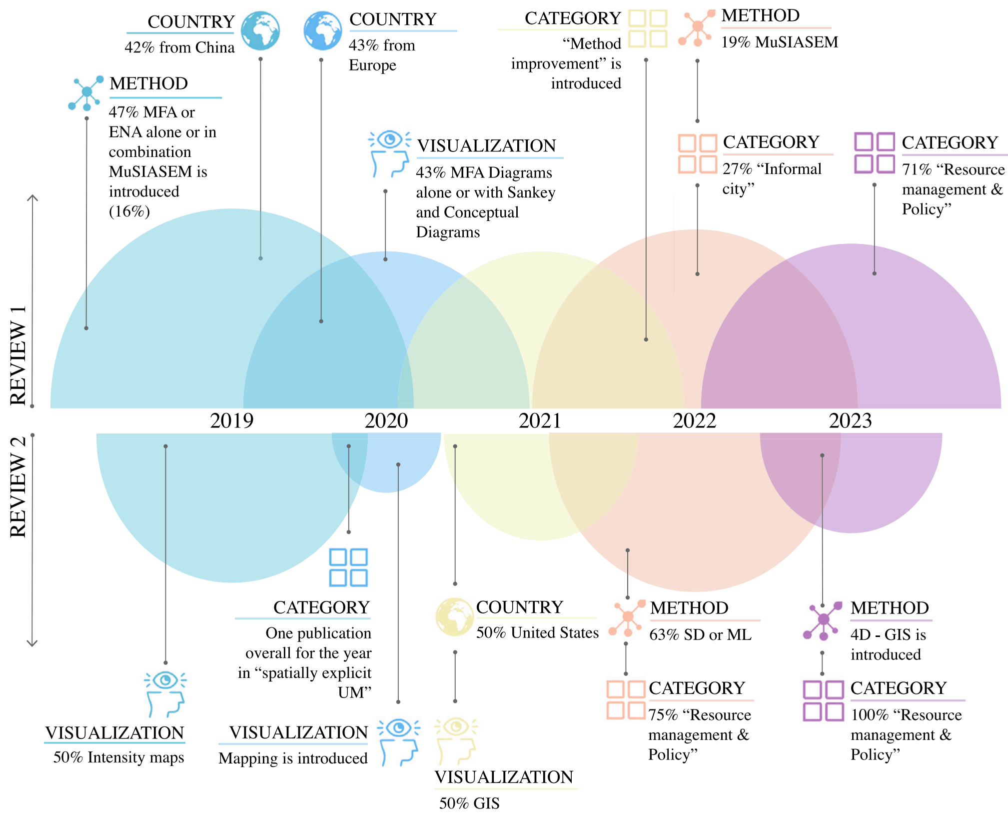


**Fig. 12.** Timeline describing Review 1 (Top) and Review 2 (Bottom) findings. Circles are representing the total papers published each year. N.B. "MFA" = material flow analysis; "MuSIASEM" = multi-scale integrated analysis of societal and ecosystem metabolism; "SD" = system dynamics; "ML" = machine learning; "GIS" = geographic information system; "UM" = urban metabolism.

effectively communicate results to a broad audience, particularly end-users in the "resource management and policy" or "city and city's hinterland" categories. However, the adoption of DTs offers a promising solution by providing a unique virtual environment that contextualizes data within the analysis, fostering deeper understanding and facilitating collaboration among researchers, urban designers and policymakers, and potentially citizens. Implementing DTs may consequently mitigate the need for a high number of less informative representations, streamlining the communication of UM analysis outcomes.

Review 2 with its focus on Industry 4.0 technologies, offers a glimpse into the future but exposes a gap in the intersection of UM and DTs. The "spatially explicit UM" category's use of technologies such as LIDAR and GIS showcases a step forward in precision in localizing flows, yet most MFAs were represented during discrete time periods. The prominent use of SD in review 2 suggests a shift towards dynamic modeling, providing a pathway for future studies. However, the lack of dynamic visualization methods across both reviews underscores a critical need for advancements in depicting UM in real-time.

This study highlights the need of UM to adapt to the technological advancements of this decade. A renewed approach will emphasize the utilization of results (Alfeld, 1995; Clarke, 2014) to provide sustainability end users with accessible and visual tools for expressing their research findings.

Most methods (such as MFA, LCA, input output) or visualizations (such as bar charts, MFA diagrams, sankey diagrams) used in the UM field (see Figs. 6 and 7) do not interoperate with CAD software (i.e. Rhinoceros 3D and AutoCAD), and Building Information Model (BIM) software (i.e. Revit, Archicad), which are typical tools employed by urban planners. Even more in an environment where the ability to readily modify planning scenarios and work with precise spatial representations holds such significant importance (Koenig, 2018). However, DTs offer a promising solution as they can incorporate the results of UM analysis and modify the 3-dimensional environment based on this information. This capability enables planners and designers to run simulations, update UM analyses, and iterate the design process, aligning with current practices in planning and design (D'Amico et al., 2022).

There are several reasons behind the lack of integration of Industry 4.0 technologies into the UM framework, despite the significant potential benefits.

The complexity and interdisciplinary nature of UM pose a significant obstacle, requiring coordination among urban planners, engineers, and data scientists (Liu et al., 2015; Olawumi & Chan, 2018). UM studies often encounter limitations due to specific data requirements, including issues related to data availability (Neves et al., 2023), quality, and interoperability (Athanassiadis et al., 2017). DTs relies heavily on vast amounts of data from various sources, contrasting with urban data infrastructure which may be fragmented, inconsistent, and outdated. There may also be a lack of awareness among urban practitioners and policymakers regarding the potential benefits and applications of Industry 4.0 technologies in UM studies. Therefore, the concept of urban DT pose significant challenges when applied to material flows in UM analysis.

Cost, infrastructure requirements, cultural, and organizational change, further impede this transition (Liu et al., 2015; Olawumi & Chan, 2018). This is especially evident in developing countries, where UM analysis for informal cities faces significant challenges, such as the lack of financial resources, technical expertise, and digital infrastructures needed to deploy and maintain advanced technology solutions for UM studies.

Embracing Industry 4.0 technologies requires cultural and organizational changes within urban planning and management institutions. Traditional decision-making processes, hierarchical structures, and resistance to change pose obstacles to the adoption of these technologies (Liu et al., 2015; Olawumi & Chan, 2018). To facilitate the integration process, programs aim to empower practitioners, researchers, and policymakers with the knowledge and skills required to effectively utilize DTs and Industry 4.0 technologies in UM studies can be promoted. Developing a framework for integrating heterogeneous data sources and formats is also crucial to enable data interoperability across UM and the development of DT platforms.

Implementing DT for UM can mitigate these limitations, by centralizing analyses within a unified framework, streamlining data storage and access, while ensuring uniformity and standardization (Caputo et al., 2019). This approach not only streamlines DT implementation but also enhances the accuracy of UM analysis.

This approach necessitates careful consideration of data quality, spatial granularity, and the representation of dynamic urban processes. In envisioning a DT for UM, it is crucial to prioritize accuracy, interoperability, and scalability to effectively model and simulate material flows, infrastructure dynamics, and socio-economic factors within urban environments. Such a DT should facilitate comprehensive analysis, informed decision-making, and the exploration of sustainable urban development pathways.

Certain emerging categories or methodologies have been scarcely observed in the reviewed papers, presenting opportunities for deeper investigation and innovation within the field of UM. Specifically, areas such as the integration of DT technologies, not found through the research on Scopus, and the application of machine learning algorithms for data analysis which remains relatively under-explored.

Moving forward, we intend to address these gaps by actively pursuing research endeavors that delve into these emerging areas, contributing to the advancement and enrichment of UM studies. By fostering interdisciplinary collaboration and embracing innovative methodologies, we aim to cultivate a deeper understanding of UM dynamics and their implications for sustainable urban development.

While our study primarily focuses on exploring the connections between UM, DTs, and Industry 4.0 technologies, it is worth noting that further analysis on categories such as “resource management and policy” could reveal how economic incentives within sustainable development policies may promote the integration of Industry 4.0 technologies in public administrations. Understanding the role of economic factors in policy-making and management strategies could encourage the adoption of advanced technologies, ultimately contributing to more effective urban governance and sustainable development practices (Hritonenko & Yatsenko, 2022; Padovan et al., 2022).

Research to enhance and standardize UM visualization is needed, and to accommodate the increasing interest from various research fields due to the interdisciplinarity of this relevant tool (Broto et al., 2012; Creutzig et al., 2019; Musango et al., 2017). A human-centered metabolism and society can be achieved by finding links between an individual’s behavior and social metabolism characteristics (Allam & Newman, 2018; Haberl et al., 2019). Industry 4.0 technologies and advancements in computational power can facilitate the digitalization of UM making it accessible to professionals and citizens (Fang et al., 2016; Ghobakhloo, 2020; Li, 2018; Musango et al., 2017) leading to socially just, inclusive, and comprehensive urban design, planning and development (Kaviti Musango et al., 2020; Keena et al., 2018; Musango et al., 2017; Zhang & Fath, 2019).

## 6. Conclusions

We presented a review of the most recent UM analyses (review 1), and then explored connections between Industry 4.0 technologies and UM (review 2).

Review 1 revealed a dominant focus of UM on optimizing urban resources and understanding their environmental impacts, (“resource management and policy” and “city and city’s hinterland” categories).

MFA and its combination with LCA emerged as prevalent methods, comprising nearly 45% of the studies analyzed in review 1. Both methods consistently employ similar visualization techniques, indicating their established status in the UM field. However, the utilization of maps to illustrate UM results was infrequent, and observed in only few instances (refer to Fig. 6).

Interestingly, the choice of visualization methods varied across different categories, implying a need for further research to identify optimal result representation for effective communication with shareholders. The predominance of the “resource management and policy” and “city and city’s hinterland” categories, underscores the necessity for exploring new impactful visualization methods to facilitate decision-making processes, policy making, and management strategies.

Review 2 demonstrated limited integration of UM with Industry 4.0 technologies, and a noteworthy absence of results in the intersection of UM and DT technologies (as summarized in Figs. 6, 7, 8, and 9), despite the pressing need to develop dynamic outcome visualization in this field (Gopal, 2016; Li et al., 2019; Stephan & Athanassiadis, 2018).

It was observed that SD and GIS emerged as the prevalent methods, to address the spatial limitations often encountered in UM analyses with all other methods employed appearing only once.

This lack of methodological consistency, characterized by the frequent use of various methods, poses challenges for the advancement and refinement of UM research methodologies. Nonetheless, the diversity in methods employed reflects the breadth of research efforts across different areas of expertise, suggesting a need for future convergence and standardization in methodological approaches.

A similar trend is observed in visualization methods, where despite the predominance of bar charts, intensity maps, and spline graphs, a wide array of other visualization techniques are utilized. While this indicates ongoing investigation, the absence of a definitive solution underscores the complexity of the field.

In this context, UM provides the conceptual framework, while DTs offer the technological platform for modeling, simulating, and optimizing urban processes toward sustainability empowering stakeholders to develop strategies for enhancing urban sustainability. In leveraging DTs, cities gain a comprehensive understanding of urban dynamics, enabling data-driven decision-making and sustainable urban planning. This integration holds the potential to mark a significant step forward in urban system analysis and optimization.

It will be necessary to implement novel frameworks encompassing diverse dimensions to enable practitioners to effectively adopt UM and DT methodologies for sustainable urban development, encompassing socio-economic dynamics, infrastructure resilience, and technological advancements (Papangelou et al., 2023).

DTs can offer a user-friendly interface, facilitating analyses and insights for practitioners irrespective of their technical proficiency. The new framework should inform evidence-based policy recommendations, ensuring consistent data updates from heterogeneous sources including spatial, sensor, socio-economic, and environmental datasets. Lastly, the integration of indicators and metrics should assist practitioners and policymakers in evaluating outcomes and assessing impacts effectively.

While the literature reviews underscore the diverse methodologies and visualization techniques employed in UM studies, a common theme emerges, the need for a cohesive and dynamic representation of the outcome and methodological standardization. The limited integration of UM with Industry 4.0 technologies, particularly DTs, as evidenced in review 2, further underscores this challenge.

The results of this literature review highlights the importance of advancing dynamic visualization methods and integrating Industry 4.0 technologies to bolster UM analyses and urban sustainability endeavors. By fostering the development of innovative visualization techniques and promoting the integration of emerging technologies, such as DTs and Industry 4.0 technologies, new insights into urban dynamics and optimized resource management strategies can be unlocked. Additionally, standardizing UM analyses holds the potential to streamline research efforts, facilitate cross-study comparisons, and foster collaboration among researchers and practitioners (Stephan et al., 2022a).

The results of this review emphasized the need to improve visualization methods and integrate Industry 4.0 technologies in UM analyses for sustainable development. Enhancing visualization techniques and adopting technologies like DTs can yield new insights for optimizing resource management. Standardizing UM analyses can streamline research, enable comparisons, and foster collaboration among researchers and practitioners.

## CRediT authorship contribution statement

**Federica Geremicca:** Writing – review & editing, Writing – original draft, Investigation, Conceptualization. **Melissa M. Bilec:** Review & editing, Supervision.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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