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Designing climate resilient energy systems in complex urban areas considering urban morphology: A technical review

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ABSTRACT

The urban energy infrastructure is facing a rising number of challenges due to climate change and rapid urbanization. In particular, the link between urban morphology and energy systems has become increasingly crucial as cities continue to expand and become more densely populated. Achieving climate neutrality adds another layer of complexity, highlighting the need to address this relationship to develop effective strategies for sustainable urban energy infrastructure. The occurrence of extreme climate events can also trigger cascading failures in the system components, leading to long-lasting blackouts. This review paper thoroughly explores the challenges of incorporating urban morphology into energy system models through a comprehensive literature review and proposes a new framework to enhance the resilience of interconnected systems. The review emphasizes the need for integrated models to provide deeper insights into urban energy systems design and operation and addresses the cascading failures, interconnectivity, and compound impacts of climate change and urbanization on energy systems. It also explores emerging challenges and opportunities, including the requirement for high-quality data, utilization of big data, and integration of advanced technologies like artificial intelligence and machine learning in urban energy systems. The proposed framework integrates urban morphology classification, mesoscale and microscale climate data, and a design and operation process to consider the influence of urban morphology, climate variability, and extreme events. Given the prevalence of extreme climate events and the need for climate-resilient strategies, the study underscores the significance of improving energy system models to accommodate future climate variations while recognizing the interconnectivity within urban infrastructure.

Introduction

Cities are complex systems characterized by their interconnected infrastructure assets, comprising the backbone of modern societies to support economic prosperity and the well-being of their citizens [1]. Given the drastic growth of cities through both densification and expansion towards adjoining boundaries, cities are becoming increasingly dependent on their infrastructure. Cities are responsible for about 66 % of global primary energy use and over 71 % of energy-related greenhouse gas emissions [2], and the urban population is projected to rise from 56 % in 2020 to 68 % in 2050 [3]. This surge in urbanization, coupled with ongoing economic growth, is expected to lead to a staggering 70 % increase in urban primary energy usage and a 50 % increase in associated carbon emissions by 2050 compared to 2013 levels [4].

Morphology, sustainability, and interconnectivity of cities

It has become crucial to introduce mitigation strategies to minimize the carbon footprint in cities while improving sustainability, and it is also essential to enhance climate resilience [5]. Addressing these challenges at the same time is demanding and sometimes controversial. As changes in the energy, transportation, and industry sectors gradually take shape, the energy sector assumes a vital role in reducing carbon emissions in transportation, building, and industry sectors [6]. For instance, replacing boilers with heat pumps and converting the fossil-fuel-based vehicle fleet into electric vehicles are among the initiatives underway. Nevertheless, these transformations will increase

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electricity demand and heighten the dependence of these sectors on evolving energy infrastructure. The energy sector needs to support these other sectors, even as it experiences a major transition to replace fossil-fuel-based power generation with renewable sources such as wind, and solar energies [7]. Dependence on this energy infrastructure poses challenges to sustainability efforts in the building, transportation, and industrial sectors [8]. It is thus important to improve the flexibility of the energy infrastructure to withstand the variability of renewable energy generation and the fluctuations brought by climate variations [9–11]. To achieve this, it is essential to take into account the interdependence of critical urban infrastructure assets (e.g., by implementing sector coupling) during the design and control phases of energy infrastructure.

Critical infrastructure systems are interdependent and interconnected at different levels; however, each component is mostly developed independently based on a sequential process regardless of its interdependencies [12]. For example, the evoked geospatial morphology of cities (also known as urban morphology) is developed and expanded independently prior to the development of the energy infrastructure. Urban morphology encompasses the physical structure and layout of cities, including their form (i.e., density, shape, layout, and height), function (i.e., the functional needs of buildings, size, and location), and structure (i.e., streets, canopies, and open spaces) [13]. With the process of urbanization, these elements have become increasingly intricate and interconnected, playing a pivotal role in the sustainability and resilience of cities. Urban morphology can affect energy consumption patterns ([14]), the distribution of energy loads ([15]), and the availability of renewable energy resources ([[16],[17]]). For instance, a study by Xie et al. [18] demonstrated that density-related morphological parameters can cause variations of 12.25 % in Energy Use Intensity (EUI) and 35.85 % in Net-EUI, considering the incorporation of photovoltaic panels in a case study of dormitory blocks in Wuhan. Considering the impacts of urban morphology at design can result in a 30 % reduction in the levelized cost of energy infrastructure, while urban density may increase urban energy demand by 27 % [19]. Moreover, Urban morphology can have a notable impact on the microclimate conditions in urban areas [20], which in turn can have a significant impact on the comfort [21], health, and well-being [22] of urban dwellers, as well as on their indoor air quality [23]. In dense urban settings, wind speed and air temperature may be dampened or amplified by up to 66 % and 39 % respectively [24]. Particularly in cities located in Mediterranean and marine west coast climates, this impact on air temperature can be more pronounced, leading to fluctuations of over 10 °Celsius at an hourly temporal resolution. Additionally, considering microclimate conditions can lead to an average deviation of 17 % and 7 % in cooling degree-days and heating degree-days, respectively, compared to simulation results based on mesoscale climate data for a case study in Karlshamn [25]. The impact of urban morphology extends beyond energy infrastructure and microclimate conditions and can also affect the urban transportation network [26], electromobility modes [27], and work-related travel behavior and lifestyle [28]. Thus, recognizing the multi-faceted impact of urban morphology is crucial for designing sustainable and resilient urban environments.

As cities continue to grow and become more densely populated, the relationship between urban morphology and urban energy

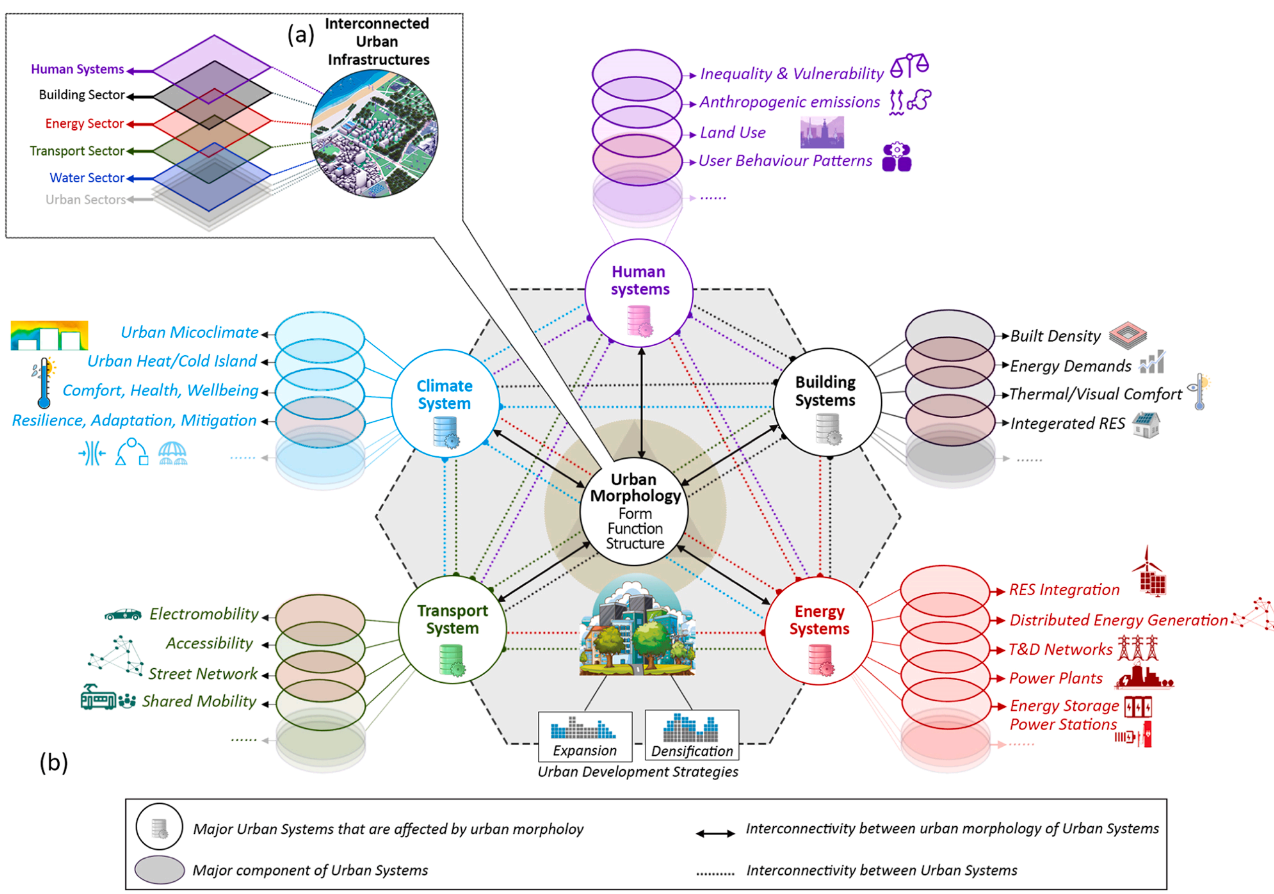

Fig. 1. Visual Representation of the Complex Interplay Between Urban Morphology and Urban Infrastructure Systems: (a) Depicts the interconnected nature of urban infrastructure, comprising various sectors with intricate relationships operating at different spatiotemporal resolutions. (b) Illustrates the significant influence of urban morphology on diverse urban systems, encompassing building, energy, transport, human, and climate systems. This study focuses specifically on investigating the interrelationships between urban morphology (at urban/building scales), climate, and energy models. Consequently, other systems, such as human, transport, and water systems, fall outside the scope of this study.

infrastructure has become increasingly important. Morphological parameters such as urban density and building layout significantly affect the cost of investment and operation, as well as the integration of renewable energy technologies in urban energy systems [[29],[30]]. The present study examines the complex relationships between urban morphology and various systems - such as humans, climate, buildings, transportation, and energy systems - within urban environments.

Fig. 1 offers a visual representation of the interconnectivity within these urban systems. In this representation, certain elements of urban systems, such as 'Electromobility' in the transport system, and 'Integrated Renewable Energy Sources' in building systems, are directly associated with the Energy system category. Urban morphology also has the potential to impact the urban water system network in various ways [[31],[32]], however, the current study does not cover this aspect. The complexity and interconnectedness of these systems highlight the need to consider the impact of urban morphology when designing sustainable and resilient cities. However, due to the significant influence of local factors such as seasonal changes in climate, energy demand patterns, and renewable energy potential, it is not feasible to identify a single optimal urban layout that can be universally applied. Therefore, it is crucial to develop methodologies that can assess and optimize urban morphology to improve both energy and climate resilience.

Resilience of sustainable cities in the era of climate extremes

Urban infrastructure assets are intertwined with several complex and heterogenic system components; a mismatch in one component can lead to cascading failures in the whole system [[33],[34]]. As a consequence of cascading failures in urban energy infrastructure, over 13 devastating blackouts occurred worldwide between 2003 and 2015 [35], with more frequent occurrences in recent years[36]. The ongoing electrification of the buildings, transportation, and industrial sectors can contribute to this problem, as it can result in a significant increase in energy demand, along with the potential shift of peak demand from summer to winter. For instance, the increasing adoption of electric vehicles (EVs) leads to heightened variability in demand patterns. The successful deployment of EVs is contingent upon the availability of adequate charging infrastructure, putting higher pressure on the energy systems while designed to account for the unique characteristics of urban morphology to optimize charging accessibility and reduce potential strain on the electricity grid. Higher integration of renewable energy sources (RES) is promoted to be a sustainable solution in this regard. However, the energy produced by RES is markedly influenced by climate variations, which may lead to a supply-demand mismatch, particularly during extreme climate events [37]. Designing urban energy systems is further complicated by the multi-dimensional impacts of climate change on both the energy [38] and building sectors [39], as well as the significant uncertainties in the climate change projections [39]. Climate change also wields a substantial impact on energy infrastructure, particularly in terms of extreme weather events[40]. The increasing frequency and intensity of events like heatwaves, cold snaps, wildfires, droughts, and hurricanes can lead to disruptions in energy systems and result in power outages. As a result, it is important to consider the potential impacts of climate change when planning and designing energy infrastructure to ensure its resilience in the face of these challenges [41]. Resilience, within the context of energy systems and climate dynamics, represents a multifaceted concept aimed at enabling systems to function proficiently even in the face of extreme climate events. This concept, initially introduced in reference to scenarios wherein a system remains operational during, or rebounds after, such climatic upheavals [42], emphasizes a system's capacity to respond to change and regain equilibrium or stability following disruptive occurrences [43]. Broadly, a resilient energy system is a system that can swiftly recuperate from shocks, extracting lessons from these incidents, and providing alternative avenues to meet energy service demands [44].

The combined effects of climate change and urbanization have also emphasized the critical need for sustainable and resilient energy systems. Urbanization is occurring at an unprecedented rate, particularly in developing countries, and has led to an increased demand for energy in urban areas. Urban overheating and the rising standards of living with the increased installation of air conditioning units during summer lead to a non-linear increase in cooling demand. This demand is further exacerbated during long-duration heatwaves. However, current cooling demand predictions oversimplify these assumptions, leading to potential inaccuracies in predicting future cooling needs in urban areas. As such, it is critical to implement sustainable and climate-resilient energy systems that can withstand the impacts of climate change and support the growing energy needs of urban areas.

Existing challenges and objectives of the study

Developing integrated urban energy system modeling platforms that account for interconnectivity and climate resiliency is essential to ensure an energy transition in a more sustainable way. However, several challenges still require attention to attain this objective. Two primary challenges include the integration of multi-sector models with diverse spatial and temporal resolutions and the requirement for high-quality datasets to construct reliable models. This can be especially challenging in cities, which have complex and interdependent infrastructure systems, making it difficult to obtain accurate and timely data.

On the other hand, there are many opportunities for improving urban energy systems through the use of big data from various modes of sensing and monitoring/Internet of Things (IoT) devices, artificial intelligence (AI), and machine learning (ML). Additionally, the availability of affordable high-performance computing is enabling the execution of intricate models and simulations that can optimize urban energy systems. Another crucial aspect of developing sustainable and resilient urban energy systems is the increasing importance of integrating renewable energy technologies with energy storage. However, the quality and quantity of energy storage technologies in relation to urban morphology, climate variations, and energy systems still remain a challenge. Therefore, a comprehensive assessment that considers urban morphology, climate, and energy infrastructure is essential for improving climate resilience and sustainability. Nonetheless, it has become extremely challenging to cover such a broad spectrum of topics and bring up expertise in a wider range of topics at the same time. To the best of the authors' knowledge, there is currently no comprehensive original or review paper that covers all the relevant areas related to urban morphology, climate resilience, and energy sustainability. This knowledge gap could potentially impede the transformation of urban areas towards enhancing climate neutrality and resilience.

This paper focuses on two areas:

- Analyzing the challenges of developing an urban model known as urban morphology, form, context, or structure, specifically tailored for urban energy systems while accounting for climate variations. We found no specific definition in the literature to identify geospatial boundaries of urban blocks, neighborhoods, or districts from a dimensional point of view; for neither urban building energy models (UBEMs) nor urban energy systems (UES) models. To address this gap, we put forth a categorization framework for urban morphology based on dimension and population-scale, accommodating diverse modeling methodologies. Alongside this, we also propose a climate model classification with three major groups of mesoscale climate models, urban climate models, and urban microscale models, with a specific focus on plausible future weather conditions and extreme events on urban energy systems.
- Proposing a structured framework that accounts for the urban morphology model, climate variations, and the occurrence frequency of extreme events throughout the design/operation process as a future pathway to achieve resilient interconnected infrastructures in cities. The proposed framework can be incorporated into both urban

energy system models and urban building energy models. It is shown that the proposed framework contributes to reducing the impacts of extreme events brought by climate change and catering to the expansion of urban areas to set pathways to the energy transition and improve sustainability levels in cities.

The paper is organized as follows: Section 2 provides an overview of the methodology used to conduct our literature review. This is followed by a review of the literature on the topic in Section 3. Section 4 outlines the workflow for assessing urban energy infrastructure, which includes urban, climate, and energy models. In Section 5, we discuss urban morphology models, starting with the relevant terminology used in literature, followed by a discussion of morphological parameters, spatial resolution, and the challenges in linking urban morphology to urban building energy models and urban energy systems. In Section 6, we explore the interconnectivity, interoperability, and energy systems within urban infrastructure systems. Section 7 focuses on the opportunities and challenges in linking urban morphology to energy systems, ranging from centralized to distributed architectures. In Section 8, we propose a framework to align urban, climate, and energy models. Section 9 presents our conclusions.

Review methodology and scope of the study

Fig. 2 illustrates the scope of the current review within the broader framework of interconnected urban infrastructure. Due to the extensive nature of this theme, a comprehensive review cannot be encapsulated within a single paper. For the purposes of this paper, we narrow our focus to the interactions among urban energy systems, urban morphology, and climate data. Consequently, other influential factors such as human systems (e.g., user behavior and engagement in energy system design/control), urban transportation, water systems, and topics concerning sustainability, resilience governance, regulations, and socioeconomic dynamics are intentionally excluded from this literature review.

In this review, we followed the PRISMA Statement (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) approach to select the relevant literature. The selection process consisted of four main steps: Identification, Screening, Eligibility, and Inclusion. The relevance of the selected papers was based on the following keywords: infrastructure, energy system, urban, morphology, climate change, microclimate, extreme, optimization, sustainable, and resilience. We expanded the search for relevant papers by using related terms and synonyms for each keyword. For example, we used “smart grid” and “energy hub” in addition to “energy system,” and “form” in addition to “morphology,” as these terms have been used interchangeably in the literature. The literature search was conducted in March 2022 and repeated in February 2023 to include newly published articles, using the following databases: Web of Science (topic/ title/ keywords/ abstract/ research area), Scopus (title/ keywords/ abstract), and Google Scholar (the first 100 rows). Furthermore, during the revision stage, we enhanced the precision of our literature search by introducing two additional pertinent keywords: ’urban design’ and ’neighborhood design’. As a result of this refinement, six new records with a focus on urban-scale energy fields were incorporated into our comprehensive literature pool in June 2023. A total of 1187 publications were extracted for further analysis at the macro-level. The interconnection between urban morphology (UM), urban-scale energy (UE), urban energy system (UES), and climate change (CC) was analyzed through four major groups: (a) UM + UE, (b) UM + UES, (c) UM + CC, and (d) UES + CC.

We used the VOSviewer tool [45] to perform a density-map network analysis based on the Total Link Strength attribute between each keyword (Fig. 3). The network analysis revealed a strong link between urban morphology and microclimate conditions studies, as well as energy demand simulation (Fig. 3-a, b). Most city-scale studies in the literature that focus on CC assessed land use, transport system, or form (Fig. 3-c), while studies on UES and CC rarely considered urban morphology and focused only on building stocks, land cover, land use, or surfaces (Fig. 3-d). A closer examination of the identified records in the literature showed an upward trend in assessing urban morphology in relation to the selected keywords, although the literature on the interconnection between energy systems, urban morphology, and climate change impacts remains scarcer (Fig. 4).

We refined our database of 1191 publications based on five inclusion criteria: (1) relevance to urban morphology modeling, (2) urban-scale energy modeling, (3) design/control of energy systems, (4) climate/energy resilience, and (5) interconnectivity in urban infrastructure. The refined database resulted in 1021 records with the highest relevance to the defined criteria. To provide an overview of the selected publications, we generated a co-occurrence network analysis map based on a content analysis of the title, keywords, and abstract (Fig. 5).

A rising global trend in awareness of the impacts of climate change is evident in the selected publications, particularly in the areas of urban-scale energy modeling and the resilience of urban areas to climate

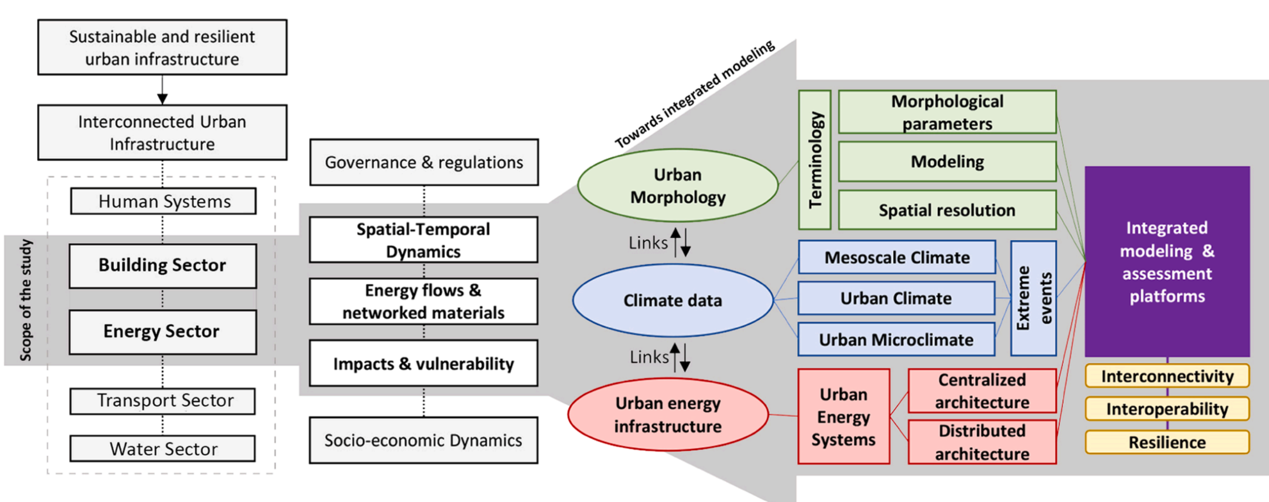

Fig. 2. Study Scope within the Framework of Interconnected Urban Infrastructure: Emphasizing Interconnectivity, Interoperability, and Resilience, with a Specific Focus on the Synergies between Urban Energy Systems and Urban Morphology. This study primarily centers on building, climate, and energy models. Additionally, the influence of the transport sector is restricted to its demand-side aspects (e.g., EVs) and their potential contribution to energy storage. The water sector, socioeconomic dynamics, and other facets of the transport sector are outside the scope of the present study.

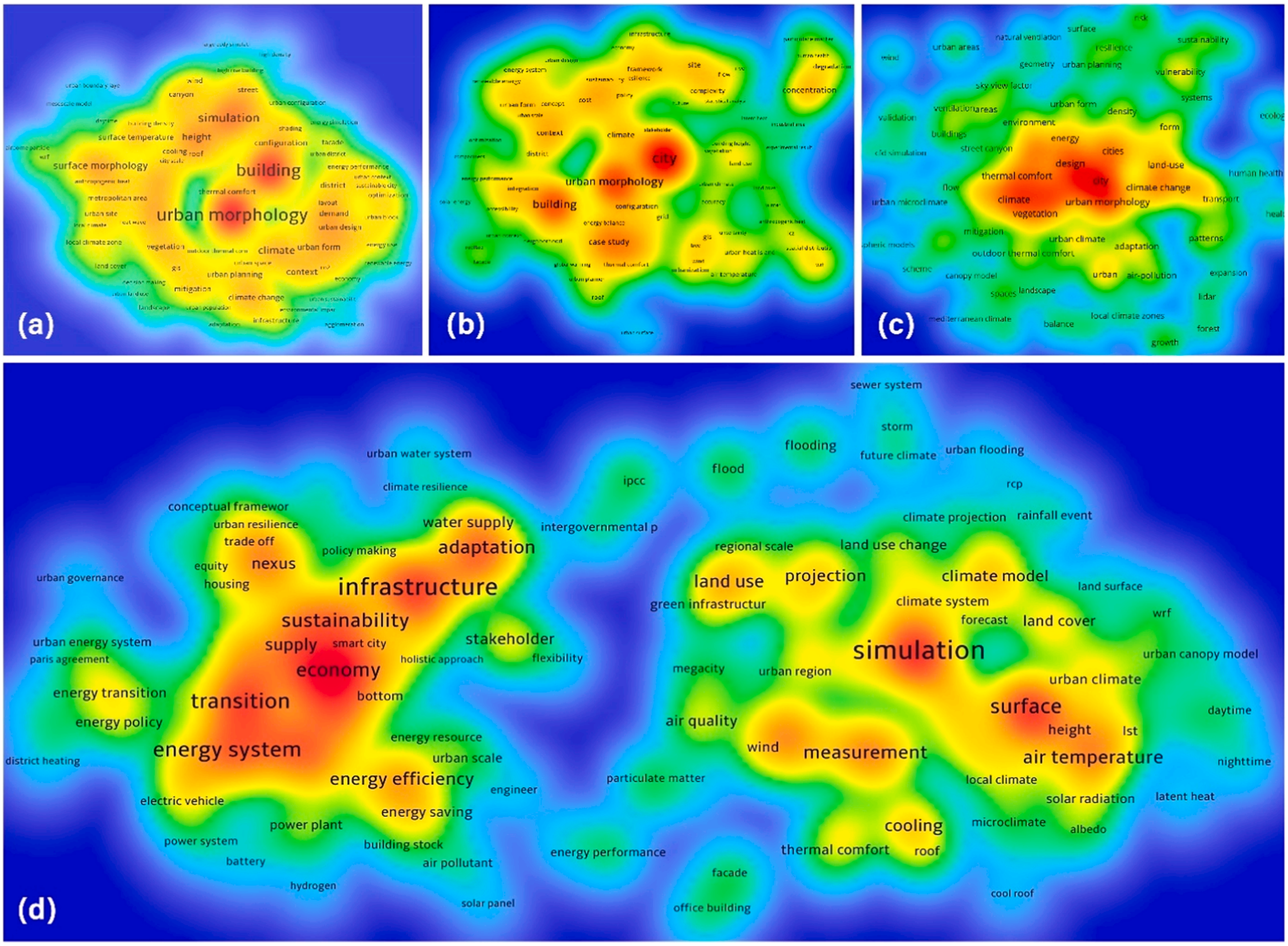

Fig. 3. Density-map network analysis of the selected publications (VOSviewer tool [45]) (a) Keywords: urban morphology+ UBEM, (b): Keywords: urban morphology+ UES, (c) Keywords: urban morphology+ climate change, (d) Keywords: UES+ climate change. Urban morphology is mainly linked to urban-scale energy studies, with few studies found in UES. Research on urban morphology and climate change has largely concentrated on urban development and mitigating urban heat island effects, with little emphasis on its impact on UES in the literature.

change. The focus of the literature on urban morphology has mostly been on developing urban-scale energy models, while the integration of climate/energy resiliency in the design/control of urban energy systems with regard to urban morphology has received limited attention.

The majority of published literature on urban morphology has focused on microclimate conditions, the urban heat island effect, air quality, and building cooling energy use. However, the link between urban morphology and energy system analysis is scarce. The same is true for the climate/energy resilience in the design and control of urban energy systems considering urban morphology, and spatial/sector interconnectivity.

At the micro-level analysis, we further evaluated the content of the 574 selected records based on five exclusion criteria to assess their eligibility. We excluded studies that focused on numerical simulation of microclimate conditions with models smaller than urban blocks and publications that did not focus on building/urban-scale energy (as shown in Fig. 6). Following these refinements, 343 records were ultimately included in the systematic review synthesis. This encompassed 68 literature review papers, and 275 research papers, after accounting for accessibility considerations.

Relevant literature reviews

Table 1 presents the focus and main findings of review studies on urban morphology and the urban energy system. It is important to note that the majority of these studies focus on policy and governance. Only one review paper addresses urban energy resilience, and another research paper focuses on co-optimizing energy systems and urban morphology.

The literature review in this field mainly concentrates on recent methods, techniques, and mechanisms for developing and implementing Urban Building Energy Models (UBEMs) or urban-scale energy models. UBEMs are a relatively recent concept, and the first comprehensive review paper outlining prospects for bottom-up UBEMs was published by Reinhart and Davila [46]. Other review papers have summarized the current state of the art in developing UBEMs with top-down or bottom-up approaches, including works by Li et al. [47] and Frassinet et al. [48]. Comprehensive reviews of recent progress in developing UBEMs and urban-scale energy models are summarized in [[49],[50]], and [51]. To date, various aspects of UBEMs have been studied. Happle et al. [52] reviewed deterministic and stochastic methods for incorporating occupant behavior in UBEMs and urban-scale energy models. Johari et al. [53] provided a comprehensive overview of the state of the art in developing top-down and bottom-up approaches and their prospects. they noted that the existing literature on urban building energy models (UBEMs) predominantly relies on aggregated or disaggregated data within specific case studies. They advocated for more holistic approaches that encompass additional dimensions like climate models, energy system models, and mobility models to enhance future UBEMs. Ferrando et al. [54] presented a systematic review that examined

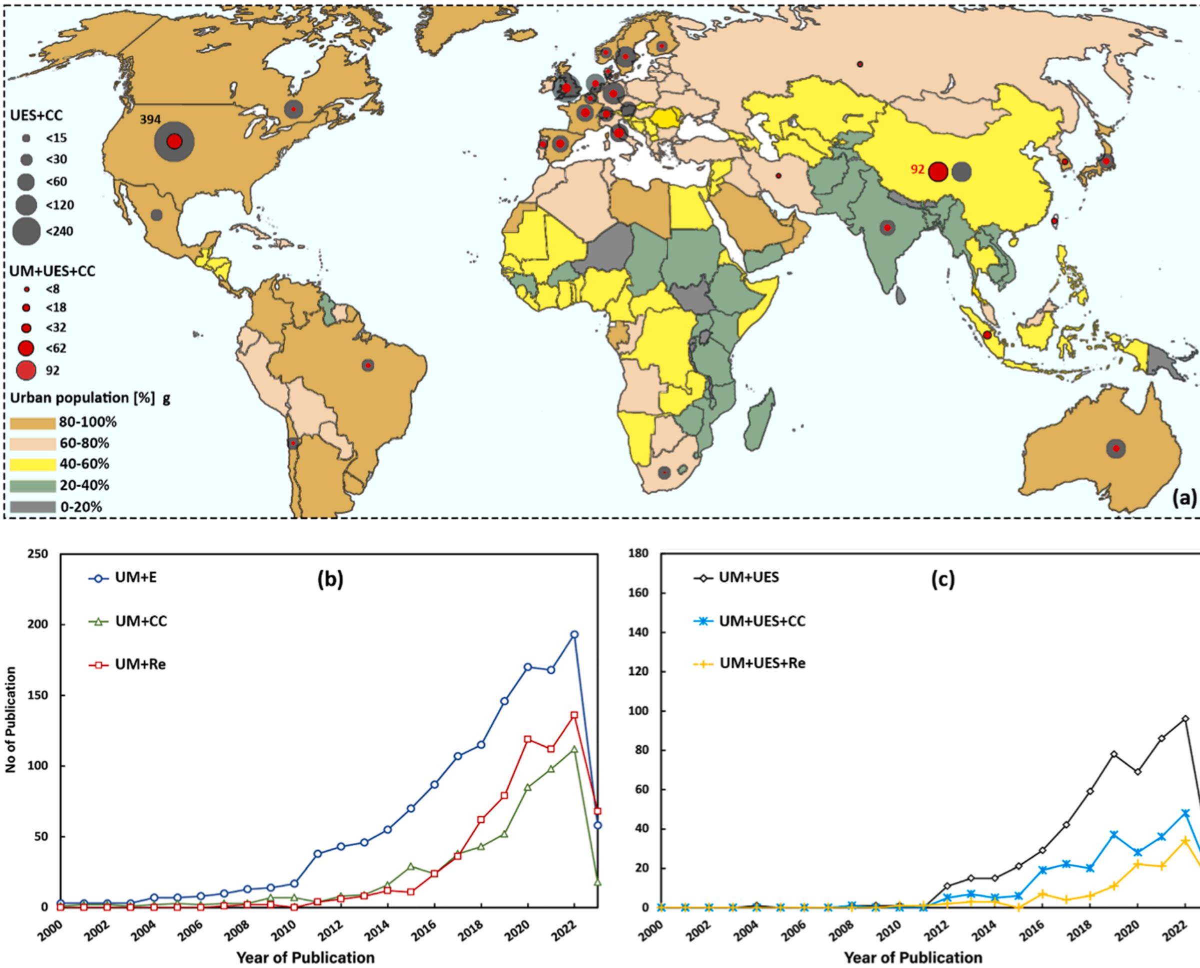

Fig. 4. (a): Geographical distribution of studies focused on UES and climate change (gray circles), urban morphology, UES and climate change (red circles), and urban population percentage in the world. The majority of studies have been carried out in developed countries; while most developing countries with high urbanization rates have fewer than 15 publications. Bottom: Number of publications per year based on title, keywords, and abstract using the Scopus database; extracted September 25, 2021: (b): urban morphology (UM) and UBEM concerning climate change (CC), and resilience (*Re*); (c): urban morphology and UES concerning climate change (CC), and resilience (*Re*). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.).

various tools, workflows, methods, and models for bottom-up physics-based urban-scale energy models from a user-centric standpoint, although they did not consider the discussion of urban morphology and urban form in this analysis.

The majority of literature review publications in this field tend to concentrate solely on systematic reviews and perspectives, often neglecting the direct correlation between the design and control of urban energy systems. Allegrini et al. [55] summarized emerging modeling and simulation methods and implementations for district-scale energy systems. Aghamolaei et al. [56] reviewed the challenges in the energy performance of district-scale energy systems. Despite several similar review papers, there is limited literature on assessing climate resilience and urban interconnectivity (sector and spatial coupling) in this field. Sharifi [[57],[58]] summarized the terminology of urban energy resilience and resilient urban forms from different perspectives. Salimi and Al-Ghamdi [59] and Ye et al. [60] provided an overview of the impacts and risks of climate change on urban energy systems. More recently, Jasiūnas et al. [61] discussed the vulnerabilities of energy systems to extreme climate events, highlighting several existing challenges, particularly due to technical failures and cyberattacks. However, to the best of our knowledge, no paper has analyzed the interconnectivity and coupled challenges of urban infrastructure as an interconnected component in relation to climate change, extreme events, or resilience. By confining the search scope to the core keywords (urban morphology/infrastructure, energy system, and resilience), only seven papers were identified.

Workflow for developing urban energy infrastructure models

The planning phase of urban energy infrastructure demands careful consideration of numerous uncertainties. These challenges can be grouped into three distinct categories: (1) urban models, (2) climate models, and (3) energy models. Each category encompasses specific attributes that necessitate thorough examination. For instance, urban models encompass the geospatial boundary of cities, known as “urban morphology” or “urban form,” including all physical, functional, geometrical, and social aspects of a city. Climate models can be classified into present and future models, serving as inputs for urban energy infrastructure models that span from microscale (commonly referred to as "microclimate" or "urban canopy layer") to mesoscale. The computational model is a flexible framework encompassing both single and multi-zone models, comprising influencing urban morphological parameters. This model should seamlessly integrate data from relevant multi-scale climate models, facilitating its integration into various simulation engines as a robust computational tool. Energy models, on the other hand, refer to the methodologies and approaches used to

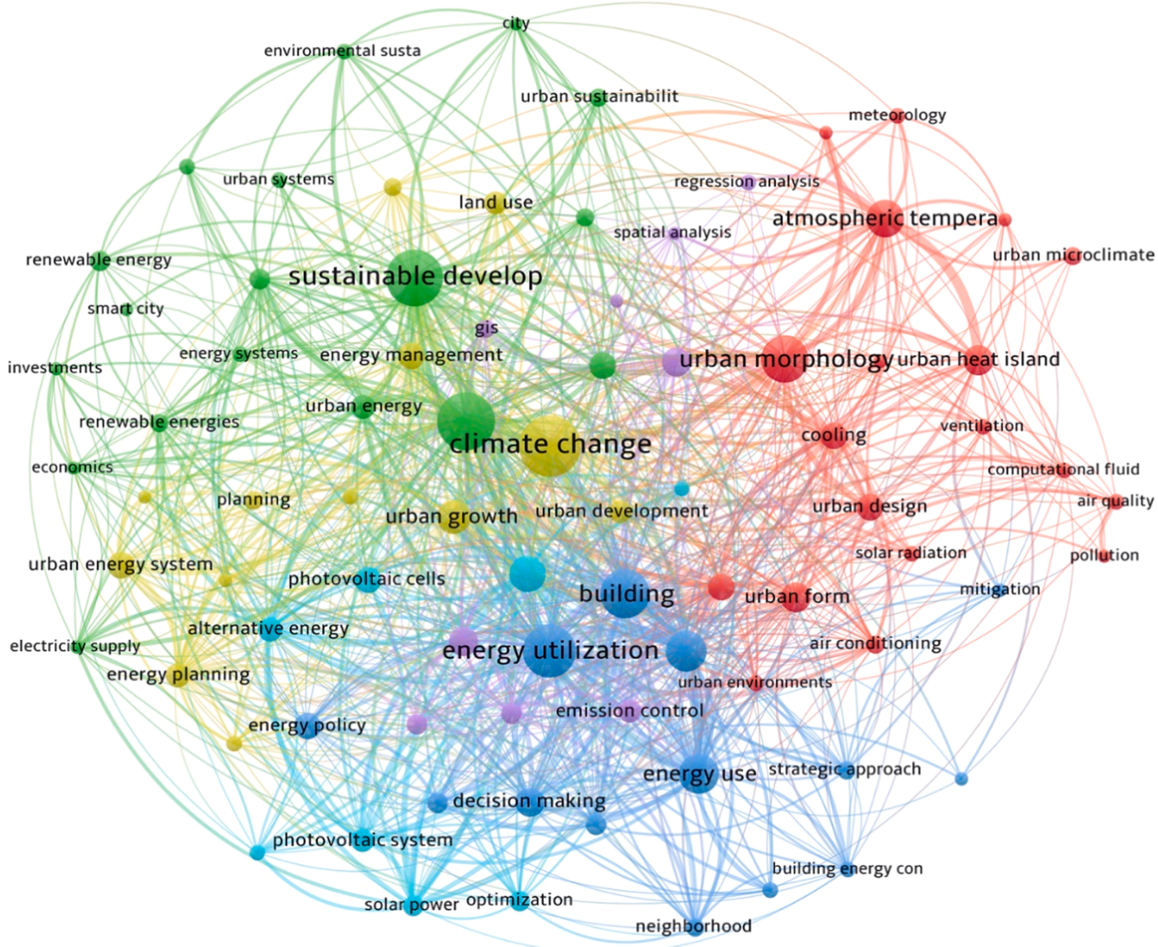

Fig. 5. Network map of selected keywords in the content analysis of the selected literature (VOSviewer tool [45]) based on title, keywords, and abstract using the Web of Science database; extracted December 25, 2021. The focus of urban morphology studies has been on microclimate, energy simulation, and spatial analysis. The majority of studies on UES and climate change have focused on land use/land cover parameters rather than urban morphology.

develop Urban Building Energy Models (UBEMs), and design and control urban energy systems, and smart grids. To build a complete urban energy infrastructure model, all three categories must be considered to some extent, depending on the objectives and limitations of the model. Fig. 7a preliminary workflow commonly for modeling urban energy infrastructure is presented. This study undertakes a distinct examination of the challenges associated with each category.

Linking urban models with energy models

Conventional Building Energy Simulation models (BESs) have been replaced by UBEMs in response to the complexity of sustainable urban energy solutions. BESs are single-step, straightforward models used to evaluate a building's energy performance, such as optimizing its heating, ventilation, and air conditioning (HVAC), lighting, and spaces [73]. In contrast, UBEMs have a multi-step process, beginning with the creation of urban and climate models, and ending with the development of energy models. The state of the art in UBEMs has been comprehensively reviewed in literature (i.e., [[69],[74]]) and can be categorized into two main modeling approaches: top-down and bottom-up [[47],[75]]. Top-down models heavily depend on aggregated historical data derived from extensive large-scale studies [76]. They have found extensive application in revealing correlations between energy demand profiles, socio-demographic and economic parameters, and climate changes in urban areas[46]. Nonetheless, their simplicity and absence of intricate urban/building physics parameters constrain the influence of urban morphology on particular land-use patterns. Furthermore, their emphasis on macroeconomic trends and historical data falls short of adequately addressing climate change and upcoming trends [77].

Bottom-up models use disaggregated data per building or urban area and consider detailed urban/building physics parameters [78]. Bottom-up models can be further divided into two categories: physics-based [54] and data-driven [79]. Physics-based models, also referred to as "engineering models," utilize inputs like building stock properties, user behavior, and climate data to generate energy demand profiles as outputs. Recent physics-based models use archetypes or architectural layouts with a graphical user interface (GUI). However, multi-zone thermal modeling requires vast building physics databases that are not always readily available. Consequently, buildings are frequently simulated using mono-zone thermal models and computed through a simulation engine. In contrast, data-driven models leverage available building stock data to anticipate urban energy demand, incorporating data on building properties, metered energy, socioeconomic factors, and climate conditions. There are several physics-based UBEM tools available, including CitySim [80], SimStadt [81], umi (urban modeling interface) [82], CityBES (City Buildings, Energy, and Sustainability) [83], CEA (City Energy Analyst) [84], UrbanOpt (Urban Renewable Building and Neighborhood Optimization) [85], BEM-TEB (Building Energy Modeling-Town Energy Balance) [86], TEASER (Energy Analysis and Simulation for Efficient Retrofit) [87], and more. These tools mostly take the characteristics of the building stock and climate data as inputs and generate energy demand profiles, thermal

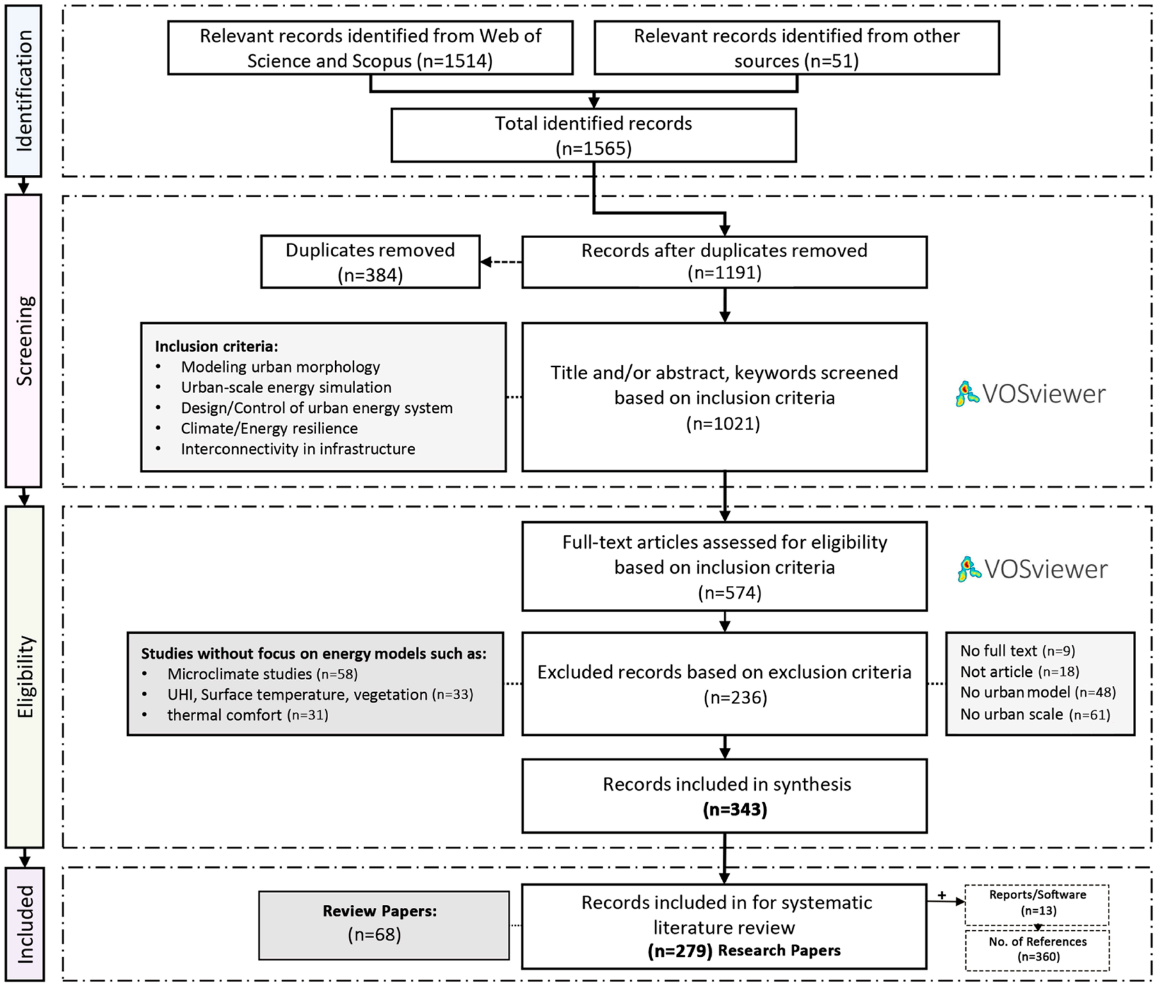

Fig. 6. The review protocol based on the PRISMA Statement workflow for the Literature selection methodology.

comfort indicators, and renewable energy potentials. Similar integrated hybrid tools are continuously being developed and improved.

UBEM tools can also be classified based on their integration with 'Building Information Modeling' or (BIM) [88] and 'Geographic Information System' (GIS) [89] databases. Considering the substantial expansion of BIM [90] and GIS models[91], such integrations offer significant advantages to UBEM tools by providing comprehensive inventories of materials and building characteristics, compared to other available alternatives such as Modelica libraries [70]. The limitations of using Modelica libraries, in contrast to the automation capabilities of BIM for building models, are highlighted in Ref [92]. Two recent instances illustrating such integrations are the DIMOSIM (District MOdeller and SIMulator) [93] and CESAR (Combined Energy Simulation And Retrofitting) [94]. DIMOSIM is a modular UBEM designed for optimizing urban energy systems, with the added advantage of being seamlessly integrated with BIM. On the other hand, CESAR exemplifies a hybrid tool, amalgamating physics-based and statistical models by utilizing GIS databases to model major urban morphological parameters. AutoBPS (Automated Building Performance Simulation) [95] is another example that is capable of developing multi-zone energy models at urban and district levels, while potentially being integrated with BIM [96] and GIS [97] databases.

Although the majority of UBEM tools offer the capability to either specify buildings individually or extract building geometries from raster/vector databases, a persistent challenge lies in defining urban morphological parameters, particularly with an emphasis on density-related factors. Furthermore, UBEM tools tend to concentrate on urban energy demand profiles, leading to a gap in integrated workflows that encompass energy system modeling (Fig. 8 and Table 2).

Developing an urban morphology model

Terminology of urban morphology

Urban infrastructure systems are inherently bound by their physical and geospatial constraints [31]. The distribution network of critical infrastructure such as energy, water, and transportation systems has distinct spatial characteristics. The urban energy infrastructure must continually adapt to meet the escalating demands of expanding cities. The interaction between urban geospatial models and energy infrastructure systems introduces heightened multivariate uncertainties and complexities in crafting effective decision-making frameworks. It is well established that geospatial characteristics of urban infrastructure assets play a critical role in energy sustainability [7], climate mitigation [107], and resilience [68]. Despite this recognition, modeling the geospatial boundaries of urban infrastructure assets remains a notable challenge both in academic research and practical application.

In the current literature, several technical terms, including “morphology,” “form,” “texture,” “fabric,” and “pattern,” have been used interchangeably to describe geospatial boundaries (Fig. 9). Over the past two decades, the prevailing term employed for assessing energy performance in urban contexts has been "urban form." Yet, confusion arises between the terminologies "morphology" and "form" concerning urban areas in the reviewed literature. While “urban form” represents

Table 1
Recent review studies concerning urban morphology and urban energy models/systems.

Year	Author (s)	Main Focus	# of Refs	Relevance to the Current Study				
				Modeling urban morphology	*Urban-scale energy simulation*	*Urban energy systems*	*Climate change/ resilience*	*Urban interconnectivity*
2015	*Allegrini* et al. [55]	Simulation of district-scale energy systems	198	–	✓	✓	–	–
2016	*Sharifi* [57]	Urban energy resilience	245	✓	–	✓	–	–
2017	*Shi* et al. [62]	Urban form optimization for energy-driven urban design	133	–	✓	✓	–	–
2018	*Aghamolaei* et al. [56]	District-scale energy performance analysis	143	–	✓	✓	–	–
2018	*Masnavi* et al. [63]	Urban resilience thinking in urban planning	71	✓	–	–	✓	–
2019	*Abbasabadi and Ashayeri* [64]	Urban energy use modeling	167	–	✓	✓	–	–
2019	*Guelpa* et al. [65]	Sustainable future energy systems	258	–	–	✓	–	–
2019	*Mauree* et al. [7]	Urban environment and climate adaptation	210	–	✓	✓	✓	–
2019	*Ferrari* et al. [50]	Tools for urban energy planning and simulations	60	–	✓	✓	–	–
2020	*Salimi and Al-Ghamdi* [59]	Climate change impacts on critical urban infrastructures	106	–	–	✓	✓	–
2020	*Sola* et al. [51]	Urban-Scale Energy Modelling with a multi-domain approach	78	✓	✓	–	–	–
2020	*Johari* et al. [66]	Urban Building Energy Modeling (UBEM)	160	✓	✓	–	–	–
2020	*Ferrando* et al. [54]	Urban Building Energy Modeling (UBEM) and bottom-up approaches	156	–	✓	–	–	–
2021	*Quan and Li* [49]	Urban form, building energy use	110	✓	✓	–	–	–
2021	*Zhang* et al. [67]	Building cluster-level and urban energy systems	137	–	✓	✓	–	–
2021	*Ye* et al. [60]	Assessment of climate change risk at the urban scale	180	–	–	✓	✓	–
2021	Jasiūnas et al. [61]	Energy system resilience	187	–	–	✓	✓	✓
2021	Nik et al. [68]	Energy system resilience	105	–	✓	✓	✓	–
2022	Wang et al. [69]	Data acquisition for UBEMs	192	–	✓	–	–	–
2022	Malhotra et al. [70]	Information modeling for UBEMS	195	✓	✓	–	–	–
2022	Horak et al. [71]	Spatio-temporal urban energy system modeling for decarbonization	128	–	–	✓	–	✓
2023	Zhou [72]	Climate Change adaptation and energy resilience	197	✓	–	✓	✓	–

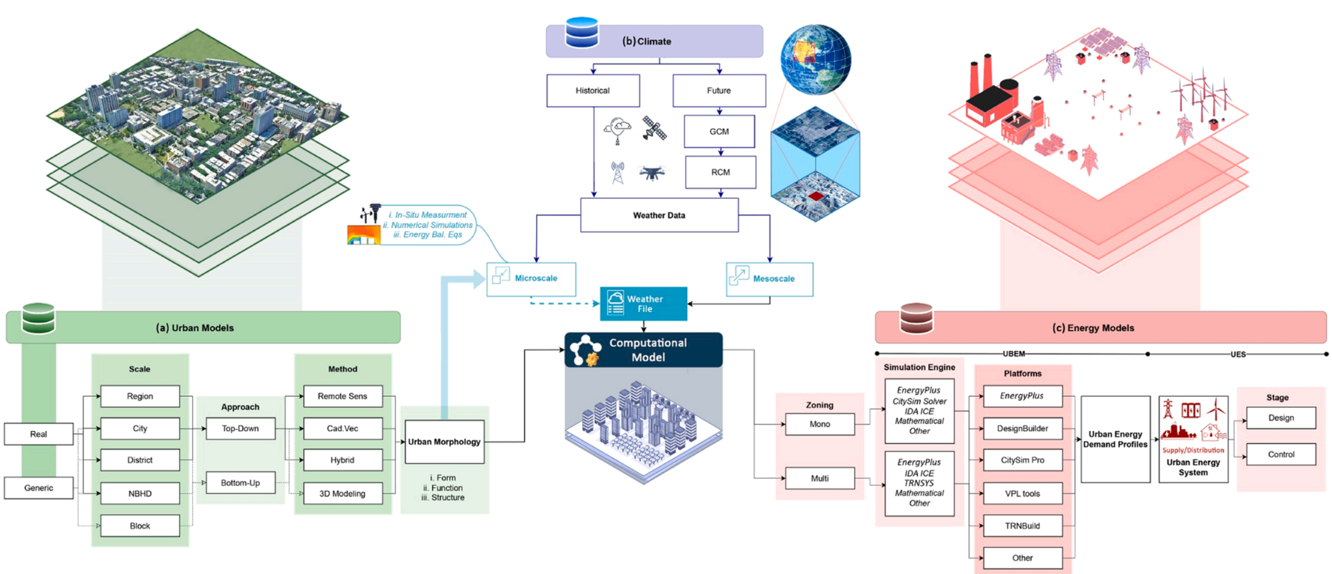

Fig. 7. Workflow of modeling urban energy infrastructure including urban, climate, and energy models. Urban morphology can be considered as the main output of an urban model.

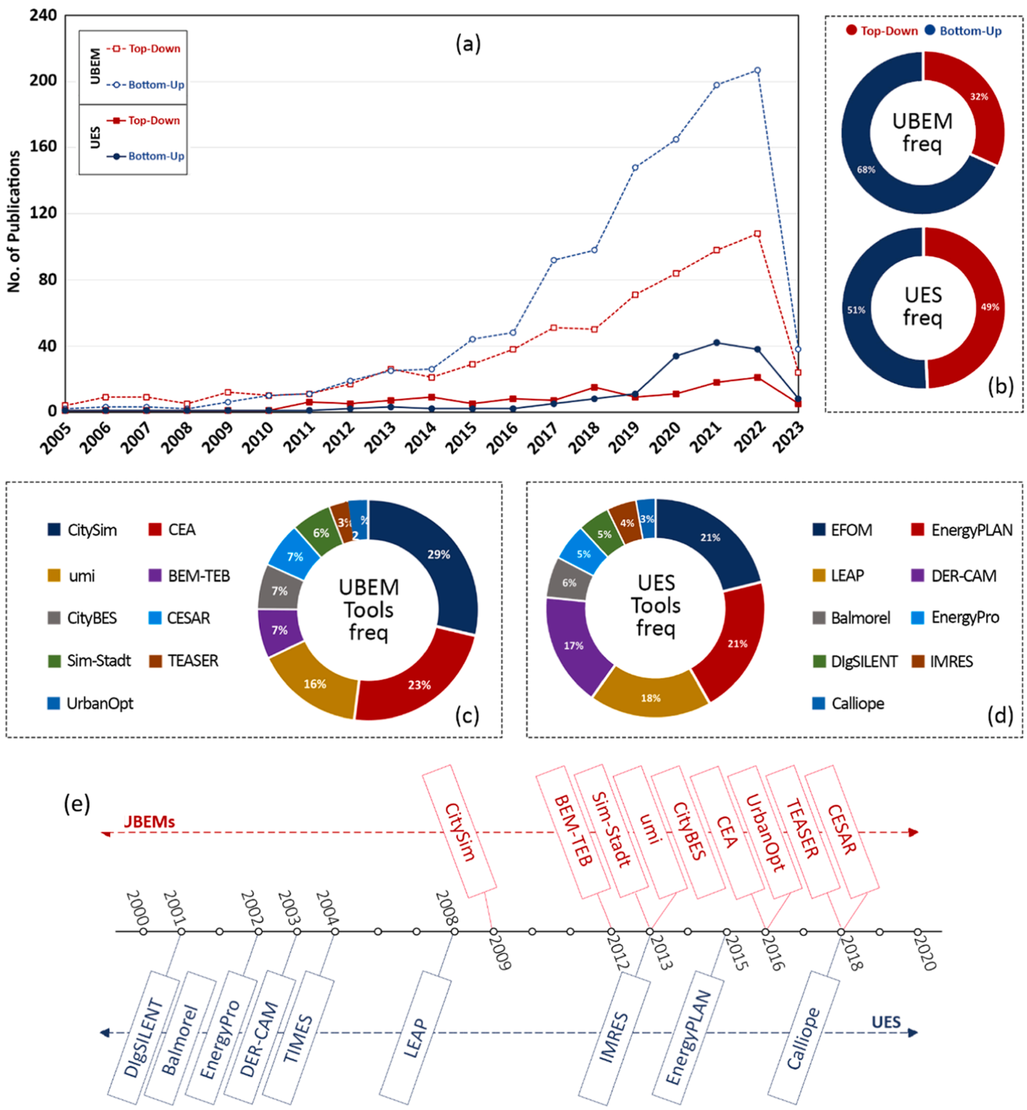

Fig. 8. (a) Number of publications with Top-Down and Bottom-Up approach during 2005–2023, (b) frequency of Top-Down and Bottom-Up approaches in UBEM and UES studies, (c) and (d) frequency of some major UBEM and UES tools in the existing literature, (e) Timeline of the first release version of some major UBEM and UES tools.

the physical complexity of urban areas, "urban morphology" refers to the study of the physical fabric of urban form and the people and processes that shape it [108]. Different definitions of urban morphology and form have been presented by Marshall and Çalişkan [109], Oliveira [110], and D'Acci [111]. It is important to distinguish between morphology, form, fabric, pattern, and texture definitions, especially in relation to assessing the energy performance of urban areas. This paper offers a comprehensive definition of morphology concerning assessing urban infrastructure assets. In this definition, "urban morphology" encompasses the form (e.g., density, shape, layout, height), function (e.g., functional needs of buildings, size, occupancy, location), and structure (e.g., street and canopy network, open and green spaces) of cities [[13], [112],[113]]. This definition incorporates all relevant technical terminologies.

Major morphological parameters and approaches

Modeling urban morphology to evaluate the energy performance of urban areas and energy systems is highly dependent on the spatial resolution required and the defined research objectives. The current literature in this area can be categorized based on the modeling approach, spatial resolution, and assessment methodology. Urban models can be divided into two main groups: realistic and hypothetical or generic [114]. Hypothetical models are often developed using generic morphological parameters, such as density and mean height [115], to assess their impacts on urban climate [16], energy performance [116], and urban comfort [117] with a comparative approach. Xu et al. [118] and Masson et al. [119] have provided a summary of the existing methods and approaches used for detecting urban morphology in urban climate research. The quality of available cadastral vector databases or the resolution of raster databases may be sufficient for most urban climate studies. However, the accessibility, quality, and resolution of site-specific geographical information remain a challenge for developing UBEMs and evaluating urban energy systems. The challenge further increases when retrieving urban/building physics parameters such as urban/building materials, architectural layouts, building age, and local climate data. The literature presents various methodologies for extracting morphological parameters, which are crucial for assessing the energy performance of urban energy systems (Fig. 10). The current state of the art in urban morphology modeling can be grouped into five main categories: (1) remote sensing methods (Raster/Vector data), (2) CityGML models, (3) 3D archetype models, (4) hybrid models, and (5)

Table 2
A summary of major UBEM and UES tools in the existing literature.

	Tool	Link	Urban model			Climate			Energy model							
			Urban morphology	Building physics	User behavior	Urban	Micro	Future	TZ	HD/CD	ELD	RES	CA	Opt	ES	Timestep
UBEM	CitySim	[80]	✓	✓	✓	✓	–	✓	Mono	✓	–	✓	–	–	–	Hour
	BEM-TEB	[86]	✓	✓	✓	–	–	–	Mono	✓	–	–	–	–	–	Hour
	Sim-Stadt	[81]	–	✓	✓	–	–	–	Mon	✓	–	–	–	–	–	Hour
	umi	[82]	✓	✓	✓	✓	–	✓	Multi	✓	✓	✓	–	–	–	Hour
	CityBES	[83]	–	✓	✓	✓	–	✓	Multi	✓	✓	✓	✓	–	✓	Hour
	CEA	[84]	✓	✓	✓	✓	–	✓	Multi	✓	✓	✓	✓	✓	✓	Hour
	UrbanOpt	[85]	✓	✓	✓	✓	–	✓	Multi	✓	✓	✓	–	–	✓	Hour
	TEASER	[87]	–	✓	✓	–	–	–	Mono	✓	✓	✓	–	–	–	Hour
	CESAR	[94]	✓	✓	✓	✓	–	✓	Mono	✓	✓	–	–	–	–	Hour

	Tool	Link	Urban model			Climate			Energy model						
			Urban morphology	Building physics	Scale	Urban	Micro	Future	Type	Sim	RES	Invst	Opt	ES	Timestep
UES	DIgSILENT	[98]	–	–	District	–	–	✓	Bot	–	✓	✓	✓	✓	Hour
	Balmorel	[99]	–	–	Region	–	–	✓	Bot	✓	✓	✓	✓	✓	Hour
	EnergyPro	[100]	–	–	District	–	–	✓	Bot	✓	✓	✓	✓	✓	Minute
	DER-CAM	[101]	–	–	District	–	–	–	Bot	–	✓	✓	✓	✓	Hour
	TIMES	[102]	–	–	Region	–	–	✓	Bot	–	✓	✓	✓	✓	Annual
	LEAP	[103]	–	–	Region	–	–	✓	Top	✓	✓	–	–	✓	Annual
	IMRES	[104]	–	–	District	–	–	–	Bot	–	✓	✓	✓	✓	Hour
	EnergyPLAN	[105]	–	–	City	–	–	–	Bot	✓	✓	✓	–	✓	Hour
	Calliope	[106]	–	–	District	–	–	✓	Bot	–	✓	✓	✓	✓	Hour

TZ: Thermal Zone; **HD**: Heating Demand; **CD**: Cooling Demand; **ELD**: Electricity Demand; **RES**: Renewable Energy Sources; **CA**: Cost Analysis; **Opt**: Optimization; **ES**: Energy Storage; Mon:**Sim**: Simulation; **Invst**: Investment Analysis; **Bot**: Bottom-Up; **Top**: Top-Down.

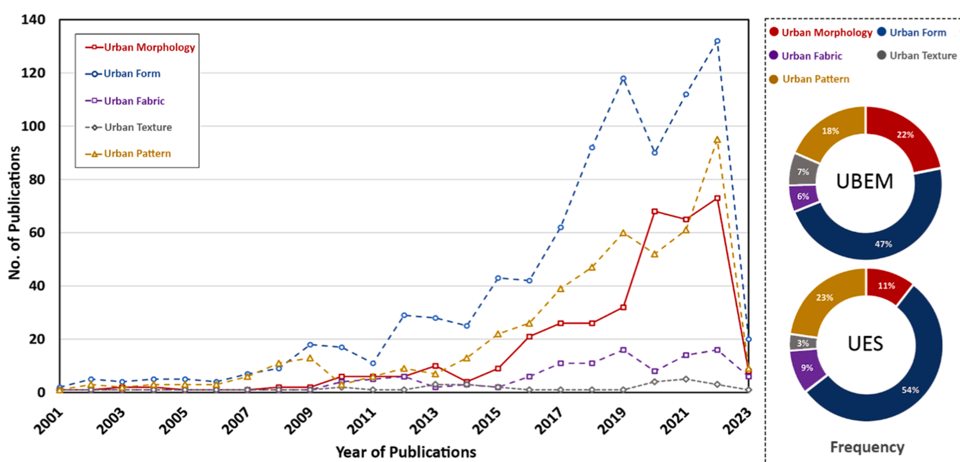

Fig. 9. Technical terms used to represent geospatial boundaries of cities to study energy performance, UES, and microclimate conditions in the past three years, a higher number of studies are using "urban morphology" to define the geospatial boundaries of cities and urban areas.

data-driven methods. Top-down modeling approaches are primarily based on remote sensing and data-driven models, while bottom-up models make use of CityGML, 3D archetype, hybrid, and data-driven models.

- Remote Sensing Methods

Remote sensing has become a widely adopted tool for analyzing land-cover patterns [120] and urban morphology detection [121], with a focus on the relationship between urban growth mechanisms (i.e., expansion [122] or densification [123]) and urban energy fluxes [124]. To accurately analyze UBEMs and UESs, high-resolution data with a large number of classes are required [91]. However, databases with resolutions finer than 10 m (m) are not always readily available for all cities. There are various open-access databases available, including the Global Human Settlement Layer (≥38.2 m) [125], the Global Urban Footprint (≥12 m) [126], the high-resolution LandScan Settlement Layer (≥8 m) [127], and the LiDAR (Light Detection and Ranging) datasets [128]. The OpenStreetMap (OSM) database retrieves footprints, building functions, and height data for urban climate research, but the quality can vary across different areas [129]. However, databases with resolutions finer than 10 m are not always readily accessible for all cities. Remote sensing methods can be divided into two broad groups: raster digital elevation models (DEMs) and vector computer-aided design (CAD) databases [55]. DEMs are pixelated grids that can be analyzed using GIS tools, while vector data are more complex to process and include polygons (e.g., building footprints, parks), lines (e.g., street centerlines, river banks), and points (non-adjacent features such as elevations or locations). Raster images can provide detailed information on vertical surfaces, but they depend on high-resolution images and are limited to 2.5D databases (2.5D raster images are flat or 2D images that include elevation or height information [130]). Studies in the literature have used both raster (e.g., [[131],[132]]) and vector (e.g., [[133],[134]]) data to develop UBEMs [135] and UES [136] models, taking into

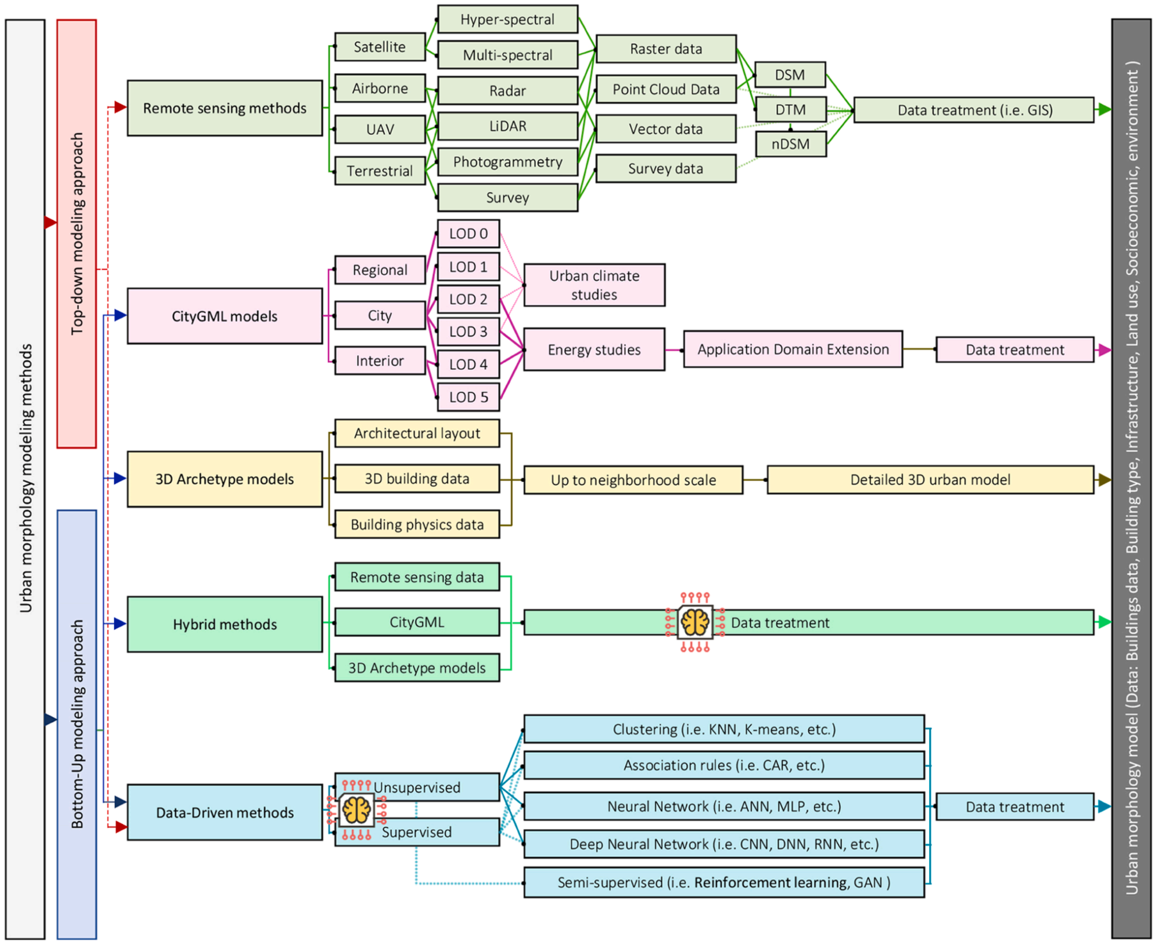

Fig. 10. Overview of major urban modeling methods emphasizing urban morphology. Hybrid and 3D Archetype methods dominate UBEM and UES modeling, while CityGML models are commonly used in urban climate studies. An increasing number of studies use Data-Driven methods with a focus on Remote Sensing databases.

account morphological parameters such as compactness, building height, and shape-to-volume ratios. For example, Alhamvi et al. [137] developed FlexiGIS, an open-source GIS-based platform that uses OpenStreetMap data to define urban model data and optimize distributed storage in urban energy systems. Li et al. [138] proposed a clustering method to develop building models based on morphological parameters (i.e., compactness, building height, Shape-to-Volume or 'S/V') extracted from raster images and vector data. Li [139] created a UBEM to estimate the energy use intensity of residential and commercial buildings in New York City, considering electrical load and gas usage. Kumar [140] assessed the solar energy potential using publicly available Meteosat satellite-derived datasets for future urban energy applications. The utilization of Unmanned Aerial Vehicles (UAVs) for urban building [141] and vegetation [142] mapping through 3D reconstructions has gained increased attention, thanks to the rapid advancements in UAV-related technologies[143]. Despite their promising potential, the literature addressing the integration of UAV images for constructing urban morphology models in UBEM or UES studies remains limited [144].

- CityGML models

The City Geography Markup Language (CityGML) standard, developed by the Open Geospatial Consortium (OGC), provides a source for retrieving topography, urban form (e.g., 3D building geometry), and urban structure (e.g., roads, water bodies) [145]. CityGML is based on LiDAR and cadastral data and has six levels of detail (LOD0–LOD5) [146]. However, the standard is not exhaustive and may not include all urban entities required for energy simulations [147]. Additionally, some of the entities in LOD3 and LOD4 are not relevant to building thermal properties, requiring further data processing to be used in energy simulations [148]. To address this, CityGML models can be extended using Application Domain Extension (ADE) or other mechanisms. Most CityGML models are automatically generated from a fusion of LiDAR and cadastral data, with major landmark buildings added manually with higher spatial resolution. Nevertheless, several studies have demonstrated the utility of CityGML models for energy simulations. For example, Bahret et al. [149] used a standard CityGML model and the SimStadt platform to optimize heat and power supply systems for 10 rural building neighborhoods in Southern Germany. Hussein and Klein [150] employed a CityGML model and the SimStadt platform to optimize inner pipe diameters for an existing district heating network in Southern Germany with less than a 5.3 % deviation from actual values. Malhotra et al. [151], by using a statistical enrichment approach using the TEASER tool, found that the main challenge in using open-source databases is the lack of essential data such as building construction year and type, which can lead to discrepancies between simulations and measured data. Despite this, CityGML models are an ongoing project for several municipalities around the world and have proven useful for decision-making platforms at larger scales.

- 3D archetype models

3D archetype models have been used widely in the literature for the early stages of urban neighborhood and energy system design. These models require extensive effort as they depend on high-resolution data, such as building physics and occupancy profiles, which must be analyzed through multi-zone thermal models. 3D archetypes can be either virtual constructs or derived from real existing databases. In the case of the latter, statistical methods, categorization techniques, and clustering approaches have been extensively employed for urban-scale studies [152]. The categorization and characterization of building stock into archetypes significantly affect the model's reliability, yet this process remains subjective and assumption-driven [153]. Cluster analysis, as an unsupervised learning technique, has been utilized in UBEM tools for developing archetype models, and a comprehensive review of various approaches with a focus on energy studies is outlined in Ref [74] and [154]. While several clustering algorithms have been utilized in energy-related studies, k-means [155] and agglomerative hierarchical clustering [156] stand out as the most frequently employed methods.

In the case of virtual constructs, several studies have adopted the 3D archetype modeling approach introduced by Ratti et al. [157]. Chow et al. [158] applied this method to district cooling systems, extrapolating 12 categories of archetypes at the district scale. Sokol et al. [153]. introduced a Bayesian-based method for developing 3D archetype models for 2662 buildings with incomplete information to estimate energy use intensity (EUI) at the district level. Javanroodi et al. [114] used an archetype-based modeling method to define 1600 urban neighborhoods and co-optimized urban morphology considering natural ventilation and cooling demand. This study found that the 3D archetype modeling approach provides higher accuracy in predicting energy demand profiles. Li et al. [159] compared the 3D archetype modeling approach with the land-use modeling approach in predicting the energy performance of two urban districts in Macau, China. The 3D archetype modeling approach was found to outperform the land-use modeling approach by 20 %. Several studies have utilized the TABULA Episcope project database [160] for developing UBEM [[161],[162]] or UES [[163],[164]] models. While open-source databases like TABULA provide important information such as class, construction year, and heating system per archetype, the reliability of the archetype modeling method remains unclear, particularly for the bottom-up approach, as heterogeneity in buildings is not considered [165]. However, the main disadvantage of 3D archetype modeling methods is their limitations in dealing with large urban areas and city-scale studies due to their dependence on high-resolution building data. Thus, this modeling method is better suited for urban area design or optimization rather than controlling existing energy infrastructure.

- Hybrid methods

In recent years, hybrid models have become increasingly popular due to their combination of various modeling methods. By incorporating different open-source databases, hybrid models have been able to reduce computational time while enhancing the accuracy of energy performance simulations with detailed spatiotemporal analysis [166]. For example, Abolhassani et al. [167] combined 3D archetype models from the TABULA Webtool with CityGML to create a high-resolution urban building energy model (UBEM) with accurate estimates of district heating and cooling demand for a case study in Montreal. Bremer et al. [168] developed a hybrid 3D-GIS approach incorporating databases such as 2.5D raster DEMs, CityGML, and LiDAR point clouds to assess solar potential in digital city models for a case study in Austria. Hosseinihaghighi et al. [156] created an urban model for the City of Kelowna, utilizing both geometric and non-geometric open-source databases, such as building footprints and energy use data, which was then transformed into a standard CityGML at LoD 2 to estimate heating demand and potential retrofitting scenarios with high accuracy.

- Data-driven methods

Conventional urban morphology modeling methods can become challenging at the district or city scale with the increased availability of data [169]. Predictive data-driven models, which fall into two categories—supervised and unsupervised learning—have been used in the literature to predict, map, benchmark, or classify the energy use of urban areas using historical energy data and existing building data [170]. This literature review focuses specifically on data-driven models that retrieve urban morphological parameters from other modeling methods described above. For example, Yu et al. [171] used data from GIS-based sources, CityGML, or field surveys to determine urban energy demand profiles with a data-driven model. Ali et al. [172] proposed a framework for predicting energy demand at the urban scale through the use of GIS data and deep learning methods. Nageler et al. [173] developed a data-driven model utilizing GIS-based data to estimate heating and hot water demand. Fuchs et al. [174] introduced a data-driven workflow to optimize both building and district energy system models. Studies have also combined big data with GIS to estimate urban-scale energy demand [[175],[176]]. Data-driven models have also been integrated with dynamic engineering simulation engines to create UBEM workflows [[177],[178]]. Ali et al. [155] proposed a data-driven model to develop building archetypes at four spatial scales (district, regional, city, and national) in Ireland to estimate energy use. The primary obstacle faced by data-driven modeling methods is their dependence on detailed historical data of high resolution to train predictive models. Privacy concerns frequently limit the availability of disaggregated energy data in many cities, rendering this approach more applicable to top-down investigations reliant on aggregated energy data, billing records, or basic surveys. Nonetheless, the strength of data-driven models lies in their capacity to establish connections between urban morphology models and energy models. Table 3 summarizes recent developments in urban morphology modeling methods, considering the adopted spatial scale, simulation engine, and scope of the study (UBEM or UES).

Major influencing morphological parameters on energy models

Various morphological parameters have been investigated in urban infrastructure modeling literature, falling into two main categories: urban physics studies and urban energy studies. Urban physics studies focus on exploring the interaction between urban morphology and microclimate conditions [192], while urban energy studies aim to employ morphological parameters in UBEM and UES applications. The literature has mainly focused on the horizontal and vertical density of urban areas, with density-based morphological parameters being widely studied [[193],[194]]. Some of the most studied parameters include Floor Area Ratio (FAR) [135], Planner Urban Density (λ_p) [195], Urban Compactness [196], Building Height [197] or Mean Building Height [198], Building Coverage Ratio (BCR) [199] or Building Site Coverage [200], Building Volume Density (BVD) [201], Frontal Area Density (λ_f) [202], Surface to Volume Ratio (S/V) [203], and Vegetation Cover Density [204]. Other morphological parameters related to urban form elements include Architectural Layouts [205], the Cardinal Orientation of building/urban areas [206], and Building Relative Compactness (Rc) [207]. The most studied parameters related to urban function elements are building program, urban surface materials (albedo), public open space [208], and occupancy density [209]. In terms of urban function elements, canyon geometry (i.e., Height-to-Width or 'H/W' [210] and Length-to-Width or 'L/W' ratios [211]), Sky View Factor (SVF) [212], and urban street network [213] have also been widely studied. Fig. 11 presents a summary of the most commonly studied urban morphological parameters and their significant impact on urban energy performance.

The impacts of urban morphology on energy performance in urban areas have been widely studied, leading to a substantial body of knowledge (Table 4). However, effectively modeling urban morphology remains a challenge due to the diverse parameterization methods and the varied interpretations of density-related parameters. Some parameters, such as the Floor Area Ratio (FAR) and Planner Urban Density (λp), have similar definitions in the literature and are represented in different ways (such as Plot Area Ratio [PAR] [13] or Impervious

Table 3
Recent developments in urban modeling methods with a focus on urban morphology.

Method	Ref	Year	Location	Climate data	Spatial scale	Studied parameters	Simulation	User data	Morphology	Scope	
										UBEM	UES
Remote sensing	[134]	2016	USA	TMY	City	CD, HD, ELD	*E+*	✓	✓	✓	–
	[138]	2018	China	TMY	District	EUI	umi/ *E+*	✓	✓	✓	–
	[133]	2019	Netherland	–	Neigh	System sizing, cost, DWH	Comsof Heat	–	–	–	✓
	[135]	2019	Italy	TMY	City	HD	CitySim	✓	✓	✓	–
	[139]	2020	USA	TMY (UWG)	City	EUI, ELD	*E+*	✓	✓	✓	–
	[137]	2021	Ireland	–	Regional	RES, ES,	–	–	–	–	✓
	[140]	2021	India	–	Regional	RES	–	–	–	–	✓
	[132]	2021	South Korea	–	City	NGas, ELD	–		✓	✓	–
	[179]	2023	China	–	City	NDVI,					
CityGML	[180]	2015	Italy	Monthly	District	HD, DHW	Empirical	–	–	✓	–
	[181]	2016	Germany	–	District	CD, HD	TEASER		✓	–	✓
	[182]	2019	Finland	TRY	District	DHP,	Apros	–	–	–	✓
	[150]	2021	Germany	TRY	Neigh	DHN, HD, Pomp power	SimStadt	–	–	–	✓
	[149]	2021	Germany	TRY	Block	DHN, HD, cost	INSEL	–	–	–	✓
	[151]	2022	Germany	TRY	District	HD	Dymola/ Modelica	–	–	–	✓
3D archetype	[158]	2004	Hong Kong	TMY	District	CD, DCS, ELD	TRNSYS	–	–	–	✓
	[159]	2016	Macau,	–	Neigh	EUI, Co2E	eQuest	–	–	✓	–
	[153]	2017	USA	TRY	Building/city	EUI	*E+*	✓	–	✓	–
	[183]	2018	Switzerland	Daily	Building/ regional	EUI	SwissRes mode	✓	–	✓	–
	[184]	2018	UK	–	Building/Neigh	EUI, DHP	ESP-r	–	–	–	✓
	[185]	2021	Spain/ Ecuador	TMY	Building/ regional	EUI, DHW, ELD, CD, HD	*E+*	–	–	✓	–
	[19]	2021	Greece	TMY, RCMs	Neigh	CD, HD, ELD, CA, RES	*E+*	✓	✓	–	✓
	[27]	2021	Sweden	TMY	District	CD, HD, ELD, CA, RES	*E+*	✓	✓	–	✓
	[186]	2022	China	TMY	Neigh	CD, HD	*E+*	–	✓	✓	–
Hybrid	[166]	2017	Switzerland	TMY	Block	HD	Monte Carlo	✓	–	✓	–
	[167]	2022	Canada	TMY	Neigh	DHP	*E+*	✓	✓	–	✓
	[168]	2016	Austria	–	Neigh	SolarP	SAGA	–	✓	–	✓
	[156]	2022	Canada	–	Building/ District	EUI, HD	INSEL	✓	–	✓	–
	[187]	2021	USA	TMY	Building/city	EUI	*E+*	✓	–	✓	–
	[188]	2023	China	–	Neigh	SolarP	Empirical	–	✓	–	✓
Data-driven	[173]	2017	Austria	TMY	Building /District	NGas, ELD	IDA ICE	✓	–	–	✓
	[177]	2018	USA	TMY	Neigh (campus)	CD, HD, ELD	*E+*	✓	–	✓	–
	[189]	2019	Sweden	TRY	Building/ District	HD, EP	*E+*	✓	–	–	✓
	[190]	2019	USA	–	Building/City	EUI	Calculation in R	–	–	✓	–
	[172]	2020	Ireland	–	Regional/ district	EUI	*E+*, TRNSYS	✓	–	–	✓
	[79]	2020	USA	TRY	Building/City	CD, HD	DOE ref	–	–	✓	–
	[191]	2021	China	TMY	Neigh	EUI, PV	*E+*	✓		✓	–

Ground Surface Fraction [214]). Building Volume Density (BVD) [201] and Volume Area Ratio (VAR) [114] have similar definitions with minor differences. Other examples are the average ratio of the total area to the volume of buildings within an urban area (S/V) and the Form Factor Index (FFI) [15]. This variability arises from the widespread application of urban morphology and the absence of an integrated platform for standardizing parameterization approaches. Therefore, it is crucial to develop integrated platforms or frameworks to standardize urban morphology parameterization approaches for UBEMs and UES models.

Urban Form (a) Planner Urban Density (λ_p) as the total area of the ground floor divided by the total area of the selected case study, (b) Plot Area Ratio (PAR) as the ratio of the gross area of the built area to the total area of the selected case study. Other similar parameters include Floor Area Ratio and Impervious Ground Surface Fraction, (c) Mean Building Height (MBH) defined as the average height of all buildings divided by the total number of buildings. Other similar parameters include Building Height, (d) Volume Area Ratio (VAR) calculated as the total volume of buildings divided by the total area of selected case study, (e) Frontal Area Density (λ_f) defined as total facade surface area of buildings divided by total area of the selected part of the case study, (f) Site Coverage Index (SCI) defined as the total area of each building footprint divided by the area of its sub-site, similar parameters such as Building Coverage Ratio has been used in the literature, (g) Vegetation Density (VD) defined as area of vegetation divided by total area of selected case stud, similar parameters such as Green Area Ratio has been used in the literature, and Normalized Difference Vegetation Index (NDVI) used in remote sensing method defined as difference between visible and near-infrared reflectance of vegetation cover.

Urban Function (h) Building type, program, or function, (i) Building systems and materials including all building physics-related variables such as U-value, building age, HVAC systems as well as surface material albedo, (j) Occupancy Density indices: UD_{occ} as number of inhabitants in the selected urban area divided by its total area, and D_{occ} as number of occupants of a building divided by its total area,

Urban Structure (k) Sky View Factor (SVF) as the ratio of sky hemisphere visible from the ground, (l) H/W calculation for symmetrical and asymmetrical urban canyons.

The role of spatial resolution in modeling urban morphology for energy models

A crucial factor in the study of urban morphology is the resolution at

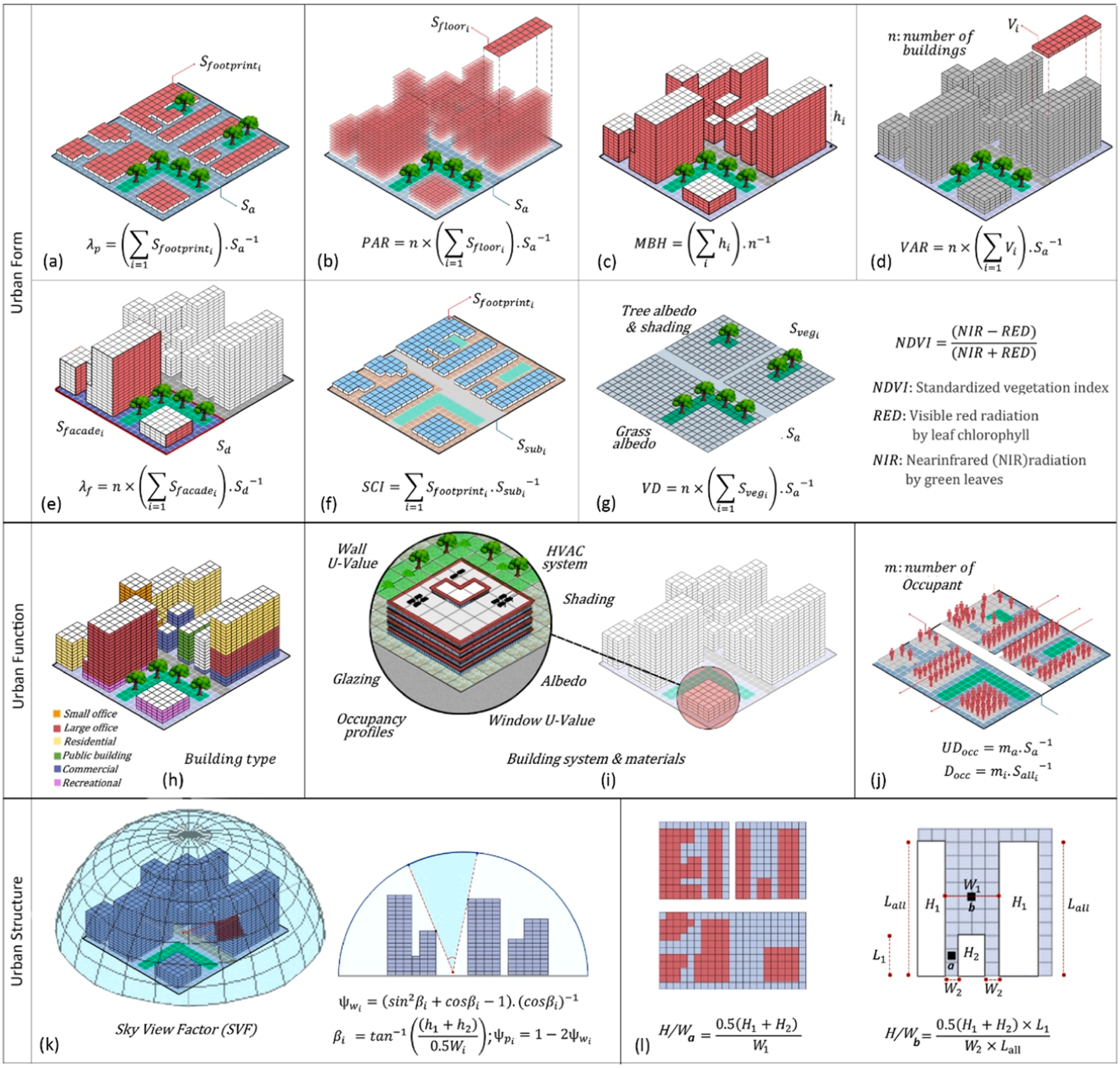

Fig. 11. Major morphological parameters studied in the current literature:.

which urban areas are analyzed. There is no uniform agreement on the definition of spatial scales in urban energy performance assessments. The commonly studied scales in both generic and real urban areas include urban blocks, neighborhoods, districts, areas, or regions. Each spatial scale has different definitions based on the particular field of study. For instance, Oke et al. [215] defined urban morphological scales in terms of urban meteorology as urban blocks (500 × 500 m), neighborhoods (2 × 2 km), districts (25 × 25 km), and regions (100 × 100 km). Stewart and Oke [216] introduced local climate zones (LCZ) for urban temperature regulation, employing diverse geometric and surface cover properties, leading to the identification of ten built types and seven land cover types. However, the literature on urban-scale energy models lacks a comprehensive and standardized approach to account for urban morphology as also reported by Wong et al. [115]. The definition of geospatial boundaries for urban blocks, neighborhoods, or districts remains elusive in literature, as it is highly influenced by geographical context [217].

Towards a unified definition of urban areas

Mostly, urban areas are categorized based on socioeconomic characteristics (such as population density and number of buildings) and accessibility (such as walkability and the need for urban transport modes [218]), which vary between countries. For example, Guo and Bhat [219] defined neighborhoods as walkable surroundings, and districts as accessible spaces by using urban transportation modes. Eggimann et al. [218] characterized an urban space as a "neighborhood" with a range of 150–500 inhabitants in Switzerland, while the minimum number of residents per neighborhood in Sweden is 200 [220]. In Germany, a thinly populated urban area is defined as having at least 300–500 inhabitants per square kilometer (km^2) [221]. The literature on UBEM and UES also lacks a specific definition for the development of an urban morphology model. For example, Vartholomaios [222] created 360 distinct urban blocks with a maximum length of 100 m, while Tsirigoti and Tsikaloudaki [223] defined several urban blocks based on the morphological characteristics of Greece, with a maximum length of 110 m (up to 6864 m^2). Ratti et al. [157] used a neighborhood model with

Table 4
Recent developments in urban modeling methods with a focus on urban morphological parameters.

Ref	Year	Location	Modeling		Spatial scale	Climate data	Simulation	Urban morphology																			Scope	
								Form											Function					Structure				
			Type	Method				$\lambda_{p,}$ PAR	*BCR*	*S/V, FFI*	*SCI*	*BVD*	*BH*	λ_F	*Layout*	*VD*	*Roof shape*	*Orientation*	*Building type*	*Occupancy*	*Public space*	*Material*	*Glazing*	*Street network*	*H/W, L/W*	*SVF*	*UBEM*	*UES*
[236]	2017	Portugal	Real	Data-driven	Buil/City	–	–	✓	✓	✓	–	–	–	–	–	✓	–	✓	✓	–	–	✓	–	✓	✓	–	✓	–
[222]	2017	Greece	Gen	Archetype	Block	TMY	*E+*	✓	–	✓	✓	–	✓	–	✓	–	–	✓	–	✓	✓	✓	–	–	✓	✓	✓	–
[29]	2018	Palestine	Gen	Archetype	NBH	TMY	CS	✓	✓	✓	–	–	✓	–	–	–	–	–	✓	✓	–	✓	✓	–	✓	–	–	✓
[223]	2018	Greece	Real	Archetype	NBH	TMY	EcT	✓	–	✓	✓	–	✓	–	✓	–	–	–	✓	–	–	✓	✓	–	✓	–	✓	–
[114]	2018	Iran	Gen	Archetype	NBH	TMY	*E+*	✓	✓	✓	✓	✓	✓	✓	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
[30]	2019	Switzerland	Real	Remote sensing	District	TMY	CS	✓	–	✓	–	–	✓	–	✓	✓	✓	–	✓	✓	✓	✓	✓	–	✓	✓	–	✓
[237]	2019	UK	Real	Hybrid	City	TMY	*E+*	✓	–	–	–	–	✓	–	–	–	–	–	–	–	✓	–	–	✓	–	–	✓	–
[15]	2020	UAE	Gen	Archetype	NBH	TMY	CS	✓	–	✓	–	–	✓	–	✓	–	–	–	✓	✓	–	✓	✓	–	–	–	–	✓
[238]	2020	Italy, France, Finland	Gen	Archetype	NBH	TMY	*E+*	✓	–	✓	–	–	✓	–	–	✓	–	–	✓	✓		✓	✓	–	–	–	✓	–
[239]	2020	USA	Gen	Archetype	NBH	TMY	*E+*	✓	–	✓	–	✓	–	–	✓	–	–	✓	✓	✓	–	✓	–	–	✓	–	✓	–
[240]	2020	China	Real	Hybrid	NBH	TMY	*E+*	✓	✓	✓	✓	–	✓	–	–	–	–	–	✓	✓	✓	✓	✓	✓	✓	–	✓	–
[241]	2020	Netherland	Real	Remote sensing	City	–	–	✓	–	✓	–	✓	✓	–	–	✓	–	–	–	–	–	–	–	–	–	–	✓	–
[27]	2021	Sweden	Gen	Archetype	District	TMY	*E+*	✓	✓	✓	✓	✓	✓	✓	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓	–	–	✓
[19]	2021	Greece	Gen	Archetype	NBH	RCM	*E+*	✓	✓	✓	✓	✓	✓	✓	✓	✓	–	–	✓	✓	✓	✓	✓	✓	✓	–	–	✓
[231]	2021	Austria	Real	Archetype	NBH	TMY	*E+*	✓	✓	✓	–	✓	✓	–		–	–	–	✓	✓	✓	✓	–	✓	✓	–	✓	–
[228]	2021	China	Gen	Archetype	NBH	TMY	*E+*	✓	✓	✓	–	–	✓	✓	–	–	✓	✓	✓	✓	–	✓	–	–	✓	–	✓	–
[191]	2021	China	Gen	Archetype	NBH	TMY	*E+*	✓	✓	–	–	–	✓	–	✓	✓	–	–	✓	✓	–	✓	✓	✓	✓	–	✓	–
[197]	2021	UAE	Gen	Archetype	NBH	TMY	IES-VE	✓	–	✓	–	–	✓	–	–	–	–	–	–	✓	✓	✓	–	–	–	–	✓	–
[242]	2022	Switzerland	Real	Remote Sensing	NBH	TMY	EM	✓	✓	–	✓	–	✓	–	✓	–	✓	✓	✓	✓	–	✓	✓	–	✓	✓	✓	–
[243]	2022	China	Gen	Archetype	NBH	TMY	*E+*	✓	✓	–	✓	–	✓	–	✓	–	–	✓	✓	✓	✓	✓	✓	–	–	✓	✓	–
[244]	2022	Norway	Real	Archetype	NBH	TMY	IDA ICE	✓	✓	–	–	–	✓	–	✓	–	–	✓	✓	✓	✓	✓	✓	✓	–	–	✓	–

250 m dimensions in London, Toulouse, and Berlin. Costanzo et al. [224] studied the campus of Yasar University in Turkey with an approximate dimension of 200 * 150 m as an urban neighborhood. Other studies have defined neighborhood-scale with dimensions of 400 × 400 m [16], 450 × 450 m [225], and 500 × 500 m [226]. Kamal et al. [227] studied a 1500×2500 m urban district in Qatar, while Zhang and Gao [228] defined an 880×880 m urban area as a “district” and Perera et al. [27] developed a 1000×1000 m district model. However, the dimensions used to define urban blocks, neighborhoods, and districts vary greatly among different studies. A similar approach and neighborhood dimensions have been used by several other studies (e.g., [[197],[229–231]]). District models with similar dimensions have been developed and studied in several other works (e.g., [[232],[233]]). On the contrary, several studies have used different dimensions to define urban blocks (e.g., [191]), neighborhood models (e.g., [234]), or district models (e.g., [235]).

Impact of spatial resolution on energy performance

One major challenge for UBEM and UES studies is to determine the impact of spatial resolution on the energy performance of an urban area. Most studies have adopted a specific case study based on the previously mentioned scales, but the interconnectivity between morphological units (e.g., two or more neighborhoods or districts) has rarely been considered (e.g., [27]). Future urban energy studies should take into account both the geospatial scale and the connectivity between units within an urban area. To address this issue, an urban morphology spatial scale guide is introduced in this study based on the dimensions and population-scale proposed by Oke et al. [215], with a specific focus on UBEM and UES models (Fig. 12). The defined spatial scales in the literature are categorized as block, neighborhood, district, city, and regional. An urban block is typically defined as a set of buildings less than 200 m in length. Neighborhood-scale studies mostly focus on an area with dimensions ranging from 200 to 500 m. An area with dimensions of 500–2 km is considered an urban district scale, while case studies between 2 and 10 km are defined as a city scale. Regional-scale energy models have dimensions of 10–100 km. The term “urban area” or “urban scale” in the literature is usually referred to as any scale larger than an urban block, but no specific definition can be found.

Challenges in linking urban morphology and energy models with climate models

The complexity and dynamics of the global climate system bring many challenges when developing climate models that can be used for urban energy planning. The required spatiotemporal resolution is a critical factor in this regard. The spatial resolution of climate models in connection with urban energy flows can be divided into three main categories: mesoscale climate models (Fig. 13-a,b), urban climate models (UCM in Fig. 13-c), and urban microclimate models (UMM in Fig. 13-d).

Within the scope of UBEM and UES models, mesoscale climate data encompasses historical or projected weather data representative of typical conditions. This data can be sourced from diverse sources like satellite images, global climate models, or non-site-specific weather stations. Employing such typical weather data guarantees uniformity and facilitates cross-case study result comparisons[245]. The most

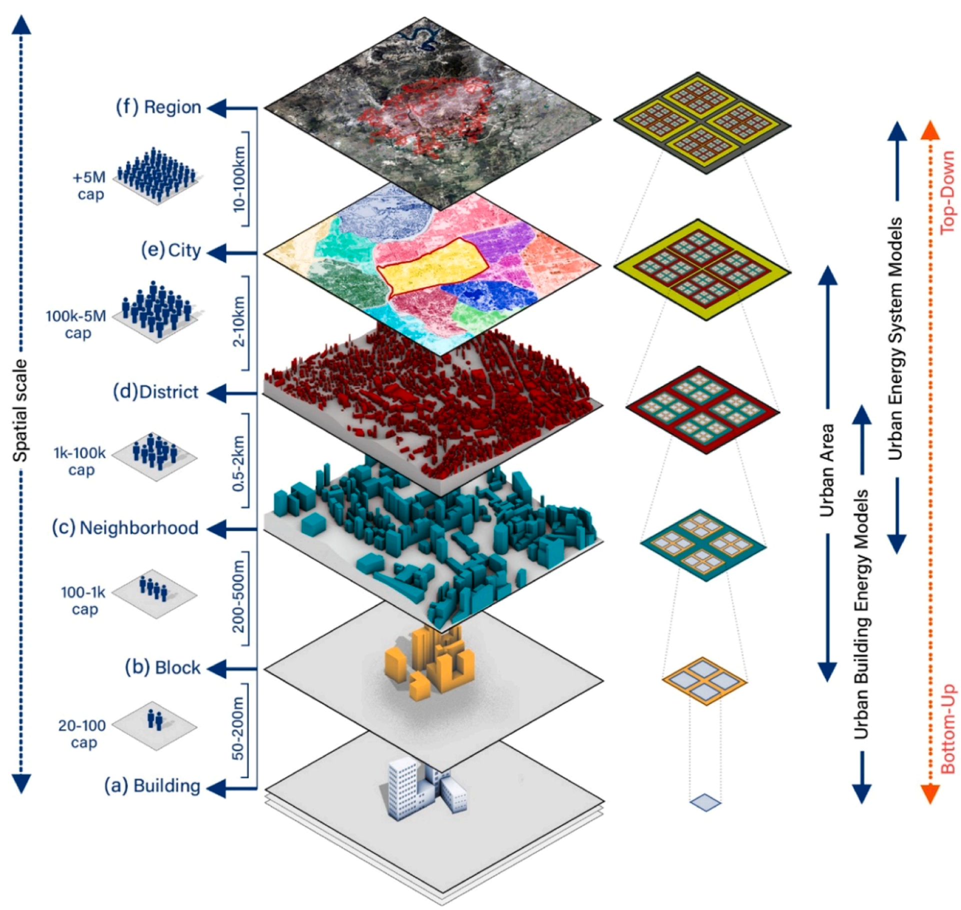

Fig. 12. Schematic Depiction of the Urban Spatial Scale in Relation to UBEM and UES Studies: (a) Building-scale represents a single building, (b) Urban block represents an area with dimensions ranging from 50 to 200 m and consisting of several buildings, (c) Urban neighborhood encompasses an area with dimensions ranging from 200 to 500 m and is comprised of several urban blocks, (d) Urban district represents an area with dimensions ranging from 500 to 2000 m, (e) City is a large urban settlement that encompasses several urban districts, and (f) Region encompasses a single city and its agglomeration area or multiple cities.

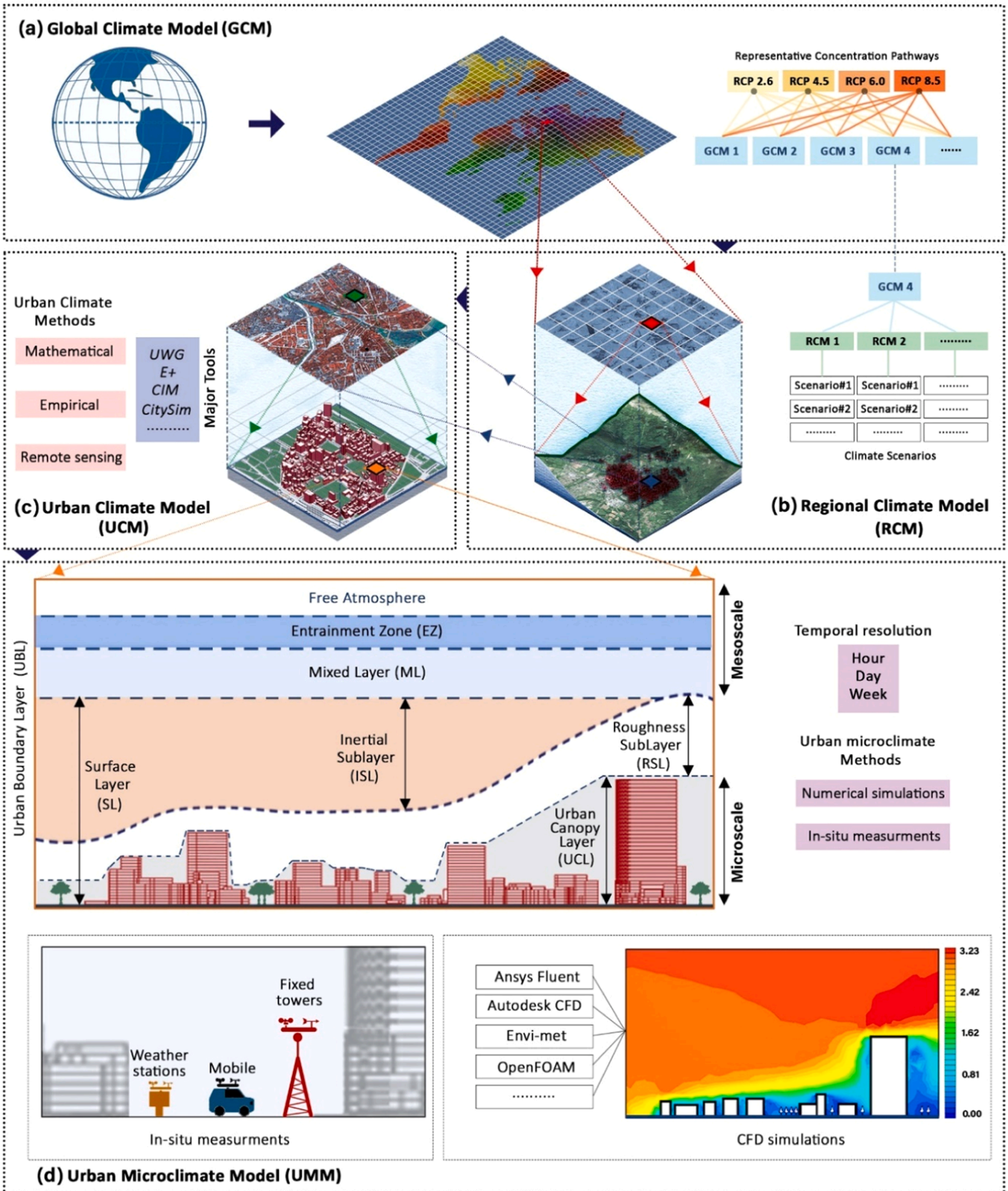

Fig. 13. Climate model in urban infrastructure: (a) Global Climate Model: GCM (100–300 km) and its relation with RCPs, several GCMs have been developed in recent years; (b) Regional Climate Model: RCM (20–50 km), several climate scenarios can be created based on each RCM; (c) Urban Climate Model: UCM generated using mathematical, empirical, and remote sensing methods; (d) Urban Microclimate Model (UMM) defined as microscale or Urban Canopy Layer (UCL) in the Urban Boundary Layer (UBL), generated using numerical simulations and in-situ measurements.

common representative weather data are typical meteorological year (TMY) data, introduced by Hall et al. [246] and based on selecting the typical meteorological month (TMM) for each month. Typical weather data are mostly synthesized from historical data (usually 10 years or more) representing the climate conditions of a given location for a "typical year" [247]. Other editions of TMYs such as TMY2 (1994), and TMY3 (2008) also have been used widely in the literature [248]. Recent updates of TMY files (TMYx) have been accessible for thousands of locations globally [249]. Different organizations, like the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) and Chartered Institution of Building Services Engineers (CIBSE), have also produced various typical or reference weather datasets to be used in long-term evaluation of buildings or energy systems. These include Weather Year for Energy Calculations (WYEC) [250], International Weather for Energy Calculation (IWEC) [250], Test Reference Year (TRY), and Design Summer Year (DSY) [[251],[252]].

Despite high availability, typical weather data have several drawbacks. These files fail to account for local climate (they can be adopted within a 30–50 km distance from the selected case) or extreme weather conditions [253], and can lead to an underestimation or overestimation of peak demands [254] (Table 5).

Urban climate models (UCMs)

Urban climate models (UCMs) analyze the climate of a specific location, taking into account the impact of the urban morphology and focusing on air temperature variations. UCMs are created using mathematical models, empirical methods (i.e., UWG, CIM, CitySim), or remote sensing techniques (i.e., LiDAR or satellite imagery) [255]. Simulation engines such as CitySim and EnergyPlus use ray tracing and true view factor algorithms to calculate the impact of shading on air and surface temperature levels. Most tools used to create UCM data are based on urban energy balance models within the urban canopy layer (UCL). The Urban Weather Generator (UWG) [256], for example, considers urban climate impacts by examining urban energy balance equations. This includes temperature, wind speed (by Log wind profile), evaporation (by vegetation coverage), and anthropogenic heat emissions. UWG generates annual, and hourly profiles of climate variables within a reasonable computational time by morphing traditional TMY files [257]. This model has been used widely in urban-scale digital and computational design workflows [[258],[259]]. Mauree et al. [260] formulated a 1D Canopy Interface Model (CIM) designed to incorporate surface turbulent fluxes within the urban canopy layer, establishing a connection between mesoclimate and urban climate. The CIM model underwent validation against in-situ measurements [261] and has found application in evaluating the energy efficiency of urban areas [262] as well as energy systems [[29],[263]]. Chen et al. [264] developed a data-driven model utilizing CityGML LOD 2 to forecast urban air temperature. Remote sensing techniques have been employed to investigate urban heat islands and air pollution; however, their application has not been directed toward studying urban energy infrastructure (i.e., [[265],[266]]). Behrwani et al. [267] and Schaefer et al. [268] provided a review of remote sensing applications in the urban climate field. Although UCMs are effective in accurately estimating air temperature, they have limited accuracy in predicting wind speed and lack the ability to provide temperature and wind speed profiles within urban canyons. This limitation makes them inadequate for urban comfort studies. Improving spatial resolution from a UCM to a UMM is essential for capturing the intricate impacts of complex urban morphologies.

Urban microclimate models (UMMs)

Urban microclimate models represent the relationship between climate variables at the microscale with very high spatiotemporal resolution. They can be created through numerical simulations or short- or long-term in-situ measurements. Computational fluid dynamics (CFD) simulations are the most commonly used method in the present literature to estimate urban microclimate conditions with a focus on air/surface temperature, wind speed, and relative humidity (e.g., [[200],[201]]). While CFD simulations are accurate, they are also computationally expensive and require detailed validation studies [269], making it challenging to couple CFD solvers with urban building energy models (UBEMs) and urban energy systems (UES) models. Short or long-term in-situ measurements can also capture climate variables at the microscale using fixed or mobile weather stations [202], meteorological towers [203], or mobile sensors such as vehicles [204] or unmanned aerial vehicles (UAV) [[205],[206]]. However, conducting on-site measurements for every instance of urban morphology is impractical due to technical and financial constraints. The main challenges with UMMs are their substantial computational demands and expenses, leading to their typical coupling with UBEMs for representative days or weeks. Given the well-established impact of microclimate on building energy performance, it is important to develop more user-friendly tools and frameworks that can be coupled with UBEMs and UES models.

Table 5
Recent developments in urban climate modeling with a focus on UBEMs and UES models.

Ref	Year	Location	Climate						Spatial scale	Morphology	Energy Simulation	Studied parameters	Scope	
			Reso	Considering Extremes	Type	Period	UCM	UMM					UBEM	UES
[283]	2016	Portugal	Month	–	–	2014–2023	–	–	Building/regional	–	MCS	CA	–	✓
[284]	2016	China	Annual	–	–	2015–2024	–	–	Building/city	–	MCS	ED, CA	–	✓
[114]	2018	Iran	Hour	–	TMY	–	✓	✓	NBH	✓	E+	HD, CD, WS, T	✓	–
[29]	2018	Palestine	Hour	–	TMY	–	✓	–	NBH	✓	CitySim	ED, PV, Wind, CA	–	✓
[285]	2019	France	3Hour	✓	RCM	2041–2046	–	–	Building/regional	–	–	CD, PV, Wind, CA	–	✓
[30]	2019	Switzerland	Hour	–	RCM	2017–2050	✓	–	District	✓	CitySim	ED, PV, Wind, CA	–	✓
[258]	2019	Spain	Hour	–	TMY	–	✓	✓	NBH	✓	E+	HD, CD, WS, T	✓	–
[286]	2019	Canada	Hour	✓	TRY	1971	–	✓	District	✓	CityBEM	HD, CD, WS, T	✓	–
[15]	2019	UAE	Hour	–	TMY	–	✓	–	NBH	✓	CitySim	ED, PV, Wind, CA	–	✓
[40]	2020	Sweden	Hour	✓	RCM	2010–2099	–	–	Building/city	–	Matlab	ED, PV, Wind, CA	–	✓
[225]	2020	Netherlands	Hour	–	–	–	✓	–	District	✓	–	HD, CD, T	–	✓
[259]	2020	Italy	Hour	–	TMY	–	✓	–	NBH	✓	E+	HD, CD, T	✓	–
[27]	2021	Greece	Hour	–	TMY	–	✓	–	District	✓	E+	ED, PV, Wind, CA	–	✓
[228]	2021	China	Hour	–	TMY	–	–	✓	NBH	✓	E+	HD, CD, T	✓	–
[19]	2021	Greece	Hour	✓	RCM	2010–2099	✓	–	NBH	✓	E+	ED, PV, Wind, CA	–	✓
[287]	2021	China	Hour	✓	MERRA-2	2015–2035	–	–	Building/city	–	–	CA,	–	✓
[231]	2021	Austria	Hour	–	TMY	–	✓	–	NBH	✓	E+	HD, CD, T	✓	–
[25]	2022	Sweden	Hour	✓	TMY/RCM	2010–2099	✓	✓	NBH	✓	E+	HD, CD, T	✓	–
[288]	2022	China	Hour	–	Historical	–	–	–	NBH	✓	–	EUI, HD, EI, CD	✓	–
[289]	2023	Italy	Hour	–	TMY	–	✓	–	NBH	✓	Empirical	HD, CD	✓	–

Future climate data

As awareness of climate change continues to grow, future climate models are increasingly being used to evaluate the response of buildings and energy systems to climate variations. To do so, meteorological data for a baseline or reference year and future weather datasets are used. Baseline/reference year data can be generated out of historical monitored meteorological data or Global Climate Model (GCM) / Regional Climate Model (RCM) simulations over a historical climate [270]. These future weather datasets are predicted using GCMs or downscaled RCMs with a spatial resolution ranging from 20 to 300 km [271], taking into account different representative concentration pathways (RCPs) based on anthropogenic greenhouse gas (GHG) concentrations developed by the Intergovernmental Panel on Climate Change (IPCC) [272]. However, GCMs cannot be directly linked to building and energy models due to their coarse resolution [273], so they must be downscaled dynamically or statistically to reflect local climate conditions [274]. Statistical downscaling approaches such as morphing techniques are based on correlating historical/current average metrological data with GCM data. Dynamical downscaling, on the other hand, provides the possibility of reflecting extreme weather conditions by using physics-based calculations with desired spatial and temporal resolutions. A comprehensive review of different downscaling approaches and techniques is reviewed by Tapiador et al. [275] and Moazami et al. [253].

Assessing the resilience of current urban energy infrastructure against both short- and long-term climate variations demands the inclusion of both typical and extreme weather conditions. However, this task is complicated by the uncertainties tied to extreme weather scenarios [276]. Synthesizing multiple available RCPs, GCMs, and RCMs can help mitigate this uncertainty (Fig. 10-a), but handling the large datasets and computational demands of these simulations remains a challenge [277]. Additionally, there are still barriers to accessing future weather files for different locations that are compatible with existing urban energy simulation engines. This is why the majority of studies in the literature have focused on typical future weather conditions through statistical downscaling and have underestimated extreme weather conditions in their assessments [68]. Several attempts have been made to reduce the computational demands of dynamic downscaling and to account for extreme weather conditions in future weather files. For example, Summer Reference Years (SRYs) were introduced by Jentsch et al. [278] to account for extreme warm conditions, while Schulz et al. [279] created the Extreme Meteorological Year (XMY) based on four combinations of extreme events. Guo et al. [280] developed the Typical Hot Year (THY) and Typical Cold Year (TCY) using one GCM (ERA5), while Nik [39] introduced a method for synthesizing future weather datasets accounting for typical and extreme weather conditions. The application of these methods to building [[253],[281]] and urban energy system [[19],[40]] design has been well-studied.

In summary, a substantial hurdle within the field of urban energy studies is obtaining future weather data that take into account both typical and extreme weather conditions globally. This challenge escalates in complexity when designing and operating flexible and robust UESs and developing corresponding assessment models. To account for uncertainties in future climates, the inclusion of multiple climate scenarios with fine spatiotemporal resolution is imperative [282]. Furthermore, it is crucial to establish a seamless integration between urban climate and microclimate models with UBEMs and UES models to assess the climate resilience and robustness of future UESs in the face of climate change.

Integrating energy optimization into urban morphology

Urban morphology and the energy system planning process are two contrasting areas that are often handled by multiple expert groups having less communication in between. This disjointed approach results in missed opportunities to improve the sustainability and resilience of urban areas. Thus, there is a need to explore promising methods that can integrate urban planning and urban energy system design to address this issue.

Challenges in linking urban morphology and energy systems

The energy sector is undergoing a major transition in energy generation, conversion, system operation, distribution, and transmission. Large-scale integration of renewable energy technologies is beginning to replace traditional fossil-fuel-based generation technologies [290]. Renewable energy technologies such as solar photovoltaic (PV) and wind are intermittent; unlike fossil-fuel-based generation technologies, power generation from renewable technologies varies with the weather conditions. At the same time, renewable energy technologies are distributed [291]. For example, solar PV panels may be installed on the rooftops of buildings throughout the city, while coal power may be generated only at a few locations. Balancing the demand from equipment susceptible to changing weather conditions and generating from several locations is extremely challenging. In addition, other local constraints such as space and visual impact hinder the integration of renewable energy technologies [292]. A comprehensive overview of the building-integrated PV in the urban context is presented in Ref [293]. . Increased stochasticity in energy demand makes it even more challenging to match demand and generation. Therefore, understanding the energy demand of the building sector plays a crucial role when designing urban energy systems. In this regard, the role of building/urban simulation models becomes very important, as described in Section 6 [294]. Merely coupling building simulation models to energy system models is inadequate for gaining a comprehensive understanding of changes in energy demand, as building energy demand is affected by a range of factors [54]. Urban, regional, and global climate models can be particularly helpful in addressing the significant variations in heating and cooling energy demands, which are heavily influenced by local climate conditions. Similarly, the incorporation of transportation models can provide insights into the impact of occupancy and electric vehicle charging demand on energy demand [295]. However, integrating these models with energy system models results in a significant increase in the complexity of the energy models. [296].

Centralized modeling architectures

Centralized model architecture is often used when developing holistic design tools that link the building sector with energy systems [7]. This approach assumes that all interactions are known to the centralized agent, which makes all operational decisions regarding both the building and energy infrastructure. The centralized approach is a common one in the energy system design process, which has significantly evolved during the last decade. Recent trends are to consider uncertainty [297] and multi-stage planning [298] and to introduce decision models [263]. Despite the significant evolution of the centralized approach in the energy system design process, extending it beyond the energy system to the urban scale to capture urban morphology poses challenges [[299],[300]]. Studies have focused on the optimal operation of distributed energy infrastructure, linking optimal dispatch and optimal power flow problems [301]. However, there is a need to consider distribution in addition to generation and explore the interlinks between the building, transportation, and industrial sectors. Linking urban morphology and energy systems requires consideration of energy systems, distribution, and energy demand of buildings, and this brings many challenges to the centralized modeling architecture.

Careful consideration of the energy flow in the building sector requires a comprehensive understanding of building physics, urban climate conditions, and building usage patterns [302]. Addressing these issues requires moving beyond the boundaries of the energy system and optimization engines. and linking them with urban data, building simulation, and future climate data. Several studies have linked energy system design with urban data, building simulation, and energy system optimization [303]. Energy infrastructure design using such workflows can be achieved with reasonable computational resources. However, co-optimization of both building and energy infrastructure may take reasonably higher computation resources [304]. For example, Evins [305] reports that it takes three days to optimize both energy system design and building design, considering parametric optimization of the building. Moving from building to urban scale heightens the challenge, as it requires consideration of urban climate. Moreover, the influence of future climate variations needs to be considered as well [302], so it is important to link climate models with the energy models, which notably extends the workflow.

Present state-of-the-art climate-energy system-urban morphology models

Incorporating urban climate in the energy system enables stakeholders to discuss the impact of urban morphology in the energy system optimization process. Perera et al. [29] examined the impact of urban morphology on the energy system and found that higher urban densities lead to the urban heat island effect, resulting in higher peaks and fluctuations in energy demand, leading to a higher system cost. Mohajeri et al. [30] presented a comprehensive workflow that considers both urban form and energy system in comparing urban densification and expansion scenarios, highlighting how urban form greatly influences renewable energy integration. Perera et al. [15] investigated the influence of both urban form and density on energy systems and revealed that certain urban morphologies favor the improvement of the autonomy level while reducing the cost, emphasizing the importance of optimizing both urban morphology and energy system design. Urban morphology plays a crucial role in improving climate resilience. Perera et al. [19] optimized both urban morphology and energy system design by considering future extreme climate events, using extensive workflows coupling energy system models, building simulation models, 3D modeling, and climate models to support the assessment

Table 6 highlights several review papers that have been published on the topic of linking climate resilience with energy systems, yet the impacts of urban morphology have been overlooked in these reviews. Similarly, the literature has extensively examined the effect of future climate variations on energy system optimization (as evidenced in Table 6), while having limitations in their poor connectivity with urban morphology. For example, Perera et al. [[40],[306]], used high-probable low-impact events with the support of stochastic optimization as well as stochastic-robust optimization to consider the impacts of future climate variations on an extreme event. Furthermore, Mavromatidis et al. used stochastic [19] and robust [307] optimization techniques. The complex coupling of global/regional climate and energy system models made it challenging to further extend the models to consider the impacts brought up by urban morphology. Perera et al. [308] moved beyond the uncertainties brought up by future climate variations and considered the uncertainties with the support of machine learning techniques (generative algorithms). A major step towards bridging urban morphology, climate models, and energy systems is been presented by Perera et al. [37] through the development of a multi-scale spatiotemporal model coupling regional, urban, and urban-micro climate models with energy system models. A comprehensive consideration of urban morphology has been performed in this study by using archetypes. However, the major limitation of this study is the impact of extreme climate events such as wildfires, tornados, and floods has not been taken into consideration. Given that urban morphology plays a vital role in enhancing resilience to wildfires [309], floods, and tornadoes, it is crucial to account for the full spectrum of extreme events when considering urban morphology.

Decisions concerning urban morphology have a significant impact on the functionality of cities, which extends beyond the energy sector. However, incorporating other sectors such as transport and industry can complicate these workflows, making them challenging to manage within the current modeling framework. As a result, it is crucial to move beyond a single-agent or centralized architecture and devise more intricate frameworks that help to improve sustainability in cities.

Distributed modeling architectures

Distributed architecture is becoming popular for presenting complex interactions with urban systems [310]. The use of distributed models such as cellular automata has already been initiated [311]. However, the complexity of energy systems demands a move to more advanced strategies, such as multi-agent systems to present complex interacting flows between different actors within the energy domain [[312],[313]]. An agent may be used to present a particular sector or region within the interconnected infrastructure. Multi-agent architecture has been used within the energy sector, mostly for the dispatch arrangement [[314],[315]]. Interactions between different parts of the energy system, such as energy storage, dispatchable generation, and users have been presented using multi-agent models. Complex interactions among several microgrids (each consisting of several components) have been presented using multi-agent models in recent studies [[316],[317]]. Data-driven methods such as reinforcement learning have been used in this regard to facilitate the consideration of complex interactions [318]. Multi-agent models have not been used often for design purposes, but they have been used to optimize interconnected distributed energy systems consisting of a group of distributed energy systems [[319],[320]]. These models enable stakeholders to consider complex energy flows. However, extended computational resources are required when considering non-cooperative scenarios [320].

The potential of multi-agent models has not been used to design interconnected energy infrastructure considering multiple sectors, leading to multi-sector multi-agent architecture (MSMA). MSMA architecture can consider multiple modes of interaction between different agents, leading to a better understanding of the urban energy ecosystem. Helping stakeholders to understand the complex multi-mode interactions inherent in urban ecosystems will play a vital role in the energy modeling community.

Interconnectivity, interoperability, and resilience

Designing and operating interconnected infrastructure for sustainable energy systems requires a comprehensive understanding of interconnectivity and interoperability. Interconnectivity refers to the ability of different sectors, such as energy, transport, and industry, to exchange information and resources seamlessly [321]. Interoperability, on the other hand, refers to the ability of different systems, devices, and technologies to work together efficiently and effectively [322]. During the design process, it is crucial to consider interconnectivity and interoperability to ensure the smooth operation of the infrastructure. Considering interconnectivity brings many challenges. Besides the main challenges discussed in the design process, there can be many challenges during operation. Operating several sectors and considering the interactions among them while addressing the requirements in each is a difficult task. During the design process, we assume ideal operating conditions, which may significantly change when operating. Bottlenecks can occur when trying to facilitate interoperability, especially when multiple technologies and systems are involved. To address these challenges, machine learning algorithms and IoT platforms can assist in achieving interoperability. Machine learning algorithms can help in identifying patterns and predicting the behavior of interconnected infrastructure [323], while IoT platforms can facilitate communication and coordination among different systems and devices [324]. Nonetheless, considering these aspects at the early design stage will be a challenge that needs to be addressed when connecting cities to a sustainable energy infrastructure.

The resilience of interconnected infrastructure is another essential aspect of the mix, especially concerning extreme events such as heatwaves and hurricanes. The energy sector is particularly vulnerable to

Table 6
Recent developments with a focus on interconnectivity within urban infrastructure, considering urban models, climate/energy resilience, and urban energy systems.

REF	Year	Climate scenarios	Extreme events	High probable low-impact	GCM/ RCM	Urban Climate	Urban morphology	Uncertainty human systems	Energy			RES		Uncertainty	Resilience	Flexibility	Optimization			Stage		Perspective/ review
									Electricity	Heating	Cooling	Wind	PV				Deterministic	Stochastic	Robust	Design	Operation	
[325]	2013	✓	✓	–	✓	–	–	–	✓	✓	✓	✓	✓	✓	–	–	–	–	–	✓	✓	✓
[326]	2013	✓	✓	–	–	–	–	–	✓	✓	✓	✓	✓	–	–	–	–	–	–	–	–	✓
[327]	2013	–	✓	–	–	–	–	–	✓	–	–	–	✓	–	–	–	–	–	–	–	–	✓
[328]	2014	✓		–	–	–	–	–	✓	✓	✓	✓	✓	–	–	–	✓	–	–	✓	–	✓
[329]	2015	–	✓	–	–	–	–	–	✓	–	–	✓	–	–	–	–	–	–	–	–	–	–
[330]	2017	–	✓	–	–	–	–	–	✓	–	–	✓	–	–	–	–	–	–	–	–	–	–
[307]	2018	✓	–	–	✓	–	–	–	✓	✓	✓	–	✓	–	–	–	–	–	✓	✓	✓	–
[331]	2018	✓	–	✓	✓	–	–	–	✓	✓	✓	–	✓	–	–	–	–	✓	–	✓	✓	–
[306]	2019	✓	–	–	✓	–	–	–	✓	✓	✓	✓	✓	✓	–	✓	–	✓	–	✓	✓	–
[285]	2019	✓	✓	–	✓	–	–	–	✓	–	–	✓	✓	–	–	–	✓	–	–	✓	✓	–
[332]	2019	–	✓	–	✓	–	–	–	✓	–	–	–	–	–	–	–	✓	–	–	–	✓	–
[333]	2019	–	✓	–	–	–	–	–	✓	–	–	✓	–	–	–	–	–	–	–	–	–	–
[334]	2019	✓	✓	–	✓	–	–	–	✓	–	–	✓	✓	–	–	–	–	–	–	–	–	–
[335]	2019	–	✓	–	–	–	–	–	✓	–	–	✓	✓	✓	–	–	–	–	–	–	✓	–
[40]	2020	✓	✓	✓	✓	–	–	–	✓	✓	✓	✓	✓	✓	–	–	–	✓	✓	✓	✓	–
[19]	2020	✓	✓	–	✓	–	–	–	✓	✓	✓	✓	✓		–	–	✓	–	–	✓	✓	–
[336]	2020	–	✓	–	–	–	–	–	✓	–	–	✓	✓	✓	–	–	✓	–	–	–	✓	–
[337]	2020	–		–	–	–	–	–	✓	–	–	✓	✓	–	✓	✓	–	–	–	–	–	✓
[68]	2021	✓	✓	–	✓	–	–	–	✓	✓	✓	✓	✓	✓	–	–		✓	✓	✓	✓	✓
[338]	2021	✓	✓	–	✓	–	–	–	✓	–	–	✓	–	–	–	–	–	–	–	–	–	–
[308]	2022	✓		–	✓	–	✓	✓	✓	✓	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	–
[41]	2023	✓	✓	✓	✓	–	–	–	✓	✓	✓	✓	✓	✓	–	–	–	–	–	✓	✓	✓
[37]	2023	✓	✓	✓	✓	✓	✓	–	✓	✓	✓	✓	✓	✓	–	–	✓	✓	✓	✓	✓	–
[339]	2023	✓	–	–	✓	–	✓	–	✓	✓	✓	✓	✓	✓	✓	–	–	✓	–	✓	✓	–

such extreme events. Often, deterministic models are used when designing interconnected infrastructure, and they do not facilitate consideration of such extreme events. These events usually have multi-dimensional impacts influencing many sectors. For example, extreme climate events can simultaneously influence energy generation, distribution/transmission, and the building sector. Failures in one sector can easily penetrate the other sectors and lead to a cascading failure in the interconnected infrastructure, leading to a blackout that can strongly amplify the impacts of the original event. Therefore, it is important to consider security while modeling interconnected infrastructure when developing models for it. In addition, it is important to consider the cyber-physical interactions that will play a major role when coupling energy and urban morphology (especially considering the interconnectivity). Unfortunately, the authors did not come across any publications linking smart grids, energy planning, and urban morphology.

Towards climate-resilient energy infrastructures

The preceding sections underscored the necessity of developing integrated modeling and assessment platforms and identified several challenges and obstacles associated with considering the interconnectivity, improving interoperability, and the climate resilience of urban energy infrastructure. The major challenges in this regard are: (1) intricate and diverse energy flows within urban areas, (2) absence of an unified definition of urban morphology, and ambiguous parameters/indicators tailored for design and optimize of energy systems, (3) complexity of developing the right urban morphology models for UBEM and UES at urban scale, (4) lack of multi-scale climate models tailored for energy systems and renewable energy sources integration with fine spatiotemporal resolution at urban and microscales, (5) inadequate structures for conveying climate model results to energy models or generating realistic future weather datasets for energy and resilience analyses, (6) insufficient methods and frameworks for designing and optimizing energy systems for future climate, particularly in extreme climate events (e.g., heatwaves, cold snaps), and (7) absence of integrated modeling and assessment platforms and frameworks that consider the nexus between urban, climate, and energy models, ensuring the resilience of urban energy infrastructure.

Ensuring the resilience of urban energy infrastructure is crucial, especially when considering the impacts of both typical and extreme weather conditions. Nonetheless, as discussed in Section 6.5, the majority of literature on assessing or designing urban energy systems does not account for extreme events. Therefore, there is a need to develop integrated modeling platforms and frameworks to assess/design resilient energy infrastructure that considers extreme events, while also taking into account the complexities of urban morphology and urban systems. To achieve this goal, it is necessary to have a thorough understanding of extreme events, including their frequency, magnitude, and impact on urban energy infrastructure.

Extreme events often result from a combination of interacting physical processes across multiple spatial and temporal scales [340]. The interactions between critical infrastructures are usually poorly constrained due to the great complexities of the systems and the numerous and widely disparate actors [341]. The high density, complexity, climate-dependency, and interdependency of urban systems and infrastructures can increase the risk of cascading failures [[342],[343]], not only from extreme climate events but also from unusual or abnormal events, such as altered weather cycles. Predicting such cascading failures is extremely challenging due to the high complexity of the governing relations and systems. Knowing about the complex interactions between extreme climate events and their impacts, shaped by physical drivers and societal forces, Raymond et al. [341] presented a multidisciplinary argument for the concept of connected extreme events, suggesting approaches for producing climate information to be used in decision-making. They reviewed some methods for investigating connected extreme events and their impacts, grouping them into statistical, modeling, and socio-physical approaches. Some efforts have been made to model and estimate cascading failures considering the energy network. For example, Cadini et al. [343] created a simulation framework to assess the reliability indices of power transmission grids and depict cascading failures caused by extreme weather events. This was achieved by integrating stochastic models for weather and cascading failures and taking into account uncertainties related to repair processes.

Any framework for assessing and enhancing the resilience of complex systems should be built based on gathering and analyzing past data (fact-based information on weather extremes) and assessing future risks because of climate change. Decision support systems succeed in facilitating the analysis of past severe weather events; however, the support provided for climate change hazards is quite limited [344]. Estimating the frequency or intensity of extreme weather events is complex since understanding both the spatiotemporal characteristics of extremes and the effect of global warming on them is complex. An approach to handle this complexity is to reduce the dimensionality of the event, for example by considering an averaged singular time series over the spatial domain of interest. However, this usually leads to underestimating climate variations and the occurrence frequency of extreme events [345].

Urban energy systems, as the vital component of urban infrastructures, should have integrated urban weather, environment, and climate services that inform and increase understanding of extreme weather events. This becomes possible "through a combination of dense observation networks, high-resolution forecasts, multi-hazard early warning systems, and climate services for reducing emissions" [342]. According to Becker et al. [346], to account for urban resilience, energy management, risk, and resource management we need to adopt a more systematic approach, moving from well-defined city models towards city system models. Moreover, more than a quantitative description of the urban processes, we need to understand their complexities and interdependencies qualitatively. In this regard, they presented the City System Model (CSM) concept, investigating an urban energy planning use case in Berlin and integrating social-spatial dynamics in simulation.

To assess the climate vulnerability of complex urban systems, Apreda et al. [347] developed a hierarchical model considering physical, environmental, and socioeconomic indicators and identifying three relevant subsystems. They evaluated the combined effect of the climate hazard with the exposure and the vulnerability of the subsystems. Zscheischler et al. [340] suggest the use of bottom-up (or scenario-neutral) approaches to understand the nature of risks and identify the impactful drivers and/or hazards in relation to climate variables. For example, understating the performance of climate-sensitive components of an urban energy system. This will become a system-centric approach, which according to Zscheischler et al. [340] contrasts with top-down or scenario-led approaches. In the latter, future climate scenarios are incorporated into the impact assessment models. They motivate the shift from top-down to bottom-up approaches, comparing that to the shift from impact analysis (tracing impacts of a single hazard to multiple outcomes) to vulnerability analysis (characterizing the multiple causes of a single outcome) in socioeconomic studies of climate change risks.

In previous works [[19],[40]], we have shown that the combination of bottom-up and top-down (considering multiple climate scenarios for the latter) approaches are needed to assess the climate resilience of urban energy systems and prepare for future risks. The bottom-up models are needed to model the interactions of systems with climate and each other, while top-down models are needed to investigate multiple future climate scenarios and uncertainties, otherwise, we cannot provide a comprehensive picture of probable future conditions, which may make the assessment biased.

The role of citizens and social resilience can also become very important in enhancing the climate resilience of interconnected urban infrastructures. Bozza et al. [348] modeled urban networks as hybrid social–physical networks (HSPNs) and proposed a framework for quantifying the disaster resilience of urban systems while ensuring an adequate level of social and environmental sustainability. They identified social indicators in connection to catastrophic events and handled different kinds of information simultaneously. Prouty et al. [349] developed a system dynamics (SD) model to consider factors and dynamics that influence municipalities' decision-making process (considering socioeconomic approaches, technology and economic policies, and socio-technical behavior changes) and to determine an appropriate wastewater infrastructure portfolio for a coastal community considering future climate extremes and variations.

Additionally, variable renewable energy (VRE) and urban demand are highly affected by climate conditions, causing a mismatch in demand and generation profiles. Extreme weather events are one of the main reasons for energy disturbances and can significantly hamper the integration of renewable energy [350]. Demand-side uncertainties can become intensified in urban areas due to increased complexities and intensified extreme conditions [[24],[208]]. In combination with other uncertainties such as building performance, occupant behavior, and control strategies [[351],[352]], it becomes challenging to design and control the urban energy system [15]. A sustainable transition solution that does not account for climate change adaptation can induce vicious cycles and worsen the situation in the future [353]. A major change in the environment of a complex system can induce a chain reaction of responses between the components of the system at the local level, which can lead to a global behavior—a phenomenon referred to as "emergence" [354]. Improper assessment of the complex and contingent nature of connected extreme events increases the risk of crossing unknown tipping points in terms of response capacity [341]. It is possible to take advantage of the characteristics of complex systems to reach higher flexibility and resilience since they can adapt, self-organize, and emerge to enhance their resilience [355]. This increases the importance of energy control systems and the adopted approaches. In connection to complex systems, there have been considerable developments in methodologies for multi-agent systems (MASs) [356]. As shown by several researchers, it is possible to increase the flexibility and resilience of energy systems by integrating relevant AI-based and MAS approaches into energy management (e.g., [[357],[358]]). A major challenge in this regard is the increased computational load. Nonetheless, as demonstrated by Nik and Hosseini [359], it becomes feasible to overcome the challenge through innovative designs that harness the capabilities of multiple AI-based and nature-inspired solutions.

In response to the above-mentioned challenges, we propose a framework that emphasizes the interconnectivity of urban energy infrastructure, while considering urban morphology (Fig. 14). This framework includes an urban model that considers urban climate and microclimate data, a climate change model that accounts for extreme weather events, and design optimization of urban energy systems. The proposed framework relies on using cutting-edge AI-based methods and approaches, to handle big data and large datasets more effectively. It is essential to emphasize that the definition of resilience indicators, the assessment of risks, and the development of remedies are inherently tailored to the particular characteristics of each system, thus there is no universal formula that applies universally. Nevertheless, through the implementation of this framework, urban energy infrastructure can be designed to withstand climate variations in extreme conditions while taking into account the intricate interconnections within urban environments. To carry out such an assessment, the following steps are imperative:

- Step 1: Formulate an integrated model of interconnected urban infrastructure considering urban morphology, including form, function, and structure, and taking into account the influencing parameters tailored for energy systems.
- Step 2: Extend the model's purview to encompass the transportation sector and other relevant domains, such as water systems.
- Step 3: Develop an (AI-based) multi-scale climate model that provides for mesoscale, urban climate, and urban microclimate data

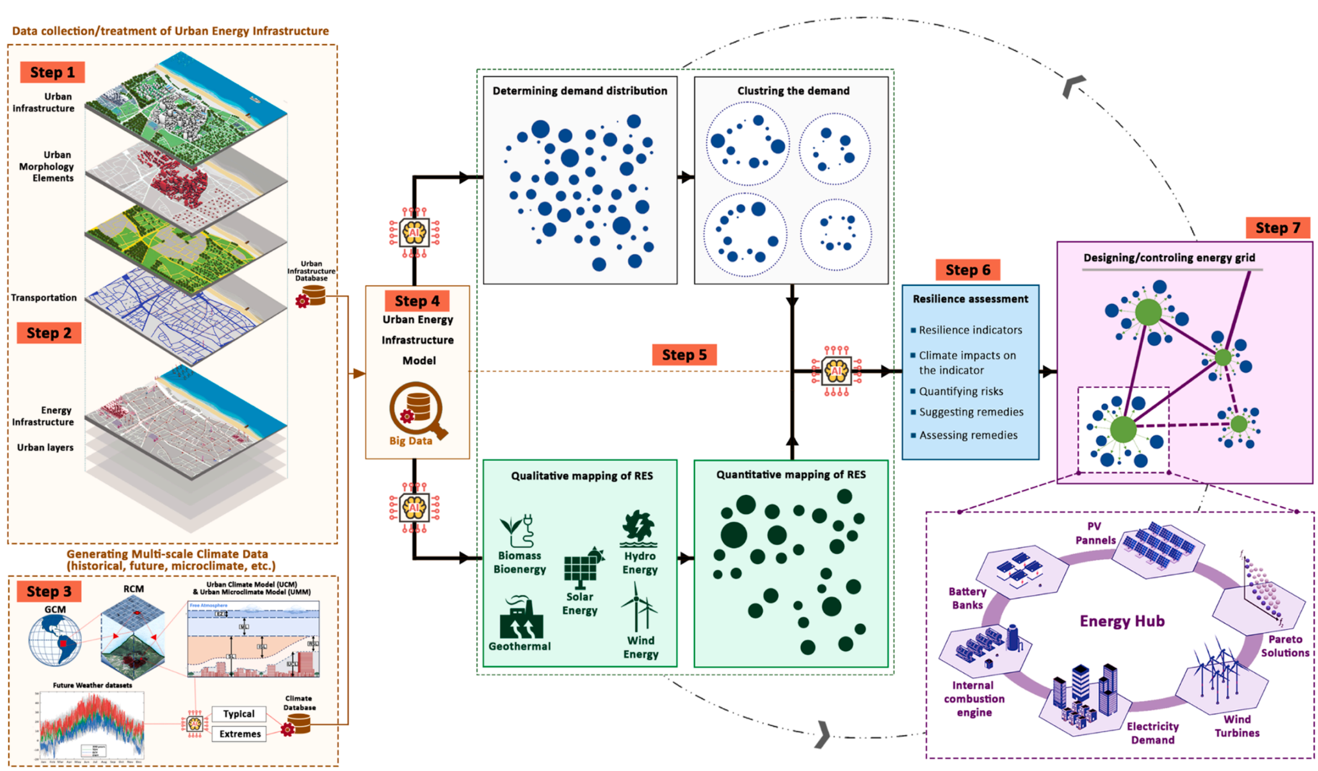

Fig. 14. A framework to connect interconnected urban infrastructure, urban morphology, energy infrastructure, and other urban layers. Sector/spatial coupling and the interconnectivity between each layer are the major challenges in developing UES models and improving their resilience to extreme events. The energy network is replaced by designing an electrical hub demand/supply.

with a focus on extreme climate events. Ensure that the weather data accounts for future climate uncertainties and extremes.

- Step 4: Utilize AI-based methods and approaches to conduct data treatment of urban energy infrastructure models.
- Step 5: Determine demand distribution, cluster demand, qualitative mapping of renewable energy sources (RES), and quantitative mapping of RES.
- Step 6: Undertake resilience assessment using relevant indicators, quantify risks, and suggest feasible remedies.
- Step 7: Optimize the energy grid at the design or control stage based on identified criteria. Repeating steps 5–7 to reach the desired threshold for the energy grid.

The proposed framework emphasizes the intricate interconnections within urban infrastructure and underscores the importance of the availability of fine spatiotemporal resolution climate data. As a demonstration of considering interconnectivity, Perera et al., [27] introduced the 'Urban Cell' concept through developing an interconnected urban infrastructure encompassing the energy, building, and transportation sectors. Employing a modular approach, the model optimizes the sizing of distributed energy systems, integrating renewables, energy storage, and dispatchable sources, while simultaneously optimizing urban morphology within distinct modular units. Regarding the incorporation of proper weather data, establishing a seamless connection between multi-scale climate data and energy models is pivotal for ensuring climate resilience in energy systems. Integrating urban climate and microclimate data into the optimization of energy system designs, particularly under extreme conditions such as heatwaves or cold snaps, is crucial. Given the computational complexity of providing microclimate data, fine-grained spatiotemporal resolution data becomes particularly relevant during such extreme events. In contrast, integrating urban climate data is strongly suggested for energy system design and control, as demonstrated in Ref [37].

To facilitate resilient urban energy infrastructure design, incorporating more refined spatiotemporal resolution data that encompasses multiple climate scenarios is essential. For instance, Nik's approach [39] involved analyzing approximately 390 distinct scenarios, spanning 13 future climate scenarios over 30-year intervals. This method facilitates the consideration of even the most extreme climatic conditions at an hourly temporal resolution while addressing the inherent uncertainties in climate projections. Finally, linking the impacts of urban morphology to climate projection is another means of ensuring the reliability of urban energy-related solutions. Such an approach is demonstrated in Ref [25], where they downscaled future weather data considering 13 climate scenarios over 30-year intervals from mesoscale to microscale using an urban climate model. Regardless of the adopted tool and simulation engines, the proposed framework is indispensable for effectively addressing the intricate challenges posed by climate variations and uncertainties, while counting for interconnectivity within urban systems.

While encompassing the expansive domain of urban energy infrastructure, it's important to note that this review's concentration alongside the proposed framework was exclusively on the interconnections among urban morphology, climate data, and urban energy systems. As a result, other pivotal factors like human systems (such as user behavior and engagement in energy system design/control), urban transportation, water systems, and subjects related to governance and regulations, as well as socioeconomic dynamics have been deliberately omitted from this literature review and proposed framework. Thus, further investigation is required to count those influential and essential aspects of urban systems in the design and control of urban energy systems.

Concluding remarks

A sustainable transition in urban energy infrastructure is critical for reliable climate change mitigation and adaptation of urban areas. Urban energy infrastructure has the potential and responsibility to facilitate this transition by increasing the integration of renewable energy sources and contributing to adaptation plans. However, developing sustainable and resilient urban energy systems that ensure reliable solutions face several challenges. The intricacies of energy flow within cities, the lack of a unified definition of urban morphology, and ambiguous parameters and indicators for energy system optimization are major obstacles. Developing appropriate urban morphology models for urban building energy models (UBEM) and urban energy systems (UES) at the urban scale is complex and requires multi-scale climate models tailored for energy systems and renewable energy sources with fine spatiotemporal resolution. However, such models are currently lacking. Additionally, inadequate structures for conveying climate model results to energy models or generating realistic future weather datasets for energy and resilience analyses further complicate matters. There are also insufficient methods and frameworks for designing and optimizing energy systems for future climate, particularly in extreme climate events such as heatwaves and cold snaps. Finally, the absence of integrated modeling and assessment platforms and frameworks that consider the nexus between urban, climate, and energy models presents a significant challenge to ensure the resilience of urban energy infrastructure.

A major obstacle in the field of urban energy studies is the availability of reliable climate data that considers both typical and extreme weather data in a local context. This challenge is particularly complex when designing resilient and reliable energy systems, and when developing corresponding evaluation models. To accommodate the uncertainties associated with future climate changes, various climate scenarios with high spatial and temporal precision must be taken into consideration. Moreover, seamless integration among microclimate, urban climate, building energy, and urban energy system models is crucial to ensure the resilience of urban energy infrastructure against abnormal climate conditions. Such a seamless link between climate models and energy system models requires a thorough understanding of the impacts of urban morphology, encompassing model development, influential parameter identification, and the interplay of morphology with microscale climate variables.

Despite existing challenges, as future outlooks, there are also opportunities for improving the resilience of urban energy infrastructure. Leveraging big data from various sensing modes, and IoT devices, and employing AI and machine learning offer promising avenues. Affordable high-performance computing is making it possible to run complex models and simulations, which can be used to optimize urban energy systems. Essential energy storage technologies, like batteries, ensure energy supply-demand equilibrium and provide backup during extreme weather or grid disruptions. To tackle the task of resilient urban energy design, we proposed a framework that emphasizes the interconnectivity of urban infrastructure and uses cutting-edge AI-based methods. The framework includes an integrated model of urban infrastructure, an AI-based multi-scale climate model focused on extreme climate events, and a resilience assessment to identify indicators and suggest solutions. By optimizing the energy grid at the design or control stage based on identified criteria, the framework can ultimately lead to more sustainable and adaptable cities. For the effectiveness of the proposed framework, it is crucial to accumulate and analyze data from diverse sources prior to decision-making. This can be achieved through data analytics and a dynamic model of the urban energy system, which can provide a comprehensive understanding of the system's behavior and vulnerabilities. By incorporating the proposed framework with data analytics and a dynamic model, urban energy infrastructure can be designed and optimized to withstand climate variations in extreme conditions while considering the intricate relationships within urban environments.

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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