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Urban Building Energy Modeling: State of the Art and Future Prospects

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Abstract
During recent years, urban building energy modeling has become known as a novel approach for identification, support and improvement of sustainable urban development initiatives and energy efficiency measures in cities. Urban building energy models draw the required information from the energy analysis of buildings in the urban context and suggest options for effective implementation of interventions. The growing interest in urban building energy models among researchers, urban designers and authorities has led to the development of a diversity of models and tools, evolving from physical to more advanced hybrid models. By critically analyzing the published research, this paper incorporates an updated overview of the field of urban building energy modeling and investigates possibilities, challenges and shortcomings, as well as an outlook for future improvements. The survey of previous studies identifies technical bottlenecks and legal barriers in access to data, systematic and inherent uncertainties as well as insufficient resources as the main obstacles. Furthermore, this study suggests that the main route to further improvements in urban building energy modeling is its integration with other urban models, such as climate and outdoor comfort models, energy system models and, in particular, mobility models.

Keywords
Urban building energy modeling, Urban energy planning, Bottom-up energy modeling, Building archetype, Energy simulation, Thermal zoning

Abbreviations

ADE	Application domain Extension
BEM	Building energy modeling
CDD	Cooling degree day
CFD	Computational Fluid Dynamic
DEM	Digital elevation models
GIS	Geographic information system
HDD	Heating degree day
HVAC	Heating, ventilation and air conditioning system
LiDAR	Light detection and ranging
LOD	Level of detail
MRT	Mean radiant temperature
OGC	Open Geospatial Consortium
SRDBM	Spatial relational database management systems
UBEM	Urban building energy modeling/Urban building energy model
UCM	Urban canopy model
UHI	Urban heat island

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1 Introduction

The world's population is currently 7.7 billion, as of January 2019, and more than half of this population resides in urban areas. Projections show that the urbanization, i.e., the gradual shift from rural to urban residency, combined with an overall human population growth, will lead to a 50% increase in urban population by 2050 [1]. On the other hand, urban areas are recognized as the main contributors in energy and climatic challenges as they use more than 70% of the world's final energy and account for more than 70% of global greenhouse gas (GHG) emissions [2]. As cities grow and urban activities expand, these values also increase.

In response to the growing rate of urbanization, combined with climate change, urban planning has been adapted to include sustainable development strategies. Moreover, as cities run on energy, integration of energy planning with conventional sustainable urban development paradigms is necessary [3], [4]. Integrated urban energy planning is a complex approach focusing on energy flows into, throughout and out of cities [3], [5]. To understand the drivers and patterns of the energy flows, the elements of the urban metabolism are analyzed, among which buildings and their influential roles are well recognized. The building stock has a significant share in energy use and GHG emissions, and at the same time offers a great potential for energy efficiency and integrated sustainable energy solutions [2]. The necessity of implementing the urban integrated energy planning on the one hand, and the key role of buildings in the energy balance of cities, on the other hand, have led to the emergence of novel city-scale building-oriented studies [6].

In city-scale energy modeling of buildings, the primary approach is to quantify the energy performance of buildings in an urban context for different spatiotemporal resolutions. Moreover, these models are capable of being used in further urban planning and development of existing as well as planned areas. Understanding the diurnal and seasonal energy use patterns for every location in a city gives the authorities a deeper insight into how to balance the energy supply and demand and prevent from instabilities and shortages in the energy system. These models also support scenario planning and benchmarking for retrofitting of buildings and integrating renewable energy solutions in the energy systems of cities. Moreover, planning for and analyzing new city districts will not be as challenging if the proper models are used. Overall, city-scale energy modeling of buildings offers a suitable tool for guiding the stakeholders, city planners and decision-makers in understanding urban energy systems and enables them to formulate energy plans, suggest sustainable initiatives and decide on constructive policies [3], [7], [8].

1.1 Brief overview of city-scale energy modeling of buildings

Over the last decades, dynamic thermal modeling and simulation of buildings and their energy systems have been a common approach to planning, demonstration and evaluation of energy conservation measures and thermal comfort improvement in individual buildings [9]. However, considering the buildings' interaction with surrounding buildings and the urban environment [10], [11], their role in renewable resource envelope solutions [12], and the dynamic influences of buildings' energy use on district energy systems [13], [14], building energy studies have been shifting focus from individual buildings to cluster and city-level solutions.

With regard to the hierarchy of input information and the modeling strategy, studies on urban energy flows can be categorized into top-down and bottom-up models [15]–[17]. Top-down modeling is an approach that relies on data on an aggregated level to express the relation between energy use and associated drivers such as socio-econometric variables and climate. Due to the simplicity of the models, their reliance on aggregated historical data, and their independence on detailed technological descriptions, they have been vastly used in urban energy studies such as [18], [19]. However, dependence on historical macroeconomic energy trends and lack of technological detail make these models less suitable to examine changes in technology for current and future development studies.

Bottom-up models, in contrast, are built up from extensive data on a disaggregated level for estimation of individual building energy use and extrapolation of the aggregated energy demand. Concerning the level of detail in the end-use information and the applied methodology, bottom-up models are divided into three categories: statistical, engineering (physical) and hybrid models. The bottom-up statistical models can represent the relations of individual end-use energy with buildings' characteristics and socioeconomic indicators [20]–[22]. On the other hand, the engineering models make use of physical and technological characteristics of individual buildings to compute the required energy demand. These models have the highest level of flexibility in evaluating technological developments and energy efficiency scenarios. Nonetheless, the need for extensive empirical data and the inherent uncertainties in applied assumptions, particularly for human activities and occupancy profiles, motivate the use of hybrid models. In the hybrid models, while the buildings are modeled according to their physical characteristics (just like in the engineering models), the required data, particularly the occupant's related data, is obtained from analysis of the historical energy use intensity (as in the statistical models). Thus, the shortcomings of both models are more likely to be compensated to achieve a more sophisticated model [23]–[26]. In the literature, the method for bottom-up city-scale energy modeling of buildings that includes physical models of heat and mass transfer in and around buildings are referred to as "urban building energy modeling" [7].

1.2 Previous reviews in the field of city-scale energy modeling of buildings

In terms of city scale-energy modeling of buildings, many review articles have been dedicated to summarizing and synthesizing different aspects of the field, such as in [15], which presents an audit of regional and national energy modeling techniques and critically discusses their strengths and weaknesses. This review is one of the very first studies on detailed characterization and categorization of top-down and bottom-up city-scale energy models of buildings. Nonetheless, modeling approaches have changed considerably since 2009, when the study was published, and despite being a valuable resource, this cannot be reflective of the complete field anymore.

Following the same terminology, Kavgic et al. [17] offered a brief overview of top-down and bottom-up models. The main focus of this review is on elaboration of some selected bottom-up residential stock models and their applications. Similarly, this review is not up-to-date and also is not inclusive enough.

Keirstead et al. [27] presented a formal definition for urban energy systems, incorporated both processes of acquiring and using energy and evaluated the main attributes of previous urban energy models, namely, technology design, building design, urban climate, systems design, and policy assessment. However, what makes this review different from the others is its approach towards human activity and land use models and evaluation of their integration into urban energy system models. While in this review a unique approach was used to address the field, it is more focused on the concepts rather than the technologies and methodologies.

Allegrini et al. [14] paid special attention to energy systems and their interactions with buildings. This viewpoint led to an inclusive review on models and tools that are used in simulation of energy systems. Moreover, due to the importance of the interactions between the local microclimate and buildings, the possibilities of modeling microclimate components were also discussed. Nonetheless, not all of the suggested tools are necessarily capable of being used in district- or city-scale energy modeling and not all have been used in previous studies. Although this review justifies the interactions between buildings and the energy systems in districts, no overview of the building energy modeling is given.

For the first time in the field, Reinhart and Cerezo Davila [7] presented a brief and concise overview of the bottom-up engineering (physical) methods specifically. They termed the bottom-up engineering modeling as "urban building energy modeling (UBEM)" which has recently become known and used as a common term in the field. This review includes the most important aspects of UBEM, yet it is lacking an investigation of future prospects, approaches and possibilities.

Similar to the work done by Swan and Ugursal [15] , Li et al. [16] provided an up-to-date summary of city-scale energy modeling techniques in the two broad categories of top-down and bottom-up approaches. Despite being an inclusive review, considering the extent of the field, many notable studies in the area of UBEM were not included or thoroughly discussed.

While most of the previous reviews have covered the general aspects of city-scale energy modeling, particularly top-down and bottom-up approaches, others aimed to survey more specific topics of the field, ranging from occupancy models [28] and microclimate models and their integration with UBEM [29] to the energy-saving potential in developed models [30].

1.3 Aim of this review

As can be concluded from the previous section, in the context of city-scale energy modeling of buildings and, specifically, bottom-up engineering (physical) modeling referred to as UBEM, it is necessary to provide a new literature review that summarizes the previous studies, highlights the research gaps and suggests new horizons for the field. The goals of this review is therefore to:

- Provide an extensive overview of the bottom-up engineering (physical) modeling known as UBEM.
- Analyze existing studies and outline a methodology for developing urban building energy models (UBEMs). The main approach is to encompass all different parts of the workflow, in particular those that have not been extensively discussed before, e.g., building archetypes, databases and visualization.
- Introduce the latest improvements of the field and identify the research gaps.

- Explore models for other parts of the urban environment that interconnect with buildings, e.g., urban mobility, and try to find a common ground for their integration to UBEM.
- Finally, propose how to bridge the research gaps and suggest what to focus on in future works.

Overall, the novelty of this review is in its objective to survey approaches, opportunities and challenges in UBEM specifically, and to broaden the horizon for integrated urban building energy models that would include not only the urban building energy models but also urban mobility models, urban climate models, and the like.

1.4 Outline of the work

This paper is structured in four main sections as follows. In Section 2, urban building energy modeling, state-of-the-art and best practices are highlighted. However, considering the large extent of the field, this section is divided into subsections, each introducing one important part of the UBEM methodology from model development and model simulation to visualization of the results and databases. Section 3 presents the latest developments in other areas of urban modeling and tries to find a common ground between these models and UBEMs, which could be potentially used for further improvement of UBEM in future studies. In Section 4, a discussion on findings, challenges and opportunities, as well as suggestions for further research and development, is included. Finally, in Section 5, the conclusions from this review is presented.

2 Urban building energy modeling

As in individual building energy modeling (BEM)[1], the UBEM procedure is composed of several steps, including the development of energy models of buildings from their geometric and non-geometric properties and simulation of the models in a simulation engine. However, the modeling procedure is not as straightforward and is associated with different challenges and uncertainties. Inferred from the literature and previous studies, an overview of the modeling procedure in UBEM is illustrated in Figure 1. The modeling procedure for an UBEM starts with identification of the geometrical properties of buildings, i.e., shape, geometry and geospatial positions, through 3D models of the city (see Section 2.1.1). In addition, non-geometrical properties of buildings, i.e., material, system and occupancy, are defined by building archetypes that represent the most important characteristics of the building stock (see Section 2.1.2). Then, together with predefined climatic conditions (see Sections 2.2.1.1), all the required inputs are imported to an UBEM simulation engine in which the thermal model is initiated and simulated (see Section 2.2.2). The simulation results for energy demand in cities as well as the input parameters can be stored in a database and visualized in a suitable application (see Section 2.3).
By listing some of the key properties of the existing models, at the end of this section, some of the most important UBEM studies with respect to the content of this section are also summarized in Table 4.

[1] For further details on building energy modeling, the reader is referred to [31].

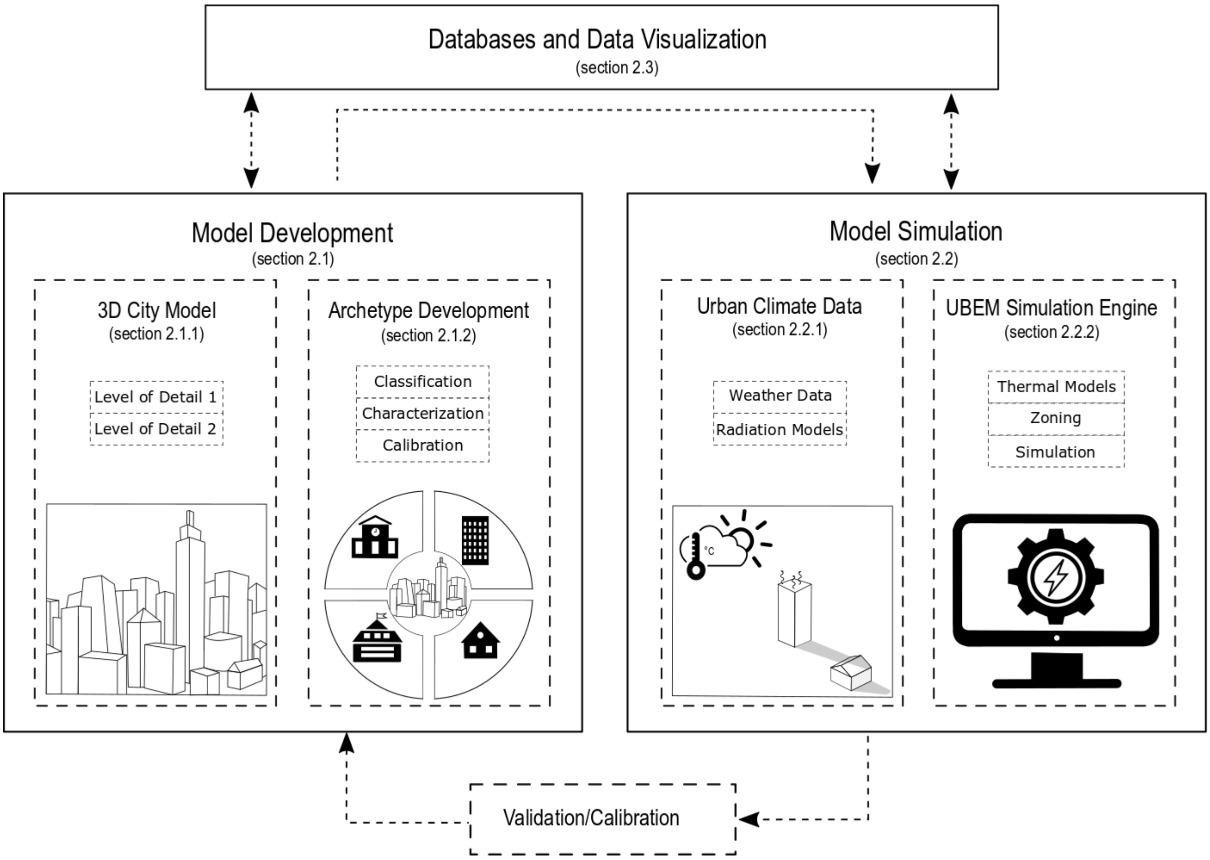

Figure 1. Overview of Urban Building Energy Modeling.

2.1 Model Development

2.1.1 3D city model

As for BEM, UBEM also requires a description of the geometry of the buildings and their surroundings, which affects the building energy and thermal performance. The geometry can be further characterized with short- and long-wave optical properties of surfaces, for example, their solar reflectance. The UBEM accuracy is dependent on the level of detail and accuracy of the 3D city model, as fundamental parameters are calculated from the geometry, such as outdoor exposed surfaces and conditioned space, as well as the relation between different buildings (e.g., two buildings sharing the same wall) and exposition to radiation from the sky, sun and the urban context.

Energy demand estimation is indeed one typical example of a non-visualization oriented application of 3D city models [32]. 3D city models are a representation of the different components of the city, in particular of buildings. 3D city models can be obtained with different acquisition methods [32], including, for example, photogrammetry and laser scanning, e.g., light detection and ranging (LiDAR), or a virtual extrusion of the building footprints. Table 1 lists the main characteristics of the 3D city model for some sample UBEM application studies.

Most of the studies use standard cadastral information, such as building footprints and height to generate by virtual extrusion a shoe-box model of buildings, which corresponds to Level of Detail 1 (LOD1) according to the Open Geospatial Consortium (OGC) classification [33]. Some studies, especially those also targeting solar potential analysis, provide a more detailed geometrical representation of the buildings, including the actual shape of the building (LOD2), or even overhangs, dormers and other architectural details (which we will refer to as LOD2+). However, it should be noted that the error due to a coarse LOD can be compensated by the use of some data as non-geometrical attributes of the geometry; for example, the volume of the attic in a gable roof that is not represented in a LOD1 model can be added to the volume calculated from the shoe-box model. In this sense, the importance of having LOD higher than LOD1 in UBEM is secondary, as shown by Nouvel et al. [34]. Moreover, some details present in a LOD3, such as roof overhangs, are not part of the building thermal envelope [35], making them unsuitable for building energy simulations without specific processing.

If not already included in its semantics, an important component of the 3D city model for UBEM application is the topological relation between geometrical objects with different thermal properties, such as the contact with the ground and the walls shared between different thermal zones. Some algorithms have been developed [36], [37] to solve this type of adjacency problem in UBEM.

In addition to building geometry, the main other components of 3D city models are topography (terrain and horizon/far-field obstructions) and vegetation. Topography can be easily generated from Digital Elevation Models (DEM), which are widely accessible in most locations. Vegetation can be reconstructed using LiDAR data or georeferenced databases providing the characteristics of trees.

For large-scale studies, the 3D city model is usually subdivided in tiles, to be more easily processed by computational methods. To this end, Romero Rodríguez et al. [38] showed the optimal tile characteristics (size and overlap) for UBEM and solar potential applications.

Table 1. Characteristics of the 3D city models used in some sample UBEM application studies.

Study	*Components of 3D city model*	*Surface attributes*	*Level of Detail*	*Source of geometry information*
Perez [39]	Buildings, terrain, horizon	Shortwave reflectance	LOD1	Cadaster
Fonseca et al. [40]	Buildings, terrain		LOD1	Cadaster
Cerezo Davila et al. [36]	Buildings		LOD1	Cadaster
Peronato [36]	Buildings, terrain, horizon, vegetation	Shortwave reflectance	LOD2+	3D cadaster and LiDAR data
Weiler et al. [41]	Buildings, terrain		LOD2	3D cadaster

2.1.2 Archetype development

Data collection and model characterization for each individual building in UBEM is difficult, hence abstracting the building stock into representative archetypes is a useful and often necessary approach. Although most of the surveyed studies relied on simple archetype development from readily available data and building information standards, application of machine learning techniques has opened up new horizons to this field, which has resulted in increased accuracy but also higher complexity of the models. In these approaches, building archetypes are identified in three main steps. First, the building stock is classified into different groups, according to their similar characteristics and energy demand. Second, representative building archetypes are characterized. Third, to address the uncertainties of the used parameters in archetype models, the archetypes are calibrated against measured energy use data at different spatiotemporal aggregations. These three steps are reviewed in more detail below.

2.1.2.1 Archetype classification

Classification of the building stock into sub-groups of typologically identical buildings and identification of representative buildings may involve various technical methods. The applied methodologies can be divided into three main categories:

- Deterministic Classification

In a deterministic approach, buildings are classified according to their theoretical energy use determined by some parameters such as use-type, age, shape and floor area. The building use typology (e.g., residential, administrative, commercial, etc.) presents an approximation to the energy demand profile, and the year of construction or the effective year (i.e., the year at which the building were under a major refurbishment) can allow a good estimation of construction materials and systems [36], [42], [43]. In addition to these four parameters, depending on the availability of data, the type of heating, ventilation and air conditioning systems (HVAC) [44] or the climatic conditions [45] are often used as other indicators for classification of the archetypes. This categorization of buildings, using readily available data from public or municipal datasets, e.g., Geograpical information system (GIS) data, is the most applied method in UBEM studies. However, generic classification of the archetypes using the simplified deterministic approach misrepresent the real diversity of the buildings, which may result in inaccurate energy demand patterns, particularly for higher spatiotemporal resolutions.

- Probabilistic classification

Another approach in archetype classification is to use historic energy demand data as an auxiliary indicator, by which categorization of the buildings significantly improves [46]. Statistical identification of the parameters with the strongest correlation to real energy use intensity can accurately represent the diversity of the energy demand in different archetypes [46]–[48]. Categorization of the buildings with respect to their actual energy demand can significantly reduce the uncertainties associated with deterministic classification methods based on theoretical relations between indicators and energy use. However, availability of measured energy use data and access to such information are the main challenges in applying the probabilistic approaches.

- Cluster analysis

Implementation of clustering techniques in archetype classification is a rather novel approach in UBEM [49]. Data clustering is a well-known data mining method which provides an unsupervised classification of the data according to their similarities, e.g., patterns, and representative elements [50]. Although the clustering approach is a new concept in UBEM, they are widely employed by the utility companies to classify the consumers based on their electricity use profile in order to set specific electricity tariff structures or demand side management schemes [51], [52]. However, in most of these studies, the buildings' characteristics are not of importance and the main norm in classification of the consumers is the profiling information acquired from smart metering. In classification of the building stock by clustering methods, the building features that influence the thermal behavior of the buildings are identified and translated into cluster classifiers [49], [53]–[57]. When the clusters have been identified, it is possible to select the most representative case as the chosen archetype for the given group. Unlike in the deterministic or probabilistic methods, in clustering techniques, the membership information is not used as a prior input; instead, the classification of the buildings results from hidden structures with the thermal energy demand.

2.1.2.2 Archetype characterization

After classification of the building stock and identification of the archetypes, each reference building has to be characterized by the non-geometric parameters, including the construction materials, infiltration, HVAC types, and occupancy profiles. Depending on the availability of data, these parameters are deterministically or probabilistically defined, as outlined below.

- Deterministic characterization

In deterministic characterization of the archetypes, depending on the level of granularity, characteristics of the archetypes are sometimes taken from a "real case", i.e., one of the buildings of the class. By having access to building audits and building stock information, actual or averaged values of each parameter are acquired and assigned to the corresponding archetypes [47]. However, due to the constraints in having access to building-level data sources, it is less common to conduct a pure deterministic characterization. Thus, building model parameters are instead compiled from building codes and standards, literature or previous studies. In Europe, under the scope of a European project known as TABULA [58], one of the most comprehensive residential building typology information datasets, has been developed for 20 European countries. The results are freely accessible as a web tool to be used in building-oriented studies. Two other European projects, Odyssee-Mure [59] and Entranze [60], are other examples of databases that can be applied for European building characterizations.
Despite the functionality of the deterministic characterization of archetypes, to cope with the inherent uncertainties associated with the input data and the usually limited or non-existent information on occupants-related parameters, probabilistic approaches are suggested instead.

- Probabilistic characterization

In building- and energy-oriented studies, probabilistic models of occupants' presence and action have already been developed and extensively improved [59]–[61]. The occupants' behavior is known as one of the main drivers of energy use in buildings; however, in the field of UBEM, it is still not a well-developed topic. Most of the previous UBEMs relied on deterministic parameters and schedules for occupants' behavior [36], [44], [64], while only a few took the probabilistic evaluation into account [65], [66]. A comprehensive review of the occupancy models in UBEM is given by Happle et al. [28].

With a wider approach, not only the occupant-related information but also other uncertain characteristics of buildings (e.g., air change rate, window-to-wall ratio and thermal properties) can be treated stochastically. As in the studies by Famuyibo et al. [48], Cerezo et al. [46] and Sokol et al. [42], based on deterministic values and assumptions, empirical distributions of the unsure parameters were obtained from uncertainty modeling techniques and applied to the model.
However, by analyzing the previous works it is evident that the probabilistic methods have not been completely introduced to UBEM yet. As regards the inherent complexity of probabilistic methods and their extensive computation procedure, they will increase the complexity along with the accuracy of the urban building energy models. Nonetheless, it is expected that this method will find its position in urban energy modeling as well as in individual building studies.

2.1.2.3 Archetype calibration

In an attempt to address the uncertainties associated with characterization of the archetypes, and to reduce the discrepancies between predicted energy demand and actual measurements, calibration methods are needed in building energy studies [42], [67]–[69]. If the energy use intensity is available, in the simplest method, the calibration will be an iterative process of adjusting the few uncertain parameters in order to reach a reasonable approximation to measurements [70]. However, due to the limitations in deterministic characterization of the archetypes and the growing tendency towards probabilistic parameterization, novel calibration methods focus on adjusting the results based on probability distributions assigned to each uncertain parameter [71]. Among all calibration techniques available for BEM [72], in UBEM the Bayesian calibration in capturing the uncertainties of stochastic parameters was proven to be successful [42], [68], [69], [71].
Booth et al. [71] conducted a Bayesian calibration posterior distribution method to determine the uncertain parameters and integrated it with a Monte-Carlo model to create a full probabilistic calibration method for developing a stochastic urban scale domestic energy model. Kristensen et al. [68], [69] developed a multilevel simultaneous modeling and calibration framework. By means of a set of observed data and Bayesian inference, the uncertain parameters were calibrated in a hierarchal setting. Cerezo et al. and Sokol et al. [42], [46], [73] proposed a Bayesian approach based on an iterative process of error analysis between dynamic thermal simulation and monthly or annually aggregated data.
The archetype development methods in some of the UBEM studies are summarized in Table 2. Note that only the most representative studies are included in this table.

Table 2. Archetype approach in some sample UBEM studies.

Study	*Classification method*	*Characterization*	*Calibration*	*Novelty*
Caputo et al. [74]	Deterministic	Deterministic	-	-
Sokol et al. [42]	Deterministic	Deterministic and probabilistic	Iterative Bayesian calibration techniques	- Automate calibration of the uncertain parameters.
Famuyibo et al. [48]	Probabilistic	Probabilistic	-	- Clustering the building construction parameters with respect to each other.
Kristensen et al. [68]	Deterministic	Probabilistic	Bayesian calibration techniques	- Simultaneous modeling and calibration (Hierarchical calibration).
Booth et al. [71]	Deterministic	Probabilistic	Bayesian calibration techniques	- Prior uncertainty distribution analysis to form posterior uncertainty models and calibrated parameters.
Ghiassi and Mahdavi [53]	Clustering	Deterministic	-	- Automated building sampling by multivariate cluster analysis.
Li et al. [55]	Clustering	Deterministic	-	- Use of satellite image for clustering

2.2 Model simulation

In BEM, once buildings' information (geometric and non-geometric) is ready, it is imported to a simulation engine, in which thermal models are defined and simulated for desired weather conditions. Similarly, in the most recent UBEM workflows, once the 3D models of buildings and the characteristics of the representative archetypes are prepared, in an iterative process, the thermal models of buildings are generated automatically and simulated under certain climatic conditions. As a result, the urban energy demand for different spatiotemporal resolutions can be extracted from the model. Once properly validated, the model can be reliably used for further urban energy integrated planning and development studies. A survey of thermal modeling and energy simulation for urban climate in previous works is included below.

2.2.1 Urban climate data

As in BEM, the UBEM simulation is conducted for a certain weather condition acquired from measurement data. However, unlike BEM, in most UBEM studies the urban context and its influences on the radiation component of the urban climate is considered through radiation models. The radiation modeling and shading analysis are usually conducted by internal calculations or co-simulation with other tools.

2.2.1.1 Weather data

Due to the direct influence of weather conditions on the thermal energy demand of buildings, importing an appropriate weather dataset to the model is important for the accuracy of the results [75]. In dynamic building energy modeling, several different weather data sets are commonly used [76]. Typical weather data obtained from historic measurements (20-30 years) of weather components, referred to as typical meteorological years (TMYs), are the predominant climate data used in UBEM [77]. Albeit, there are a few studies which relied on different sources of data. For example, Buffat et al. [78] focused on the daily mean temperature acquired from the MeteoSwiss measured on a daily basis and interpolated by measurements of 70 to 110 weather stations. The radiation data was calculated from the synthetic algorithms of satellite information [78].

2.2.1.2 Radiation models

Estimating the solar radiation reaching the building surfaces is crucial for calculating the energy balance of a building. In an urban context, solar access is often limited. The exact geometry is also influencing the long-wave radiation exchanges between different surfaces, which can be calculated with similar methods by some of the reviewed engines (EnergyPlus and SRA).
We can distinguish between three main methods for solar radiation considering shading (and in some cases interreflections) from the urban geometry:

- Viewshed analysis

In a raster 2.5D model, the maximum angle of obstruction around the sensor point (i.e., one or more pixels composing the model) is calculated; this is used to generate a viewshed, i.e. the angular distribution of sky obstructions, which is subsequently overlaid on the sky and sun contributions. This method, which is common in GIS-based solar potential analysis, was adapted for applications with vector 3D city models since the first version of CEA [40].

- Backward raytracing

In a 3D model, rays are cast from selected sensor points on exterior surfaces. If a ray intersects a reflecting surface (e.g., another building surface), one (specular) or multiple (diffuse) rays are bounced off until reaching either a fixed maximum number of bounces or the sky/sun. Radiance [79] is an advanced physically-accurate rendering engine, which is used by Daysim [80] to compute annual simulations. EnergyPlus also includes a backward raytracing algorithm which supports diffuse and specular materials and one interreflection, using a fixed amount of rays from the sensor points on the building faces.

- Radiosity

In a 3D model, view factors are calculated for each face of a mesh describing the 3D model, to calculate the contribution of each of them to the radiant energy balance. This method was first developed in computer graphics [81]. CitySim and its predecessor SunTool implement a Simplified Radiosity Algorithm (SRA) [82], [83] which is suitable for predicting short and long-wave radiation on large urban models.

In Table 3, we display the features of solar radiation simulation engines used in urban building energy models. Some solar radiation simulation engines are used by multiple tools, and, conversely, some tools allow the user to choose among different solar radiation engines. Compared to solar radiation studies, the resolution of the discretization of surfaces in sensor points is low, with usually one sensor point considered per each semantic surface (e.g., a wall), while EnergyPlus considers one sensor per each vertex of the surface. In viewshed analysis and backward raytracing the sensor points are independent from the obstructing urban geometry, while in radiosity algorithms view factors have to be calculated on all mesh faces composing the 3D model. With regards to the sky model, most engines have implemented state-of-the-art anisotropic sky models such as the Perez models [84], [85]. All engines include a sample of the actual sun positions, which are usually computed for all daylight hours only for some representative days. Daysim (in its default daylight coefficient method), for example, includes 65 direct sun positions for latitudes around 45°, calculated on all full-hour solar times for the 21st day of each 4th month when the sun is above the horizon.

It is interesting to note that EnergyPlus was conceived as a building energy modeling simulation tool, but it is currently used also in UBEM. This is particularly due to its flexible parameters with regards to the solar radiation models, which can be set to include full inter-reflections of external and indoor surfaces. Similarly, also Daysim was conceived and is still primarily used for climate-based daylight modeling, while it has been adapted also for urban solar radiation studies and integrated in the later versions of CEA.

Table 3. Features of solar radiation models implemented in common UBEM engines.

Engine	*Supported tools*	*Wave*	*Sensor per surface*	*Method*	*Inter-reflections*	*Sun positions*	*Sky*
EnergyPlus [86]	[87], CityBES [88]	Short-Long	1 per vertex	Raytracing	Single, diffuse and specular	Hourly, every 18 days	Anisotropic [85]
SRA [82], [83]	CitySim, SimStadt[1]	Short-Long	1 per mesh face	Radiosity	Multiple, diffuse-only	Hourly, every month	145 Tregenza patches; Anisotropic based on [84]
Daysim [80]	CEA	Short	Can be set by the user	Raytracing	Multiple	Hourly, every 4 months	145 Tregenza patches; anisotropic [84]
SolarAnalyst [89]	CEA	Short	N/A	Viewshed	No	Half-hourly, every month	16x16 sectors; Isotropic

2.2.2 UBEM simulation engine

The urban building energy modeling simulation engine is the main core of an UBEM, which takes the responsibility in translating all the input parameters into mathematical equations, generates the model and performs the simulation. Here, more details on UBEM simulation engines and their components are included.

2.2.2.1 Thermal models

The thermal behavior of a building can be described by the numerical equations of heat and mass flows inside, through, and outside of the building envelope, referred to as the thermal model of the building. Thermal modeling in the field of UBEM is associated with complexity and diversity. However, in terms of modeling strategy, all the previously developed UBEMs used either of two approaches: some relied on existing computer-based BEM tools and used them as the main core of their UBEM, while the others developed their own tailor-made thermal modeling algorithms. These two approaches are described below.

- Computer-based BEM modeling tools

There no doubt about the maturity of BEM and the application of computational simulation tools in modeling, analysis and optimization of individual building energy systems [90]. Therefore, one of the most common approaches in development of UBEM simulation engines is to take full advantage of the already established BEM tools. However, not every tool is capable of being coupled with the automated UBEM procedure. Among the available tools, EnergyPlus [86], IDA ICE [91] and TRNSYS [92], prove to be the most feasible ones in an UBEM simulation engine [93]. Hong et al. [88] and Reinhart et al. [94] based their models upon the energy simulation in EnergyPlus, and Nageler et al. [44] developed an UBEM using the co-simulation of IDA ICE for building models, TRNSYS for the energy supply units and Dymola/Modelica for district heating networks [44]. However, despite proven application of such tools in UBEM, most of the studies agree on increased complexity of the model. Thus, to facilitate the modeling and calculation procedure, simplified methodologies, particularly for shading and adjacency, are suggested [95]. However, some other studies approached this in a different way and instead developed their own tailor-made models.

- Tailor-made thermal modeling algorithms

A tailor-made simulation engine is a refinement of numerical thermal models based on building construction and material information, as well as losses and gains. In the context of UBEM, modeling techniques based on the electrical analogy of heat transfer, i.e., resistance and capacitance (R-C), are known for their popularity. Kämpt and Robinson [96] conducted a comparative study on their already developed R-C model for a range of building configurations and concluded on the reliability and applicability of their R-C techniques for large-scale applications. Accordingly, the urban simulation tool Citysim [64] was developed in the same way. The tool city energy analyst (CEA), developed by Fonseca and Schlueter [97], was also developed around the R-C network suggested by the European Committee for Standardization on calculation of heating and cooling load in buildings. The other common category of tailor-made models rely on minimizing the number of required parameters and equations of the thermal models of buildings by means of reduction algorithms. These "model reduction methods" have been used in some of the notable studies. Kim et al. [98] derived a detailed Modelica-based model out of simplified physical models of buildings. The simplification was conducted in a preprocessing stage using reduction algorithms. The Citysim [64] precursor, Suntool [65], also applied a reduction method, known as a grey-box model [26], to develop thermal models of buildings in the urban context.

2.2.2.2 Zoning configuration

In the simplest methodology, the thermal behavior of the building is modeled in one single zone for each building archetype [24], [65]. Relying on a simple heat balance model for the whole building, the computation time is considerably reduced in the single-zone models, while the accuracy of the results is adversely affected [99]. As the single-zone models are unable to completely capture the effects of the urban context and microclimate on the heat performance of the buildings, and as they fail to represent multi-use buildings, multi-zone thermal models are suggested instead [95], [100].

In multi-zone models, each building archetype is comprised of several thermal zones. There are different alternative zoning configurations, some of which follow the ASHRAE 90.1 Appendix G [101] guidelines for envelope settings and zoning configurations in buildings. Some examples of different multi-zone configurations are presented and compared by Smith [102]. However, in the context of UBEM, attention is paid mainly to two alternatives. In the first method, each building includes one thermal zone per each floor, as in [36]. In the other one [95], as in the ASHRAE guidelines, each floor is divided into five zones: one core zone and four perimeter zones. Although developing multi-zone models for building archetypes is feasible, in practice, detailed exploration of the buildings is a trade-off between the complexity of the model and the accuracy of the results. Therefore, for the sake of simplicity, each uniform-use building can be divided into three sections. The ground floor and the top floor are modeled explicitly while the intermediate floors are modeled as one floor which is later scaled up to the whole set of floors after the simulation is done as in [95]. The separation of the buildings in three sections and using floor or zone multipliers accelerate the simulation process at the same time as it yields accurate results. The most common zoning configurations in UBEM are illustrated in Figure 2.

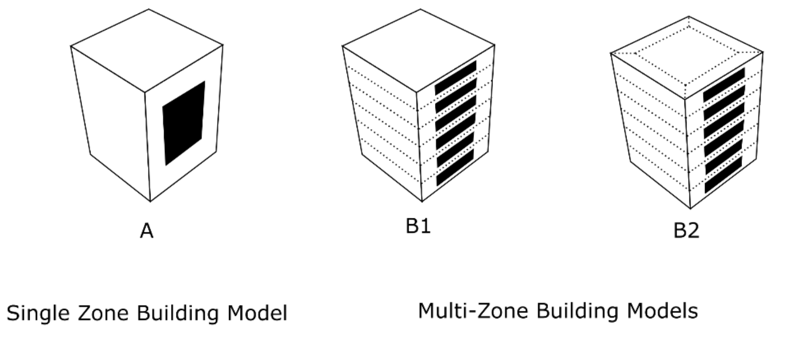

Figure 2. Zoning configurations: A. Single-zone model. B1. Multi-zone model, one zone per each floor and B2. Multi-zone model, five zones per each floor.

Regardless of the zoning configuration, to obtain the aggregated energy demand of the city, the thermal models of the buildings can be generated either for the chosen archetypes or for each individual building in the city. If only the representative archetypes are modeled, the simulation results have to be scaled up. The upscaling of the results from archetypes to clusters and the whole city is done by means of multiplication factors; for example, Heiple et al. [70] used the floor weighted area in order to obtain the city-wide energy demand while Caputo et al. [74] multiplied the results by the number of existing buildings in the identified building groups. On the other hand, generation of thermal zone models for all the buildings can be done using 3D city models of the whole city [87]. With a 3D building model of the whole city, influences of the urban context and solar radiation on the energy performance of the buildings can be taken into consideration. However, converting 3D models of a large number of buildings to thermal models is not a straightforward process, and automated zoning algorithms are required. With the focus on the auto zoning process, Dogan et al. [100], [103] recommend an automated shoebox model in creating multi-zone models from the 3D building models. The shoe-box algorithms automatically discretize the buildings and abstract them into one or several perimeter and core models that are placed in representative locations within the building. Moreover, the buildings are clustered based on their identical geometries. The energy model of each shoebox then extrapolated to the whole building. With a different method, Chen and Hong [95] developed an automatic pixel-based algorithm to divide 2D building polygons into 4 perimeters and a core. They used the pixels and color codes to separate the indoor space into representative thermal zones.

2.2.2.3 Energy simulation and validation

As discussed in the previous sections, the thermal behavior of a building is described by single or multi-zone thermal models, and the thermal models are defined by numerical equations of heat and mass transfer through BEM tools or tailor-made models, referred to as an UBEM simulation engine.

The UBEM engines perform the simulation procedure either using quasi-steady-state methods and calculate the heat balance over a sufficiently long period (i.e., month or year)[78] [104], or use a dynamic approach and produce results on short time steps (e.g. hourly) [94]. Although the thermal mass of buildings is ignored in the steady-state methods, the approximations are good enough to be used for aggregated energy analysis. In dynamic building energy simulations all energy phenomena in, around and through the building envelope are captured, not only for annual but also for hourly or even sub-hourly time steps. Accurate calculation of the energy performance of buildings considerably improves the results compared to the quasi-steady state methods and, consequently, the increased complexity of the method leads to an incremental rise in computation time. [105]

Most of the previous studies underline the extensive computation time required for dynamic simulation of UBEMs, but it is noted that only a few have presented the corresponding values. The paper introducing the very first UBEM tool, known as Suntool [65], is one of the few studies that clearly discussed the calculation time, including both pre-processing and energy simulation. By conducting a parametric study of the simulation time as a function of number of buildings and for two building types, it was proven that by increasing the numbers of buildings by 50%, i.e., from 100 buildings to 200, the simulation time for their tool could increase by roughly 50% for mixed-use buildings (one storey office and six storey apartments) and slightly more than 50% for residential buildings (two storey detached houses).

As has been mentioned before, to reach a certain level of accuracy while keeping the model complexity down, alternative strategies were applied by model developers; for example, Chen and Hong [95] made use of floor multipliers in energy calculation of multi-storey buildings, and Dogan and Reinhart [100] abstracted the thermal model generation by shoebox algorithms. To evaluate the simplification methods, the simulated energy demand is normally compared with measured data and validated for different spatiotemporal resolutions.

In UBEM, validation of the results is critical, not only because of simplifications made in the simulation procedure but also because of the models' dependency on building archetypes in the absence of detailed building stock information. Abstracting all buildings to a few representative archetypes misrepresents the real diversity of buildings and usage patterns. Therefore, the reliability of the results and their applicability in sustainable urban development are highly dependent on validation of the model against aggregated measurement data. In most of the UBEM workflows, the results were compared with energy use and fuel consumption on an aggregated level.

In [36], hourly and annual results from a UBEM tool were validated against the energy use and fuel consumption of the city of Boston and showed 5-20% averaged deviations for each zip code. Remmen et al. [66] compared the simulated results from their developed tool known as TEASER, not only for each archetype and on the building level, but also for the district level. When comparing the results for the year 2013, they found a 5.6% annual discrepancy on the district level.

Table 4. Summary of key properties of some of the notable UBEM studies.

Study	*Case study*		*Methodology*			*Temporal resolution*
	Location	Archetype	Development	Simulation core	Results and validation	
Robinson et al. [65] **SUNtool**	Olympic Village, Greece	Two archetypes use/type. (two-storey detached residential building and seven-storey mixed use apartment).	Buildings' form by Microsoft DirectX (rendering engine for Java 3D). Presentation of the results with XML files.	- Developed in Java. - Four classes of the Model: thermal, stochastic, plant and microclimate. - Application of grey-box reduction factor models for thermal modeling of buildings.	10 minutes of simulation time for 100 single-zone residential buildings and around 18 minutes for 100 multi-zones buildings of mixed use.	Hour
Heiple et al. [70]	Houston, US	30 archetypes of use (residential, commercial), climate (HDD and CDD)[1], (age), and primary heating.	Use of parcel GIS data. Iterative calibration of individual simulation results within 10% of measurements.	- Modeling the prototype buildings in DOE-2 in conjunction with eQUEST.	2.5% and -1.3% deviation from disaggregated state energy use intensity (EUI) for Jan and Aug respectively (as examples).	Hour
Robinson et al. [7], Kämpf and Robinson [8] **CitySIM**	District of Matthäus, Basel, Switzerland	Group of 26 individual shelters belonging to different years.	Creation of an XML file from the graphical user interface which comprises the geometrical and non-geometrical characterization of the urban scene.	- Radiation, thermal, occupancy and plant and equipment modeling. - Integration of models in one solver. - Use of R-C network to generate thermal models of buildings.	The results were aligned with previous evaluations of the algorithms to propose decent results.	Hour
Reinhart et al. [94] **UMI**	-	-	Massing model of the neighbor or city including the buildings, vegetation and shading objects by CAD modeling platform, Rhinoceros.	- Thermal modeling of the multi-zone buildings in Energy Plus. - Additional models for daylighting, outdoor comfort and walkability.	-	-
Nouvel et al. [104], [107] **SimStadt**	Neighborhood of Ludwigsburg, Germany	14000 buildings categorized based on different ages and types.	3D model of city from CityGML (LOD1 and LOD2).	- Quasi-static monthly energy balance (ISO 13790) for single-zone building models.	2% to 31% deviation from actual consumption (depends on availability of data).	Month

[1] Heating degree day (HDD) and cooling degree day (CDD)

Study	Case study		Methodology			Temporal resolution
	Location	Archetype	Development	Simulation Core	Results and Validation	
Tuominen et al. [108] **REMA model**	Finland	12 use/type/age. Detached houses, apartments, commercial buildings and holiday homes.	Excel-based tool to calculate and accumulate the thermal energy demand based on building archetypes.	- Dynamic energy simulation of archetype in IDA ICE. - Cumulative energy calculation in the model separately.	National energy analysis and future development scenarios.	Year
Reiderer et al. [109] and Perez et al. [110] **DIMOSIM**	-	-	-	- Implementation of single zone and multi-zone R-C thermal models in MATLAB. - Integration with stochastic occupancy models and solar masks, local and central energy generators and thermal distribution system.	Validation according to ASHRAE guideline 140. 45.6 seconds computation time for 700 simple thermal modeling.	Hour (minute is possible)
Cerezo et al. [36]	Boston, US	83541 buildings. 52 use/age. Including all building types.	Combination of building footprint and GIS database to create massing models of buildings.	- Auto generation of multi zone thermal models by UMI tool.	5% to 20% discrepancy in average EUI.	Hour
Fonseca et al. [97], [111] **CEA**	City of Zug, Switzerland	1392 buildings. 172 use/age/active year.	Developed in Python and built as extension of ArcGIS. Four-dimensional visualization. Variables grouped in 5 databases.	- Hybrid model including statistical analysis of annual regional energy data - Physical computation of hourly energy demand from R-C models according to European committee for standardization (CEN) guidelines.	The annual energy service error reported as 1% to 19% on district-level, while calculated as 4% to 66% on building level.	Hour
Buffat et al. [78]	St.Gallen and alpine village called Zernez, Switzerland	1845 +120 buildings 21 use/age. Only residential buildings.	Massing models from building footprints of cadastral surveys combined with GIS datasets and novel digital elevation model from LiDAR point clouds.	- Space heat demand model derived from SIA 380/1 norm.	Median simulated heat demand deviated less from measured data in multi-family houses and mixed residential buildings than in single-family houses (over-estimated). Existence of some systematic errors.	30 min

Study	*Case study*		*Methodology*			*Temporal resolution*
	Location	Archetype	Development	Simulation Core	Results and Validation	
Hong et al. [88] and Chen et al. [112] **CityBES**	Downtown San Francisco, US	540 small and medium-sized offices and retail buildings + 1087 shading buildings.	CityGML data sets processed to determine the shading/adjacent buildings as well as weather file for each building.	- Pixel-based auto zoning algorithm targeting the ASHREA multi-zone buildings. - EnergyPlus integrated with Open studio development kit. - Integrated energy conservation measures scenarios.	Pattern-based calibration approach. 10 minutes simulation time is required for annual simulation with 5 minutes time step.	-
Nageler et al [44], [113]	Semi-virtual case study of Graz West, Austria	1561 buildings and a new development area in 18 sub-districts and 83 buildings per model.	Existing building geometry acquired from integration of buildings' ground plan from GIS and buildings' height from laser scanning data. A plus shaped replacement cubature with 75 m length and the derived height from framework plans and glazing ratio of 0.35%	- Co-simulation platform (BCVTB) framework of IDA ICE for buildings' models, TRNSYS for energy supply unit and Dymola/Modelica for district heating network. - Identification of thermal zones according to building use and up to three zones for existing buildings.	Computational time 2 houtr per model. Validation of model for 4 types of buildings in the case study: the existing buildings, the replacement cubature derived from the framework plan, buildings under planning, and buildings not yet planned.	15 minutes
Remmen et al. [66] **TEASER**	Belgium Germany Bad Godesberg, Bonn, Germany	24 buildings with 8 different types (year/use). 200 buildings (offices and laboratories). Urban scale with 2897 residential and office buildings.	Building characterization from CityGML and German building stock datasets	- Development of the Reduced Thermal Network model by Modelica AixLib and IEA-EBC Annex 60 library.	The simulation methodology almost agreed with the calculation of the annual heat demand (only 5.6% discrepancy reported) for the case of future developments scenarios for the neighborhood.	-
Wang et al. [114] **CESAR**	Urban and sub-urban parts of Zürich and village of Zernez, Switzerland	227 + 100 + 114 multi- and single family houses. 7 age groups.	2.5D GeoData of Swiss buildings processed in ArcGIS.	- Automated building-by-building energy modeling in EnergyPlus. - Accounting for multi-zone buildings and shading buildings. - Retrofitting models for 5 periods to the year 2050.	Accurate heating demand calculation at district level (-1% deviation with annual measurements)	Hour

2.3 Databases and data visualization

UBEM is usually based on large datasets with a high resolution both spatially and temporally, containing, for example, high-resolution 3D geometry and extensive time series of simulated energy values. For this reason, different computationally efficient solutions to manage these data are needed, including storage, processing and visualization. In terms of data storage, there are both relational databases and file-based systems. Data interoperability between the different stakeholders using UBEM is also a crucial functionality for which standardized formats and platforms have been developed. [115]

The most popular data format is based on the Open Geospatial Consortium (OGC) standard CityGML. The only alternative format, INSPIRE, partially based on CityGML, is conceived for a larger granularity and is less flexible with regards to energy applications [35]. CityGML is an XML-based structure designed to describe complex urban geometries such as the one presented in Section 2.1.1. CityGML can be seen as the city-scale counterpart of Building Information Modeling (BIM) formats such as IFC and gbXML and some works focus, in fact, on lossless conversion between these formats, e.g., from IFC to CityGML [116].

CityGML presents several Application Domain Extensions (ADEs) that are used to enrich the 3D city model and to model user-defined objects and attributes [117]. According to the review by Biljecki et al. [117], three ADEs have been used in UBEM applications, two of them being designed more specifically for energy efficiency projects. The Energy ADE developed by Agugiaro et al. [115] is a comprehensive ADE that targets many energy applications in buildings. It can be considered the city-scale equivalent of the BIM format gbXML, which was conceived to share information between building energy models. It should be noted that the CityGML Energy ADE is intended to describe the building physics, occupant behavior, construction and materials, and energy systems parameters to be used in building performance simulation but also for storing the calculated energy demand values. It is complementary to the Utility Network ADE [118], which was developed to describe energy networks between buildings.

In order to overcome the limitations of file-based databases, which are unsuitable for large 3D city models, 3DCityDB [119] provides an importer from CityGML to spatial relational database management systems (SRDBMSs) such as ORACLE Spatial and PostgreSQL/PostGIS. SRDBMS systems are supported by most GIS systems and other ETL (Extract, Transform, Load) tools. At the current development status, 3DCityDB does not support generic ADEs. However, the Energy ADE has a database implementation that is compatible with 3DCityDB.

3D city models have many visualization-oriented applications [32]. Despite the fact that the analysis of energy potential is not linked with the visualization features, the results are often communicated through the use of interactive 3D interfaces. For these reasons, 3DCityDB exports the 3D city model in some typical visualization-oriented formats such as KML and Collada. It is also integrated with CesiumJS [120], a popular Virtual Globe Platform that allows web-based visualization and interaction with 3D city models. Other tools use GIS-embedded 3D visualization capabilities [40] or rely on KML files to exchange information with other popular 3D mapping tools such as GoogleEarth [37].

Overall, we can distinguish between two main visualization strategies for the results of UBEM:

- False-color visualization of the 3D geometry, in which the color usually indicates the building energy demand or other energy-related indicators as, e.g., in [104].
- Heat maps showing the spatial distribution of the energy demand across a city by resampling the data to a grid as, e.g., in [36], [37].

It should be noted that the two strategies above can be implemented in either 3D or 2D, but the 3D version does not substantially improve the communication of the results compared to the 2D one, unless a finer spatial granularity than whole buildings is implemented (e.g., heating demand for each floor).

We can also consider UBEMs that target more specifically the neighborhood scale and urban design applications. In this case, some works have focused on visualization solutions oriented to computer graphics and 3D modeling, such as Rhinoceros. This is the case of the UMI tool [94], but also the City Energy Analyst (CEA) [111] is developing support for this interface in order to bridge the gap between UBEM and urban/building designers. In Table 5 the data management and visualization solutions of some notable UBEM studies are presented.

Table 5. Data management and visualization solutions of some notable UBEM studies.

Tool/study	*Platform*	*Format*	*Data format(s)*	*Visualization*
Cerezo Davila et al. [36]	Rhinoceros	Database, File	N/A	N/A
Peronato [37]	Rhinoceros	File	Tabular text, KML	GoogleEarth
Fonseca et al. [40]	ArcGIS	File	SHP files	ArcScene
Weiler et al. [41]	...	Relational database (3DCityDB)	CityGML	CesiumJS

3 Future prospects of UBEM

In the context of UBEM, buildings play a central role in the final energy demand estimations. However, buildings are not the only contributors; other elements of the urban environment, such as urban climate and urban energy systems, can influence the urban energy demand or be influenced by it. Although these urban models have not escaped the attention of the model developers, not all the UBEMs have incorporated them. Thus, in this section, an overview of these models and their potential integration with UBEM is provided.

3.1 Integration with urban climate models

The urban landscape and activities create a local climate different from the surrounding rural environment. The ambient temperature in cities is higher, a phenomenon referred to as the urban heat island (UHI) effect, which is due to a set of features; the local wind pattern is disturbed by the thermophysical and geometrical characteristics of the buildings, and solar radiation is reduced as a result of the decreased sky view factor caused by buildings and other obstacles [121]. The results of previous studies prove that the thermal energy performance of buildings is strongly contingent upon the urban climate and the surrounding environment [122]. Therefore, to accurately evaluate the heating and cooling demand of buildings, possible integration of urban climate models with UBEM has received increased attention in recent years. The urban climate can be modeled on different spatial scales, from mesoscale to micro-scale.

Meso-scale meteorological models are weather forecasting methods that are combined with urban parametrization to predict the urban climate at high resolutions (around 0.2 -1 km) [123]. Parametrization is the process by which the important physical schemes that cannot be captured directly by the forecasting methods are determined for different spatial resolutions. The model resolution refers to the horizontal and vertical scales, which can be resolved by the numerical models for the area of interest [124]. Urban parameterization studies are divided into three main categories; slab models and two types of urban canopy models (UCMs), single-layer and multi-layer UCMs. In slab models, the thermal effect of the city on the atmosphere is determined using the modified heat capacity, thermal conductivity, surface albedo, roughness length and moisture availability for the urban surfaces and calculating the vertical energy and momentum flux to the atmosphere. UCMs use climatic parameters such as radiation, heat, moisture and momentum to estimate the energy flux from 3-dimensional urban surfaces such as walls, roofs and roads, to the atmosphere. The main difference between single and multi-layer UCMs lies in the representation of the vertical structure. In single-layer UCMs, the energy flux is averaged over the building height, while in multi-layer UCMs it is obtained from many sub-layers, which leads to higher resolution as well as higher complexity in the model. Due to the relatively complete scheme, UCMs are the most commonly applied models for simple energy modeling, particularly for simulation of UHI effects. [124]–[127]

However, due to the large spatial resolution of the mesoscale models, they are unable to capture the heat and fluid dynamics in and around buildings. Moreover, the mesoscale models are complex to develop and expensive to compute. Thus, for a detailed model at meter-scale resolution, the micro-scale urban climate models, referred to as microclimate models, have been introduced [11], [128].

The microclimate models encompass different concepts to determine the interdependence of buildings and the urban local climate. The main principle is to use the climatic components such as ambient temperature, humidity, and local wind, as well as the solar and longwave radiation, and the buildings' form and texture, to evaluate the local climate and the thermal behavior within the building blocks [11], [129]. At the building level, the knowledge about microclimate modeling is broad and suggested methods are proven as in the tools SOLENE-microclimate

[130], and UMsim [129]. However, at city-level modeling, complexity of the urban structure and calculation of the ground and surface temperature pose challenges to the modeling procedure [29], [129]. To cope with these, different approaches in integral modeling of microclimatic components such as radiation and convection have been assessed. As discussed in Section 2.2.1.2, estimation of the radiation component of the microclimate in UBEM is attainable. The convective heat transfer, on the other hand, is a component of local air temperature and urban wind profile, which are normally estimated by the flow models. In most urban microclimate models, the flow models are resolved by computational fluid dynamic (CFD) methods [131], which are capable of being integrated into the BEM studies. However, due to the inherent complexity of CFD, they are not considered as a promising option for inclusion in UBEM. Therefore, the number of UBEM studies considering integration of CFD with city-scale building models is negligible, and most of previous workflows ignored its influences on building energy performance.

3.2 Integration with urban energy system models

As has been discussed, buildings are the main components of urban energy studies, and their influence on urban energy flows is both on the demand and production, i.e., in the case of on-site generation of heat and electricity. When evaluating the energy performance of buildings on the urban-scale it is also important to consider which impacts their consumption and generation patterns have on the energy infrastructure that they are connected to. Extending the analysis of urban energy systems beyond the buildings requires including models of local energy utilities and energy distribution systems. District/urban energy system models is a well-developed field and the number of articles published in this area is considerable. Some of the available approaches, methods and tools for district-scale energy system modeling were summarized in a literature study by Allergrini et al. [14].

A more comprehensive definition of urban energy system models has been provided in recent research. There, an urban energy system is defined as "a formal system that represents the combined process of acquiring and using energy to satisfy the energy service demands of a given urban area" [27]. Most of the UBEMs developed so far are limited to the demand-side. However, some UBEMs could be recognized as urban energy system models according to the definition above, including not only the buildings but also other parts of the energy systems, such as generation and distribution systems. CitySim [64] integrated the calculations on HVAC systems with the district energy conversion system (ECS), comprised of different technologies of generating and storing heat and electricity to meet the buildings' needs. For the sake of simplicity, these technologies were modeled based on performance curves with unlimited capacity in providing the energy. Nageler et al. [44] integrated the UBEM with two other models, one for distribution systems modeled in Dymola/Modelica and one for the energy supply units in TRNSYS, using the co-simulation interface for running simulations simultaneously in these software.

Of all the surveyed models, CEA [111] provides the most far-reaching combination of a UBEM with urban energy models. The model consists of several modules. A demand module includes the building energy simulations and determines the end-use heating, cooling and electricity demand, and a supply system optimization module includes thermal networks and optimized distribution systems. Additionally, alternative energy technologies are modeled in another module including techno-economic models of several production, storage and distribution units. This allows CEA to be used for optimization and analysis of complete urban energy systems.

3.3 Integration with thermal comfort models

Thermal comfort of building occupants is the main factor influencing energy demand in buildings, yet it has been given little consideration in UBEM studies. Braulio-Gonzalo et al. [132] included the assessment of discomfort hours, while these were calculated on the archetypes and later extrapolated at the larger scale through statistical modeling. Some engineering bottom-up UBEM studies mention the use of set-points for indoor air temperature [40], [87] and moisture content [40] to control the simulated HVAC system. The application of comfort models controlling, for example, the operative temperature or the evaluation of discomfort situations in engineering-modeled buildings seem in general not appropriate for the level of detail of engineering bottom-up models, in particular, due to the limited information regarding radiant sources and airflow for indoor spaces.

Nevertheless, UBEM opens new perspectives on simulation of thermal comfort and heat stress in outdoor spaces. Extensive literature reviews have been conducted in the field, in particular on the models for outdoor thermal comfort [133], [134]. The Universal Thermal Climate Index (UTCI) [135] is one of the most recent outdoor comfort models and has been applied to all climates [134].

The growing interest in outdoor comfort is not limited to hot climates, but also in cities at temperate climates suffering from the Urban Heat Island effect [136] or evaluation of discomfort due to cold [137]. Moreover, outdoor comfort is one of the factors influencing outdoor activities [133], even if it was shown that in some cases people tend to voluntarily choose uncomfortable situations, such as sunlight in a park [138]. More specifically, the willingness to walk or cycle is mentioned as influenced by favorable outdoor comfort conditions [137], [139], [140].

Some UBEM tools or their simulation engines are used as support for outdoor comfort studies and have therefore a double application potential. Naboni et al. [141] present a review of tools used for predicting the Mean Radiant Temperature (MRT) applied at the urban scale, some of which are based on UBEM simulation engines, such as CitySim and EnergyPlus. A comparison between the features of the two engines can be found in a work by Miller et al. [142]. Input parameters for MRT models such as wind speed, airspeed, relative humidity, long- and short solar radiation are also needed for (urban) building energy modeling. Moreover, long-wave radiation emitted by buildings should be also included in the energy balance for MRT, whence the possible synergies between UBEM and outdoor comfort studies.

3.4 Integration with urban mobility models

The human-related effects on energy consumption in buildings has been one of the most studied topics in recent years. There are different models developed for occupants' presence and action on building-level as in [61], [62] to present close-to-reality estimations on occupants-related energy demand. However, only a few studies are accounting for the urban-level occupants' behavior in buildings. For example, in a recent study done by Mohammadi and Tylor [143], the spatial impacts of human behavior on the energy demand of buildings were evaluated using predictions on human mobility and urban mobility-based models. To predict the spatiotemporal dependencies between human mobility and energy demand in buildings, positional records of the individuals and the residential electricity use were analyzed over a course month for the city of Chicago. As a result, they developed a multivariate autoregressive model to predict the monthly electricity consumption with respect to the urban-level human behavior. Focusing on this dependency, Robinson et al. [64], developed an activity-based tool based on spatial information on individual transportation and integrated that to their UBEM, CitySim, as a pre-processing step. This mobility tool, known as MATSim-T, was designed to exchange the results on arrival and departure time of occupants with the main model and alter the occupancy model accordingly. Thus, considering the proven correlations between human mobility patterns with energy demand in buildings and possible integration of UBEM with mobility models, the urban mobility models are further discussed here.

Mobility is the principal part of the 'urban metabolism' [144], which relates to the movement of people in the urban areas. In general, mobility models can be recognized by two scales, namely, individual motilities and general population flows [145]. Individual mobility models taking a certain level of uncertainty into account regarding the freedom of action in individuals leading to a degree of randomness in the patterns of travel. Nevertheless, several studies have shown that individual paths are far from randomness while individual activities have more discipline and easier to predict, which can be used to predict individual motilities. Application of individual mobility models have been widely studied and used in geography, transport and urban planning [146], [147].

The population level models can be categorized into four main groups including gravity models, intervening opportunities models, radiation model, and transportation models. Gravity models are commonly used mathematical model for predicting interplay between two or more locations to estimate the flows, the independent factors for prediction of population, communication size, amount of citation, and distance [148]–[150]. The gravity model mainly used many types of mobility network such as shipments [151] highway [152] travelers[153]–[155].

The first intervening opportunities model was introduced by Stouffer [156]. He prepared a conceptual and formal model for human mobility and asserted that the number of cumulative between the origin and the destination is the key point in migration. The model is used to estimate the migration patterns between services and residences.

The extended radiation model applies a conditional probability approach to accomplish a trip between two separate locations by considering the spatial distribution of opportunities. In the original version of the radiation model, the number of opportunities is approximated by the population, but the total inflows to each destination can be used too [155]–[157]. The main advantage of the radiation model compared with other spatial interaction models is the absence of a parameter to calibrate the observed data. However, this advantage limits the model to be robust against the possible changes in the spatial scale [155]–[158]. To overcome this drawback, a radiation model with opportunities' selection [159] as well as an extended radiation model [160] have been proposed. In the extended version, according to the spatial distribution of opportunities, the conditional probability to perform a trip between two locations is ensue from the survival analysis framework. The number of chances is approximated by crowd in the based prescription of the radiation model while the total number of internal flows to each final location can be used [155]–[157]. The privilege of this model to another one is the lack of using a parameter to calibrate the

observed data. Furthermore, this privilege demonstrates a restriction on the model to be not sturdy enough against the shift in the spatial scale [155]–[158].
As discussed, temporal fluctuations of energy demand in buildings are driven by human activities and spatial mobility patterns. On the other hand, the urban-level human behavior is possible to predict using human mobility models. Thus, possible integration of urban mobility models with UBEMs for predicting the urban occupancies and also net-zero transportation, e.g., electric vehicle charging, is one of the main opportunities for improving urban energy studies.

4 Discussion and suggestions for further research

The review of the state-of-the-art shows that the research on urban building energy modeling is still growing in volume. Although the hybrid modeling raises the possibilities and facilitates the shortcomings of only engineering (physical) models, based on the survey of previous research, it is argued that there are still some noticeable gaps in hybrid UBEM that have to be further studied:

- Archetype development using data mining and machine learning techniques,

As mentioned previously, archetype development is one of the biggest challenges in UBEM. There is a great deal of uncertainty about the building stock due to, i.e., lack of availability of good quality data, which makes it hard to proceed with building archetypes. On the other hand, abstracting all the buildings of a city in a few classes, and sampling the characteristics of each class in one building archetype may not cover the diversity of buildings. Even though various known models have used a deterministic classification of the buildings, the results show a large deviation from measurement data. This underlines that the sampling criteria in deterministic methods are not inclusive enough, particularly when occupants' behavior is discussed. The probabilistic nature of the occupancy and energy use in the buildings, as well as the uncertainty in archetype development have sparked a discussion on the importance of data-analysis in UBEM and hybrid modeling. As was presented, some of the most recent studies used supervised and unsupervised machine learning techniques in developing building archetypes. Yet, no proven method has been established. However, most of these studies agree on iterative calibration of the archetypes by Bayesian statistics. This means that although the calibration methods are more generalized, there is still a need for further improvement of the archetype development process, particularly in classification and characterization methodologies. Machine learning algorithms are one of the promising approaches to this, even though their accuracy depends on extensive and high-quality sample data, which is hard to access.

- Improved computing power,

Most advancements in the area of UBEM are found in the process of thermal modeling and energy simulation of buildings. By taking full advantage of tailor-made algorithms of heat and mass transfer or using commercial energy simulation software as the core in the UBEM simulation engines, accurate energy calculations can be done. However, computation time is one of the greatest obstacles for large-scale energy simulation of buildings. To overcome this issue, different studies applied various approaches, ranging from very simple methods of upscaling results from archetypes to the whole city by means of multiplication factors, to advanced shoebox algorithms and building clustering for speeding up the building-by-building energy modeling. Parallel computing and cloud computing are the other alternatives in accelerating the energy simulation procedure. Improved computing power offers the possibility of faster simulation even for more complex models.

- Model validation,

While most of the studies present no estimation on the required computation time, others lack in validating their models against measurement data. As regards the level of uncertainty associated with modeling and simplification techniques, reliability of the UBEMs is strongly connected with validation of results. As not all the previous models were validated, their validity is difficult to judge.

Apart from the advancements in UBEM, the main future prospect of UBEM is deemed to be in integrated modeling and integration of the models with other urban models:

- Integration of UBEM with urban microclimate models,

As regards the direct influence of urban climate on the energy performance of buildings, association of UBEM with microclimate models was frequently argued for in previous works. Radiative exchange from and between buildings is a valuable piece of information that UBEM can provide to microclimate models that can be used, for example, for outdoor comfort studies. It can be argued that these already give a good understanding of the microclimate in many urban situations with reduced wind flow, while the greatest constraint is on outdoor wind flow models and their integration to (U)BEM studies. Despite the maturity of the field of CFD and its proven application in calculation of the energy and mass flows around the buildings, their complexity is a challenge. This leads to low scalability from building to district and city scale. However, by increasing the computation power and developing alternative microclimate models, the chance of integration of UBEM with full microclimate models is improved. Thus, urban climate models and their possible integration to UBEM should be surveyed.

- Urban occupancy and integration of UBEM with urban mobility models,

While most of the UBEMs have focused on the physical drivers of the urban energy flux, occupant-driven factors have been given less consideration. Realistic modeling of human activity on the building level is achieved through existing deterministic and stochastic models. Nonetheless, as for BEM, these models are not fully capable of being used in urban studies; hence, there is a need for occupancy models to be developed in urban occupancy models. Urban mobility models essentially account for human activities in both space and time. Although these models have been traditionally incorporated in urban transport planning, their integration into UBEM would potentially improve modeling of occupants' behavior (presence and activity) in buildings. Compared to the urban climate models, urban mobility models related to UBEMs have barely been discussed and except few, e.g., [27] and [64], no other practical result is found in the literature. Thus, given the importance of filling the research gap, the integration of the urban mobility models with UBEMs cannot be overlooked.

5 Conclusion

During the last decade, a large body of research has been conducted in the field of bottom-up engineering (physical) energy modeling of buildings known as urban building energy modeling. These models detail buildings and their energy systems to determine energy flows throughout cities and can be used for energy planning and city development. However, the survey of the state-of-the-art studies proves that these models cannot capture the variations in building physics as well as occupants' behavior in all their complexities and, thus, the modeling procedure needs to be combined with data-driven and probabilistic methods. Developed out of advantages of both engineering and statistical approaches, such hybrid models are considered to be promising methods in future UBEMs. Yet, no model is accurate unless it properly outlines the model uncertainties, calibrates the uncertain parameters, and validates the simulation results against measured data. While calibration techniques have found their way into UBEM, particularly in archetype development, most of the existing models are lacking in validation procedures.

Besides hybrid modeling, this review underlines the future significance of UBEM in integrated modeling, i.e., integration of UBEM with urban models such as climate, energy systems, thermal comfort and particularly with mobility models. While some of these models have been considered for further development and integration with UBEMs, almost no published research considers integration of spatiotemporal human activity patterns through urban mobility models, despite their importance for occupancy patterns in buildings. Thus, this review strongly emphasizes the necessity of integration of UBEM with urban mobility modeling to advance occupancy modeling and associated uncertainties in city-scale energy analysis of buildings.

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References

[1] H. Ritchie and M. Roser, "Urbanization," *Our World Data*, Jan. 2019, Accessed: 17-Jan-2019. [Online]. Available: https://ourworldindata.org/urbanization.
[2] "European Commission," *European Commission - European Commission*. https://ec.europa.eu/commission/index_en (accessed Oct. 23, 2018).
[3] S. Torabi Moghadam, C. Delmastro, S. P. Corgnati, and P. Lombardi, "Urban energy planning procedure for sustainable development in the built environment: A review of available spatial approaches," *J. Clean. Prod.*, vol. 165, pp. 811–827, Nov. 2017, doi: 10.1016/j.jclepro.2017.07.142.
[4] S. Cajot, M. Peter, J.-M. Bahu, A. Koch, and F. Maréchal, "Energy Planning in the Urban Context: Challenges and Perspectives," *Energy Procedia*, vol. 78, pp. 3366–3371, Nov. 2015, doi: 10.1016/j.egypro.2015.11.752.
[5] J. Rosales Carreón and E. Worrell, "Urban energy systems within the transition to sustainable development. A research agenda for urban metabolism," *Resour. Conserv. Recycl.*, vol. 132, pp. 258–266, May 2018, doi: 10.1016/j.resconrec.2017.08.004.
[6] S. N. G. Lo, B. Norton, and A. Mannis, "Domestic energy use and air quality; a case study of the city of Belfast," *Appl. Energy*, vol. 68, no. 1, pp. 1–18, Jan. 2001, doi: 10.1016/S0306-2619(00)00044-1.
[7] C. F. Reinhart and C. Cerezo Davila, "Urban building energy modeling – A review of a nascent field," *Build. Environ.*, vol. 97, pp. 196–202, Feb. 2016, doi: 10.1016/j.buildenv.2015.12.001.
[8] T. Hong *et al.*, "Commercial Building Energy Saver: An energy retrofit analysis toolkit," *Appl. Energy*, vol. 159, pp. 298–309, Dec. 2015, doi: 10.1016/j.apenergy.2015.09.002.
[9] V. S. K. V. Harish and A. Kumar, "A review on modeling and simulation of building energy systems," *Renew. Sustain. Energy Rev.*, vol. 56, pp. 1272–1292, Apr. 2016, doi: 10.1016/j.rser.2015.12.040.
[10] A. Gros, E. Bozonnet, C. Inard, and M. Musy, "Simulation tools to assess microclimate and building energy – A case study on the design of a new district," *Energy Build.*, vol. 114, pp. 112–122, Feb. 2016, doi: 10.1016/j.enbuild.2015.06.032.
[11] V. Dorer *et al.*, "MODELLING THE URBAN MICROCLIMATE AND ITS IMPACT ON THE ENERGY DEMAND OF BUILDINGS AND BUILDING CLUSTERS," in *Proc. 13th Conference of International Building Performance Simulation Association*, Accessed: 23-Oct-2018. [Online]. Available: https://pdfs.semanticscholar.org/9462/418a5feb9ad29968fbecff11eb0f2580d036.pdf.
[12] X. Zhang *et al.*, "A review of urban energy systems at building cluster level incorporating renewable-energy-source (RES) envelope solutions," *Appl. Energy*, vol. 230, pp. 1034–1056, Nov. 2018, doi: 10.1016/j.apenergy.2018.09.041.
[13] R. Ramírez-Villegas, O. Eriksson, and T. Olofsson, "Assessment of renovation measures for a dwelling area – Impacts on energy efficiency and building certification," *Build. Environ.*, vol. 97, pp. 26–33, Feb. 2016, doi: 10.1016/j.buildenv.2015.12.012.
[14] J. Allegrini, K. Orehounig, G. Mavromatidis, F. Ruesch, V. Dorer, and R. Evins, "A review of modelling approaches and tools for the simulation of district-scale energy systems," *Renew. Sustain. Energy Rev.*, vol. 52, pp. 1391–1404, Dec. 2015, doi: 10.1016/j.rser.2015.07.123.
[15] L. G. Swan and V. I. Ugursal, "Modeling of end-use energy consumption in the residential sector: A review of modeling techniques," *Renew. Sustain. Energy Rev.*, vol. 13, no. 8, pp. 1819–1835, Oct. 2009, doi: 10.1016/j.rser.2008.09.033.
[16] W. Li *et al.*, "Modeling urban building energy use: A review of modeling approaches and procedures," *Energy*, vol. 141, pp. 2445–2457, Dec. 2017, doi: 10.1016/j.energy.2017.11.071.
[17] M. Kavgic, A. Mavrogianni, D. Mumovic, A. Summerfield, Z. Stevanovic, and M. Djurovic-Petrovic, "A review of bottom-up building stock models for energy consumption in the residential sector," *Build. Environ.*, vol. 45, no. 7, pp. 1683–1697, Jul. 2010, doi: 10.1016/j.buildenv.2010.01.021.
[18] D. J. Sailor and L. Lu, "A top–down methodology for developing diurnal and seasonal anthropogenic heating profiles for urban areas," *Atmos. Environ.*, vol. 38, no. 17, pp. 2737–2748, Jun. 2004, doi: 10.1016/j.atmosenv.2004.01.034.
[19] J. Tornberg and L. Thuvander, "A GIS energy model for the building stock of Goteborg," in *Proc. 25th ESRI International User Conference*, p. 16.

[20] C. E. Kontokosta and C. Tull, “A data-driven predictive model of city-scale energy use in buildings,” *Appl. Energy*, vol. 197, pp. 303–317, Jul. 2017, doi: 10.1016/j.apenergy.2017.04.005.
[21] S. Torabi Moghadam, J. Toniolo, G. Mutani, and P. Lombardi, “A GIS-statistical approach for assessing built environment energy use at urban scale,” *Sustain. Cities Soc.*, vol. 37, pp. 70–84, Feb. 2018, doi: 10.1016/j.scs.2017.10.002.
[22] B. Howard, L. Parshall, J. Thompson, S. Hammer, J. Dickinson, and V. Modi, “Spatial distribution of urban building energy consumption by end use,” *Energy Build.*, vol. 45, pp. 141–151, Feb. 2012, doi: 10.1016/j.enbuild.2011.10.061.
[23] G. Mutani and V. Todeschi, “Space heating models at urban scale for buildings in the city of Turin (Italy),” *Energy Procedia*, vol. 122, pp. 841–846, Sep. 2017, doi: 10.1016/j.egypro.2017.07.445.
[24] R. Nouvel, A. Mastrucci, U. Leopold, O. Baume, V. Coors, and U. Eicker, “Combining GIS-based statistical and engineering urban heat consumption models: Towards a new framework for multi-scale policy support,” *Energy Build.*, vol. 107, pp. 204–212, Nov. 2015, doi: 10.1016/j.enbuild.2015.08.021.
[25] A. Nutkiewicz, Z. Yang, and R. K. Jain, “Data-driven Urban Energy Simulation (DUE-S): Integrating machine learning into an urban building energy simulation workflow,” *Energy Procedia*, vol. 142, pp. 2114–2119, Dec. 2017, doi: 10.1016/j.egypro.2017.12.614.
[26] F. Déqué, F. Ollivier, and A. Poblador, “Grey boxes used to represent buildings with a minimum number of geometric and thermal parameters,” *Energy Build.*, vol. 31, no. 1, pp. 29–35, Jan. 2000, doi: 10.1016/S0378-7788(98)00074-7.
[27] J. Keirstead, M. Jennings, and A. Sivakumar, “A review of urban energy system models: Approaches, challenges and opportunities,” *Renew. Sustain. Energy Rev.*, vol. 16, no. 6, pp. 3847–3866, Aug. 2012, doi: 10.1016/j.rser.2012.02.047.
[28] G. Happle, J. A. Fonseca, and A. Schlueter, “A review on occupant behavior in urban building energy models,” *Energy Build.*, vol. 174, pp. 276–292, Sep. 2018, doi: 10.1016/j.enbuild.2018.06.030.
[29] L. Frayssinet, L. Merlier, F. Kuznik, J.-L. Hubert, M. Milliez, and J.-J. Roux, “Modeling the heating and cooling energy demand of urban buildings at city scale,” *Renew. Sustain. Energy Rev.*, vol. 81, pp. 2318–2327, Jan. 2018, doi: 10.1016/j.rser.2017.06.040.
[30] M. Brøgger and K. B. Wittchen, “Estimating the energy-saving potential in national building stocks – A methodology review,” *Renew. Sustain. Energy Rev.*, vol. 82, pp. 1489–1496, Feb. 2018, doi: 10.1016/j.rser.2017.05.239.
[31] J. L. M. Hensen and R. Lamberts, *Building Performance Simulation for Design and Operation*. Routledge, 2012.
[32] F. Biljecki, J. Stoter, H. Ledoux, S. Zlatanova, and A. Çöltekin, “Applications of 3D City Models: State of the Art Review,” *ISPRS Int. J. Geo-Inf.*, vol. 4, no. 4, pp. 2842–2889, Dec. 2015, doi: 10.3390/ijgi4042842.
[33] OGC, “OGC City Geography Markup Language (CityGML) Encoding Standard - version 2.0.” Open Geospatial Consortium (OGC), 04-Apr-2012, [Online]. Available: https://portal.opengeospatial.org/files/?artifact_id=47842.
[34] R. Nouvel, M. Zirak, V. Coors, and U. Eicker, “The influence of data quality on urban heating demand modeling using 3D city models,” *Comput. Environ. Urban Syst.*, vol. 64, pp. 68–80, Jul. 2017, doi: 10.1016/j.compenvurbsys.2016.12.005.
[35] G. Agugiaro, J. Benner, P. Cipriano, and R. Nouvel, “The Energy Application Domain Extension for CityGML: enhancing interoperability for urban energy simulations,” *Open Geospatial Data Softw. Stand.*, vol. 3, no. 1, p. 2, Mar. 2018, doi: 10.1186/s40965-018-0042-y.
[36] C. Cerezo Davila, C. F. Reinhart, and J. L. Bemis, “Modeling Boston: A workflow for the efficient generation and maintenance of urban building energy models from existing geospatial datasets,” *Energy*, vol. 117, pp. 237–250, Dec. 2016, doi: 10.1016/j.energy.2016.10.057.
[37] G. Peronato, “Urban planning support based on the photovoltaic potential of buildings: a multi-scenario ranking system,” Ecole polytechnique fédérale de Lausanne, Lausanne, Switzerland, 2019.
[38] L. Romero Rodríguez, R. Nouvel, E. Duminil, and U. Eicker, “Setting intelligent city tiling strategies for urban shading simulations,” *Sol. Energy*, vol. 157, pp. 880–894, Nov. 2017, doi: 10.1016/j.solener.2017.09.017.
[39] D. Perez, “A framework to model and simulate the disaggregated energy flows supplying buildings in urban areas,” PhD thesis, Ecole polytechnique fédérale de Lausanne, 2014.
[40] J. A. Fonseca, T.-A. Nguyen, A. Schlueter, and F. Marechal, “City Energy Analyst (CEA): Integrated framework for analysis and optimization of building energy systems in neighborhoods and city districts,” *Energy Build.*, vol. 113, pp. 202–226, Feb. 2016, doi: 10.1016/j.enbuild.2015.11.055.
[41] V. Weiler, J. Stave, and U. Eicker, “Renewable Energy Generation Scenarios Using 3D Urban Modeling Tools—Methodology for Heat Pump and Co-Generation Systems with Case Study Application †,” *Energies*, vol. 12, no. 3, p. 403, Jan. 2019, doi: 10.3390/en12030403.

[42] J. Sokol, C. Cerezo Davila, and C. F. Reinhart, “Validation of a Bayesian-based method for defining residential archetypes in urban building energy models,” *Energy Build.*, vol. 134, pp. 11–24, Jan. 2017, doi: 10.1016/j.enbuild.2016.10.050.
[43] C. S. Monteiro, A. Pina, C. Cerezo, C. Reinhart, and P. Ferrão, “The Use of Multi-detail Building Archetypes in Urban Energy Modelling,” *Energy Procedia*, vol. 111, pp. 817–825, Mar. 2017, doi: 10.1016/j.egypro.2017.03.244.
[44] P. Nageler, G. Schweiger, H. Schranzhofer, T. Mach, R. Heimrath, and C. Hochenauer, “Novel method to simulate large-scale thermal city models,” *Energy*, vol. 157, pp. 633–646, Aug. 2018, doi: 10.1016/j.energy.2018.05.190.
[45] S. Heiple and D. J. Sailor, “Using building energy simulation and geospatial modeling techniques to determine high resolution building sector energy consumption profiles,” *Energy Build.*, vol. 40, no. 8, pp. 1426–1436, Jan. 2008, doi: 10.1016/j.enbuild.2008.01.005.
[46] C. Cerezo, J. Sokol, S. AlKhaled, C. Reinhart, A. Al-Mumin, and A. Hajiah, “Comparison of four building archetype characterization methods in urban building energy modeling (UBEM): A residential case study in Kuwait City,” *Energy Build.*, vol. 154, pp. 321–334, Nov. 2017, doi: 10.1016/j.enbuild.2017.08.029.
[47] G. Dall’O’, A. Galante, and M. Torri, “A methodology for the energy performance classification of residential building stock on an urban scale,” *Energy Build.*, vol. 48, pp. 211–219, May 2012, doi: 10.1016/j.enbuild.2012.01.034.
[48] A. A. Famuyibo, A. Duffy, and P. Strachan, “Developing archetypes for domestic dwellings—An Irish case study,” *Energy Build.*, vol. 50, pp. 150–157, Jul. 2012, doi: 10.1016/j.enbuild.2012.03.033.
[49] G. Tardioli, R. Kerrigan, M. Oates, J. O’Donnell, and D. P. Finn, “Identification of representative buildings and building groups in urban datasets using a novel pre-processing, classification, clustering and predictive modelling approach,” *Build. Environ.*, vol. 140, pp. 90–106, Aug. 2018, doi: 10.1016/j.buildenv.2018.05.035.
[50] A. K. Jain, M. N. Murty, and P. J. Flynn, “Data Clustering: A Review,” *ACM Comput Surv*, vol. 31, no. 3, pp. 264–323, Sep. 1999, doi: 10.1145/331499.331504.
[51] G. Chicco, R. Napoli, and F. Piglione, “Comparisons among clustering techniques for electricity customer classification,” *IEEE Trans. Power Syst.*, vol. 21, no. 2, pp. 933–940, May 2006, doi: 10.1109/TPWRS.2006.873122.
[52] A. K. Tanwar, E. Crisostomi, P. Ferraro, M. Raugi, M. Tucci, and G. Giunta, “Clustering analysis of the electrical load in european countries,” in *2015 International Joint Conference on Neural Networks (IJCNN)*, Killarney, Ireland, 2015, pp. 1–8, doi: 10.1109/IJCNN.2015.7280329.
[53] N. Ghiassi and A. Mahdavi, “Reductive bottom-up urban energy computing supported by multivariate cluster analysis,” *Energy Build.*, vol. 144, pp. 372–386, Jun. 2017, doi: 10.1016/j.enbuild.2017.03.004.
[54] A. Schaefer and E. Ghisi, “Method for obtaining reference buildings,” *Energy Build.*, vol. 128, pp. 660–672, Sep. 2016, doi: 10.1016/j.enbuild.2016.07.001.
[55] X. Li *et al.*, “Developing urban residential reference buildings using clustering analysis of satellite images,” *Energy Build.*, vol. 169, pp. 417–429, Jun. 2018, doi: 10.1016/j.enbuild.2018.03.064.
[56] R. A. Lara, F. Cappelletti, P. Romagnoni, and A. Gasparella, “Selection of Representative Buildings through Preliminary Cluster Analysis,” In *Proc. International high performance buildings conference*, p. 11, 2014.
[57] M. P. Guillaumet, P. Borges, M. Rosas-Casals, and O. Travesset-Baro, “BUILDING ARCHETYPES IN URBAN ENERGY MODELS. A COMPARATIVE CASE STUDY OF DETERMINISTIC AND STATISTICAL METHODS IN ANDORRA.,” in *Proc. uSIM18 Urban Energy Simulation*, p. 10.
[58] “IEE Project TABULA.” http://episcope.eu/iee-project/tabula/ (accessed Mar. 13, 2019).
[59] “Energy Efficiency Trends & Policies | ODYSSEE-MURE.” http://www.odyssee-mure.eu/ (accessed Apr. 09, 2019).
[60] “ENTRANZE : Welcome to ENTRANZE project page.” https://www.entranze.eu/ (accessed Apr. 09, 2019).
[61] J. Widén and E. Wäckelgård, “A high-resolution stochastic model of domestic activity patterns and electricity demand,” *Appl. Energy*, vol. 87, no. 6, pp. 1880–1892, Jun. 2010, doi: 10.1016/j.apenergy.2009.11.006.
[62] J. Widén, M. Lundh, I. Vassileva, E. Dahlquist, K. Ellegård, and E. Wäckelgård, “Constructing load profiles for household electricity and hot water from time-use data—Modelling approach and validation,” *Energy Build.*, vol. 41, no. 7, pp. 753–768, Jul. 2009, doi: 10.1016/j.enbuild.2009.02.013.
[63] J. Widén, A. M. Nilsson, and E. Wäckelgård, “A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand,” *Energy Build.*, vol. 41, no. 10, pp. 1001–1012, Oct. 2009, doi: 10.1016/j.enbuild.2009.05.002.
[64] D. Robinson *et al.*, “CITYSIM: COMPREHENSIVE MICRO-SIMULATION OF RESOURCE FLOWS FOR SUSTAINABLE URBAN PLANNING,” in *Proc. International IBPSA Conference*, p. 8.

[65] D. Robinson *et al.*, “SUNtool – A new modelling paradigm for simulating and optimising urban sustainability,” *Sol. Energy*, vol. 81, no. 9, pp. 1196–1211, Sep. 2007, doi: 10.1016/j.solener.2007.06.002.
[66] P. Remmen, M. Lauster, M. Mans, M. Fuchs, T. Osterhage, and D. Müller, “TEASER: an open tool for urban energy modelling of building stocks,” *J. Build. Perform. Simul.*, vol. 11, no. 1, pp. 84–98, Jan. 2018, doi: 10.1080/19401493.2017.1283539.
[67] K. Sun, T. Hong, S. C. Taylor-Lange, and M. A. Piette, “A pattern-based automated approach to building energy model calibration,” *Appl. Energy*, vol. 165, pp. 214–224, Mar. 2016, doi: 10.1016/j.apenergy.2015.12.026.
[68] M. H. Kristensen, R. E. Hedegaard, and S. Petersen, “Hierarchical calibration of archetypes for urban building energy modeling,” *Energy Build.*, vol. 175, pp. 219–234, Sep. 2018, doi: 10.1016/j.enbuild.2018.07.030.
[69] M. H. Kristensen, R. Choudhary, R. H. Pedersen, and S. Petersen, “Bayesian Calibration Of Residential Building Clusters Using A Single Geometric Building Representation,” in *Proc. 15th IBPSA Conference*, p. 10, 2017.
[70] S. Heiple and D. J. Sailor, “Using building energy simulation and geospatial modeling techniques to determine high resolution building sector energy consumption profiles,” *Energy Build.*, vol. 40, no. 8, pp. 1426–1436, Jan. 2008, doi: 10.1016/j.enbuild.2008.01.005.
[71] A. T. Booth, R. Choudhary, and D. J. Spiegelhalter, “Handling uncertainty in housing stock models,” *Build. Environ.*, vol. 48, pp. 35–47, Feb. 2012, doi: 10.1016/j.buildenv.2011.08.016.
[72] D. Coakley, P. Raftery, and M. Keane, “A review of methods to match building energy simulation models to measured data,” *Renew. Sustain. Energy Rev.*, vol. 37, pp. 123–141, Sep. 2014, doi: 10.1016/j.rser.2014.05.007.
[73] C. Cerezo, J. Sokol, C. Reinhart, and A. Al-Mumin, “THREE METHODS FOR CHARACTERIZING BUILDING ARCHETYPES IN URBAN ENERGY SIMULATION. A CASE STUDY IN KUWAIT CITY.,” *Proceedings of BS2015: 14th Conference of International Building Performance Simulation Association*, p. 9.
[74] P. Caputo, G. Costa, and S. Ferrari, “A supporting method for defining energy strategies in the building sector at urban scale,” *Energy Policy*, vol. 55, pp. 261–270, Apr. 2013, doi: 10.1016/j.enpol.2012.12.006.
[75] Y. J. Huang and D. B. Crawley, “Does it Matter Which Weather Data You Use in Energy Simulations?,” in *Proc. American Council for an Energy-Efficieny Economy (ACEEE) summer study on energy efficiency in buildings*, p. 11.
[76] M. Herrera *et al.*, “A review of current and future weather data for building simulation,” *Build. Serv. Eng. Res. Technol.*, vol. 38, no. 5, pp. 602–627, Sep. 2017, doi: 10.1177/0143624417705937.
[77] G. Evola, L. Marletta, and D. Cimino, “Weather data morphing to improve building energy modeling in an urban context,” *Math. Model. Eng. Probl.*, vol. 5, no. 3, pp. 211–216, Sep. 2018, doi: 10.18280/mmep.050312.
[78] R. Buffat, A. Froemelt, N. Heeren, M. Raubal, and S. Hellweg, “Big data GIS analysis for novel approaches in building stock modelling,” *Appl. Energy*, vol. 208, pp. 277–290, Dec. 2017, doi: 10.1016/j.apenergy.2017.10.041.
[79] G. Ward, *Radiance*. Berkeley, CA, USA: Environmental Energy Technologies Division of Lawrence Berkeley National Laboratory, 1997.
[80] C. F. Reinhart, “Daylight Availability and Manual Lighting Control in Office Buildings - Simulation Studies and Analysis of Measurements,” PhD Thesis, University of Karlsruhe, 2001.
[81] C. M. Goral, K. E. Torrance, D. P. Greenberg, and B. Battaile, “Modeling the interaction of light between diffuse surfaces,” *Comput. Graph.*, vol. 18, no. 3, p. 10, 1984.
[82] D. Robinson and A. Stone, “Solar radiation modelling in the urban context,” *Sol. Energy*, vol. 77, no. 3, pp. 295–309, Sep. 2004, doi: 10.1016/j.solener.2004.05.010.
[83] D. Robinson and A. Stone, “A simplified radiosity algorithm for general urban radiation exchange,” *Build. Serv. Eng. Res. Technol.*, vol. 26, no. 4, pp. 271–284, 2005.
[84] R. Perez, R. Seals, and J. Michalsky, “All-weather model for sky luminance distribution— preliminary configuration and validation,” *Sol. Energy*, vol. 50, no. 3, pp. 235–245, 1993.
[85] R. Perez, P. Ineichen, R. Seals, J. Michalsky, and R. Stewart, “Modeling daylight availability and irradiance components from direct and global irradiance,” *Sol. Energy*, vol. 44, no. 5, pp. 271–289, Jan. 1990, doi: 10.1016/0038-092X(90)90055-H.
[86] “EnergyPlus | EnergyPlus.” https://energyplus.net/ (accessed Jan. 10, 2019).
[87] C. Cerezo Davila, C. F. Reinhart, and J. L. Bemis, “Modeling Boston: A workflow for the efficient generation and maintenance of urban building energy models from existing geospatial datasets,” *Energy*, vol. 117, pp. 237–250, Dec. 2016, doi: 10.1016/j.energy.2016.10.057.
[88] T. Hong, Y. Chen, S. H. Lee, and M. A. Piette, “CityBES: A Web-based Platform to Support City-Scale Building Energy Efficiency,” in *Proc. Urban Computing 2016*, p. 9.

[89] P. Fu and P. M. Rich, “A geometric solar radiation model and its applications in agriculture and forestry,” in *Proceedings of the Second International Conference on Geospatial Information in Agriculture and Forestry*, 2000, vol. 1, pp. 357–364, Accessed: 17-Jul-2015. [Online]. Available: http://solar.maps.umn.edu/assets/pdf/fu_rich_2000.pdf.
[90] K. Mahmud, U. Amin, M. J. Hossain, and J. Ravishankar, “Computational tools for design, analysis, and management of residential energy systems,” *Appl. Energy*, vol. 221, pp. 535–556, Jul. 2018, doi: 10.1016/j.apenergy.2018.03.111.
[91] “IDA ICE - Simulation Software | EQUA.” https://www.equa.se/en/ida-ice (accessed Jan. 10, 2019).
[92] “TRNSYS : Transient System Simulation Tool.” http://www.trnsys.com/ (accessed Jan. 10, 2019).
[93] F. Johari, A. M. Nilsson, M. Åberg, and J. Widén, “Towards urban building energy modelling: a comparison of available tools,” in Proc. *eceee 2019 Summer Study on energy efficiency*, 1515-1524, p. 10, 2019.
[94] C. F. Reinhart, T. Dogan, J. A. Jakubiec, T. Rakha, and A. Sang, “UMI - AN URBAN SIMULATION ENVIRONMENT FOR BUILDING 2 ENERGY USE, DAYLIGHTING AND WALKABILITY,” 203, Accessed: 22-Aug-2018. [Online]. Available: http://www.ibpsa.org/proceedings/BS2013/p_1404.pdf.
[95] Y. Chen and T. Hong, “Impacts of building geometry modeling methods on the simulation results of urban building energy models,” *Appl. Energy*, vol. 215, pp. 717–735, Apr. 2018, doi: 10.1016/j.apenergy.2018.02.073.
[96] J. H. Kämpf and D. Robinson, “A simplified thermal model to support analysis of urban resource flows,” *Energy Build.*, vol. 39, no. 4, pp. 445–453, Apr. 2007, doi: 10.1016/j.enbuild.2006.09.002.
[97] J. A. Fonseca and A. Schlueter, “Integrated model for characterization of spatiotemporal building energy consumption patterns in neighborhoods and city districts,” *Appl. Energy*, vol. 142, pp. 247–265, Mar. 2015, doi: 10.1016/j.apenergy.2014.12.068.
[98] E.-J. Kim, G. Plessis, J.-L. Hubert, and J.-J. Roux, “Urban energy simulation: Simplification and reduction of building envelope models,” *Energy Build.*, vol. 84, pp. 193–202, Dec. 2014, doi: 10.1016/j.enbuild.2014.07.066.
[99] G. Kokogiannakis, P. Strachan, and J. Clarke, “Comparison of the simplified methods of the ISO 13790 standard and detailed modelling programs in a regulatory context,” *J. Build. Perform. Simul.*, vol. 1, no. 4, pp. 209–219, Dec. 2008, doi: 10.1080/19401490802509388.
[100] T. Dogan and C. Reinhart, “Shoeboxer: An algorithm for abstracted rapid multi-zone urban building energy model generation and simulation,” *Energy Build.*, vol. 140, pp. 140–153, Apr. 2017, doi: 10.1016/j.enbuild.2017.01.030.
[101] “Home | ashrae.org.” https://www.ashrae.org/ (accessed Feb. 22, 2019).
[102] L. Smith, “Beyond the Shoebox: Thermal Zoning Approaches for Complex Building Shapes,” ASHRAE Transactions . 2012, Vol. 118 Issue 2, p141-148. 8p.
[103] T. Dogan, C. Reinhart, and P. Michalatos, “Automated multi-zone building energy model generation for schematic design and urban massing studies,” in *Proc. IBPSA eSim Conf.*, p. 14.
[104] R. Nouvel *et al.*, “SimStadt, a new workflow-driven urban energy simulation platform for CityGML city models,” in *Proceedings of International Conference CISBAT 2015 Future Buildings and Districts Sustainability from Nano to Urban Scale*, 2015, pp. 889–894, Accessed: 14-Feb-2017. [Online]. Available: https://infoscience.epfl.ch/record/213437/files/9_NOUVEL1187.pdf.
[105] A. Gasparella and G. Pernigotto, “Comparison Of Quasi-Steady State And Dynamic Simulation Approaches For The Calculation Of Building Energy Needs: Thermal Losses,” p. 11, 2012.
[106] J. H. Kämpf and D. Robinson, “OPTIMISATION OF URBAN ENERGY DEMAND USING AN EVOLUTIONARY ALGORITHM,” in *Proc. IBPSA Conference*, 2009.
[107] R. Nouvel, M. Zirak, H. Dastageeri, V. Coors, and U. Eicker, “URBAN ENERGY ANALYSIS BASED ON 3D CITY MODEL FOR NATIONAL SCALE APPLICATIONS,” p. 8.
[108] P. Tuominen, R. Holopainen, L. Eskola, J. Jokisalo, and M. Airaksinen, “Calculation method and tool for assessing energy consumption in the building stock,” *Build. Environ.*, vol. 75, pp. 153–160, May 2014, doi: 10.1016/j.buildenv.2014.02.001.
[109] P. Riederer, V. Partenay, N. Perez, C. Nocito, R. Trigance, and T. Guiot, “Development of a simulation platform for the evaluation of district energy system performances,” *Unpublished*, 2015, doi: 10.13140/rg.2.1.4668.8401/1.
[110] N. Perez, P. Riederer, C. Inard, and V. Partenay, “Thermal building modelling adapted to district energy simulation,” in *Proc. IBPSA Conference*., p. 8.
[111] J. A. Fonseca, T.-A. Nguyen, A. Schlueter, and F. Marechal, “City Energy Analyst (CEA): Integrated framework for analysis and optimization of building energy systems in neighborhoods and city districts,” *Energy Build.*, vol. 113, pp. 202–226, Feb. 2016, doi: 10.1016/j.enbuild.2015.11.055.
[112] Y. Chen, T. Hong, and M. A. Piette, “City-Scale Building Retrofit Analysis: A Case Study using CityBES,” *Build. Simul.*, p. 8, 2017.

[113] P. Nageler *et al.*, “Novel validated method for GIS based automated dynamic urban building energy simulations,” *Energy*, vol. 139, pp. 142–154, Nov. 2017, doi: 10.1016/j.energy.2017.07.151.
[114] D. Wang, J. Landolt, G. Mavromatidis, K. Orehounig, and J. Carmeliet, “CESAR: A bottom-up building stock modelling tool for Switzerland to address sustainable energy transformation strategies,” *Energy Build.*, vol. 169, pp. 9–26, Jun. 2018, doi: 10.1016/j.enbuild.2018.03.020.
[115] G. Agugiaro, J. Benner, P. Cipriano, and R. Nouvel, “The Energy Application Domain Extension for CityGML: enhancing interoperability for urban energy simulations,” *Open Geospatial Data Softw. Stand.*, vol. 3, no. 1, p. 2, Mar. 2018, doi: 10.1186/s40965-018-0042-y.
[116] R. Stouffs, H. Tauscher, F. Biljecki, R. Stouffs, H. Tauscher, and F. Biljecki, “Achieving Complete and Near-Lossless Conversion from IFC to CityGML,” *ISPRS Int. J. Geo-Inf.*, vol. 7, no. 9, p. 355, Aug. 2018, doi: 10.3390/ijgi7090355.
[117] F. Biljecki, K. Kumar, and C. Nagel, “CityGML Application Domain Extension (ADE): overview of developments,” *Open Geospatial Data Softw. Stand.*, vol. 3, no. 1, p. 13, Aug. 2018, doi: 10.1186/s40965-018-0055-6.
[118] T. Kutzner and T. H. Kolbe, “Extending Semantic 3D City Models by Supply and Disposal Networks for Analysing the Urban Supply Situation,” p. 13, 2016.
[119] Z. Yao *et al.*, “3DCityDB - a 3D geodatabase solution for the management, analysis, and visualization of semantic 3D city models based on CityGML,” *Open Geospatial Data Softw. Stand.*, vol. 3, no. 1, Dec. 2018, doi: 10.1186/s40965-018-0046-7.
[120] D. G. De Paor, S. J. Whitmeyer, and C. Bentley, “CESIUM — A virtual globe with strong potential applications in geoscience education,” in *Geological Society of America Abstracts with Programs*, Albany, New York, 2016, doi: 10.1130/abs/2016NE-272098.
[121] H. E. Landsberg, *The Urban Climate*. Academic Press, 1981.
[122] M. Santamouris *et al.*, “On the impact of urban climate on the energy consumption of buildings,” *Sol. Energy*, vol. 70, no. 3, pp. 201–216, Jan. 2001, doi: 10.1016/S0038-092X(00)00095-5.
[123] K. W. Oleson, G. B. Bonan, J. Feddema, M. Vertenstein, and C. S. B. Grimmond, “An Urban Parameterization for a Global Climate Model. Part I: Formulation and Evaluation for Two Cities,” *J. Appl. Meteorol. Climatol.*, vol. 47, no. 4, pp. 1038–1060, Apr. 2008, doi: 10.1175/2007JAMC1597.1.
[124] D. J. Stensrud, *Parameterization Schemes: Keys to Understanding Numerical Weather Prediction Models*. Cambridge University Press, 2007.
[125] G. F. Garuma, “Review of urban surface parameterizations for numerical climate models,” *Urban Clim.*, vol. 24, pp. 830–851, Jun. 2018, doi: 10.1016/j.uclim.2017.10.006.
[126] H. Kusaka, H. Kondo, Y. Kikegawa, and F. Kimura, “A Simple Single-Layer Urban Canopy Model For Atmospheric Models: Comparison With Multi-Layer And Slab Models,” *Bound.-Layer Meteorol.*, vol. 101, no. 3, pp. 329–358, Dec. 2001, doi: 10.1023/A:1019207923078.
[127] F. Salamanca, A. Martilli, M. Tewari, and F. Chen, “A Study of the Urban Boundary Layer Using Different Urban Parameterizations and High-Resolution Urban Canopy Parameters with WRF,” *J. Appl. Meteorol. Climatol.*, vol. 50, no. 5, pp. 1107–1128, Dec. 2010, doi: 10.1175/2010JAMC2538.1.
[128] D. Mauree, J. Kämpf, and J.-L. Scartezzini, “Multi-scale modelling to improve climate data for building energy models,” presented at the 14th International Conference of IBPSA - Building Simulation 2015, BS 2015, Conference Proceedings, 2015, pp. 979–986.
[129] R. Yao, Q. Luo, and B. Li, “A simplified mathematical model for urban microclimate simulation,” *Build. Environ.*, vol. 46, no. 1, pp. 253–265, Jan. 2011, doi: 10.1016/j.buildenv.2010.07.019.
[130] B. Morille, N. Lauzet, and M. Musy, “SOLENE-microclimate: A Tool to Evaluate Envelopes Efficiency on Energy Consumption at District Scale.,” *Energy Procedia*, vol. 78, pp. 1165–1170, Nov. 2015, doi: 10.1016/j.egypro.2015.11.088.
[131] Y. Toparlar, B. Blocken, B. Maiheu, and H. van, “A review on the CFD analysis of urban microclimate,” *Renew. Sustain. Energy Rev.*, vol. 80, pp. 1613–1640, 2017, doi: 10.1016/j.rser.2017.05.248.
[132] M. Braulio-Gonzalo, M. D. Bovea, M. J. Ruá, and P. Juan, “A methodology for predicting the energy performance and indoor thermal comfort of residential stocks on the neighbourhood and city scales. A case study in Spain,” *J. Clean. Prod.*, vol. 139, pp. 646–665, Dec. 2016, doi: 10.1016/j.jclepro.2016.08.059.
[133] L. Chen and E. Ng, “Outdoor thermal comfort and outdoor activities: A review of research in the past decade,” *Cities*, vol. 29, no. 2, pp. 118–125, Apr. 2012, doi: 10.1016/j.cities.2011.08.006.
[134] S. Coccolo, J. Kämpf, J.-L. Scartezzini, and D. Pearlmutter, “Outdoor human comfort and thermal stress: A comprehensive review on models and standards,” *Urban Clim.*, vol. 18, pp. 33–57, Dec. 2016, doi: 10.1016/j.uclim.2016.08.004.
[135] G. Jendritzky, R. de Dear, and G. Havenith, “UTCI—Why another thermal index?,” *Int. J. Biometeorol.*, vol. 56, no. 3, pp. 421–428, May 2012, doi: 10.1007/s00484-011-0513-7.

[136] G. J. Steeneveld, S. Koopmans, B. G. Heusinkveld, L. W. A. van Hove, and A. a. M. Holtslag, "Quantifying urban heat island effects and human comfort for cities of variable size and urban morphology in the Netherlands," *J. Geophys. Res. Atmospheres*, vol. 116, no. D20, 2011, doi: 10.1029/2011JD015988.
[137] S. Ebrahimabadi, "Outdoor Comfort in Cold Climates," PhD Thesis, Luleå University of Technology, Luleå, 2015.
[138] S. Thorsson, M. Lindqvist, and S. Lindqvist, "Thermal bioclimatic conditions and patterns of behaviour in an urban park in Göteborg, Sweden," *Int. J. Biometeorol.*, vol. 48, no. 3, pp. 149–156, Feb. 2004, doi: 10.1007/s00484-003-0189-8.
[139] T. Rakha, "Towards comfortable and walkable cities : spatially resolved outdoor thermal comfort analysis linked to travel survey-based human activity schedules," Thesis, Massachusetts Institute of Technology, 2015.
[140] M. V. Tabib, A. Rasheed, and T. Priya Uteng, "Methodology for assessing cycling comfort during a smart city development," *Energy Procedia*, vol. 122, pp. 361–366, Sep. 2017, doi: 10.1016/j.egypro.2017.07.286.
[141] E. Naboni, M. Meloni, S. Coccolo, J. Kaempf, and J.-L. Scartezzini, "An overview of simulation tools for predicting the mean radiant temperature in an outdoor space," *Energy Procedia*, vol. 122, pp. 1111–1116, Sep. 2017, doi: 10.1016/j.egypro.2017.07.471.
[142] C. Miller, D. Thomas, J. Kämpf, and A. Schlueter, "Urban and building multiscale co-simulation: case study implementations on two university campuses," *J. Build. Perform. Simul.*, vol. 11, no. 3, pp. 309–321, May 2018, doi: 10.1080/19401493.2017.1354070.
[143] N. Mohammadi and J. E. Taylor, "Urban energy flux: Spatiotemporal fluctuations of building energy consumption and human mobility-driven prediction," *Appl. Energy*, vol. 195, pp. 810–818, Jun. 2017, doi: 10.1016/j.apenergy.2017.03.044.
[144] J. Clift, R and Druckmna, A and Christic, I and Kennedy, C and Keirstead, "Urban metabolism: a review in the UK context. Government Office for Science," 2015.
[145] H. Barbosa *et al.*, "Human mobility: Models and applications," *Phys. Rep.*, vol. 734, pp. 1–74, 2018, doi: 10.1016/j.physrep.2018.01.001.
[146] T. L. Magnanti, "Shortest Paths , Single Origin-Destination Network Design , and Associated Polyhedra," 1993.
[147] N. Caceres, J. P. Wideberg, and F. G. Benitez, "Deriving origin – destination data from a mobile phone network," pp. 15–26, doi: 10.1049/iet-its.
[148] G. K. Zipf, "The P1 P2 / D Hypothesis : On the Intercity Movement of Persons Author (s): George Kingsley Zipf Source : American Sociological Review , Vol . 11 , No . 6 (Dec ., 1946), pp . 677-686 Published by : American Sociological Association Stable URL : http:/," *Am. Sociol. Rev.*, vol. 11, no. 6, pp. 677–686, 1946.
[149] V. Palchykov, M. Mitrovic, H. H. Jo, J. Saramäki, and R. K. Pan, "Inferring human mobility using communication patterns," *Sci. Rep.*, vol. 4, pp. 1–6, 2014, doi: 10.1038/srep06174.
[150] R. K. Pan, K. Kaski, and S. Fortunato, "World citation and collaboration networks: Uncovering the role of geography in science," *Sci. Rep.*, vol. 2, pp. 1–7, 2012, doi: 10.1038/srep00902.
[151] P. Kaluza, A. Kölzsch, M. T. Gastner, and B. Blasius, "The complex network of global cargo ship movements.," *J. R. Soc. Interface*, vol. 7, no. 48, pp. 1093–103, 2010, doi: 10.1098/rsif.2009.0495.
[152] W. S. Jung, F. Wang, and H. E. Stanley, "Gravity model in the Korean highway," *Epl*, vol. 81, no. 4, pp. 0–6, 2008, doi: 10.1209/0295-5075/81/48005.
[153] D. Balcan, V. Colizza, B. Gonçalves, H. Hu, J. J. Ramasco, and A. Vespignani, "Multiscale mobility networks and the spatial spreading of infectious diseases.," *Proc. Natl. Acad. Sci. U. S. A.*, vol. 106, no. 51, pp. 21484–9, 2009, doi: 10.1073/pnas.0906910106.
[154] F. Simini, M. C. González, A. Maritan, and A. L. Barabási, "A universal model for mobility and migration patterns," *Nature*, vol. 484, no. 7392, pp. 96–100, 2012, doi: 10.1038/nature10856.
[155] A. P. Masucci, J. Serras, A. Johansson, and M. Batty, "Gravity versus radiation models: On the importance of scale and heterogeneity in commuting flows," *Phys. Rev. E - Stat. Nonlinear Soft Matter Phys.*, vol. 88, no. 2, pp. 1–8, 2013, doi: 10.1103/PhysRevE.88.022812.
[156] M. Lenormand, A. Bassolas, and J. J. Ramasco, "Systematic comparison of trip distribution laws and models," *J. Transp. Geogr.*, vol. 51, pp. 158–169, 2016, doi: 10.1016/j.jtrangeo.2015.12.008.
[157] M. Lenormand, S. Huet, F. Gargiulo, and G. Deffuant, "A Universal Model of Commuting Networks," *PLoS ONE*, vol. 7, no. 10, 2012, doi: 10.1371/journal.pone.0045985.
[158] X. Liang, J. Zhao, L. Dong, and K. Xu, "Unraveling the origin of exponential law in intra-urban human mobility," *Sci. Rep.*, vol. 3, 2013, doi: 10.1038/srep02983.
[159] F. Simini, A. Maritan, and Z. Néda, "Human Mobility in a Continuum Approach," *PLoS ONE*, vol. 8, no. 3, 2013, doi: 10.1371/journal.pone.0060069.
[160] Y. Yang, C. Herrera, N. Eagle, and M. C. González, "Limits of predictability in commuting flows in the absence of data for calibration," *Sci. Rep.*, vol. 4, pp. 1–9, 2014, doi: 10.1038/srep05662.