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Modelling building energy use at urban scale: A review on their account for the urban environment

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ABSTRACT

While more and more cities are planning towards sustainable development and climate resilience, a thorough understanding of the spatiotemporal pattern of building energy demand can be valuable for evidence-based city design and climate change mitigation. Energy demand in buildings is heavily influenced by its surrounding built and climatic environment. This requires simulation that is sensitive to the heterogeneity of buildings and climatic complications in dense urban settings. This paper provides a comprehensive review that documents and cross-compares the major methods to simulate building energy use at urban scale. The reviewed literature were acquired by using the search strings "urban-scale, city-scale or large-scale", "building energy, energy use, electricity use, energy consumption or thermal load" and "simulation, forecast, modelling or mapping" in the Web of Science database from 2010 to 2021. The result highlighted major differences in strengths, limitations and field of application of different methods based on modelling inputs, outputs and approaches to incorporate urban environment to the modelling. It also identified that future development of urban-scale building energy use should explore more ways to incorporate the spatial variation in weather and morphological conditions, especially in dense urban settings that experience greater environmental challenges.

1. Introduction

Taking up 0.63 % of the Earth's surface [1], urban areas are, responsible for as much as 76 % of the world's energy demand and greenhouse gas emissions [2]. A more detailed analysis reveals that, among all urban activities, buildings typically host the most significant energy use due to the aggregated energy demand for space cooling, heating, lighting and ventilation. In Tokyo, for example, buildings account for roughly 67 % of the city's total electricity usage [3], whereas the number in Hong Kong reaches as high as 90 % [4]. Without appropriate and timely interventions, the demand for energy use is only expected to rise under the ever-increasing trend of affluent living standards and urbanisation. Facing the threat of climate change, cities around the world have been planning towards sustainable development and climate resilience. As city-level energy transition and planning strategies are becoming more common in the late 2010s [5], the pressing need for a thorough understanding of the energy dynamic at the city level thereby arises, especially for cities with compact urban settings.

Building energy modelling can be fundamentally grouped into top-down or bottom-up approaches [6,7]. The top-down approaches typically work on the aggregated energy data and pertinent variables like macro-economic indicators, income, tax revenues, fuel prices and data on climatic trend. As the output tends to be a historical time series energy use pattern, they are deemed more efficient for revealing the temporal fluctuation of energy use [8], understanding the interplay between the energy sector and the economy at large [9], and performing macro-level retrofit analysis of national building stocks [10]. However, they only put limited consideration of variables in individual end-uses and rarely describe in detail the performance of building components and the built environment [11]. Relying heavily on the historic energy-economy interaction, top-down approaches also lack the ability to explore technological options for energy conservation where environmental and socio-economic conditions have not been previously experienced and modelled [9]. The bottom-up approaches, on the other hand, use data extracted from individuals or groups of buildings to calculate their energy usage, which can then be extrapolated to reflect that in the region or nation [12]. In contrast to the top-down models, the disaggregated nature of the input data allows the bottom-up approaches

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to provide a more detailed diagnosis on energy end-use, for example, its interplay with socio-demographic relation [13], occupant behaviour [14] and physical properties of buildings and their surrounding [15]. Powered by the technical advances in simulation and data sharing in the past two decades, bottom-up building energy simulation at the urban scale is becoming an emerging solution to support evidence-based sustainable city and energy planning. As a useful tool to visualise the energy dynamic in areas ranging from city district, city region to inter-cities scale, urban-scale simulation can be valuable for power suppliers and urban managers to formulate optimal operational strategies with higher energy efficiency [8,14–16]. The simulation can also encourage energy transition by providing useful information for alternative energy sources like geothermal, solar energy and biomass investment and supply network.

Building energy use is a complex, multi-scale and cross-sectoral system, which is significantly influenced by its surrounding environment. Evidence from Hong Kong shows that cooling demands can rise nearly 30 % in response to every 1 °C increment of hourly outdoor temperature [17]. Similar correlation was also reported from the city-block scale data in Osaka City, Japan [18]. The impact of certain weather elements varies across different climates. For instance, temperature elasticity of the electricity demand in warm climates is up to three times higher than that in mild and cold climates [19], while the impact of humidity on latent cooling is tested to be more significant in subtropical climates [20]. The impact becomes more significant in the urban environment where urban morphology complicates the climatic conditions. The impact becomes even more prominent in the urban environments where compact topography, more anthropogenic heat sources and less open spaces are typically found. As a result of these phenomena, the urban heat island effect, observed in worldwide cities where its air temperature is higher than that in their rural counterparts [21], further complicates the energy use in buildings. Each degree of urban heat island was found to reduce 22–26 % of space heating and increase 18–24 % of space cooling in an Italian case study [22]. In an impact analysis by Santamouris, an average global energy penalty of 0.74 kWh/m^2/K as a result of each degree of urban heat island was reported [23]. Given the unique environmental and climatic challenges in cities where a wide diversity of buildings is found, there is a pressing need to review how energy use in buildings can be simulated in ways that are sensitive to the urban environment.

In response to the increasing need for urban-scale building energy modelling, a rising number of reviews were conducted, each focusing on different aspects. Reinhart and Cerezo Davila [6] conducted one of the first reviews on the data input, thermal modelling and result validation of the emerging simulation methods. Ferrari et al. [24] reviewed the district-level estimation of building energy use, explicitly those with hourly energy profile. Hong et al. [12] provided an extensive review covering most aspects of conducting an Urban Building Energy Modelling, with an emphasis on its potential applications. Happle et al. [25] reviewed the urban building energy models in terms of their modelling approaches of occupant behaviour. Fathi et al. [26] presented a systematic review on urban building energy performance forecasting that adapted machine learning techniques. Ferrando et al. [27] provided a user-oriented overview of the tools of physics-based urban scale energy modelling. Lauzet et al. [28] reviewed the strategies of chaining urban microclimate models and urban building energy models. Despite the importance of these review efforts in identifying the generic modelling approaches and application of urban-scale simulation, an overall review from the perspective of how the urban environment is incorporated into the simulation is missing. This review, therefore, aims to fill this research gap with the following objectives:

- To document the key methods to simulate building energy use at the urban scale based on modelling inputs and outputs
- To review the approaches to incorporate the urban environment into the simulation
- To cross-compare the strengths, limitations and applications of selected methods
- To explore the emerging needs of model development for high-density cities and climate-resilient cities

This paper is structured as follows. This section introduces the background upon which this paper is built, followed by the methodology this paper adapted and the scope of articles reviewed. Later sectors of the paper present the overview of the review literature, followed by the review result of the common approaches in modelling building energy use with different input and output, as well as the existing approaches to factor in an urban environment in the simulation. Lastly, conclusions and future applications are presented.

2. Methods

In the process of identifying relevant studies, Web of Science was chosen as the search engine as it stores peer-reviewed research literature with multi-disciplinary nature, which is essential for building energy simulation study as it is related to the branches of structural engineering, physics, data science, spatial planning and urban design to name a few. Three levels of screening were performed in the quest for credible reference. The keywords of "urban-scale" OR "city-scale" OR "large-scale" were used in the search to filter studies at the desired magnitude. The "building energy" OR "energy use" OR "electricity use" OR "energy consumption" OR "thermal load" were then incorporated. For the nature of studies, keywords of "simulation" OR "forecast" OR "modelling" OR "mapping" were used. The exact context and wording of sources may be diverse as some may not specifically mention any key terms yet present similar concepts. The range of publication years of literature was defined as 2010 to 2021.

In the process of identification, 76 articles were acquired. The articles were then screened manually by checking the titles, abstract and keywords. Sources that can facilitate the achievement of the research objectives was scrutinised in detail, whereas special attention was put on simulations with application in the urban environment. Records that were deemed irrelevant for this piece of research, such as top-down simulation were removed after an extra step was taken by scanning for information that is useful for understanding the interplay between energy use and urban environment. The overarching notion hereby lies in their applicability and reference for conducting climate and place-sensitive simulation. Finally, after the relevant literature was identified, the necessary information was extracted, processed and synthesized in the analysis step.

3. Results

3.1. Overview of the literature

After reviewing all the collected literature, an increasing trend of the number of papers by year was observed (Supplementary Material Fig. 1), indicating the urban-scale modelling is of increasing relevance and importance. In terms of the categorical breakdown, most papers were conducted in the field of Energy Fuels, Construction Building Technology and Engineering Civil (Supplementary Material Fig. 2). While a few studies were conducted in the field of Environmental Studies and Environment Sciences, this finding corresponds to the need to investigate the topic from the perspective of urban environment and planning.

To obtain a more solid grounding for the succeeding review, keyword co-occurrence analysis can help to identify the key focus domains and common research topics [29]. Keywords that appeared more than three times in the retrieved documents were identified and analysed by VOSviewer [30]. The output of the co-occurrence analysis is presented in Fig. 1. The node size represents the frequency of terms that appeared in all literature, while the line thickness reflects the strength of connections between the terms. The terms 'building', 'energy demand',

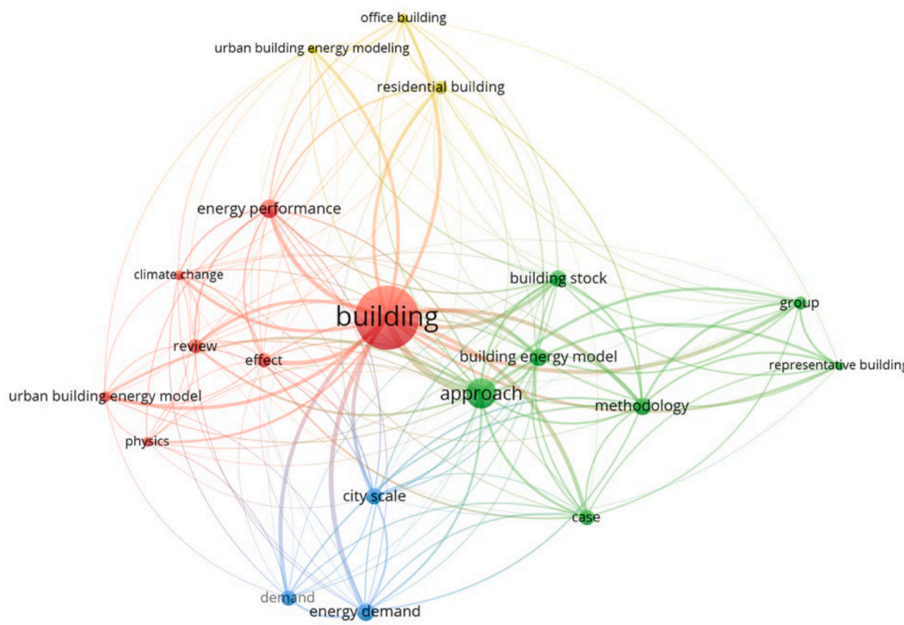

Fig. 1. Keyword co-occurrence analysis of the reviewed articles.

'building energy model' and 'city-scale' have the highest occurrences as the search strings of this review paper. Other frequently occurred terms include 'approach' and 'methodology'. It can be interpreted that a substantial amount of studies focused on model development and simulation approaches, which are applied and tested in real-world case studies. Four clusters of keywords were also identified: building end-use modelling (yellow), city-scale energy demand (blue), modelling approaches (green) and energy performance analysis (red). Understanding the components of each cluster can help direct the research focus in the next session. For instance, the presence of 'climate change' and 'physics' in the same cluster indicates that their linkage should be further explored, similar indication applied for 'physics' and 'climate change', as well as 'building stock' and 'representative building'.

While the model development and simulation approach were found to receive most research attention, the understanding of methods based on modelling inputs and outputs can aid future research on understanding the building energy dynamics in cities.

3.2. Approaches based on modelling inputs

Based on the data inputs, modelling approach of modelling building energy can be fundamentally divided into three main categories: **(1)**

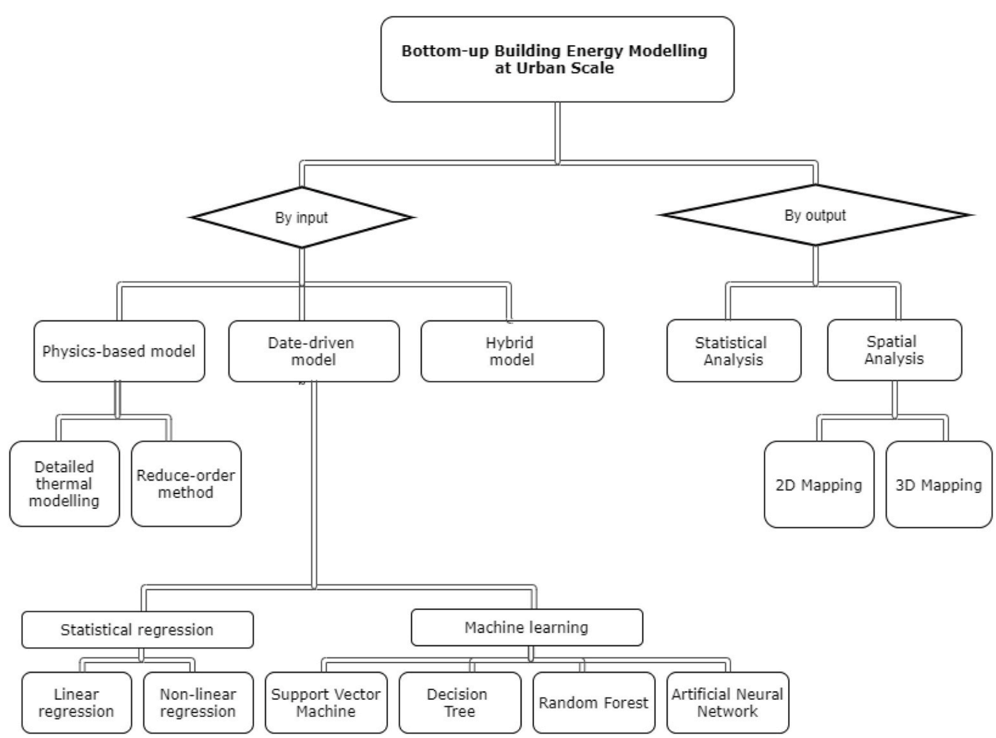

Fig. 2. Classification of urban-scale building energy models.

physics-based models, which calculate explicitly the energy consumption in buildings using geometric data, (2) data-driven models, which employ data mining or machine learning techniques to display energy behaviours, and (3) hybrid models, which combine elements from both physics-based and data-driven models (Fig. 2).

3.2.1. Physics-based models

Physics-based models, also known as engineering-based models or analytical models, deduce energy by using heat and mass flow equations [7,8]. By calculating the thermodynamics within a building and its surrounding environment, the simulation can offer a thorough diagnosis of the building's performance and its thermal loads, which can indicate the energy demand for temperature regulation and prediction on prospective usage [31]. The most conventional method is performing a multi-zone model, which employs complex physics equations to deduce the thermal dynamic of each building unit and then added up to compute the thermal loads of the whole building. Since traditional methods require a substantial amount of technical data of each building unit, which must be assembled and managed with considerable computation volume and research time, it is less frequently used in urban-scale simulation. To reduce computation volume and time for a larger scale simulation, redeveloped physics-based model is typically applied for simulation using simplified input of, for example, thermal data [32], boundary conditions [33] and building shapes [34]. For instance, Dogan and Reinhart [35] introduced a novel approach named Shoeboxer model to reduce the computational volume and complexity. By abstracting and clustering building volumes into a group of 'shoebox' models for thermal simulation, the Shoeboxer model can address the thermal variation in different parts of the building, i.e. core-area and perimeter-area, while being nearly 300 times than the traditional multi-zone model. Similarly, Zheng et al. [36] proposed a parallel computation building-chain model, in which city model are broke down into building units that are linked by thermal conditions.

Due to its technological nature, physics-based models present certain competence and limitations. The physics-based model has the advantage to inform evidence-based approaches for building retrofit measures for building benchmarking. The models can also evaluate the effectiveness of different energy conservation measures on building construction and operation [9]. However, one of the issues identified is the limited capacity in handling data that cannot be physically measurable, for example, socio-economic variables and individual user information [36–38]. As the physics-based models are calibrated by variation of the infiltration rate and heat transfer, this implies that its model output is based on heating load prediction, as opposed to heating energy use which is heavily influenced by occupant behaviour and other socio-economic variables.

3.2.2. Data-driven models

Data-driven models is a relatively new approach for two reasons: increasing data availability and technological advances. Traditionally, sensors that obtain building energy data came with low accuracy [39], metered data was rarely collected and analysed in detail. The release of more smart home applications and intelligent metering devices in recent years has fuelled the digitalisation of energy systems, allowing energy data to become more fully and extensively available [40]. For instance, an innovative study, which was conducted at the scale of 900 buildings in San Antonio, Texas, utilised mobile positioning data, available through location-based service applications, to harvest occupant profiles and urban-scale energy demand [41].

Data-driven models can be broadly grouped into regression-based methods, probability-based methods and clustering-based methods (Table 1), each with their distinctive functions to serve specific research interests.

Regression-based methods, which are found to be the most common in the literature reviewed, are usually applied to predict energy use. As prediction can be made on building energy demand based on historic usage and scenario analysis of, for example, variances in climatic condition [3] and projected demographic changes [52], it can be useful for establishing a long-term strategy for sustainability and combating climate change. An emerging sub-field of regression-based methods is machine learning methods, such as support vector machine [43,44], decision trees [33], random forest [44,46] and artificial neural networks [17,43]. Possessing the ability to learn from data using computer algorithms, machine learning models are beneficial for handling a substantial amount of data and applying to large-scale study such as urban-scale modelling [53]. A comparative study among three algorithms, namely linear regression, random forest and support vector machine, was performed by Kontokosta and Tull [44] with the case of 1.1 million buildings in New York City. It is shown the difference between their mean absolute errors is insignificant, yet their performance showed slight variations when simulating at different spatial scales. Support vector machine provided the most accurate result for predicting energy use based on official energy data, whereas linear regression was the most accurate for the entire city.

Table 1
Reviewed studies with data-driven elements.

Data-driven elements			Reference
Regression-based methods	Regression algorithms	Linear regression	[42–45]
		Multiple linear regression	[45]
	Machine learning method	Support vector machines	[43,44]
		Decision trees	[33]
		Random Forest	[44,46]
		Artificial neural networks	[17,43]
Probability-based methods	Bayesian regression		[47–49]
	Probability Distribution		[50]
Clustering-based methods	K-means clustering		[11,32,46,50, 51]
	hierarchical clustering		[46]
	clustering medoids		[46]

In the case of incomplete and uncertain information, probability-based methods can be applied to deduce energy demand based on prior empirical data and naturally accounts for uncertainties, deriving the missing information at scales ranging from residential neighbourhood to city. For instance, Hedegaard et al. [48] used Bayesian regression to calibrate heating and water usage profiles of 159 houses in a neighbourhood of Aarhus, Denmark. Choudhary [47] used Bayesian regression to estimate the energy use intensity of non-domestic building stock of Greater London based on energy data from established reports, energy audits and benchmarking values.

With its ability to identify the hidden structures of a large dataset, clustering-based methods can characterise the spatiotemporal pattern of energy use [54], as well as the grouping of data into selected parameters [11,55]. Xu et al. [50] produced general monthly energy use curves of six Chinese cities in Jiangsu Province by clustering the smart meter data of 86,672 households into 16 clusters based on, firstly, their monthly average electricity use level and, secondly, use pattern. The result of the two-step clustering was then fit into 14 electricity use pattern parameters using probability distributions to generate the electricity use curves of the entire province. However, as the training process of clustering-based methods requires the input of complete datasets, the clustering-based method is rarely used to simulate urban-scale building energy due to the problem of energy data scarcity or incomplete data. As an example, Tardioli et al. [46] augmented the clustering result for city-scale predictive modelling by identifying 65 representative buildings from a dataset of 8785 buildings by using K-means clustering, hierarchical clustering and clustering medoids. The clustering result was then extended to predict the energy use of 4829 additional buildings by using the random forest algorithm with an average accuracy of 89.6 %.

3.2.3. Hybrid models

In regards to the limitation of physics-based and data-driven models, an increasing amount of study has married the two models to leverage their advantages, generating more comprehensive simulation results for different purposes. For instance, in the multi-scale framework developed by Nouvel et al. [56], the statistical method can be calibrated with an engineering method as correction factors in the case of missing or uncertain building physics information, while the engineering method can provide a statistical model with refurbishment-related information for large scale renovation and sustainable policies. Fonseca and Schlueter [11] joined the output of statistical and analytical calculations of energy use of 1392 buildings in a Swiss city in order to reduce the uncertainty of results derived from simplified physics-based models. Their integrated model was able to a generate simulated outcome of higher reliability result with 1 % and 19 % errors at neighbourhood and city districts scale respectively.

Different components from the two models can be combined differently. Cheung et al. [9] firstly calculated the envelope heat gains of typical public housing block types in Hong Kong, then used the output to train the artificial neural network to simulate the cooling energy use of all public housing in Hong Kong. Roth et al. [42] stimulated the energy demand in 1 million buildings using statistical methods and optimised the simulation result with physics-based on individual buildings in targeted areas. Girardin et al. [16] performed a statistical analysis of measured consumption data in Geneva, Switzerland and used the result to predict future demand on heating and cooling loads using a heat exchange model for buildings.

3.3. Approaches to present modelling output

Despite its nature of data input, the modelling results can be displayed statistically or spatially. In studies that adopted statistical presentation, energy data collected in individual buildings can easily be extrapolated to different temporal scales. For instance, Nutkiewicz, Zheng and Rishee [31] displayed the energy use of 22 buildings in an urban university campus in California, USA at daily, monthly and yearly scale; Ren, Paevere and McNamara [39] presented the predicted energy usage of 5000 Census Collection Districts in New South Wales, Australia with hourly, daily and yearly resolution. In other words, statistical presentation is beneficial when the temporal course of energy use is of interest. Energy graphs can also demonstrate the correlations between energy use and different variables, which help to identify the influencing factors of energy use. For example, Fracastoro & Serraino [38] visualised the investment potential in retrofit technologies with energy-saving curves simulated with data on geometry, construction, meteorology and internal conditions. However, the statistical presentation cannot show the spatial distribution of energy use in urban areas. Hence it is less useful in informing urban planning policy.

Spatial presentation refers to the use of geospatial techniques to present energy use at large scale. By displaying the spatial distribution of building energy use, the spatial presentation helps to identify the pain point or key action areas for energy planning and conservation. Spatial presentation can aid the understanding and facilitate urban decision making by non-specialists in view of the complexity of energy systems [46,54]. An additional strength of spatial presentation is the ability to capture spatial variations in climatic conditions. For example, in the study by Rosser et al. [34], 3D city model that represent urban scenes was used to assess and present the building energy use that was sensitive to the inter-building effect; Vázquez-Canteli and Kämpf simulated the building energy use of the Junction District in Geneva, Switzerland using physics-based models and created a geometrical 3D model to analyse and present the building energy use in different climate change scenarios [57].

3.3.1. Overview of urban environment

In urban areas where constant development and redevelopment projects take place, it is common to find a wide diversity of buildings with varying types, ages and forms. In order to address the heterogeneity of buildings in an urban environment, understanding the common parameters can facilitate more accurate estimation of building energy use. Building height and area indicate the intensity of its energy use. For building age, different construction periods signify the shift in building traditions and energy requirements, which are usually defined in local energy standards and law [38]. Land use is also a typical parameter to estimate the level and pattern of energy consumption. For instance, the energy used for lighting in business city blocks was found to be insensitive to solar radiation, different from residential and mixed city blocks [18]. The ability to identify and analyse the various characteristics of buildings in an urban environment is the key to accurate simulation.

To fully understand a building's energy performance, it is important to consider not only the buildings own technical properties but also its surrounding built environment and impact from climatic conditions. For instance, the abundance of high-rise buildings would alter [58] or weaken [59,60] wind flow, which eventually would exuberate the heat gain in some buildings through infiltration and deteriorate the indoor thermal comfort [61]. Potential wind dynamics in urban areas can also be reflected by calculating urban morphology data such as sky view factors and surface roughness length [62]. The presence of adjacent buildings would impact the solar gain of buildings and energy use for their lighting [63]. Neglecting the inter-building effect, as reported by Pisello et al. [64], could result in an error in energy simulation of as high as 71.9 %. While calculating these impact by individual building may require significant amount of urban fabric data and calculation effort, generic data such as area density and mean height of buildings can be the alternatives to estimate the impact of surrounding geography on building energy use [65].

3.3.2. Addressing the variety of buildings

3.3.2.1. Use of Geographical Information System. With its wide-ranging functions of storing, managing, analysing and presenting data, Geographical Information System (GIS) is found to be commonly used to incorporate the urban environment in modelling city-scale building energy. As the simulation of urban-scale building energy requires a substantial amount of data input, the use of GIS allows data of wide diversity to be easily integrated and possessed using spatial reference code. Despite using physical data or metered energy data, it is essential to obtain building geometric data such as building height, building footprints and the number of floors to estimate the intensity of building energy use in urban areas. Such physical settings of the urban environment can be represented and quantified in GIS, which can incorporate more features in the urban environment at the later stages. In some cities, detailed building footprints and other geometric data are stored in the form of polygon type shapefiles in the government database, for example, Land Use Tax Lot Output in New York City [32,43,44], Boston GIS in Boston [37], Basic Registration of Addresses and Buildings in Dutch cities like Leiden [66].

In addition to the function of combining different types of data, GIS also supports data pre-processing to facilitate modelling at a later stage. One of the examples would be how Cerezo Davila et al. [37] applied polygon simplification techniques in GIS ArcMap to reduce the number of points of footprint polygons, in order to shorten the simulation time due to the complex shapes of buildings extracted from satellite and flyover imagery. Some studies even went a step further to use GIS for data generation. In the case of missing or faulty data, which was demonstrated by Yang et al. [66].

3.3.2.2. Building segmentation. Collecting details about the envelope and energy system of individual buildings at the urban scale can be time-consuming, not to mention the possibility of unavailable or inaccessible measurements. One of the most common solutions targeting the heterogeneity of buildings is the use of archetype models, which are the building typologies that contain similar values for key input parameters to deduce energy use. By collecting simple background data on buildings without detailed geometric or metered data, each building can be assigned an archetype and its predictive energy use. The data would then be scaled up and multiplied by the number of buildings represented by them, allowing calibrating to represent multi-level energy performance. For instance, Fracastoro & Serraino [38] segmented over 870, 000 buildings in the Italian provinces of Piedmont & Lombardy into 3168 archetypes. After deducing the thermal load of each archetype with data on geometry, transmission and ventilation, the trained data was then calibrated and aggregated to show multi-level analysis energy performance. The segmentation of building is typically achieved by using data-driven techniques, most commonly clustering-based methods to conduct statistical zoning, which facilitates the characterisation of buildings with their respective prototype.

In this review, the most common features used for building segmentation are identified to be *Construction Period, Building Structure (height and size)* and *Building Use/Type* (Table 2). This finding agrees with the report by Kontonkosta and Tull [44] that the top six features: *Year Built, Number of Floors, Proportion Residential, Proportion Office, Proportion Retail, and Borough.* They were reported as the most predictive of electricity use and could significantly improve the accuracy of the building-level simulation.

Despite the benefit of simplifying the computation process, categorising buildings into archetypes can mispresent the diversity of occupant behaviour, envelop individuality and differences in the HVAC system, which can result in 15 % error in simulation according to a validation study [37]. To minimise the potential loss of information in simulation using building archetypes, the calibration requires a sufficient understanding of the local energy laws and requirements, before identifying appropriate parameters to characterise buildings are identified. When the method is implemented in cities with a rich diversity of buildings and complex urban forms, a wide and sufficient range of building prototypes should be developed in response to the morphological contexts.

Urban morphological factors can be incorporated as indicative parameters for building segmentation, which was demonstrated in a number of simulations: Yamaguchi et al. [55] selected zoning/configuration patterns as one of the parameters for clustering as it will “affect the thermodynamic characteristics of buildings”; Caputo et al. [39] defined building archetypes with different form factors to represent buildings in urban areas of low, medium to high, and high density; One of the keys for accurate large-scale simulation is the ability to incorporate a greater number of factors that influence power consumption [68]. In reality, however, urban morphology factors are observed to be less prioritised in the feature selections. One plausible explanation is that most studies are constrained by the computational capacity and can only use the strongest predictors of energy demand for segmentation. Whilst more and more data mining techniques have been investigated to integrate more predictors with reduced computation time, the rising accessibility and applicability of big data technology are expected to further increase research capability in better incorporating urban form in large-scale simulation. For instance, Ma and Cheng [43] identified the vegetation cover of New York City using satellite imagery, then calculated the Normalised Difference Vegetation Index, and used it as one of the 216 features to predict city-wide energy use.

3.3.3. Incorporating urban climate

The data input of building envelopes and the climate effect on them are also essential to simulate the thermal load in buildings. Typical geometry features that are related to urban climate data include building footprint (height, floor space), glazing ratio and thermal transmittance (U-value) of window, wall and roof et cetera. For example, glazing ratio affects the amount of interaction between indoor and outdoor environment, whereas vertical-to-horizonal building area ratios as it determines building surface area exposed to the outside environment.

Upon the input of geometric data, weather data is required to set the boundary conditions in order to deduce the thermal balance between the building and its surrounding. This review found that almost all simulations considered the factor of temperature as outdoor temperature significant affects building thermal load in means of convective and conductive heat transfer [69]. Most studies adopted the degree-day method, which is built upon the assumption that space heating energy demands for buildings are directly proportional to their heat loss in response to urban atmospheric conditions. For example, heating degree-day refers to the sum of departures of mean daily air temperature from the base temperature, which is defined and computed differently in varying contexts and regions [70]. Other weather parameters included radiation, humidity and wind profile (Table 3). In terms of air humidity, as solar heat is absorbed by water bodies, air with a greater amount of water vapour would result in higher latent and sensible heat and hence impacting the thermal energy demand.

In our review, most urban-scale simulations adopting thermal modelling used city-wide weather data, and the most common source is airport weather stations (Table 3). It means that most simulations are built upon the assumption that the climate in an urban environment is homogenous. For instance, Kristensen et al. [49] obtained the hourly temperature data from a central weather station and assumed that it was

Table 2
Parameters of building archetypes in selected studies.

Paper	City	Number of buildings	Number of Archetype	Geometrical parameters		Non-geometrical parameters			
				Density	Structure (size/height)	Construction period	Building use/type	Occupancy	Fuel source/ Energy efficiency
[3]	Milan, Italy		56		4 (form factor)	7	2		
[11]	Zug, Switzerland	1392	172			6 + 6 renovation periods	16		
[34]	Nottingham, UK	50	30		5 (built form)	6			
[37]	Boston, US	83541	52			4	13		
[46]	Geneva, Switzerland	13614			9	10	3		
[51]	Beirut, Lebanon	3630	30			6	5		
[55]	Osaka, Japan		612	9 (zoning patterns)	5		4		4
[66]	Leiden, Netherlands	14321	30			6	5		
[38]	Piedmont & Lombardy, Italy	877,124	3168	3 (building contiguity)	4	4		7	11
[67]	Ile-des Soeurs, Canada	Around 1500			17 (window-wall ratio)	10			
[48]	Aarhus, Denmark	18475	11			11			

Table 3
Meteorological factors considered in selected studies.

Ref	City	Weather Parameters				Spatial Scale				Temporal Scale	Source			TMY
		Temperature	Humidity	Solar radiation	Wind	State	City	Block	Building	Hourly	Airport Weather Station	Openweather	City weather station	
[11]	Zug, Switzerland	✓	✓	✓									✓	
[17]	Hong Kong, China	✓	✓				✓							✓
[33]	San Francisco, USA	Not specified					✓			✓				
[37]	Boston, USA	Not specified					✓				✓			✓
[42]	New York City, USA	Not specified					✓			✓		✓		✓
[48]	Aarhus, Denmark	✓		✓			✓			✓				
[51]	Breuit, Lebanon	Not specified					✓				✓			
[65]	Leiden, Netherlands	✓		✓			✓			✓			✓	
[38]	Piedmont & Lombardy, Italy	✓		✓										
[66]	Ile-des Soeurs, Canada	✓		✓	✓		✓		✓	✓	✓			
[62]	Strasbourg, France	✓		✓	✓				✓	✓	✓		✓	
[63]	Ostfildern, Germany	✓		✓			✓							✓

'adequately representative' of the weather condition of the study area. Fracastoro and Serraino [38] assumed the solar irradiance values recorded in the regional capital could represent the solar irradiance of the whole region, albeit with their geographical difference. One of the possible reasons for the effect of microclimate often disregarded is that most of the reviewed simulations were conducted in low-density cities (Table 3), where the effect of urban form on weather conditions is limited. As a result, the effect of microclimate is often seen to be disregarded in the simulation. Having that said, a few simulations have considered the zonal variation in climatic conditions, which can be categorised into two major approaches: simulating weather data at a finer scale and manipulating morphological data.

3.3.3.1. Simulating weather data at finer scale. Incorporating of simulated weather data at a finer scale can help increase building energy use modelling in the urban environment where spatial variations of weather conditions are significant. The more direct approach is by coupling the microclimate model with the energy model. For instance, Katal et al. [60] integrated City Building Energy Modelling (CityBEM) with City Fast Fluid Dynamics Model (CityFFD) to derive the total energy demand that is sensible to the microclimate. CityFFD is a 3D fast fluid dynamics solver that predicts local microclimate using numerical modelling techniques, and CityBEM calculates the heat transfer and infiltration using the indoor, outdoor and building surface temperatures. More specifically, microclimate data are exchanged between the two models. The average wind speed, directions and temperatures around each surface of buildings were calculated in CityFFD and input for CityBEM to derive the indoor thermal condition, which was then applied as the input boundary conditions for CityFFD to deduce the energy use. The use of pseudo weather measurements resulted in a significant difference in building surface temperature at 2.5 °C [60], allowing a more accurate estimation of the energy performance. However, running a microclimate model requires a substantial amount of technical environmental and geometric data. Therefore, even more substantial computation volume and research time are needed when it is coupled with the energy model therefore requires a considerable computation volume and research time.

Kohler et al. demonstrated the use of another model by using the case study of Strasbourg, France [71]. The authors firstly obtained the city-scale base temperature from the non-hydrostatic regional Weather and Research Forecasting (WRF) model, then generated the vertical hourly temperature profile of building by calculating radiative interactions and turbulent exchanges between buildings and the urban atmosphere in the WRF model. Lastly, hourly building energy signature at floor scale was computed and aggregated for different urban forms. Since the use of degree-day method and WRF/urban climate modelling system require only simplified cubic building geometry [71], it is beneficial to predict energy use without detailed housing stock information or long-term historical energy data. A similar approach is adopted in the model developed by Ortiz et al. [72] for New York City, in which urban morphology parameters such as average building height, major land use and area fraction were defined at a spatial resolution of 1 km × 1 km in order to match with those in the urbanised WRF model.

3.3.3.2. Manipulating morphological data. While the urban morphological effect on climate is proven to significantly influence the accuracy of simulation [73], some studies deduced the spatial variation in weather conditions by manipulating urban morphological data. For instance, based on the assumption that buildings in areas with similar urban parameter values share a similar microclimate, Quan et al. [36] defined 50 microclimate zones in Manhattan using four parameters of urban morphology, i.e. canyon height, canyon ratio, pervious road fraction and building roof fraction and calculated their associations with the urban heat island effect based on data from the central weather stations. The refined dry-bulb temperature was then used to simulate thermal loads in buildings for the whole region. Morphological information can be generated in the GIS as well. For instance, Ma and Cheng [43] utilised GIS to calculate the distance of the buildings to the coast in relation to natural cooling, the density value of population and traffic, and the Normalised Difference Vegetation Index. These features were then used with 213 other features as predictors to model city-wide building energy use by using machine learning algorithms.

Inter-building effects can also be captured from urban morphology data. As spatially proximal structures may influence the heat gain and radiation of buildings [74], data such as distance between buildings and vertical-to-horizontal area ratios can be used to derive the shading effect. For instance, in the simulation by Krayem et al. [51] where "each building (of height H) that is 3.78H away from the target building is considered as a building that casts a shadow", shading effects were hence factored in when deriving the heat-balance of buildings in Beirut, Lebanon. Similarly, the shading sub-engine in the simulation by Quan et al. [36] was built upon GIS data on building height, tree canopy and topographical data. Although the sub-engine method assumes an identical window-to-wall ratio of each façade, it can reduce a net mean bias error of 2 % by capturing the interaction with solar radiation using only geometric data and GIS system [34].

4. Discussion

In the preceding section, major methods to simulate building energy use at an urban scale were listed and analysed based on the modelling inputs, outputs and approaches to incorporate the urban environment. Table 4 and Table 5 summarised their respective strengths and limitations, as well as their potential applications.

Simulation of building energy use can be based on physical data or metered energy data. Models based on different data input present their respective competencies, thereby allowing distinctive fields of application. As physics-based models require a large amount of technical data and intensive computation volume, it is mainly applied in studies for more technical purposes, such as informing energy planning, operational optimisation and large-scale building retrofit measures. While physical scenarios and energy systems of buildings can be simulated in physics-based models, they also support energy use forecasting upon scenario settings, which is informative for decision-making in urban planning and development. Another common application of physics-based models is thermal comfort analysis, which facilitates air temperature and quality control in the urban environment.

In comparison, data-driven models rely on historical energy usage data, thereby are commonly used to estimate building energy use when limited physical information on the building can be gathered. Data-driven models can reveal the effects of individual covariates [44], such as climatic conditions, states of building and occupants' behaviours. With the substantial amount of metered data that can be easily extrapolated, data-driven models have the strength to derive different temporal courses of energy use. The data-driven models also support simulation at a larger scale when the energy data at respective scales are available, whereas physics-based models are limited to neighbourhood or district scale as substantial computational volume is required.

However, these two methods display respective incompetence when the simulation is conducted at a large scale, especially in terms of data collection and processing. As data-driven models require the actual consumption in buildings, its application could be hindered by the data availability of city-wide metered data. Although some cities have made it legally binding to reveal energy data of building, like the energy disclosure ordinance in New York City (LL84), in cities without the data available, researchers may have to obtain them through special arrangement with utility providers [47] or with government departments [44]. This results in an emerging trend of using hybrid models, in which elements of simplified physics-based models and data-driven models are combined, to produce more accurate simulation results. Although more robust modelling designs are needed [9,16,42], hybrid models can leverage the strengths of two models. Hence, it is becoming more widely applied in urban scale studies.

Similarly, the choice of modelling output presentation is determined by research interests as statistical presentation and spatial presentation serve different purposes. When the temporal course of building energy use is of interest, statistical presentation is typically used as data can be easily extrapolated. However, the modelling outcomes can be highly technical and thereby are mainly used to support energy planning and optimisation decision-making. Spatial presentation, on the other hand, can be easily comprehended as it displays the spatial distribution of energy use. It is particularly useful for informing urban planning and design where cross-sectoral decision-making is involved.

Several approaches to incorporate the urban environment were summarised in this review. With wide-ranging functions such as data integration, pre-processing and generation, GIS is commonly used to support urban-scale modelling. Energy data of each building can be directly input into the GIS and combined with geometric information, allowing physical settings of urban environment to be represented and quantified. Using building archetypes to predict large-scale energy use is another widely applied approach identified. Instead of requiring detailed geometric or metered data of each building, building

Table 4
Cross-comparison of different approaches based on modelling input and output.

Classification based on	Approaches	Strengths	Limitations	Applications
Input	**Physics-based models**	• Capable of capturing the actual thermodynamic of buildings • Can be simulated without historical data [35,36]	• Detailed physical and technical data required • Intensive computational volume and time required	• Energy planning and operational optimisation • Energy use upon scenario settings • Thermal comfort analysis • Mainly applied to simulation at the neighbourhood or district scale
	Data-driven models	• Capable of revealing the effect of individual covariates • Capable to reveal the temporal courses of energy use	• Large number of sampling energy data required [41] • Limited capacity to characterise energy services • Coarse temporal and spatial scale	• Energy use forecast when limited building data is provided • Can be applied to simulation at the neighbourhood, district or city scale
	Hybrid models	• Leverage the advantages of physics-based and data-driven models [11,56]	• Robust modelling designs required [9,16,42]	• Useful for simulation at the neighbourhood, district or city scale
Output	**Statistical presentation**	• Energy data can be extrapolated to different temporal scales [31,39] • Display the correlation between energy use and different variables	• Less capable to the display the spatial variations in energy use	• To display energy usage pattern when its time course is of interest • To support energy planning and conservation policies [38]
	Spatial presentation	• Display the spatial distribution of energy use [34,57] • Easily understood [46,54]	• Less capable to the display the temporal variations in energy use	• To display energy usage pattern when its spatial distribution is of interest • To inform evidence-based urban planning and design

Table 5
Cross-comparison of different approaches to incorporate the urban environment.

Approaches	Strengths	Limitations	Applications
Use of GIS	• Facilitate integration of building and energy data [• Support data pre-processing and generation [37,66]	• Subjected to the availability of the GIS database	• Can be applied to simulation at the neighbourhood, district or city scale
Building segmentation	• Building data of each building is not required • Studies are highly scalable and easily applied to larger areas [38,43]	• Detailed understanding of the dynamics of buildings required	• End-use and housing stock energy use modelling • Especially useful for high-density cities with wide variety of buildings
Simulating weather data at finer scale	• Capable of generating a more accurate prediction • Capable of incorporating the effect of microclimate in urban areas [71,72]	• Intensive computational volume and time required [60] • Fine scale weather data is needed	• Mainly applied to simulation at the neighbourhood or district scale
Manipulating morphological data	• Capable of capturing the spatial variations in weather data without the need of microclimate modelling [36,73] • Easily conducted	• Coarse spatial resolution	• Especially useful for cities with compact settings [43] • Applied to simulation at the neighbourhood, district or city scale

segmentation help estimate large-scale building energy use based on assigned parameters, making it especially suitable for high-density city modelling with a wide variety of buildings. Once the archetypes are established upon a detailed understanding of energy features and requirements, they can also be applied to predict energy use in large areas, i.e. city-scale or even inter-cities or national scale modelling.

As for the climate environment, it is identified that most studies incorporated city-wide weather conditions in energy use modelling. However, in urban areas where weather conditions are significantly impacted by the complex urban settings, extra effort is needed to incorporate their spatial variation, which can be achieved by simulating weather data at a finer scale and manipulating morphological data. However, coupling microclimate and building energy model at urban scale may face computational difficulties due to a substantial amount of data required, making it more applicable for simulation at neighbourhood and district scale. Manipulating morphological data, as a rising alternative to reflect localised weather conditions, is becoming an emerging solution under the trend of advancing data mining and geographical information technology. Comparatively, this approach is simpler to compute and conduct. Therefore, it can be applied to simulation at a more wide-ranging scale. It can also incorporate the real-world urban settings and their effects into the simulation. Therefore, is applicable for modelling in cities and areas without available micro-climatic data.

5. Conclusion and applications

Understanding the landscape of energy use in a city is the first step towards energy transition, climate resilience and other sustainable goals. This review collected and analysed the major methods to simulate building energy use at the urban scale a based on the modelling inputs, outputs and approaches to incorporate the urban environment. The strengths and limitations of the methods were compared to explore the possible applications and future needs in the model development. While physics-based models and data-driven models are suitable for different scales of simulation and research objectives, the availability of data typically is determines the choice between them. In response to their incompetence, hybrid models, in which elements of simplified physic-based models and data-driven models are combined, are becoming an emerging solution. With the advance of machine learning and big data technology, more robust simulation designs and model development are expected to leverage the advantages of physics-based and data-driven models.

Given that buildings energy use is sensitive to not only building internal conditions but also its surrounding built and climatic environment, the key to produce a more accurate simulation depends on its ability to capture the impacts of various contextual factors. While GIS is capable and commonly used to represent and quantify the urban physical environment, building segmentation is a significantly useful in modelling the building energy use of cities with a wide diversity of buildings. However, this review identified that insufficient consideration had been put on the effect of zonal variation in weather conditions within the cities and their influences on thermal loads in buildings. This can be reasoned by the observation that most modelling studies were conducted in low-density cities, where the effect of urban forms on weather conditions is limited. While compacted cities such as Asian megacities experience greater vulnerability to climate change [75] and more extreme weather conditions [76] due to their climatic profile and dense morphology, this review highlights the need to put more attention on the urban heating island effect and other climatic complications in high-density urban settings. Another possible challenge that hinders the account of spatial variation in weather conditions is the intensive computation effort and data it requires. In response, an emerging research trend of using urban morphological data to reflect the micro-climates is observed. In the future, urban and energy data will become more accessible, and, by consequence, more creative use of urban morphological data is expected to better incorporate the urban climatic environment.

Declaration of competing interest

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

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Appendix A. Supplementary data

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