Energy & Buildings 248 (2021) 111175

Contents lists available at ScienceDirect

Energy & Buildings

journal homepage: www.elsevier.com/locate/enb

Urban building energy model: Database development, validation, and application for commercial building stock

Rezvan Mohammadiziazi [a], Samuel Copeland [a], Melissa M. Bilec [b,*]

[a] Department of Civil and Environmental Engineering, University of Pittsburgh, 3700 O'Hara St., 341 Benedum Hall, Pittsburgh, PA 15261, USA

[b] Department of Civil and Environmental Engineering, University of Pittsburgh, Deputy Director, Mascaro Center for Sustainable Innovation, 3700 O'Hara St., 153 Benedum Hall, Pittsburgh, PA 15261, USA

ARTICLE INFO

Article history:
Received 9 March 2021
Revised 14 May 2021
Accepted 7 June 2021
Available online 11 June 2021

Keywords:
Urban building energy model
Urban database
Image processing
Energy simulation
Energy conservation
Building archetype
Commercial buildings

ABSTRACT

Achieving citywide building energy reduction goals require extensive understanding of energy use at scale, which is challenging due to scarce and disparate data. Despite attention to urban building energy models (UBEM), unexplored aspects and missing details in this emerging field have remained, including further exploring non-homogenous commercial buildings, providing a detailed structure to create UBEMs for replication purposes, and developing methods to mitigate data scarcity and dependency. In this study, a structure is proposed using commercial buildings in Pittsburgh, Pennsylvania. We provide a description of an archetype library with relevant sources to improve reproducibility and describe a novel framework to create a database focusing on façade reconstruction through photogrammetry and image processing. For our UBEM, twenty archetypes that comprised eight commercial use types were identified. The average annual energy use intensity was estimated between 74 and 1302 kWh/m^2 for different use types. The simulation results also showed discrepancy in energy use of the buildings with similar use types. Validating the results utilizing actual data revealed an overall 7% error. Employing the model to evaluate energy conservation strategies showed energy use reduction of 2–5% for the entire stock. Outcomes of this research can aid policy makers in instituting energy goals and efficiency regulations.

1. Introduction

In the past decades, scientists have addressed the urgency of energy consumption and greenhouse gas (GHG) emissions from different sectors including the building sector. The building sector in the U.S. accounts for 39% of energy use with commercial buildings responsible for approximately half of this portion [1]. The continuous and growing rate of urbanization has resulted in urban buildings becoming the center point of energy consumption and GHG emission reduction strategies and ambitious targets. In this context, cities and countries around the world have formulated short-term and long-term energy and environmental goals that include energy reduction [2], shifting towards renewable energy sources [2], and selecting building materials with less environmental impacts [3]. For example, Los Angeles, California planned to reduce energy use per floor area of buildings 22% and 44% by 2025 and 2050, respectively [4]. Another example is California Title 24 which mandates new buildings to be equipped with photovoltaic systems for electricity generation [5]. The City of Pittsburgh, a member of the 2030 District Network and accounting for nearly 25% of floor spaces committed to this network, has established building energy and water reduction goals [6]. Achieving these goals for all cities and regions requires actionable and effective energy conservation (EC) strategies for buildings, especially existing buildings through renovation and retrofit. In addition to the demand side, launching actions and planning for renewable energy generation and supply systems, distributed energy resources (DER) [7], and district heating and cooling systems can also aid in accomplishing the energy goals. For regional decision makers to institute practical and effective energy efficiency policies and climate actions, thorough understanding of energy use of buildings in an urban area is essential.

Critical to understanding energy use is data and information about energy consumption and characteristics of buildings. Some cities have building energy data obtained through disclosure and benchmarking laws, along with voluntary approaches including the aforementioned 2030 District [6,8,9]. However, there are a significant number of cities and areas that lack benchmarking ordinances and laws. Another challenge facing of local governments is budget limitations for enforcement and processing of the data

* Corresponding author.
E-mail addresses: rezvanziazi@pitt.edu (R. Mohammadiziazi), scopeland@pitt.edu (S. Copeland), mbilec@pitt.edu (M.M. Bilec).

https://doi.org/10.1016/j.enbuild.2021.111175
0378-7788/

Nomenclature

AI	Artificial intelligence
API	Application Programing Interface
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
CBECS	Commercial Building Energy Consumption Survey
CBES	Commercial Building Energy Saver
DEM	Digital Elevation Model
DER	Distributed Energy Resources
DOE	Department of Energy
DSM	Digital Surface Model
EC	Energy conservation
EUI	Energy use intensity
fov	field of vision
GHG	Greenhouse Gas
GIS	Geographic Information System
ID	Identification
KS	Kolmogorov-Smirnov
LED	Light Emitted Diodes
LiDAR	Light Detection and Ranging
PDF	Probability distribution function
PE	Percent error
RECS	Residential Energy Consumption Survey
SVS	Street View Static
TMY	Typical Meteorological Year
UBEM	Urban building energy model
USGS	United States Geological Survey
WPRDC	Western Pennsylvania Regional Data Center
WWR	Window to wall ratio

into meaningful reports and visualizations. Hence, urban energy modeling tools and frameworks can be beneficial to overcome these challenges, as they can enable studying trends of citywide building energy demand, evaluating impacts of EC strategies on heating and cooling energy consumption, finding hotspots related to energy and emissions, and identifying suitable locations for developing district energy systems.

In this article, a modeling structure, established on advanced imaging and remote sensing techniques, is proposed and used for acquiring data and simulating urban building energy use. This structure is designed to maximize the use of actual data as a substitute for secondary data or assumptions and provide a road map to extract information from resources and standards. The commercial buildings in Pittsburgh, Pennsylvania is selected to develop and test the modeling structure. In addition, the outcomes of this research aid the city in its efforts toward reducing energy and emissions and combating climate change and aims to serve as a precedent for urban areas.

Urban scale studies are categorized into two major approaches - top-down and bottom-up [10,11]. The top-down approaches encompass macro-level variables and adopt statistical or machine learning methods to explore the energy use of buildings at a large spatial scale in relation to socio-economic aspects (e.g., income, education) [12]. For instance, Mostafavi et al. [13] developed a model based on the Residential Energy Consumption Survey (RECS) to predict residential energy use based on several factors such as household size and ages of the occupants. While top-down approaches provide a broad view of energy demands, their ability to associate building- or stock-level characteristics with energy consumption are limited. Alternatively, bottom-up approaches (e.g., cluster analysis and urban building energy modeling) can incorporate individual buildings characteristics into the modeling process and study energy use at finer spatial scale such as building-, neighborhood-, and zip code-level. One bottom-up approach is cluster analysis in which the energy use of a building stock is examined based on different characteristics or features of buildings such as use type, ownership status, and thermo-physical attributes [14,15]. Conducting cluster analysis for a historic district in Italy, Lucchi et al. [15] concluded that geometric and thermo-physical features had higher correlation to building energy use compared to building age and can be utilized for energy demand assessment. Using cluster analysis requires extensive information about features and energy use of all buildings at scale. Another bottom-up approach is urban building energy modeling.

While definitions of this emerging area are evolving, the literature is gathering consensus that urban building energy models (UBEM) are bottom-up, physics-based models that unlock the capability of spatiotemporal energy demand analysis in an urban area. These models couple heat and mass transfer mechanisms of clusters of buildings with 3D models to simulate energy use [16,17]. Principally, UBEMs are developed using either building prototypes or archetypes. In order to create *prototypes*, buildings are clustered into groups and for every group average values of *geometric parameters* (e.g., height, aspect ratio) along with predominant classes for non-geometric parameters (e.g., window U-value, HVAC coefficient of performance) are determined and utilized to create energy models. On the other hand, *archetypes* are groups of buildings that only share similar *non-geometric parameters* which are determined based on predominant classes for every group. Defining archetypes for an urban building stock will be described in detail further in this paper. Many studies have explored urban building energy modeling for different cities worldwide [18–29]. We have reviewed these articles to identify gaps and best practices (see Table 1).

1.1. Urban building energy modeling – Residential buildings

A review of the existing literature has revealed that several approaches for developing UBEMs have emerged to assess the energy consumption of residential buildings. In one of the earlier studies, Shimoda et al. [18] created 460 residential prototypes for Osaka, JP based on 23 household types (e.g., household with two employed members) and 20 dwelling types (e.g., detached house with floor area more than 150 m^2, apartment with floor area of 110–119 m^2) and simulated hourly energy use of every prototype over one year. Through accessing the number of buildings grouped under every prototype, the annual energy consumption of homes in the city was estimated. An 18% lower estimation from the model compared to the field surveys from 1999 was attributed to irregular occupants' behavior in using appliances, air conditioner, and lighting. Despite a comprehensive description of non-geometric parameters, it was unclear how the prototypes for the 3D models were developed, such as how to determine the geometric parameters or envelope properties.

Further, Cerezo et al. [19] and Sokol et al. [20] explored the importance of probabilistic approaches for determining non-geometric parameters of archetypes in Kuwait City, KW and Cambridge, Massachusetts, respectively in simulating the urban residential building energy use. In Kuwait City, their probabilistic approach focused on occupancy rate, lighting density, plug load, hot water peak flow, and heating/cooling set points; these parameters were modeled from either arrays of predefined values or

Table 1
Overview of scopes in existing literature on urban building energy modeling. R, C, and EC are abbreviations for residential buildings, commercial buildings, and energy conservation, respectively.

Articles	General building use type			Prototype vs Archetype		Envelope properties		Incorporating EC strategies	
	R	R and C	C	Prototype	Archetype	Not described/Assumption	Actual/Measured	High cost	Low/Medium cost
[18]	●			●		●		●	
[19]	●				●		●		
[20]	●				●	●			
[21]	●			●		●			
[22]	●				●	●			
[23]		●			●	●			
[24]		●		●		●			
[25]		●			●	●			
[26]		●			●	●			
[27]		●		●		●			
[28]			●		●	●		●	
[29]	●				●	●			
[30]	●			●		●			

Bayesian calibrations. Deterministic parameters (window to wall ratio, glazing type, wall material, roof material, cooling system) were gathered through in-person audits. When compared with the metered annual energy use, the Kuwait City results showed significant improvement in the model's accuracy due to using probabilistic approaches versus a deterministic approach (the mean error reduced from 16% (deterministic approach) to 1% (probabilistic approach)) [19]. However, calculation methods specifically related to window to wall ratio (WWR), an envelope property, were not clarified, for example, how were the in-person audits conducted.

Although these studies [18–20] and others listed in Table 1 [21,22,29,30] investigated many aspects of residential UBEMs and proposed strategies to improve urban models, there are unexplored spaces especially regarding the diversity of envelope properties and building facades, along with reproducibility challenges. We aim to address these gaps in our work.

1.2. Urban building energy modeling – Commercial and residential buildings

As shown in Table 1, while the majority of UBEMs focused on residential buildings, in part due to less complexity of envelope properties and mechanical systems, some studies focused on both residential and commercial buildings [23–27]. In the absence of building- and energy-related data, Heiple and Sailor [24] used aggregated information from Commercial Building Energy Consumption Survey (CBECS) [31] and RECS [32] to create residential and commercial prototypes for Houston, Texas. The prototype building energy models, created using eQuest and DOE-2, simulated the daily energy use of the city. Through validating the aggregated results with the surveys data, the authors showed marginal difference between the model and survey results of 2.5% and −1.3% for August and January, respectively [24]. However, a gap remains related to the performance of various building types and which building type requires a more detail prototype. Ding and Zhou [27] utilized the prototype methodology to explore energy data scarcity of a city in China. First, they formed three prototypes, a residential apartment and two office buildings. Second, a building energy database was developed by stochastic analysis that encompassed various mechanical- and occupancy-related variables. Characterizing and modeling the citys' buildings using aggregated information (e.g., [24]) or without accounting for actual use types, envelope properties, geometric parameters, and orientation (e.g., [27]) may lead to building energy performance challenges. We aim to resolve these concerns for cities and areas, which suffer from data paucity, through our proposed modeling structure.

In a thorough study, Cerezo et al. [23] hypothesized whether developing an UBEM was feasible for residential and commercial buildings using publicly available Geographic Information System (GIS) data. To test the hypothesis, the authors created a model for Boston, Massachusetts and validated results based on CBECS and RECS since metered energy use data was not available for the city at the time of study. While Boston has a richer GIS data, which included building footprint, roof and ground heights, construction year, use type and number of floors, compared to many cities in U.S. like Pittsburgh, Pennsylvania, lack of both building archetypes and data were still introduced as major barriers by the authors [23].

1.3. Urban building energy modeling – Commercial buildings

To date at the time of this writing, only one study by Chen et al. [28] focused on two types of commercial buildings (office and retail) by developing a tool that automized creation of UBEM. The tool generates 3D models of buildings based on footprint, height, and number of floors. The tool uses secondary data from Commercial Building Energy Saver (CBES) to build the energy models; it does not compile an archetype library that reflects on non-geometric parameters and envelope properties specific to an urban area. The modeling structure in this article intends to describe a holistic approach for developing databases and to mitigate dependency of UBEMs on secondary data, which is the key barrier to the converging UBEM outcomes and energy use of buildings in real-world. In this study, the pattern and variation of the energy consumption relative to different commercial buildings are also analyzed.

1.4. Objectives of the study

The objectives of this study were to:

- Compile a unified modeling structure that maps methods, resources, and the steps essential to develop a comprehensive database of commercial buildings with a focus on actual envelope properties and façade reconstruction.
- Focus on commercial buildings to close the gap regarding the building use type.
- Validate the results of the UBEM with the actual energy data.
- Employ the model to evaluate impacts of low to medium cost EC strategies on the total energy use and different end uses which is not explored as shown in Table 1.

By achieving the objectives, this paper aimed to contribute both to the field of urban building energy modeling and the region, while providing a path for other regions as well.

Based on the earlier discussion, the energy use of residential buildings has been investigated. The consistency in energy performance of residential stock has enhanced the overall results that focuses on this type of buildings. While some studies have included both residential and commercial buildings, the results of these models are still overshadowed by the consistent performance and simple characteristics of residential buildings. Increasing the knowledge about the energy performance of buildings at scale and improving UBEMs require special attention to commercial buildings. In addition, in the time of unforeseen crisis like Covid-19 pandemic, when there is a drastic energy demand shift from commercial to residential buildings, it is useful to have an urban model focusing on commercial building stock. This model will enable energy suppliers and utilities to estimate the energy demand reduction from the commercial stock and how the capacity could be directed toward residential buildings. While this is not the first study concentrating on commercial buildings [28]; it is the first, to our knowledge, that incorporates advanced imaging and remote sensing techniques to obtain envelope properties, which are not available in many city databases, and have been largely based on assumption and expert judgement in urban models. By using street-level digital images, the modeling related to the building envelope, especially WWR will be refined.

As mentioned, many regions have aggressive energy reduction goals without adequate planning. The region of this study, Pittsburgh, Pennsylvania, is a part of the 2030 District Network, in which each region or district commits to 50% reduction in building energy, water consumption, and emissions from transportation below a baseline by the year 2030. In Pittsburgh, the majority of its district is comprised of commercial buildings. This study, therefore, can provide policy makers, urban planners, and entities working towards these goals with actionable strategies to aid in ensuring success.

2. Materials and methods

Development of an UBEM is a multi-layer process especially because in many cities, including Pittsburgh, the required data is not readily available and is scattered over various references or resources. This section provides a detailed modeling structure regarding creating a comprehensive database and generating the model through five phases. Phase one describes the commercial buildings in the studied region together with available data. In the second phase, development of an archetype library is explained. The third phase presents a novel photogrammetry and image processing framework that was used to retrieve the envelope properties and for constructing the facades of buildings. To estimate building's height, LiDAR analysis was conducted (phase four). Finally, integrating all the information to generate the urban model for commercial buildings is explained in phase five. A visualization, that displays the integration of these phases, is shown after their description in Fig. 4. Moreover, the graphical synthesis of methods and results is provided in Supplementary Materials, Fig. S1.

2.1. Phase 1 – Description of the commercial buildings in the studied region

Pittsburgh is a city in western Pennsylvania located in cold climate (zone 5A) according to the U.S. DOE climatic boundaries [33]. The city houses the University of Pittsburgh and Carnegie Mellon University both with sizable commercial spaces. Recently, companies like Google, FedEx, and Facebook have opened offices in the city, which is another indicator of the growing commercial stock. This specific study contains a commercial building stock that belongs to the University of Pittsburgh and the City of Pittsburgh [34] and comprises total number of 209 buildings. This stock was selected because of a few reasons. First, the 2030 District goals motivated this work. Second, the commercial stock consisted of a variety of different commercial building use types. Table 2 shows the percentage of floor area for different use types. Finally, the actual annual energy use of buildings from 2017 was reported to our research team, which was used for validating the results. In addition to the actual annual energy use, the floor area, property tax identification (ID), and the construction year were provided to our team. Essential to urban energy modeling is geolocating buildings to identify the location on map, orientation, and footprint (i.e., polygon shape of a building plan). For this purpose, the geospatial data that included Pittsburgh's building footprint was obtained from the Western Pennsylvania Regional Data Center (WPRDC) in GIS format [35]. The property tax ID of the buildings was cross referenced with GIS data in order to identify the corresponding footprints. However, this information was insufficient to develop an UBEM; the additional input information for creating the model was the *geometric parameters*, *non-geometric parameters*, and *envelope properties*. The subsequent sections are allocated to illustrate how the missing information was gathered or measured.

2.2. Phase 2 – Archetype library development

Urban building energy modeling streamlines the modeling process by classifying buildings into homogenous groups, known as archetypes, that have similar characteristics [12]. One robust example is the TABULA project in which an archetype library was developed for the building stock of fifteen European countries [36].

Creating an archetype library consists of two major steps: classification and characterization [19,37]. With respect to classification, buildings are 'binned' into groups based on one or more categories. In this article, the selected categories were based on two criteria: first, the categories must be available for all buildings; second, they should be relevant to energy consumption. According to these criteria, several categories have been proposed and utilized for classification by different studies such as use type, construction period, shape ratio, heating and cooling systems, and climate condition [14,16,24]. As Monteiro et al. suggested, defining more detailed archetypes increases the homogeneity of groups and may improve the precision or accuracy of urban energy models [21]. The challenge, in this regard, is that these categories are usually not available in public databases or are labor intensive to obtain for all the buildings in the stock or the city [19].

In this study, *use type and construction period* were used for classification; twenty archetypes were created for the commercial stock, comprised of eight commercial use types that were built during three construction periods (not all use types spanned the construction periods). Table 3 provides a list of the archetypes with additional descriptions. The majority of the publicly available resources like building codes, standards (e.g., ASHRAE standards), and surveys (e.g., CBECS) have included non-geometric parameters according to use type and construction periods [38]. Therefore, the classification of use type and construction period facilitated extracting these parameters of buildings from various resources during the characterization step.

Characterization is described as assigning values or classes of non-geometric parameters to every archetype. Drawing on the work from [19,20], these parameters can be determined through

Table 2
Percentage of floor area for different use types of the 209 commercial buildings in the studied region.

	Commercial building use type							
	Education	Lodging	Office	Parking garage	Public assembly	Public order and safety	Warehouse	Other
Floor area (%)	31	24	14	7	14	5	1	4

Table 3
Archetypes defined by construction period and use type for the commercial building stock in Pittsburgh. The third column is a description of sub-categories that formed the broader use types. Note: sub-categories are coded by Latin numeric to avoid redundancy.

Construction period	Commercial use type	Commercial use type sub-categories
Pre-1980	Education	School, college, university I
	Lodging	Dormitory, fraternity, sorority, nursing home II
	Office	Administrative office, social services, city hall III
	Parking garage	Multistory parking, underground parking IV
	Public assembly	Recreation center, senior center, library, museum V
	Public order and safety	Police station, fire station, medic center VI
	Other	Laboratory, observatory, mixed-use VIII
1980–2004	Education	I
	Lodging	II
	Office	III
	Parking garage	IV
	Public assembly	V
	Public order and safety	VI
	Warehouse	Non-refrigerated warehouse, distribution center VII
	Other	VIII
Post 2004	Education	I
	Lodging	II
	Public assembly	V
	Public order and safety	VI
	Other	VIII

either deterministic (single value or class for each parameter) or probabilistic (multiple values or classes for each parameter) approaches which both have their own advantages and disadvantages. The non-geometric parameters that are required for energy simulation depend on zoning (single zone or multi zone), the software engine used for simulation, and the thermal modeling approach. For this research, the three sets of non-geometric characterization parameters were occupancy, envelope composition, and mechanical/electrical systems. We found that characterizing the archetypes via gathering information from several resources is cumbersome mostly because a thorough outline that can guide urban modelers on where to find a certain parameter does not exist. Therefore, Table 4 was compiled as a road map to fill this gap and aid future modelers in conducting urban studies.

Some of the parameters needed modification or additional processing prior to being imported into the energy simulation. For example, ASHRAE standards on ventilation and indoor air quality [39,40] specified the minimum ventilated air per occupant (cfm/person); however, the ventilation rate (cfm/m^2) was needed for energy simulation in this study. Thus, the minimum ventilation (cfm/person) was divided by occupancy rate (m^2/person), obtained from [38,41,42], and the ventilation rate was calculated for every archetype. Additionally, the predominant classes of roofs for all archetypes (e.g., built up, slate or tile shingle, asphalt, concrete, metal surfacing) were determined by analyzing CBECS data for climate zone 5A, where Pittsburgh is located. Further, based on these classes, roof compositions and corresponding specifications such as the u-value were extracted from ASHRAE standards on energy efficient design [43–45]. Determining specifications of windows (u-value and solar heat gain coefficient) and flooring for all archetype followed the same process as was done for roofs. Ultimately, the non-geometric parameters, that are listed in Table 4, formed the archetype library and were stored in a csv file used in energy simulation.

2.3. Phase 3 – Photogrammetry and image processing framework

Envelope properties including external wall material, WWR, and floor count (number of floors above ground) are known to influence energy consumption [34,52,53], yet they have been under-reported in UBEMs due to cities' database deficiency and technological barriers. For instance, in the Boston work, WWRs were considered between 0.1 and 0.8 per use type based on authors' judgement [23]; how the WWR and external wall materials were determined was not clarified in other studies [22,24]. As previously delineated in the introduction, incorporating detailed envelope properties through reconstructing facades is one of the objectives of this research. To achieve this objective, a framework, comprising photogrammetry (acquiring façade images) and image processing (interpreting images), was developed and utilized.

Information about the surrounding environment and objects including building facades can be obtained by taking and analyzing aerial or street-level images. The quality and availability of aerial images are usually impacted by high-rise buildings in dense urban areas as they block vision of neighboring facades [54]. Hence, our framework was built using street-level images of facades obtained from Street View Static (SVS), which is an application programming interface (API) designed by Google to provide 360° images of numerous locations on the earth [55]. Employing SVS API provided the opportunity to download images in JPEG or PNG formats, that is not possible through regular Google Street View. Moreover, SVS API enabled us to adjust image attributes without using pointing devices, which mitigates randomness and enhances accuracy. To obtain the images, the buildings' centroids were found using GIS analysis to determine the latitudes and longitudes coordinates of the centroid points for all buildings. These coordinates were then imported to the SVS API for every building, separately, to access the façade images. As mentioned above, this semi-automatic API enables users to remotely control the attribute of

Table 4
Outline of resources and references for developing an archetype library. Note: operating schedules encompass several sub-schedules like occupancy schedule, heating setpoint schedule, cooling setpoint schedule, HVAC schedule, etc.

	Non-geometric parameter	Resources/References
Occupancy-related	Operating schedules	- Engineering assumption - DOE commercial reference buildings [38] - Consulting with local experts
	Occupancy rate	- DOE commercial reference buildings [38] - Literature [41,42]
	Plug and process loads	- DOE commercial reference buildings [38] - Literature [41,42,46]
	Ventilation rate	- Literature [41,42,46] - ASHRAE standards [39,40]
	Service hot water demand	- Literature [47,48]
Envelope composition	Roof	- CBECS [49] - ASHRAE standards [43–45]
	Window	- CBECS [49] - ASHRAE standards [44,45] - DOE commercial reference buildings [38]
	Flooring	- ASHRAE standards [44,45]
	Infiltration/Air leakage	- Literature [50] - DOE commercial reference buildings [38]
Mechanical/Electrical systems	Lighting density	- ASHRAE standards [44,45] - DOE commercial reference buildings [38]
	HVAC system	- ASHRAE standards [44,45] - DOE commercial reference buildings [38] - Consulting with local experts
	Water heating system	- Literature [51] - ASHRAE standards [44,45] - Consulting with local experts

an image by changing the vertical angel of camera (pitch), horizontal angel of camera (heading), field of vision (fov), and resolution (size) in order to find images with desired quality. Also, the remote-control capacity allowed our team to check images and maintain consistency (similar pitch, fov, and size) for different facades, which is critical to determine the material of the facades. Ultimately, the images of all buildings were downloaded, stored, and further processed.

We relied on agent-based processing for this study. Fig. 1 illustrates the process. The external wall material (eight types as shown in Fig. 1) and floor count were identified. According to the external wall type, the wall compositions and corresponding specifications were extracted from ASHRAE standards [43–45]. Accurate information about the floor count is important in energy simulations since it affects number of thermal zones. Next, the images were transferred into an area calculator software, SketchAndCalc, to measure the total area of the windows and the gross wall area, and then estimate the WWR, that is defined as area of window divided by area of wall above the ground [56,57]. Following Eq. (1), the WWR of building i with n facades was estimated. This process was replicated for all buildings.

$$WWR_i = \frac{\sum_{j=1}^{n} WWR}{n} \tag{1}$$

In order to investigate the importance of including the measured WWR of buildings in every region and city, the WWR values of the studied buildings, estimated through this framework, were compared to values derived from CBECS [49] for the same commercial use types that were located in U.S. cold climate. As displayed in Fig. 2, in Pittsburgh approximately 26% of commercial buildings

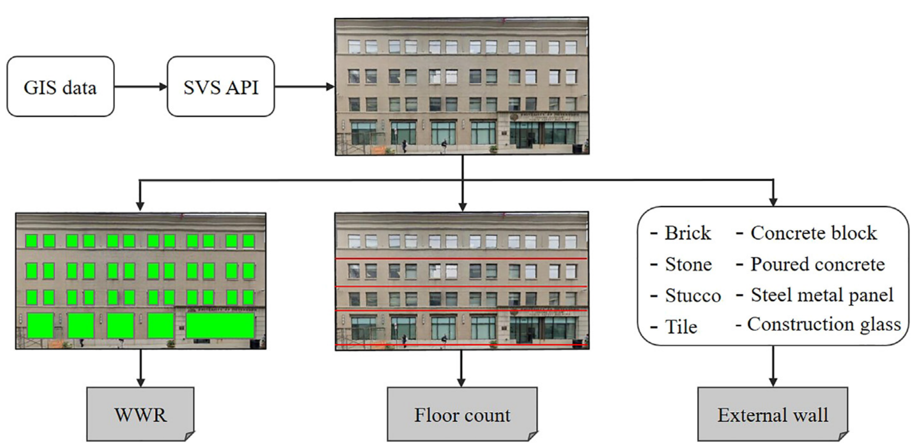

Fig. 1. Process flow diagram of photogrammetry and image processing framework for retrieving envelope properties. SVS API and WWR refer to Street View Static API and window to wall ratio, respectively.

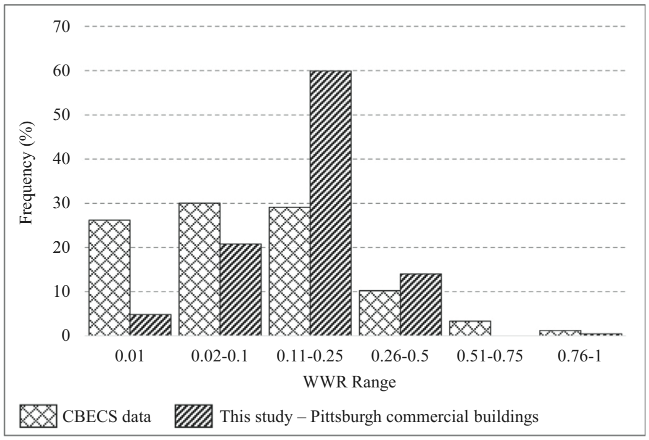

Fig. 2. Comparison of measured window to wall ratio (WWR) for the studied buildings with WWR from Commercial Building Energy Consumption Survey (CBECS) data [49].

have a WWR less than 0.1; on the other hand, based on CBECS data, almost 56% of buildings have a WWR less than 0.1. Also, the majority of the studied buildings (60%) have a WWR between 0.11 and 0.25; whereas, 29% of the buildings in CBECS fall into this category. The comparison reveals that employing CBECS would have resulted in underestimating WWR of Pittsburgh commercial buildings. This difference confirmed the fact that surveyed data like CBECS may not represent façade architecture and the WWR that are specific to a region or city. It should be noted that while selecting equal WWR intervals or ranges for this comparison would be beneficial, the WWR of buildings were specified as predefined ranges in CBECS rather than exact values [49]. Therefore, we were not able to select equal ranges and the predefined ranges in CBECS were utilized for this comparison.

2.4. Phase 4 – LiDAR analysis

GIS data at the municipal- or city-level is often 2-dimensional and lacks the elevation or height, a key geometric parameter for energy modeling. Some studies [19,58] tried to reconstruct the volumetric models of buildings via visual inspection and site surveys, but logistics and time consideration can limit adoption at scale. Others [26,30] used standard reference building heights but precision of this method remains uncertain [38,59]. We addressed the height issue by using LiDAR analysis. LiDAR, Light Detection and Ranging, is a remote sensing technique to examine earth and objects on the earth. Fig. 3 displays the procedure used in this paper for determining the building height. Two sets of GIS compatible datasets were utilized: 1) the commercial building footprint in *shape* file format (see section 2.1), 2) airborne LiDAR data in *las* format obtained from U.S. Geological Survey (USGS).

The raw LiDAR data was adopted to create the elevation models; Digital Elevation Model (DEM) and Digital Surface Model (DSM). The DEM contains the elevation of the earth's surface with reference to a specific datum, whereas the DSM contains the elevation of different objects on the earth (i.e., buildings, city furniture, vegetation, and bridges) with reference to the same datum. Thus, subtracting the DEM's elevations from the DSM's elevations results in a new model that only includes the object's height above the earth. To distinguish the height of the commercial building from other objects across the city; first, the new height model was filtered in relationship to the building footprint. Next, several random points, that were inscribed by the building footprint, were generated and synthesized with the height model; therefore, every point was assigned a height. Sometimes roofs are pitched or having height variations, and reconstruction of these types of roof was difficult and time consuming. So, a simplified approach was used in which heights of points (inscribed by a building footprint) were averaged for every building independently and considered as the final value of a building's height. While this simplification may affect precision of the thermal modeling, we believe that the associated error is negligible as it is averaged out when estimating the aggregated energy use for the entire stock.

2.5. Phase 5 – Urban model generation

When all required input information was gathered or estimated, an energy model of each building in the stock was generated to simulate energy use utilizing EnergyPlus, an open source program designed by U.S. DOE [60]. Model generation was a multi-step task that included creating 3D models, assigning envelope properties, defining thermal zones, and assigning non-geometric parameters to zones (see Fig. 4).

The 3D models represented the volumetric shape and orientation of the buildings. In the most basic models, a combination of a rectangle footprint and height forms the volumetric shape that is known as a shoe box model. However, we aimed to develop more detailed 3D models. The building footprints, from phase 1, were imported from ArcGIS to SketchUp, which is a drawing computer program, using Spirix Import Shapefile add-in tool, then they were extruded based on the buildings' height, from phase 4, to form the volumetric shapes. This approach provided a volumetric shape similar to the actual building. Next, the floor count and

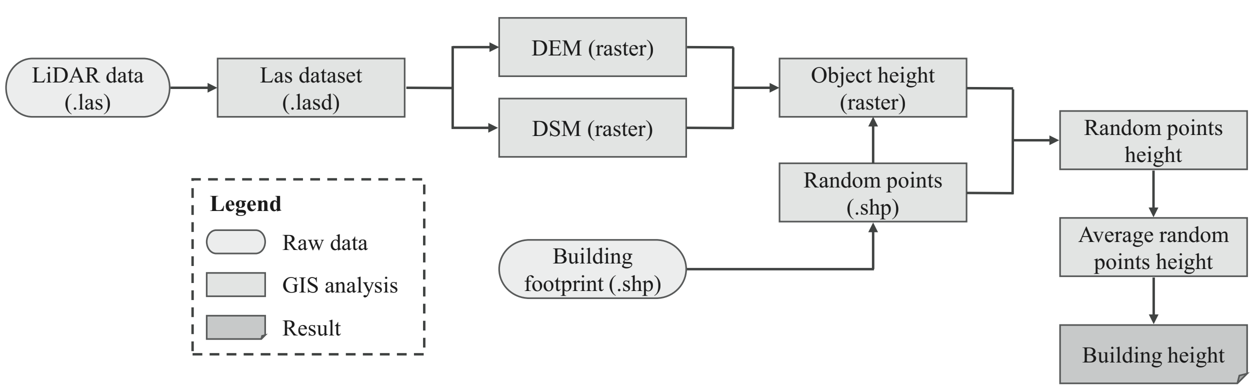

Fig. 3. LiDAR analysis for building height estimation. DEM and DSM refer to Digital Elevation Model and Digital Surface Model, respectively. Note: the texts in the parentheses (e.g., shp) illustrate the file format of different stages of GIS-based analysis.

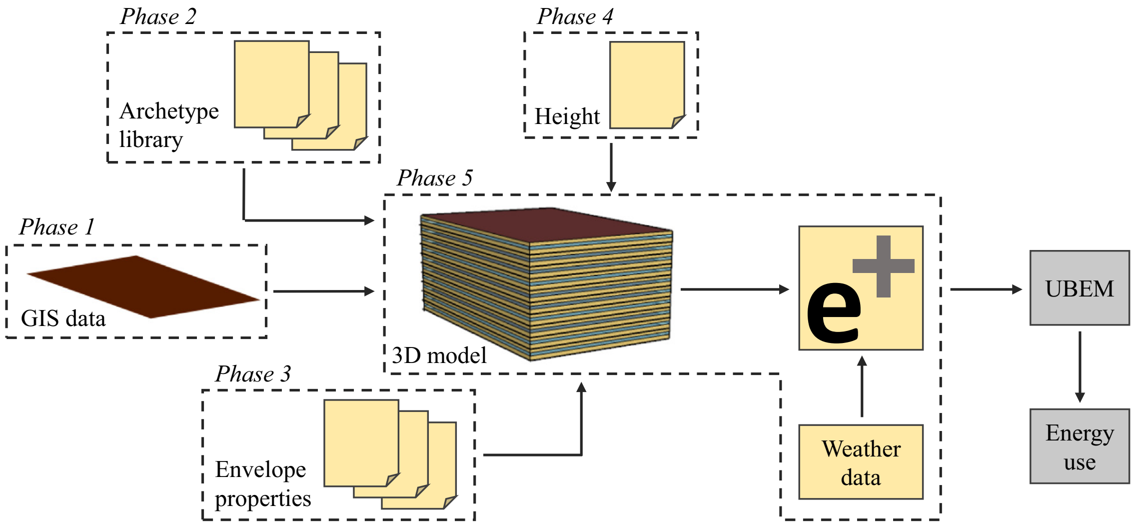

Fig. 4. Graphical overview of generating the urban building energy model.

WWR, from phase 3, were assigned to the 3D models of every building, separately. It was assumed that windows were evenly distributed among facades and located one meter above the ground. Considering five thermal zones per floor, a common practice in energy modeling of individual buildings, increases both model generation and running time [23]. So, in order to have a multi-zone model and avoid run time issues, one thermal zone was defined for each floor of buildings. The boundary condition of the external walls, floors, and roof were completed in SketchUp and by leveraging the OpenStudio add-in tools. Upon completion of the 3D models, they were converted to idf format, the operational format of EnergyPlus, and imported into EnergyPlus.

To complete the energy modeling, according to use type and construction period, an appropriate archetype, from phase 2, was selected for a respective building and non-geometric parameters were appointed to different thermal zones of the building. As an example, one thermal zone in the archetype, that represented the lodging buildings constructed prior to 1980, was specified for laundry activities. The plug and process load of this zone was defined in a way that included energy consumption of laundry appliances such as washer and dryer. Weather variables such as dry bulb temperature, wind velocity, also have substantial impact on energy consumption. Typical Meteorological Year (TMY) data has been broadly used in building energy analysis as weather input. TMY data embodies 8760 sample points representing median values of weather variables for every hour over one year [61]. One of the recent TMY data is TMY3 for which hourly weather variables were calculated based on historical data between 1991 and 2005. For this urban model, TMY3 from the Pittsburgh International Airport weather station, which represented the average weather condition of Pittsburgh, Pennsylvania, was employed. Once the weather data was imported into EnergyPlus, the energy models were completed, and simulations were run for every building in the stock.

The simulation results were analyzed in section 3 to identify the pattern of energy use for different commercial use types and to validate the UBEM. The implications of different EC strategies on the annual energy use of the building stock were assessed through adopting the UBEM. Three EC strategies including temperature set points adjustment, upgrading lighting systems, and plug and process load reduction were selected. To implement these strategies, the primary values for heating and cooling set points, lighting density, and plug and process loads, which were determined during characterization, were modified in the energy models and simulations were run for every building again.

3. Results and discussion

3.1. Energy use pattern correlated with commercial use types

The simulated annual energy use intensity (EUI) of the buildings was calculated and mapped as displayed in Fig. 5. EUI is summation of energy consumed by various end uses including space heating, space cooling, ventilation, lighting systems, internal equipment and appliances, water systems (e.g., pumps), and water heating systems normalized by floor area. The simulated annual EUI, averaged over the use types, ranged from 74 kWh/m^2 to 1302 kWh/m^2 for parking garages and warehouses, respectively. The high annual EUI for warehouse can be attributed to high intensity internal equipment and their schedules such as refrigerators and fans that are operating throughout the day without interruption. Buildings categorized as ‘other’ followed by education buildings had second and third highest average annual EUI. The former housed mixed-use spaces including offices, medical centers, restaurants, and retail stores which typically have higher energy consumption. The latter housed research activities, laboratories, and server rooms with high intensity equipment that resulted in greater energy consumption compared to the rest of commercial use types. Finding the lowest annual EUI for parking garages was expected given that these buildings did not have space heating and cooling, which dominated the energy use compared to the other end uses.

Space heating, cooling, and lighting together comprised between 36% and 93% of the total energy use for various use types. Apart from parking garages with no heating systems, the share of space heating from total energy use was estimated at 23% for education buildings, which is the lowest compared to rest of use types in the stock. Two reasons can be posited. First, energy consumed by internal equipment and appliances (plug and process loads) dominated energy use of education buildings. Second, heat gain due to operation of these equipment compensated for heating and reduced space heating demand for this use type. Whereas, for lodging buildings, 65% of the total energy use was allocated to space heating since the majority of these buildings were dormitories and not 100% operational during the cooling season. Therefore, the energy consumed for space cooling along with the plug and process loads was reduced and resulted in heating became the dominant energy load. Aligned with significant impact of weather condition on trend of energy use, we found that in this commercial building stock the share of space cooling from total energy use

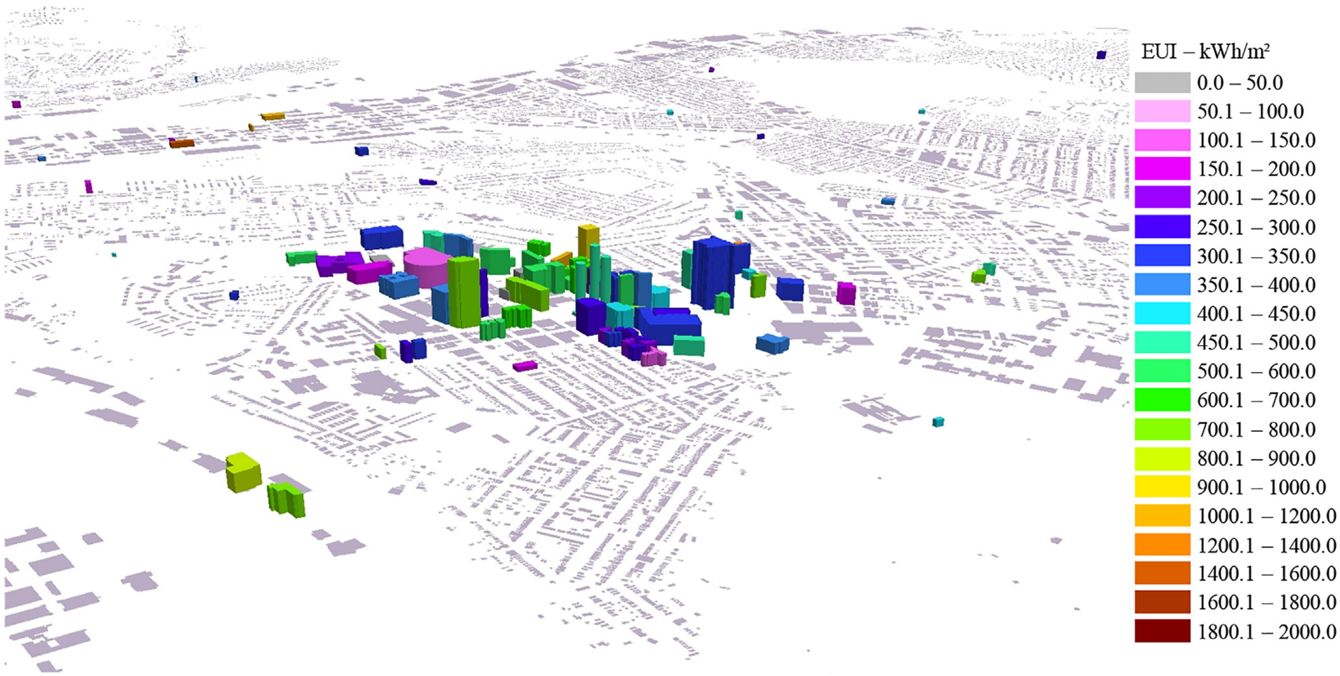

Fig. 5. Simulated annual energy use intensity (EUI) of the commercial buildings in the urban building energy model (UBEM) for Pittsburgh, Pennsylvania. Note: we only included buildings for which we had actual energy use for this UBEM for validation purposes.

(0–12%) was fairly lower than that of space heating because Pittsburgh is located in a cold climate with severe winter weather and milder summers. Besides discrepancy in the simulated energy use pattern of different commercial use types, there were variations in the simulated energy use of buildings with similar use types.

3.2. Variations in the simulated energy use of buildings with the same use type were identified

Frequency distributions for the annual simulated and actual EUIs and probability distribution functions (PDF) for annual simulated EUIs are shown in Fig. 6a and b, accordingly. While the thermal zoning was similar for the buildings with the same use type, the simulated annual EUI varied for different buildings (see Fig. 6b). This variation was because the solar heat gain and heat loss were different for buildings due to the diversity of the orientation and WWR, which their influential role on the energy use of buildings are well-studied in the literature [62–64]. Thus, it can be inferred that considering the actual building orientation, obtained from geospatial data, and the WWR, measured through photogrammetry and image processing, likely improved the urban model's accuracy. Moreover, incorporating the external wall material specific to each building and consequently wall composition, which impacts the heat transfer between buildings and unconditioned environment, was another reason for the variation of simulation results within one use type.

The PDF of the annual simulated EUI for seven types of buildings (excluding lodging buildings) followed a lognormal distribution as shown in Fig. 6b. Buildings with lower EUIs had higher frequency than buildings with high EUIs. Another important finding to be addressed is that PDFs were right-skewed; therefore, the higher EUIs are more scattered. Furthermore, through comparing the frequency distributions of simulated and actual EUIs (Fig. 6a), it can be concluded that the UBEM's results were more concentrated whereas actual data were dispersed. This was mostly because when characterizing archetypes, the occupancy-related and mechanical/electrical systems parameters were assumed fixed for every archetype, which is a known limitation of UBEMs. Nonetheless in the real-world, these parameters differ for every individual building, consequently the actual EUI had a wider range. The simulated frequency distributions of the public assembly and public order and safety buildings showed more similarity with actual frequency distributions compared to the rest of use types. This similarity was likely due to less complex mechanical systems and occupancy-related parameters of public assembly and public order and safety buildings. By examining the average annual EUIs, presented in Table 5, the difference between the overall simulated and actual energy use was not significant in this building stock. Thus, it pointed to the conclusion that despite inherent complexity and diversity of commercial buildings, the UBEM was able to provide accurate estimation of energy consumption.

3.3. The UBEM was validated according to actual data

One of the contributions of this research was focusing on commercial buildings to advance the field. To examine the accuracy of the UBEM developed for solely commercial buildings without leveraging steady energy performance of residential buildings, it is imperative to validate results based on actual data. One path for validation is estimating and interpreting modeling error, which can be defined as deviation between simulated energy use and actual energy use [65]. Modeling errors can be generated from numerous sources from inaccuracy of simulation engine and the uncertainty of input information, to simplification applied to various stages of developing the model. In this order, the percent error (PE) was estimated using the aggregated energy use of each use type. The mean PE of the annual EUI was estimated based on Eq. (2), where *Mean* EUI_{aj} was the average annual actual EUI for use type *j*, and *Mean* EUI_{sj} was the average annual EUI obtained from the UBEM for use type *j*.

$$Mean\ PE_j = \frac{|Mean\ EUI_{aj} - Mean\ EUI_{sj}|}{Mean\ EUI_{aj}} \times 100 \tag{2}$$

As shown in Table 6, the mean PE varied according to the use type. The low PE for the education buildings was likely because most of these buildings belonged to the University of Pittsburgh

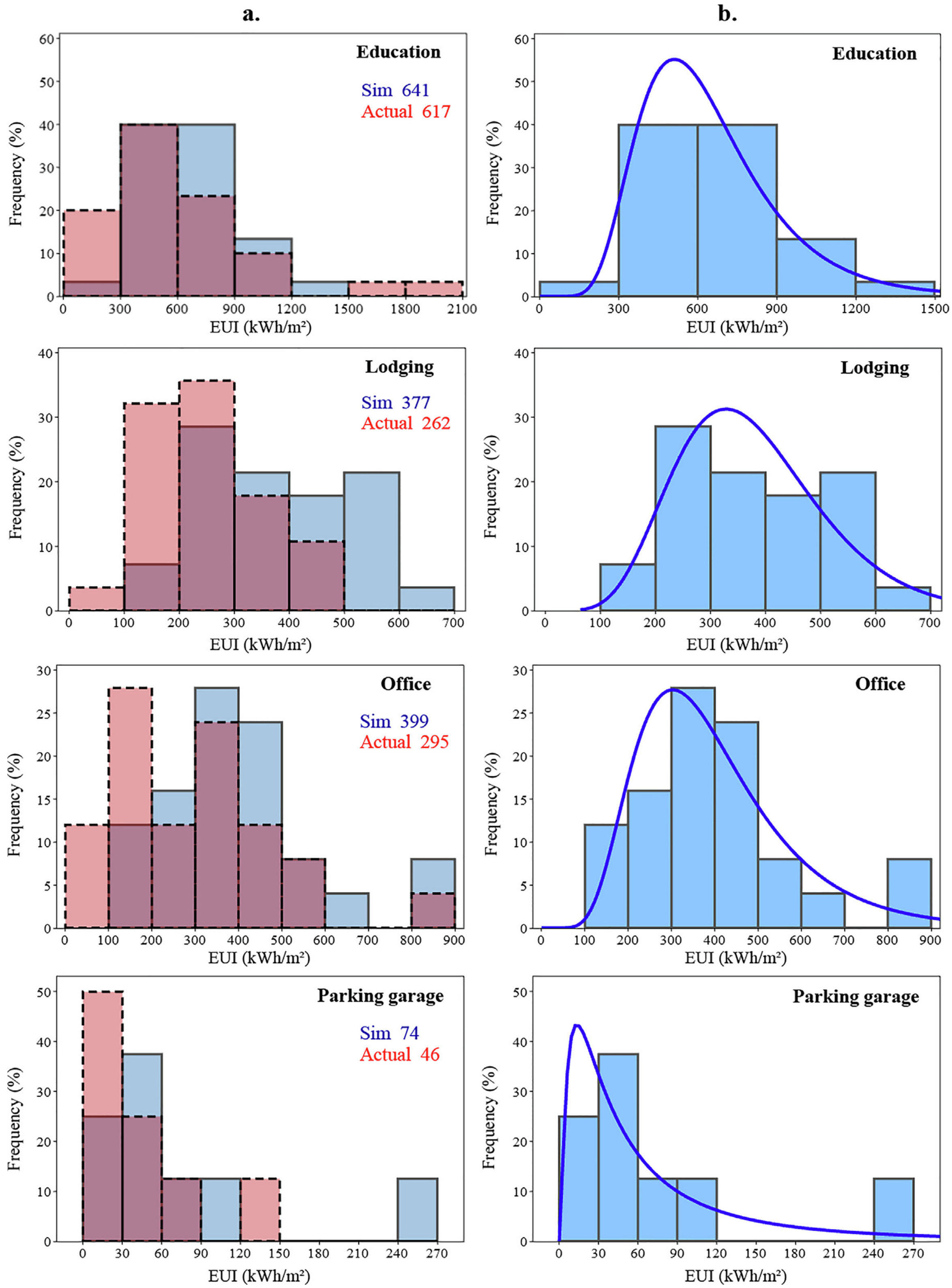

Fig. 6. a) Frequency distributions of annual simulated and actual EUIs for eight use types; b) PDF and frequency distribution of annual simulated EUIs. The average annual simulated EUI (Sim) and the average annual actual EUI (Actual) are shown in blue and red texts, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

and consulting with building managers aided our team in characterizing archetypes with greater similarity to real-world operation. The error for lodging, other, and office buildings were almost similar and can be mainly traced to various operating schedules and internal equipment. Surprisingly, comparing average simulated EUI with the average actual EUI of parking garages showed considerable difference (63%). Ventilation systems were defined during the archetype characterization for parking garages. However, some of these buildings were designed with vehicular barrier walls instead of external walls and used natural ventilation rather than

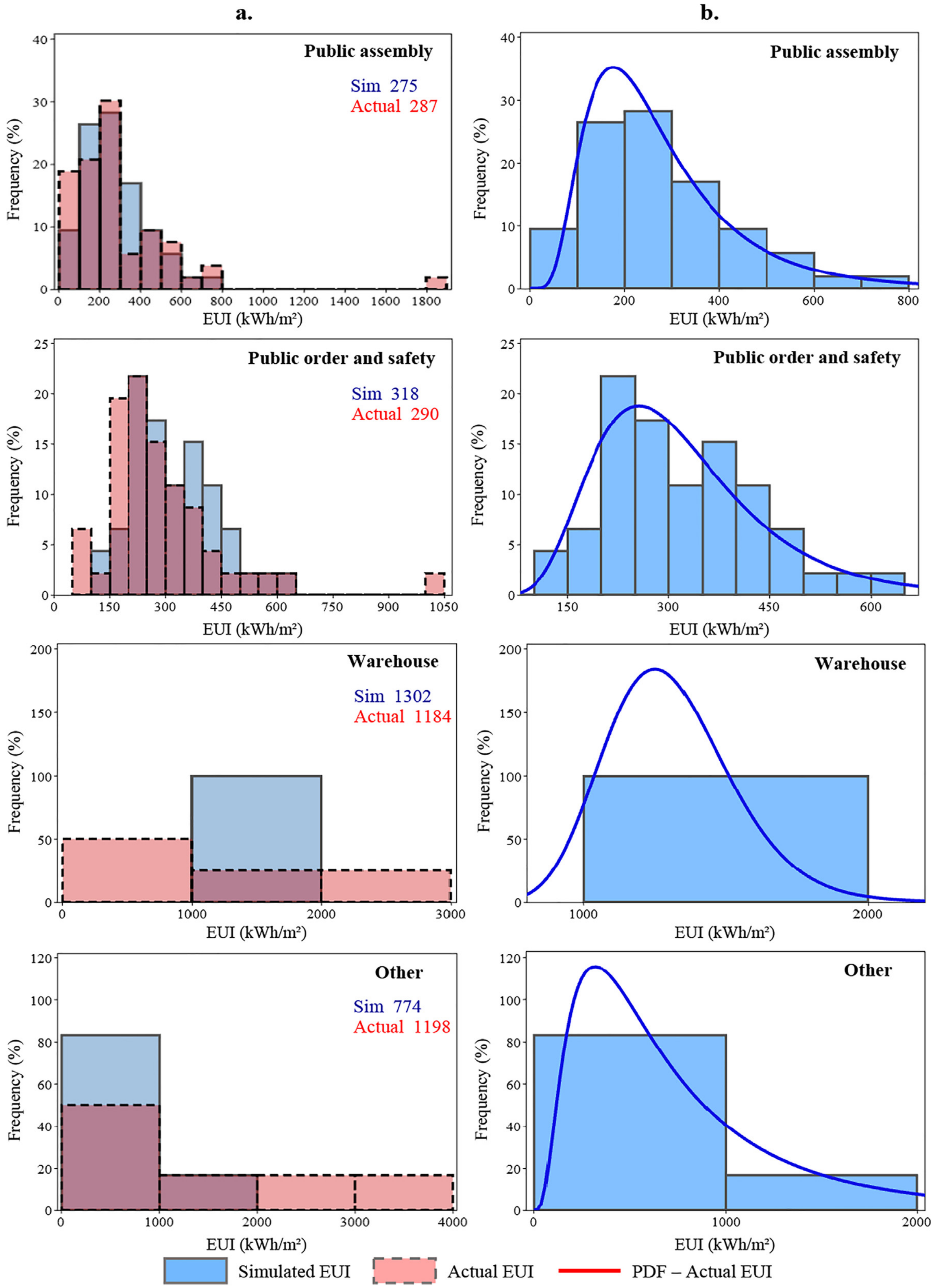

Fig. 6 (*continued*)

Table 5
Average annual simulated and actual energy use intensity for eight commercial use types and for the overall studied building stock.

	Average annual EUI (kWh/m^2)	
	Simulated	Actual
Education	641	617
Lodging	377	262
Office	399	295
Parking garage	74	46
Public assembly	275	287
Public order and Safety	318	290
Warehouse	1302	1184
Other	774	1198
Overall	126	117

ventilation systems (e.g., fans). So, their actual energy use was much lower than the simulated values, but this difference did not have a considerable impact on overall model error since the energy use of parking garages were low compared to other buildings.

Overall modeled PE was 7%, which is within acceptable range (1–15%) suggested by existing literature [23]. In addition to error estimation, two-sample Kolmogorov-Smirnov (KS) test was adopted to explore the similarity of distributions of simulated EUI and actual EUI. The benefit of the test is showing if the UBEM's outcomes represent the commercial building stock of Pittsburgh and whether the distributions of energy use, acquired from the model, can be utilized in future to scale up outcomes to the entire city or not.

The KS test is a non-parametric test providing insights on the statistical difference of two samples [66]. The null hypothesis is that the two distributions are not statistically different, and it is not rejected when the p-value is greater than a specific significance level. Usually, the significance levels are assumed to be 0.05 or 0.01. We compared the p-values for every use type with a significance level of 0.05. According to the results of KS test, displayed in Table 6, the null hypothesis was not rejected for all the buildings except lodging buildings, which confirms that distributions of simulated and actual EUI are not distinct. The statistical difference for lodging buildings may be correlated with operating schedules and other occupant behaviors, which can be addressed through implementing a probabilistic approach during the lodging archetype characterization to define occupant-related parameters. However, such this approach first requires comprehensive behavioral data that is not currently available, and second is computationally intensive. Another solution is to randomly select a sample of the lodging buildings, conduct occupants' surveys, and recalibrate lodging archetypes based on surveys in a future study. Regardless of minor difference for lodging buildings, from both error estimation and KS test results it can be concluded that the UBEM represented the commercial stock of Pittsburgh and verified to be accurate. So, it can be further employed to evaluate EC strategies.

3.4. Selected energy conservation strategies reduced energy consumption of the commercial stock by 2–5%

For policy makers and urban planner, broad knowledge about impacts of energy efficiency programs on energy performance of existing buildings at scale is essential as it aids them in refining codes and standards as well as structuring regional retrofit guidelines and regulations. On this basis the UBEM was utilized to assess energy reduction or savings of the studied building stock in concert with EC strategies. As mentioned earlier, three low to medium cost EC strategies [67]; temperature set points adjustment, upgrading lighting systems to LEDs, and plug and process load reduction were selected and applied. The rest of this section is allocated to discuss findings.

Raising cooling set point from 24 °C to 25.5 °C and lowering heating set point from 21 °C to 20 °C was the first strategy with no cost. The new temperature set points are within temperature spectrums that provide comfortable indoor environment for occupants [67,68]. The cumulative energy use of the building stock prior to adjusting set points was simulated as 521 GWh which reduced approximately 5% after changing set points to new values in the UBEM. In addition to the cumulative energy use of the stock, the total EUI averaged over the entire stock reduced by 4% (see Table 7). Also, the impact of this EC strategy on dominant end uses (space heating, space cooling, and lighting) was estimated, which showed that the reduction in average cooling EUI (27%) was much higher than other two end uses.

Replacing traditional incandescent bulbs, which convert 90% of energy to heat, with Light Emitted Diodes (LEDs) is a well-known strategy to conserve energy. As reported by the Department of Energy, LEDs consume 4 to 5 times less energy than incandescent bulbs [69]. In order to examine the impact of this strategy on the building stock, lighting density (W/m^2) was reduced between 50% and 75% for different buildings. Shifting to LEDs resulted in percent decreases for the average total EUI, average cooling EUI, and average lighting EUI as presented in Table 7. On the other hand, average heating EUI increased by 3%. This is because heat generated from lighting system decreased when using LEDs and heating system should run more to compensate for the heat. Ultimately heating demand was simulated to be increased.

Utilizing more energy efficient internal equipment and appliances for example those with ENERGY STAR label would reduce plug and process loads. The amount of energy conserved varies greatly for different equipment and appliances. For instance, ENERGY STAR refrigerators and washers consume about 10% and 40% less energy, respectively than standard ones [70]. In this study, it was assumed that plug and process loads would reduce by 15% and energy savings was estimated. The average reductions for total and cooling EUIs were less than set point adjustment and upgrading lighting systems. Moreover, average lighting EUI was remained unchanged, as expected, and the average heating EUI showed a slight increase. When the plug and process load decreases, amount

Table 6
Percent error (PE) and Kolmogorov-Smirnov (KS) test results for annual energy use intensity.

Commercial use type	Mean PE (%)	KS test	
		P-value	0: null hypothesis not rejected; 1: null hypothesis rejected
Education	4	0.071	0
Lodging	44	0.012	1
Office	36	0.156	0
Parking garage	63	0.980	0
Public assembly	4	0.429	0
Public order and Safety	10	0.342	0
Warehouse	10	0.771	0
Other	35	0.474	0

Table 7
Percentage of energy use change as a result of energy conservation strategies. Positive values represent reduction and negative values represent increase.

	Cumulative energy use (%)	Average total EUI (%)	Average heating EUI (%)	Average cooling EUI (%)	Average lighting EUI (%)
Temperature set points adjustment	5	4	9	27	0
Upgrading lighting systems to LEDs	4	10	−3	11	72
Plug and process load reduction	2	2	−1	2	0

of rejected heat by equipment and appliances reduces. Thus, heating system would run more to meet the demand of buildings. Evaluating the EC strategies at an urban scale provided insights on how energy ecosystem of urban buildings would alter, and which strategy yielded higher promise.

4. Limitations

One of the known limitations of simulating energy consumption at scale using an UBEM is the uncertainty associated with characterizing the non-geometric parameters during archetype development. While we tried to mitigate the impact of this uncertainty by close inspection of buildings in the commercial stock and consulting with building managers about operation and systems, lack of access to design documents of buildings and consequently their non-geometric parameters still remain as a limitation. Another limitation of this research pertains to photogrammetry. When acquiring images of various facades of a building utilizing SVS API, the goal was to maintain the consistency of images' attributes. Nonetheless, to attain full coverage of façades, image attributes of few buildings were not consistent over different facades which is being explored as part of our future research. Additionally, typical meteorological data from the weather station, located outside the City, may not represent the micro-climate condition in the City as well as weather condition in 2017, which was employed as a base year for validating simulation results from the UBEM.

5. Conclusions

This paper described a holistic and detailed modeling structure for developing an UBEM focusing on commercial buildings. With the aim of increasing reproducibility of future UBEMs, we provided an archetype library with sources, along with proposing and implementing an advanced imaging technique to retrieve envelope properties and reconstruct façades as well as LiDAR analysis. The major findings of this work are:

- The WWRs between 0.11 and 1 had higher frequencies in the studied building stock (74%) when compared to CBECS buildings (44%). Therefore, using CBECS data, rather than measuring WWR based on photogrammetry and image processing framework, would have led to underestimating WWR.
- The average annual EUI for different building use types was simulated between 74 kWh/m^2 and 1302 kWh/m^2. This range showed that energy use of commercial buildings was highly related to use type.
- Validating the simulation results with actual data showed the overall acceptable PE of 7% for the studied building stock. The PE for different building use types were estimated between 4% (education buildings) and 63% (parking garages). Ventilation systems were considered when simulating energy use of parking garages; however, some of these buildings did not have ventilation systems in real-world. Therefore, the average simulated EUI was somewhat higher than the average actual EUI for parking garages resulting in the highest PE compared to other use types.
- The KS test results revealed that the distributions of simulated and actual EUI were similar for seven use types (p-values were greater than 0.05). However, the p-value for lodging buildings was calculated as 0.012 showing that the distributions of simulated and actual EUI were statistically different for this use type. This difference can be attributed to variable schedules and occupant behavior.
- The average EUI of the studied building stock was reduced 2–10% as result of three EC strategies. All three EC strategies reduced the average cooling EUI (2–27%); whereas, upgrading lighting systems to LEDs and plug and process load reduction slightly increased the average heating EUI by 3% and 1%, respectively. These increases were because rejected heat from lighting systems and different appliances and equipment was declined; thus, heating demand increased.

In addition to providing policy makers, urban planners, and utility companies with insights about trends of energy use, the results of this study can be used to provide guidance about EC strategies for the commercial building stock at urban scale. So, relying on this information policy makers and urban planners can advocate for converting EC strategies from voluntary actions to regulations.

As part of future work, the model can be utilized to evaluate simultaneous implementation of the three EC strategies as well as more aggressive and high-cost strategies such as upgrading heating/cooling systems and improving envelope airtightness. Additionally, the environmental impact associated with energy consumption of the studied commercial buildings can be assessed through employing the amount of different energy sources. There are some studies that have integrated building energy use mostly at individual building-level with climate change based on physics-based or machine learning approaches [71–73]. The UBEM can be employed to predict changes in energy use of buildings in Pittsburgh, Pennsylvania region due to weather variation caused by climate change. Furthermore, the resiliency of energy supply network in time of extreme weather events (i.e., heat wave and cold wave) can be evaluated by meshing the UBEM with extreme meteorological year data. Technical aspects that require improvement are accessing documents of all buildings in the city, that includes basic data regarding buildings and their energy use, together with automating the photogrammetry and image processing framework. Artificial intelligence (AI) methods have been used to automize image processing especially in medical fields; therefore, we plan to resolve current challenges and implement AI methods for façade image processing at urban scale.

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.

Acknowledgements

This work was supported by the National Science Foundation [Grant No. 1934824]. Any opinions, findings, and conclusions or recommendations expressed in this article are those of the authors and do not necessarily reflect the views of the National Science Foundation.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2021.111175.

References

[1] U.S. Energy Information Administration, Monthly Energy Review, Washington, DC (US), 2020.
[2] M.K. Singh, S. Mahapatra, J. Teller, An analysis on energy efficiency initiatives in the building stock of Liege, Belgium, Energy Policy 62 (2013) 729–741, https://doi.org/10.1016/j.enpol.2013.07.138.
[3] S. Trachte, A., De Herde, Choix des Matériaux - Ecobilan de Parois, Architecture et, Climat (2010).
[4] Office of Los Angeles Mayor, L.A.'s Green New Deal: Sustainable City Plan, Los Angeles, CA (US), 2019. Available: http://plan.lamayor.org/sites/default/files/pLAn_2019_final.pdf.
[5] R.B. Weisenmiller, P. Bozorgchami, L. Froess, C. Meyer, D. Ashuckian, D. Bohan, K. Douglas, A. McAllister, D. Hochschild, J.A. Scott, Building Energy Efficiency Standards for Residential and Nonresidential Buildings, California Energy Commission (2018).
[6] P. Colao, A. Mendicino, J. Cramer, M. Zeigler, J. McKinney, Pittsburgh 2030 District Progress Report, Green Building Alliance, 2019.
[7] J. Driesen, F. Katiraei, Design for distributed energy resources, IEEE Power Energy Mag. 6 (3) (2008) 30-40.
[8] A. Agalloco, R. Freeh, Municipal Energy Benchmarking, The City of Philadelphia Mayor's Office of Sustainability (2014).
[9] B. Hooper, F. Apaliski, L. Hirsch, H. Gurfel, M. Brill, C. Liu, M. Henn, San Francisco Existing Commercial Buildings Performance Report, San Francisco Department of the Environment and Urban Land Institute, 2014.
[10] W. Li, Y. Zhou, K. Cetin, J. Eom, Y. Wang, G. Chen, X. Zhang, Modeling urban building energy use: A review of modeling approaches and procedures, Energy 141 (2017) 2445–2457.
[11] S. Torabi Moghadam, C. Delmastro, S.P. Corgnati, P. Lombardi, Urban energy planning procedure for sustainable development in the built environment: A review of available spatial approaches, J. Clean. Prod. 165 (2017) 811–827, https://doi.org/10.1016/j.jclepro.2017.07.142.
[12] L. Carnieletto, M. Ferrando, L. Teso, K. Sun, W. Zhang, F. Causone, P. Romagnoni, A. Zarrella, T. Hong, Italian prototype building models for urban scale building performance simulation, Build. Environ. 192 (2021), https://doi.org/10.1016/j.buildenv.2021.107590 107590.
[13] N. Mostafavi, M. Farzinmoghadam, S. Hoque, Urban residential energy consumption modeling in the Integrated Urban Metabolism Analysis Tool (IUMAT), Build. Environ. 114 (2017) 429–444, https://doi.org/10.1016/j.buildenv.2016.12.035.
[14] L. Filogamo, G. Peri, G. Rizzo, A. Giaccone, On the classification of large residential buildings stocks by sample typologies for energy planning purposes, Appl. Energy 135 (2014) 825–835, https://doi.org/10.1016/j.apenergy.2014.04.002.
[15] E. Lucchi, V. D'Alonzo, D. Exner, P. Zambelli, G. Garegnani, A density-based spatial cluster analysis supporting the building stock analysis in historical towns, Proc. 16th IBPSA Int. Conf. Exhib. (2019) 2–4.
[16] C.F. Reinhart, C.C. Davila, Urban building energy modeling–A review of a nascent field, Build. Environ. 97 (2016) 196–202, https://doi.org/10.1016/j.buildenv.2015.12.001.
[17] M. Ferrando, F. Causone, T. Hong, Y. Chen, Urban building energy modeling (UBEM) tools: A state-of-the-art review of bottom-up physics-based approaches, Sustain. Cities Soc. 62 (2020), https://doi.org/10.1016/j.scs.2020.102408 102408.
[18] Y. Shimoda, T. Fujii, T. Morikawa, M. Mizuno, Residential end-use energy simulation at city scale, Build. Environ. 39 (8) (2004) 959–967, https://doi.org/10.1016/j.buildenv.2004.01.020.
[19] C. Cerezo, J. Sokol, S. AlKhaled, C. Reinhart, A. Al-Mumin, A. Hajiah, Comparison of four building archetype characterization methods in urban building energy modeling (UBEM): A residential case study in Kuwait City, Energy Build. 154 (2017) 321–334, https://doi.org/10.1016/j.enbuild.2017.08.029.
[20] J. Sokol, C.C. Davila, C.F. Reinhart, Validation of a Bayesian-based method for defining residential archetypes in urban building energy models, Energy Build. 134 (2017) 11–24, https://doi.org/10.1016/j.enbuild.2016.10.050.
[21] C.S. Monteiro, A. Pina, C. Cerezo, C. Reinhart, P. Ferrão, The use of multi-detail building archetypes in urban energy modelling, Energy Proc. 111 (2017) 817–825, https://doi.org/10.1016/j.egypro.2017.03.244.
[22] U. Ali, M.H. Shamsi, C. Hoare, E. Mangina, J. O'Donnell, A data-driven approach for multi-scale building archetypes development, Energy Build. 202 (2019), https://doi.org/10.1016/j.enbuild.2019.109364 109364.
[23] C.D. Cerezo, C.F. Reinhart, J.L. Bemis, Modeling Boston: A workflow for the efficient generation and maintenance of urban building energy models from existing geospatial datasets, Energy 117 (2016) 237–250, https://doi.org/10.1016/j.energy.2016.10.057.
[24] S. Heiple, D.J. Sailor, Using building energy simulation and geospatial modeling techniques to determine high resolution building sector energy consumption profiles, Energy Build. 40 (8) (2008) 1426–1436, https://doi.org/10.1016/j.enbuild.2008.01.005.
[25] É. Mata, A.S. Kalagasidis, F. Johnsson, Building-stock aggregation through archetype buildings: France, Germany, Spain and the UK, Build. Environ. 81 (2014) 270–282, https://doi.org/10.1016/j.buildenv.2014.06.013.
[26] A. Krayem, A. Al Bitar, A. Ahmad, G. Faour, J.-P. Gastellu-Etchegorry, I. Lakkis, J. Gerard, H. Zaraket, A. Yeretzian, S. Najem, Urban energy modeling and calibration of a coastal Mediterranean city: The case of Beirut, Energy Build. 199 (2019) 223–234, https://doi.org/10.1016/j.enbuild.2019.06.050.
[27] C. Ding, N. Zhou, Using residential and office building archetypes for energy efficiency building solutions in an urban scale: A China case study, Energies 13 (12) (2020) 3210, https://doi.org/10.3390/en13123210.
[28] Y. Chen, T. Hong, M.A. Piette, Automatic generation and simulation of urban building energy models based on city datasets for city-scale building retrofit analysis, Appl. Energy 205 (2017) 323–335, https://doi.org/10.1016/j.apenergy.2017.07.128.
[29] I. De Jaeger, G. Reynders, C. Callebaut, D. Saelens, A building clustering approach for urban energy simulations, Energy Build. 208 (2020), https://doi.org/10.1016/j.enbuild.2019.109671 109671.
[30] C. Molina, M. Kent, I. Hall, B. Jones, A data analysis of the Chilean housing stock and the development of modelling archetypes, Energy Build. 206 (2020), https://doi.org/10.1016/j.enbuild.2019.109568 109568.
[31] U.S. Energy Information Administration, Commercial Buildings Energy Consumption Survey (CBECS), Washington, DC (US), 1999.
[32] U.S. Energy Information Administration, Residential Energy Consumption Survey (RECS), Washington, DC (US), 2001.
[33] M.C. Baechler, J. Williamson, T.L. Gilbride, P.C. Cole, M.G. Hefty, P.M. Love, Guide to Determining Climate Regions by County, Pacific Northwest National Laboratory (PNNL), Richland, WA (US), 2015.
[34] R. Mohammadiziazi, M.M. Bilec, Developing a framework for urban building life cycle energy map with a focus on rapid visual inspection and image processing, Proc. CIRP 80 (2019) 464–469, https://doi.org/10.1016/j.procir.2019.01.048.
[35] Western Pennsylvania Regional Data Center, Open portal data. https://data.wprdc.org/dataset, 2018 (accessed 15 June 2018).
[36] T. Loga, N. Diefenbach, B. Stein, C. Balaras, O. Villatoro, K. Wittchen, Typology Approach for Building Stock Energy Assessment - Main Results of the TABULA Project, Institut Wohnen und Umwelt, Darmstadt (DE), 2012.
[37] T.M. Gulotta, M. Cellura, F. Guarino, S. Longo, A bottom-up harmonized energy-environmental models for europe (BOHEEME): A case study on the thermal insulation of the EU-28 building stock, Energy Build. 231 (2021), https://doi.org/10.1016/j.enbuild.2020.110584 110584.
[38] M. Deru, K. Field, D. Studer, K. Benne, B. Griffith, P. Torcellini, B. Liu, M. Halverson, D. Winiarski, M. Rosenberg, U.S. Department of Energy Commercial Reference Building Models of the National Building Stock, National Renewable Energy Laboratory (NREL), Golden, CO (US), 2011.
[39] ASHRAE, ASHRAE Standard 62-1989–Ventilation for Acceptable Indoor Air Quality, Atlanta, GA (US), 1989.
[40] ASHRAE, ASHRAE Standard 62.1-2013–Ventilation for Acceptable Indoor Air Quality, Atlanta, GA (US), 2013.
[41] B. Liu, R.E. Jarnagin, W. Jiang, K. Gowri, Technical Support Document: The Development of the Advanced Energy Design Guide for Small Warehouse and Self-storage Buildings, Pacific Northwest National Laboratory (PNNL), Richland, WA (US), 2007.
[42] S. Pless, P. Torcellini, N. Long, Technical Support Document: Development of the Advanced Energy Design Guide for K-12 Schools-30% Energy Savings, National Renewable Energy Laboratory (NREL), Golden, CO (US), 2007.
[43] ASHRAE, ASHRAE Standard 90-1975–Energy Conservation in New Building Design, Atlanta, GA (US), 1975.
[44] ASHRAE, ASHRAE Standard 90.1-1989–Energy Efficient Design of New Buildings Except Low-Rise Residential Buildings, Atlanta, GA (US), 1989.
[45] ASHRAE, ASHRAE Standard 90.1-2004–Energy Standard for Buildings Except Low Rise Residential Buildings, Atlanta, GA (US), 2004.
[46] R. Hendron, Building America Research Benchmark Definition: Updated December 20, 2007, National Renewable Energy Laboratory (NREL), Golden, CO (US), 2008.
[47] R.E. Jarnagin, B. Liu, D.W. Winiarski, M.F. McBride, L. Suharli, D. Walden, Technical Support Document: Development of the Advanced Energy Design Guide for Small Office Buildings, Pacific Northwest National Laboratory (PNNL), Richland, WA (US), 2006.
[48] ASHRAE, HVAC Applications–ASHRAE Handbook Fundamentals, 2007.
[49] U.S. Energy Information Administration, Commercial Buildings Energy Consumption Survey (CBECS), Washington, DC (US), 2012.
[50] G.G. Akkurt, N. Aste, J. Borderon, A. Buda, M. Calzolari, D. Chung, V. Costanzo, C. Del Pero, G. Evola, H.E. Huerto-Cardenas, F. Leonforte, A. Lo Faro, E. Lucchi, L. Marletta, F. Nocera, V. Pracchi, C. Turhan, Dynamic thermal and hygrometric simulation of historical buildings: Critical factors and possible solutions, Renew. Sustain. Energy Rev. 118 (2020), https://doi.org/10.1016/j.rser.2019.109509 109509.
[51] D.W. Winiarski, W. Jiang, M.A. Halverson, Review of Pre-and Post-1980 Buildings in CBECS-HVAC Equipment, Pacific Northwest National Laboratory (PNNL), Richland, WA (US), 2006.
[52] ASHRAE, ASHRAE Handbook Fundamentals–Design Conditions for HARARE KUTSAGA Airport, 2005.
[53] C. Massart, A. De Herde, Conception de Maisons Neuves Durables: Elaboration D'Un Outil D'Aide à La Conception de Maisons à Très Basse Consommation D'Energie, Architecture et, Climat (2010).

[54] T. Dogan, M. Knutins, CitySeek: towards urban daylight models based on GIS data and semi-automated image processing, Proc. Symp. Simul. Archit, Urban Des, 2018.
[55] Google, Google Street View Static API. https://cloud.google.com/, 2020 (accessed 10 August 2020).
[56] M. Deru, P. Torcellini, Standard Definitions of Building Geometry for Energy Evaluation, National Renewable Energy Laboratory (NREL), Golden, CO (US), 2005.
[57] N. Nazarian, N. Dumas, J. Kleissl, L. Norford, Effectiveness of cool walls on cooling load and urban temperature in a tropical climate, Energy Build. 187 (2019) 144–162, https://doi.org/10.1016/j.enbuild.2019.01.022.
[58] R. Gupta, M. Gregg, Using urban energy modelling to rapidly assess potential for climate change mitigation and adaptation of UK homes, Build. Simul. Optim, Conf, 2014.
[59] Y. Wu, L.S. Blunden, A.S. Bahaj, City-wide building height determination using light detection and ranging data, Environ. Plan. B: Urban Anal. City Sci. 46 (9) (2019) 1741–1755, https://doi.org/10.1177/2399808318774336.
[60] D.B. Crawley, L.K. Lawrie, C.O. Pedersen, F.C. Winkelmann, Energy plus: Energy simulation program, ASHRAE J. 42 (4) (2000) 49–56.
[61] H. Yassaghi, P.L. Gurian, S. Hoque, Propagating downscaled future weather file uncertainties into building energy use, Appl. Energy 278 (2020), https://doi.org/10.1016/j.apenergy.2020.115655 115655.
[62] F.H. Abanda, L. Byers, An investigation of the impact of building orientation on energy consumption in a domestic building using emerging BIM (Building Information Modelling), Energy 97 (2016) 517–527, https://doi.org/10.1016/j.energy.2015.12.135.
[63] B. Andersson, W. Place, R. Kammerud, M.P. Scofield, The impact of building orientation on residential heating and cooling, Energy Build. 8 (3) (1985) 205–224, https://doi.org/10.1016/0378-7788(85)90005-2.
[64] E. Nault, T. Jusselme, S. Aguacil, M. Andersen, Strategic environmental urban planning - A contextual approach for defining performance goals and informing decision-making, Build. Environ. 168 (2020), https://doi.org/10.1016/j.buildenv.2019.106448 106448.
[65] H.E. Huerto-Cardenas, F. Leonforte, N. Aste, C. Del Pero, G. Evola, V. Costanzo, E. Lucchi, Validation of dynamic hygrothermal simulation models for historical buildings: State of the art, research challenges and recommendations, Build. Environ. 180 (2020), https://doi.org/10.1016/j.buildenv.2020.107081 107081.
[66] S.N. Goodman, Toward evidence-based medical statistics. 1: The P value fallacy, Ann. Intern. Med. 130 (12) (1999) 995–1004.
[67] J.C. Lam, K.K. Wan, L. Yang, Sensitivity analysis and energy conservation measures implications, Energy Convers. Manag. 49 (11) (2008) 3170–3177, https://doi.org/10.1016/j.enconman.2008.05.022.
[68] A. Ghahramani, K. Zhang, K. Dutta, Z. Yang, B. Becerik-Gerber, Energy savings from temperature setpoints and deadband: Quantifying the influence of building and system properties on savings, Appl. Energy 165 (2016) 930–942, https://doi.org/10.1016/j.apenergy.2015.12.115.
[69] U.S. Department of Energy, Lighting Choices, 2021. https://www.energy.gov/energysaver/save-electricity-and-fuel/lighting-choices-save-you-money.
[70] U.S., Environmental Protection Agency, ENERGY STAR Certified Appliances (2012).
[71] R. Mohammadiziazi, M.M. Bilec, Application of machine learning for predicting building energy use at different temporal and spatial resolution under climate change in USA, Buildings 10 (8) (2020) 139, https://doi.org/10.3390/buildings10080139.
[72] X. Wang, D. Chen, Z. Ren, Assessment of climate change impact on residential building heating and cooling energy requirement in Australia, Build. Environ. 45 (7) (2010) 1663–1682, https://doi.org/10.1016/j.buildenv.2010.01.022.
[73] L. Troup, M.J. Eckelman, D. Fannon, Simulating future energy consumption in office buildings using an ensemble of morphed climate data, Appl. Energy 255 (2019), https://doi.org/10.1016/j.apenergy.2019.113821 113821.