Chapter 24
Urban Data and Building Energy Modeling: A GIS-Based Urban Building Energy Modeling System Using the Urban-EPC Engine

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Abstract There is a lack of building energy modeling in current planning support systems (PSS) while building energy efficiency is getting greater attention. This is due to the current limitations of energy modeling at the urban scale and the inconsistency between the available urban data and that required for modeling. The chapter seeks to fill this gap by developing a GIS-based urban building energy modeling system, using the Urban-EPC simulation engine, a modified Energy Performance Calculator engine. This modeling system is compatible with other planning tools, enhanced by the combination of physical and statistical modeling, and adjustable in its resolution, speed and accuracy. Through processing the Data Preparation, Pre-Simulation, Main Simulation and Visualization and Analysis models in this energy modeling system, the urban data related to the basic building information, mutual shading, microclimate and occupant behavior are collected, modified, and synthesized in the GIS platform and then used as the input of the Urban-EPC engine to get energy use of every building in a city, which could be further visualized and analyzed. The method is applied in Manhattan to show its potential as an important component in PSS to inform urban energy policy making.

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1 Introduction

The energy used in buildings is a large share of overall energy use, e.g. 20–40 % in developed countries, and the potential for reduction is drawing the attention of planners and policy makers (Perez-Lombard et al. 2008). Although it was stated from a long time ago that energy use is an important aspect in planning support systems (PSS) for the sustainable urban development (Harris and Batty 1993; Mohammadi et al. 2013; Snyder 2003), the investigation of building energy use is still rare in the PSS field. Only a few researchers have incorporated a "Performance/Evaluation Model" that measures building energy use in PSS and Geodesign and used the results as the criteria to evaluate different planning scenarios (Quan et al. 2013; Yeo et al. 2013).

The discrepancy between the lack of building energy assessments in PSS and Geodesign models and the increasing need to assess the energy performance of different urban forms is due to two reasons: modeling limitations and data inconsistencies. First, there are significant modeling limitations in measuring large-scale building energy use. Traditional engineering-based building energy modeling tools, including the US standard program DOE-2 and its successor EnergyPlus (Crawley et al. 2001), IES-VE (Virtual Environment by Integrated Environmental Solution, a commercial building simulation tool) (Integrated Environmental Solutions Limited 2012), analyze only an individual building as a single system for simplification (Al-Homoud 2001). There are four major groups trying to scale this up to the city level, but none have provided a sufficient solution to account for the influence of urban contexts at different spatial scales. The first group scales energy assessment from single buildings to urban areas directly by using simple building stock approaches. However despite the discussion of spatial variations in the "*second order uncertainty*" (Booth et al. 2012), little concern was placed on the influence of building locations and their urban contexts. The second group is considerably aware of the urban context in their modeling (Pisello et al. 2012; Wong et al. 2011). However their approaches tend to be confined by specific urban settings and are hard to apply to other places. The third group has developed fully fledged energy modeling methods for the urban environment, including CitySim and UMI (Reinhart et al. 2013; Robinson et al. 2009). But as stand-alone software, they require tedious data transferal and rebuilding from ArcGIS data as widely used in urban studies. The last group led by Steemers and Ratti has developed the LT model to measure building energy based on raster data in GIS (Ratti and Richens 2004). But their specific assumptions of occupant behavior and the resolutions of the raster limit its use at the city scale.

Besides the unawareness of urban context, the engineering-based methods in the four groups require basic knowledge of building physics, HVAC (heating, ventilation and air conditioning) systems, etc., which are unfamiliar to most planners. This calls for a simplified, cross-scale, context-sensitive and GIS-based modeling method to measure urban building energy use in PSS.

Second, data inconsistency is another obstacle in developing and applying the building energy modeling in PSS. On the one hand, there are plenty of urban data available such as building intensity and population. On the other hand, building energy modeling methods require very detailed building component data, such as building shapes, materials, fenestrations, occupant schedules and HVAC systems, which are lacking at the urban scale (Al-Homoud 2001; Flaxman 2010). Due to such discrepancies between the available urban data that could provide general building information and the missing specific building-level data for detailed building information required by the building energy modeling, researchers and planners have only been able to estimate building energy use in small areas using surveys of detailed building data (Reinhart et al. 2013; Robinson et al. 2009), or to roughly estimate the building energy performance in large areas with simplified assumptions (Quan et al. 2013). Developing urban building energy modeling requires finding a way to use related information in urban data to get the detailed information as building scale data, which connects data at urban and building scale.

In order to fill those research gaps, this chapter aims to develop a GIS-based urban building energy modeling system using what we call the Urban-EPC engine, a modified version of a reduced-order building energy model called the Energy Performance Coefficient Calculator, or EPC for short. The EPC is an implementation of the ISO 13790:2008 standard, which lays out a calculation recipe for normatively estimating building energy performance using basic physics-based equations involving a comparatively small set of parameters and normative statements about the assumed usage scenario, system efficiency, etc. per functional type of building (ISO 2008). The underlying model of the EPC is much smaller than tools such as EnergyPlus, resulting in not only faster computational speed, but also an input parameter set that is much smaller and simultaneously aggregated to a level more commensurate with urban GIS data. Through its simplicity and unified modeling assumptions, this approach forms the basis for assessing building energy performance in a standardized and transparent way (Hogeling and Van Dijk 2008). Because of this, the EPC is well-suited for rating the energy performance of both new and existing buildings. In addition, the normative assumptions were calibrated on a large collection of different buildings, making the calculator well suited for the macro-level calculations as reported in this chapter, e.g. where the information about individual buildings is thin.

The EPC recipe is based on the hourly heat balance of the whole building using inputs such as wall and window areas, shading coefficients, material properties, net functional floor area, lighting density, internal heat production from appliances, plug loads, temperature set points and occupancy schedules. The calculation goes through three steps. Based on hourly calculations in the local weather conditions, the heating and cooling loads are calculated. This thermal demand is then translated into the delivered energy (electric and gas) used by the building systems. The translation is driven by macro system efficiency factors, normatively defined per system type. Finally, with the addition of data on other electricity usage in the building, the total consumption can be calculated and translated into primary energy units, i.e. the summation of the primary energy (gas, coal, oil) that is consumed by the generation sites. Comparative analyses have shown that the calculator is accurate for the purpose described in this chapter (Kim et al. 2013; Lee et al. 2013).

This energy modeling method has five advantages over previous methods:

Urban context sensitive: the modeling takes the influence of urban context into account and is able to estimate building energy performance in different urban environments.
Urban data driven: it utilizes abundant urban data to inform building energy modeling, providing building details and urban contexts, using DOE (Department of Energy) reference buildings (Deru et al. 2011) as the complement.
GIS based: it is based on the ArcGIS platform, widely used software in PSS, and therefore it is relatively easy for planners to run the modeling and visualize the results.
Planning oriented: as a geo-based modeling method, it allows planners to easily map the simulated energy use and overlay them with other planning mappings for further analysis.
Resolution controlled: the temporal resolution of the modeling could be changed to provide hourly, daily, weekly, monthly or annual building energy use results. Similarly, the accuracy resolution can also be changed to the high, medium and acceptable levels. It allows users to adjust the trade-offs between accuracy and speed with purposes of analysis.

This modeling system requires ArcGIS 10.x and Microsoft Excel to be installed on the PC being used.

2 Methodology

The methodology of the modeling system incorporates three aspects: the influence of the urban context on building energy use; the role of urban data in building energy simulation; and the integration of data processing and energy simulation as one modeling system. Urban-EPC enhances EPC to account for these first two aspects; a larger software architecture then coordinates the Urban-EPC to realize the third.

2.1 The Influence of Urban Context on Building Energy Use

It is well discussed that building design, system efficiency and occupant behavior have considerable impacts on building energy consumption (Al-Homoud 2001). Besides the three factors, some scholars are aware of the importance of urban context in building energy (Golany 1996; Mitchell 2005; Ratti et al. 2005; Steadman 1979). However, few comprehensive studies have been conducted to date and the ways in which urban context influences building energy use are still unclear. Such influences can be explored using a systems perspective. Although a single building is already a complex system, in a larger urban system it is seen as only one component. In such a “system of systems” or “network of networks” (Ackoff 1971; Batty 2013; Maier 1998), the interactions among different components can significantly affect the individual performance and the overall system performance. The influence of urban context on building energy captures such system interactions including the following three types:

Interactions between a building and other buildings and obstructions: As solar radiation on the building facades influences building energy use significantly, the obstruction of sunlight by surrounding buildings, trees and other obstructions plays an important role in building energy use. Such interactions among geometries are known as external shading effects or mutual shading effects (Littlefair 1998; McPherson and Simpson 2003; Ok 1992; Quan et al. 2014; Ratti et al. 2005; Rode et al. 2013; Yezioro and Shaviv 1994; Yi and Malkawi 2009). The effects generally increase building energy use during winter and reduce it during summer because of less solar gain.

Interactions between a building and the microclimates around it: Aspects of the local climate—including air temperature and wind patterns—can be modified by urban form-related factors, e.g. reduced radiative heat loss and turbulent heat transfer in urban canyons, increased thermal storage within buildings and impervious surfaces, anthropogenic heat release in the urban context, etc. (Eliasson 2000; Hassid et al. 2000; Oke et al. 1991; Steemers 2003; Wong et al. 2011). Often known as the ‘urban heat island effect’, modified urban microclimates can reduce building energy in winter and increase it in summer (Kolokotroni et al. 2006; Santamouris et al. 2001).

Interactions between buildings and occupants: The occupancy pattern, including the density and behavior, could lead to variations of building energy use in the same building. Although the influence of occupant behavior is still unclear (Branco et al. 2004; Guerra Santin et al. 2009), the impact of occupant density is straightforward.

The influences of these interactions are measured in this modeling system as mutual shadings, zonal microclimates and occupant densities by different tools and engines to inform the building energy simulation. To assess those influences, urban scale data are needed.

2.2 The Role of Urban Data in Building Energy Simulation

There is an ever-increasing supply of urban data. Enormous amounts of information are produced and collected through traditional commercial and administrative censuses and surveys, and more recently from mobile and social media data such as real-time geo-labeled tweet data, traffic data, etc. (Döllner and Hagedorn 2007; Reades et al. 2007). Urban data are of diverse types (e.g. population, economics, transportation), available at various scales (e.g. census tracts, neighborhoods, cities), in different formats (spatial and aspatial data), all collected for different points in time or time periods. Such rich resources could greatly inform urban building energy modeling after a careful selection of what is required directly and indirectly by the simulation engine.

The core simulation engine of the Urban-EPC consists of the EPC, reference building models from the US Department of Energy (DOE), a shading engine, a microclimate engine, and an occupancy engine. In the EPC, general building component information such as floor areas and room volumes are taken from building footprint data, parcel data and land use data in the urban dataset. However, some detailed building data such as materials, heating, ventilation and air conditioning (HVAC) systems, and window-wall ratios, are also required by the EPC which cannot be found in the urban data. A set of commercial reference building models, developed by the US Department of Energy (DOE) and representative of the national building stock, are used to provide missing building model inputs. These contain three categories of building vintage (based on the construction year), each of which includes 16 building types representing most of the commercial buildings across 16 US climate zones. Model inputs, including geometry, envelope, material properties, building usage and operational schedules were developed from several building databases such as F.W. Dodge building stock and forecast data (Dodge Data and Analytics 2005), engineering studies, design standards and guidelines such as ASHRAE (1989, 2004), and statistics such as the Commercial Building Energy Consumption Survey (CBECS) (U.S. Energy Information Administration 2005). Detailed building information can be determined by linking reference building types with the information of the building function and construction year provided by the urban data. Using the reference building, the Urban-EPC model manages to get the detailed information of each building based on its related urban data, and thus reduces data inconsistency between available urban data and required building data.

In the Urban-EPC core engine, three sub-engines capture the influence of urban context on building energy. The shading engine uses the building footprint, tree canopy, topography and parcel data to calculate external/mutual shading effects on the windows. The microclimate engine takes weather information, building footprint, land cover, vegetation, street, and block data as input to estimate local air temperature and wind patterns. The occupancy engine utilizes population and job data to generate occupant density and use schedules of residential, commercial and public buildings.

This Urban-EPC model requires the parameters shown in Table 1 as inputs, all of which could be found in the urban data complemented by the reference building database.

However, the availability of related urban data varies from city to city. In some cities, open-source urban data may be greatly limited.

Table 1 Input requirements of the Urban-EPC model and related urban data

Model components	Required input parameters	Data source	Related urban data	Specific urban data sources
Detailed building information	Building shapes (e.g. total floor areas, volumes, façade areas, rooftop areas)	Urban data	Building footprint data, parcel data, topography data	City Department of Planning
	Window to wall ratios	Reference building and urban data	Building footprint data, parcel data, land use data	City Department of Planning
	Building materials	Reference building and urban data	Building footprint data, parcel data, land use data	City Department of Planning
	HVAC system	Reference building and urban data	Building footprint data, parcel data, land use data	City Department of Planning
Shading engine	Building geometries	Urban data	Building footprint data, parcel data, topography data	City Department of Planning
	Other obstruction geometries	Urban data	Tree canopy data, topography data	City Department of Planning, City GIS Portal
Microclimate engine	Urban canyon parameters	Urban data	Urban block shape data, building footprint data, parcel data, street network data	City Department of Planning
	Percentage of pervious surfaces and building rooftops	Urban data	Land cover data, building footprint data, vegetation data, tree canopy data	City Department of Planning, City GIS Portal
	Weather data	Imbedded in EPC and urban data	Weather station data	NOAA (National Oceanic and Atmospheric Administration)
Occupant behavior modification	Occupant density	Reference building and urban data	Population distribution data, job distribution data	U.S. Census Bureau
	Occupant behavior	Reference building and urban data	Detailed population distribution data, detailed job distribution data	U.S. Census Bureau

2.3 The Integration of Data Processing and Energy Simulation as One Modeling System

Based on an understanding of the influence of the urban context, the core Urban-EPC engine and its related urban data, a GIS-based urban building energy modeling system is developed.

2.3.1 Structure of the Modeling System

The modeling system developed in this chapter contains four major models: the Data Preparation Model, the Pre-Simulation Model, the Main Simulation Model and the Visualization and Analysis Model. This modeling system uses urban data from various sources as its input, integrates and refines them into a new set of data required by the pre-simulation engines, provides the resulting data to the main simulation model, and visualizes and analyzes the final results with other urban data. The modeling system structure and its data flow are shown in Fig. 1.

The whole system runs on the GIS platform except for the main simulation engine, which runs in Excel but is organized and linked to GIS by ArcPy, "*a site package that builds on the successful arcgisscripting module*" (Esri 2012). The whole modeling system is developed in two GIS tool forms based on a trade-off between usability and speed: the ModelBuilder toolboxes and the ArcPy codes. The ModelBuilder approach is easy to use for planners, but is also relatively slow. The ArcPy codes run much faster but require basic knowledge of ArcPy. Generally the ModelBuilder approach is more useful for energy simulation of small areas while the ArcPy approach is the better choice for large urban areas.

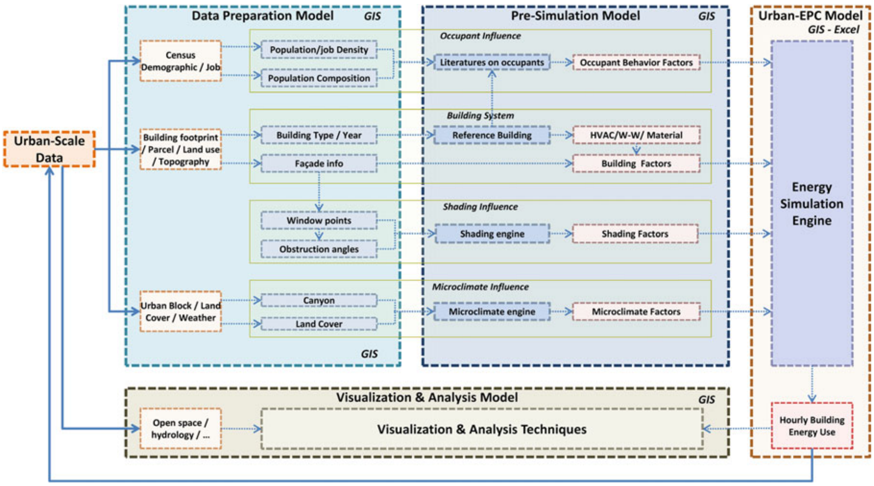


Fig. 1 Structure and the data flow of the urban building energy system

2.3.2 Data Preparation Model

The Data Preparation Model organizes, modifies and integrates the urban data from different sources into a new dataset to inform pre-simulation engines. Within this model, there are four streams of data flow. The first data stream starts with the building, parcel, land use, and topography data, sorting and transforming them into inputs, encoding the building function, construction year, building shape and detailed façade dimensions in eight orientation categories (as required by the EPC). From the façade information, the second data stream provides sample window point matrices and calculates their obstruction angles for the shading engine; this engine measures where solar direction radiation is blocked due to surrounding obstructions within a certain distance, as shown in Fig. 2. The obstruction angle then equals arctan(H/D). The third data stream extracts population density, job density and population composition information such as age, gender and education information from the demographic and job data. The fourth data stream uses urban block, street, land cover, and weather data to calculate canyon height, canyon ratio (the canyon height/the canyon width) and impervious surface ratio, which are important input parameters in the microclimate engine.

2.3.3 Pre-simulation Model and Main Simulation Model

The pre-simulation model includes the reference building dataset and the three urban context engines and provides important inputs to the Urban-EPC engine. The reference buildings are used to determine more detailed building information based on building functions and construction years. The shading simulation engine takes the obstruction angles of each window from all possible directions, and compares them with the zenith angle of the sun every hour throughout a year to find whether a window is shaded and then calculates the shading factor as the percentage of shaded windows on each façade. The microclimate simulation engine parameterizes urban characteristics from the urban block, street and land cover data into four urban parameters in each microclimate zone: canyon height, canyon ratio, pervious road

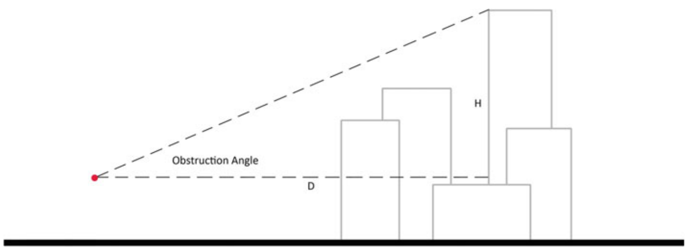


Fig. 2 The obstruction angle of one point

fraction and building roof fraction. It relates microclimate changes to these urban parameters through explicit statistical formulations such that buildings with similar urban parameter values share a similar microclimate, i.e. hourly ambient temperature and wind data. Then, by dividing all of the buildings into several climate zones and assuming that buildings in the same zone share a set of typical urban parameter values, the number of microclimate simulations can be reduced to only the number of zones. This dividing process is performed using a K-means clustering algorithm (MacQueen 1967), which selects 50 climate zones and the typical values for each zone such that the average difference between values of a single building and the typical values of its microclimate zone is minimized. The modification of occupant density is based on the population density and job density from urban data while the occupant behavior change is referred to the related literature.

Taking as input the detailed building information from the reference building approach, the shading factors of each building from the shading engine, the ambient temperature and wind data of each microclimate zone from the microclimate engine, the modified occupant behavior data from the occupancy engine, as well as the general building information extracted directly from the urban data, the core engine generates the hourly energy consumption of each building throughout a year in the Main Simulation Model. The results are then aggregated into monthly and annual building energy use data.

2.3.4 Visualization and Analysis Model

In the Visualization and Analysis Model, simulated building energy use is mapped to building GIS data for visualization. The simulated energy data are generated in this modeling system from the urban data and now they become a new part of the urban data in GIS format. They can be easily overlaid with other urban data for further analysis such as the density-energy relations. Also, since the models and engines are loosely coupled in the whole system, new engines and modules could be added to this system to extend its analysis capacity.

3 Case Study: Energy Performance of Buildings in Manhattan

The Manhattan borough in New York City is taken as a test case to demonstrate how the proposed urban building energy modeling system works in an actual urban area. The simulation results are then compared with measured data from 2012.

3.1 Case Area

According to the borough boundary and building footprint data of Manhattan (NYC Department of City Planning 2014; NYC Department of Information Technology and Telecommunications 2014), there were 45,920 buildings with the total floor area of 43,743,004 sq. ft. in 2013.

3.2 Data Preparation

In the Data Preparation Model, related urban data were organized to provide the inputs for the simulation. Although data production dates range from 2010 to 2013, this study makes the assumption that urban changes during these four years are minimal and that all the data represent Manhattan in 2012.

3.2.1 General Building Information

The building footprint data only contain the buildings' geometric information. In order to get other information such as building types, built years, etc., the parcel-level PLUTO (Primary Land Use Tax Lot Output) data was joined to the building footprints (NYC Department of City Planning 2014), as shown in Fig. 3a. However, the geometric data in both dataset does not quite match and so some corrections were made to estimate the building heights and number of stories, with references to Google Earth 3D buildings.

Based on the orientations, the facades were categorized into eight groups, as shown in Fig. 3b. Because the Manhattan grid has its particular orientation of 29°, the eight default orientations in the EPC calculator were modified in this case study by adding 29 degrees to each, which became 29°, 74°, 119°, 164°, 209°, 254°, 299° and 344°. The areas of those categorized facades, as well as the building floor areas and volumes were calculated as the input of the energy simulation model.

3.2.2 Mutual Shading Data

In this case study, only buildings are considered as obstructions in the shading effect. Since the GIS building footprint data already contains elevation data, the facades can be readily located without additional topography data. Then, point matrices were generated on facades wider than 5 ft. and higher than one storey to represent samples of windows, assuming that windows are evenly distributed at each floor on the facades. The vertical spacing of the point matrices is the storey

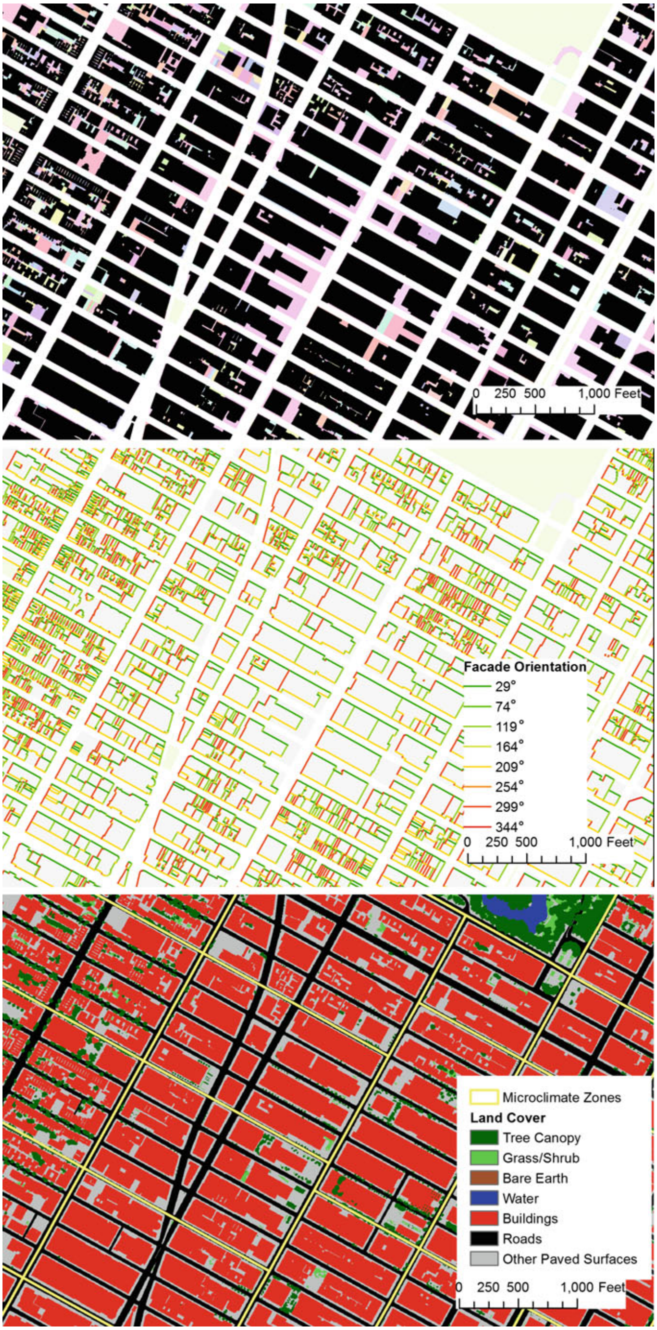


Fig. 3 *Top* Overlaying of the building footprints and PLUTO parcel data; *Middle* Categorized facade orientations; *Bottom* Microclimate zone overlaid on the land cover; all in Midtown, Manhattan

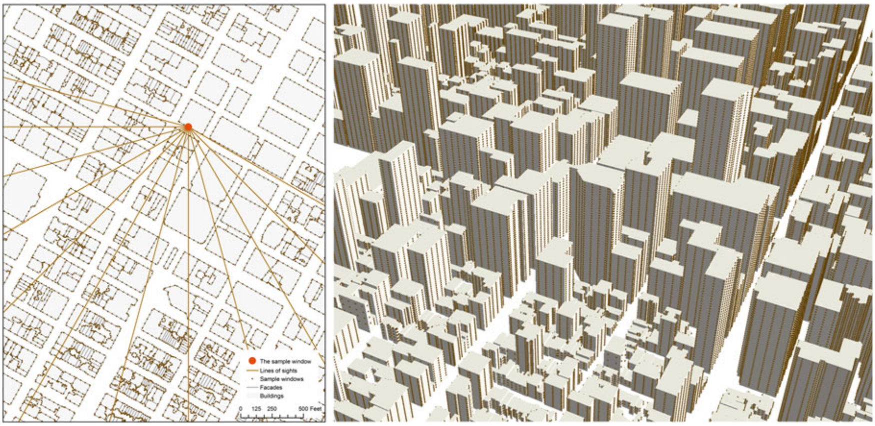


Fig. 4 Point matrices on the façades and the lines of sight from a sample point

height, while the horizontal spacing is set at 40 ft. for simplicity. Overall there are 397,404 points generated on the facades of 45,920 buildings in Manhattan.

From each point representing a sample window position, lines of sight were generated in GIS with the angle interval of 15°, which is the average angle that the sun's position changes by every hour throughout a year in New York City (NYC) (SunEarthTools.com 2014). The maximum obstruction angle along each line was calculated by intersecting the buildings with the line of sight. The length of the line of sights was set to be 3281 ft. (1 km) to intersect buildings lower than 500 and 6562 ft. (2 km) to intersect buildings taller than 500 ft. Considering the solar path throughout 2012 in Manhattan, the possible angles of the lines of sight are limited. Therefore a 397,404 × 17 matrix was generated with the rows as the points and the columns as the maximum obstruction angles along lines of sight. The point matrices and the lines of sight are shown in Fig. 4.

3.2.3 Microclimate Data

In this study, census tracts were chosen as the spatial units to divide Manhattan into 288 parts and further aggregated to 257 microclimate zones to match the spatial extents of the PLUTO data. In each part, average street width and average building heights were calculated to get the urban canyon widths and heights based on the building footprints, PLUTO, and street data. Pervious road fractions and building roof fractions were measured by extracting information from the land cover data overlaid by census tracts in Manhattan, as shown in Fig. 3c.

3.2.4 Occupant Density Data

To estimate occupant densities, the block level population data from the 2010 Census TIGER (Topologically Integrated Geographic Encoding and Referencing) and the block level job data from LODES (Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics) were joined to the census blocks and aggregated to the microclimate zones to get the population and job densities (United States Census Bureau 2014a, b). Those density data were then applied to buildings within the zones as the occupant densities for residential and commercial buildings. Occupant behavior modification was not tested in this case.

3.3 Energy Simulation Using the Urban-EPC Engine

The Pre-Simulation Model uses the shading, microclimate, and occupancy engines to determine hourly shading factors for building facades, hourly ambient temperatures for each microclimate zone, and occupant density data. Detailed building information were obtained from the reference building dataset for NYC. These data, together with the building information, were used as the input of the simulation to estimate the hourly total energy use, electricity use and gas use of each building in Manhattan throughout the year of 2012.

3.4 Visualization and Analysis

The resulting estimates of building energy use were joined back to the building data and visualized in ArcGIS to show the distribution of annual building energy use in Manhattan in 2012, as in Fig. 5. It is clear that the buildings consuming the most energy are located in downtown and midtown. However, the mapping of building energy use intensity tells another story. The comparison of building energy use and its intensity shown in Fig. 6 suggests that although the skyscrapers in the downtown and midtown areas consume the most energy, their energy intensities measured by energy use per floor areas are moderate compared to the mid-rise and low-rise buildings on the island. How building energy efficiency varies with building form and density could be further analyzed based on the results of this energy modeling system.

There is also a temporal dimension in the output of the modeling system. The hourly result data can show the fluctuation of building energy over 24 h in a typical day in Manhattan, or can be aggregated to show the monthly variation of average building energy use intensity to better understand the dynamics of the building energy use, as in Fig. 7.

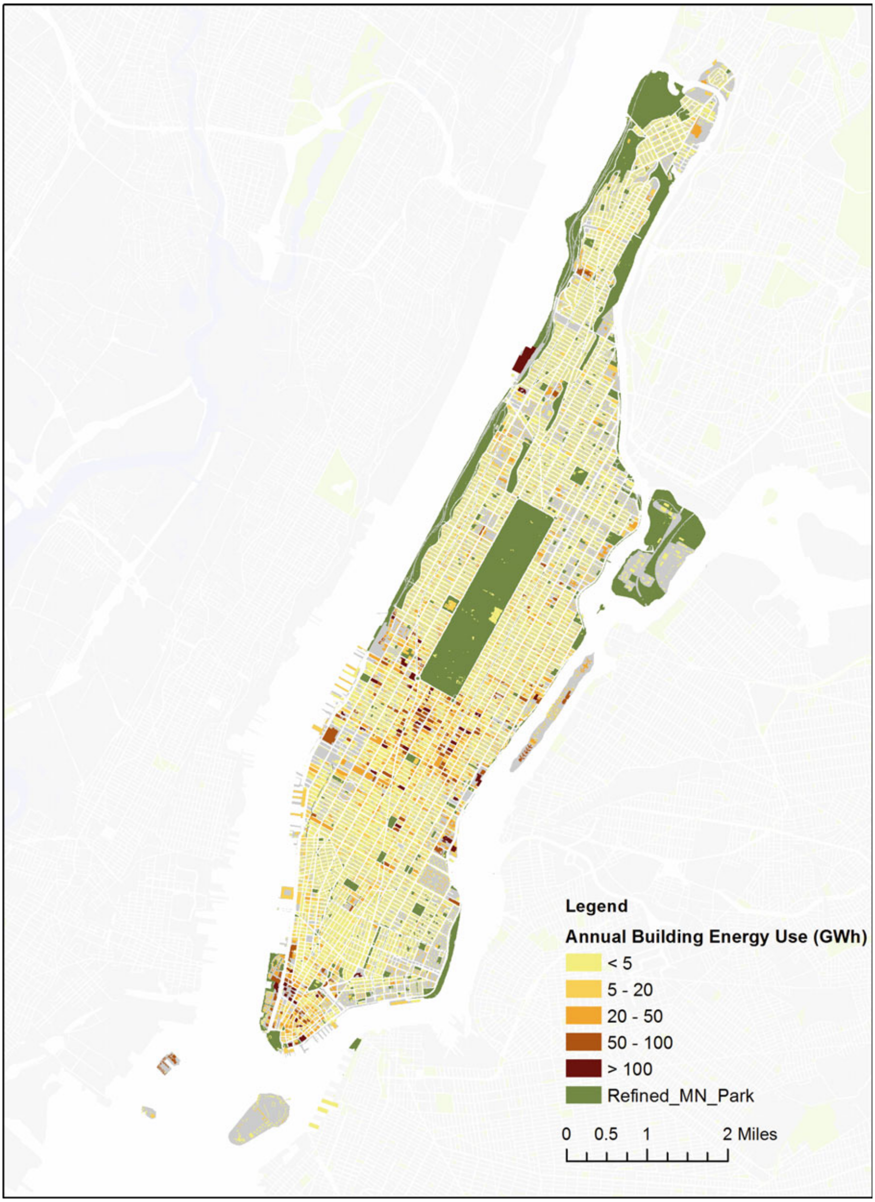
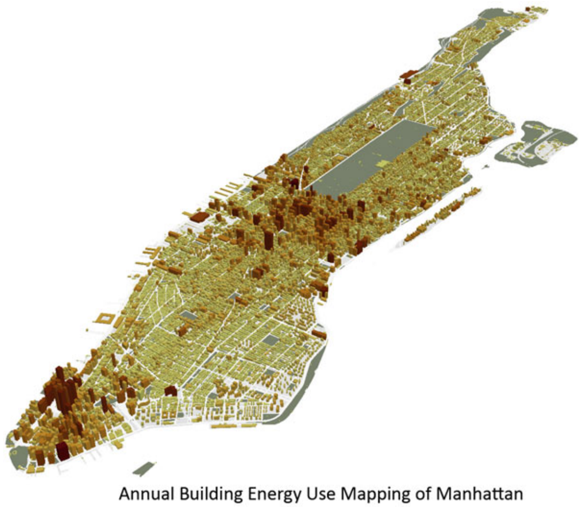
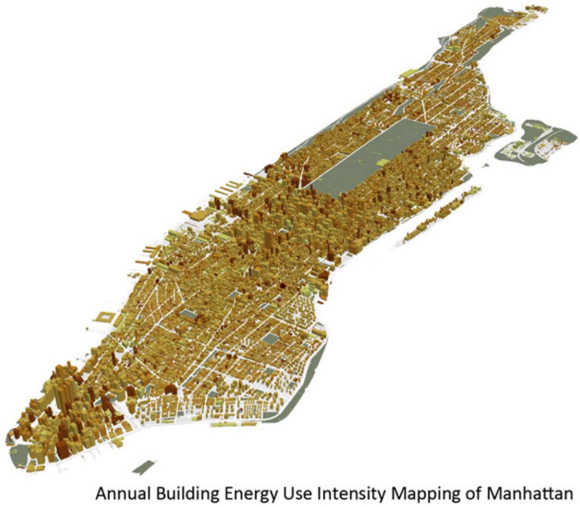


Fig. 5 Building energy use mapping in Manhattan in 2012 (kWh)

Fig. 6 Comparison of (*top*) building energy use (EU) mapping and (*bottom*) building energy use intensity (EUI) mapping of Manhattan





3.5 Validation

The reliability and accuracy of the urban building energy modeling system is critical when applied to support planning practice and policy making. However, so far, few building energy modeling studies at the urban level has been rigorously validated based on a large dataset of measure data. In this case study, the validation used a building energy use dataset in 2012 provided under the Local Law 84 (LL84) published by The New York City Department of Buildings (DOB), which requires "*annual benchmarking data to be submitted by owners of buildings with*

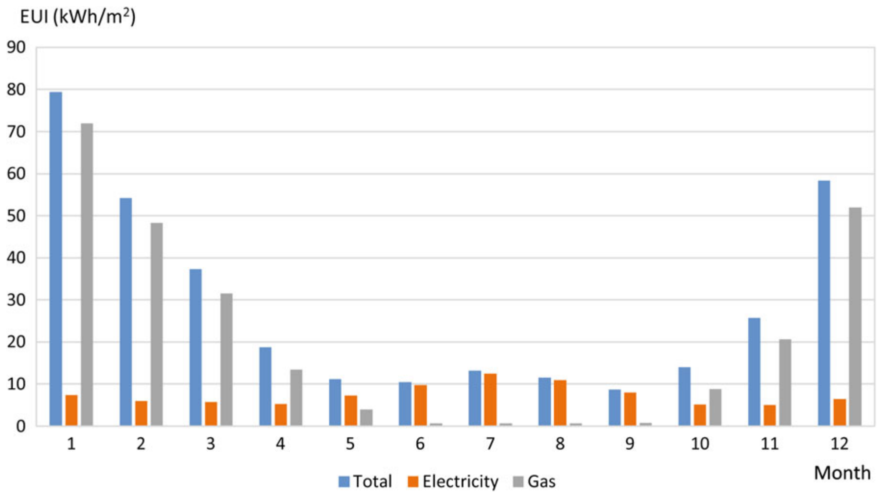


Fig. 7 Average monthly building energy use intensity (EUI) of Manhattan

more than 50,000 sq. ft. for public disclosure" (The City of New York 2014). The 2012 LL84 dataset contains the annual energy use data of 1680 buildings in Manhattan, and after cleaning up missing and outlier data, 1118 buildings were left as the dataset for validation.

The validation shows that in 80.1 % of the buildings, the estimated energy use is within the range of 0.5–2 times of the measured energy use, suggesting an overall good fit (Fig. 8). The NMBE (net mean bias error) is 0.28, which suggests that the total estimation of all EUI is larger than the reported by around 28 %. The CVRMSE (coefficient of variance root mean square error) is 0.69 at the same time, indicating that for estimation of a single building the average error is around 69 %. Comparing the two indices to the ASHRAE (American Society of Heating, Refrigerating Air-Conditioning Engineers) standard of 0.05 for NMBE and 0.15 for CVRMSE for monthly energy consumption of a single building, the accuracy is sufficient for the urban level building energy simulation given so many uncertainties in the assumed data and modeling parameters.

To understand to what extent the urban context engines improve the modeling system, results from five modeling method scenarios were compared, including modeling with no urban context engines, modeling with the shading engine, modeling with the microclimate engine, modeling with the occupancy engine and modeling with all three engines (i.e. the full urban context). The results indicate that the urban context engines improve the modeling considerably, and that there is the trade-off between the influences of shadings which tends to increase heating loads which are the major loads in NYC and other factors which are likely to reduce heating loads, as shown in Table 2 and Fig. 9.

The total time used for the above simulation of the hourly energy use of 45,920 buildings in Manhattan was 80 h using a desktop computer with an Intel i7 CPU

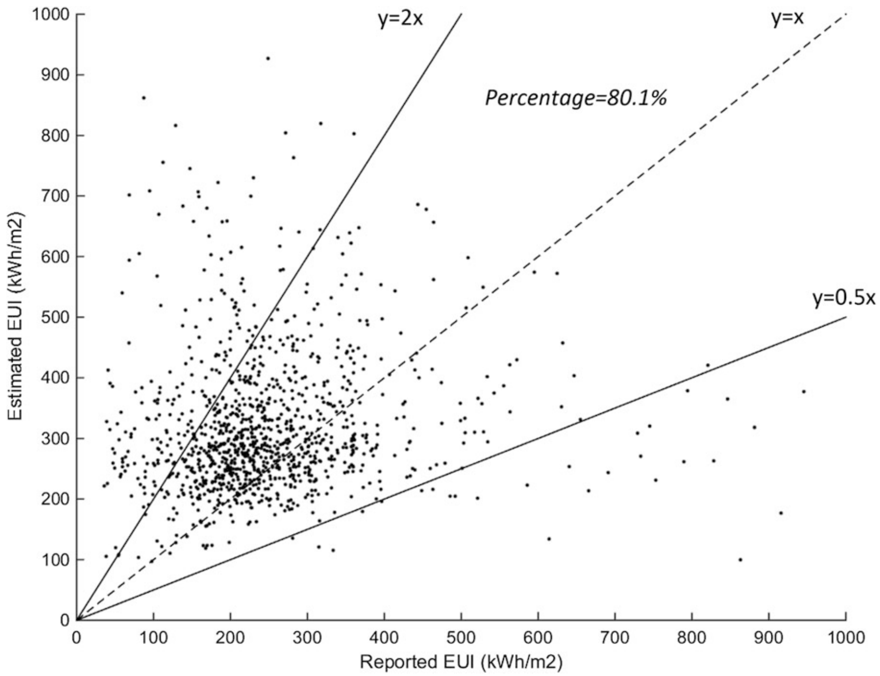


Fig. 8 Scatter point chart of the estimated and reported EUI (*upper line* estimated data = 2* reported data; *lower line* estimated data = 0.5* reported data)

Table 2 Validation results of the urban-EPC modeling and the traditional EPC modeling methods

Modeling method	NMBE	CVRMSE
EPC with urban context (all 3 engines)	0.28	0.69
EPC with shading	0.52	0.85
EPC with microclimate	0.33	0.70
EPC with occupant behavior	0.43	0.81
EPC	0.50	0.83

and 32G RAM, which is quite good for such large and dense urban area. The use of more computers with lower modeling resolutions can reduce the simulation time to one day or less.

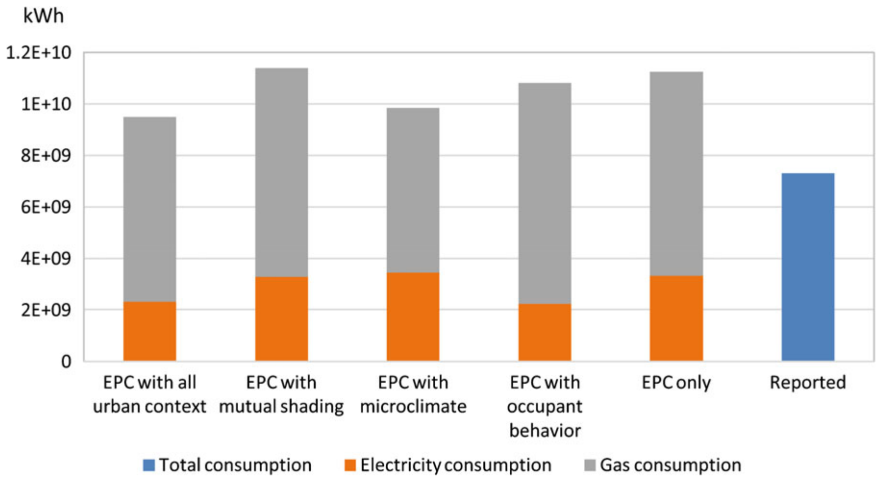


Fig. 9 Comparison between different modeling scenarios

4 Conclusions

There is a lack of an urban-context-aware building energy modeling method in PSS despite the fact that the issue of building energy efficiency is receiving greater attention. This is due to the inability of building energy modeling to account for the urban context and the inconsistency between the available urban data and the required building data in traditional building energy modeling tools. Although planners have access to abundant urban data, applications using these data for energy performance assessments of different urban design scenarios rarely occur.

This chapter has tried to explain a methodology that aims to fill this gap. The GIS-based urban building energy modeling system that has been outlined can be applied to other planning studies, enhanced by the combination of the building physical modeling and statistical dataset, and adjustable in its resolution, speed and accuracy. The modeling system as a process of using urban data to inform urban building energy use was demonstrated using the case study of Manhattan. The results show an acceptable level of accuracy for modeling such a large and dense urban area based on a relatively simple method.

The modeling method also reveals some problems with data management and tool platforms. On the data side, data inconsistency, low-level detail, and missing information are common in urban data for many cities, especially for the information required by building energy modeling. For example, building data and PLUTO data have huge inconsistencies in building heights. Better management is required to collect, examine, organize and share urban data in each city. In some cities where open-source urban data are limited, planners need to use the BAD (Best Available Data) to inform energy assessment and support policy making, as long as reasonable assumptions are made or appropriate substitute data are chosen (Klosterman 2008).

On the tool platform side, although GIS is a powerful analytical platform, it becomes less capable when dealing with detailed data at a large scale. Data volume increases considerably when the spatial level of urban studies goes down from cities and districts to buildings, facades and even windows. As a consequence, GIS tools become slow and often show errors because of memory limitations. ArcPy codes run faster than the tools but are still much slower than the previous VBA language. Therefore, GIS computation needs to be improved for handling big data in building energy modeling.

This urban building energy modeling system shows its potential to contribute to PSS. Its inclusion in PSS could help planners better understand how urban form performs in terms of building energy use. It can also evaluate the environmental, economic and social impact of large-scale energy-related renovation proposals, e.g. implementation of white roofs or low-e glass, so as to support policy making at the urban level. More importantly, it provides estimates of the spatial distribution of the building energy use in a city, which allows planners and policy makers to adjust energy supply to optimize the whole energy system. When applied to design proposals, this modeling system could assist designers to reconfigure the land use patterns and building layouts for better building energy performance.

The development of this urban building energy modeling system exemplifies how to link building-scale engineering modeling with meso-scale urban data to inform planning practice. It allows planners and policy makers to look at urban data through the lens of energy performance, and to reconsider where related urban data are, how urban data can be managed, and most importantly, what urban data can inform urban energy policies.

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