BUILDING ENERGY MODELLING AT URBAN SCALE: INTEGRATION OF REDUCED ORDER ENERGY MODEL WITH GEOGRAPHICAL INFORMATION

Qi Li[1], Steven Jige Quan[2], Godfried Augenbroe[1], Perry Pei-Ju Yang[1,2], Jason Brown[1]
[1]School of Architecture, Georgia Institute of Technology, Atlanta, USA
[2]School of City and Regional Planning, Georgia Institute of Technology, Atlanta, USA

ABSTRACT

This study uses Manhattan, New York City, NY as an example to demonstrate an urban-scale building energy modelling methodology that integrates a reduced-order energy model with geographical information system (GIS). GIS provides general building information that either directly serves as model inputs, or links to the specific prototype building models for more detailed building and system specifications. This methodology also considers impact of urban context on building energy consumption by parameterizing and quantifying urban environment into microclimate related parameters, with urban heat island (UHI) effect and mutual shading in the case study as examples. The result proves its capability in estimating overall urban scale building energy use for a specific city under certain climate conditions.

INTRODUCTION

Energy conservation in buildings has been receiving increasing attention in recent years due to its large share in total energy consumption (Perez-Lombard et al. 2007) and growing concern on energy crisis and global climate change. This also affects urban planning considerations and the development of energy standards and policies that address energy related issues at urban scales. Nevertheless, urban-scale building energy modelling has always been a challenging task due to the huge number of buildings at the urban scale and the trade-off between accuracy and speed in simulation process. Widely used bottom-up engineering-based building stock models, unlike top-down or statistical bottom-up modelling methods, consider building thermodynamic processes and physical principles that enable it to support retrofit analysis at large scale or development of technology related energy standards and policies (Swan and Ugursal 2009a; Kavgic et al. 2010).

However, employing detailed dynamic energy models in most current building stock models, if using a one-building-at-a-time modelling strategy, requires laborious time and effort in data collection, model creation and simulation (Reinhart et al. 2013; Sehrawat and Kensek 2014) at the urban scale. Creation of prototype buildings as an aggregation of the whole building stock, on the other hand, relies on appropriate grouping of buildings into several categories that each prototype building represents, and development of representative input parameters for each detailed prototype model. This becomes even more challenging and the result is susceptible to either a loss of accuracy or prohibitive computational effort (Shimoda et al. 2007) if the aggregation level is inappropriate. At the same time, the impact of urban context, spatial characteristics, and urban morphology has received great attention in the building simulation literature especially on microclimate conditions (Wong et al. 2011; Pisello et al. 2012; Sun and Augenbroe 2014). However, most building stock models ignore it in aggregating single building energy consumption into urban-scale result (Jones et al. 2007; Swan et al. 2009b; Booth et al. 2012; Zhao, 2012). This ignorance may lead to considerable inaccuracy in the estimation, misunderstanding of interaction mechanisms between building and surrounding environment, and inadequate recognition of spatial characteristics in energy management.

This paper reports the progress of an ongoing work that addresses these issues by integrating urban-scale geographical information system (GIS) with reduced-order single building energy models at three levels. First, general footprint and height data directly apply to the model as a representation of general building geometry. Second, information about building type, built year/vintage, population density, etc. determine the typical detailed model inputs from an input repository based on reference/prototype building models and national building energy standards. Third, information in building geometry, as a representation of the urban morphologic characteristics, serves in quantifying the microclimate conditions that adjust the boundary conditions in single building energy calculation. Compared with previous published work (Quan et al. 2015a, 2015b), this paper focuses on the modelling methodology associated with building energy models and the implementation of urban context in terms of model inputs. In addition to the Department of Energy (DOE) commercial reference building models (Deru et al. 2011), it also uses the residential prototype building models (BECP 2012), which include single and multi-family housing models, as a supplemental source of the model input. At the same time, it uses a simplified monthly-calculation based energy model that significantly reduces computational load without compromising estimation accuracy. Finally, it provides discussions on the future improvement on model quality and data consistency, as well as its potential in supporting urban level energy management in real practice. The following sections will use Manhattan as a case study to demonstrate the methodology, followed by the result, validation and conclusions.

METHODOLOGY

Background

Geographic information system (GIS) is a data visualization, analyses and interpretation (Esri 2015) application for large spatial scales that first appeared in the early 1960s. Since the 1990s, it has grown in popularity when it became available on personal computers (Drummond and French 2008). Its comprehensive capabilities in spatial database management, analyses, modelling, and visualization satisfies the professional needs of regional and urban planners, and has now become a standard software in planners' tool kit. The percentage of US local governments that adopt GIS went up to near 90% in 1997 (Warnecke et al. 1998; Yeh 1999; Drummond and French 2008). It is now an important component in Planning Support Systems (Batty and Densham 1996; Klosterman 1997).

This study takes the Manhattan borough in New York City, New York as a test case to demonstrate the application of this methodology in a real urban environment. The borough includes 45,920 buildings with a total floor area of 43,743,004 ft^2 (4,063,858 m^2) in 2013 (NYC Department of City Planning, 2014; NYC Department of Information Technology and Telecommunications, 2014), of which 45,917 buildings meet modelling data requirement. Although the whole dataset contains information collected from 2010 to 2013, it assumes that the changes at the urban level are negligible and therefore ignored in the case study. This study uses GIS as the main platform for processing urban data, retrieving information, and performing the energy calculations in the spreadsheet-based EPC models with the obtained model inputs.

Introduction of reduced-order energy model

This paper uses a reduced-order building energy model, the Energy Performance Certificate calculator (EPC), as the physical model. It came from the effort of Energy Performance in Buildings Directive (EPBD) that has focused on methodologies for calculating and rating the energy performance of new and existing buildings, and resulted in the international standard ISO 13790:2008 (ISO 2008). It considers simplified thermodynamic processes with a quasi-steady-state formulation of building monthly heat balance and aggregated building parameters like general geometry, envelop properties, occupancy schedules and lighting/equipment usage profiles. Under certain assumptions about usage scenarios, HVAC system types and efficiency, etc., it calculates the space heating and cooling loads based on monthly average local weather conditions, and then translates them into delivered energy via normatively-defined macro system efficiency factors. Different from hourly calculation methods used in Quan (2015a), it employs so-called utilization factors to compensate for the discrepancy caused by ignorance of dynamic effects. Several comparative studies have shown that the EPC model is capable of providing a quick estimation of building energy consumption with acceptable accuracy (Kim et al. 2013; Lee et al. 2014), which makes it ideal for urban-scale energy modelling, wherein only general building information are available and the total consumption instead of detailed dynamic is of primary interest.

Geographical information process

The footprint data (NYC Department of City Planning, 2014) and height of each building provides the main information about building geometry. This study uses the parcel-level Primary Land Use Tax Lot Output (PLUTO) data, including building type, vintage, etc., to supplement general building information and map with footprint data after performing appropriate corrections. Detailed building and system information comes from selected prototype building models according to the building type information in PLUTO, as will be elaborated in the next section. This includes the window-to-wall ratio of each façade and building floor-to-floor height that serve in calculating the window area and total floor area of each building.

Two other important data sources in the GIS platform are the block-level population data from the 2010 Census TIGER (Topologically Integrated Geographic Encoding and Referencing) and employment data from LODES (Longitudinal Employer-Household Dynamics Origin-Destination Employment Statistics) (United States Census Bureau 2014a, b). They help in adjusting the default occupancy density in office and residential buildings that inherited from prototype building models, as well as lighting, equipment and domestic hot water usage densities, assuming constant usage per person.

Detailed building model inputs

Due to the lack of detailed information about actual building usage, system type, operation scenario, etc., assumptions that apply to most general cases becomes a practical choice. Given the building type information of each building from PLUTO data, this method chooses a corresponding prototype building model that represents common conditions and serves as the data source for detailed building model inputs. The first category of the building model repository comes from DOE commercial reference buildings (Deru et al. 2011), which includes energy models of

16 building types across 16 U.S. cities (Table 1), and of which the models in Baltimore, Maryland serve as the data source since it locates in the same climate zone as New York City. The original models also consist of three categories according to building vintage: pre-1980, post-1980 and new construction (pre-2004). Models of the same building type but within different categories share the same building form, area and operation schedules, whereas the insulation values, lighting levels, HVAC equipment types and efficiencies reflect the differences. These differences come from the minimum requirements in building standards of different time (ASHRAE 1989; ASHRAE 2004), whose newer versions (ASHRAE 2007; ASHRAE 2010) were also included to consider stringent requirements of building performance in recent years.

Table 1
Building type and representative city in commercial reference building models

BUILDING TYPE	CITY
Large Office	Miami, Florida
Medium Office	Houston, Texas
Small Office	Phoenix, Arizona
Warehouse	Atlanta, Georgia
Stand-alone Retail	Los Angeles, California
Strip Mall	Las Vegas, Nevada
Primary School	San Francisco, California
Secondary School	Baltimore, Maryland
Supermarket	Albuquerque, New Mexico
Quick Service Restaurant	Seattle, Washington
Full Service Restaurant	Chicago, Illinois
Hospital	Boulder, Colorado
Outpatient Health Care	Minneapolis, Minnesota
Small Hotel	Helena, Montana
Large Hotel	Duluth, Minnesota
Midrise Apartment	Fairbanks, Alaska

The second category, as supplemented in this case study, includes single-family detached house and multi-family low-rise apartment buildings from residential prototype building models (BECP 2012), created according to the 2006, 2009 and 2012 editions of the International Energy Conservation Code (IECC). It has both models with four heating system types and four foundation types, from which the study chose the gas furnace and slab foundation out of simplicity since no actual data is available to designate specific types for each building. In addition, specific models for New York City are available and therefore constitute the model inputs directly.

Urban context: urban heat island effect

The urban heat island (UHI) effect represents the temperature increase in an urban area due to distinct characteristics of built-up structures and anthropogenic activities. UHI affects building energy consumption mostly via heat transfer through envelope transmission and ventilation, which are one of the main causes of heating and cooling need in building spaces. Following Sun and Augenbroe (2014), this study uses the Town Energy Budget (TEB) model (Masson 2000) and the Interaction Soil–Biosphere–Atmosphere (ISBA) model (Noilhan and Planton 1989; Noilhan and Mahfouf 1996) to quantify the magnitude of UHI via parameterization of the local urban environment. It approximates complex urban morphology into simplified microclimate zones, and assumes all buildings identical and homogeneously distributed over a regular grid in each zone. Values of four urban parameters, i.e. canyon height, canyon aspect ratio, coverage of vegetation area and buildings specify the characteristics of each zone.

This case study uses census tracts as the basis for identifying the microclimate zones. The "census tract" is an area that is roughly equivalent to a neighbourhood. The Census Bureau defines and uses this concept for population analysis (U.S. Department of Commerce, Economics and Statistics Administration, U.S. Census Bureau 1994). Under the assumption that the urban environments within one census tract are similar, this case study defined 257 climate zones after the aggregation of the 288 census tracts to match the zoning data, and then calculates the four urban parameters separately. It assumes urban the streets with the side buildings of the same height defines the urban canyon, whose width and height then reflect the virtual canyon parameters. Due to the lack of street width information in GIS data, here uses a simplified method to calculate the canyon width by dividing the area of roads by the total length of the block perimeters within, and estimate the canyon height as the average height of buildings in each microclimate zone. At the same time, the land cover data in Manhattan contains the classification of tree canopy, grass/shrub, bare earth, water, building roofs, roads, and other paved surfaces, which provides the classifications of different land cover (U.S. Geological Survey 2012) and hence good estimates of the two urban parameters concerning land coverage.

To reduce computational effort and reflect similar microclimate conditions within a large scope, these 257 microclimate zones are further aggregated into 50 zones in the end, according to the similarity of parameter values. It then calculated the UHI effect, represented as the monthly average difference compared with dry-bulb temperature in weather stations. The resultant actual temperature then served in energy calculations as the true ambient temperature.

Urban context: mutual shading

Another important impact of urban context on building energy consumption comes from mutual shading, referring to the shading from surrounding buildings especially on windows that lead to a decrease in solar heat gain. This effect becomes significant especially in urban areas where tall buildings are highly concentrated. Urban morphology data from GIS can ideally compute the actual magnitude of mutual shading on any location if used altogether with the solar path for city at certain geographic location. However, its realization requires prohibitively expensive computational effort, which lead to the simplified method as in this study. Processing the urban data in calculating mutual shading includes several manipulations in the GIS. In general, it determines the location of each window under assumptions of general window-to-wall ratio on each façade, and then calculate the monthly-average obstruction angle of each window due to adjacent buildings (Figure 1). Then it aggregates obstruction angles from individual windows into that of each façade on a single building, and supplies it directly to the EPC model where a custom module can then calculate the shading effect based on solar zeniths. This adjusts the actual solar heat gain through windows and thus the heating and cooling need of the building considered. More details of determining obstruction angles for each virtual window can be found in Quan et al. (2015a).

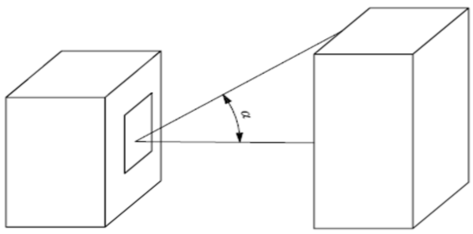

Figure 1: Demonstration of obstruction angle

RESULTS AND DISCUSSION

Model validation

Validation of this methodology uses a dataset of building energy consumption in 2012, provided as required by Local Law 84 of the New York City Department of Buildings that mandates “annual benchmarking data to be submitted by owners of buildings with more than 50,000 sq. ft. for public disclosure” (The City of New York, 2014). It contains the annual total site energy consumption and energy use intensity (EUI) of 1680 buildings in Manhattan, 1178 of which satisfy the requirement of data quality. The comparison considers EUI from the sum of electricity consumption for cooling, lighting, plug load and gas consumption for heating and domestic hot water. Due to the limitation of prototype building models in considering extreme cases, the comparison neglects buildings with reported EUI larger than 1000 kWh/m^2, resulting in a final comparison of 1144 data points. This study also performed an evaluation of the impact of urban context by modelling the energy use without including the adjustment due to UHI and mutual shading.

Table 2 Validation 1 shows the calculated criteria of agreement according to Equation 1:

$$NMBE = \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{n\bar{y}}, CVRMSE = \frac{1}{\bar{y}}\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \quad (1)$$

in which y_i is the reported EUI for ith building, $\hat{y}_i$ is the corresponding estimate, and n is the total number of data points, i.e. 1144. The net mean bias error (NMBE) represents the estimation error in terms of all the data points, and the root mean square error (RMSE) represents the average estimation error for individual buildings. The results indicate that the model estimation has an overall good agreement with the reported data for the total group of buildings. On the other hand, estimation in terms of individual buildings shows a larger discrepancy with expected error of 57% for a single building. This agrees well with the third criterion that around 83% of all the estimations fall within an error bound of 50% to 150%.

Table 2
Criteria of agreement

	NMBE	CV RMSE	PERCENTAGE WITHIN ±50%
Validation 1	-0.06	0.57	82.5%
Validation 2	-0.06	0.14	100%

Figure 2 shows the distribution of reported and estimated EUI of all 1144 buildings, representing the model quality in terms of the overall urban energy use profile. It agrees well with the conclusion about overall estimation accuracy, especially the modes of empirical distributions as represented by the histograms. However, it also shows that reported data has larger variations than estimated, since input values in prototype building models represent only the general circumstances.

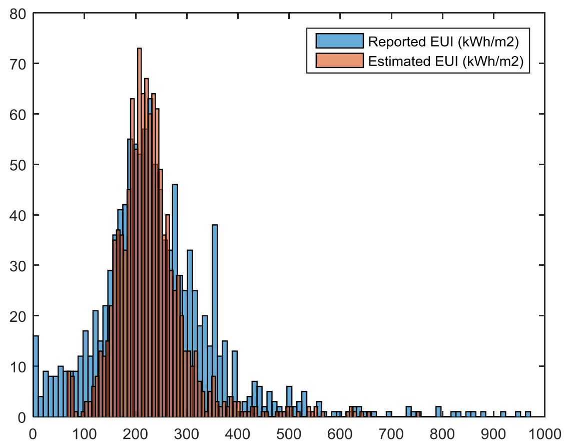

Figure 2 Histogram of reported and estimated EUI

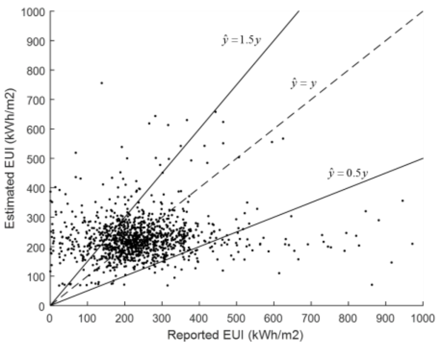

Figure 3 Comparison of estimated and reported EUI for individual buildings

As for the estimation accuracy on individual buildings, Figure 3 shows the comparison of estimated and reported EUI for each pair of data points. Most of the points fall within the range between $\hat{y} = 0.5y$ and $\hat{y} = 1.5y$. However, there's no clear linear correlation between estimated and reported EUI due to outliers that goes beyond the scope of prototype models.

Because the modelling methodology uses only general building information, including footprint shape, building height, total floor area, zoning type, registration data etc., and the factors that have important impact on the energy performance, like construction type, occupation hours, building operation schedules, are all inferred from the general information, the average estimation error of 57% for individual buildings can be expected. Aggregation at a higher level can reduce the error to 6% for the whole building collection in Manhattan. To further test the model accuracy, this study aggregates the aforementioned 1144 buildings based on zip code to reflect an intermediate aggregation level, which results in 44 groups of buildings. The number of buildings in each zip code group ranges from 1 to 79 with an average of 26, a medium of 23 and a standard deviation of 19.67. Table 2 also shows the result of validation at this zip code level, shown as Validation 2. Note that NMBE remains the same since it also evaluates the error of all 1144 buildings as a whole. It clearly indicates that the model has achieved an acceptable accuracy when consider buildings with a group size of around 30.

In a summary, the validation proves that this modelling methodology can estimate the overall energy use profile and the general trend. Its improved accuracy on aggregated groups of buildings enables it to support retrofit analysis at comparable scales. Nevertheless, accurate estimation of individual building energy use may go beyond its current capability due to limited availability of more detailed building usage information. Future improvement may involve more reliable data resource as either detailed usage information for model inputs, or monthly utility bills, smart-meter readings, aggregated block-level energy consumptions to improve the model via use of calibration techniques. In addition, validating the model capability may involve predicting energy consumption against actual measurements under unprecedented conditions, such that estimation of retrofit impact as an extrapolation can remain reliable. Applying the same methodology on other cities could be another validation method.

Impact of urban context

To explain the impact of urban context on large-scale building energy modelling, Table 3 shows the result of agreement of calculation without considering the urban context, and the difference from the result in Table 2 for Validation 1 case. A non-parametric Bootstrapping algorithm (Efron 1979) estimates the standard deviation of each criterion, and take the average value of estimates with and without urban context. The result compared with the difference indicates that consideration of urban context result in a significant difference on NMBE, the estimation of overall model agreement, whereas it may not necessarily improve the accuracy due to other discrepancies. Its impact on individual building estimate is also negligible, seen from the insignificant differences in RMSE and percentage.

Table 3
Criteria of agreement, without urban context, Validation 1- individual buildings

	NMBE	CV RMSE	PERCENTAGE WITHIN ±50%
Value	0.04	0.59	81.6%
Difference	0.10	0.02	0.9%
Std.	0.02	0.02	1.1%

Similarly, Table 4 shows the bootstrap results at group level based on zip code, i.e. Validation 2, which agrees with the result of Validation 1. Note that the standard deviation of percentage within ±50% is 0 since the base case has a 100% coverage, and therefore any subset of the whole group will also have 100% coverage, which lead to a 0 standard deviation. Therefore, it is not recognized as a proof of significant difference in percentage within ±50%.

Table 4
Criteria of agreement, without urban context, Validation 2 - buildings grouped based on zip code

	NMBE	CV RMSE	PERCENTAGE WITHIN ±50%
Value	0.04	0.12	97.7%
Difference	0.10	-0.02	2.3%
Std.	0.02	0.02	0%

To consider two aspects of urban context, i.e. UHI effect and mutual shading separately, this study also performed another two simulation scenarios, one only considers the former context and the other only the latter, and calculate the relative difference between them and the baseline scenario, where both aspects are considered, as a reflection of separate impact. It calculates the differences on electricity and gas usage for each building to assess the impact on cooling and heating separately. Table 5 shows the resultant mean and median of the distribution for each group. As seen in the results, neglect of UHI would generally result in a 5% underestimation in electricity usage and 18% overestimation in gas usage, which agrees with the knowledge that ambient temperature increase due to UHI lead to increased cooling load and decreased heating load. On the other hand, while the impact of mutual shading shows a similar agreement with experience, the magnitude of impact becomes negligible even for the maximum difference when compared with model accuracy.

Table 5
Distribution statistics of usage difference (%) of individual buildings

GROUP	MEAN	MEDIAN	MAX	MIN
UHI Elec.	-4.96	-4.99	-15.92	0
UHI Gas	18.08	15.22	195.06	0
MS Elec.	0.06	0.04	1.84	0
MS Gas	-0.01	0.00	-0.01	0

The impact of urban context on individual buildings might largely depends on the urban density. To test this pattern, this study uses floor-area ratio (FAR) to represent urban density, which is the ratio of total building floor area to the footprint area. Using the census tract as the research unit, the relative difference in both annual electricity and gas consumption that caused by the two impacts individually are regressed against the average building density of all the tracts expect two whose has very few buildings. Results in Table 6 indicate that the coefficients of the FAR in UHI-electricity model is significant and the R^2 value indicates a strong correlation between UHI and essentially cooling load, because the land cover and the height-to-width ratio of the urban canyon, used to estimate UHI effect, is highly related to building density. On the other hand, although both coefficients of FAR are significant, the magnitude suggested by the value is almost negligible compared to UHI. In addition, the correlations indicated by R^2 are weaker than UHI-electricity, since the shading effect also largely depends on façade orientations, window areas and positions, etc., such that the urban density alone may not fully explain its variation.

Table 6
Regression statistics of impact against FAR

IMPACT	ENERGY TYPE	FAR COEF.	R^2
UHI	Electricity	0.015*	0.445
	Gas	0.003	0.003
MS	Electricity	0.000*	0.259
	Gas	0.00006*	0.346

** Significant at 0.05 level*

Urban scale modelling result

The energy simulation of 45917 buildings in Manhattan alone took around 40 minutes on a single core, a large decrease in computational effort compared with the hourly method in Quan et al. (2015a, b). Figure 4 shows the monthly total building energy use in Manhattan, where gas as the source of heating and domestic hot water usage is the dominant consumption. Figure 5 and 6 show the energy use map of the Manhattan in both building annual total energy consumption and EUI. They clearly identify the areas with intense energy consumption, an important spatial characteristic of urban-scale building energy use.

Compared with most existing building stock models, an important feature of this proposed methodology is the consideration of urban context mostly in terms of microclimate conditions. While this paper only considers urban heat island effect and mutual shading, further study on local wind speed, which affects convective heat transfer on building exterior facades, natural ventilation and infiltration, will likely reveal stronger correlation between urban context and urban energy use. Use of first principle models as the energy calculation basis, on the other hand, allows it to provide an overall city building energy use picture related to climate conditions, city functions and morphology. This possibly can inform decision-making process in urban energy management, large-scale retrofit analysis, and especially development of technology-related energy standards and policies for a city under specific urban and climate conditions.

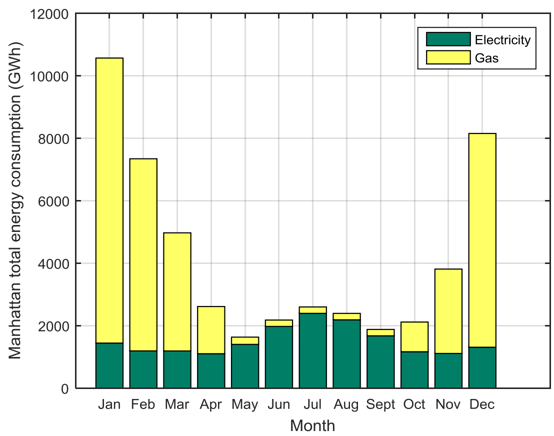

Figure 4 Monthly total building energy consumption

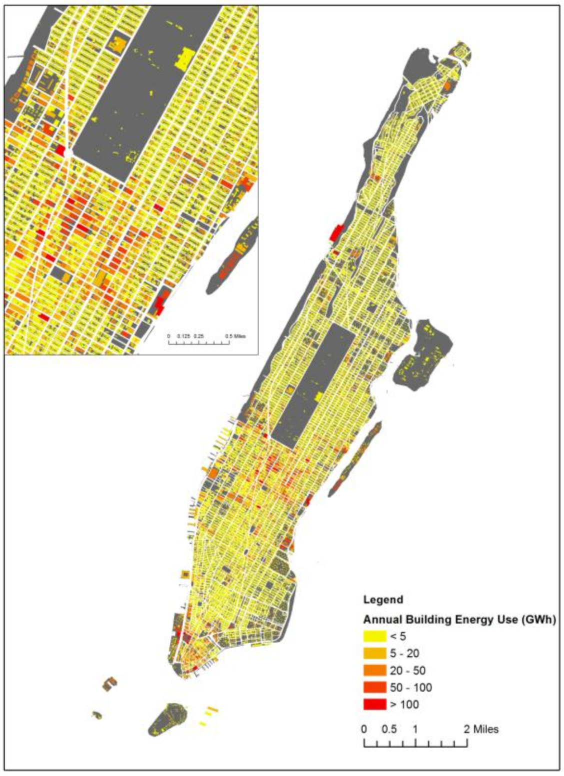

Figure 5 Building energy use map of Manhattan, total annual energy consumption

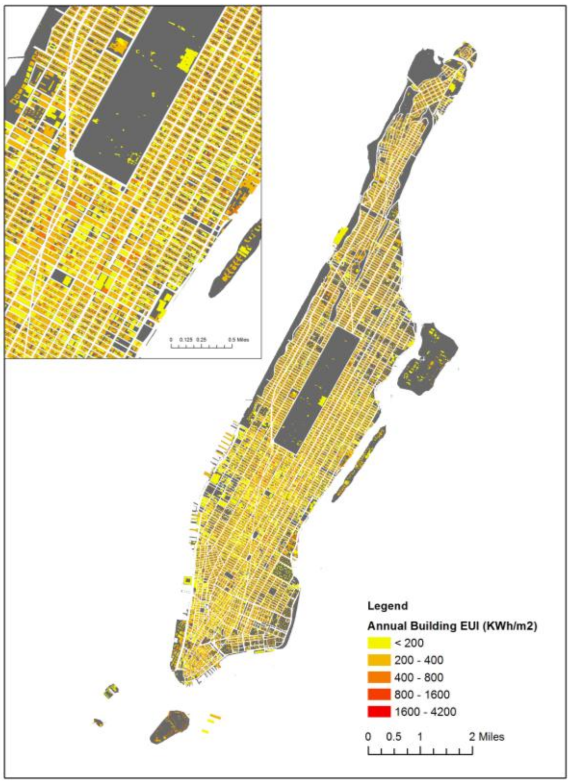

Figure 6 Building energy use map of Manhattan, total annual EUI

Finally, use of simple monthly calculation in this methodology may especially fit with the situation when limited information is available due to its simplified input requirements, convenient model configurations and fast computation. It also help conceptualize the whole city as an entire input space of limited dimension with correlated distributions for model inputs. This conceptualization allows for the introduction of high performance computing algorithms to reduce computational effort in handling various data source and large data quantities when integrated problems about the overall urban scale energy flow is of interest.

CONCLUSION

This paper proposed an urban-scale building energy modelling methodology that integrates geographical information with physical principle based simple energy calculation tool. This methodology considers the impact of urban context on building energy use, which can serve as an experimental tool to analyze the correlation between urban morphology and the modifier on aggregated urban energy consumption. Intended for large scale urban modelling instead of individual buildings, this methodology enables retrofit analysis and energy related policy development based on the group of physical models. Future improvement in data sources, model inputs, and the use of calibration techniques can further realize its potential in supporting spatial analysis of urban energy consumption.

REFERENCES

ASHRAE. (1989). Energy Efficient Design of New Buildings Except Low-Rise Residential Buildings. ANSI/ASHRAE/IESNA Standard 90.1-1989. Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers.

ASHRAE. (2004). Energy Standard for Buildings Except Low-Rise Residential Buildings. ANSI/ ASHRAE/IESNA Standard 90.1-2004. Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers.

ASHRAE. (2007). Energy Standard for Buildings Except Low-Rise Residential Buildings. ANSI/ ASHRAE/IESNA Standard 90.1-2007. Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers.

ASHRAE. (2010). Energy Standard for Buildings Except Low-Rise Residential Buildings. ANSI/ ASHRAE/IESNA Standard 90.1-2010. Atlanta, GA: American Society of Heating, Refrigerating and Air-Conditioning Engineers.

Batty M, Densham PJ. Decision Support, GIS, and Urban Planning1996. Available from: http://www.acturban.org/biennial/doc_planners/decission_gis_planning.htm.

BECP 2012. Residential Prototype Building Models. http://www.energycodes.gov/development/residential/iecc_models/.

Booth AT, Choudhary R, Spiegelhalter DJ. Handling uncertainty in housing stock models. Building and Environment. 2012;48(0):35-47.

Esri. What is GIS 2015 [cited 2015 May 11th]. Available from: http://www.esri.com/what-is-gis.

Deru, M., et al., 2011. U.S. Department of energy commercial reference building models of the national building stock. Golden, Colorado: National Renewable Energy Laboratory.

Drummond WJ, French SP. The Future of GIS in Planning: Converging Technologies and Diverging Interests. J Am Plann Assoc. 2008;74(2):161-74.

ISO 13790:2008. Energy performance of buildings - Calculation of energy use for space heating and cooling. 2008.

Jones P, Patterson J, Lannon S. Modelling the built environment at an urban scale—Energy and health impacts in relation to housing. Landscape and Urban Planning. 2007;83(1):39-49.

Kavgic M, Mavrogianni A, Mumovic D, Summerfield A, Stevanovic Z, Djurovic-Petrovic M. A review of bottom-up building stock models for energy consumption in the residential sector. Building and Environment. 2010;45(7):1683-97.

Kim JH, Augenbroe G, Suh HS. Comparative study of the LEED and ISO-CEN building energy performance rating methods. Proceedings of Building Simulation 2013. Chambery, France. 2013. 3104-3111 p.

Klosterman RE. Planning support systems: A new perspective on computer-aided planning. J Plan Educ Res. 1997;17(1):45-54.

Masson V. A physically-based scheme for the urban energy budget in atmospheric models. Boundary-Layer Meteorology. 2000;94(3):357-97.

Noilhan J, Planton S. A simple parameterization of land surface processes for meteorological models. Monthly weather review. 1989;117(3):536-49.

Noilhan J, Mahfouf JF. The ISBA land surface parameterisation scheme. Global and Planetary Change. 1996;13(1-4):145-59.

NYC Department of Information Technology & Telecommunications. Building footprints GIS file. 2014. Available from NYC Department of Information Technology & Telecommunications. 2014. https://nycopendata.socrata.com/

NYC Department of City Planning. Bytes of the Big Apple. 2014. Available from NYC Department of City Planning, 2014. http://www.nyc.gov/html/dcp/html/bytes/applbyte.shtml.

Perez-Lombard L, Ortiz J, Pout C. A review on buildings energy consumption information. Energy and Buildings. 2008;40(3):394-8.

Pisello AL, Taylor JE, Xu X, Cotana F. Inter-building effect: Simulating the impact of a network of buildings on the accuracy of building energy performance predictions. Building and Environment. 2012;58:37-45.

Quan SJ, Li Q, Augenbroe G, Brown J, Yang PP. 2015a. Urban data and building energy modeling: a GIS-based urban building energy modeling system using the Urban-EPC engine. The 14th International Conference on Computers in Urban Planning and Urban Management. Cambridge, MA USA 2015.

Quan SJ, Li Q, Augenbroe G, Brown J, Yang PP. 2015b. A GIS-based energy balance modeling system for urban solar buildings. The 7th International Conference on Applied Energy. Abu Dhabi, United Arab Emirates. 2015.

Reinhart C, Dogan T, Jakubiec JA, Rakha T, Sang A. Umi-an urban simulation environment for building energy use, daylighting and walkability. 13th Conference of International Building Performance Simulation Association, Chambery, France 2013.

Sehrawat P, Kensek K. Urban energy modeling: GIS as an alternative to BIM. 2014 ASHRAE/IBPSA-USA Building Simulation Conference, Atlanta, USA 2014.

Shimoda Y, Asahi T, Taniguchi A, Mizuno M. Evaluation of city-scale impact of residential energy conservation measures using the detailed end-use simulation model. Energy. 2007;32(9):1617-33.

Sun Y, Augenbroe G. Urban heat island effect on energy application studies of office buildings. Energy and Buildings. 2014;77(0):171-9.

Swan LG, Ugursal VI. Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. Renewable and Sustainable Energy Reviews. 2009;13(8):1819-35.

Swan LG, Ugursal VI, Beausoleil-Morrison I. Implementation of a Canadian residential energy end-use model for assessing new technology impacts, in: Proceedings of Building Simulation, Glasgow, 2009, pp. 1429–1436.

The City of New York. (2014). About LL84. Retrieved from http://www.nyc.gov/html/gbee/html/plan/ll84_about.shtml, Accessed December 1 2014.

United States Census Bureau. (2014a). LEHD origin-destination employment statistics (LODES). Retrieved from: http://lehd.ces.census.gov/data/.

United States Census Bureau. (2014b). TIGER Products. Retrieved from: https://www.census.gov/geo/maps-data/data/tiger.html.

U.S. Department of Commerce, Economics and Statistics Administration, U.S. Census Bureau. Census Tracts and Block Numbering Areas.: U.S. Census Bureau; 1994.

U.S. Geological Survey. USGS Land Cover 2012. Available from: http://landcover.usgs.gov/usgslandcover.php.

Warnecke L, Beatiie J, Kolin C, Lyday W. Geographic information technology in cities and counties: a nationwide assessment. Chicago: Urban and Regional Information Systems Association; 1998.

Wong NH, Jusuf SK, Syafii NI, Chen Y, Hajadi N, Sathyanarayanan H, et al. Evaluation of the impact of the surrounding urban morphology on building energy consumption. Sol Energy. 2011;85(1):57-71.

Yeh AGO. Urban planning and GIS. In: Longley PA, Goodchild MF, Maguire DJ, Rhind DW, editors. Geographical Information Systems. 2nd ed. New York: John Wiley and Sons; 1999.

Zhao F. Agent-based modeling of commercial building stocks for energy policy and demand response analysis. PhD thesis. School of Architecture, Georgia Institute of Technology. 2012.