Energy and Buildings 45 (2012) 141–151

Contents lists available at SciVerse ScienceDirect

Energy and Buildings

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

Spatial distribution of urban building energy consumption by end use

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ARTICLE INFO

Article history:
Received 25 August 2011
Received in revised form 12 October 2011
Accepted 31 October 2011

Keywords:
Urban energy planning
Building energy consumption
GIS

ABSTRACT

The current energy distribution infrastructure in many urban areas either cannot support anticipated future energy use or would require significant rehabilitation even if current use were maintained. Understanding the dynamics of local energy use is an important precondition of understanding how to remedy this situation. This paper builds a model to estimate the building sector energy end-use intensity (kwh/m^2 floor area) for space heating, domestic hot water, electricity for space cooling and electricity for non-space cooling applications in New York City. The model assumes that such end use is primarily dependent on building function, whether residential, educational or office for example, and not on construction type or the age of the building. The modeled intensities are calibrated using ZIP code level electricity and fuel use data reported by the New York City Mayor's Office of Long-Term Planning and Sustainability. The end-use ratios were derived from the Residential and Commercial Building Energy Consumption Survey's Public Use Microdata. The results provide the ability to estimate the end-use energy consumption of each tax lot in New York City. The resulting spatially explicit energy consumption can be a valuable tool for determining cost-effectiveness and policies for implementing energy efficiency and renewable energy programs.

1. Introduction

Increasing energy prices, concerns about climate change and sustainability have made the issues of building-sector energy efficiency, renewable energy and re-use of waste energy paramount. In reaction many major cities have created plans for the future that attempt to reduce energy consumption and the associated greenhouse gases. In particular, a few have called for the addition of distributed generation (DG) technologies [1–3]. The incorporation of distributed energy generation into the current centralized paradigm creates many hurdles for planners, policy makers, and engineers.

For New York City (NYC), a dense urban environment, over two thirds of the energy consumption is from buildings [4]. Whether a building uses energy for space cooling, space heating, domestic water heating or electricity driven applications is critical to understanding future opportunities for energy reduction and sustainable utilization. Early opportunities for reducing primary energy consumption through distributed generation will depend upon the spatial proximity of the different energy end uses.

For example, spatial proximity can allow cost-effective re-use of waste heat streams from gas-fired distributed generation, also called cogeneration or combined heat and power (CHP). Spatially distributed energy use information can permit one to identify cost-effective engineering retrofit opportunities. A solar resource on one building's rooftop could be valuable for another building nearby. A utility may need to identify areas where local generation may offset costs of increased transmission to accommodate additional capacity from plug-in hybrid vehicles. Although these many objectives can conflict with each other, some energy and infrastructure planners are confident that these competing objectives can be met with careful analysis [5]. A building-by-building energy consumption model would be a starting point for such analyses by planners and could be utilized by the private sector to offer energy efficiency services.

The policies instituted to regulate the energy market have many and varied implications on distributed generation. Meyers and Hu in 2001 proposed many policies at the national and state level that could help facilitate DG such as uniform interconnection standards and national energy efficiency and emissions standards [6]. Many have been adopted in some form by the regulatory entities but more detailed policies are needed with the application of DG becoming available to more people through technological innovation. In the deregulated market, conflicts arise between the energy production and energy distribution markets. Ropenus et al. detail the issues that arise with various levels of vertical integration, regulation of energy distributors and compensation of distributed energy generators [7]. With the potential future high penetration levels of

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0378-7788/$ – see front matter © 2011 Published by Elsevier B.V.
doi:10.1016/j.enbuild.2011.10.061

distributed generation, energy distributors may need to institute locational pricing signals to indicate where the least cost locations are for interconnection to the distributor. Whether these areas of available infrastructure coincide with areas where distributed generation is technically and economically feasible should be on the agenda for policy makers before such a scheme is accepted.

Engineers must be able to understand the various flows of energy and match energy generation technologies with the appropriate demands to identify where and when infrastructure upgrades are appropriate. For example, in a dense urban setting, such as that of New York City, the space for siting of distributed generation technologies or storage systems could become a hindrance to the adoption of these technologies, whereas close proximity could reduce the costs through adoption at scale and the engineering costs of design and distribution. The energy model discussed in the paper can serve as a foundation for analysis of distributed generation technologies for engineers, planners and policy makers.

Energy modeling is not a new concept and has been performed by other researchers. Swan et al. [8] provided a review of energy modeling techniques of the residential sector although many of the methods can be extrapolated to the commercial sector as well. The primary modeling techniques explored in the review were top-down and bottom-up approach. From the definitions given by Swan, the model developed in this paper is a bottom up model. For many models, the primary goal is to model a building or region but a few bottom-up models have been employed to model a city or large sector. Yamaguchi [9] modeled 612 prototypical buildings incorporating stochastic occupant behavior, various zoning configurations, HVAC systems, and building construction characteristics. These models were aggregated into representative districts and extrapolated to the city scale. The resulting model allowed for the analysis of various energy efficiency and district energy reduction measures. Heiple and Sailor [10] created 30 prototypical buildings incorporating various aspects of the building construction and occupant behavior. The energy intensities were aggregated to the city level providing hourly information of electricity and natural gas usage for Houston. Brownsword et al. [11] developed a model to predict diurnal energy demand profiles for specific sectors of the city of Leicester in the United Kingdom dependent upon the type and size of consumer and electricity data provided by various sources. The difference between the models previously mentioned and the one developed in this paper is that there is zip code level validation of the energy intensities. Many of the models developed prototypical buildings with limited measured energy consumption information with respect to the city represented. A few validated values at the entire city scale but validation of over hundreds of parameters by a few numbers is hardly desirable. In addition, the model developed in this paper provides some sense of error associated with the energy intensities for various building types. Other models however provide hourly values of energy consumption, which are necessary for evaluating energy system alternatives and is a topic of future work. In addition they have incorporated into their models the characteristics of various building types allowing for the analysis of energy efficiency alternatives. The purpose of the current model is to discuss the impacts of various distributed generation technologies, which can be accomplished without detailed building characteristics. In this paper, the methodology for a spatially explicit model of annual building energy consumption by primary end use for the 859,134 tax lots of New York City is discussed.

2. Methodology

Annual end-use energy consumption intensities were developed by performing a robust multiple linear regression to obtain electricity and total fuel intensities for 8 different building functions: residential 1–4 family, residential multi-family, office, store, education, health, warehouse and other commercial. In addition to the eight building functions, intensities were determined for specific building functions in different locations throughout the city: residential 1–4 family buildings in Manhattan, and residential multi-family buildings in the Bronx and office buildings in Manhattan. Total fuel includes natural gas, steam, fuel oil #2, fuel oil #4 and fuel oil #6. The electricity and total fuel intensities were then apportioned into base electric, space heating, water heating, and space cooling end uses by ratios derived from the Residential Energy Consumption Survey (RECS) [12] and the Commercial Building Energy Consumption Survey (CBECS) [13] end use estimation. The base electric end use includes energy consumed for appliances, lighting, ventilation, and refrigeration. The annual end-use intensities were then applied to building floor area across New York City to determine the spatial distribution of energy consumption for the four primary end uses. The following sections discuss how the data for the regression was gathered, the regression methodology, and how the end-ratios were derived.

2.1. Data collection

The New York City Mayor's Office of Long-Term Planning and Sustainability provided the annual electricity and natural gas, steam, or fuel oil consumption for 191 zip codes. They gathered the data from the major utilities in New York City, Con Edison, National Grid, and the Long Island Power Authority, and estimated the fuel oil consumption using the methodology described in the Inventory for Greenhouse Gas Emissions [4]. The energy consumption values for fuel oil are estimated and not measured so they may deviate from the true fuel oil consumption of New York City adding a source of error to the analysis. The inventory is updated annually and data from 2009 was used. It is important to note that weather has a large impact on energy consumption from year to year indicated by the high correlation between the consumption of fuel oil, natural gas, and to some extent steam with heating degree days [4]. For the year 2009, annual heating and cooling degree days were close to the 30 year average suggesting that minimal bias is introduced from choosing this particular year [14].

In addition to annual energy consumption, information about the building stock was collected. The New York City Department of City Planning maintains information on NYC building stock in a geo-rectified database, PLUTO [15]. The database is updated annually and the 2009 version was used in the data collection process. Among other characteristics described in the database, the total building floor area for each tax lot is provided. There are approximately 1 million buildings on 859,134 tax lots in New York City. Since PLUTO's finest resolution is by tax lot, the model is not able to distinguish between individual buildings on the same tax lot. The building floor area for each tax lot in PLUTO is placed into 8 different building categories: commercial, residential, office, retail, garage, storage, factory, and other. In addition, each tax lot is given one of 196 building class codes, each designated by a letter and a number, to describe the main building use. Both the building class designations and the building area categories were used to place the building area into a particular building function. The building area in each category was placed using the logic detailed in the following paragraphs.

For the residential sector, if building area is classified as a one-family dwelling, two-family dwelling, primarily one-family dwellings with two stores or offices, primarily one-family dwellings with one store or office, primarily two-family dwellings with one store or office, primarily three-family dwellings with one store or office, primarily four-family dwellings with one store or office, three-family walk up apartment or four-family walk up apartment, the residential area is placed into residential 1–4

Table 1
Total building floor area by building function from PLUTO 2009 (m^2).

	Total floor area (m^2)	% building floor area
Residential 1–4 family	133,850,279	27
Residential multi-family	187,896,563	38
Office	48,672,838	10
Store	22,519,566	5
Education	20,316,722	4
Health	9,752,847	2
Warehouse	24,737,421	5
Other commercial	47,796,677	9

family. If the residential area has not been already assigned, then the residential area is classified as residential multi-family.

For the commercial sector, if the building area is classified as an educational facility then the building function is classified as education. If the building is classified as a hospital or health facility then the building function is classified as health.

Once the building area for education and health was allocated, the remaining office building area is classified as office, the retail area is classified as store, the storage and garage area as Warehouse, and the factory and other areas are classified as other. The building area breakdown for the eight building types is shown in Table 1. The residential 1–4 family, residential multi-family and the office building functions comprise 75% of New York City building floor area. The store, education, health, and warehouse building functions account for 16% of the building floor area while other commercial building functions represent the remaining 9%.

In this classification scheme, some building functions are better defined than others, i.e. consumption patterns, or intensities across buildings of different age or construction are not dramatically different from each other as long as the function is similar. The residential building function however is a very significant portion of the area in the city. For this functional category, it is advantageous to take into account the differences between a 1–4 family and a multi-family residence. A multi-family residence in New York is likely to be an older rental building with multiple tenants or a newer tall condominium building with common areas of more windows. In either case the energy consumption intensity is different than that of a 1–4 family home, which is likely to be owner occupied. Therefore residential buildings were classified as either residential 1–4 family or residential multi-family. The education function, however, includes elementary, junior, senior high schools, theological seminaries, colleges and universities. Each of these functions can have different occupancy behaviors and schedules leading to a higher variance in the modeled consumption if grouped in a single building category. In such cases the model would show a poor fit and could be a source of error.

2.2. Robust multiple linear regression

There are many methods for predicting energy consumption in buildings. Tso and Yau performed a study comparing three methods of predicting electricity consumption: regression analysis, decision tree, and neural networks [16]. They found that decision tree and neural networks performed better in different seasons but the difference in error between the three methods were minimal, indicating that, as a predictive tool, linear regression is a valid method.

The method of multiple linear regression has been used by researchers previously to predict energy consumption using many different predictors. The predictors used range from building construction, occupancy patterns, population, and economic indicators [17,18]. Also the CBECS report [19] indicates that the principal building function, building size, and location have a large impact on energy use. They also found that the energy intensity by year constructed was not statistically different between different building age categories. For the current analysis to develop end-use intensities for each building function, the total floor area of each building type was used as a predictor for electricity and total fuel consumption.

By using the building floor area as predictors, the coefficients produced by a linear regression would result in the commonly used metric of building energy use intensities or energy usage index. In the analysis this commonly used performance metric is assumed to be constant with varying building size. Using building floor area and building function as predictors of annual energy consumption may not capture all of the variation; but it does accommodate many other aspects such as occupancy patterns, building equipment, and building size. Huang et al. performed a sensitivity analysis and observed a decreasing trend of energy consumption intensity in buildings from approximately 9290 to 92,900 m^2 with larger decreases for smaller buildings. The change in energy intensity across the entire range was about 27% [20]. This analysis was only performed for an office building and may not reflect the trend of energy consumption intensities for other building functions, such as a residential or education. In contrast, the U.S. Energy Information Administration reported the findings from the CBECS and found that the energy intensity for commercial buildings did not vary significant over the 93–46,500 m^2 range, with the 930–2300 m^2 range having the lowest intensity [19]. For the analysis presented here, energy consumption intensities are assumed to be constant allowing for the application of linear regression.

The theory of ordinary multiple linear regression is based in many assumptions. A principle assumption is that the data are normally distributed. Given the large proportion of 1–4 family homes, the distribution of building area is slightly skewed towards the lower values. There are many ways to adjust the model to compensate for this error but many of the methods result in non-additive models and result in coefficients that are not interpretable using the common energy intensity metrics. To develop an additive model, robust estimators were used. There are many types of robust estimators but three were considered for the regression: least absolute deviation, trimmed least squares, and M-estimators. Each of these methods minimizes different functions to obtain a regression model. For the least absolute deviation, the sum of the absolute values of the residuals is minimized. The least trimmed squares minimizes the sum of the square of the residuals but removes values considered outliers and only takes into account a subset of the data. Since searching the entire space for the subset that best minimizes the sum of the square of the residuals is impossible, a random selection of subsets is incorporated leading to an approximate solution. The M-estimator minimizes a function of the residuals, e, and weights values based on the median absolute residuals, $1/2e^2$ for $|e| > k(\mathrm{MAR})$ and $k(\mathrm{MAR}) \times |e| - 1/2k(\mathrm{MAR})^2$ for $|e| > k(\mathrm{MAR})$. Each of the three estimators was used to fit the data using preliminary predictors. It was found that the M-estimator yielded the best results by calculating positive coefficients, smaller residual values, and more rejections of the null hypothesis for each of the estimated coefficients. For the final analysis, a robust linear regression using the Huber M-estimation was employed. This method fits the linear model

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in} + \varepsilon \tag{1}$$

by minimizing the objective function

$$\sum_{i=1}^{n} \rho(e_i) = \sum_{i=1}^{n} \rho(y_i - \bar{y}_i) \tag{2}$$

where

$$\rho(e) = \begin{cases} \frac{1}{2}e^2 & \text{for } |e| \le k \\ k|e| - \frac{1}{2} & \text{for } |e| > k \end{cases} \tag{3}$$

and

$$k = 1.994 \times \text{MAR} \tag{4}$$

For the energy analysis, y_i is the electricity or total fuel consumption for a given ZIP code, x_{ik} is the total floor area of each building function k in ZIP code i, β_i are the electricity or total fuel intensities fit by the regression, ε is the random error, $\bar{y}_i$ is the fitted value of the electricity or total fuel consumption, and MAR is the median absolute residual. In addition to the M-estimation, the Huber sandwich technique was employed to obtain a more robust estimation of the standard error. For each regression, ZIP codes with incomplete data were removed resulting in the use of 170 observations.

While performing the statistical analysis using building function, and then mapping the results across the city, the errors between the model and the zip-code data revealed some systematic patterns with borough affiliations. While boroughs represent distinct geographic and administrative parts of the same city, the historic growth of the city around Manhattan as the prime office and residential space makes it unique. Manhattan with its high-rise buildings (with foot traffic entering/leaving from the ground floor) and high share of financial, fashion and media sectors may have a lower intensity of heating compared to a street-level office space that caters to multiple walk-in clients. Similarly it is possible that high-rise multi-family residential space in Manhattan with a greater density of apartment units could have a larger electrical intensity and a lower heating intensity. There are many intricacies of Manhattan that make the borough different than other parts of the city, therefore an additional predictor for Manhattan was incorporated to obtain a better fit to the data.

The predictors used in the electricity regression were residential 1–4 family, residential multi-family in Manhattan (Residential Multi-Family MN) residential multi-family in the remainder of the city (Residential Multi-Family NYC-MN), office, store, education, health, warehouse, and other commercial. The predictors used in the total fuel regression were residential 1–4 family, residential multi-family in Manhattan and the Bronx (Residential Multi Family MN/BX), residential multi-family in the Brooklyn, Queens, and Staten Island (Residential Multi-Family BK/QN/SI), office in Manhattan (Office MN), office in the remainder of the city (Office NYC-MN), store, education, health, warehouse, and other commercial. Note that the abbreviations for the borough specific building types will be used throughout the paper however for the end use allocation the residential 1–4 family, residential multi-family and office building functions will be considered without borough specific designations.

2.3. End use allocation

Four end uses were considered in the analysis: base electric, space cooling, space heating, and water heating. In this paper these four end uses are called primary end uses. Base electric includes uses such as appliances, lighting, and refrigeration. Energy for cooking is not included in the primary end uses. The city provided data was not by end use but by energy carriers: electricity, natural gas, heating oil, and steam. For the analysis the energy provided by natural gas, steam, and fuel oil were considered one source called total fuel. What is however very useful for engineering analysis is further separating the total fuel consumption into that consumed for space heating as opposed to water heating since the former is seasonal

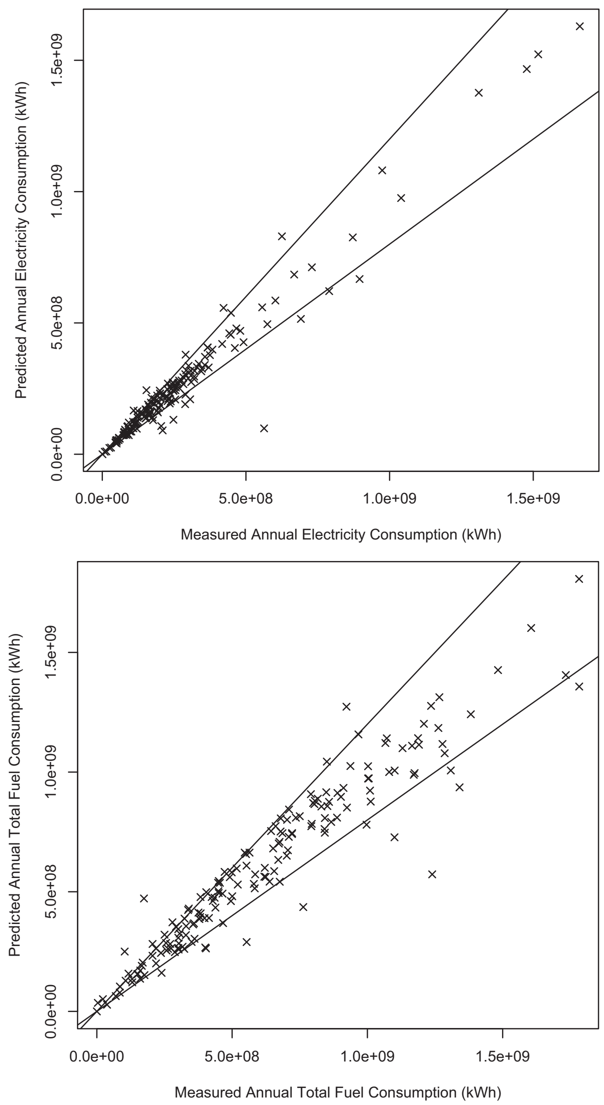

Fig. 1. Measured vs. predicted annual energy consumption for both electricity and total fuel, 2009.

and the later is less likely to vary with seasons. Similarly it is useful to separate electric consumption into that for space cooling loads and that for all other purposes, with the former being seasonal use. In the model, it is assumed that energy consumed for both space heating and water heating was provided entirely from total fuels and not from electricity since a breakdown by ZIP code of electric space heating is not available. The ratio of energy consumed for space cooling to that for base electric applications and the fractions of total fuel used for space heating, hot water, and cooking were determined using the public use micro-data from both the RECS and CBECS [12,13]. The surveys obtain, among other information, national averages of annual end-use energy intensities for various building types.

Since the end use breakdowns vary significantly across the United States, buildings from the RECS and CBECS were only selected from the Middle Atlantic region, which includes New York State, Pennsylvania, and New Jersey. In the survey weights are given to each data point to reflect how many buildings nationally are similar to it. Since only the Middle Atlantic region was considered, the weights were not used. The fractions of the base electric and space cooling end uses sum to 1. The space heating and water heating end uses however do not sum to 1, since cooking is not included in the analysis but in some building types is a significant portion of total fuel usage.

The breakdown of total fuels into primary end-uses such as space heating and hot water would depend upon specific building function. For example an office space is unlikely to use much domestic hot water where a residential space would use a significant amount. Hence the determination of the primary end-use ratios was carried out for each of the eight building function categories. It is important to note that the store category is very diverse in its end-use energy profile. Restaurants in particular are unique in that, with respect to retail stores, they consume a significant amount of energy for cooking and refrigeration purposes. There are over 18,000 food service and drinking establishments in New York City but in comparison to the approximately 1,000,000 buildings in New York City this single category is not statistically significant. This but will cause some error when breaking down end uses since restaurants comprise approximately 30% of retail, food-service and drinking establishments in New York City [21].

Both the RECS and CBECS defined many more building categories than the eight functions defined previously, therefore each of the building categories was placed into one of the eight designated building functions. For example, the office category in the CBECS, since it directly corresponds with the office building function, was placed in office. However the religious building category is described in the CBECS as buildings in which people gather for religious activities such as chapels, churches, mosques, synagogues, and temples, so it is best placed in other. The other building function was not broken down into the primary end uses because the mix of buildings included in this function can have significantly different patterns of energy consumption and are very distinct for New York City. The building categories from the RECS and CBECS that were placed in this building function were essentially not used in the end-use breakdown. As with the area classification system, the grouping of buildings with different occupancy schedules and consumption patterns could lead to large deviations from the average end-use consumption values.

The RECS and CBECS also designate more end uses than the four primary end uses of interest. As with the building functions, end uses designated in the RECS or CBECS were placed into primary end uses with the exception of the miscellaneous end use. This end use was not considered as a portion of either the electricity or the total fuel for any building type since the energy consumption was minimal for many buildings and the mixture of energy sources supplying this end use is unclear.

For each building type, with the exception of building categories describing stores, the proportion of electrical or fuel energy allocated to one of the four end uses was apportioned by

$$f_{i,j} = \frac{e_{i,j}}{\sum_{k=1}^{4} e_{i,k} \times \delta_{k,j}} \tag{5}$$

where $e_{i,j}$ is the average energy intensity for building function i for end use j, $f_{i,j}$ is fraction of electricity or total fuel apportioned to end use j and building function i, and $\delta_{k,j}$ equals 1 if the end use k uses the same fuel as end use j. For the store building function, the energy consumption by end use varies significantly between the building categories within the function, such as restaurants and grocery stores, and some categories were surveyed more than others. To obtain an average that does not just reflect the sampling method, the averages for each end use were taken for each building category included in the store building function. Then the average of each building category was used for the average energy intensities, $e_{i,j}$ and $e_{i,j}$. The proportion of electricity or total fuel allocated to each end use for each building function is depicted in Table 2.

3. Results and discussion

The following sections will discuss the outcomes of the regression analysis, the application of the end-use intensities, and the spatial distribution of the annual energy consumption by end use.

3.1. Robust multivariate linear regression

The estimated coefficients, standard error, and p-values for both the electricity and total fuel robust multivariate linear regression are shown in Tables 3 and 4, respectively. For both the electricity and total fuel regression, all predictors rejected the null hypothesis for an alpha value of 0.05 indicating that the estimated intensities are statistically significant. In the following paragraphs, the predicted values from the model will be compared to the data provided by the city, which will be termed measured values.

Some building types have larger standard error than others, meaning that the true energy intensities for a particular building categorized as one of these building functions may deviate more from the estimated intensities then other building types with lower standard error. Each of the residential building functions for electricity and total fuel as well as the Office NYC-MN building function for total fuel have low standard errors which could be explained by the fact that the occupancy patterns, types of appliances and building configuration are not that dissimilar from building to building. In addition, these building types represent 74% of the New York City building stock providing a larger sample to estimate the energy intensities. For the store, education, health, warehouse, and Office MN building function, the standard error is larger for both electricity and total fuel, which may be indicative of the many different types of buildings included within a single building function or the small amount of ZIP codes with building area in those functions.

The measured and predicted annual energy consumption for both electricity and total fuel is shown in Fig. 1. Also two lines with slopes of 1.2 and 0.8 are shown on the plot and any points between them indicate agreement of the predicted and measured energy consumption within ±20%. The percent difference between the fitted and measured consumption was calculated and shown on a map in Fig. 2 to provide a geographical display difference between the fitted and measured values. For electricity consumption, 86% of the fitted ZIP codes were modeled within ±20% of the measured consumption. ZIP codes with larger discrepancies were located primarily in Manhattan and Queens, with a few ZIP codes located in Brooklyn and the Bronx. For total fuel consumption, 77% of the fitted ZIP codes were modeled within ±20% of the measured consumption. ZIP codes with larger discrepancies were mainly located in the financial district and upper west side of Manhattan, industrial areas of Queens, and Staten Island.

The results from the robust linear regression indicate that the fit to the city is sufficiently good, within ±20%, although the difference between the modeled values and the measured values is smaller for electricity than for the total fuel. This difference can be attributed to the fact the measured data for the electricity consumption is more accurate than that for total fuel. Electricity generation and distribution is well regulated and there are precise methods in place to monitor its allocation. In addition, electricity is only distributed when there is a demand. Fuel oil and even some natural gas are purchased in anticipation of demand and for back up power systems. In the data collection process this energy is considered to be consumed when in actuality it may not all be used within the year.

The predictive capabilities of the model seem to deviate from the measured consumption in various places within the city. Most

Table 2
Fraction of annual energy consumed by end use and building function.

Building function	Base electric	Space cooling	Total electricity	Water heating	Space heating	Total fuel (including cooking)
Residential 1–4 family	0.85	0.15	1	0.23	0.74	1
Residential multi-family	0.82	0.18	1	0.23	0.71	1
Office	0.86	0.14	1	0.05	0.93	1
Store	0.93	0.07	1	0.16	0.61	1
Education	0.90	0.10	1	0.10	0.89	1
Health	0.84	0.16	1	0.29	0.68	1
Warehouse	0.94	0.06	1	0.09	0.91	1

Table 3
Estimated annual electricity intensities, annual electricity intensity standard error, and *p*-value by building type.

Building function	Estimated electricity intensity (kWh/m^2)	Std. error (kWh/m^2)	*p*-Value
Residential 1–4 family	49.2	4.30	$<2.2 \times 10^{-16}$
Office	276	4.66	$<2.2 \times 10^{-16}$
Store	180	54.0	8.6×10^{-4}
Education	142	26.0	4.6×10^{-8}
Health	229	47.9	1.8×10^{-6}
Warehouse	119	30.3	8.6×10^{-5}
Other commercial	32	16.2	0.049
Residential Multi-Family MN	88.9	12.0	1.2×10^{-6}
Residential Multi-Family NYC-MN	54.7	4.98	$<2.2 \times 10^{-16}$

of the variation can be explained by the energy consumption of the ZIP code being dominated by one use. Many ZIP codes with large deviations from the measured consumption include places such as a race track, Coney Island attractions, Grand Central Station, a large group of apartments owned by one owner, a large fish market, airport, Roosevelt Island, Riker's Island prison, and a hospital committed to energy efficiency. If each of these specific buildings or group of buildings has energy practices significantly different from other buildings in the same classification, the model will not be accurate. In general, perhaps there are additional predictors other than building floor area such as average household income or cultural deviations that account for these disparities. More information is needed to determine the reasoning behind these spatially local deviations. The estimates do however provide an upper level understanding of how building energy is distributed through out the city.

Figs. 3 and 4 show the estimated coefficients from the robust multivariate linear regression and their respective standard errors. These intensities were compared to the aggregated building category data from CBECS and RECS. The other commercial building type does not include a comparison since the mix of other commercial buildings in New York City is very specific and cannot be generalized to the Middle Atlantic region. Depicted in the figures in addition to the estimated intensities and their standard errors are the range of intensities for electricity and total fuel for each building type excluding the upper and lower 10% from CBECS or RECS. The borough specific energy intensities are compared to the RECS and CBECS ranges based on their general building function: for electricity residential multi-family and for total fuel residential multi-family and office.

In comparison to the RECS and CBECS values, the electricity and total fuel energy intensities fall within the ranges reported with

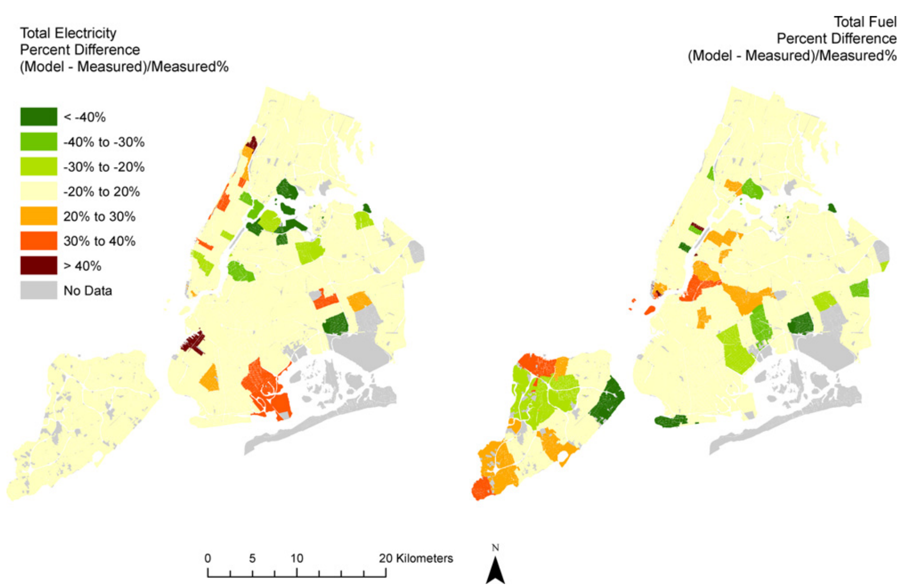

Fig. 2. Percent difference between modeled and measured annual energy consumption, 2009.

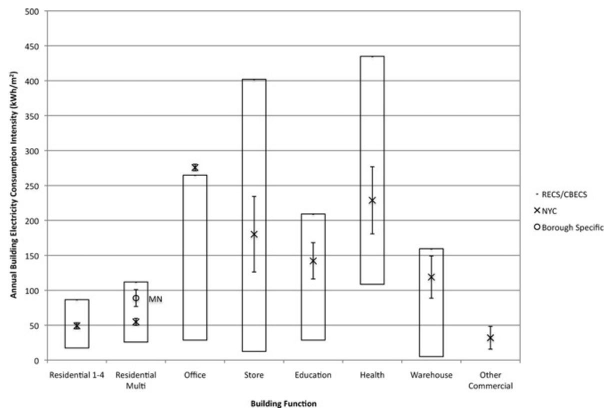

Fig. 3. Annual building electricity consumption intensity estimates by building function (kWh/m^2), 2009.

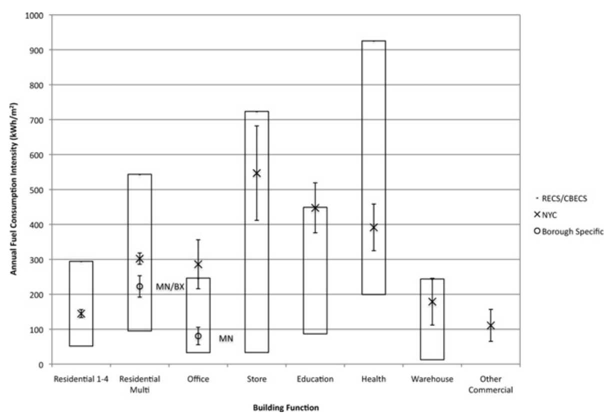

Fig. 4. Annual building total fuel consumption intensity estimates by building function (kWh/m^2), 2009.

the exception of the office building function for electricity and the Office NYC-MN building function for total fuel. In addition, the upper range of the standard deviation for the education building function falls outside of the range reported by CBECS.

In Figs. 3 and 4, one can clearly see the relationships between the borough specific intensities. For electricity, the energy intensity for residential multi-family in Manhattan is about 35 kWh/m^2 larger than that of a residential multi-family building in the rest of New York City (Residential Multi-Family NYC-MN). For total fuel, the energy intensity for residential multi-family in Manhattan and

Table 4
Estimated annual total fuel intensities, annual total fuel intensity standard error, and *p*-value by building type.

Building function	Estimated total fuel intensity (kWh/m^2)	Std. error (kWh/m^2)	*p*-Value
Residential 1–4 family	145	11.5	$<2.2 \times 10^{-16}$
Store	547	135	5.2×10^{-5}
Education	447	71.6	4.1×10^{-10}
Health	392	66.9	4.9×10^{-9}
Warehouse	179	66.8	7.5×10^{-3}
Other commercial	111	45.7	0.015
Residential Multi-Family MN/BX	223	30.8	5.3×10^{-8}
Residential Multi-Family BK/QN/SI	302	16.2	$<2.2 \times 10^{-16}$
Office MN	80.6	25.1	1.4×10^{-3}
Office NYC-MN	286	70.1	4.9×10^{-6}

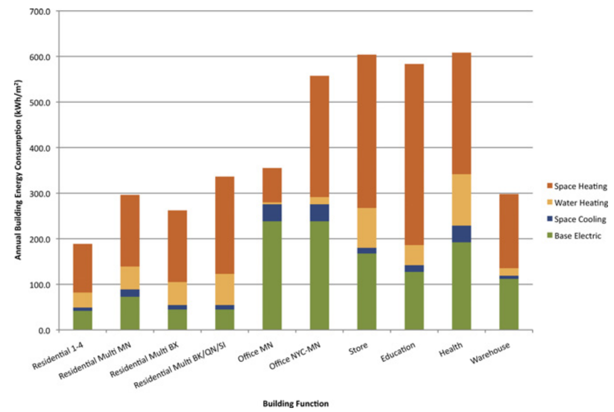

Fig. 5. Annual building energy consumption intensities by end use and building function (kWh/m^2), 2009.

the Bronx (Residential Multi-Family MN/BX) is about 80 kWh/m^2 less than a residential multi-family in the rest of New York City (Residential Multi-Family BK/QN/SI). Also for total fuel, the energy intensity of office in Manhattan (Office MN) is approximately 200 kWh/m^2 less than that of office in the rest of New York City (Office NYC-MN). There are many factors that could contribute to the difference between the borough specific estimated intensities and the differences between the estimated values and those reported by the RECS and CBECS such as different energy dissipation rates of office equipment to different infiltration rates due to building construction or foot traffic but a full analysis is outside the scope of this paper.

3.2. Annual end-use intensities

The primary end-use ratios discussed in Section 2.3 were applied to the electricity and total fuel intensities for each building function resulting in the primary end-use intensities displayed in Fig. 5. The standard error was less than 2.5% for each end use and building function. In Fig. 5, there are three different residential multi-family building functions: residential multi-family in Manhattan (Residential Multi MN), residential multi-family in the Bronx (Residential Multi BX) and residential multi-family in the remaining boroughs (Residential Multi BK/QN/SI). This resulted from the combinations of the electricity intensities for Manhattan and the fuel intensities for Manhattan and the Bronx. Similarly for office, there are two different office building functions designated in Fig. 5: office buildings in Manhattan (Office MN) and office buildings in the remainder of the city (Office NYC-MN).

The health, store, and education building functions have the highest intensity when one adds all the four end uses, annually requiring approximately 600 kWh/m^2 each. The corresponding intensity for the residential 1–4 family function is nearly one-third of that for health, store and education. When it comes to specific primary end uses, the consumption intensities are also quite different depending upon building function. For example, an office space uses 4.5 kWh/m^2 for water heating whereas a residential space can use nearly ten times that. Energy for space cooling is minimal for all building functions ranging from 7 to 37 kWh/m^2 annually. Space heating, however, is the dominant end use for each building function with the exception of office buildings in Manhattan whose dominant end use is base electric. The space heating energy consumption intensities range from 75 to 335 kWh/m^2, with the education, health, and store building functions at the higher end of the range. Although with respect to overall energy consumption, the residential building functions consume smaller amounts

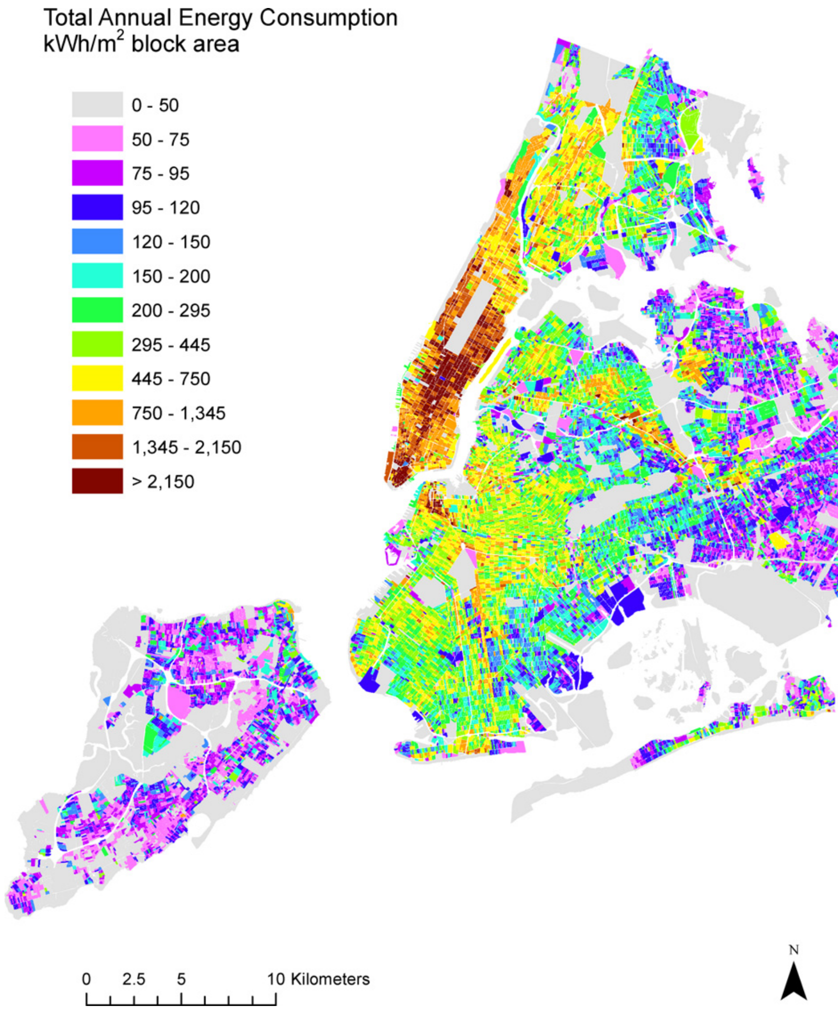

Fig. 6. Annual building energy consumption by block area (kWh/m^2), 2009.

of energy for space heating. As a proportion of total energy consumption, space heating for residential building functions ranges from 55% to 65% of the total energy consumption. For base electric applications, office buildings in all of NYC consume the most energy, 240 kWh/m^2, which makes base electric the dominant primary end use for that building function.

3.3. Spatial distribution of building energy consumption

Applying the energy intensities to all of the building area in New York City produced the spatial distribution of building energy consumption in New York City. The total annual energy consumption for each block normalized by block land area is shown in Fig. 6. As one would expect a consumption normalized by block area would show particularly high values for parts of the city where the buildings are tightly packed and tall. Hence a block located in midtown Manhattan, has one of the largest annual energy consumption when normalized by block area consuming as much as 8000 kWh/m^2. To provide a sense of scale in terms of power, the power consumption of the block averaged over all hours in the year is about 17.6 MW.

Large tracts with such high block area normalized energy consumption are located primarily in the central business and financial districts that consist primarily of tall buildings. The areas of Manhattan with lowest energy consumption are in the neighborhoods of Harlem, East Greenwich Village, and West Greenwich Village. There are a few areas of large energy consumption outside of Manhattan such as downtown Brooklyn, western Bronx, Astoria, and a few concentrated areas along major transportation routes. Other than these areas the total energy consumption diminishes rapidly with distance from Manhattan. The lowest areas of total energy consumption per block area, less than 120 kWh/m^2, are located in the eastern portions of Queens and Staten Island, which are comprised of primarily 1–4 family residential structures.

The annual base electric, space cooling, water heating, and space heating energy consumption for Manhattan only are shown in Fig. 7 to show the main differences in the magnitude of consumption and spatial variation within the primary end-use consumption. Across Manhattan, the space heating consumption is larger than any other end use, reflective of the individual end-use breakdown since most building types consume more energy for space heating than any other end use. The largest concentration of space heating energy consumption is located in the central business district and along the upper east and west sides. This pattern is different for the base electric and space cooling energy demand where the largest concentration of energy consumption is located primarily in the central business district only. This difference is explained by the large amount of energy consumed for space heating in residential buildings and stores as opposed to office buildings. The effect of

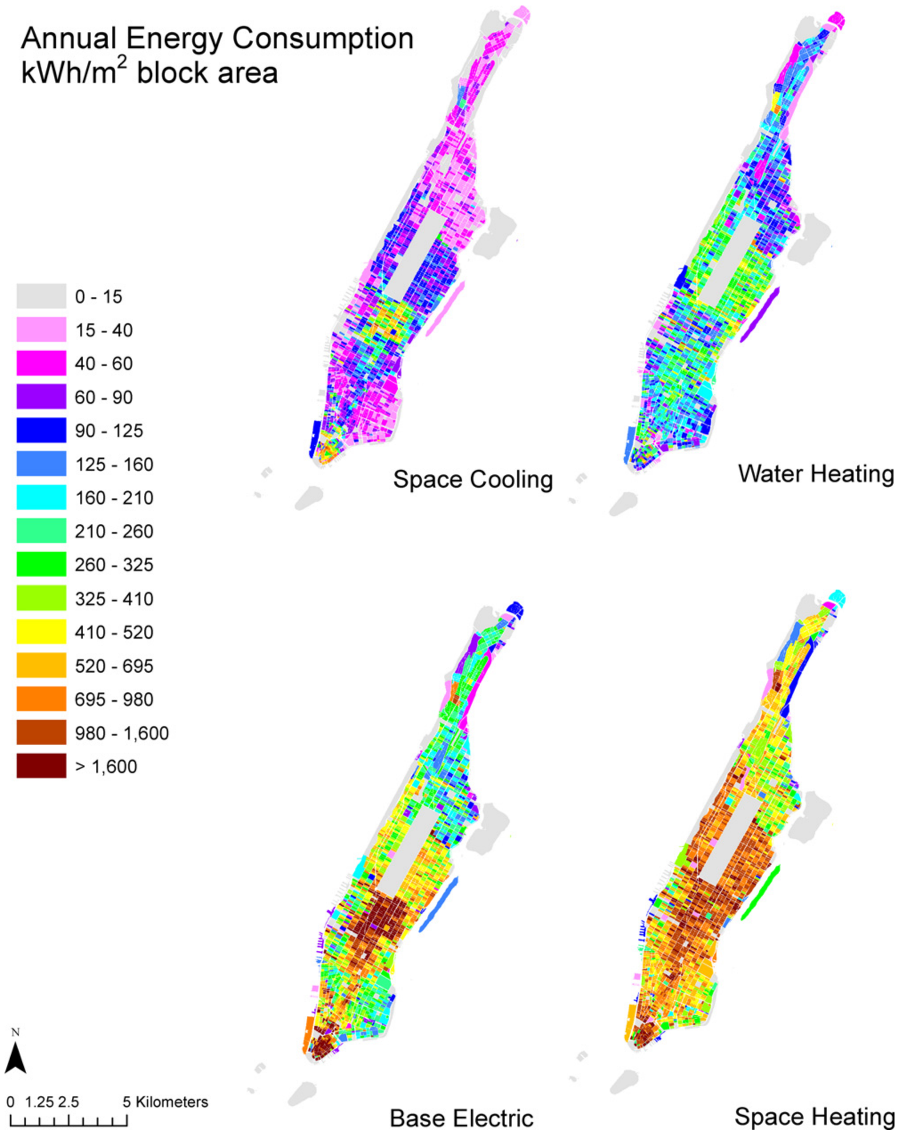

Fig. 7. Annual space cooling (top left), water heating (top right), base electric (bottom left) and space heating (bottom right) energy consumption by block area (kWh/m^2).

the distribution of residential and office buildings can be observed in the distribution of the water heating consumption pattern as well. The areas consuming large amounts of energy for water heating are located in the upper east and west sides with significantly lower consumption in the central business district. As mentioned previously residential buildings consume 10 times more energy for water heating than an office building.

For distributed generation, a focus of future work, the breakdown of the energy consumption estimates by end use allows for more detailed spatial analysis of the impacts of distributed technologies. Consider a block located between 123rd and 122nd street and 3rd and 2nd avenue in Manhattan. For this mixed-use block with 72% of residential space and 22% of office and store space, the corresponding power for base electric would be 1.2 MW and that for domestic hot water would be 0.5 MW. The base electric and water heating end uses would not have significant seasonal variations. This block, that is not served by the Con Edison district steam system, could possibly be a good location for a combined heat and power system as the waste heat of a decentralized natural gas powered reciprocating engine satisfying only a quarter of the electricity load could easily satisfy the energy needs for water heating since such a system could potentially produce 0.6 MW of waste heat. The spatial proximity of these loads is also important in determining the feasibility of combined heat and power systems and by providing the energy model in conjunction with the spatial location such an analysis can be performed. The water heating to base electric ratio for each block of New York City is depicted in Fig. 8. The ratios change block by block throughout the city showing that the feasibility of different energy generating systems will vary depending on location. Also shown in Fig. 8 is the water heating to base electric ratio in ascending order for each block in New York City. The large percentage of the blocks in New York City having a heat to electric ratio of 0.78, that of residential 1–4 family buildings, is shown in Fig. 8 by the purple colored blocks and the constant section of the plot in the lower right corner. These areas are indicative of the many blocks in Brooklyn, the Bronx, and Queens consisting of only residential 1–4 family structures. Aside from these blocks if one considers all of the buildings on a

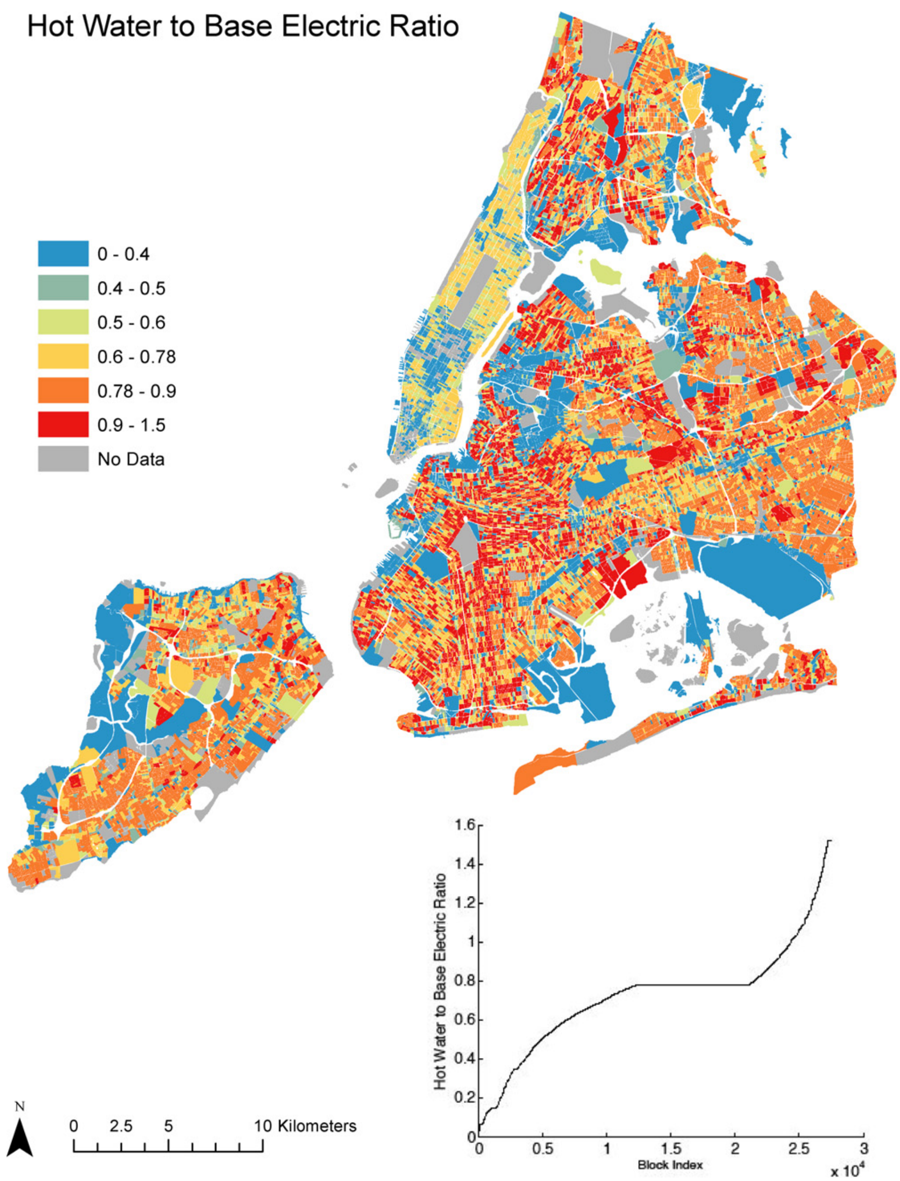

Fig. 8. Annual hot water to base electric energy consumption ratio by block.

block as opposed to singular tax lots, one can obtain almost any thermal to electric ratio between the highest and lowest ratios for any individual building function. Extrapolating further, potentially one could choose the buildings to aggregate to obtain the desired ratio for whatever the technical system under consideration. This raises important regulatory issues, however, related to whether this violates Con Edison's territorial franchise rights, etc. [22].

In addition to the analysis of combined heat and power systems, the ratio of thermal to electric demand is also important in determining the feasibility of systems of utilizing solar energy. When considering a combined solar thermal and photovoltaic system, the limiting factor is the amount of roof space/façade space. In order to convert the maximum amount of useful energy, the proper percentage of area should be covered with either a photovoltaic or solar thermal system. By knowing the thermal to electric ratio, one can determine the best combination of these technologies for the largest impact in terms of economics and emissions.

Although the model provides a suitable starting point for upper level analysis, the current limitations are that the energy consumption values are annual. Hourly energy profiles would allow for more accurate assessments of distributed generation and of how much energy could actually be used by a demand center. In particular photovoltaic and solar thermal heating systems rely on the intermittent energy of the sun. To be able to quantify the impacts of these technologies completely, hourly as well as spatial knowledge of the energy demand is needed. Measuring hourly energy consumption by end use for each building in New York City for even a few typical days will be quite an amazing feat but one that is very far into the future and would require restructuring of energy provider privacy policies. Models will need to be developed in the interim and for this reason hourly energy consumption profiles by building function and end use are topics for future analysis. In addition more spatially explicit energy consumption data would allow for more accurate estimates at smaller spatial resolutions.

4. Conclusion

The annual building energy consumption values determined in this analysis have many implications. Many energy policies strive to make electricity less carbon intensive, which is very practical for an office building that supplies most of its energy needs with electricity. For a residential building however, most of the energy is consumed for space heating and domestic hot water purposes. These end uses are typically supplied by fossil fuels. Domestic hot water, for example, is very substantial in residential buildings accounting for approximately a fourth of all fossil fuel energy used in these buildings and residential buildings comprise 65% of NYC's building stock. Converting domestic hot water heaters from carbon intensive fuels to renewable solar energy could have enormous impacts in meeting citywide carbon reduction goals and since water heating systems are already equipped with thermal storage the intermittency of energy provided by the sun may not be a large issue. In addition to the end use of individual building types, the spatial arrangement of these loads can have a large impact on the feasibility of micro combined heat and power systems. Combined heat and power systems are most economical when the system can be run at constant load and if all of the excess waste heat can be used. Since office buildings are large consumers of electricity for base electric applications, a non-seasonal end use, if this building was located next to residential buildings the waste heat could be fully utilized by nearby neighbors reducing energy losses. The spatial energy consumption model by end use developed in this paper will allow different distributed generation options and energy reduction measures to emerge from urban patterns of demand. This will assist urban planners and policy makers in identifying the most promising directions for future urban energy infrastructures and for cities to meet their local energy efficiency and greenhouse gas mitigation targets.

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