On the Spatio-Temporal End-User Energy Demands of a Dense Urban Environment

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Abstract

Many growing major metropolitan centers face increased peak electrical load, especially during extreme heat events. This impacts the reliability of the electric grid raising the costs for energy demands. It is therefore imperative to better understand the energy consumption profile in the building sector for scales of large cities. This understanding is not only paramount to users to avoid peak demand charges but also to utilities to improve load management.

This study aims to develop an energy-demand forecasting tool at a city scale using high resolution weather data interfaced with a single building energy model. We focused our work on New York City (NYC) which has a comprehensive building dataset. We identified 51 building archetypes, based on the building function (residential, educational or office), the age of the building, and the land use type. The single building simulation software used is EnergyPlus which was coupled to an urbanized Weather Model (WRF) for weather forecast input.

Individual buildings were linked to the archetypes and they are scaled up using the total floor area of the building. The single building energy model is coupled to the weather model resulting in energy maps of the city. These maps provide an energy end-use profile for NYC for total and individual components including lighting, equipment and HVAC. The methodology was validated with single building energy data for a particular location, and with city scale energy demand profiles from records showing good agreements in both cases.

1. Introduction

1.1. Why cities matter

Today, Cities play an important role in addressing global climate change and mitigating these risks. More than half of the world's inhabitants live in urban areas, where population growth is expected to continue through the 21st century. Already, cities are responsible for more than 70 percent of global energy-related carbon dioxide emissions [1]. Thereby, this high rate of urbanization impacts negatively the environment, causing increased pollution, the modification of the physical and chemical properties of the atmosphere, local climate and weather [2], and the covering of the soil surface.

Moreover, as a result of a changing climate, the number of extreme weather events is increasing (storms, high winds, heavy downpours, and heatwaves). One important phenomenon that drives the energy consumption is heat waves. The frequencies of these events are projected to increase over the 21st century [3,4] as well as its duration, and severity [5,6]. Dense urban regions have the compounded environmental challenge of heat waves and of urban heat islands (UHIs). The UHI is due to a higher thermal state of the microclimate of cities when compared to rural areas. Buildings inhibit dissipation of heat due to the larger thermal mass and reduce airflow. Waste heat from air conditioners, vehicles, and other equipment also contributes to increase the effect of urban heat island effect. Coupled with the lack of vegetation, the abundance of concrete, which represents a large reservoir of heat, contributes to the increase of the temperature. Several studies have reported UHI as a local environmental impact such as cases in Sacramento, California [7], San Juan, Puerto Rico [8], and New York City, New York [9]. As a result, the UHI contributes to increase the energy demand for cooling during summer periods. Recent studies show energy demand will increase by 15% for cooling over the 21st century [10], and summer loads will increase by 10% for most building in the United States [11]. Added to that, the high temperature during a heat wave results in significant increase of energy demand and consumption to a point where the electrical grid may be at risk which contributes to the increasing of electricity outages [12].

Utilities and urban planners lack tools for a better understanding to the various energy's flows and to project how the demand would increase in the near future. This lack of information contributes to building of oversized power plant and an increase of the energy prices due to those investments. Reducing the electricity bill comes necessarily with finding out what is driving consumption, whether it is the space cooling, or space heating, or just electric equipment.

Comprehensive energy efficiency policies may come from an understanding of a global view of a city's energy consumption. For instance, distributed and shared energy resources may lead to significant efficiencies. Spatial proximity may allow for cost-effective district cooling and heating solutions instead of having individual energy systems. This article presents tools that may enable to explore these options and to generate data for in-depth analysis for city scale energy demands.

The article is organized as follows; first we rationalize why New York City was chosen as a case study, this will be followed by presenting the methodology with a focus on the energy modeling and the set of data collection used. Model validation is followed by presenting the results for one building and for the entire city. The article closes with the use of the tools to study the energy end-use hourly distribution including spatial distributions or energy maps for mean and extreme weather conditions.

1.2. Why New York City?

The abundant data already collected by city agencies and a comprehensive sustainability plan (PlaNYC [13]) at the city scale, makes of New York City an ideal city where we could launch a high-resolution energy end-use map. In New York City, buildings account for the majority of the energy use and carbon emissions reaching 73% in 2014 [13]. After the devastating Sandy Storm (2012), the city launched the 80X50 target in September 2014; consisting in reducing 80 percent of greenhouse gas emissions by 2050. As part of this process, buildings have been identified as a key target area where cost-effective reductions can be made [14]. Thus, the city has estimated that improvements in buildings can reduce 60 percent the total greenhouse gas (GHG) emissions.

1.3. Problem assessed

The main problem addressed by this study is to evaluate building energy consumption at an accurate spatio-temporal resolution for different categories of buildings. The Urban Building Energy Modeling (UBEM) is a nascent research field. Indeed, Reinhart et al. [15] provided a review of the simulation methods and the different techniques mainly used: bottom-up and top-down approaches. The model developed in this paper is a bottom up model, because top-down models are not that accurate when it comes to investigate a complex and more integrated energy-supply scenario.

An UBEM requires the combination of several data sets including, climate data, building information, and usage schedule. As for the weather data, many studies used the typical meteorological year (TMY) data [16,17] as input to the model. This 20 to 30 years weather records data does not take into account the urban-microclimate and its specificities. Due to the lack of insulation in NYC Buildings, the weather has a major impact on the energy consumption of the buildings. A few models validated values at the entire city scale. The most developed building energy end-use intensity at large scale model was created by Howard et al. [18], coincidently for NYC. They used a linear regression model calibrated using ZIP code level electricity data. However, their model only considers annual energy use intensities. On the contrary, the proposed model here provides hourly data which may be useful to urban planners in identifying the peaks over seasons and future needs.

1.4. Definition of a Heat Wave

According to the US National Weather Service (NWS) definition, a heatwave in the Northeast of US occurs when the surface temperature reaches 90°F for three consecutive days, while a heat advisory occurs when the heat index (combination of temperature and relative humidity) is greater than 102°F (32.2°C) for two consecutive days [19]. A heat advisory indicates that the population maybe at risk of heat strokes [20]. Figure 1 below shows the modeled heat index for a heat wave event that took place in the 21st of July 2015. This figure shows the gradient of heat index across NYC, result of the microclimate induced by the diversity of density of buildings and the coastal environment. Heat wave causes droughts, for instance, periods in which cooling water shortages occurred in Europe in 2003. The lack of water supply impacts negatively power plants and caused more than 30 nuclear power plant in Europe to reduce their production because of limitations in the possibilities to discharge cooling water [21]. In the meantime, the energy demands is at its peaks during those phenomena causing blackouts, like the one that occurred in 2003 in USA [12]. In short, energy demands peak during extreme heat events, and they will be a focus scenario of this article.

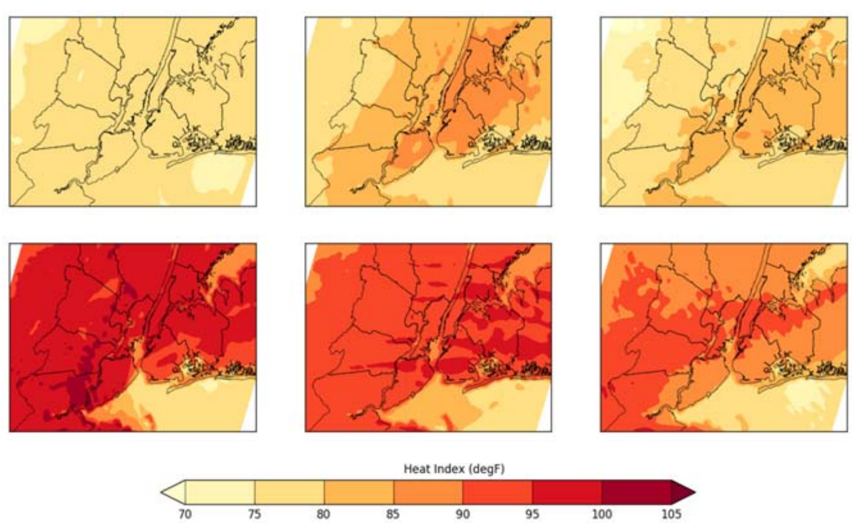


Figure 1: *Heat Index for 4am (top row) and 3pm (bottom row) for the three days of the forecast (21st to 23rd July 2015).*

2. Methodology

The development process for the building energy model is divided into three main steps: data collection, energy modeling, and results validation. The Primary Land Use Tax Lot Output (PLUTO) data, launched by the New York City Department of City planning, was used to identify the function of the building considering its Land Use Class and Building Class, and the year of built. For energy modeling, a set of building archetypes i.e. building sample that characterizes a group of buildings with comparable properties was used [22-24]. A secondary academic school building reference model was first developed as a test case, the other archetypes were taken from the set of reference buildings issued by the US DOE [25].

2.1. Data Collection

2.1.1. Weather data (uWRF)

Weather data to drive the single building energy model (EnergyPlus) was taken from the urbanized Weather Research Forecast Model (uWRF, 3.5.1) developed and maintained by the National Center for Atmospheric Research (NCAR). WRF is a mesoscale atmospheric model that takes into account the fluxes exchanged between buildings and the atmosphere. The urban model is composed of a Building Energy Parameterization (BEP) and a Building Energy Model (BEM) as described in Salamanca and Martilli [25] and Martili et al. [26], respectively. It computes the evolution of indoor temperature as a function of energy production and consumption in the building, the radiation coming through the windows, and the fluxes of heat exchanged through the walls and roofs as well as the impact of the air conditioning system as shown in Figure 2. For this study, we used a spatial configuration of the model consisting of three nested grids, 9, 3, and 1km, centered in NYC. The two nested domains use two-way nesting, in which calculations from the finer resolution grid are used to update coarser resolution grid points. All domains use 50 vertical levels, with 15 within the bottom 3 km. The model is initialized with North American Regional Reanalysis (NARR, 2006) 32 km resolution data. Further details of uWRF configuration used for this study can be found in Ortiz et al. [27].

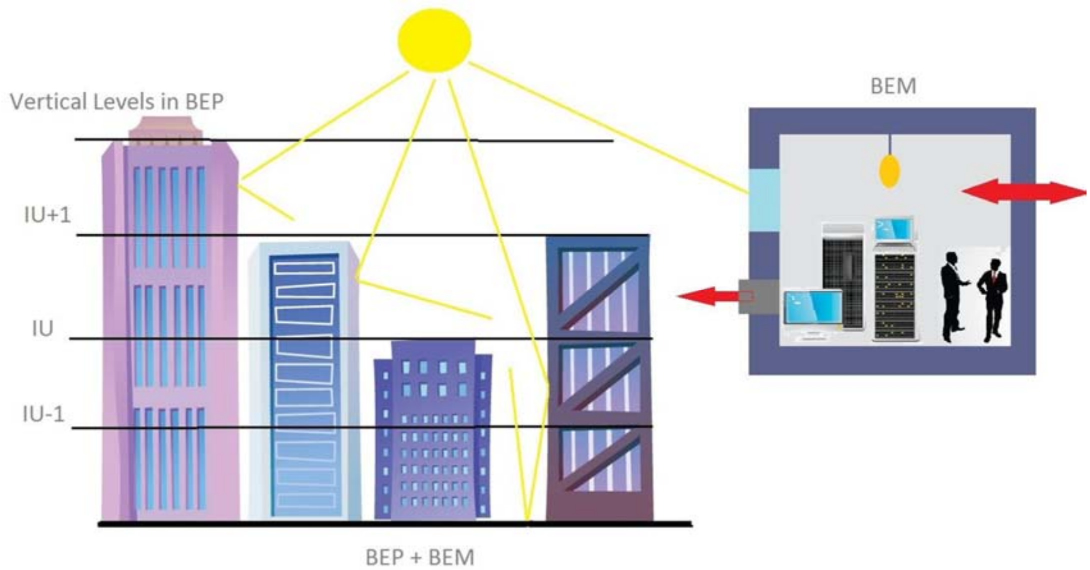


Figure 2: *uWRF Modelisation: This model provides the weather data to drive the energy models, in this case EnergyPlus.*

2.1.2. PLUTO data

The department of New York City Planning launches this data annually since 2009. It consists of an extensive land use and geographic data at the tax lot level. The PLUTO files contain more than seventy fields derived from data maintained by city agencies, ranging from zip code location, coordinate of the lot, to the build year of built. There are 1 million buildings distributed in 859134 tax lots. The version 15v1 was used for this research.

2.1.3. Additional Programming Tools Used

- EnergyPlus (version 8.5.0) is a public access building energy simulation tool developed by the US DOE. It is used by engineers, architects, and researchers to model both energy consumptions for heating, cooling, ventilation, lighting, and plug and process loads and water use in buildings. Weather files for EnergyPlus are provided by uWRF at the specific locations of the individual buildings.

- Python (version 2.7) is an interpreted, object-oriented, high-level programming language with dynamic semantics. Python supports modules and packages, which encourages program modularity and code reuse. Python was used to write scripts to automate the running of EnergyPlus for a city scale analysis.
- A geographic information system (QGIS 2.16.2) lets us visualize, question, analyze, and interpret data to understand relationships, patterns, and trends. This tool was used to create an interactive map of NY with the energy end use per building.

2.2. Energy Modeling

Reference buildings used were developed by the US DOE for use in studies that aim to characterize 70% of all the US buildings Stock [25]. We used sixteen types of buildings ranging from Hotel, Restaurant, to school, hospital, midrise apartment, for sixteen cities across the US. Relevant to our study, the reference buildings of Baltimore city were taken as our reference due to its proximity to NYC and the range of buildings in both places are similar.

Table 1: *Total building floor area by building function from PLUTO 2015 (m^2)*

	total floor area (m^2)	% building floor area
One Family apartment[1]	96483572	18.8
High-Rise apartment	133850279	27.0
Mid-Rise apartment	97694009	19.0
Large Office	38672838	7.0
Small Office	19752847	3.5
Education	20316722	4.4
Warehouse	24737421	5.7
Stand Alone Retail	70316243	14.6

[1] One Family Apartment represents one or two stories residential house.

For the residential sector, if building's land use is classified as a one-two family building, this latter is linked to medium rise apartment archetype, whereas if the residential building is classified as Multifamily Walk-up Buildings or Multi-Family Elevator Buildings, it is identified as a High rise apartment. For the commercial sector, if the building area is identified as an educational facility then the building is classified as a Secondary School. If the building is classified as a hospital or health facility, then the building is classified as Hospital. Finally, for the office building type, we have Small/Medium/Large Office building depending on the number of floor per building.

For the Commercial buildings, we have as archetypes: Strip Mall, Large/Small Hotel, Stand Alone Retail. Last but not least, the warehouse archetype was also considered in this pre-selection because their end-use profile differs from all the previous types of buildings that we mentioned.

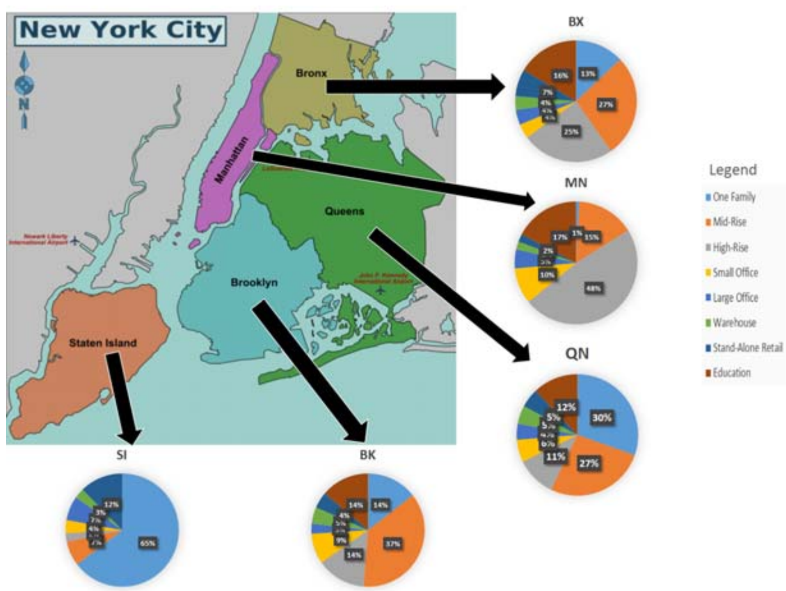


Figure 3: New York City map: Spatial building type distribution by borough (Manhattan, Brooklyn, Bronx, Queens, Staten Island)

In the classification table (cf Table 1), we see that Residential buildings account for almost 65% of the NYC total floor area, mainly located in the Queens (QN), Brooklyn (BK), Bronx

(BX) and Staten Island (SI). Indeed, we notice in Figure 3 that 44% of One Family Buildings are located in QN and 28% in BK. However, the majority of High Rise Buildings (40%) are situated in Manhattan (MN). The Education, Hospital, Warehouse represents only 11% of building floor area while the Stand-Alone Retail building comprise 14% and the Office encompass the 10% remaining.

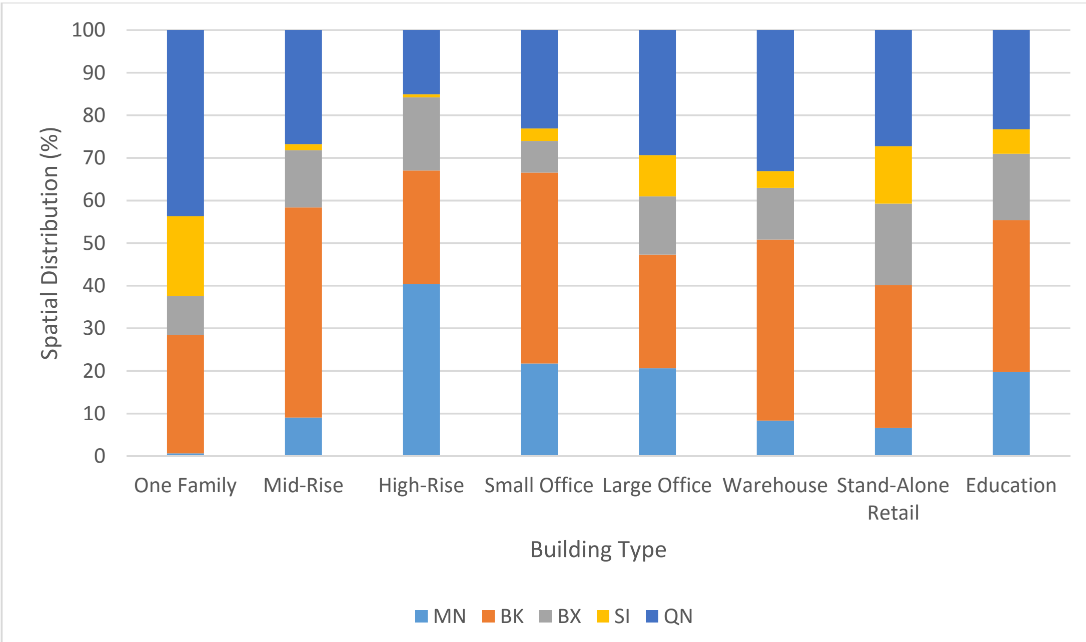


Figure 4: *Spatial distribution of buildings type in New York City (in percentage)*

2.3.System Implementation

To implement the multi-model and multi-dimensional modeling strategy, first the Python script selects the corresponding uWRF weather data as inputs to the EnergyPlus Model corresponding to the closest location to the buildings. Then, it reads the PLUTO file to collect information about a specific building. Knowing the class of the building, the program will automatically select the corresponding archetype and runs the EnergyPlus file with the uWRF weather file previously selected. The final step consists in the data visualization. Using the output of EnergyPlus, we plot a map of the city or region considered of energy-end use or energy demand. Figure 5 shows the whole flow process.

Figure 5: *Coupling uWRF and EnergyPlus for data processing and QGIS for data visualization*

3. Results and Discussions

3.1. Validation

3.1.1. Case of City College of New York

To validate the modeling strategy, we used building data from the City College of New York which was considered as a Secondary School reference building archetype. We used a single building energy model to model thermal loads and energy usage of the whole campus for the duration of the simulation. We modeled one of the campus' building of which we had its detail building parameters (architecture data, and equipment data) and also its own consumption data (power demand and fuel consumption). The next step consisted on comparing and validating the result of the EnergyPlus simulated model of that particular building with its own consumption data. Due to the lack of meter per building (for instance, there were only one HVAC meter for almost all the campus), we could not repeat the previous process for each building. The previous one-building model was scaled up using the total HVAC area to the whole campus to get an image of the Campus total consumption. Figure 6 shows the comparison between simulation and actual data for selected days for the month of July of 2015, which coincided with a heat wave event as shown in the right hand axis, showing the heat index (gray line). The average error between campus data and modeled results is about 15% of the total demand.

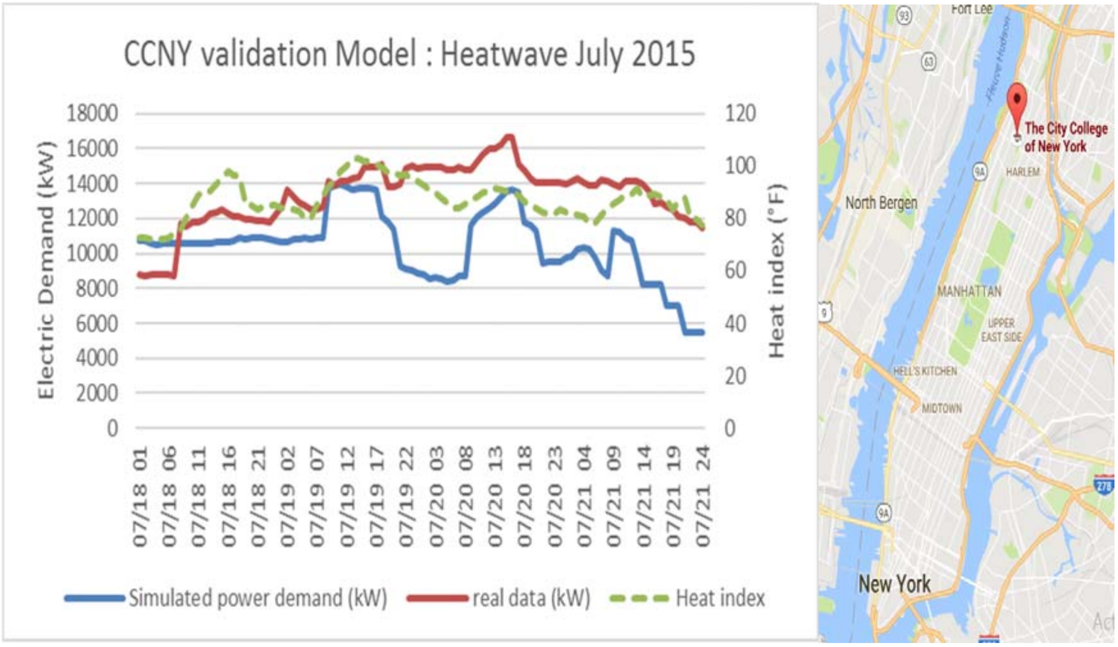


Figure 6: CCNY Validation model for the Heat Wave of July 2015

3.1.2. City Scale Validation

An additional validation simulation was conducted for the summer of 2015 (1st July-22nd July) at the city scale. Summer electricity energy data was used as it was available for the whole city while Fuel Consumption for the whole city was not available. We compared the NYISO (New York Independent System Operator; http://www.nyiso.com/public/index.jsp), Zone-J data to the total simulated demand for three days (July 20-22nd, 2015) and results are shown in Figure 7. The discrepancy between actual data shown can be explained by the fact that NYISO reflects the demand of the Whole city not just the buildings. This demand includes the transportation needs for electricity and many other services that consumes electricity. When the A/C demand is at its minimum (for our case it was on the 7th-8th of May 2015 when the weather was mild), we make the assumption that the difference between the NYISO real Data curve and the Total Simulated demand provides an approximation of all the other electricity needs that aren't related to Building Consumption. Through this method we find an average demand other forms of energy equal to **522 MW**. Adjusting the forecasted energy demand by this minimum value, our average error for the whole city decreases from 29% to 10%.

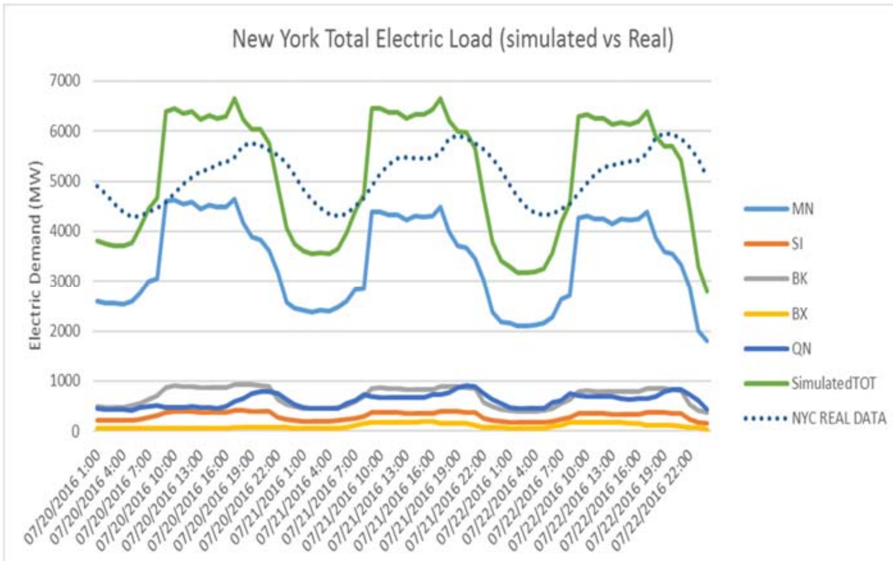


Figure 7: *Validation of the City scale model of New York City (20th -22nd July 2015)*

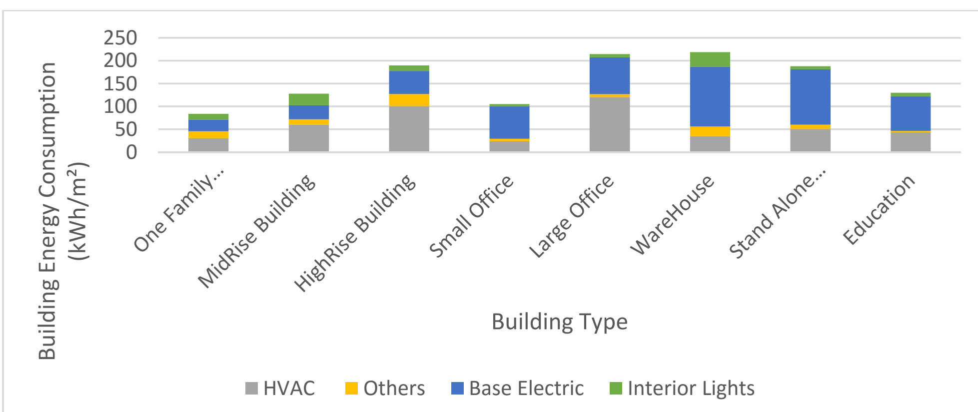


Figure 8: *Distribution of the energy end-use consumption by building function for the summer period (July 1st until July 22nd)*

Figure 8 shows the energy consumption intensities per building type during the summer period are shown. In the figure, 'Others' refers to the energy end-use that is different from

HVAC, Base Electric, and interior Lights. This may include energy needed for the water heating, and exterior lights. It can be noted that depending on the function of the building, the uses differs. For instance, the Office uses more energy for the electric equipment (base Electric) than the residential sectors, while for small office, consumption of 70% of the energy is used as base electric (electric equipment). Whereas One Family building and Mid-Rise building uses only 29% and 23%, respectively for electric equipment. The HVAC represents the main driver of the consumption during the summer in the residential sector. It consumes between 35% for One Family Building to 52% for High-Rise Building.

3.2. Results for Heat Wave vs Non-Heat Wave days

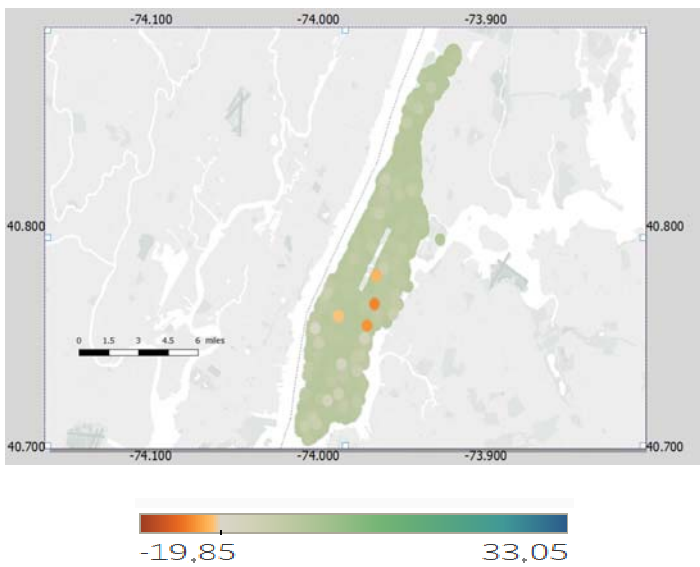


Figure 9: *Heat wave vs non-heat wave (21 July vs 13 June 2015): Energy demand (W/m²)*

Figure 9 shows the differences of energy demand for a heat wave day (July 21 2015) minus a heat wave day (June 13 2015) for Manhattan. We noticed that the total demand presents some discrepancies that vary depending on the type of the building. The causes of those differences may be seen by zoom into the Mid-Rise Buildings of Mid –Town, Manhattan as shown in Figure 10 where energy demand differences between a heat wave day and a non-heat wave day are shown. The peak demand is 33 W/m² difference and the average difference is around 5W/m².

Figure 10: *Difference of Energy demand between a heat wave case and a non-heat wave case: Zoom-in on the South of Manhattan*

We further notice that the main discrepancies may occur for the cooling demand. Indeed, the electricity gap differences represents only 2 W/m² whereas the average HVAC Demand is 40 W/m². As for the building type, The Residential buildings (One Family, Mid-Rise, high-Rise) and some Small office buildings present the highest rate of HVAC Demand with an average of 25 W/m² (Figure 11). For Residential buildings, the HVAC also represents the main driver of the consumption so it is normal to notice these high differences. As for the Small buildings, it could be due to the fact that those type of buildings aren't well insulated compared to Large Office so the impact of the weather is more important on those buildings.

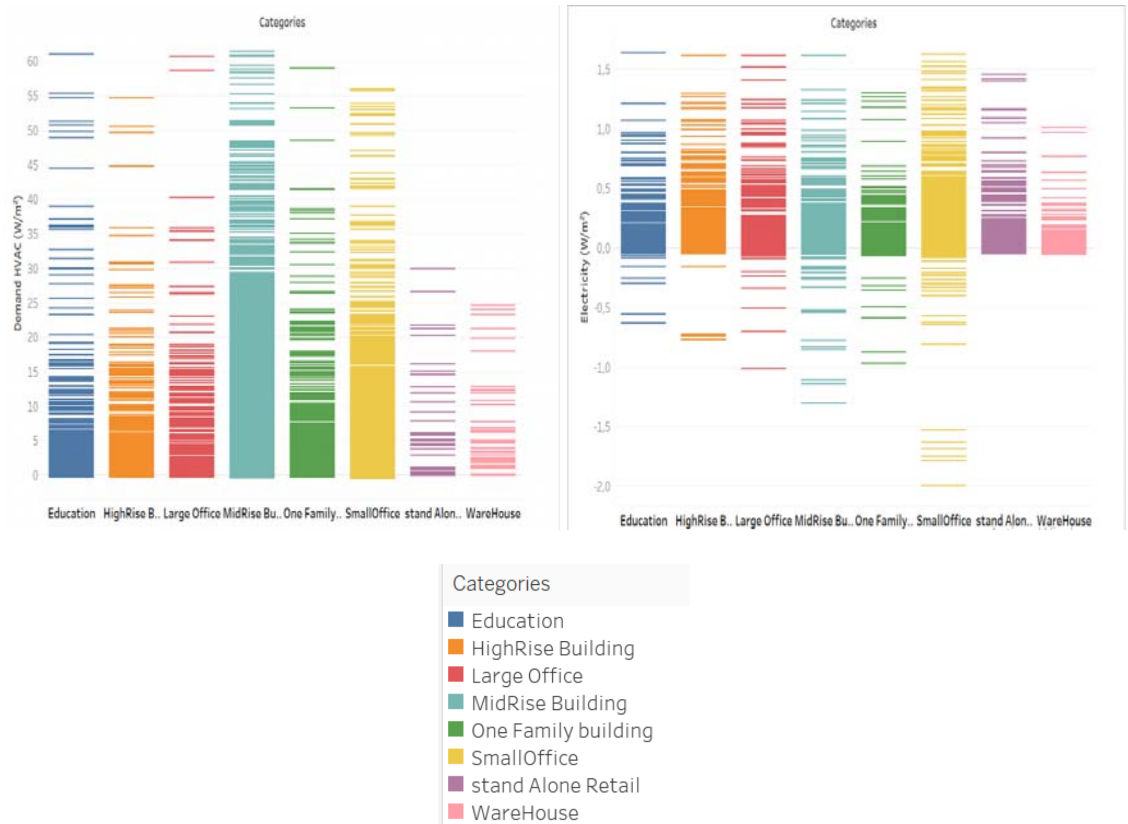
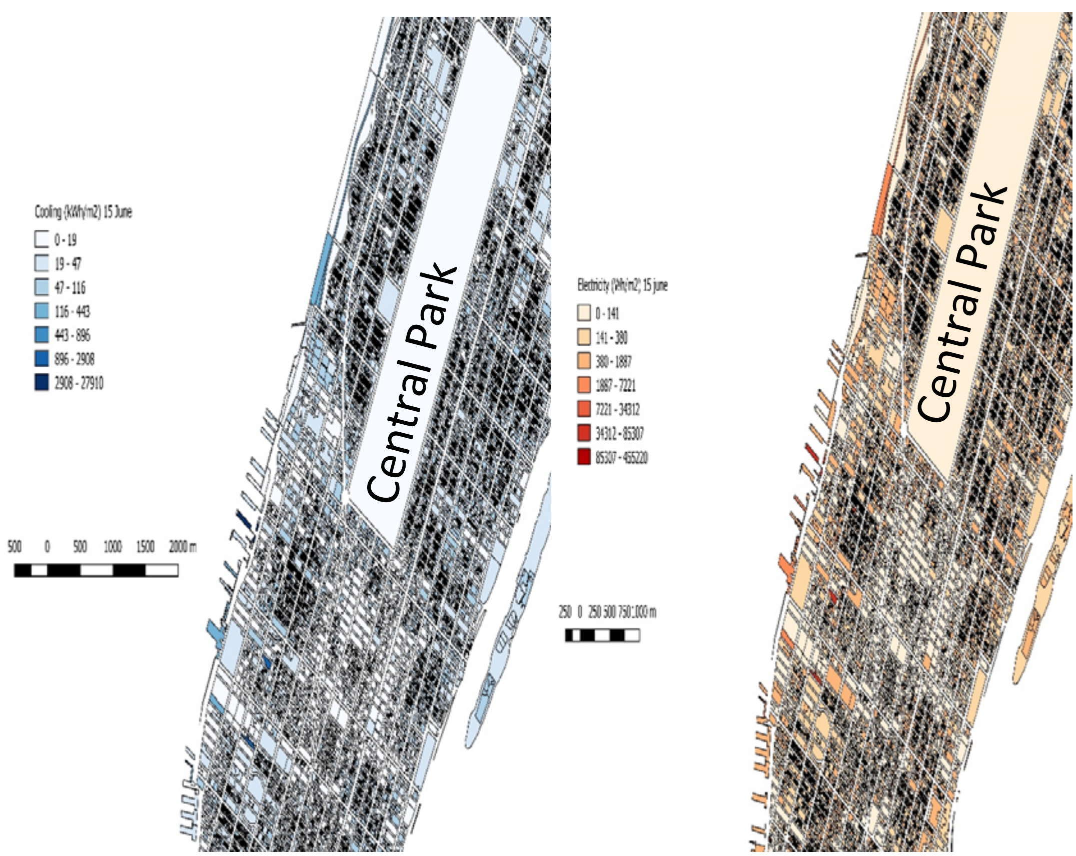


Figure 11: *Difference Electricity (Left) and HVAC Demand (Right) between Heat wave vs non-heat wave and function of the building type*

3.3.Spatial distribution of building energy Consumption

The outputs of the simulation were plotted into energy maps using QGIS Software (Version 2.16.2) to get a more comprehensive view of the spatial distribution of the energy consumption in New York City, and results are shown in Figure 10. As expected the financial district is the highest energy-consumption district in the whole city in all three categories. This energy map shows the intensity per square meter of the energy consumption per type of usage for each area. For better representation, we focus on one section of Manhattan, in midtown. The daily base electric, space cooling and interior lights energy consumption for Manhattan only are shown in this Fig. 10 where the main differences in the magnitude of consumption and spatial variation within the primary end-use consumption of a typical summer day (15 June

2016) are clearly shown. Across Manhattan, the space cooling consumption is larger than any other end use, reflective of the individual end-use breakdown since most building types consume more energy for space cooling than any other end use. The largest concentration of space cooling and base electric energy consumption is located in the central business district. This pattern is different for the interior lights energy demand where the largest concentration of energy consumption is located primarily in the upper west side and east side. This difference is explained by the large needs for space cooling and electric equipment in office buildings as opposed to residential buildings.



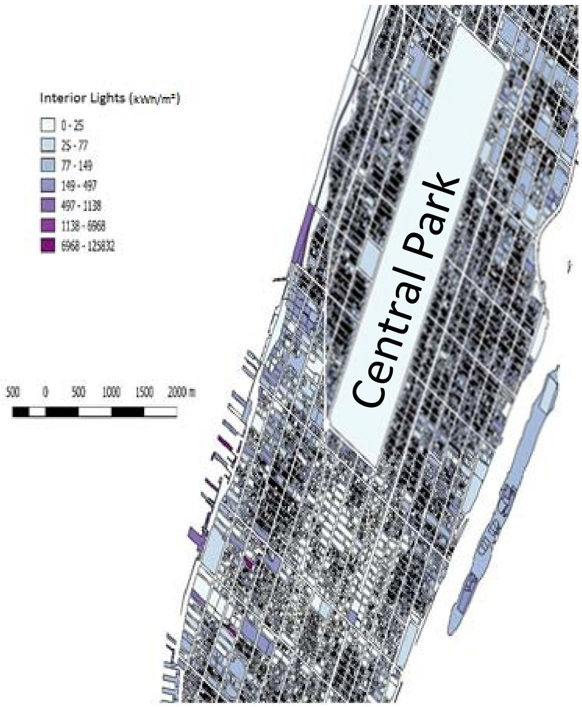


__Figure 12__ :Spatial distribution of energy demand by end use : top right Base Electricity, top left Cooling, down Interior lights (for June 15 2015) for Midtown, Manhattan, NY.

3.4.Hourly distribution of building energy Consumption

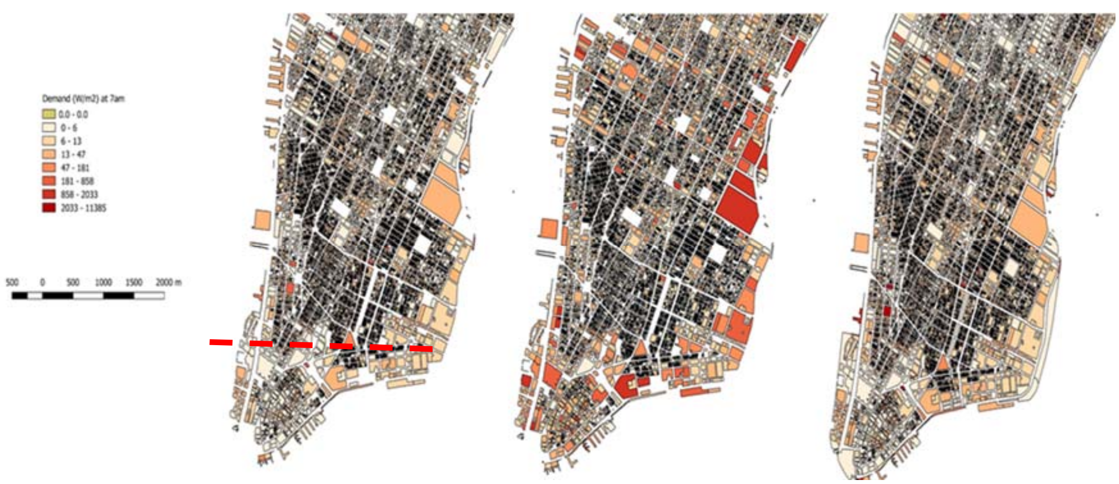


Figure 13: *Hourly energy demand : left (7 am), middle (3 pm), left (9pm)*

The evolution of the consumption during the day is shown in Fig. 14, where it is noticeable clearly a shift during the daytime between the consumption. For instance, during the morning, at around 7 am, the residential neighborhood consumes more than the office area. During noon, we notice a shift in the consumption with a peak demand that reaches its max in the Financial District. We can also notice that there is a shift of the demand between 7 am and 3 pm and again between 3pm and 9pm. First, in the morning, the maximum is reached for a residential area (downtown Manhattan) with a peak demand of 350 W/m^2. At 3pm, the peak is around 2000W/m^2 and finally at 9pm this peak decreases to reach 810 W/m^2.

The previous energy maps can be useful to estimate the feasibility of different energy generating systems depending on location such as combined heat and power system, or combined solar thermal and photovoltaic system. For instance, let's consider a block located between 123rd and 121st street and 3rd and 2nd avenue in Manhattan. For this mixed-use block with 70% of residential space and 25% of office and store space, the corresponding power for base electric would be 1.5 MW and that for domestic hot water would be 0.7 MW. This block, that is not currently served by the local steam system [29], could possibly be a good location for a combined heat and power system. 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.

Conclusions

In this study we present the development of a city scale energy-demand forecasting tool using high resolution weather data interfaced with a single building energy model. We focused our work on New York City (NYC) which has a comprehensive building dataset. We identified 51 building archetypes using PLUTO data. A Python script was developed to link each individual buildings to those archetypes and run the EnergyPlus file of that particular archetypes using the corresponding weather file. Weather data for EnergyPlus was provided by an urbanized weather forecast model (uWRF). The methodology was validated with single building energy data for a particular location, and with city scale energy demand profiles from records from the New York System Operator (NYISO) showing good agreements in both cases.

A case study was taken to illustrate the methodology which consisted of the summer of 2015, which included a heat wave event (July 19-22, 2015). Results for heat wave case indicate peak demands of 2000W/m^2 reached at 3PM on July 21st , with maximum values in the business district. Another case study consisted on comparing the sensitivity of the demand between a heat wave and a non-heat wave day. Results showed an average difference of 5W/m^2 with a peak demand is 33 W/m^2 for some Residential Area. The Main driver of that difference was the HVAC.

The hourly energy consumption profile for NYC determined in this analysis has many implications. First, it gives a better understanding to how energy is distributed during a day, and how it is spatially distributed. It may also assist facilities and urban planners to manage the electric grid and the power generation. Indeed, knowing the spatial distribution of loads will be very useful to identify ideal locations for the implementation of distributed energy generation or renewable energy systems such as combined heat and power systems (CHP). Moreover, this approach allows estimating how much energy could be produced if solar panels are installed at a given location, thus giving a clear insight for building stakeholders on when the system will be profitable. Last but not least, this method has the potential to inform urban planners and policy makers of targeting localized energy efficiency and GHG mitigation measures.

Acknowledgements

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