Explaining spatial variations in residential energy usage intensity in Chicago: The role of urban form and geomorphometry

Chaosu Li[1], Yan Song[1], Nikhil Kaza[1], and René Burghardt[2]

Accepted for publication in Journal of Planning Education & Research

Please cite the paginated version

Abstract

Understanding the spatial pattern of energy consumption within buildings is essential to urban energy planning and management. This study explores the spatial complexity of residential energy usage intensity, with a focus on urban form and geomorphometry attributes. Using spatial regression models, we find that while vegetation and isolation have more local impact on energy intensity, urban porosity and roughness length have consistent spillover effects on building electricity usage intensity in Chicago. Additionally, these relationships are seasonally varied. The results highlight the importance of spatially explicit policies and clear urban design and form frameworks for improving urban energy efficiency

Key Words

energy consumption, urban form, geomorphometry, microclimate, urban sustainability

Author Biographies

Chaosu Li is a postdoctoral researcher in the Department of City & Regional Planning at the University of North Carolina at Chapel Hill. He is interested in land use and environmental planning, urban sustainability, and Geographic Information Systems.

1 University of North Carolina, Chapel Hill, NC, USA

2 University of Kassel, Kassel, Hesse, Germany

Corresponding Author:

Chaosu Li, Department of City and Regional Planning, University of North Carolina, 405 New East, Campus Box 3140, Chapel Hill, NC 27599-3140, USA.

Email: chaosuli@live.unc.edu

Yan Song is a professor in the Department of City & Regional Planning at the University of North Carolina at Chapel Hill. Her research interests include low carbon and green cities, and spatial analysis of urban spatial structure and urban form.

Nikhil Kaza is an associate professor in the Department of City & Regional Planning at the University of North Carolina at Chapel Hill. He studies the phenomena of plans and their uses in public and private decision-making. Of particular interest are urban development processes, energy planning and land use impacts.

René Burghardt is a lecturer in the department of Department of Environmental Meteorology at the University of Kassel. He is interested in urban climate and Geographic Information Systems.

1. Introduction

Energy use in buildings is known to be one of the major sources of greenhouse gas (GHG) emissions from cities, and most of the emissions are from building operations (Norman, MacLean, and Kennedy 2006; Swan and Ugursal 2009; Ramesh, Prakash, and Shukla 2010). In developed countries, energy consumption in buildings has exceeded other major sectors, such as transportation and industrial use (Pérez-Lombard, Ortiz, and Pout 2008; Rode et al. 2014). For instance, in the United States, about 39% of total energy is consumed in residential and commercial buildings, and the building sector has become the largest energy consumption sector (EIA 2018). Meanwhile, a growing interest in the sustainability of energy resources in major metropolitan areas is apparent throughout the world. Although building energy efficiency and renewable energy polices at the metropolitan level are pervasive across the United States and are somewhat effective to date (Wedding and Crawford-Brown 2007), opportunities of future energy efficiency may be enhanced if the design of the built environment and the resulting urban form are also considered.

Previous studies on building energy consumption by planning scholars mainly focus on the effects of occupant behavior (e.g., Lutzenhiser 1992; 1993); the adoption and diffusion of energy-efficient technologies (e.g., Andrews and Krogmann 2009a; 2009b); specific city-level policies on building energy efficiency, such as benchmarking policy (e.g., Meng, Hsu, and Han 2017; Hsu 2014); and urban form and development patterns (Ewing and Rong 2008; Wilson 2013; Ko and Radke 2014; Redacted). A less studied area of urban building energy consumption is how building energy use intensity (EUI) pattern varies spatially, as well as how this variation is associated with demographic, socioeconomic, structural, as well as urban form and geomorphometry[1] factors. Empirically modeling building energy use intensity (EUI), measured by building energy consumption per square foot, is particularly relevant since it is a direct measure of building energy performance in energy management practice. Additionally, identifying factors that affect residential energy performance at the neighborhood level would potentially provide spatially targeted residential energy management and efficiency policy, which can be coordinated with urban land-use planning and design.

This study aims to explore the spatial complexity of residential EUI at the neighborhood scale to shed light on the role of urban form and geomorphometry on residential energy efficiency. We first review current literature on factors affecting residential energy consumption, especially urban form and geomorphometry relevant determinants. We present our data collection and coding, urban form and geomorphometry measures, as well as spatial regression methods. We then present the results for the study area in Chicago and set these in the context of existing literature. In addition, we discuss the limitations of this study. Finally, we conclude with potential policy implications.

2. Prior research

A high degree of consensus emerges among existing studies on disaggregated residential energy consumption studies that larger housing units, in terms of floor area or volume, consume more energy, which is consistent for both heating and cooling (Mardookhy et al. 2014; Filippín, Ricard, and Flores Larsen 2013; Redacted; Perez-Lombard 2008). Housing type also plays an important role, as detached single-family units tend to consume more energy than attached multifamily units (Jones, Fuertes, and Lomas 2015; Redacted; Min, Hausfather, and Lin 2010). In addition, old and poorly insulated dwelling units often consume more energy (Catalina, Virgone, and Blanco 2008; Redacted; Filippín, Ricard, and Flores Larsen 2013; Min, Hausfather, and Lin 2010; Redacted; Chen, Matsuoka, and Liang 2017; Estiri 2015). Besides physical characteristics, demographic correlates of building energy consumption that have been identified by previous literature include income, tenure type, household size, and the existence of elderly residents (Jones, Fuertes, and Lomas 2015; Redacted; Ewing and Rong 2008; Estiri 2015; Redacted; Chen, Matsuoka, and Liang 2017; Chen, Wang, and Steemers 2013).

The relationship between urban density and energy consumption have traditionally been limited because of paucity of data.. Larivière and Lafrance (1999) modeled the relationship between annual electricity consumption per capita and urban density using a sample at the city level and conclude that cities with higher density use less electricity per capita. However, the effect is much larger on gasoline consumption (Larivière and Lafrance 1999), since there are other important factors at city level, other than density, determine electricity consumption at the city level. Cooper et al. (2001) examined the tradeoffs of densification for both stationary (residential) and mobile (transportation) energy use in Belfast and corroborated that corridor-based densification land use policy can achieve significant reductions in mobile energy consumption and modest reductions in stationary energy usage linked to residential layout design. A widely cited study by Holden and Norland (2005) affirmed that housing density in residential areas is negatively associated with household energy consumption in eight residential areas in Greater Oslo Region, while controlling other important covariates including housing type.

In recent years, researchers have been increasingly interested in evaluating how various urban form elements affect residential energy consumption (Ko and Radke 2014; Wilson 2013; Ko 2013; Lee and Lee 2014; Redacted; Chen, Matsuoka, and Liang 2017; Quan et al. 2014); most of these studies corroborate that urban form and surrounding land use play a moderate but important role in influencing building energy consumption (Hsu et al. 2017; Steemers 2003; Redacted). These studies have identified urban form features of residential developments, such as neighborhood density, green space, tree canopy, street configuration, and street aspect ratio[2] are closely related to household energy consumption (Ko and Radke 2014; Wilson 2013; Ko 2013; Lee and Lee 2014; Redacted; Chen, Matsuoka, and Liang 2017). The most consistent connection between land use features and building energy consumption in the literature is the presence of urban green space. Relevant studies also documented the positive benefits of urban parks and gardens on urban temperatures, as well as heat island effects (Bowler , Knight, and Pullin 2010; Steeneveld et al. 2011) and building energy consumption (Ko 2013). Some existing studies have identified the macro-level urban form, such as density and compactness, is generally associated with low heating loads in winter for buildings (Høyer and Holden 2003; Rode et al. 2014). Chen et al. (2017) verified that buildings in a subtropical climate should be clustered to maximize the inter-building shadow while increasing non-built land use percentages in the adjacent areas, so as to reduce household energy usage. Additionally, Redacted, Hsu et al. (2017), Kontokosta and Tull (2017), Scofield (2014), and Quan et al. (2015) have claimed that a key variable that is missing from existing research is solar insolation for buildings.

Despite the resurgence in research attention that is currently devoted to the relationship between urban form and building energy consumption, this relationship is still unclear. Existing research mainly focuses on electricity consumption (Jones, Fuertes, and Lomas 2015; Ko and Radke

2014; Wilson 2013; Redacted); there has been few studies that explore the natural gas consumption in winter, which is mainly used for housing heating. Moreover, most previous studies have ignored potential spatial autocorrelation in building energy consumption of different neighborhoods (e.g., Chen et al., 2017). Factors that affect sub-municipal variations in residential EUI are not well established. In addition, there have been few studies that analyze the effects of building energy consumption by using urban geomorphometry, which has already been identified in the previous literature to be a significant determinant of solar insolation and natural ventilation (Coseo 2013; Chun and Guldmann 2014; Shi, Katzschner, and Ng 2017; Nakata-Osaki, Souza, and Rodrigues 2018). Further studies are needed to examine the net effects of solar radiation, heat island effects, and neighborhood ventilation (Ko 2013; Redacted; Chen, Matsuoka, and Liang 2017).

It is also worthwhile to note that research in this field are conducted at multiple scales, from the disaggregated household or parcel level (e.g., Ko and Radke 2014; Wilson 2013; Redacted) to the largely aggregated city or county level (Lee and Lee 2014). Meanwhile, factors influencing residential energy also exist at various scales, from the occupancy pattern at the household level to the architectural style and construction techniques associated with a particular subdivision to the microclimate conditions of neighborhoods and regions[3]. In this study, in order to capture the within city spatial effects and better quantify some neighborhood-level urban form induced microclimate features (e.g., ventilation, insolation) while controlling the important occupancy pattern and building covariates, we pick census tract as our unit of analysis.

Therefore, this study aims to advance the empirical understanding of how urban form and geomorphometry at the census tract level shape residential energy use intensity (EUI). We attempt to explain the spatial variations in residential electricity and gas EUI in terms of urban radiation intensity, neighborhood ventilation, vegetation density, and associated microclimate after controlling for socioeconomic and demographic factors, housing type, and building characteristics. Based on monthly energy usage data for different energy sources, three-dimensional building dataset, Digital Elevation Model (DEM), Landsat TM satellite image, and U.S. Census demographic information, we attempt to single out the importance of urban form and geomorphometry in understanding energy usage patterns. This study also aims to better understand the other spatial determinants of tract-level residential energy consumption patterns and to elucidate spatially explicit energy conservation strategies.

3. Data and methods

3.1. EUI data

We obtained monthly breakdown of energy consumption data for the year 2010 from the City of Chicago, which is among the select few cities that have made building energy consumption data available to public in recent years. Chicago is the most populous city in Illinois, United States, which is situated in the "hot summer humid continental" climate zone with warm, often humid summers and cold winters. The building energy consumption dataset form Chicago City Data Portal[4] contains 67,051 records grouped at the census block level including several different types of energy users (e.g., single-family, multi-family, industrial, commercial, and municipal users). We only extracted information on energy usage for residential use, then aggregated annual and seasonal electricity consumption and gas consumption data to census tracts. We aggregated the energy consumption data to census tract level since this approach would provide a continuous surface to evaluate the spatial variations of energy consumption intensity across the city (Chang, Parandvash, and Shandas 2010). Additionally, we were able to integrate several important variables such as income, housing characteristics and occupancy, which can be gathered at this level from U.S. census. The response variables of interest in this study include annual electricity EUI, summer electricity EUI, and winter gas EUI[5].

3.2. Urban form and geomorphometry measures

As mentioned in the previous section, although existing studies have revealed the relationship between urban geomorphometry variables (e.g., roughness length), solar insolation, and mircoclimate (Gál and Unger 2009; Redacted; Coseo and Larsen 2014; Chun and Guhathakurta 2015; Chun and Guldmann 2014), few has extended this relationship to building energy consumption. This study attempts to examine this linkage by including three variables that measure urban porosity, wind circulation, and solar insolation respectively by using three-dimensional urban data.

The first geomorphometry variable is urban porosity, which is defined as the ratio quantifying the volume of air in outdoor urban spaces (dotted areas in Figure 1) within the urban canopy layer[6]. It directly measures how penetrable a defined urban area is for the airflow (Gál and Unger, 2009). We constructed a 3D building database using data from Chicago City Data Portal and Open Street Map and calculated this variable using a GIS extension in ArcGIS10.5 (Redacted). The equation defining urban porosity is (Redacted; Gál and Unger, 2009):

$$P_{h-var} = \frac{A_T h_{UCL} - V_B}{A_T h_{UCL}} \quad (1)$$

where $P_{h\text{-}var}$ is the urban porosity index, h_{UCL} is the height of the urban canopy layer, V_B is the total volume of buildings[7], and A_T is the total plot area. Subsequently, the average value for $P_{h\text{-}var}$ is calculated for each census tract in our sample.

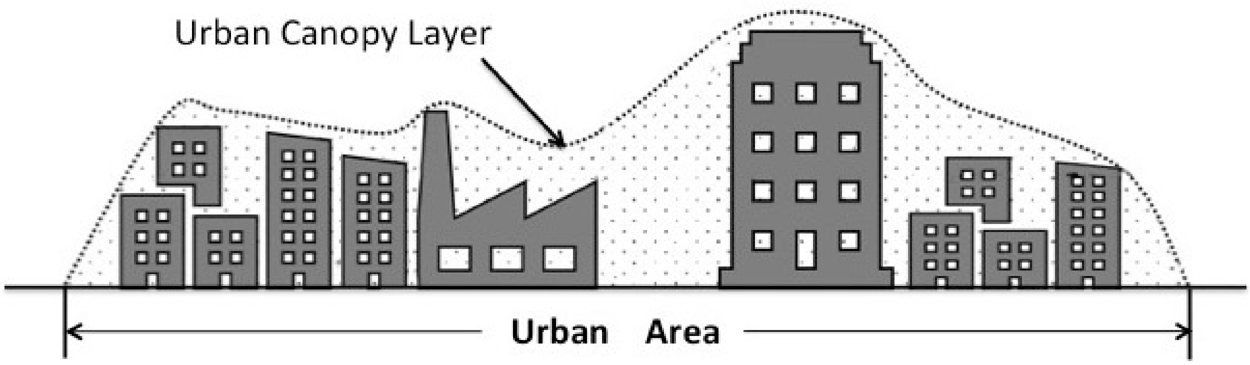


Fig. 1 The concept of urban porosity

The second geomorphometry variable we included in this study is roughness length, which is widely used in urban climate studies that measure the wind circulation of the 3D shape of urban environment (Shi, Katzschner, and Ng 2017). Generally, a high roughness length value indicates a low wind speed (Redacted; Gál and Unger, 2009). Similar to the urban porosity index, the roughness length index was calculated using a GIS extension in ArcGIS10.5[8] (Redacted). The roughness length is computed as follows (Figure 2):

$$Z_o = H(1 - \lambda P^{0.6})\, e^{-\sqrt{\frac{0.4}{\lambda F}}} \qquad (2)$$

where $\lambda F = {}^{AF}/_{AT}$ and $\lambda P = {}^{AP}/_{AT}$.

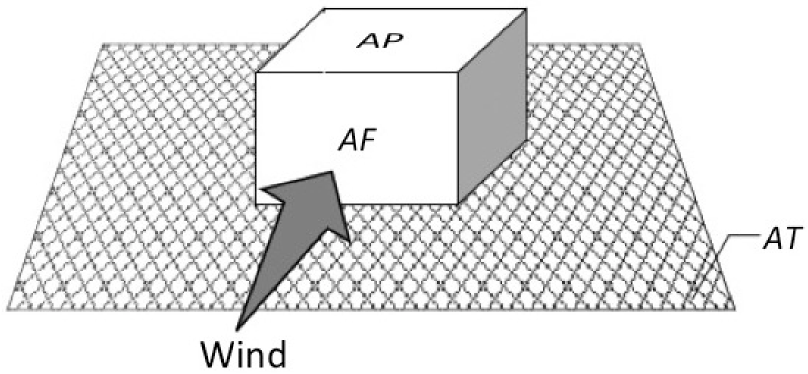


Fig. 2 Illustrated parameters for the roughness length calculation

Z_o is the roughness length index. *H* is volumetrically averaged building height. λF is the frontal area ratio, which is measured as the proportion of total frontal area[9] of buildings (*AF*) inside a plot area of the total plot area (*AT*). Building coverage ratio (λP) is calculated using building coverage area (*AP*) divided by the total plot area (*AT*).

Another geomorphometry variable we used in this study is solar insolation[10] intensity (Hsu et al. 2017) . This variable was calculated using the area radiation analysis tool in ArcGIS10.5 solar radiation toolbox. We created a building height raster data of Chicago[6] and joined it to the digital elevation model (DEM) of Cook County from U.S. Geological Survey and used the newly generated DEM to calculate the area solar radiation in summer, winter, and the whole year. Furthermore, we calculated the solar insolation intensity index, dividing the total radiation by total volume of buildings. Then we extracted the residential land from the radiation map output by using the land use inventory from Chicago Metropolitan Agency for Planning and calculated the annual and seasonal solar radiation intensity index for residential land use. This insolation accounts for shadows of neighboring buildings and other objects.

As indicated in previous literature, the presence of urban green space and vegetation cover has been identified as an important factor that moderates urban heat island effects (Chun and

Guldmann 2014; Chun and Guhathakurta 2015), which could in turn affect building energy consumption (Redacted; Wilson 2013; Ko 2013; Ko and Radke 2014). In this study, the normalized difference vegetation index (NDVI) was also calculated, which has been used extensively to measure vegetation cover in urban environments[12]. NDVI is calculated from the amount of reflectance observed in two bands or portions of the electromagnetic spectrum, namely, the near infrared (Landsat Band 4) and red (Landsat Band 3). The summer, winter, and annual NDVI were calculated using Landsat TM satellite images in the year 2010 and ArcGIS10.5[13]. Thereafter, the average value of the summer, winter, and annual NDVI for each census tract was obtained. We also included population density, building orientation[14], and distance to large water bodies as urban form related variables in this study.

3.3. Variable coding, descriptive statistics, and spatial patterns

In addition to urban form and geomorphometry variables, a dataset from the US Census was assembled at the tract level for building age, housing occupancy and tenure status, and household socioeconomic and demographic factors (e.g., household size and income, and the presence of elderly residents) to account for other factors that influence residential energy consumption, which have been identified in the previous literature (see Table 1 for descriptive statistics). The annual electricity usage intensity refers to the annual residential electricity usage per square footage by census tract in the year 2010, in the unit of kWh/ft^2. The summer electricity usage intensity was calculated using the household electricity data from June 2010 to September 2010. Accordingly, winter gas consumption intensity was derived from the data in January, February, March, and December of 2010. Subsequently, the unit of winter gas consumption intensity was converted to kWh/ft^2 for comparison. Not surprisingly, all the EUI variables are right-skewed. Therefore, they were transferred to the natural log form.

Table 1
Descriptive statistics (N=780).

Variables	Mean	*SD*	Min.	Max.	Source
Dependent variables					
Annual electricity usage intensity (kWh/ft^2)	5.66	1.90	1.85	26.11	City of Chicago Data Portal
Summer electricity usage intensity (kWh/ft^2)	2.29	0.84	0.71	12.88	City of Chicago Data Portal
Winter gas usage intensity (kWh/ft^2)[a]	19.49	4.30	5.84	44.16	City of Chicago Data Portal
Independent variables					
Proportion of single-family square footage for electricity[b]	0.41	0.29	0	1	City of Chicago Data Portal
Proportion of multifamily houses (with <7 households) for electricity	0.49	0.27	0	1	City of Chicago Data Portal
Proportion of multifamily houses (with 7+ households) for electricity	0.11	0.18	0	1	City of Chicago Data Portal
Proportion of single-family square footage for gas	0.41	0.29	0	1	City of Chicago Data Portal
Proportion of multifamily houses (with <7 households) for gas	0.48	0.27	0	1	City of Chicago Data Portal
Proportion of multifamily houses (with 7+ households) for gas	0.11	0.19	0	1	City of Chicago Data Portal
Proportion of housing units built before 1940	0.48	0.21	0	0.93	
Proportion of housing units built before 1940-1959	0.24	0.16	0	0.84	U.S. Census Bureau, 2010 five-year American Community Survey
Proportion of housing units built before 1960-1979	0.15	0.12	0	0.76	U.S. Census Bureau, 2010 five-year American Community Survey
Proportion of housing units built before 1980-1999	0.07	0.08	0	0.64	U.S. Census Bureau, 2010 five-year American Community Survey
Proportion of housing units built after 2000	0.06	0.09	0	0.66	U.S. Census Bureau, 2010 five-year American Community Survey
Housing occupancy rate	0.87	0.08	0.38	0.98	U.S. Census Bureau, 2010 five-year American Community Survey
Average household size (persons)	2.68	0.66	1.28	4.37	U.S. Census Bureau, 2010 Summary File 1
Proportion of household with elderly residents (age>65)	0.21	0.11	0	0.58	U.S. Census Bureau, 2010 Summary File 1
Median household income (1000$)	47.56	22.57	10.22	151.25	U.S. Census Bureau, 2010 five-year American Community Survey
Homeownership rate	0.44	0.20	0.04	0.94	U.S. Census Bureau, 2010 Summary File 1
Population density (persons/acre)	29.04	20.10	0.61	208.98	Calculated using U.S. Census Bureau, 2010 Summary File 1

Building orientation[c]	0.60	0.27	0	1	Calculated using building shapefile complied from Chicago Data Portal and Open Street Map, and ArcGIS
Distance to Lake Michigan (miles)	4.00	2.44	0.09	10.89	Calculated using U.S. Census Bureau, 2010 census tract shapefile and ArcGIS
Annual insolation per building volume (10^6 WH/m^3)	6.15	2.94	0.08	22.62	Calculated using multiple datasets[d] and Arc GIS
Summer insolation per building volume (10^6 WH/m^3)	3.11	1.49	0.04	11.46	Calculated using multiple datasets and ArcGIS
Winter insolation per building volume (10^6 WH/m^3)	0.17	0.14	0.01	2.38	Calculated using multiple datasets and ArcGIS
Annual vegetation index (NDVI)	0.12	0.04	0.01	0.26	Calculated using Landsat TM satellite image and ArcGIS
Summer vegetation index (NDVI)	0.16	0.04	0.03	0.36	Calculated using Landsat TM satellite image and ArcGIS
Winter vegetation index (NDVI)	0.08	0.03	-0.02	0.20	Calculated using Landsat TM satellite image and ArcGIS
Urban porosity	0.77	0.07	0.59	0.98	Calculated using multiple datasets and ArcGIS
Urban roughness length	1.04	1.25	0.07	13.42	Calculated using multiple datasets and ArcGIS
Building Coverage Ratio[e]	0.46	0.09	0.09	0.89	Calculated using Calculated using building shapefile, land use inventory from Chicago Metropolitan Agency for Planning, and ArcGIS

Notes: [a] The original unit for gas consumption in the dataset is therm. We convert it to kWh for easy comparison.

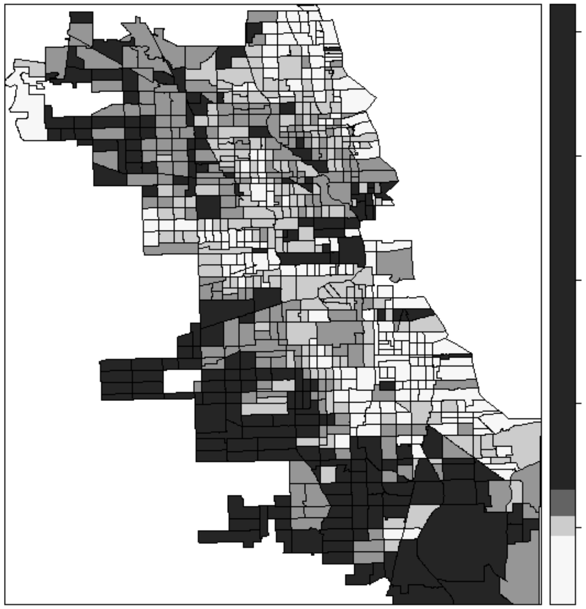
[b] The square footage of each housing type associated with the electricity and gas data is different in certain tracts. Thus, we create this variable differently for electricity and gas.

[c] Building orientation refers to floor area weighted proportion of residential buildings that are within 15 degrees of east-west orientation.

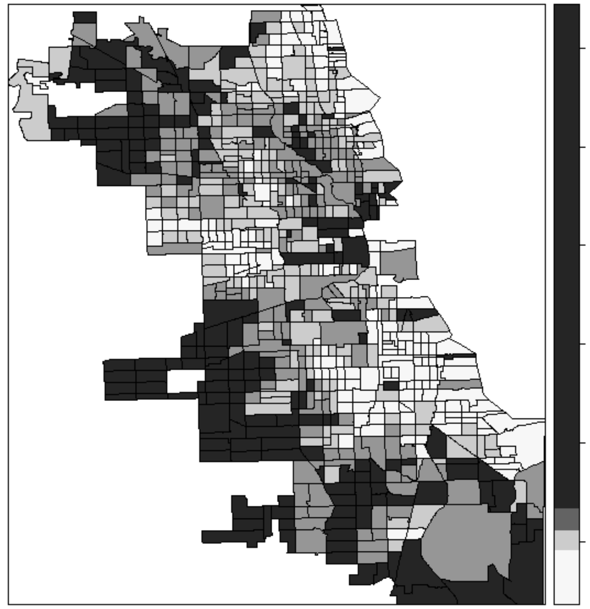
[d] These datasets include building shapefile complied from Chicago Data Portal and Open Street Map, Digital Evaluation Model from U.S. Geological Survey and land use inventory from Chicago Metropolitan Agency for Planning.

[e] Building coverage ratio is not used in the regression models. It is used to quantify densification scenarios in the discussion section.

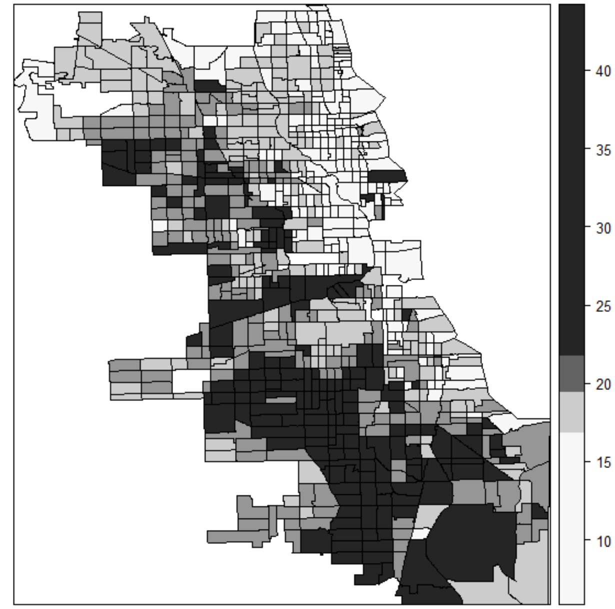
There exists a positive spatial autocorrelation in EUI, suggesting that residential energy consumption patterns are not randomly distributed across Chicago, but are spatially correlated (see Figure 3). Higher electricity usage can be observed in central areas of Chicago near downtown areas as well as a few of the suburbs in the northwestern and southwestern edges (see Figure 3a). Electricity and winter gas usage intensity distribution across the city show similar patterns, except for several tracts to the north of downtown and near the north edge of the city, where residential buildings may rely less on gas for heating in winter (see Figures 3b & 3c). By overlaying the EUI map and population density map, we can observe the negative correlation between electricity EUI and population density by census tract. In addition, there exist some positive relationships between EUI and annual insolation intensity, vegetation index, and urban porosity. This makes sense because neighborhoods with higher EUI are often times located in low density areas, which are associated with more insolation and less building volume, more vegetation cover, and higher level of urban porosity. Additionally, building orientation and urban roughness do not appear to have apparent spatial relationship with EUI at the census tract level.



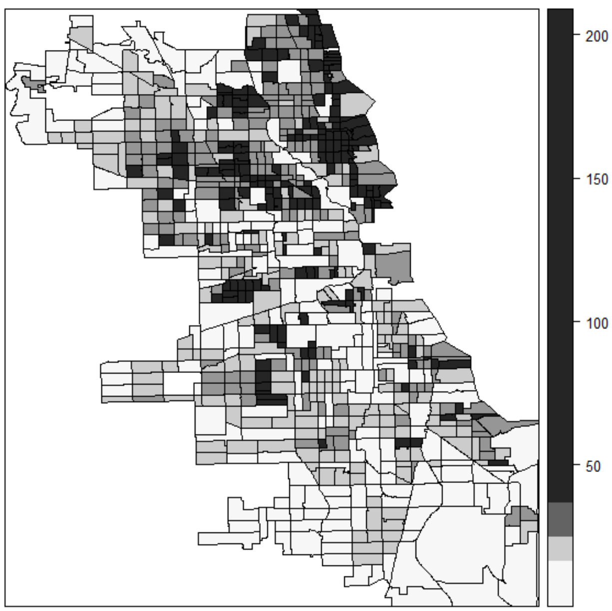
(a) Average annual electricity usage intensity (kWh/ft^2)



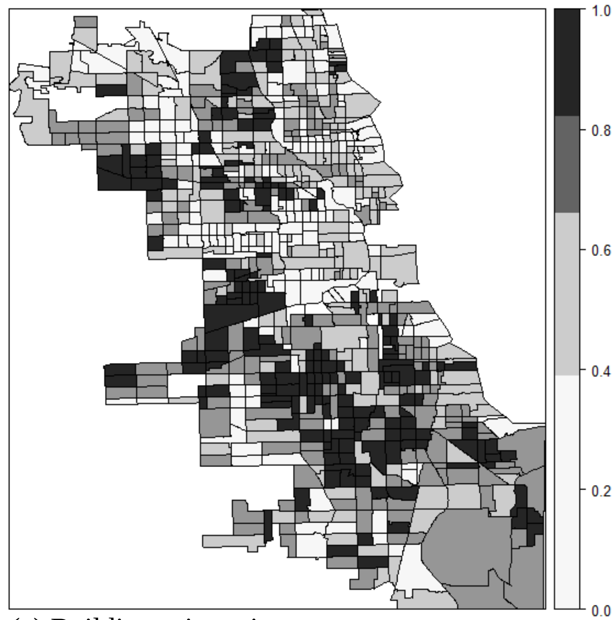
(b) Average summer electricity usage intensity (kWh/ft^2)



(c) Average winter gas usage intensity (kWh/ft^2)

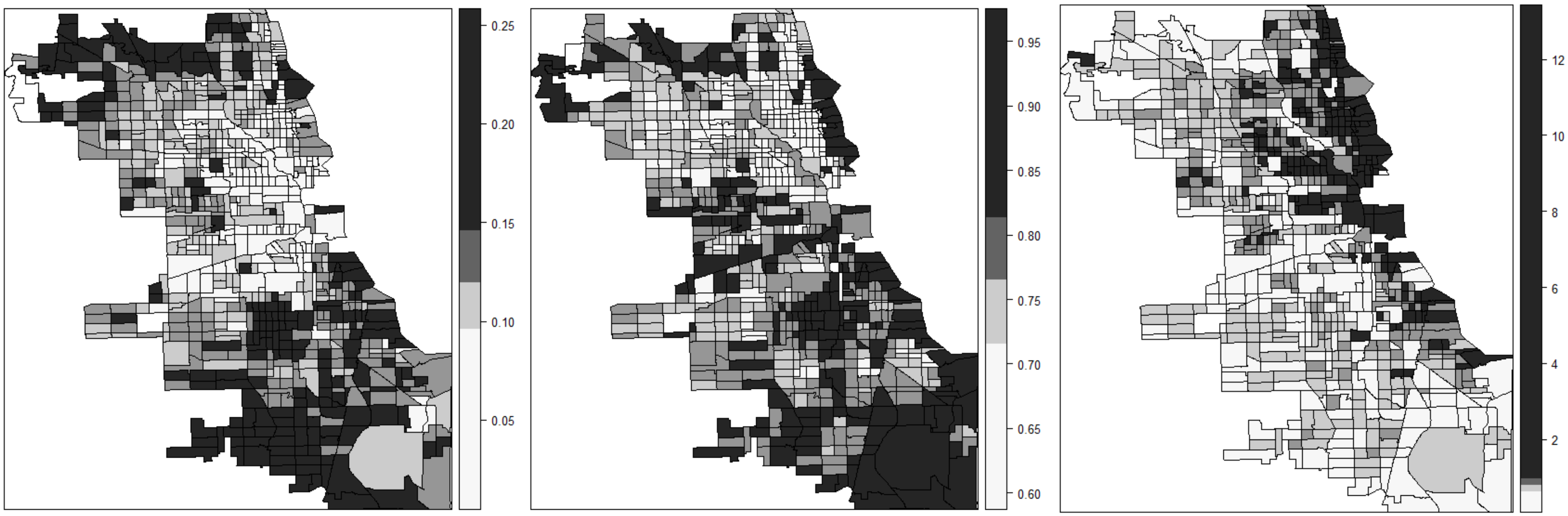


(d) Population density (persons/acre)



(e) Building orientation

(f) Annual insolation per building volume (10^6 WH/m^3)



(g) Annual vegetation index (NDVI) (h) Urban porosity (i) Urban roughness length

Fig. 3 Spatial patterns by census tract in Chicago

3.4. Model specification

First, the Ordinary Least Square (OLS) regression models are estimated[15]. The Moran's I statistics indicate spatial autocorrelation exists in the residuals of all the electricity and gas models[16]. We used Lagrange Multiplier statistics[17] to further identify that spatial error model as the right model specification for spatial dependence. The Spatial Error Model (SEM) for this study is specified as follows:

$$Ln(Y) = \alpha + \beta X + \eta Wu + \varepsilon \tag{3}$$

$$\varepsilon \sim N_{iid}(0, \sigma^2 I) \tag{4}$$

where Y is the EUI variable for each census tract, X is the set of explanatory variables including urban form and geomorphometry, as well as control variables of socioeconomic and demographic factors, housing type, and building characteristics. W is the spatial weight matrix, which is based on first-order queen contiguity in this instance.

If the impacts of some explanatory variables affect not only the dependent variable in the reference census tract but also the dependent variable in the proximal neighboring census tracts, then the immediate neighbor influences can be captured in the model by spatially lagged independent variables. In this case, some urban form relevant variables regarding urban ventilation and vegetation might have this type of influence on building energy consumption. For instance, the urban ventilation level in a census tract may affect not only residential energy consumption in that census tract, but also residential energy consumption among neighboring census tracts. Therefore, we included spatially lagged independent variables for these urban form and geomorphometry variables in our model and estimated the OLS models. We again examined the residuals from the OLS using the Moran's I statistic to test for spatial autocorrelation among residuals and Lagrange Multiplier statistics as a likely clue for model selection[18]. Finally, we selected the Spatial Durbin Error Model (SDEM), which accounts for spatial dependence among the error terms and the exogenous interaction effect. The final model is specified as follows:

$$Ln(Y)= \alpha + \beta X + \gamma WX' + \eta Wu + \varepsilon \tag{5}$$

$$\varepsilon \sim N_{iid}(0, \sigma^2 I) \tag{6}$$

where Y is the EUI variable for each census tract; X is the set of explanatory variables including urban form and geomorphometry, as well as control variables of socioeconomic and demographic factors, housing type, building characteristics. γ vector represents the estimates for the lagged independent variables of urban porosity, roughness length, and NDVI. Following Call and Voss (2016), the set of predictors X' is assumed to be a subset of the predictors X. It is also not a requirement that spatial matrix W in equations (5) be the same, although in this study we assume a row standardized first-order queen specification for each. The models were estimated using the spdep package in R (R Development Core Team, 2014). The annual and seasonal EUI variables are tested using SEM and SDEM, respectively, including the annual electricity, summer electricity, and winter gas.

4. Results

The base models (SEM1, SEM2, SEM3) are spatial error models that include all the explanatory variables for the EUI dependent variables; extended models (SDEM1, SDEM2, SDEM3) include both explanatory variables in the base models and spatially lagged variables of NDVI, urban porosity, and roughness length, which adjust for their neighboring influences on EUI (see Table 2). Overall, the addition of the lagged variables can improve the model fit for the annual and summer electricity EUI models, which indicates that the urban form variables in the neighboring tracts can help explain the electricity EUI in its reference tract. This combination yields a relatively strong model fit (pseudo-R^2 =0.57 and 0.65). Summer electricity usage models generally have more explanatory power than annual models, which might be explained by the fact that a larger proportion of summer electricity is used for cooling.

Table 2
Annual and seasonal spatial regression results.

Variable	EUI (Annual Electricity)		EUI (Summer Electricity)		EUI (Winter Gas)	
	SEM1	SDEM1	SEM2	SDEM2	SEM3	SDEM3
Proportion of single family square footage	0.217***	0.201***	0.275***	0.263***	0.127***	0.126***
	(0.059)	(0.057)	(0.059)	(0.056)	(0.045)	(0.045)
Proportion of multifamily square footage (with 7+ households)	-0.055	-0.096*	-0.170***	-0.215***	-0.482***	-0.491***
	(0.060)	(0.058)	(0.059)	(0.057)	(0.047)	(0.047)
Proportion of housing units built before 1940	-0.576***	-0.578***	-0.523***	-0.532***	0.177**	0.185**
	(0.102)	(0.098)	(0.102)	(0.098)	(0.082)	(0.082)
Proportion of housing units built 1940-1959	-0.648***	-0.676***	-0.594***	-0.610***	0.269***	0.272***
	(0.110)	(0.106)	(0.109)	(0.105)	(0.087)	(0.088)
Proportion of housing units built 1960-1979	-0.310***	-0.284**	-0.263**	-0.234**	0.229**	0.241**
	(0.119)	(0.114)	(0.118)	(0.113)	(0.096)	(0.096)
Proportion of housing units built 1980-1999	-0.257*	-0.268**	-0.143	-0.140	-0.016	-0.020
	(0.139)	(0.137)	(0.138)	(0.136)	(0.111)	(0.112)
Housing occupancy rate	0.556***	0.539***	0.683***	0.667***	0.266***	0.260**
	(0.127)	(0.125)	(0.125)	(0.123)	(0.103)	(0.105)
Average household size	0.064***	0.085***	0.054**	0.073***	0.061***	0.066***
	(0.022)	(0.020)	(0.022)	(0.020)	(0.018)	(0.018)
Proportion of household with elderly residents (age>65)	-0.046	-0.002	-0.135	-0.101	0.119*	0.123*
	(0.089)	(0.087)	(0.088)	(0.086)	(0.071)	(0.071)
Median household income	-0.0004	-0.001	0.001	0.001	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.001)

Homeownership rate	0.071	0.038	0.070	0.049	-0.253***	-0.255***
	(0.088)	(0.086)	(0.087)	(0.085)	(0.071)	(0.071)
Population density	-0.0001	-0.0002	-0.0002	-0.0003	-0.0005	-0.0005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0005)	(0.0005)
Building orientation	-0.016	-0.013	-0.050*	-0.042	0.008	0.006
	(0.029)	(0.027)	(0.029)	(0.027)	(0.023)	(0.023)
Distance to Lake Michigan (miles)	0.009	0.010*	0.014**	0.015***	0.004	0.003
	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)
Solar insolation index						
Annual insolation intensity	0.033***	0.039***				
	(0.005)	(0.005)				
Summer insolation intensity			0.062***	0.075***		
			(0.011)	(0.010)		
Winter insolation intensity					-0.035	-0.038
					(0.051)	(0.051)
Vegetation Index						
Annual NDVI	-0.984***	-1.002***				
	(0.318)	(0.319)				
Summer NDVI			-1.140***	-1.127***		
			(0.247)	(0.253)		
Winter NDVI					0.181	0.234
					(0.311)	(0.313)
Ventilation index						
Urban porosity	0.075	0.142	0.036	0.108	0.168	0.176
	(0.180)	(0.184)	(0.172)	(0.176)	(0.162)	(0.164)
Roughness length	0.030***	0.014	0.030***	0.013	-0.003	-0.006
	(0.009)	(0.010)	(0.009)	(0.010)	(0.007)	(0.008)
Spatial lag term						
Lag of annual NDVI		0.682				
		(0.477)				
Lag of summer NDVI				0.097		
				(0.359)		
Lag of winter NDVI						0.554
						(0.591)
Lag of urban porosity		-0.950***		-0.904***		-0.295
		(0.254)		(0.238)		(0.249)
Lag of roughness length		0.086***		0.077***		0.021
		(0.015)		(0.014)		(0.013)
Constant	1.248***	1.726***	0.265	0.770***	2.362***	2.514***
	(0.206)	(0.257)	(0.203)	(0.252)	(0.172)	(0.241)
Observations	780	780	780	780	780	780
Log Likelihood	213.180	235.384	220.103	241.651	384.932	386.759

Akaike information criterion (AIC)	-384.361	-422.768	-398.205	-435.302	-727.864	-725.517
Pseudo-R^2	0.544	0.569	0.630	0.650	0.591	0.593
Wald Test	94.471***	31.165***	88.882***	25.960***	145.630***	128.999***
Likelihood ratio (LR) Test	55.119***	22.974***	47.011***	18.230***	101.399***	90.322***

Notes: (1) Standard errors in parentheses.
(2)*p<0.1,**p<0.05,***p<0.01.
(3) In each instance, ''Lag'' refers to a spatial lag computed using a row-standardized first-order Queen spatial weights matrix.

4.1. Impacts of urban form and geomorphometry factors

The regression results reveal the effects of tract-level urban form and geomorphometry variables on residential EUI. Roughness length, which is negatively associated with the intensity of wind circulation, seems to have a significant effect on electricity usage intensity ($p < 0.01$ in SEM1 and SEM2) when other important covariates have been controlled for. The results indicate that, if the roughness length index of a certain census tract is reduced by 10 (approximately from the highest to the lowest value in Chicago), its annual and summer electricity EUI would be reduced by 30%. This makes sense given the fact that Chicago has hot and humid summers. Whereas in the anticipated direction, this effect is not statistically significant for winter gas usage intensity ($p > 0.1$ in SEM3 and SDEM3). Similarly, solar radiation intensity is significantly related to electricity usage intensity ($p < 0.01$ in SEM1, SDEM1, SEM2, and SDEM2) as excessive solar insolation might increase the cooling loads in summer, especially in low-density residential developments. According to the results of Model SDEM2, if the summer solar insolation intensity index of a certain census tract is increased by 10 WH/m^3 (approximately from the lowest to the highest value by census tract in Chicago), its summer electricity EUI would be increased by 75%, which is a considerable change. Nevertheless, the opposite effect of solar insolation is not significant for winter gas usage intensity ($p>0.1$ in SEM3 and SDEM3). As expected, NDVI, which measures the average density of vegetation in each tract, is significantly related to electricity usage intensity ($p < 0.01$ in SEM1 and SEM2) but not with gas usage intensity in winter. An increase of NDVI by 0.1, all things being equal, would lead to a decrease of summer electricity EUI of a census tract by 11.4%. Additionally, the results show no statistically significant association between neighborhood porosity and EUI for both electricity and gas consumption. The results reveal that distance to large water bodies (Lake Michigan) has positive effects on summer electricity usage intensity, which indicates that the tract's geographic proximity to Lake Michigan would significantly reduce residential electricity intensity in summer. After controlling other urban form and geomorphometry factors related to urban ventilation, solar radiation, and vegetation level, building orientation does not appear to be significant predictors of EUI. Population density is not significantly related to EUI either, which is consistent with previous findings as studies have revealed that, when it comes to energy intensity (e.g., electricity consumption/ft^2), population density is not significant (Chen, Matsuoka, and Liang 2017), although a high population density is associated with a low household energy usage (Ko and Radke 2014; Ewing and Rong 2008).

Extended models (SDEM1-3) in this study include some spatially lagged independent variables, which adjust for neighboring influences on EUI. The porosity level in a specific tract, for instance, may be similar with the porosity level in neighboring counties (spatial clustering), and may also be related with EUI in neighboring counties (spatial spillover effects). The spatially lagged porosity is negatively related to the electricity usage intensity in the neighboring tract. The porosity in the neighboring tracts can potentially reduce both annual and summer electricity usage intensities, a large proportion of which is used for cooling: an increase of porosity level in the neighborhood tracts by 0.1 would lead to a decrease of annual and summer electricity EUI in the reference tract by 9.5% and 9.0%, respectively. Nonetheless, no statistically significant associations between spatially lagged porosity and winter gas usage intensity exist. A significant positive association has been found for the spatially lagged roughness length and electricity EUI, which indicates that high levels of wind circulation in the neighboring tract can potentially reduce the electricity usage intensity in the reference tract ($p < 0.01$ in SEM1 and SEM2). As the lagged roughness length is controlled for, the roughness length itself becomes insignificant, which indicates that the wind circulation level is operating at a different scale than census tract. Again, no significant lagged effects of roughness length on winter gas usage intensity are found. Additionally, little evidence in our results indicates that NDVI have neighboring effect on EUI as the lagged NDVI is not significant in either electricity or winter gas usage models.

4.2. Impacts of other factors

In addition to urban form and geomorphometry variables, housing type, building age, ratio of occupied housing units, and household size are consistent determinants of EUI at the tract level, which coincides with the existing theory. A nuanced finding in the study is that, when controlling other important covariates, census tracts with a high percentage of old buildings are associated with a low electricity usage intensity, which might be attributed to less usage of air conditioning and other high-consumption appliances (Baker and Rylatt 2008; Chong 2012; Tiwari 2000). On the contrary, in the winter gas intensity model, tracts with a high percentage of old buildings are associated with a high gas usage intensity, which is consistent with the existing theory that older homes generally consume more energy for home heating because of insufficient thermal insulation. Additionally, tracts with a high proportion of elderly residents (age > 65) are associated with high gas usage intensities, probably due to the fact that they generally spend more time at home and also may need more natural gas for home heating in winter as elderly residents commonly require warmer ambient temperatures to feel comfortable. Interestingly, the median income is not a significant predictor of electricity usage intensity. Unexpectedly, tracts with a high median income are associated with a low gas usage intensity ($p < 0.05$ in SEM3). A likely explanation is that the thermal insulation level of the residential buildings in high income tracts is generally better, thereby reducing gas usage intensity. Finally, the results suggest a significant low gas usage intensity in tracts with highly privately owned dwelling units, which is consistent with the findings from other studies (e.g., Ndiaye and Gabriel 2011).

5. Discussion

There are still several limitations in this study. First, our data are aggregated to the census tract level, which means it is not possible to control for the detailed household level characteristics or individual behavior, or to generalize to the individual or the household level (Robinson 2011; Call and Voss 2016). In addition, the process of aggregating data will inevitably cause some loss of information or bias. Modifiable areal unit problem may be another issue; inferences drawn in this study may differ if the spatial unit changes, for example using a finer spatial resolution such as the census block. Nevertheless, several control variables (e.g. building age, and tenure type) are unavailable at finer spatial scale. Finally, the external validity of this study is still limited as it focuses on a single city in a single climate zone. Future research should evaluate various urban forms under various climates to obtain urban form strategies that produce net benefits for building energy efficiency in each climate (Ko 2013). In addition, future studies could include air temperature data at a very fine geographic scale, which is a more direct measure of urban heat island effect, to explore the pathways in which various urban forms and elements shape building energy efficiency.

Notwithstanding these limitations, this study contributes to the literature by establishing spatially explicit knowledge of various determinants of EUI at the census tract level, especially urban form and 3D geomorphometry variables that have not been extensively studied. Previous studies have established the linkage between urban ventilation variables (e.g., urban porosity, and roughness length) and urban climate (Gál and Unger 2009; Redacted; Coseo and Larsen 2014; Chun and Guhathakurta 2015; Chun and Guldmann 2014). Our study extends this linkage to the EUI in residential buildings, and also reveals their spatial spillover effects.

In consideration of building energy efficiency, this study validates that the consequence of compact development may be more complicated than generally expected. Efforts to examine the pros and cons of compact residential development must comprehensively consider solar insolation intensity, vegetation amount, and ventilation level (Redacted; Ko 2013; Quan et al. 2014; Quan et al. 2015). In the case Chicago, a highly compact development is generally associated with less radiation intensity per building volume, which can potentially decrease cooling EUI. On the contrary, compact residential subdivisions generally have low NDVI, thereby increasing cooling loads. Similar effects can be found in urban ventilation given that significant compact developments are associated with poor natural ventilation, which, in turn, increases cooling EUI in summer.

In order to isolate these pathways through which urban densification action could affect building energy efficiency, and to explore the net effect of urban densification policy on residential EUI, we use a 3x3 grid to better illustrate the various outcomes: the center grid represents the reference tract that will experience the urban form change in terms of building coverage ratio

(BCR) ; while the building coverage ratio of 8 neighboring tracts remain unchanged to better quantify the spillover effects of the densification policy of the reference tract. For simplicity's sake, we also assume the spatial weights of all the tracts are the same. Three densification scenarios are considered, with the BCRs of the reference tracts changed from 0.2 to 0.4, 0.4 to 0.6, and 0.6 to 0.8 respectively. We use the Loess Curve Fitting method[19] to trace the change of urban porosity, urban roughness length, NDVI, and isolation density associated with BCR increase of each densification scenario. Then we further quantify the annual electricity usage intensity (AEUI) change of each census tract based on the coefficients of relevant urban form and geomorphometry variables in our spatial regression results (Table 3). We do not quantify the gas usage intensity change since none of the urban form and geomorphometry variables are significant in the winter gas model.

Table 3
Annual Electricity Usage Intensity (AEUI) change of different densification scenarios (low, medium, high).

	NDVI induced EUI change (reference tract)	Insolation intensity induced EUI change (reference tract)	Porosity induced EUI change (neighboring tract)	Roughness length induced EUI change (neighboring tract)	Total EUI change (reference tract)	Total EUI change (neighboring tract)
Scenario 1(BCR:0.2-0.4)	3.54% (1.33%, 5.76%)	-12.16% (-15.21%, -9.10%)	0.97% (0.46%, 1.48%)	-0.89% (-1.20%, -0.59%)	-8.61% (-13.88%, -3.34%)	0.08% (-0.74%, 0.89%)
Scenario 2(BCR:0.4-0.6)	5.71% (2.15%, 9.27%)	-18.24% (-22.82%, -13.66%)	1.17% (0.56%, 1.79%)	1.36% (0.90%, 1.83%)	-12.53% (-20.67%, -4.39%)	2.53% (1.46%, 3.62%)
Scenario 3(BCR:0.6-0.8)	2.17% (0.82%, 3.53%)	-9.74% (-12.18%, -7.29%)	-0.34% (-0.51%, -0.16%)	5.19% (3.41%, 6.96%)	-7.57% (-11.36%, -3.76%)	4.85% (2.90%, 6.80%)

Note: 95% predication intervals in parentheses.

In scenario 1 (low-density scenario), increasing the BCR by 0.2 would bring about 8.61% AEUI decrease of the reference tract basically because less insolation intensity would decrease AEUI (-

12.16%); densification would decrease NDVI values, but this would only leads to 3.54% AEUI increase. In the low-density scenario, less insolation intensity level brought about by more mutual shading between buildings is the determining factor of improved AEUI; ventilation only play a minor role, as it only leads to 0.08% AEUI increase of the neighboring tract. In scenario 2 (medium-density scenario), ventilation becomes much more important, as densification leads to 2.53% AEUI increase of each neighboring tract because of less ventilation. This is a considerable effect since there are 8 neighboring tracts in our scenarios. Again, the AEUI improvement brought about by less insolation intensity (18.24%) is more than AEUI increase (5.74%) through less NDVI level. Thus, densification still leads to 12.53% AEUI improvement of the reference tract. In scenario 3 (high-density scenario), densification (increasing the BCR by 0.2) would cause huge adverse effects to the wind circulation level of the reference tract, which leads to 4.85% AEUI increase of each neighboring tract.

The results of this analysis provide evidence that, in the case of Chicago, densification strategy to increase the BCR would be desirable for the low-density tracts, but might not act as an effective policy to improve AEUI for existing medium- and high-density tracts since less ventilation would leads to AEUI increase of the neighboring tracts. This research suggests that the influence of ventilation works through adjacent tracts in reducing cooling energy intensity, especially in a city like Chicago with hot and humid summers. The spatial spillover effects must be carefully considered when developing these policy strategies in summer to reduce AEUI. For instance, the surface roughness must be kept low to potentially formulate the ventilation path, especially in dense urban environments (Barlag and Kuttler 1990; Gál and Unger 2009). The findings of this study suggest that urban ventilation should not be neglected for urban planning and design in cities with hot and humid climates.

The magnitude of the relationship between NDVI and summer EUI also provide empirical support for area-based requirement for tree-planting. Detailed design guidelines concerning the amount and placement of trees be set aside or replanted should be implemented for both new development and existing development with low NDVI (Stone and Rodgers 2001) for better residential energy performance. The findings of this study again highlight the importance of solar radiation management strategies in achieving high residential energy efficiency, as excessive isolation intensity is associated with more summer cooling energy consumption (Wilson 2013). Besides replying on reflective roofing and paving materials to enhance urban albedo[20] for radiation management, planners and urban designer should conduct solar radiation analysis at early stages of site plan and establish the linkage between isolation intensity and energy efficiency.

6. Conclusions

This study examined the impacts of urban form and geomorphometry on EUI in Chicago using 2D and 3D spatial information. Spatial regression models were estimated to explore the urban form and geomorphometry relevant drivers of residential EUI at the census tract level, as well as their spillover effects. The results confirm an evident role of various urban forms and geomorphometry elements in affecting residential electricity usage intensity. In the electricity EUI models, urban porosity and roughness length have consistent spillover effects on electricity usage intensity during summer and the whole year. Little evidence that NDVI has a similar spillover effect was found. However, NDVI can significantly reduce electricity usage intensity in its reference tract. Insolation intensity has a positive correlation with electricity usage intensity, especially in summer. The expected opposite effect of solar intensity is insignificant for winter gas usage intensity. The results also affirm the significant effects of proximity to large water body (Lake Michigan) in shaping summer electricity usage intensity. This study also provides a nuanced finding that, when controlling other important covariates, census tracts with a high percentage of old buildings are associated with a low electricity usage intensity and high gas usage intensity.

This study can also aid planners to think critically about low-carbon urban form and formulate spatially explicit policies/programs and regulations to improve residential energy efficiency through land use patterns. Neighborhood-based urban form should become part of the policies to promote sustainable energy consumption in conjunction with efforts to increase building energy efficiency at the building or household levels (e.g., building energy use benchmarking ordinance and weatherization assistance programs). Our findings indicate urban ventilation strategies (e.g., urban porosity requirement) could be useful for cities in the hot and humid climate zone. Planners and urban designers should consider the immediate context of the candidate sites during the design phase and evaluate the ventilation level of the surrounding neighborhoods. Furthermore, the neighborhood-based spatial policy, such as area-based tree-canopy requirements and solar radiation management strategies, should be carefully considered for better building energy performance. Land use strategies and designs that account for urban microclimates could be useful in reducing energy consumption of residential neighborhoods.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Notes

1. Geomorphometry refers to land surface analysis by extracting surface parameters and objects. This study specifically uses three-dimensional building data and existing digital elevation model to explore the factors affecting urban solar radiation and microclimate (e.g., urban heat island effect).

2. Aspect ratio is also referred to as H/W ratio. It measures the important geometrical detail about a street canyon, which is calculated as canyon height (H) divided by canyon width (W).

3. We thank the editor for this viewpoint.

4. The dataset can be downloaded at https://data.cityofchicago.org/Environment-Sustainable-Development/Energy-Usage-2010/8yq3-m6wp/data, which displays several units of energy consumption for households, businesses, and industries in the City of Chicago during 2010. It is also worthwhile to mention that, the residential electricity and natural gas data in Chicago is provided by ComEd and People Natural Gas with a consistent pricing scheme across the city. Thus, energy price was not considered as a factor that causes spatial variations in electricity/gas consumption across the city.

5. We only include winter gas EUI variable for gas consumption because residential gas in Chicago is mainly used for heating; in summer the EUI is quite low and annual EUI very close to

winter EUI. We do not include winter electricity EUI since it is not mainly used for heating, thus we cannot effectively evaluate the role of urban from and geomorphometry in influencing EUI.

6. Urban canopy layer is defined as the warm layer of air near the ground level in the urban microclimate literature.

7. In this study, building volume is roughly quantified as building footprint area multiplied by building height.

8. It is worthwhile to note that the roughness length index should be calculated with a wind direction defined. We calculated this index using eight cardinal and ordinal directions. We got the roughness length index for each plot by averaging the value for each direction using equal weights and calculated the mean value for each census tract.

9. The frontal area is the measurement of building walls facing the window flow in a particular direction. Please see Redacted (2014) and Gál and Unger (2009) for further details on how it is calculated in ArcGIS.

10. Insolation is the amount of solar radiation energy received on a given surface area during a given time. In this study, we divide the total radiation by total volume of buildings to calculate the solar insolation intensity index for residential building at census tract level for summer, winter, and the whole year.

11. The building height raster data was created using the 3D building database complied form Chicago City Data Portal and Open Street Map.

12. We used the mean value of the Normalized Difference Vegetation Index (NDVI) to measure the amount of vegetation cover at the census tract level. NDVI has previously been used in a

large body of urban heat island studies. Higher NDVI values indicate dense and healthy vegetation coverage, while lower NDVI values often indicate impervious surfaces in urban areas.

13. We calculated the summer, winter and NDVI using Landsat TM satellite images in July and December respectively. Annual NDVI was calculated as the mean value of Landsat TM satellite images in April, July, October, and December.

14. Building orientation was calculated by computing the main axis of each residential building polygon. Then the weighted arithmetic mean was calculated for each census tract, weighted by the total floor area of each building.

15. Multicollinearity amongst explanatory variables was examined using the variation inflation factor (VIF). The collinearity statistics (tolerance <1, VIF<10) suggests no significant multicollinearity issues with the OLS model.

16. The Moran's I values the residuals for annual electricity, summer electricity, and winter gas models are 0.166, 0.147, and 0.193 respectively, which are all significant at the 0.001 level.

17. Lagrange Multiplier statistics is commonly used as a tool to select appropriate spatial models among spatial error models, spatial lag models, and the combination of spatial lag and spatial error models. The common features of these three types of these spatial models are discussed extensively in basic econometric literature.

18. After adding the spatially lagged terms of urban porosity, roughness length, and NDVI, the Moran's I values the residuals for annual electricity, summer electricity, and winter gas OLS models are 0.125, 0.109, and 0.207 respectively, which are all significant at the 0.001 level. Again, the Robust Lagrange Multiplier statistics for standard error models are consistently

significant for electricity and gas models ($p < 0.001$), which further support the notion that there is unresolved spatial heterogeneity in the error terms after spatial lagged terms of urban porosity, roughness length, and NDVI are added.

19. Loess Curve Fitting was conducted in R to trace the relationship between BCR and relevant urban form and geomorphometry variables. Degree was set to 2 to better trace the nonlinear curves.

20. Albedo is the ratio of the amount of solar radiation reflected by a surface feature to the amount incident upon it. A typical example to increase albedo in urban areas is New York City's CoolRoofs program:http://www.nyc.gov/html/coolroofs/downloads/pdf/annual_report_2013.pdf.

References

Andrews, Clinton J., and Uta Krogmann. 2009a. "Explaining the Adoption of Energy-Efficient Technologies in U.S. Commercial Buildings." *Energy and Buildings* 41 (3): 287–94. doi:10.1016/j.enbuild.2008.09.009.

Andrews, Clinton J., and Uta Krogmann. 2009b. "Technology Diffusion and Energy Intensity in US Commercial Buildings." *Energy Policy* 37 (2): 541–53. doi:10.1016/j.enpol.2008.09.085.

Baker, Keith J., and R. Mark Rylatt. 2008. "Improving the Prediction of UK Domestic Energy-Demand Using Annual Consumption-Data." *Applied Energy* 85 (6): 475–82. doi:10.1016/j.apenergy.2007.09.004.

Barlag, A. B., and W. Kuttler. 1990. "The Significance of Country Breezes for Urban Planning." *Energy and Buildings* 15 (3–4): 291–97. doi:10.1016/0378-7788(90)90001-Y.

Bowler Buyung-Ali, L., Knight, T.M., and Pullin, A.S., D E. 2010. "Urban Greening to Cool Towns and Cities: A Systematic Review of the Empirical Evidence." *Landscape and Urban*

Planning In Press,. doi:Yes.

Burghardt, René. 2014. “Development of an ArcGIS Extension to Model Urban Climate Factors Development of an ArcGIS Extension to Model Urban Climate Factors,” no. September.

Call, Maia A., and Paul R. Voss. 2016. “Spatio-Temporal Dimensions of Child Poverty in America, 1990–2010.” *Environment and Planning A* 48 (1): 172–91. doi:10.1177/0308518X15597907.

Catalina, Tiberiu, Joseph Virgone, and Eric Blanco. 2008. “Development and Validation of Regression Models to Predict Monthly Heating Demand for Residential Buildings.” *Energy and Buildings* 40 (10): 1825–32. doi:10.1016/j.enbuild.2008.04.001.

Chang, Heejun, G Hossein Parandvash, and Vivek A Shandas Nohad Toulan. 2010. “Spatial Variations of Single-Family Residential Water Consumption.” *Urban Geography* 31 (7): 953–72. doi:10.2747/0272-3638.31.7.953.

Chen, Jun, Xiaohong Wang, and Koen Steemers. 2013. “A Statistical Analysis of a Residential Energy Consumption Survey Study in Hangzhou, China.” *Energy and Buildings* 66. Elsevier B.V.: 193–202. doi:10.1016/j.enbuild.2013.07.045.

Chen, Yen-Jong, Rodney H Matsuoka, and Tzu-Min Liang. 2017. “Urban Form, Building Characteristics, and Residential Electricity Consumption: A Case Study in Tainan City.” *Environment and Planning B: Urban Analytics and City Science*, no. 1: 239980831769015. doi:10.1177/2399808317690150.

Chong, Howard. 2012. “Building Vintage and Electricity Use: Old Homes Use Less Electricity in Hot Weather.” *European Economic Review* 56 (5): 906–30. doi:10.1016/j.euroecorev.2012.02.009.

Chun, B, and J Guldmann. 2014. “Landscape and Urban Planning Spatial Statistical Analysis and Simulation of the Urban Heat Island in High-Density Central Cities.” *Landscape and Urban Planning* 125. Elsevier B.V.: 76–88. doi:10.1016/j.landurbplan.2014.01.016.

Chun, B, and S Guhathakurta. 2015. “Daytime and Nighttime Urban Heat Islands Statistical Models for Atlanta.” *Environment and Planning B: Planning and Design* . doi:10.1177/0265813515624685.

Cooper, J., T. Ryley, and A. Smyth. 2001. “Energy Trade-Offs and Market Responses in Transport and Residential Land-Use Patterns: Promoting Sustainable Development Policy.” *Urban Studies* 38 (9): 1573–88. doi:10.1080/00420980126673.

Coseo, Paul J. 2013. “Evaluating Neighborhood Environments for Urban Heat Island Analysis and Reduction By.”

Coseo, Paul, and Larissa Larsen. 2014. “How Factors of Land Use/Land Cover, Building Configuration, and Adjacent Heat Sources and Sinks Explain Urban Heat Islands in Chicago.” *Landscape and Urban Planning* 125. Elsevier B.V.: 117–29. doi:10.1016/j.landurbplan.2014.02.019.

EIA. 2018. “August 2018.” *August 2018 Monthly Energy Review*. Vol. 35. doi:10.1002/da.22823.

Estiri, Hossein. 2015. “Energy Research & Social Science A Structural Equation Model of Energy Consumption in the United States : Untangling the Complexity of per-Capita Residential Energy Use.” *Energy Research & Social Science* 6. Elsevier Ltd: 109–20. doi:10.1016/j.erss.2015.01.002.

Ewing, Reid, and F. Rong. 2008. “The Impact of Urban Form on US Residential Energy Use.” *Housing Policy Debate* 19 (1): 1–30. doi:10.1080/10511482.2008.9521624.

Filippín, C., F. Ricard, and S. Flores Larsen. 2013. “Evaluation of Heating Energy Consumption Patterns in the Residential Building Sector Using Stepwise Selection and Multivariate Analysis.” *Energy and Buildings* 66: 571–81. doi:10.1016/j.enbuild.2013.07.054.

Gál, T., and J. Unger. 2009. “Detection of Ventilation Paths Using High-Resolution Roughness Parameter Mapping in a Large Urban Area.” *Building and Environment* 44 (1): 198–206. doi:10.1016/j.buildenv.2008.02.008.

Holden, Erling, and Ingrid Norland. 2005. “Three Challenges for the Compact City as a Sustainable Urban Form: Household Consumption of Energy and Transport in Eight Residential Areas in the Greater Oslo Region.” *Urban Studies* 42 (12): 2145–66. doi:10.1080/00420980500332064.

Høyer, Karl G., and Erling Holden. 2003. “Household Consumption and Ecological Footprints in

Norway – Does Urban Form Matter?” *Journal of Consumer Policy* 26 (3): 327–49. doi:10.1023/A:1025680422704.

Hsu, David. 2014. “Improving Energy Benchmarking with Self-Reported Data.” *Building Research and Information* 42 (5): 641–56. doi:10.1080/09613218.2014.887612.

Hsu, David, Ting Meng, Albert Han, and Daniel Suh. 2017. “Further Opportunities to Reduce the Energy Use and Greenhouse Gas Emissions of Buildings.” *Journal of Planning Education and Research*, 0739456X1773967. doi:10.1177/0739456X17739674.

Jones, Rory V., Alba Fuertes, and Kevin J. Lomas. 2015. “The Socio-Economic, Dwelling and Appliance Related Factors Affecting Electricity Consumption in Domestic Buildings.” *Renewable and Sustainable Energy Reviews* 43. Elsevier: 901–17. doi:10.1016/j.rser.2014.11.084.

Ko, Yekang. 2013. “Urban Form and Residential Energy Use: A Review of Design Principles and Research Findings.” *Journal of Planning Literature* 28 (4): 327–51. doi:10.1177/0885412213491499.

Ko, Yekang, and John D. Radke. 2014. “The Effect of Urban Form and Residential Cooling Energy Use in Sacramento, California.” *Environment and Planning B: Planning and Design* 41 (4): 573–93. doi:10.1068/b12038p.

Kontokosta, Constantine E., and Christopher Tull. 2017. “A Data-Driven Predictive Model of City-Scale Energy Use in Buildings.” *Applied Energy* 197. Elsevier Ltd: 303–17. doi:10.1016/j.apenergy.2017.04.005.

Larivière, Isabelle, and Gaëtan Lafrance. 1999. “Modelling the Electricity Consumption of Cities: Effect of Urban Density.” *Energy Economics* 21 (1): 53–66. doi:10.1016/S0140-9883(98)00007-3.

Lee, Sungwon, and Bumsoo Lee. 2014. “The Influence of Urban Form on GHG Emissions in the U.S. Household Sector.” *Energy Policy* 68. Elsevier: 534–49. doi:10.1016/j.enpol.2014.01.024.

Lutzenhiser, Loren. 1992. “A Cultural Model of Household Energy Consumption.” *Energy* 17 (1): 47–60. doi:10.1016/0360-5442(92)90032-U.

Lutzenhiser, Loren. 1993. “Social and Behavioral Aspects of Energy Use.” *Annual Review of Energy and the Environment* 18 (1): 247–89. doi:10.1146/annurev.eg.18.110193.001335.

Mardookhy, Minoo, Rapinder Sawhney, Shuguang Ji, Xiaojuan Zhu, and Wenjun Zhou. 2014. “A Study of Energy Efficiency in Residential Buildings in Knoxville, Tennessee.” *Journal of Cleaner Production* 85: 241–49. doi:10.1016/j.jclepro.2013.09.025.

Meng, Ting, David Hsu, and Albert Han. 2017. “Estimating Energy Savings from Benchmarking Policies in New York City.” *Energy* 133: 415–23. doi:10.1016/j.energy.2017.05.148.

Min, Jihoon, Zeke Hausfather, and Qi Feng Lin. 2010. “A High-Resolution Statistical Model of Residential Energy End Use Characteristics for the United States.” *Journal of Industrial Ecology* 14 (5): 791–807. doi:10.1111/j.1530-9290.2010.00279.x.

Nakata-Osaki, Camila Mayumi, Léa Cristina Lucas Souza, and Daniel Souto Rodrigues. 2018. “THIS – Tool for Heat Island Simulation: A GIS Extension Model to Calculate Urban Heat Island Intensity Based on Urban Geometry.” *Computers, Environment and Urban Systems* 67 (October 2017). Elsevier: 157–68. doi:10.1016/j.compenvurbsys.2017.09.007.

Ndiaye, Demba, and Kamiel Gabriel. 2011. “Principal Component Analysis of the Electricity Consumption in Residential Dwellings.” *Energy and Buildings* 43 (2–3): 446–53. doi:10.1016/j.enbuild.2010.10.008.

Norman, Jonathan, Heather L. MacLean, and Christopher a. Kennedy. 2006. “Comparing High and Low Residential Density: Life-Cycle Analysis of Energy Use and Greenhouse Gas Emissions.” *Journal of Urban Planning and Development* 132 (1): 10–21. doi:10.1061/(ASCE)0733-9488(2006)132:1(10).

Pérez-Lombard, Luis, José Ortiz, and Christine Pout. 2008. “A Review on Building Energy Consumption Information.” *Energy and Buildings* 40 (3): 394–98. http://dx.doi.org/10.1016/j.enbuild.2007.03.007.

Perez-Lombard, Ortiz and Pout 2008. 2008. “A Review on Buildings Energy Consumption Information ´” 40: 394–98. doi:10.1016/j.enbuild.2007.03.007.

Quan, Steven Jige, Athanassions Economou, Thomas Grasl, and Perry Pei Ju Yang. 2014. “Computing Energy Performance of Building Density, Shape and Typology in Urban

Context." In *Energy Procedia*, 61:1602–5. doi:10.1016/j.egypro.2014.12.181.

Quan, Steven Jige, Qi Li, Godfried Augenbroe, Jason Brown, and Perry Pei-ju Yang. 2015a. "Urban Data and Building Energy Modeling: A GIS-Based Urban Building Energy Modeling System Using the Urban-EPC Engine." In *Planning Support Systems and Smart Cities*, 447–69. doi:10.1007/978-3-319-18368-8.

Quan, Steven Jige, Qi Li, Godfried Augenbroe, Jason Brown, and Perry Pei-Ju Yang. 2015b. "Urban Data and Building Energy Modeling : A GIS-Based Urban Building Energy Modeling System Using the Urban-EPC Engine." In *Planning Support Systems and Smart Cities*, edited by Stan Geertman, Joseph Jr Ferreira, Goodspeed Robert, and John Stillwell, 447–69. Cham, Switzerland: Springer International Publishing. doi:10.1007/978-3-319-18368-8.

Ramesh, T., Ravi Prakash, and K. K. Shukla. 2010. "Life Cycle Energy Analysis of Buildings: An Overview." *Energy and Buildings* 42 (10): 1592–1600. doi:10.1016/j.enbuild.2010.05.007.

Robinson, W. S. 2011. "Ecological Correlations and the Behavior of Individuals." *International Journal of Epidemiology*. doi:10.1093/ije/dyr082.

Rode, Philipp, Christian Keim, Guido Robazza, Pablo Viejo, and James Schofield. 2014. "Cities and Energy: Urban Morphology and Residential Heat-Energy Demand." *Environment and Planning B: Planning and Design* 41 (1): 138–62. doi:10.1068/b39065.

Scofield, John. 2014. "ENERGY STAR Building Benchmarking Scores: Good Idea, Bad Science." *ACEEE Summer Study on Energy Efficiency in Buildings,* 267–82. files/4565/3-725.pdf.

Shi, Yuan, Lutz Katzschner, and Edward Ng. 2017. "Science of the Total Environment Modelling the Fine-Scale Spatiotemporal Pattern of Urban Heat Island Effect Using Land Use Regression Approach in a Megacity." *Science of the Total Environment*. Elsevier B.V. doi:10.1016/j.scitotenv.2017.08.252.

Steemers, Koen. 2003. "Energy and the City: Density, Buildings and Transport." *Energy and Buildings* 35 (1): 3–14. doi:10.1016/S0378-7788(02)00075-0.

Steeneveld, G. J., S. Koopmans, B. G. Heusinkveld, L. W. A. van Hove, and A. A. M. Holtslag. 2011. "Quantifying Urban Heat Island Effects and Human Comfort for Cities of Variable Size and Urban Morphology in the Netherlands." *Journal of Geophysical Research* 116 (D20): D20129. doi:10.1029/2011JD015988.

Stone, Brian, and Michael O. Rodgers. 2001. "Urban Form and Thermal Efficiency: How the Design of Cities Influences the Urban Heat Island Effect." *Journal of the American Planning Association* 67 (2): 186–98. doi:10.1080/01944360108976228.

Swan, Lukas G, and V Ismet Ugursal. 2009. "Modeling of End-Use Energy Consumption in the Residential Sector : A Review of Modeling Techniques" 13: 1819–35. doi:10.1016/j.rser.2008.09.033.

Tiwari, Piyush. 2000. "Architectural, Demographic, and Economic Causes of Electricity Consumption in Bombay." *Journal of Policy Modeling* 22 (1): 81–98. doi:10.1016/S0161-8938(98)00003-9.

Wedding, G. Christopher, and Douglas Crawford-Brown. 2007. "Measuring Site-Level Success in Brownfield Redevelopments: A Focus on Sustainability and Green Building." *Journal of Environmental Management* 85 (2): 483–95. doi:10.1016/j.jenvman.2006.10.018.

Wilson, Bev. 2013. "Urban Form and Residential Electricity Consumption: Evidence from Illinois, USA." *Landscape and Urban Planning* 115. Elsevier B.V.: 62–71. doi:10.1016/j.landurbplan.2013.03.011.