Towards Smarter Cities: Linking Human Mobility and Energy Use Fluctuations across Building Types

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Abstract

Urban areas consume up to 80 percent of the world's total energy production and are growing in size and complexity. At present, urban building energy consumption is largely considered solely in terms of individual building types, neglecting the effects of residents' location-based activities that influence patterns in energy supply and demand. Here, we examine the spatial fluctuations of these effects. A spatial regression analysis of 3,613,360 positional records containing human mobility and energy consumption data across 983 areas in Greater London and 801 areas in the City of Chicago in residential and commercial buildings over the course of one month revealed spatial dependencies for both residential and commercial buildings' energy consumption on human mobility. This dependency represents a strong connection with residential buildings' energy consumption, with a spatial spillover effect. Future energy efficiency strategies should thus reflect the spatial dependencies, creating new ways for residential buildings to play a major role in energy related strategies.

1. Introduction

Urban areas now consume up to 80% of all the energy produced each year [17, 19]. This dominance raises concerns over continually increasing consumption rates and the future security of the energy supply in urban settings. In particular, residential and commercial buildings are the largest energy-consuming sectors in the economy [20] and are responsible for over one-third of the world [20], 41% of the US [10], and 40% of Europe's [11] total energy consumption. This makes our urban buildings prime targets for energy efficiency initiatives and renewable energy investment.

Researchers seeking new ways to reduce residential and commercial energy consumption continue to create effective approaches to managing supply, demand, and distribution. But, identifying opportunities for energy saving in buildings and developing the ability to reliably project future energy demands requires an holistic understanding of all the factors that contribute to consumption rates. Residential and commercial buildings each present their own unique challenges but also unique opportunities for energy efficient investments that will achieve significant reductions in both energy and emissions. Globally, total energy demand is expected to rise by more than 25% between 2010 and 2040 based on current projections [23]. In its latest Annual Energy Outlook report, the U.S. Energy Information Administration projects annual decreases of 0.3% in residential energy consumption but increases of 0.6% per year in the commercial sector from 2013 through 2040 [10]. These projections are based on the characteristics of the buildings themselves and are independent of their location, focusing on measures such as appliance efficiency, commercial Combined Heat Power (CHP) use, aggregate commercial square footage, and/or increased use of electricity over natural gas for buildings [10]. However, these projected consumption trends for residential and commercial buildings are sure to be subject to exogenous effects if spatial dependencies do in fact exist. Identifying driving forces for energy consumption using a linear regression perspective assumes that buildings are independent of each other in terms of the way they consume energy in urban areas. But, if there are such spatial dependencies, this approach overestimates the degrees of freedom and can lead us to believe that some of the coefficients affecting energy consumption are significant when they are not.

This issue becomes especially pressing in urban settings, with their expected population increase of nearly 70% by 2050 [33]. A growth of this magnitude, with the accompanying expansion of human activities, will directly drive increases in the number of buildings, energy consumption, and service utilization. Therefore, developing a better understanding of the driving factors governing buildings' energy consumption that goes

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beyond their mere physical characteristics and takes into account occupant-driven effects within the spatial context in which they exist is rapidly becoming imperative. “People and Communities” [9] are a critical part of smart cities, which have been traditionally overshadowed by the importance of technological advancements [4, 9]. Their participation in the governance and management of the city [9] can create opportunities for reducing energy consumption and CO_2 emissions. Urban populations engage in a wide range of daily activities spread across various locations, so their energy consumption patterns will typically be associated with these location-based activities. As yet, it is unclear whether this creates any spatial dependency in buildings’ energy consumption in urban areas. More significantly, do these dependencies fluctuate across building type? And, if so, are human activities an exogenous variable that can explain these dependencies?

This study investigates the significance of urban spatial effects on building energy consumption by exploring the underlying spatial reliance and developing a deeper understanding of whether a similar spatial dependency exists in human mobility as an indicator for urban human activities. Overlooking urban spatial effects when estimating building energy consumption can lead to unreliable predictions and poor management decisions, jeopardizing efficiency strategies and investments.

2. Background

Much scientific work has focused on the factors driving building energy consumption at the urban scale. However, a careful examination of the existing literature reveals two striking omissions: buildings’ urban spatial context is seldom considered, so spatially dependent drivers of their energy consumption across building types are neglected; and the exogenous drivers and externalities that may exist due to different types of buildings’ spatial dependencies are not reflected in their energy consumption measures. In particular, spatial effects due to human activities have received little attention.

Shimoda et al. [30] performed a city-scale simulation for energy consumption in residential buildings based on their appliances and occupants’ activities to evaluate the effects of conservation measures in this sector. In another effort to explain variations of energy consumption in residential buildings, Kavousian et al. [21] considered external conditions such as weather and building location in their statistical model measuring the underlying determinants of daily energy use. These efforts reaffirm the need to assess the energy consumption of buildings in their urban context, taking into account their existing surroundings and any urban dynamics they are likely to encounter. However, being exclusive to a single building type, these studies have overlooked the spatially dependent variations of energy consumption across building types. It is of particular interest how individuals’ energy consumption during their daily activities, from both exclusive and shared resources, varies across building types. It is not yet clear whether energy consumption measures for different building types have any dependency on their location.

In a recent study in Switzerland, Fonseca and Schlueter [13] proposed an integrated model to characterize city-scale spatiotemporal energy consumption patterns and examined the fluctuations of consumption in residential, commercial and industrial sectors across urban districts. In an attempt to quantify future energy demands for buildings in their urban context, Choudhary [20] introduced a city-scale Bayesian model to illustrate the distribution and variations in the patterns of energy consumption across commercial buildings based on information on the existing building stock in Greater London. Developing this approach further, Choudhary and Tian [8] examined the spatial fluctuations of commercial buildings across various districts in Greater London to reveal the effects of city location and district features in comparison to the buildings’ physical characteristics, which resulted in a significant decrease in the uncertainties associated with evaluating the energy consumption of different building types. Howard et al. [18] estimated the end-use intensity of various building types in New York City using a linear regression model, based on the assumption that energy consumption primarily depends on the building’s function (e.g., residential, educational, etc.) rather than the construction type or age of the building. Such efforts conspicuously lack any explicit consideration of external drivers in variations of residential and commercial energy consumption as a result of spatial dependencies.

Information on human mobility has been used to infer location choices for daily activities and to strategize optimal accessibility to amenities [15, 32]. One recent study has proposed a method to identify clustered locations in urban areas where individuals engage in activities, inferred to be either home, work, or “other”, from human mobility data [1]. Taking advantage of the new availability of large-scale human mobility data, one of the most widely used indicators of human activities, recent research has found spatial dependencies between human mobility and building energy consumption [24]. Others have sought to analyze human mobility data to identify the energy implications of such activities in urban areas [29, 35]. As yet, however, we lack a comprehensive understanding of whether these dependencies fluctuate by building type (i.e., residential and commercial). Can intra-urban mobility thus be used to explain variations in urban energy consumption across building types?

Table 1. Data

	Greater London			**City of Chicago**		
Data	Electricity/Gas (kWh)	Digital Boundaries	Positional Records[2]	Electricity/ Gas(kWh)	Digital Boundaries	Positional Records[2]
Spatial Scale	MSOA(983)[1]		2,367,967	Census Tract		1,245,360
Temporal Scale	2013	2011	2014	2010	2010	2014
Organization	**DECC** (Dept. of Energy & Climate Change)	**GLA** (Greater London Authority)	**Twitter**	**data.cityofchicago.org**		**Twitter**

[1]Middle Layer Super Output Areas (983)—MSOA: Min Population 5000, with an Overall Mean of 7200,
[2] Public Twitter Stream API Twitter: https://dev.twitter.com/streaming. This dataset remains in compliance with Twitter's non-disclosure agreement. Any accessibility request may be referred to the corresponding author.

This study assessed the energy consumption in residential and commercial buildings in Greater London in their spatial context, which is attributable to individuals' urban mobility. As an initial step, the impact of human interactions with urban buildings (residential and commercial) was explored through spatial autocorrelation analyses. We provide an assessment that reports on two main findings. First, there are spatial dependencies for urban energy consumption (electricity and gas) in both residential and commercial buildings. Second, there are spatial dependencies for urban human mobilities representing the underlying location-based human activities, and likely to explain location-based urban energy consumptions. Accurate energy consumption and demand projections in the future are thus likely to require a shift toward more location-based estimations that are tailored to take into account human mobility.

3. Method

3.1. Data

This study examined spatial autocorrelations for electricity and gas consumption data for 983 areas and 2,367,967 positional records in Greater London; as well as 1,245,360 positional records across 801 areas in the City of Chicago accounting for human mobility, as summarized in Table 1. The positional records dataset is collected by the authors [34] through the public Twitter Stream API. The MSOA (middle layer super output area) and Census Tract administrative boundaries for Greater London [27] and the City of Chicago were used as spatial levels. Our positional record data was collected from individuals who have voluntarily publicly shared location-enabled information for their Twitter accounts in Greater London and the City of Chicago and any results in this study are representative of this population.

MSOA and Census Tract-level energy consumption (electricity and gas) data for the 983 digital boundaries were obtained from the Department of Energy and Climate Change (Greater London) and the City of Chicago online datasets, which included both residential and commercial buildings. These datasets are publicly available through the corresponding organization's website and were processed to appropriate formats by the authors. Any accessibility request may be directed to the aforementioned organizations or the corresponding author.

The commercial gas consumption datasets contained less than 20 missing data values. Kriging prediction [3] was used to compensate for the missing gas consumption data under the assumption that this data was missing completely at random. Median gas consumption by location was treated as point-referenced data in this prediction process. Based on the semivariogram specifications of the commercial gas consumption data, six covariance models (i.e., Spherical, Matern, Exponential, Cubic, Circular, and Cauchy) were examined in identifying the best-fitted model using maximum likelihood estimation. Finally, the covariance model which deemed the most appropriate, the circular covariance model, was used to compensate for the missing data based on its least Akaike Information Criterion (AIC) value in the fitting process. A combination of open access packages was used from the Python programming language (e.g., *tweepy*) and R (e.g., s*spdep*) software environment for the data processing, graphics and statistical analysis performed in this study. We expect the effects from predicting these missing data to be proportionally marginal.

3.2. Radius of gyration

We opted to capture individuals' characteristic distance of their intra-urban mobility using a widely accepted indicator of large-scale human mobility, the radius of gyration $r_g(t)$ [5, 16, 31]:

$$\vec{p}_{centroid} = \frac{1}{n}\sum_{i=1}^{n}\vec{p}_i \tag{1}$$

$$r_g = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\vec{p}_i - \vec{p}_{centroid}\right)^2} \tag{2}$$

The radius of gyration $r_g(t)$ was calculated (Eq. 2) at two spatial and two temporal levels. As the individual level $r_{gi}(t)$ represents the characteristic distance traveled by a user when observed up to time t [16], every MSOA/Census Tract-level $r_{ga}(t)$ represents the deviation of the $r_{gi}(t)$s from their corresponding center point (Eq. 1). This indicator was then used to describe patterns of human mobility across spatial divisions.

3.3. Spatial autocorrelation

The correlation between energy consumption and human mobility variables (i.e., radius of gyration) in the spatial dimension was measured through spatial autocorrelation statistics [12] based on both feature locations and feature values simultaneously. Spatial autocorrelation exists when energy consumption or human mobility exhibit a regular pattern over space, in which their values at a particular location depend on the values at the surrounding points. The arrangement of values is thus not simply random. Moran's I [26] (Eq.3), an indicator for spatial autocorrelation that compares the value of a variable at one location with the values at all other locations, is a test of non-independence for whether values of human mobility or energy consumption observed in one location depend on values observed at neighboring locations. Ranging from –1 (most dispersed) to 1 (most clustered), Moran's I describes the degree of spatial concentration or dispersion for those variables with larger values for I, showing clusters of larger values being surrounded by other large values (I+) –spatial clustering, and (I–) – spatial dispersion, showing larger values being spatially enclosed by smaller values. We used Moran's I as a measure of sensitivity to extreme values of energy consumption and human mobility. Further, ranging from 0 (maximum positive autocorrelation) to 2 (maximum negative autocorrelation), with 1 indicating an absence of correlation, Geary's C [14] (Eq. 4) is also used to examine the sensitivity to differences in among spatial divisions.

$$I = \frac{N\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3}$$

$$C = \frac{N\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - x_j)^2}{2(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{4}$$

In both expressions for the Moran's I and Geary's C, n represents observations on variable x at locations i, j, where $\bar{x}$ is the mean of the x variable, and w_{ij} are the elements of the weight matrix.

3.4. Spatial regression

Spatial regression models include relationships between variables and their neighboring values and allow us to examine the impact that one observation has on other proximate observations and account for dependence between observations. Energy use in different points in space (i.e., areas of a city) cannot be regarded as being independent of each other in a simple regression analysis. This also holds true for urban human mobility. To avoid unrealistic estimates for energy consumption and take into account its dependency on human mobility (i.e., human activities), we used the Simultaneous Autoregressive (SAR) model to specify the spatial dependencies between energy consumption and human mobility. Further, we examined the spatial spillover effects and took into account externality, and thus discrepancies between residential and commercial energy consumption. Spillover effects in an economic context are regarded as events (i.e., energy consumptions) that occur because of something else (i.e., human mobility) in a seemingly unrelated context [2]. Distinguishing between a *global* and a *local* range of dependence, Anselin [2] introduces the concept of *global* spillover as one in which "every location is correlated with every other location in the system, but closer locations are more so." This relates all the locations in the system to each other and implies that changes that are occurring in a characteristic of one area will also have an impact on all the other areas. To test for the presence of spatially significant spillovers in both commercial and residential buildings, if indeed such things exist, we compared changes in human mobility with electricity and gas consumption patterns.

4. Results

4.1. Spatial dependencies

4.1.1. Human mobility. Figures 1(a) depicts the spatial distribution of human mobility in Greater London and the City of Chicago. Statistically significant (*p-value < 2.2e-16*) and positive values for *I* and *C* (*I = 0.21397, C = 0.79039*) indicate that these mobility patterns in Greater London follow a clustering distribution as opposed to a dispersed or random distribution. A similar condition holds true for the City of Chicago (*p-value < 2.86e-16; I*= 0.79039) Thus, we reject the Moran's *I* null hypothesis: the attributes being analyzed—in this case, human mobility—are randomly distributed among the features in the study area. The distribution of high values and/or low values for human mobility are more spatially clustered. As further illustrated in the four quadrants of the Moran Scatter Plot in Figures 1(b), we can classify four types of spatial autocorrelation for human mobility, suggesting a positive spatial dependence.

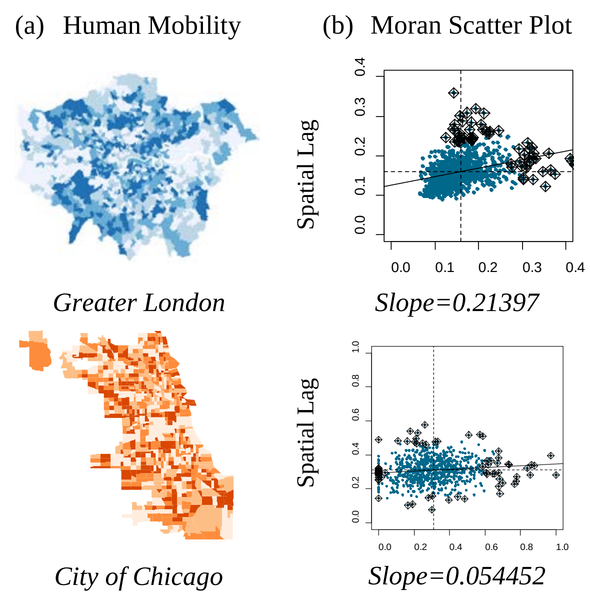

Figure 1. (a) Distribution of human mobility, (b) Moran scatter plot.

The slope of the regression line corresponds to Moran's *I* values (*Greater London: I = 0.21397; City of Chicago: I = 0.054452*). Areas of significance are the high-high (upper right), and low-low (lower left) datasets produced in the Moran analysis, both of which have significant Local Moran statistics with positive autocorrelations. The positive autocorrelation for the high-high scatter plot quadrant areas can be interpreted as clusters of regions with high human mobility, which are clustered with and depend on neighboring regions with high human mobility; low-low quadrants areas are those MSOA/Census Tracts with low human mobility that are clustered with and depend on other low human mobility areas. Similarly, we reject the null hypothesis of zero spatial autocorrelation, with the values of *C* between 0 and 1 indicating a positive correlation for human mobility compared to what can be expected from a randomly distributed mobility pattern. This implies that human mobility measures with similar attribute values are closely distributed (clustered) in space.

4.1.2. Energy consumption in residential buildings. Similar spatial autocorrelation analyses were performed for energy consumption in residential buildings across 983 MSOAs in Greater London, as well as 801 Census Tracts in the City of Chicago, for both electricity and gas consumption. We found statistically significant (*p-value < 2.2e-16*) results for both Moran's *I* and Geary's *C*, which indicate spatial dependencies for both electricity (*I = 0.406737, C = 0.60179*) and gas consumption (*I = 0.423920, C = 0.57495*). Positive autocorrelations are illustrated in Moran Scatter Plots, Figures 2(a) and 3(a), while statistically significant values are shown in Table 2 (Moran's *I*), and Table 3 (Geary's *C*).

Table 2. Spatial autocorrelation –Moran's *I*, Greater London.

		Statistic	*p*-value	Std.
Human Mobility		0.21397	< 2.2e-16	11.308
Elec	Residential	0.406737	< 2.2e-16	21.323
	Commercial	0.145925	7.759e-15	7.683
Gas	Residential	0.423920	< 2.2e-16	22.223
	Commercial	0.083444	4.707e-06	4.430

Similarly, as depicted in Table 4, statistically significant Moran's *I* values were found for energy consumption in the City of Chicago. The only exception in this case is the residential gas consumption. This condition is expected to be due to seasonal effects, meaning that gas consumption may have reduced significantly during the warmer months (i.e., August) in residential buildings in the City of Chicago. Therefore, the spatial structure observed for the average values of gas consumption in residential building across the 801 spatial divisions fails to reveal statistical significance.

4.1.3. Energy consumption in commercial buildings. We also performed spatial autocorrelation analyses for energy consumption in commercial buildings across 983 MSOAs in Greater London and 801 Census Tracts in the City of Chicago. We found statistically significant results for both Moran's *I* and Geary's *C*, again indicating spatial dependencies for both electricity (*I = 0.145925, C = 0.86391*) and gas consumption (*I = 0.083444, C = 0.90085)*. Positive autocorrelations are illustrated in Moran Scatterplots (Figures 2(b) and 3(b)). In the case of commercial buildings, both electricity and gas consumption resulted in statistically significant Moran's *I* values, confirming the presence of an underlying spatial structure for energy consumption in commercial buildings in the city of Chicago (Table 4).

Table 3. Geary's *C*, Greater London.

		Statistic	*p*-value	Std.
Human Mobility		0.79039	<2.86e-16	8.095
Elec.	Residential	0.60179	< 2.2e-16	19.322
	Commercial	0.86391	1.451e-11	12.88
Gas	Residential	0.57495	< 2.2e-16	20.575
	Commercial	0.90085	1.219e-05	4.220

Table 4. Moran's *I*, City of Chicago.

		Statistic	*p*-value	Std.
Human Mobility		0.054452	0.002666	2.7862
Elec.	Residential	0.120726	1.003e-13	7.3484
	Commercial	0.083960	1.81e-06	4.6324
Gas	Residential	0.012735	0.1564	1.0093
	Commercial	0.064632	4.548e-05	3.9135

Having found spatial dependencies and clustering distribution for both human mobility and energy consumption in residential and commercial buildings across urban areas in Greater London, we performed further spatial regression analyses to examine whether a spatial regressive model can describe meaningful relationships between the two distributions. The following section describes the statistical methods used to describe the relationships between MSOA/Census Tract-level $r_{ga}(t)$s and the corresponding energy consumption, including spatial regression analysis.

4.2. Human mobility, predictive of energy consumption

To model the spatial interdependencies of our datasets, via an autoregressive model we implicitly incorporated the spatial dependence of the human mobility data into the covariance structure. The autoregressive model for areal data tested in this study is the SAR model, which represents global dependency conditions.

In simultaneous models, exogenous variables (in this case, human mobility) are used to explain the entire spatial pattern of a dependent variable (i.e., energy consumption). We used this model to produce spatial dependence in the covariance structure as a function of fixed parameters such as the number of energy meters per MSOA/Census Tract to examine various conditions.

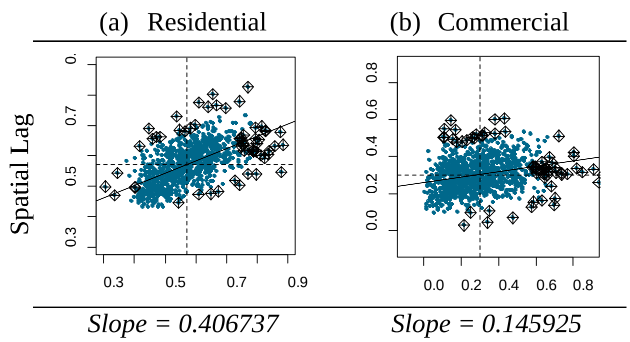

Figure 2. Moran scatter plot –electricity consumption, Greater London.

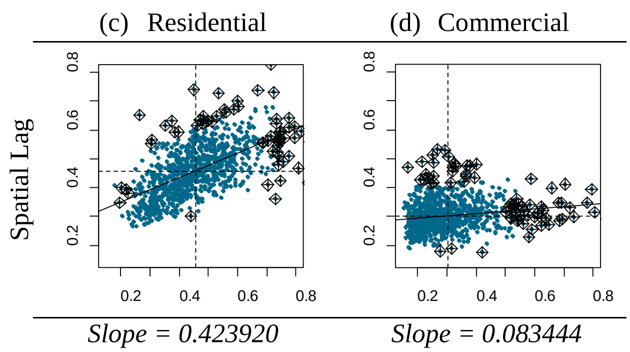

Figure 3. Moran scatter plot –gas consumption, Greater London.

These models explicitly test the impact of human mobility variables on the consumption of electricity and gas. At a global scale, the SAR model allows us to incorporate the dependence between observations that are in close geographical proximity. It is then possible to infer the pattern for all locations as a function of exogenous variables. Lower AIC values for residential energy consumption (i.e., electricity, 16008, and gas, 18023) versus commercial energy consumption (i.e., electricity, 20243, and gas, 24641) in the case of Greater London imply stronger dependencies for human mobility and energy consumption in these buildings. Likewise, for the City of Chicago, electricity consumption in residential buildings represents the strongest correlations with the smallest AIC (-2732.4) among others. Tables 5 show the spatial regression results from the SAR model for energy consumption (electricity (a) and gas (b)) per human mobility for both commercial and residential buildings in Greater London and the City of Chicago over the course of the month of August.

All spatial parameters are statistically significant, as indicated by *p*-values lower than 0.0001 for both electricity and gas consumption in residential and commercial buildings in Greater London, and the City of Chicago (Table 5). Figure 4 shows the spatial distribution of the observed values and those of the fitted SAR model in residential and commercial buildings for electricity (a) and gas (b) consumption, respectively.

5. Discussion

These results highlight the substantial influence of urban spatial effects on residential and commercial energy consumption due to the human mobility of the urban population. Urban building energy consumption is projected to increase significantly in the next few decades due to various physical characteristics of the buildings [10]. However, population growth and urbanization will exert different effects on this increased consumption due to human activities, and this will not necessarily be the same across different building types. To account for the spatial effects of human activities, we have examined urban human mobility as a potential explanatory variable and predictor of energy consumption across building types in Greater London and the City of Chicago (Table 5).

Table 5. Spatial regression: (a) residential, and (b) commercial buildings, Greater London.

	(a) Residential				(b) Commercial			
	Greater London		City of Chicago		Greater London		City of Chicago	
SAR Model	Electricity	Gas	Electricity	Gas	Electricity	Gas	Electricity	Gas
p-value	< 2.22e-16	< 2.22e-16	1.8908e-08	-	< 2.22e-16	< 2.22e-16	0.000741	0.0026676
MLA Coefficient*	0.52286	0.77733	0.3127	-	0.68172	0.52322	0.16686	0.17412
Likelihood Ratio	176.31	704.21	1370.177	-	344.88	153.85	1153.318	1259.008
AIC	16008	18023	-2732.4	-	20243	24641	-2298.6	-2510

* Maximum Likelihood Autoregressive Coefficient.

Our results reveal a spatial autocorrelation for energy consumption (electricity and gas) for both residential and commercial buildings, as well as human mobility, indicating that these variables all exhibit a structured pattern over space. Observations from nearby locations were more similar than would be expected on a random basis. Energy consumption rates in a given area for residential/commercial buildings depend not only on a building's own characteristics [10], but also the characteristics of its surrounding area [4]. Statistically significant positive contagion effects may exist for both residential and commercial energy consumption, with a stronger effect for residential buildings. However, the autocorrelations for electricity and gas consumption are not the outcome itself, but instead are attributable to missing spatial covariates in the data. Very often, missing covariates are correlated with location. Whether the neighbors have a diffusive effect on each other or spatial spillovers—where changes occurring in one area have an impact on neighboring areas exist across building types—motivated us to conduct further spatial regression analyses for this study.

Energy consumption rates cannot be regarded as being independently generated at a building level and arising solely as a result of building characteristics [4, 6, 7, 8, 9, 13, 18, 21, 30]. Possible spillover effects have to be taken into account across neighboring buildings. Considering the intrinsic spatial autocorrelation of energy consumption and human mobility in different areas of Greater London and the City of Chicago, the spatial correlation between human mobility and energy consumption manifested itself with statistically significant correlations. Changes in human mobility in region i immediately lead to increases in the observed energy consumption for all regions $i \neq j$. In other words, over time changes in human mobility create a new equilibrium steady state in the relationship between energy consumption and the distance and mobility variables.

Moreover, the smaller values of the autoregressive coefficient in the SAR model for gas consumption in commercial buildings in the case of Greater London implies that the effects of human mobility may dissipate quickly and approach zero after a relatively short distance; this effect decays more slowly as we move to higher order neighbors in residential buildings. Such spillover effects reflect the broader perspective needed when considering urban building energy consumption over a larger scale.

Where there is a spatial dependence, it is wrong to assume spatial independence in spatially indexed data. At best, an ordinary regression model would predict that changes in human mobility in region *i* will affect only the energy consumption of buildings in region *i*, with no allowance for spatial spillover effects. To test for the presence of spatially significant spillovers, and to quantify their magnitude and spatial extent would be of great interest in discerning the underlying dynamics of human mobility effects on energy consumption. For example, how far out does the impact on energy consumption of changes in human mobility in a typical region *i* extend?

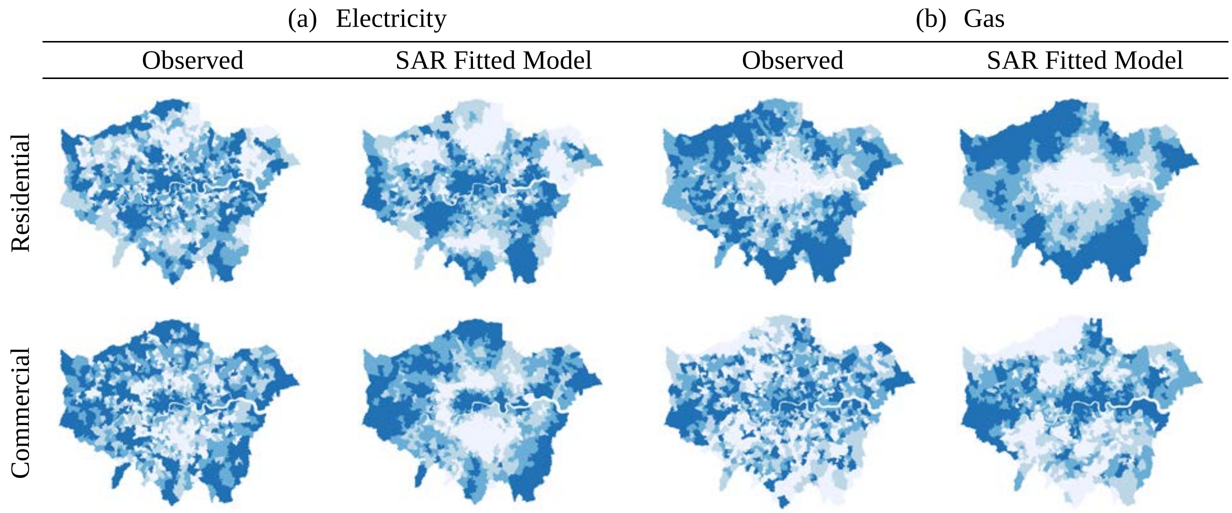

Figure 4. Spatial distributions for (a) electricity, and (b) gas consumption, Greater London.

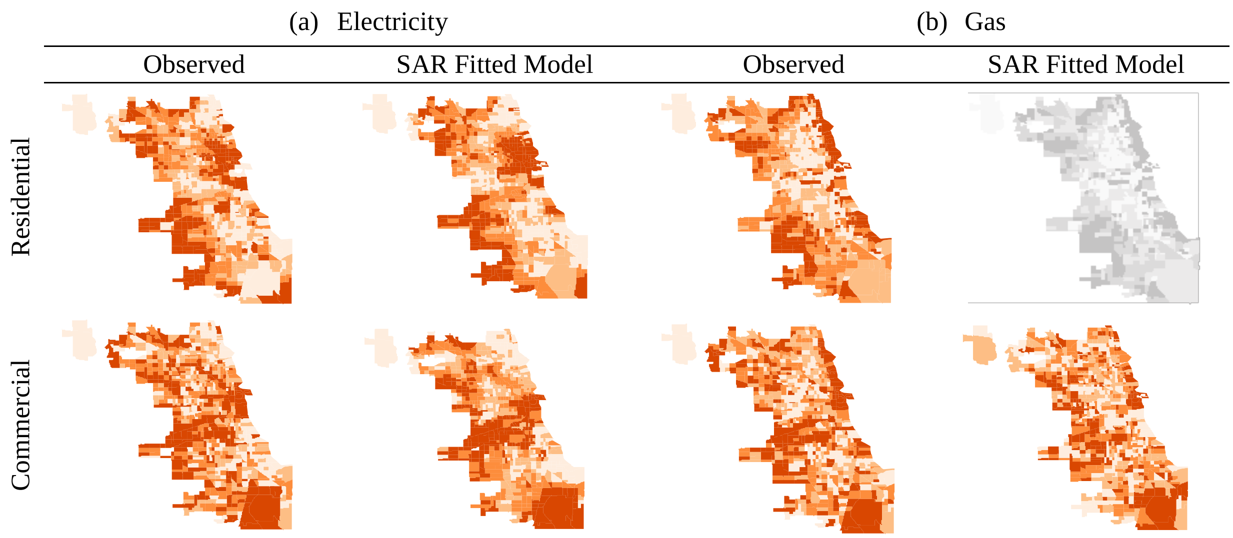

Figure 5. Spatial distributions for (a) electricity, and (b) gas consumption, City of Chicago.

Although research has examined various effects on energy consumption across building types [7, 8, 13, 18, 21, 30], our study confirmed that there are spatial effects due to human activities as indicated by human mobility [1, 15, 32] across building types, which have been overlooked by the literature. In order to cope with the continuing growth in population [33] and the corresponding increase in urban activity levels, we need to develop a better understanding of the root causes of energy consumption. Trends in energy consumption are expected to reveal critical information regarding the important roles different drivers will play in the future, making it possible to identify new opportunities for energy-efficient solutions and renewable energy investments. The use of alternative assumptions in estimating future energy demand can lead to more reliable predictions, with implications for energy consumption mitigation strategies. For example, if a building type located in a particular neighborhood is identified as having a high potential for solar capacity but the spatial dependencies reveal lower energy consumption rates in the area in future, financial expenditure versus efficiency gain trade-offs should be calculated before any investment is finalized. The relationship between energy consumption and human mobility is thus a key element for creating effective policies for urban areas. A clear picture of the demand-side diversity will facilitate the appropriate decentralization of the urban energy distribution infrastructure and reduce both waste and the vulnerabilities that typically lead to service disruptions.

6. Conclusions

Urban areas are undergoing a significant growth in population globally, with a commensurate increase in human activities. The question of how to anticipate the growing demand and supply energy for billions more in these areas requires a more holistic approach to measuring energy consumption. Current estimates are not proportional to the magnitude of the changes that are anticipated to affect consumption and demand, and are thus not representative of recent trends in building energy consumption. Spatial dependencies and their effects on energy consumption as a response to continuous changes in human activities are unknown and often neglected in these measures. Therefore, the underlying changes that will affect future demand are not clearly established. This study examined the energy consumption for both residential and commercial buildings to test whether there is a spatial dependency between intra-urban human mobility and energy consumption that varies across building types. Further, we explored whether intra-urban human mobility can be used to explain fluctuations in urban energy consumption across building types. Our results suggest that it does, with a particularly strong spatial dependency for residential buildings in energy consumption (i.e., electricity consumption for residential building for both Greater London and the City of Chicago). Although this dependency may vary if the consumption rates are significantly reduced across different urban areas (e.g., during the warmer seasons/months of the year). Research has found that such dependency is consistently significant over the course of the year for Greater London disregarding the seasonal or monthly effects [25]. Energy consumption mitigation efforts focusing on human activities are thus likely to be affected significantly by such correlations. This study sheds new light on an overlooked driver of residential and commercial energy consumption and their future trends, a topic of considerable basic and applied interest. Our findings may be particularly relevant for researchers seeking to explain the spatial patterns and causes of energy consumption related to specific land uses and identifying the impact of the spatial proximity of various end use infrastructures. The results can also be of value to business practitioners, urban planners and policy-makers, by enhancing the impact of their future efforts and eliminating the overlooked, or poorly specified, energy efficiency strategies across building types that involves the mobility of urban populations.

7. Limitations and Future Work

The choice of Greater London as one of the urban areas for this study was made for several reasons. First, London is among the world's most influential global cities [22], it is one of the biggest world capitals, and it contains over 14 million inhabitants making it the second largest megacity in Europe, after Moscow, and the World's third most active Twitter city (after Jakarta and Tokyo) [28] at the time of this study. London is thus firmly in the category of the most complex urban systems that yet exist so any inferences made based on the data gathered would likely be scalable to other systems. Further, in terms of data availability, the data for representative spatial divisions, with their associated energy consumption across a variety of scales, have been made publicly available by the city's governing body, the Greater London Authority. Similarly, energy data availability and city influence have been the rationale behind the choice of the City of Chicago. Data availability is reasonably the biggest limitation of such studies. In the current study the temporal difference between human mobility data and energy consumption in both cities are considered with the assumption that the mobility pattern of urban population is not subject to major changes by year, and is another limitation of this study. Future cross-urban studies are encouraged using a variety of temporal and spatial scales to further explore the extent of the results in this study. Moreover, examining the effects of heterogeneity in human mobility as a result of the activity patterns of different urban populations can be a valuable path for future research.

8. References

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