On the Spatial Dependencies of Human Mobility and Urban Energy Consumption

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ABSTRACT

Urban areas are responsible for consuming up to 80% of the energy produced worldwide, mainly as a result of human activities. Due to the constantly increasing world population and the shift of this population into cities, over 60% of the world population is projected to reside in urban areas by 2030 and the corresponding increase in human activities will lead to a tremendous increase in energy consumption. Current approaches to energy consumption take a narrow sectoral approach and overlook the effects of individuals' collective consumption as they visit different functional locations in a city in the course of their daily lives. They, therefore, underestimate consumption measures for exclusive vs. shared energy resources and fail to identify patterns of urban energy consumption with respect to consumers. Unreliable predictions and poor management decisions regarding future patterns of energy consumption and demand may thus lead to enormous waste in energy distribution and infrastructure investment. This paper explores the potential for developing valuable insights into energy consumption patterns in urban areas based on human activities inferred from the mobility behavior of urban populations. Through a study in Greater London covering the month of August, 2014, we analyzed 2,367,967 positional records from a location-based online social network (Twitter), and energy consumption (i.e., electricity and gas) data across 983 areas. A spatial autocorrelation analysis revealed clustering patterns for both electricity and gas consumption, as well as human mobility. Further, our spatial regression models indicate that human mobility can account for much of the distribution of energy consumption in urban environments and can be used to predict energy consumption patterns across urban areas. These results suggest data-driven approaches based on combining the mobility behavior of urban populations with geographical data including energy consumption and point of interest (POI) information can lead to further energy discoveries in urban functional regions. These findings will be of value to business practitioners, policy-makers, and research communities, enhancing their future efforts and enabling them to deal with overlooked or poorly specified aspects of urban energy consumption.

Categories and Subject Descriptors

H.2.8 [**Database Management**]: Database Applications–*Spatial databases and GIS;* H.4.m [**Information Systems Applications**]: Miscellaneous.

UrbComp'15, August 10, 2015, Sydney, Australia.

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General Terms

Experimentation, Human Factors, Measurement.

Keywords

Energy Consumption, Human Mobility, Urban Computing

1. INTRODUCTION

The way urban environments grow and meet their occupants' energy demands has a major impact on our economic, financial, and environmental future. Understanding the distribution and patterns of urban energy consumption is a significant indicator in managing and allocating resources, and this will only become more important as world energy consumption is expected to increase by up to 56% between 2010 and 2040 [1]. Urban areas are responsible for consuming up to 80% of the world's total energy production [2, 3] and they continue to grow faster than ever in population, creating the most complex built environments in human history. A 2014 United Nations report announced that 54% of the world's population now resides in urban areas, and this is predicted to rise to nearly 70% by 2050, adding 2.5 billion residents to our urban environments [4]. In addition to being dense clusters of population, urban areas are also dense clusters of human activities and daily routines involving work, home and leisure activities, all of which have an impact on areas such as transportation, energy consumption and service utilization. In spite of this, our approaches to managing energy consumption generally adopt a narrow sectoral approach or focus on specific building types (i.e., Residential, Commercial, Transportation, and Industrial). Urban areas are not used homogeneously by their residents, and this is now beginning to be addressed by a number of studies that have sought to analyze and understand the patterns of energy consumption in urban areas. Shimoda et al. [5] performed a city-scale simulation for energy consumption based on household and building types, their appliances, and occupants' activities to evaluate the effects of conservation measures in the residential sector. In an attempt to quantify future energy demand of buildings in their urban context, Choudhary [6] 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 [7] examined the spatial variability of commercial buildings across 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 energy consumption of different building types. Howard et al. [8] estimated the end-use intensity of various building types in New York City using a linear regression model, mainly built on the assumption that energy consumption is primarily based on building function (e.g., residential, educational, etc.) rather than the construction type or age of the building. In an effort to explain energy consumption variability in residential buildings, Kavousian et al. [9] developed a statistical model to disaggregate the underlying determinants of daily energy use based on buildings' characteristics, their occupants and appliances, and external conditions such as weather and building location. These efforts indicate 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 expected to encounter. In a recent study in Switzerland, Fonseca and Schlueter [10] proposed an integrated model to characterize city-scale spatiotemporal energy consumption patterns and examine the variability of consumption in residential, commercial and industrial sectors across urban districts.

Although representative, the existing approaches to identifying patterns of urban energy consumption do not reveal the correct per capita consumption measures for a city and overlook the effect of individuals' aggregated daily consumption. An individual may exhibit low consumption habits at work, but consume disproportionate amounts of energy during later hours of the day when they are at home or utilize high-energy-consuming transit modes to travel within the city. It is also of particular concern whether individuals consume energy from exclusive or shared resources during their daily activities. Although the number of occupants has been found to be one of the most significant determinants of daily maximum energy consumption [9], in the existing models they are still quantified based on census data [5]. It is apparent that urban energy consumption is spatially distributed in cities, and certain types of energy use behavior are clustered in specific spatial and temporal locations [10]. The complex mix of consumption, required services and technological adaptation required of future urban areas, which is largely driven by ever-changing patterns of human activities, will inevitably be substantially different from that in today's cities. Therefore, it is important to identify the drivers of this consumption in different regions and explore the patterns and predictors of urban energy use. Unreliable predictions and poor management decisions about future patterns of energy consumption and demand may adversely affect cities' energy resilience, leading to enormous waste in the financial resources invested in energy distribution and infrastructure.

2. Related Work

Until relatively recently it has not been easy to study the dynamics of individual activities in different spatial and temporal resolutions. Survey data, monthly bills, and conceptual frame-works were the only measures for effective decision making. Today, thanks to the recent advances in technology, computing power, and the advent of online social networks, the research challenge has shifted from data availability to identifying meaningful patterns in individuals' daily consumption to help anticipate and manage future demand. Opportunely, recent advances in both sensing technologies and urban computing methods have boosted relevant data availability in urban spaces and supported new discoveries related to these challenges [11]. The introduction of Advanced Metering Infrastructure (AMI) has made it possible to access and draw inferences from the consumption rates and patterns in residential and commercial buildings. Humans as sensors have also made available city-wide human mobility data [11] through their mobile phone signals, including GPS data [12-14], smart card commuting data [15], and location-embedded information from online social networks [16-19], all of which can be used to infer information on the mobility behavior of urban populations. Human mobility patterns can also reveal important information about the way citizens interact with their surroundings. A number of recent studies have linked this information with geographical data from city-wide points of interest (POI) such as shopping malls, retail stores and restaurants to explore activity patterns and discover the root causes of urban challenges, thus revealing urban location correlations for human behavior [18, 20-22]. Other studies have further classified the urban population into representative groups according to their daily activities [23] as they visit different functional locations in cities and identified a certain number of characteristic trip-location activity patterns – human mobility motifs [24, 25]. Human mobility have been used to infer location choices and to strategize optimal accessibility to amenities under the influence of human mobility [26, 27]. One recent study has proposed a method to find clustered locations in urban areas where individuals engage in activities, inferred to be home, work, or "other", from human mobility data [28].

As individuals engage in daily activities across various locations, they drive the energy consumption associated with their location-based activities. Therefore, researchers have sought to analyze human mobility data to identify the energy implications of such activities in urban areas [29, 30]. For example, Tulusan et al. adopted the eco-feedback technology–as used analogously to reduce energy consumption in buildings [31, 3]–in personal the transport sector (i.e., eco-driving feedback) to improve fuel efficiency and reduce fuel consumption in urban areas [33]. Zhang et al. [29] explored city-wide refueling behavior and gas usage in the transportation sector and its economic implications, while Becker at al. [13] developed new human mobility analysis techniques to determine the daily range of travel, the carbon footprint of human-to-work commutes, and other mobility characteristics in Los Angeles, San Francisco, and New York. However, all these efforts are limited to transport energy consumptions and we still lack a good understanding of whether the mobility behavior of urban populations can be translated into spatiotemporal energy consumption patterns in urban areas. Can the distribution of urban energy consumption be predicted by patterns of human mobility?

In order to assess the energy use and demand attributable to individuals' urban mobility and examine human mobility as a predictor of future energy consumption, this study examines the relationship and interdependencies of energy consumption with intra-urban human mobility behavior in Greater London. The impact of human interactions with the urban built environment is explored through a spatial regression analysis of 2,367,967 positional records accounting for human mobility, and energy consumption across 983 areas in Greater London over the course of a single month (August, 2014). This paper is organized as follows: Section 3 describes the data sources used in the study in terms of the mobility behavior of the urban population, including positional records from an online social networking platform (sub-section 3.1) as well as energy consumption (sub-section 3.2) for different areas in Greater London and their spatial distribution across urban areas. In Section 4 we explore whether intra-urban mobility can be utilized as an indicator for energy consumption through spatial regression analysis, and examine whether clustering patterns for human mobility can indeed explain clusters of energy consumption. The paper concludes with the initial findings on human mobility as a predictor for urban energy consumption and a discussion of future research directions in this area.

3. DATA

Table 1 lists the datasets used in this study, which consist of the electricity and gas consumption figures for 983 areas, and 2,367,967 positional records accounting for human mobility (described in more detail below in Section 3.1). The spatial level used here is an administrative boundary for Greater London – MSOA (middle layer super output area), which represents a minimum population of 5000, with an overall mean of 7200 [34]. The closest temporally compatible datasets are selected for study, as shown by year in Table 1; the years shown are chosen based on the availability of data for both positional records and energy consumption (electricity and gas), as well as the compatible MSOA digital boundary and energy consumption data. Fig. 1 shows a 24-hour cumulative distribution of positional records across the 983 MSOA boundaries in Greater London. The amount of information collected from online social networks is not immune from demographic issues such as the tendency of the urban population to use online social networks as well as security issues. This positional records data has been collected from individuals who have voluntarily publicly shared the location-enabled information for their Twitter accounts in Greater London and any results in this study are thus representative of this population.

Table 1. Energy consumption, Digital boundaries, and positional records data.

Data	Spatial Scale	Temporal Scale	Organization
Electricity (kWh) Gas (kWh)	MSOA*	2013	**DECC** (Department of Energy & Climate Change)
Digital Boundaries (.shp)	MSOA (#983)	2011	**GLA** (Greater London Authority)
Positional Records (tweets)	Greater London	August, 2014	**Twitter** (# tweets: 2,367,967)

*Middle Layer Super Output Area—MSOA: Min Population 5000, w/ an overall Mean of 7200 (England # MSOA: 6,781).

Spatial autocorrelation [35] is used to measure the correlation among energy consumption and human mobility variables in the spatial dimension. Moran's I [36] (Eq.1), which ranges from -1(most dispersed) to 1(most clustered), describes the degree of spatial concentration or dispersion for these variables, with larger values for I showing clusters of larger values being surrounded by other large values (I+)–spatial clustering, and (I–)–spatial dispersion indicating larger values being spatially enclosed by smaller values. It is also a test of independence to determine whether values of human mobility or energy consumption observed in one location depend on the values observed at neighboring locations. While Moran's I represents a global spatial autocorrelation for our data, Geary's C [37] (Eq. 2) is also used based on the deviations in the responses of each observation with one another, ranging from 0 (maximum positive autocorrelation) to 2 (maximum negative autocorrelation), with 1 indicating an absence of correlation. We have used Moran's I here as a measure of sensitivity to extreme values of energy consumption and human mobility, and Geary's C to evaluate the sensitivity to differences in smaller neighborhood MSOAs.

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

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

Here, n represents observations on variable x at locations i, j where $\overline{x}$ is the mean of the x variable, w_{ij} are the elements of the weight matrix.

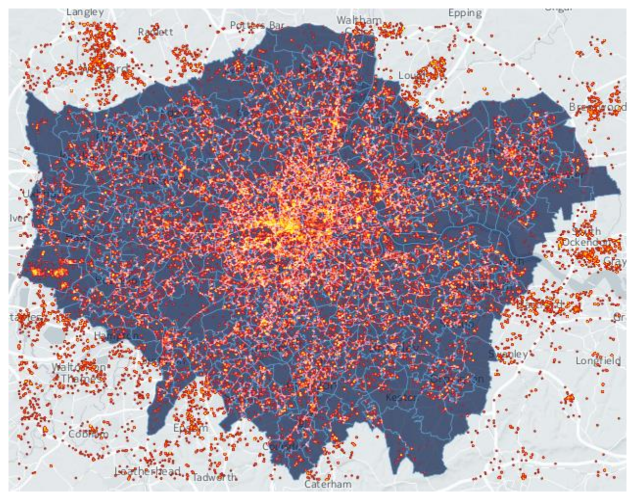


Figure 1. 24 hours cumulative distribution of positional records on August 1st, 2014 over the 983 MSOAs, Greater London.

3.1 Individual Positional Records and Human Mobility

In order to obtain an enhanced understanding of human mobility patterns, and thus improve our understanding of the relationship between individuals' mobility and energy consumption behavior, we have selected the radius of gyration *(Eq. 4)* as our metric from the three widely accepted indicators for describing large-scale human mobility patterns: the radius of gyration $r_g(t)$, trip distance distribution $p(r)$, and the number of visited locations $S(t)$ [12, 38, 39]. Of these, we consider the radius of gyration to be the most appropriate for capturing individuals' characteristic travel distance within the areas where they habitually move around in their daily activities (i.e., $r_g(t)$), as described below:

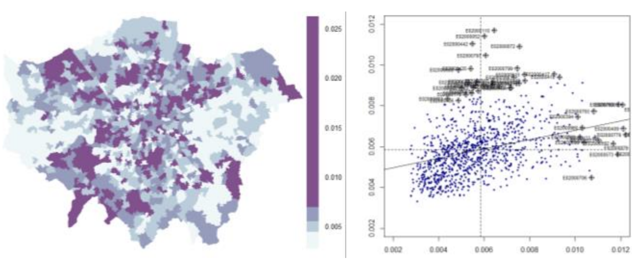
$$\vec{p}_{centroid} = \frac{1}{n}\sum_{i=1}^{n}\vec{p}_i \qquad (3)$$

$$r_g = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\vec{p}_i - \vec{p}_{centroid}\right)^2} \qquad (4)$$

Here, radius of gyration is calculated at two spatial and two temporal levels. First, the individual level $r_{gi}(t)$, is obtained per MSOA per individual per day. Second, the MSOA level $r_{ga}(t)$ is obtained per MSOA over the total time frame (in this case, one month). The individual level $r_{gi}(t)$ represents the characteristic distance traveled by a user when observed up to time t [12], so every MSOA level $r_{ga}(t)$ represents the deviation of the $r_{gi}(t)$s from the corresponding center point *(Eq. 3)*. This indicator is used to describe the patterns of human mobility across MSOAs. Figure 2 depicts the spatial distribution of human mobility in Greater London. Statistically significant ($p\text{-}value < 2.2e^{-16}$) positive values for I (examined for both row-normalized: *0.227,* and binary weight matrices: *0.222*) indicate that human mobility patterns in Greater London follow a clustering distribution as opposed to a dispersed or random distribution. As further illustrated in the four quadrants of the Moran Scatter Plot, we observe a classification of four types of spatial autocorrelation for human mobility. The slope of the regression line corresponds to the Moran's I value. 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.

Table 2. Spatial autocorrelation analysis results – Human mobility.

	Weight Matrix	Statistic	p-value	Std
Moran's I	Row-Norm.	0.22681	< 2.2e-16	12.20
	Binary	0.22247	< 2.2e-16	12.15
Geary's C	Row-Norm.	0.77256	< 2.2e-16	8.73
	Binary	0.77882	4.47e-10	6.13



(a) Human Mobility (b) Moran Scatter Plot

Figure 2. Spatial autocorrelation – Human mobility

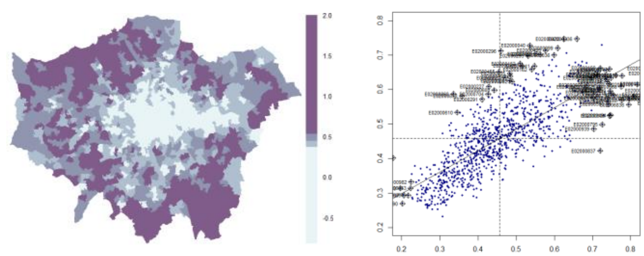
The positive autocorrelation for the high-high scatter plot quadrant areas are interpreted as clusters of regions with high human mobility, which are clustered with and dependent on neighboring regions with high human mobility. The low-low quadrant areas are those MSOAs with low human mobility that are clustered with and dependent on other low human mobility areas. Moreover, the statistically significant results for Geary's C (examined for both row-normalized: *0.773*, and binary weight matrices: *0.779*) confirm these results. High values of the C measures correspond to low values of I and the two measures are inversely related. By contrast, the high-low (bottom right), and low-high (upper left) quadrants both depict negative spatial associations.

3.2 Urban Energy Consumption

A similar spatial autocorrelation analysis can be performed for energy consumption (i.e., domestic electricity and gas) across the 983 MSOAs in Greater London. Figure 3 shows the clustering patterns and spatial dependencies of neighboring areas for domestic gas consumption and Figure 4 depicts the same results for domestic electricity consumption. We found statistically significant ($p\text{-}value < 2.2e\text{-}16$) results for both Moran's I and Geary's C, representing spatial dependencies for both electricity (examined for both row-normalized: $I = 0.590$ and $C = 0.428$, and binary weight matrices: $I = 0.582$ and $C = 0.443$) and gas consumption (examined for both row-normalized: $I = 0.622$ and $C = 0.385$, and binary weight matrices: $I = 0.626$ and $C = 0.389$). Positive autocorrelations are illustrated in the Moran Scatter Plots.

Table 3. Spatial autocorrelation analysis results – Domestic Gas Consumption.

	Weight Matrix	Statistic	p-value	Std
Moran's I	Row-Norm.	0.62217	< 2.2e-16	33.15
	Binary	0.62602	< 2.2e-16	30.23
Geary's C	Row-Norm.	0.38552	< 2.2e-16	33.87
	Binary	0.38824	< 2.2e-16	26.87



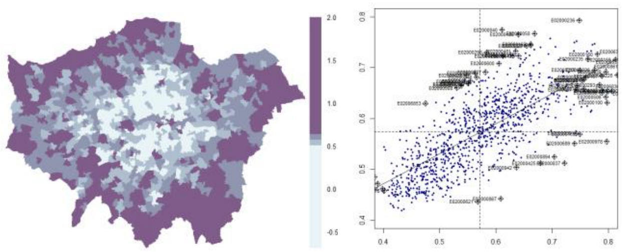
(a) Gas Consumption (b) Moran Scatter Plot

Figure 3. Spatial autocorrelation – Domestic Gas Consumption.

Having found spatial dependencies and clustering distribution for both human mobility and energy consumption across urban areas in Greater London, we examined whether a spatial regressive model can be used to identify meaningful relations between the two distributions. The following section describes the statistical methods used to determine the relationships between the MSOA level $r_{ga}(t)$s and the corresponding MSOA level energy consumptions, including the spatial regression analysis.

Table 4. Spatial autocorrelation analysis results – Domestic Electricity Consumption.

	Weight Matrix	Statistic	p-value	Std
Moran's I	Row-Norm.	0.59045	< 2.2e-16	31.46
	Binary	0.58195	< 2.2e-16	31.50
Geary's C	Row-Norm.	0.42819	< 2.2e-16	28.20
	Binary	0.44331	< 2.2e-16	24.60



(a) Electricity Consumption (b) Moran Scatter Plot

Figure 4. Spatial autocorrelation – Domestic Electricity Consumption.

4. HUMAN MOBILITY and ENERGY CONSUMPTION

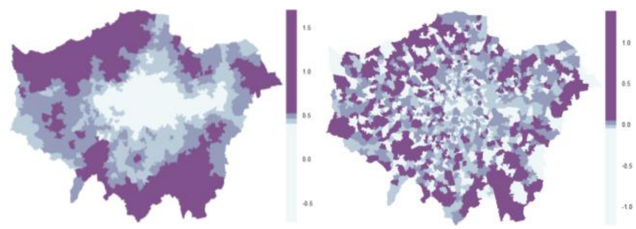
Spatial regression models are used to examine the relationships between variables and their neighboring values and allow us to examine the impact that one observation has on other proximate observations. The energy use in different areas of a city cannot be regarded as being independent of each other in a regression analysis due to spatial autocorrelation. The same statement holds true for urban human mobility. However, considering the intrinsic spatial autocorrelation of energy consumption and human mobility in the 983 different areas of Greater London, does the correlation between human mobility and energy consumption manifest itself spatially in urban areas? To answer this question we performed a spatial regression analysis as follows.

4.1 Spatial Regression Analysis

To model the spatial interdependencies of our datasets, we applied an autoregressive model to implicitly incorporate the spatial dependence of the human mobility data into the covariance structure. The two main autoregressive models for areal data tested in this study are the conditional autoregressive model (CAR) [40], which represents the first order (local) dependencies, and the simultaneous autoregressive model (SAR) [41], which represents more global dependency conditions. We used both models to produce spatial dependence in the covariance structure as a function of fixed parameters such as the number of energy meters per MSOA to examine various conditions. Figures 5 and 6 show the spatial regression results from the SAR and CAR models, respectively, for energy consumption (in this case, electricity and gas) compared to human mobility for Greater London over the course of one day in August 2014. We have also compared the results using a simple linear model. All spatial parameters are statistically significant, as indicated by *p-values* lower than 0.0001 for both electricity and gas consumption in Greater London. Figures 5 and 6 also show the spatial distribution of the fitted SAR model, as well as the residuals for gas and electricity, respectively, which is the most representative model for energy consumption per human mobility.

Table 5. Spatial regression analysis results – Domestic gas consumption per human mobility.

	Simple Linear Model	SAR Model	CAR Model
P-value	0.8618	< 2.22e-16	< 2.22e-16
AIC	-1270.241	-1955.9	-1973
R-squared	-0.0009884	-	-
Statistics	0.03033	0.13097	0.15561

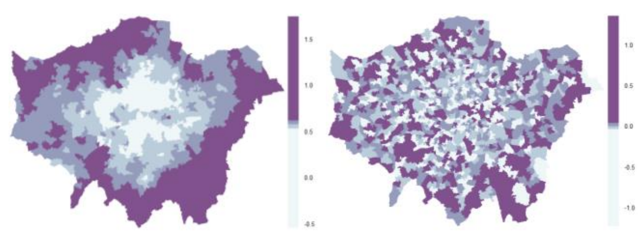


(a) Gas Consumption (b) Residuals

Figure 5. Spatial regression – Domestic gas consumption per human mobility.

Table 6. Spatial regression analysis results – Domestic electricity consumption per human mobility.

	Simple Linear Model	SAR Model	CAR Model
P-value	0.03211	< 2.22e-16	< 2.22e-16
AIC	-1837.744	-2435.7	-2445
R-squared	0.003659	-	-
Statistics	4.606	0.12879	0.1555



(a) Electricity Consumption (b) Residuals

Figure 6. Spatial regression – Domestic electricity consumption per human mobility.

These models explicitly test the impact of human mobility variables on energy consumption. At a global scale, the SAR models imply that the state of the energy consumption per human mobility for each MSOA in Greater London is influenced by that of its neighboring MSOAs. Taking a more local perspective, the CAR models imply that this holds true for a particular MSOA and its neighboring MSOAs.

5. CONCLUSIONS and FUTURE WORK

We examined how human mobility and energy consumption are spatially distributed within UK Greater London, and how the strength of the association between human mobility and energy consumption vary by area. Using 2,367,967 positional records gathered during a single month, we quantified human mobility across 983 areas of the city. A spatial autocorrelation analysis revealed clustering patterns as well as positive spatial associations for human mobility, electricity, and gas consumption among these areas. Our spatial regression analysis results indicate that the strength of the association between human mobility and energy consumption depends on spatial location, which can further be contextualized more locally based on POIs. Therefore, human mobility across different areas in Greater London can be regarded as a proxy indicator of energy consumption behavior.

This study is a step towards linking human mobility patterns to urban energy consumption. Variations of energy consumption in relation to human mobility across different areas remain to be examined in future research. However, we still lack appropriate data and analysis methods that will enable us to identify and utilize the full spectrum of energy consumption rates and patterns for each individual across time and location. Knowing individuals' movements around urban open spaces and across the physical infrastructure of our urban environments (both communal and private infrastructure) will enable us to build a comprehensive understanding of how certain types of energy behavior are clustered in specific geographical spaces and temporal locations within urban areas. In addition, it will enable us to identify the interdependencies between energy consumption, individual activities, and specific urban spatiotemporal features. The results presented in this paper suggest that human mobility can account for the collective energy consumption in urban areas, and further research should be considered to quantify and contextualize this relationship. Our ongoing research is seeking to understand urban activity patterns across different functional locations using human mobility data and then utilize the activity patterns identified to develop integrated predictive models that incorporate temporal elements of activity patterns (for example, recreation, nightlife, shopping, or education) and energy consumption. Identifying spatial regions with similar temporal activities should allow us to assess their energy consumption and thus identify the distribution of energy consumption.

To cope with the continuing growth in population and the corresponding increase in urban activities, we need to develop a better understanding of the root causes of societally significant phenomena such as energy consumption. The relationship between energy consumption and human mobility is 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 to reduce both waste and the vulnerabilities that lead to service disruptions.

6. ACKNOWLEDGMENTS

This study was supported by the National Science Foundation under Grant No.1142379. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

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