Urban Spatiotemporal Energy Flux

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(ABSTRACT)

Urban energy systems are often studied in a very similar way in the sense that the characteristics of the underlying physical infrastructure are weighted as the main determinants of energy use predictions, while the behavior of the human population in relation to this system—the so-called "energy consumers"—in time and urban spaces is effectively neglected. The spatial and temporal variations in infrastructure-population interactivity greatly complicate urban energy systems; the unremitting growth in population and advances in technology mean that the dynamic interrelationship between the population and urban environment will continue to grow exponentially, resulting in increasing uncertainties, unreliable predictions and poor management decisions given the inadequacy of existing approaches. In this dissertation, I explore the interdependencies of spatiotemporal fluctuations of human mobility as an indicator for human activities and energy use in urban areas in three main studies. First, I show that the fluctuations of intra-urban human mobility and energy use have an underlying structure across both time and space, and that human mobility can indeed be used as a predictor for energy use in both dimensions. Second, I examine how one of the dominant drivers of this structure, namely individuals' location-based activities, influence patterns in energy supply and demand across building types (i.e. residential and commercial buildings) and show how variations in the human mobility networks of two distinct urban populations (the so-called returners and explorers) can explain fluctuations in energy use. Third, I introduce an integrated approach for predicting urban energy use across time and space by incorporating these interdependencies. Generating predictive models that capture the spatiotemporal variations in these determinants in urban settings, as suggested in this research, will contribute to our understanding of how variations in urban population activities for particular times and locations influence can be applied to estimate energy use patterns in surrounding areas.

Urban Spatiotemporal Energy Flux

Neda Mohammadi

(GENERAL AUDIENCE ABSTRACT)

Today's cities are the most complex built environments in human history, containing 54% of the world population and responsible for up to 80% of the world's total energy consumption. As a result of population growth and advances in technology, the interdependencies between infrastructure, services, and individuals in urban spaces continue to increase, presaging an ambiguous future with challenges we are not yet aware of. In this research, I developed the concept of *urban spatiotemporal flux* to study the interdependencies between energy use and human activities using human mobility at various spatial and temporal scales to address the urgent need to incorporate the resulting fluctuations in energy use into future energy predictions. Intra-city human activities change more rapidly and exhibit higher levels of dynamic characteristics than the simple physical locations identified in current master plans. Previous research has tended to focus on predicting energy consumption at different spatial levels as a function of the physical characteristics of buildings or cities, often relying on sensor-based data-driven approaches. There has been some effort to explore the predictability of human mobility by building human mobility-based predictive models across applications such as traffic and travel demand predictions, human activity predictions, next place locations, epidemics and the spread of viruses, and air pollution. The two perspectives are rarely in conversation with each other, however, with only minimal integration of our understanding and predictions for different urban spatial and temporal scales. The technology that has become an integral part of everyday life in today's smarter urban environments now allows us to use human beings as "sensors" that provide useful data for predictions of energy use. Using tens of millions of yearly individual positional records across thousands of spatial divisions, along with millions of corresponding measures of energy use from energy meters in Greater London and the City of Chicago, I discovered that fluctuations in urban energy consumption are likely governed by the structure of human mobility networks and are dominated by certain populations and buildings types, among other factors. Intra-urban human mobility and energy use are not spatially randomly distributed across urban settings; instead, there is an underlying structure that explains their dependency. Temporal manifestations of these fluctuations suggest a continuous spatiotemporal relationship between human mobility and energy use, which confirms that the values observed in one location depend to some extent on what is happening at adjacent locations at around the same time. This dependency represents a strong connection with the returner populations' mobility and residential buildings' energy use and there is an associated spatial spillover effect. Future energy efficiency strategies should thus reflect these spatiotemporal dependencies, enabling planners to create new and more effective ways for both different building types and the mobility networks of the urban population to play major roles in energy related strategies, as well as helping to identify the fluctuating determinants that represent additional evidence of a spatiotemporal structure.

To my father and mother,
who never stopped believing that whatever it is that I have left to pursue,
is the right thing to do.

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It is only when we are challenged that we question, and find the limits between the known and the unknown. Only then will we realize that what we know has already become incomplete, requiring us to challenge ourselves again, continuously change, discover and rediscover.

To take complete credit for this dissertation would be misleading.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

The way urban environments grow and meet their occupants' energy demands will have a major impact on our economic, financial, and environmental future. Urban areas consume between 60-80 percent of the world's total energy production [47, 99], and they continue to grow faster than ever in population, creating the most complex built environments in human history. As a result of population growth and the shift of this population into cities—urbanization, interdependencies between infrastructure, services, and individuals are also rapidly increasing. A 2014 United Nations report announced that 54% of the world's population now resides in urban areas, and this number is predicted to rise to 66% by 2050, adding 2.5 billion to the population of urban environments [90]. Of particular concern is the prediction that world energy consumption will increase by up to 56% between 2010 and 2040 [93]. These trends clearly illustrate the global consequences of the rapid acceleration of urbanization and human activities [95] in the last hundred years.

As they grow, urban areas are expected to encounter numerous novel challenges as they strive to meet the energy demands and provide services for their growing populations, for which our current knowledge is likely to prove insufficient. The complex mix of consumption, required services and technological adaptation required of future urban areas, largely driven by ever-changing patterns of human activities, will inevitably be substantially different from that in today's cities. Unreliable predictions and poor management decisions about future patterns of energy consumption and demand will adversely affect cities' energy resilience, and lead to enormous waste in energy distribution and infrastructure investments. Crucially, population growth has the potential to grow more rapidly than energy supplies can be increased, so enhancing our ability to understand and manage short and long term urban energy resilience is vital if our cities are to continue to thrive.

Although rapid globalization, the explosion in the world's urban population, and the subsequent growth in energy consumption cannot be sustained, how can we ensure that the expected increase in urban population to nearly 6.3 billion by 2050 [90], combined with the resulting complexities, are managed to support positive outcomes for future energy efficiency and resilience? The first step is to develop a deeper understanding of the emergent behavior in energy dynamics of urban environments under the evolving complexities due to demographic changes. The ability to anticipate future dynamic trends is critical in creating resilience and ensuring we can maintain or even improve upon our existing quality of life. As suggested by the literature, an effective way to manage cities involves a bottom-up approach in which complexities and self-organization principles form within the system as a result of spontaneous order. These principles, once identified, can be utilized to align the process to the evolving demands, rather than forcing unattainable orders and structure on the system. To ensure energy resilience, urban settings must learn to mitigate and adapt to change as they deal with the increasing complexities stemming from human activities.

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 that include transportation, energy consumption and service utilization. Research has shown that the dominant source of changes in energy demand represent changes in the use of equipment; so the most important factors driving significant changes in energy demand are those that stem from the mix of personal activities in certain times and locations. Figure 1.1 shows a 24-hour cumulative distribution of an urban population's locations. It has been argued that greater changes in the future are possible as the relation between work, home, and free time and the technologies that support these activities evolve [41]. In spite of this, energy demand and consumption is currently narrowly addressed through the physical characteristics of the urban infrastructure. Although representative, this approach fails to reveal the correct fluctuations in energy use for a city. 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 use high-energy-consuming transit modes to travel within the city to a different location. Activity-based approaches [57] are often used to anticipate future demands in services and consumption of resources such as energy. However, these approaches again focus primarily on the diversity of activities rather than the heterogeneity that exists across users and the patterns of their collective activities in time and space.

Urban settings, as complex adaptive systems, experience several changing points in their services with respect to individuals' activities that are increasing due to the dynamic pressure

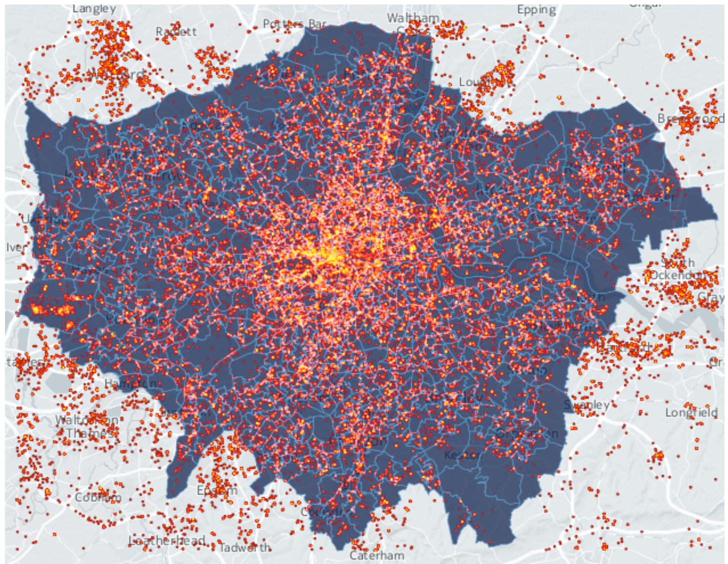


Figure 1.1: A 24-hour cumulative distribution of positional records on August 1^{st}, 2014 over the 983 spatial divisions, Greater London.

of population growth. Both spatial and temporal consumption-demand s in various urban settings are subject to vulnerabilities that make the energy system susceptible to changes of state, or collapses. A better understanding of the underlying drivers of this process will facilitate the identification of the system's reactive, recovery, and adaptive capacities across time and space. 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 frameworks 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 challenges have shifted from data availability to identifying meaningful patterns in individuals' daily consumption to help anticipate and manage future demand. 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 with a resolution never previously available. 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 (i.e. communal and private infrastructure) will enable us to build a comprehensive understanding of how certain types of energy behavior or opinion are clustered in 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.

This research comprises three cumulative studies that aim to explore fluctuations of energy use in urban settings across time and space, and address the challenges of predicting urban energy demand by examining the impact of human interactions with the urban built environment as understood by individuals' intra-urban mobilities. Because of the progressive nature of these studies, I have allowed them to dictate the structure of this work. Study 1 is entitled 'Urban Energy Spatial Flux: Human Mobility as a Predictor' and investigates whether human mobility can indeed be used to explain spatial fluctuations of urban energy use. Study 2 is entitled 'The Interplay Between Dominant Drivers of Urban Energy Flux: Populations Mobility Networks and Building Types' and is intended to explore the underlying relationships between spatiotemporal fluctuations of human mobility and energy consumption as related to particular human mobility networks of the population and building types. The research will culminate in Study 3, entitled 'Temporal Fluctuations and Space-Time Predictions of Energy Use', which will introduce a human mobility-based prediction approach for urban energy demand, incorporating the driving elements of it's fluctuations across time and space.

Chapter 2

Urban Energy Spatial Flux: Human Mobility as a Predictor

Anticipating future energy demand especially in our rapidly growing urban areas, which are dense hubs of both consumer population and CO_2 emissions, is a major research agenda. We urgently require a better understanding of how urban populations interact with municipal energy systems and the resulting impact on energy demand across city neighborhoods. Currently, the physical characteristics of urban infrastructure are the main determinants in predictive modeling of the demand side of energy; overlooking any influence related to fluctuating human activities. Here, I show how applying intra-urban human mobility as an indicator for interactions of the population with local energy systems can be translated into spatial imprints to predict the spatial distribution of energy use in urban settings. These findings establish human mobility as an important element in explaining the spatial structure underlying urban energy flux and suggest the utility of a human mobility driven approach for predicting future urban energy demand.

The earth's fast expanding urban spaces are growing in terms of both technology and population at a rapid rate, 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 [90]. It was not until 1950 that New York became the world's first megacity with a population of 10 million or more inhabitants [89], but over the following decades others joined the category and today's 28 megacities are projected to increase to 41 by 2030 [90]. A growth of this magnitude has significant implications for global energy, as urban areas are major consumers (up to 80%) of the world's total energy production, and an increase of up to 56% in global energy requirements has been predicted between 2010 and 2040 [93]. Managing and allocating resources and generating credible predictions of future energy demand requires a clear understanding of the spatial distribution and patterns of urban energy consumption by identifying the factors and indicators that determine and influence the demand side of energy.

The spatial distribution of energy use in urban areas depends on human activities and people's daily routines. Certain types of energy use behavior are clustered in specific spatial and temporal locations [33]. These include work, home and leisure activities, all of which have an impact on future energy demand in distinct areas of the city. For example, individuals may practice low consumption habits at work but then consume disproportionate amounts of energy later in the day when they arrive home and they may be consuming energy from either exclusive or shared resources. It is thus 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 due to non-quantified human dimensions of energy use may adversely affect cities' energy resilience, leading to enormous waste in the financial resources municipalities invest in energy distribution and infrastructure.

2.1 Urban Energy Flux and Demand Prediction

In predicting future energy demand, spatial patterns currently tend to be primarily characterized in terms of physical determinants of the urban infrastructure such as building types [23, 83], city location and district features [22], and building age and function [46], generally also taking into account external conditions such as weather and geographic location [56]. However, given that the planet's urban population is predicted to rise by an additional 2.5 billion inhabitants in urban environments by 2050 [90], the scale and diversity of the human activities driving energy consumption continues to expand [27]. The spatial distribution of energy use thus remains in a continuous state of flux and the resulting intricate interdependencies between infrastructure, services, and individuals presage an ambiguous future in which we will face challenges of which we are not yet aware. This means that existing approaches, which are principally based on the physical characteristics of urban infrastructure, will fail to reliably explain patterns of urban energy, and lead to widely inaccurate predictions of energy demand. This raises important questions regarding our ability to create and maintain adequate energy resources to meet demand in our large and growing population centers.

Although several studies have recognized that different human activity patterns may be responsible for fluctuations in energy consumption [39, 49], researchers have only captured this effect within limited areas, such as individual buildings, which cannot adequately represent the global patterns and structures of energy consumption at an urban level. Much of our current understanding of future patterns of energy use comes from decades of research focusing specifically on the physical properties of cities, omitting any consideration of quantified measures of human activities. Despite the importance of the role urban populations play in the transformation of energy systems [80], reflections of their fluctuating activities are largely absent from urban energy studies.

Treating urban populations as agents of change [1], with rapidly fluctuating patterns of activities, makes it possible to express higher levels of dynamics than the simple physical locations identified in current master plans [110]. To achieve reliable energy demand predictive models, an approach that incorporates patterns of human activities when quantifying spatial fluctuations of energy use is required. Recent advances in both sensing technologies and urban computing methods have greatly increased the availability of relevant data for urban spaces and supported new discoveries related to these challenges [13, 44, 79, 109]. A significant body of work has begun to focus on ways to quantify human activity patterns [44, 51, 52]. In particular, one of the most popular of the new indicators, human mobility, is now being widely studied. The growing use of humans as sensors has facilitated the collection of city-wide human mobility data [109] via individuals' mobile phone signals, which include GPS data [13, 38, 53], as has their smart card commuting data [8], and location-embedded information from online social networks [44, 107, 108], all of which can be used to infer information based on the mobility behavior of urban populations. Here, I review statistically significant indications related to the spatial interdependencies between human mobility and urban energy consumption.

2.2 Methods

I sought to investigate the interdependencies that may exist between the human activities of an urban population and energy consumption, and, if so, determine whether the distribution of urban energy consumption can be predicted by patterns of human mobility. Using radius of gyration as an indicator for human mobility, I examined the spatial distribution of human mobility and energy use and assessed possible models that could explain the present spatial structure.

2.2.1 Data

Human mobility as a possible indicator for the induced fluctuations in the spatial distribution of energy use in Greater London is examined using 18,810,222 individual positional records from an online social networking platform (Twitter) across 4,835 spatial divisions measuring radius of gyration [38]. Data from 3,438,939 electricity meters, and 3,007,392 gas meters in the same areas across 33 Greater London boroughs, over the course of 2014 was also used. Appendix A: Tables A.1 and A.2 list the datasets used in this study, showing the quantities, spatial and temporal scales, as well as the corresponding organization, for each dataset. The level of spatial divisions is based on the administrative boundaries within Greater London: each LSOA (Lower Layer Super Output Area) represents a minimum population of 1000, with an overall mean of 5000. The temporal scales for each dataset are shown by year. The latest LSOA digital boundary dataset released by the UK's Department of Energy and Climate Change (DECC) that is compatible with this datasets is for 2011. The amount of information collected from online social networks is not immune from demographic issues such as the varying tendencies of different segments of the urban population to use online social networks, as well as security issues. The 18,810,222 individual positional records data used–here accounting for human mobility–have been collected from individuals who have voluntarily publicly shared location-enabled information for their Twitter accounts in Greater London; any results in this study are thus representative of this population.

2.2.2 Radius of gyration

In order to obtain a better understanding of human mobility patterns, the radius of gyration (Eq. 2.2) was selected from among the three most widely accepted indicators used to describe large-scale human mobility patterns: the radius of gyration $r_g(t)$, the trip distance distribution $p(r)$, and the number of visited locations $S(t)$ [17, 38, 85]. Of these, the radius of gyration was deemed the most appropriate for capturing individuals' characteristic travel distance within the areas where they habitually carry out their daily activities (i.e. $r_{gi}(t)$), as described below:

$$r_{cmi}(t) = \frac{1}{N_{(t)}} \sum_{i=1}^{N_{(t)}} r_i \tag{2.1}$$

$$r_{gi}(t) = \sqrt{\frac{1}{N_{(t)}} \sum_{i=1}^{N_{(t)}} (r_i - r_{cmi})^2} \tag{2.2}$$

Here, N equals the total number of positional records per individual. The radius of gyration in this study is calculated at two spatial and two temporal levels (Figure 2.1).

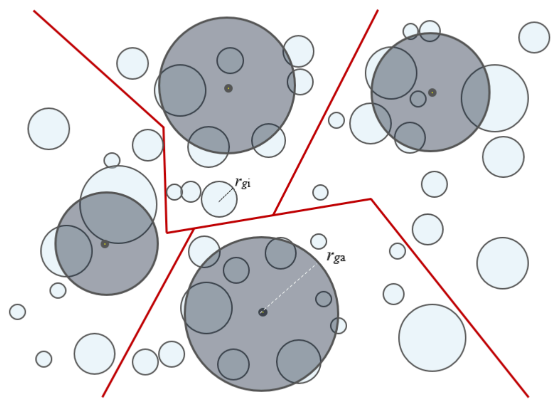


Figure 2.1: Radius of gyration at the individual-level $r_{gi}(t)$, and LSOA-level $r_{ga}(t)$.

As described in Figure 2.1, the individual-level radius of gyration in this study $r_{gi}(t)$, is obtained per LSOA per day around the center of mass of the mobility of an individual (Eq. 2.1). The LSOA-level $r_{ga}(t)$ is obtained per LSOA over the total time frame (in this case, for each month in 2014). The individual level $r_{gi}(t)$ represents the characteristic distance traveled by a user when observed up to time t [38], therefore, every LSOA level $r_{ga}(t)$ (Eq. 2.4) represents the deviation of $r_{gi}(t)s$ from the corresponding center point (Eq. 2.3). This indicator is used to describe the patterns of human mobility across LSOAs.

$$r_{cma}(t) = \frac{1}{K_{(t)}} \sum_{i=1}^{K_{(t)}} r_{cmi} \tag{2.3}$$

$$r_{ga}(t) = \sqrt{\frac{1}{K_{(t)}} \sum_{i=1}^{K_{(t)}} (\frac{r_{gi}(t)}{r_{gi}(t)_{max}}).(r_{cmi} - r_{cma})^2} \tag{2.4}$$

Here, K equals the total number of individuals for whom a minimum 3 (three) positional records is available for a selected month during the study period (2014).

2.2.3 Spatial autocorrelation

Spatial autocorrelation [32] was used to assess of the extent to which the spatial distribution of the data is compatible with spatial randomness and thus determine whether human mobility and energy consumption do indeed have spatial imprints. Spatial autocorrelation tested the spatial independence of human mobility and energy consumption across 4,835 spatial divisions in Greater London. Moran's I [70] (Eq. 2.5), which ranges from -1 (most dispersed) to 1 (most clustered), was used to describe the degree of spatial concentration or dispersion for these variables, with large values for I showing clusters of large values that are surrounded by other large values, namely (I+)–spatial clustering, and (I)–spatial dispersion, indicating large values that are 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 the global spatial autocorrelation for the data, Geary's C [35] (Eq. 2.6) was 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. Moran's I here serves as a measure of sensitivity to extreme values of energy consumption and human mobility, with Geary's C being used to evaluate the sensitivity to differences in smaller neighborhood LSOAs.

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x}).(x_j - \bar{x})}{(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}). \sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{2.5}$$

$$C = \frac{(N-1) \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x}).(x_j - \bar{x})}{2(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}). \sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{2.6}$$

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

Spatial randomness is undesirable, so to ensure that it is not in effect, I reject the situation of spatial randomness in favor of structure (i.e. spatial autocorrelation). Spatial autocorrelation analysis exactly quantifies this, providing a measure of uncertainty (p-value) by which we can reject the null hypothesis (i.e. spatial randomness). A positive spatial autocorrelation indicates that similar values are clusters in neighboring locations, which would be a structure compatible with diffusion [5].

This autocorrelation is compatible with diffusion processes, but since this is a cross sectional condition, further temporal analysis is required to confirm whether it is caused by diffusion or some other kind of contagion processes such as peer effects, social interaction, or another dynamic process and whether it is the results of a true or apparent contagion [5].

2.2.4 Spatial regression

The energy use data in different areas of a city cannot be regarded as being independent of each other in a regression analysis due to spatial autocorrelation. This also holds true for urban human mobility. However, considering the intrinsic spatial autocorrelation of energy consumption and human mobility in the 4835 LSOAs of Greater London, does the correlation between human mobility and energy consumption manifest itself spatially in urban areas? To answer this question in view of the spatial autocorrelation for human mobility and energy consumption, I investigated the nature of this structure through spatial regression as follows. Spatial regression models [96] are used to examine the relationships between variables and their neighboring values and offer a useful way to examine the impact that one observation has on other proximate observations. Starting with an ordinary least square model (Eq. 2.7), with the null hypothesis of a linear regression governing the structure of energy consumption by human mobility as a covariance.

$$y = x\beta + u \tag{2.7}$$

The expression describes the relationship between a vector of observations on the dependent variable y, a matrix of observations on the explanatory variable x (i.e. human mobility), a vector of regression coefficients β, and an error term u. The error term is required to have constant variance and must be uncorrelated (i.e. to possess homoscedasticity). While correlations explore the relationships between or among different variables, autocorrelations can be regarded as a special case, as they, explore correlations within variables across space [36].

In the search for an appropriate autocorrelation structure for the data, I tested for deviations that would violate the null hypothesis such as a non-constant variance for error terms (i.e. heteroscedasticity), correlations for the error terms induced by Spatial lag (SAR) (Eq. 2.8), or Spatial Error (SEM) models (Eq. 2.9):

$$y = \rho W y + x\beta + \epsilon \tag{2.8}$$

where, y is the dependent variable (i.e. energy consumption: electricity and gas); x is the independent (explanatory) variable (i.e. human mobility); β is the regression coefficient; ϵ is the random error term; and ρ is the spatial autoregressive coefficient; in the term ρW, which represents the spatially lagged dependent variable.

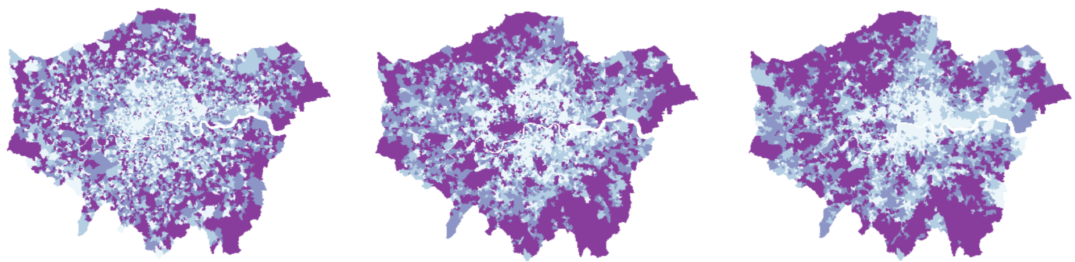
$$y = X\beta + \lambda W \xi + \epsilon \tag{2.9}$$

where, y is the dependent variable (i.e. energy consumption: electricity and gas); X is the independent (explanatory) variable (i.e. human mobility); β is the regression coefficient; ϵ is the random error term; λ is the autoregressive coefficient and ξ represents the normal distribution $(0, \sigma 2I)$ in the term $\lambda W \xi$, which represents the spatial lag for the errors.

2.3 Findings

In order to assess the energy use attributable to individuals' urban mobility and thus evaluate the potential utility of human mobility as a predictor of future energy demand, I first examined how human mobility and energy consumption are spatially distributed, including whether there are underlying processes that impose structure on these distributions that can be used to quantify these patterns or they are merely characterized by spatial heterogeneity and randomness. Figure 2.2 illustrates these distributions across the 4,835 spatial divisions (referred to in Greater London as Lower Layer Super Output Areas, or LSOAs) for human mobility, electricity and gas consumption (see Appendix A: Figures A.1 and A.2).

I found that the spatial distribution of human mobility is not random; an underlying spatial structure governs the mobility of urban population. This structure was present throughout the year with only insignificant deviations from the mean (Figure 2.3). I thus reject the null hypothesis of spatial randomness in favor of structure (i.e. spatial autocorrelation), meaning that the spatial fluctuations of human mobility are relevant and provide additional insights into the structure beyond simply values. Observations of human mobility at one location correlate with those for neighboring locations, with a possible effect on the neighboring values (i.e. values for one division depend on the values at other neighboring locations).



(a) Human Mobility (b) Electricity (c) Gas

Figure 2.2: Spatial distribution of (a) human mobility, (b) electricity, and (c) gas consumption in Greater London, LSOA-level, February 2014.

The results of spatial autocorrelation for energy consumption and human mobility in Greater London are depicted in Appendix A: Tables A.3-A.4. Statistically significant (e.g. p-value <2.2e-16) positive values for Moran's I indicate that both energy consumption (i.e. domestic electricity and gas) and human mobility patterns across the 4835 LSOAs in Greater London follow a clustered distribution as opposed to a dispersed or random distribution. Unlike the case of spatial randomness, the location of values for human mobility may not be altered without affecting the information content of the data.

As further illustrated in the four quadrants of the Moran Scatterplots (Appendix A: Figures A.3-A.4), the spatial autocorrelation for human mobility is classified in terms of four types. Appendix A: Figure A.3, shows the Moran scatterplot for energy consumption representing the clustering patterns and spatial dependencies of neighboring areas for domestic gas and electricity consumption. Unlike the case of spatial randomness, the location of values for human mobility may not be altered without affecting the information content of the data. 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. 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 LSOAs 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 confirm these results. Geary's C uses the square differences to measure similarity (i.e. dissimilarity) and spatial autocorrelation versus product (see Appendix A: Tables A.3-A.4). Between 0-2, the higher the value, the more dissimilar they are. 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.

Interestingly, this correlation appears to be particularly strong (increased spatial dependency) in *September, August, December, and January* compared to other months. The presence of spatial structure suggests that the locations of the individual mobilities' centers of mass (Eq. 2.1) will be significant, likely as a result of where and how individuals arrange their daily trips to home, work, school, shopping, leisure, and so on. Similar results were obtained for energy (electricity and gas) consumption. These spatial autocorrelations suggest predictive models that relate observations of human mobility or energy use at one location to those at other locations can be used to define their particular spatial correlation structure more effectively. Once the existence of a spatial structure for both human mobility and energy consumption was confirmed I asked: Is it likely that people's mobility (representing their daily activity patterns) is the cause of the spatial processes (diffusion, interaction, etc.) driving particular energy use patterns in particular locations? If so, does the data support this? Given the spatial autocorrelations, I conducted spatial regression analysis to visually (Appendix A: Figures A.6-A.79) and statistically (Appendix A: Tables A.5-A.12) explore this hypothesis and determine precisely how the strength of the association between human mobility and energy consumption varies by area. The results of the spatial regression analysis between human mobility and energy use performed to evaluate the contributions of human activities to energy use (electricity and gas) at the urban level revealed that the spatial distribution of energy use was not independent of human mobility; rather the spatial imprints of human mobility localized energy demand distribution. These spatial dependencies were intermittent across the year, reinforcing the finding of an underlying spatial structure for human mobility patterns.

The monthly difference was almost unnoticeable, reinforcing the utility of human mobility as a predictor for urban energy consumption (Figures 2.3-2.4). The spatial regression analysis for electricity and gas across Greater London's 4,835 spatial divisions confirmed the existence of statistically significant relationships between human mobility and energy consumption for two spatial autoregressive models (simultaneous autoregressive models consisting of both lag (SAR) and error (SEM) models), with the SAR models predominantly providing the best representations of global dependency conditions (Appendix A: Tables A.5-A.12). Table 2.1 depicts the statistical significance and parameters of the predictive SAR models

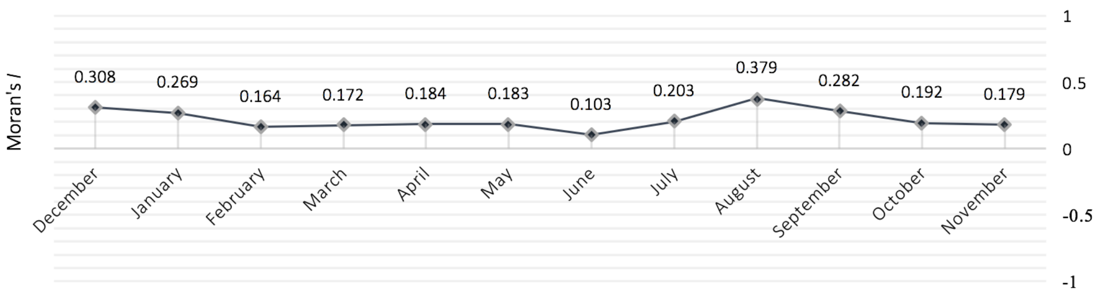


Figure 2.3: Morans I–Spatial dependence for human mobility by month, 2014.

with the lowest Akaike Information Criterion (AIC) for both electricity ($AIC = 77,037$) and gas ($AIC = 90,936$), which were achieved during the month of February.

Table 2.1: Spatial Autoregressive (SAR) model. Electricity, and gas consumption versus human mobility, February 2014.

	Spatial Lag Model (SAR)	
	Electricity	Gas
AIC for Simple Linear Model (OLS)	78,920	93,788
AIC	77,037	90,936
P-value	<2.2e-16 ***	<2.2e-16 ***
z-value	54.713	73.437
ρ	0.69301	0.77
Log likelihood	-38,514.36	-45,463.84
Approximate Std. Error	0.012666	0.010485

$p < 0.001*; p < 0.001**; p < 0.001***$

The simultaneously autoregressive (SAR) model [96], which represents more global dependency conditions appeared to be the most representative spatial model for determining the spatial dependence in the covariance structure as a function of fixed parameters such as the number of energy meters per LSOA by human mobility. Appendix A: Tables A.5-A.12, show the spatial regression results, respectively, for energy consumption (in this case, electricity and gas) compared to human mobility for Greater London over the course of a month for the full year of 2014. All spatial parameters are statistically significant, as indicated by p-values lower than 0.0001 for both electricity and gas consumption. Appendix A: Figures A.6-A.7, 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 versus 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 energy consumption versus human mobility for each LSOA in Greater London is indeed influenced by that of its neighboring LSOAs.

Except for the OLS models, the residuals for both the SAR and SEM show no systematic pattern. OLS residuals by construction are correlated because they extract information from the same dataset, even when the error terms are not correlated. Moran's I applied to the residuals (Appendix A: Tables A.5-A.12) differs from the autocorrelation Moran's I used as a descriptive statistic in section 2.2.3. Here, I examined the errors to ensure that they do not show any pattern. Observing the plots of the residuals in Appendix A: Figure A.7 and A.9, suggest that there is no structural pattern in the error terms for these models. Further, I performed the Breusch-Pagan test for heteroscedasticity [16] to confirm this claim. Unlike the residuals for the SAR and SEM models, which are evenly distributed, the residuals for the OLS models are either clustered in neighboring LSOAs by large values, or are highly asymmetric, both of which indicate missing model specifications.

I seek to determine whether the underlying causes behind the clustering patterns found for energy consumption are indeed driven by human mobility clusters. A naturally contagious process will result in clusters. For example people exchange ideas with one another, creating peer effects for energy saving and triggering clusters of lower energy consumption areas that appear at specific times in space (i.e. true contagion [5]). Alternatively, low or high energy consuming clusters may appear as a result of weather conditions in particular locaions, which is not a contagious process so, the contagious process may not apply. In this case (i.e. apparent contagion [5]), the clusters may simply be caused by some common factor that all the LSOAs are exposed to at the same time. For example, an infrastructure failure could mean that, all LSOAs affected exhibit higher energy consumption rates. Another example would be the adoption of new energy efficient technology (e.g. solar panels, new types of electric supplies, etc.) that result in clusters of low energy consumption. Is this driven by one or more individuals introducing the technology into a neighborhood, creating a peer effect whereby several buildings adopt the technology resulting in low energy consumption clusters? Have they all purchased the new technology after a heat wave? Is there a particular building arrangement in that neighborhood that is enforcing a particular activity pattern, with corresponding energy use clusters? Or, are there buildings or individuals who are causing the clusters? Understanding these very different underlying processes and casual mechanisms is especially significant for policy interventions. If the clusters are formed through diffusion, the corresponding policy should seek to facilitate diffusion, but if the reduction was gained by providing information to local residents, then it may be possible to achieve technology adoption through publicity. Therefore, incorporating an additional time dimension or structure in the spatial regression model is necessary to distinguish between heterogeneity and dependence, and spatiotemporally localize these clusters.

The results of the spatial regression analysis 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 Points of Interest (POIs). This means that human mobility across different areas in Greater London can indeed be regarded as a proxy indicator of spatial fluctuations in energy consumption behavior, with changes in human mobility explaining shifts in the pattern of energy consumption that can then be used to quantify and predict spatial flux for energy use of the urban population.

2.4 Discussion and Implications

Human mobility in urban areas has an undeniable impact on the spatial distribution of energy consumption and can thus serve as a quantitative representation of how an urban population interacts with local energy systems. The results presented in this study suggest that human mobility can be applied to translate the location-based activities of an urban population into collective energy consumption, thus accounting for the urban energy spatial flux. This elevates our understanding of the human dimensions of energy use beyond occupants' behavior at the building level [39, 50], quantifying a measure of this effect at an urban scale. Human mobility patterns at this wider scale can reveal important information about the way citizens interact with their surroundings, driving energy use. By quantifying these effects, we can measure the strength of relationships, understand interdependencies, and make more reliable predictions of future energy demands.

Findings regarding the almost invariable spatial dependencies of human mobility over the year as a result of spatial autocorrelation reveal a predictable activity pattern for urban populations and thus energy use within various urban spatial units. Given that the decentralization and efficient allocation of resources is highly dependent on how an urban populations activity patterns are distributed in space, human mobility can be used to infer location choices [37], anticipate future energy demand and strategize optimal decentralization and resource allocation to different amenities under the influence of human mobility, although further research is needed to contextualize this relationship. Knowing how individuals move around urban open spaces and across the physical infrastructure (both communal and private) of an urban landscape will enable us to build a comprehensive understanding of how certain types of energy behavior are clustered in geographical spaces and temporal locations within urban areas. It should be noted that these results do not exclude the possibility that the physical characteristics of the buildings in their spatial context [22, 23, 46, 56, 83] also significantly affect urban building energy use. However, developing a comprehensive model of location-based human activity patterns of urban populations by applying the concept of human mobility will enable us to extend studies of urban energy demand beyond the simple physical determinants of energy use. As they continue to grow ever larger, our urban areas will inevitably encounter serious challenges as they strive to meet the energy demands of their expanding populations for which our current knowledge is likely to prove insufficient. To cope with the continuing growth in population and the corresponding increase in urban activities, we need to develop a deeper understanding of the root causes of societally significant phenomena such as energy consumption.

The relationship between energy use and human mobility is a key factor for creating effective policies for urban areas. Accurate information on the spatial dependence between fluctuating patterns of human mobility and energy use, the result of an underlying social/behavioral process, can help define a predictable structure for urban energy demand. Spatial dependence is the product of an underlying location–specific activity process that leads to clusters of mobility patterns. These patterns can potentially be explained by groupings of particular populations with similar activity patterns or daily routines [74]; diffusion processes [73], where individuals in the same spatial divisions influence, acquire information, and adopt specific energy use patterns; spatial interactions [73], where individuals tend to interact with those who are spatially closer to them; dispersal processes, where individuals travel short distances (e.g. home to work) and transfer their knowledge and energy use patterns with them; externalities and spatial spillover effects [59]; and/or socioeconomic factors in spatial units that drive similar behavior.

These patterns will also enable us to identify the interdependencies between energy consumption, individual activities, and specific urban spatiotemporal features. Incorporating the spatial imprints into models will advance our understanding and knowledge of the underlying processes and how they propagate across space, shedding new light on the interconnected challenge of theory and analysis.

Perhaps the most striking example of the power of human mobilitys impact on urban energy use, and a significant implication of these interdependencies, is the possible spatial

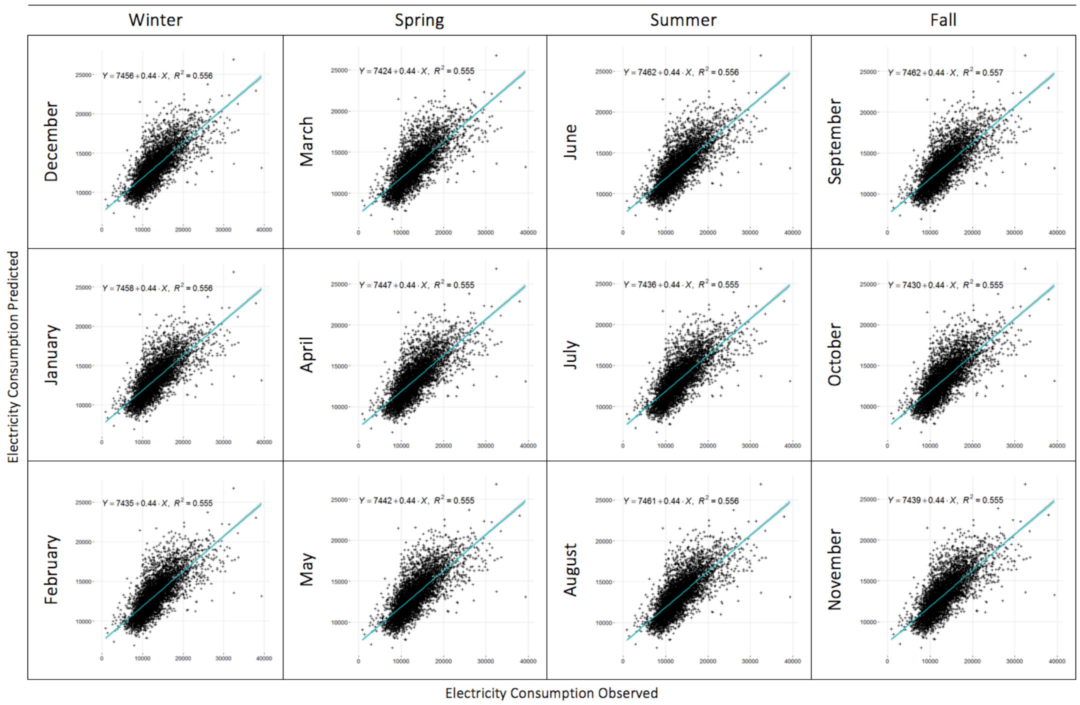


Figure 2.4: Spatial regression–Electricity consumption.

spillover effect [59] that determines whether fluctuations in energy use due to human mobility in one spatial unit (i.e. an individual LSOA) have any diffusive impact on its neighboring locations, and if so, whether there is a significant difference in the diffusive effects of these populations. The SAR (simultaneously autoregressive) models, which were found to be the most representative predictive models in this study, permit the magnitude and significance of direct spillover effects to be assessed, showing how changes in human mobility at a particular location will be transmitted to all other locations and thus how they will affect the energy consumption at the corresponding locations.

The availability of such information will allow city managers and policy makers to identify hotspots and develop effective strategies to create bigger energy efficiency spillover effects, or to restrict unwanted or excessive energy use spillover effects. When creating such strategies, individual energy consumption hotspots can be targeted based on the spatial attributes of those locations. Alternatively, particular human mobility networks can become the focus of attention. Diffusing desired effects by introducing changes in the spatial structure (for example by targeting specific buildings or areas to create bigger spillover effects), or instigating contagion by introducing changes in the flow based on contagion (changing the flow, or mobility, by targeting specific clusters of population), will bring urban planners a step closer to achieving better management and allocation of scarce energy resources. The results of this research will also be of value to business practitioners, policy-makers, and research communities by enhancing their future efforts and eliminating overlooked or poorly specified components of urban energy resilience. In particular, by creating a clear picture of the demand-side concentration and diversity, this research will facilitate the appropriate decentralization of the urban energy distribution infrastructure to reduce the vulnerabilities that lead to service disruptions. The main goal of this study has been to contribute to our emerging understanding of how energy use is changing, especially in urban environments. My ongoing research seeks to understand urban activity patterns across different functional locations using human mobility data to develop integrated predictive models that incorporate temporal elements of activity patterns (for example, recreation, nightlife, shopping, or education) and the resulting fluctuations in the patterns of energy use. Identifying spatial regions with similar temporal activities should allow us to more accurately assess their likely energy use flux and thus optimize the distribution of energy provision.

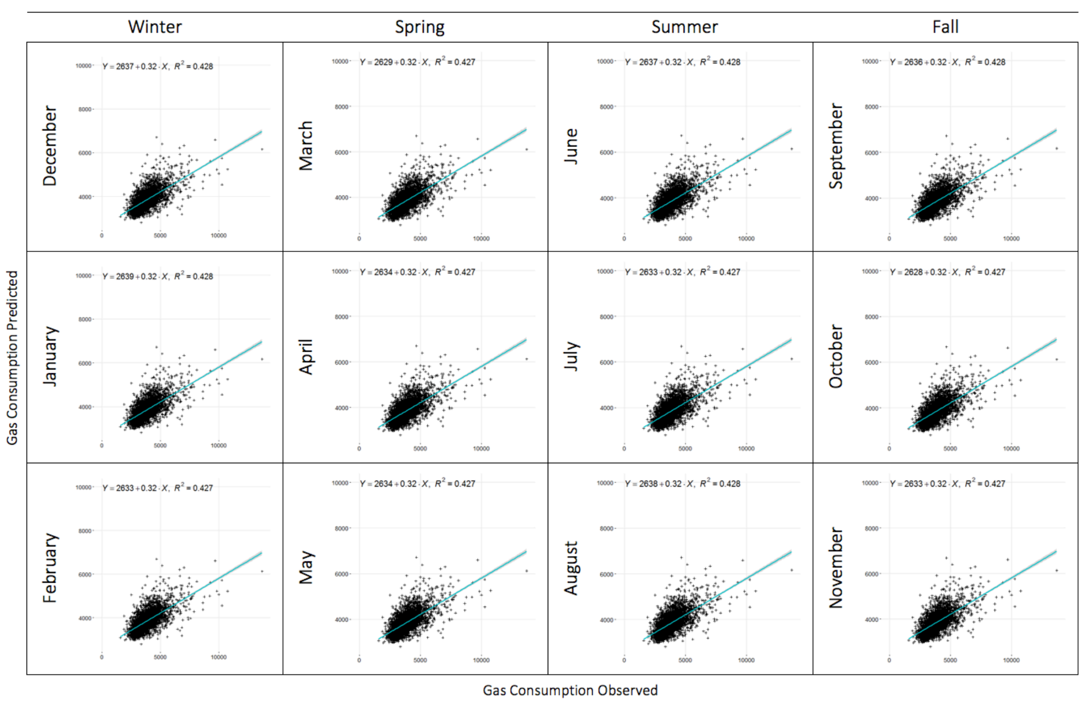


Figure 2.5: Spatial regression–Gas consumption.

This contributes to efforts to understand how the urban population interacts with local energy systems by linking human mobility patterns to spatial fluctuations of energy use. Knowing individuals' movements around urban open spaces and across the physical infrastructure of our urban environments 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 ability to understand how humans interact with urban energy systems [1] and identify evolving patterns and features in intra-urban mobility routines is important for predicting future patterns of energy demand and protecting energy resilience. Attaining global reductions in energy use and CO_2 emissions will demand a paradigm shift in the way we treat energy demand. A clear picture of demand-side diversity that extends beyond the merely physical characteristics of our urban infrastructure will facilitate a more appropriate decentralization of urban energy distribution, thus reducing both, and the vulnerabilities that lead to service disruptions in our ever more complex urban settings.

Chapter 3

The Interplay Between Dominant Drivers of Urban Energy Flux: Populations Mobility Networks and Building Types

Intra-city trips are undertaken by urban populations as a result of individuals engaging in activities across various locations, thus driving energy consumption. Spatial fluctuations in this energy use are thus often associated with the locational distribution of urban building types (i.e. residential and commercial). However, as consumers, people exhibit heterogeneous patterns in their daily activities and the number of locations they visit. Here, I investigate the interplay between populations' mobility networks as an indicator of their daily activity patterns and building types by comparing a total of 27,764,197 positional records from an online social networking platform, Twitter, with energy consumption (i.e. electricity and gas) in Greater London and the City of Chicago over the course of twelve (12) months. The statistically significant spatial dependency between energy use and returners' human mobility networks indicate the dominant role of this population in relation to residential and commercial buildings, suggesting that spatial fluctuations in urban energy consumption are governed by the structure of human mobility networks in relation to building types, among other factors. Future energy efficiency strategies should reflect these spatial dependencies, creating new opportunities for developing better energy related strategies.

Today's cities are the most complex built environments in human history, containing 54% of the world population [90] and responsible for up to 80% of the world's total energy consumption [47, 99]. In particular, residential and commercial buildings are the largest energy-consuming sectors in the economy [2] and are responsible for over one-third of the world [2], and over 40% of the US and Europe's [20, 92] [40] total energy consumption, making urban buildings a major target for energy efficiency initiatives and investment in renewable energy systems. However, as a result of population growth and urbanization, the interdependencies between buildings, services, and individuals in urban areas continue to increase. The parallel rise in the scale and nature of human activities in tomorrow's urban environments [27] will directly drive increases in the number of buildings, energy consumption, and service utilization; meaning that the complex mix of operations and demands, technology adaptation, and lifestyles in future cities will be substantially different. The major shift in urban energy demand stem from the mix of personal activities occurring at specific times and locations [78]. During the course of the day, people engage in a range of different activities scattered across various locations, thus driving the energy demand in those locations. Identifying opportunities for energy saving in different building types and developing the ability to reliably project future energy demands requires a holistic understanding of the factors that contribute to consumption rates.

Global energy demand is expected to rise by more than 25% between 2010 and 2040 [68]; the U.S. Energy Information Administration projects annual decreases of 0.3% in residential energy consumption in the U.S. but increases of 0.6% per year in the nations' commercial sector from 2013 through 2040 [92]. These estimates are based solely on the buildings' characteristics and are independent of their locations, focusing instead 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 [92]. However, building types' characteristics are not solely responsible for consumption rates as their energy use measures are also subject to exogenous effects. Identifying the forces driving energy consumption using a linear regression perspective assumes that buildings are independent of each other and of their consumer populations in terms of the way they use energy in urban areas, which is clearly not the case. Developing a better understanding of the underlying factors governing buildings' energy consumption that extends beyond their mere physical characteristics to take into account population-driven effects is thus becoming imperative.

Urban populations engage in a wide range of daily activities and travel between different locations as they do so, so their energy consumption patterns are typically associated with these location-based activities. We do not yet know whether this variation creates any spatial dependency in energy consumption of buildings in urban areas. For example, do these dependencies fluctuate across building type? If so, are human activities of different urban populations an exogenous variable that can explain these dependencies? There is thus a pressing need to explore how best to ensure that the expected increase in urban populations, with the accompanying rise in the amount, diversity, and complexity of individual activities, all of which will have a significant impact on energy consumption, are managed to support positive outcomes for future energy demand, efficiency and resilience. Understanding variations in the activities of urban populations can contribute to better perceptions of location-specific energy demands and the associated spatiotemporal fluctuations by addressing questions such as: "How are the current fluctuations in the patterns of energy consumption as related to their stimulating urban population activities?" and "Which regions and building types should we expect to experience increases/decreases in demand as a result of these interdependencies?"

In this study I investigate the interplay between urban populations' mobility and energy use across building types. I confirm the predominant role of the interaction between urban populations and building types in energy consumption by examining the underlying spatial reliance between human mobility as an indicator for urban residents' activities in relation to the building types they visit in the course of their daily lives. Understanding the distribution and fluctuating patterns of urban energy consumption in this way can be a significant indicator in managing and allocating current and future resources.

3.1 Spatial Fluctuations of Urban Energy Use

There is a substantial body of research on the determinants of energy consumption in urban settings, much of which has explored the underlying drivers of its fluctuations [3, 33, 57, 77, 105] in both spatial [28, 33, 46, 105], and temporal [29, 33, 54, 98, 102] dimensions. It has been argued that such fluctuations are driven by urban form, density and texture [9, 12, 28, 30, 76, 87, 100], building characteristics [6, 19, 25, 100], building age [3], and function [46]; other researchers have identified population density [12], socioeconomic elements [9, 105], and individual behaviors as having an effect. Given that buildings are generally the biggest consumers of energy in urban areas, these fluctuations tend to be directly associated with different building types and their unique characteristics. Reports in the literature reveal two important omissions: a building's urban spatial context is seldom considered, so the spatially dependent drivers of energy consumption across building types are not taken into account; and the exogenous drivers and externalities frequently linked to different types of buildings' spatial dependencies and their specific consumer populations are not reflected in their energy consumption measures. In particular, spatial effects due to the activities of different consumer populations have received little attention.

In a recent Swiss study, Fonseca and Schlueter [33] proposed an integrated model to characterize city-scale spatiotemporal energy consumption patterns, focusing particularly at fluctuations in consumption in residential, commercial and industrial sectors within urban districts. Seeking to quantify future energy demands for buildings in an urban context, Choudhary [23] proposed a city-scale Bayesian model for the patterns and variations in energy consumption across commercial buildings in Greater London; Choudhary and Tian [22] then moved to examine spatial fluctuations in the energy usage of commercial buildings in various parts of Greater London to compare the effects of city location and district features with the physical characteristics of individual buildings, significantly decreasing the uncertainties associated with evaluating the energy consumption of different building types. Howard et al. [46] developed a linear regression model to estimate the end-use intensity of various building types in New York City based on the assumption that energy consumption primarily depends on a building's function (e.g. residential, educational, etc.) rather than its construction type or age. Such efforts conspicuously fail to consider any external drivers for variations in residential and commercial energy consumption as a result of spatial dependencies, however. Zhang et al. [105] analyzed the spatial variations of energy consumption for 30 provincial capital cities in China using parallel comparison and quantitative analysis, concluding that their different geographic features, economic development levels and the availability of local energy sources were among the main determinants of fluctuations in their energy consumption and thus recommending the use of a type-based management system for urban energy systems. Rey et al. [77] took a slightly different approach in their study of residential energy consumption in 7 neighborhoods in Swiss cities to evaluate the effects of centrality on total energy consumption, finding that occupant density was more representative than built density. As all the above studies were restricted to a single building type, they all ignored spatially dependent variations of energy consumption across building types. It remains to be seen how individuals' energy consumption during their daily activities varies across building types and whether the energy consumed by different building types depends on their location. Activity-based approaches [55, 66] are often used to anticipate future demand for services and the consumption of resources, but once again these approaches focus primarily on the diversity of activities rather than the heterogeneity that exists across users and the patterns of their collective activities in time and space. In order to be able to reliably locate high/low energy consuming locations, we need to track the population themselves. Location-based activities do not fully represent the extent of usage, but the movements of consumers do.

Researchers studying human mobility have investigated the spatiotemporal variations of population movements [13, 38, 44, 60, 84, 111] and linked these variations to patterns of activities, or motifs [18, 44, 81], as well as land-use or cities' functional regions [21, 37, 51, 86, 103]. While spatiotemporal variations in human mobility appear to have been extensively studied, the link between recurring patterns in the mobility of different populations due to their activities and fluctuations in buildings energy consumption remains elusive.

3.2 Human Mobility Networks

Human mobility has been shown to account for much of the human activity observed city-wide [18, 44, 51], providing a convenient way to identify clustered locations in urban areas where individuals engage in activities, inferred to be either home, work, or "other", from human mobility data [4]; and to predict urban energy consumption due to the associated spatial dependencies [69]. However, the spatiotemporal patterns of human mobility and energy consumption are far from homogeneous across urban settings. Despite the fundamental laws governing human mobility and travel distance at larger scales [17, 38, 85], the distribution of the human mobility radius of gyration [44] suggests that intra-city daily human mobility is largely heterogeneous [38, 79], with individuals exhibiting variations in their daily activities, the number of locations they visit over time, and hence their daily mobility. The significance of this variability in travel behavior, as well as its analytical rationale and policy implications, are the subjects of a long standing debate [55]. The earliest work in this area examining the dynamics and rhythms in mobility behavior was limited to survey data [7], applying travel-activity survey data to explore spatial variability in activity-travel behavior [18]. Later, it became possible to gather data on the temporal variability of individuals' daily activities in order to identify structures and clustering activities at different times of the day [51]. Schneider et al. [79] explored individuals' daily mobility in the form of networks of visited locations in two different cities (Paris and Chicago), and across different datasets (a travel survey and mobile phone billing data) and found recurring sets of 17 daily mobility networks that they labelled human mobility motifs. They further discovered that 90 per cent of the individuals surveyed visited only seven daily locations. A more recent study [111] examined the spatiotemporal variability of human mobility through statistical analysis and networked-based clustering methods at both the individual and aggregate levels in Singapore in order to identify diversity. Louf and Barthelemy [61] took this a step further, reporting that the structure of human mobility patterns governs a variety of urban quantities, including the quantity of CO_2 emitted and the total consumption of gasoline. Pappalardo et al. [74] classified individuals into two populations with distinct mobility patterns: returners, and explorers, with the returners being those individuals whose mobility network is dominated by a few recurrent preferred locations (e.g. home, work) and the explorers' mobility networks spanning a much larger number of different locations. They found significant correlations between these mobility networks and individuals' social interactions, as well as their role in the diffusion phenomenon.

Understanding whether the distinct mobility patterns of these two populations can explain spatial fluctuations in energy consumption is thus of fundamental importance and can result in better predictions, better management and the more effective allocation of resources. Here, I explore whether one population exerts a disproportionate influence over the spatial consumption of energy in urban areas and whether this influence is focused predominantly on a specific building type (i.e. residential or commercial) by examining the most highly preferred locations in individual residents' mobility networks in Greater London and the City of Chicago, over the course of one year. As an initial step, the impact of the interactions of the two populations (returners and explorers) with urban buildings (residential and commercial) is examined via a spatial autocorrelation analyses of a total of 27,764,197 positional records accounting for human mobility of individuals in Greater London (18,996,107) across 983 areas and the City of Chicago (8,798,090) across 801 spatial divisions, in conjunction with energy consumption data (electricity and gas) for the same areas and spatial divisions. I provide an assessment that reports on two main findings. First, the results identified spatial dependencies for urban energy consumption (electricity and gas) in both residential and commercial buildings. Second, spatial dependencies were found for the mobilities of different urban populations (returners and explorers) representing their underlying location-based human activities that likely explain fluctuations in the location-based urban energy consumption. Accurate energy consumption and demand projections in the future are thus likely to require a shift toward more location-based estimations that take into account the human mobility networks of different populations.

3.3 Methods

3.3.1 Data

For this study, 18,966,107 positional records (collected over the course of a year, namely 2014) of 281,129 individuals, of whom 171,474 were identified as returners and 109,655 as explorers, along with the electricity and gas consumption records by 3,827,379 and 3,040,544 building meters distributed across 983 spatial divisions in Greater London were examined. These spatial divisions consist of MSOAs (Middle Layer Super Output Areas), which are administrative boundaries representing a minimum population of 5,000 with an overall mean of 7,200 in Greater London. Likewise, 8,798,090 positional records and 105,092 individuals (i.e. 65,206 returners and 39,886 explorers), along with the electricity and gas consumption of 645,005 and 751,842 building meters distributed across 801 spatial divisions were examined for the City of Chicago (see Appendix B: Tables B.1-B.4). The spatial divisions in this case consisted of Census Tracts with an average population of 4,000. The commercial gas consumption dataset contained missing data values across spatial divisions. Kriging prediction [11] was used to compensate for the missing consumption data under the assumption that this data was missing completely at random. Energy 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 was deemed the most appropriate, the circular covariance model, was used to compensate for the missing data based on its least AIC value in the fitting process.

The positional records included in the study consisted of those individuals with at least three distinct records across two different spatial divisions within the duration of the study. Timestamped positional records were streamed from an online social networking platform (in this case Twitter) and logged if the user allowed this. The users were then classified into one of two distinct populations (returner and explorer) based on their 2 (two) most frequently visited locations. I then explored whether each population's mobility exhibited a meaningful spatial imprint that would serve as an indicator for energy consumption through spatial autocorrelation and regression analysis.

3.3.2 Radius of gyration

Radius of gyration $r_g(t)$: (Eq. 3.2) [38] was selected as the metric for measuring human mobility in this study from among the most widely accepted indicators for describing large-scale human mobility patterns to capture individuals' characteristic travel distance within the area they habitually move around in during the course of their daily activities. The radius of gyration was calculated at two spatial and temporal levels for each of the two study populations. The individual level $r_{gi}(t)$ is the characteristic distance traveled by a user when observed up to time t, so every MSOA/Census Tract level $r_{ga}(t)$ represents the deviation of $r_{gi}(t)s$ from the corresponding center point (Eq. 3.1). This indicator was then used to describe the patterns of human mobility across MSOA/Census Tracts.

$$r_{cmi}(t) = \frac{1}{N_{(t)}} \sum_{i=1}^{N_{(t)}} r_i \tag{3.1}$$

$$r_{gi}(t) = \sqrt{\frac{1}{N_{(t)}} \sum_{i=1}^{N_{(t)}} (r_i - r_{cmi})^2} \tag{3.2}$$

Here, N equals the total number of positional records per individual. The radius of gyration in this study is calculated at two spatial and two temporal levels.

Next, I ranked the 983 MSOAs and 801 Census Tracts for each individual based on their frequency of visits. After identifying the two most frequently visited divisions for each individual, the individual-level $r_{gi}(t)$ was obtained per MSOA (Greater London) or Census Tract (City of Chicago) per day. The MSOA/Census Tract level $r_{ga}(t)$ was then obtained per MSOA/Census Tract over the total time frame (in this case one month, repeated for 12 months, 2014). At the spatial level, I calculated the weighted radius of gyration per MSOA/Census Tract and the total radius of gyration for each individual for the study period and calculated the s-radius of gyration (Eq. 3.3) for each individual for the top 2 (two) most frequently visited spatial divisions.

$$r_g^{(s)} = \sqrt{\frac{1}{N_s} \sum_{i=1}^{N_s} (r_i - r_{cm}^{(s)})^2} \tag{3.3}$$

Here, *S=1,2*.

Finally, I compared the total r_g and $r_g(s)$ of each individual through a Support Vector Machine (SVM) classification such that the population was split into two distinct classes: returners and explorers [74]. s-returners, with $r_g(s) \approx rg$, are those individuals whose characteristic traveled distance is dominated by their s-th most frequently visited spatial division, while the mobility network of s-explorers, with $r_g(s) \ll rg$, spanned multiple spatial divisions and could not be reduced to s locations.

3.3.3 Heterogeneity and spatial randomness

A spatial autocorrelation analysis was performed for energy consumption (electricity and gas) across building types as well as urban mobility for two distinct populations (returners and explorers) across 983 MSOAs in Greater London and 801 Census Tracts in the City of Chicago to measure the correlation between energy consumption and human mobility variables in the spatial dimension and assess the extent to which their spatial distributions are compatible with randomness.

Moran's I(Eq. 3.4), which ranges from -1 (most dispersed) to 1 (most clustered), was applied to describe the degree of spatial concentration or dispersion for energy consumption and human mobility (of returners and explorers). This also provided a useful test of independence to determine whether the values of returners and explorers' human mobility or energy consumption observed in one location depended on the values observed at neighboring locations.

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x}).(x_j - \bar{x})}{(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}). \sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{3.4}$$

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

Finally, I used *Getis-Ord G* and *Gi** (Eq. 3.5 and 3.6) to perform a hotspot analysis for returners and explorers as well as the energy consumption for residential and commercial buildings.

$$G = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{i,j} x_i x_j}{\sum_{i=1}^{n} \sum_{j=1}^{n} x_i x_j}, \forall j \neq i \tag{3.5}$$

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{S \sqrt{\frac{[n \sum_{j=1}^{n} w_{i,j}^2 - (\sum_{j=1}^{n} w_{i,j})^2]}{n-1}}}, \bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}, S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n}} \tag{3.6}$$

3.3.4 Spatial regression

In view of the spatial autocorrelation between human mobility and energy consumption, I investigated the nature of this structure through spatial regression. Further, I examined the spatial spillover effects [59] 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. Distinguishing between global and local ranges of dependence, Anselin [5] 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, I compared changes in human mobility with electricity and gas consumption patterns. Starting with an ordinary least square model (Eq. 3.7), with the null hypothesis of a linear regression governing the structure of energy consumption by human mobility as a covariance.

$$y = x\beta + u \tag{3.7}$$

In the search for an appropriate autocorrelation structure for the data, I tested for deviations that would violate the null hypothesis such as a non-constant variance for error terms (i.e. heteroscedasticity), correlations for the error terms induced by Spatial lag (SAR) (Eq. 3.8), or Spatial Error (SEM) models (Eq. 3.9):

$$y = \rho W y + x\beta + \epsilon \tag{3.8}$$

where, y is the dependent variable (i.e. energy consumption: electricity and gas); x is the independent (explanatory) variable (i.e. human mobility); β is the regression coefficient; ϵ is the random error term; and ρ is the spatial autoregressive coefficient; in the term ρW, which represents the spatially lagged dependent variable.

$$y = X\beta + \lambda W\xi + \epsilon \tag{3.9}$$

where, y is the dependent variable (i.e. energy consumption: electricity and gas); X is the independent (explanatory) variable (i.e. human mobility); β is the regression coefficient; ϵ is the random error term; λ is the autoregressive coefficient and ξ represents the normal distribution $(0, \sigma 2I)$ in the term $\lambda W\xi$, which represents the spatial lag for the errors.

3.4 Findings

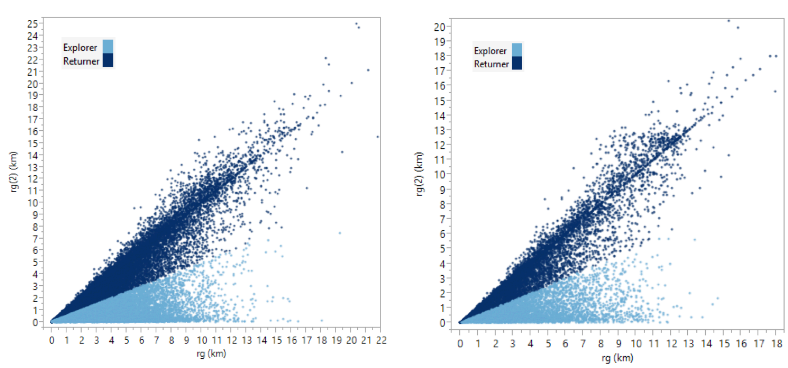
Figure 3.1 shows the distribution of returners-explorers in terms of their radius of gyration (total (r_g) and two most frequently visited spatial divisions' $(r_g^{(2)})$ for (a) Greater London, and (b) the City of Chicago. Appendix B: Figures B.1-B.6 depict the spatial distributions of their mobility measures as well as energy consumption (i.e, electricity and gas) for residential and commercial buildings in both Greater London and the City of Chicago.

The randomness hypothesis for the mobility of both returners and explorers is rejected in favor of spatial structure (see Appendix B: Tables B.5-B.14). This condition holds true repeatedly over the course of the entire 12 month study period in 2014, except for the explorers population during the month of *January* in Greater London, and the months of *December* and *April* in the City of Chicago, meaning that both populations' movements through different temporal states follow very similar spatial dependencies with possibly minimal effects from seasonal conditions. The spatial autocorrelation results confirm that for the human mobility of returners and explorers, location is not only relevant but also provides additional information beyond simple values.

Likewise, there is a spatial structure underlying the fluctuations in energy use (electricity and gas) across building types (residential and commercial), indicating that these variables also exhibit a structured pattern over space. Observations from nearby locations were more similar than would be expected on a random basis. The exceptions for this condition is gas consumption in Greater London's commercial buildings, as well as gas consumption in the City of Chicago's residential buildings during the summer (i.e. months of *June, July, and August*). Energy consumption rates in a given area for residential/commercial buildings thus appear to depend not only on a building's own characteristics [92], but also on the characteristics of its surrounding area [56]. Statistically significant positive contagion effects may influence both residential and commercial energy consumption, with a stronger effect for gas consumption for residential buildings in Greater London and electricity consumption for residential buildings in the City of Chicago. However, the autocorrelations for electricity and gas consumption are not the outcome itself, but instead are attributable to missing spatial covariates in the data, which are often correlated with location.

As illustrated in the four quadrants of the Moran scatterplots (see Appendix B: Figures A.11-A.19), there are four types of spatial autocorrelation for the variables. A positive spatial correlation indicates clustered values in similar locations, with areas of significance being the datasets in the high-high (upper right), and low-low (lower left) quadrants. The positive autocorrelation for the high-high scatterplot quadrant areas can be interpreted as indicating regions with high gas consumption or human mobility for returners or explorers which are clustered with and dependent on neighboring regions with high values for the corresponding variable. In contrast, the low-low quadrant areas are those spatial divisions with low energy consumption (electricity or gas) across building types (residential and commercial) or human mobility for returners or explorers that are clustered with and dependent on other low value areas. The two remaining quadrants, high-low (bottom right) and low-high (upper left), both depict negative spatial associations.

The results for the hotspot analysis suggest a stronger relationship between hotspots of electricity consumption in residential buildings and the human mobility of returners than that of explorers in Greater London (see Appendix B: Tables B.15-B.24). This condition also holds true for electricity consumption in commercial buildings, however the hotspots for gas consumption in commercial buildings were not statistically significant.



(**a**) Greater London (**b**) City of Chicago

Figure 3.1: Recurrent vs. overall mobility of populations (i.e. returners and explorers), May 2014. (a) Greater London, (b) City of Chicago.

Table 3.1 shows the statistical coefficients for these analyses in May 2014, which suggest that those spatial divisions with high electricity/gas consumer residential building values are also surrounded by high human mobility returners. The larger the value of G, the more intense the clustering of these high values (hotspots), indicating that hotspots of returner mobility exhibit a very similar spatial clustering to that of energy consumer residential buildings hotspots (Figure 3.2). This condition is not clearly apparent for the case of the City of Chicago. Although statistically significant electricity consumption hotspots are identified, the corresponding hotspots for the returners and explorers populations are not statistically significantly observable (see Appendix B: Tables B.15-B.24 and Figures B.12-B.16).

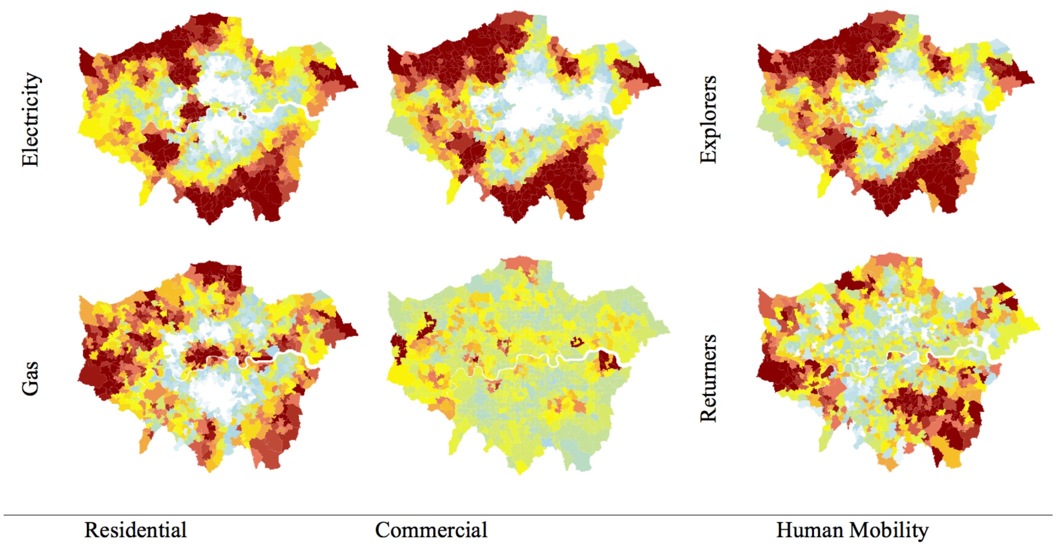


Figure 3.2: *Getis-Ord Gi* Hotspots, Greater London (May).

Whether neighboring areas have a diffusive effect on each other or experience any spatial spillovers—where changes occurring in one area have an impact on neighboring areas, which would exist across building types—motivated me to conduct further spatial regression analyses for this study by incorporating the variation in human mobility of two distinct urban populations (returners and explorers).

3.5 Predominant Drivers of Energy Consumption

Having identified the dominant role played by returners in the spatial imprints of energy consumption, the next step is to understand the dependencies that exist between their mobility patterns and their energy consumption compared to explorers. Although, the energy usage in different areas of a city cannot be regarded as being truly independent of one another in a regression analysis due to the identified spatial autocorrelation, the same statement does

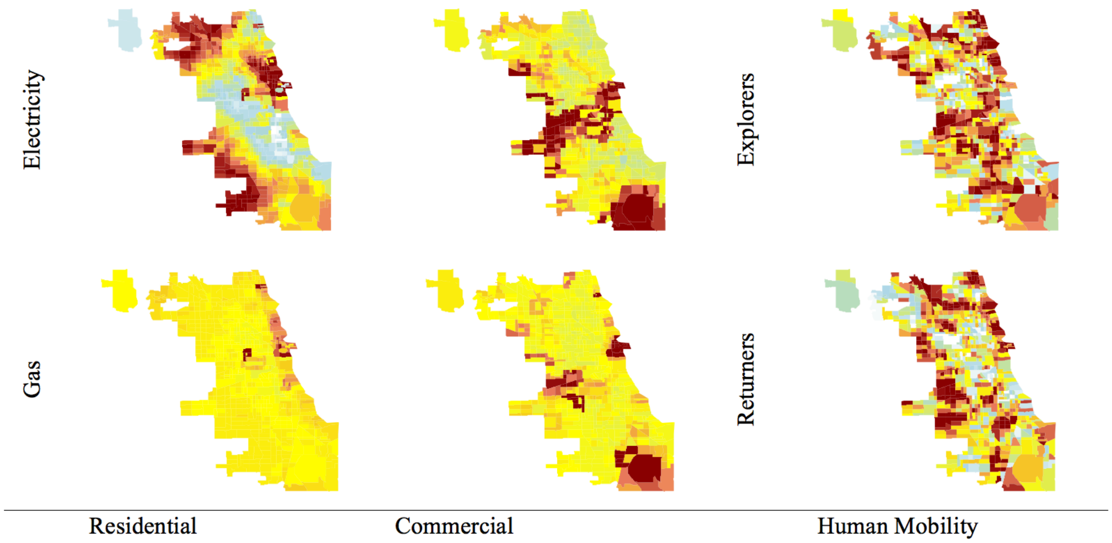


Figure 3.3: *Getis-Ord Gi* Hotspots, City of Chicago (July).

hold true for urban human mobility for different populations (i.e. returners and explorers). In other words, considering the intrinsic spatial autocorrelation of energy consumption and human mobility in the 983 different areas of Greater London and the 801 spatial division of the City of Chicago, does the correlation between the human mobilities of the returners and explorers and electricity consumption by residential buildings manifest itself as being spatially different in different urban areas?

Table 3.1: Spatial autocorrelation–*Getis-Ord Gi*.

	(a) Greater London			(b) City of Chicago		
	Statistic(G)	p-value	SD	Statistic(G)	p-value	SD
Returners	5.926972e-03	0.006603	2.4781	8.567457e-03	0.003148	2.7319
Explorers	5.971599e-03	0.001896	2.8949	8.599385e-03	0.02741	1.9203
Residential						
Gas	6.804931e-03	<2.2e-16	17.924	7.725959e-03	0.5986	-0.24977
Electricity	6.472315e-03	<2.2e-16	13.083	8.630438e-03	0.0021	2.8583
Commercial						
Gas	6.181046e-03	0.305	0.50995	1.995099e-02	0.001782	2.9143
Electricity	6.32768e-03	<2.2e-16	10.478	1.428466e-02	4.945e-08	5.3287

To answer this question, I performed a spatial regression analysis. Exploring the relationships between energy consumption and the human mobility of returners and explorers in each MSOA/Census Tract and their neighboring values allowed us to examine the impact that a single observation has on other proximate observations. Having found spatial dependencies and clustering distributions for the human mobilities of both returners and explorers with energy consumption, I modeled their spatial interdependencies, by applying autoregressive models to implicitly incorporate this spatial dependence into a covariance structure. The two main autoregressive models for areal data used in this study were simultaneous autoregressive models consisting of both lag (SAR) and error (SEM) models to represent global dependency conditions and identify spatial dependence in the covariance structure as a function of fixed parameters such as the number of energy meters per MSOA/Census Tract and to examine various conditions across building types. I also compared the results using a simple linear model, as well as developing a third model in which returners and explorers are both considered as covariates (see Appendix B: Tables B.25-B.40 and Figures B.17-B.19, Greater London and Tables B.41-B.56 and Figures B.20-B.23, City of Chicago).

Table 3.2 shows the statistical significance and parameters for all three models. As indicated by their p-values lower than 0.0001, these models all produced statistically significant results that can be used to predict energy consumption based on the human mobility of the population. However, with respect to the AIC measures, the SAR model with the lowest AIC value (Greater London: AIC = -17,33.4; City of Chicago: AIC = -2691.7) that incorporates data for returners only is the most representative spatial model and predictor for the electricity consumption of residential buildings. The multivariate SAR that incorporates data for explorers only performed the least well (Greater London: AIC = -1726.5; City of Chicago: AIC = -2691.4), with considerably less support than the best model. These models all explicitly test the impact of human mobility variables on energy consumption. At a global scale, they imply that the state of the energy consumption per human mobility network of returners and explorers for each MSOA in Greater London or Census Tract in the City of Chicago is influenced by that of its neighboring spatial divisions and that this influence is better explained by returners and through spatial lag models implying a significant role for this population in the spatial distribution of energy consumption by residential buildings. A significant implication of these interdependencies relates to the possible spillover effects, namely whether or not the fluctuations occurring in energy consumption due to the human mobility of returners and explorers in one spatial division will have any diffusive impact on neighboring spatial divisions and if so, whether there is a significant difference in the diffusive effects of these populations.

The OLS and SEM models do not allow the spillover effect to be explored due to their spatial independence limitations, but the SAR models, which are also the most representative predictive models, do permit the magnitude and significance of direct spillover effects to be assessed, thus showing how changes in human mobility at a particular location will be transmitted to all other locations and how they will affect their energy consumption. Having such information will allow city managers and policy makers to identify hotspots and develop strategies to support bigger energy efficiency spillover effects, or to restrict unwanted or excessive energy use spillover effects. When creating such strategies, individual locations in terms of building types (e.g. hotspots for energy consumption by residential buildings) can be targeted based on the spatial attributes of those locations. Alternatively, particular human mobility networks (consisting of either returners or explorers) can become the focus of attention. Whether diffusing desired effects by introducing changes in the spatial structure (e.g. targeting specific buildings or areas), or instigating contagion by introducing changes in the flow (targeting specific populations), planners will be one step closer to ensuring better management and allocation of energy resources in urban areas.

Table 3.2: Spatial regression–Electricity consumption per human mobility network in residential buildings.

	(a) Greater London			(b) City of Chicago.		
	OLS	SAR	SEM	OLS	SAR	SEM
Returners						
p-value	5.429e-09	<2.2e-16	<2.2e-16	0.4066	9.2e-09	7.937e-09
AIC	-1367.7	-1733.4	-1726.1	-2660.7	-2691.7	-2691.9
R-squared	0.03313	-	-	-0.00039	-	-
Statistic	5.886	0.66556	0.67405	-0.83	0.31419	0.3128
Explorers						
p-value	0.00175	<2.2e-16	<2.2e-16	0.5339	9.0509e-1	8.619e-09
AIC	-1343.4	-1726.5	-1724.7	-2660.4	-2691.4	-2691.5
R-squared	0.00893	-	-	-0.00077	-	-
Statistic	3.139	0.67562	0.67811	-0.622	0.313	0.31347

$OLS : SimpleLinearModel$

$SAR : SpatialLagModel$

$SEM : SpatialErrorModel$

3.6 Discussion and Implications

The dominant role played by returners' human mobility networks on the urban energy consumption for residential buildings highlights the importance of the impact of the various activities of urban populations on current and future energy usage across different building types. The relationship between the spatial variations in returners' mobility—which are driven by their routine activities as they visit different locations—and energy consumption at these locations greatly improves our understanding of how energy demand is distributed in an urban setting. Moreover, the predominant role of residential buildings in this process highlights the major influence of urban spatial effects on residential and commercial energy consumption due to the human mobility of the urban populations. Energy consumption rates can no longer be regarded as being independently generated at a building level or as arising solely as a result of individual building characteristics [19, 22, 23, 33, 46, 56, 83]; instead, possible spillover effects must also be taken into account across neighboring buildings. The intrinsic spatial autocorrelation of energy consumption found in this study, as well as the crucial roles of returners' and explorers' mobility in two very different cities, Greater London and the City of Chicago, show a spatial correlation between human mobility and energy consumption that is statistically significant. The interplay between the human mobility networks and energy consumption in both cities reveals that changes in human mobility in region i immediately lead to increases in the observed energy consumption for all neighboring regions ij. Over time, changes in the mobility of returners and explorers will create a new equilibrium in the relationship between energy consumption and both distance and mobility variables. Moreover, the smaller values of the autoregressive coefficient for gas consumption in commercial buildings implies that the effects of human mobility may dissipate relatively quickly, approaching zero after a short distance, although this effect decays more slowly for higher order (i.e. non-immediate) neighbors in residential buildings. Such spillover effects reflect the broader perspective needed when considering urban building energy consumption over a larger scale. Understanding the resulting continuous state of flux across urban areas, their underlying dynamics and the drivers of heterogeneity in consumption and demand is thus fundamental for making accurate demand predictions.

Urban areas are undergoing a significant growth in population worldwide, accompanied by a corresponding increase in human activities. Energy consumption by all types of urban buildings is projected to increase significantly [92], population growth and urbanization will exert different effects on this increased consumption due to human activities, but this will not necessarily be the same across different building types. In order to address the continuing growth in population [90] and increases in urban activity levels, it is necessary to develop a better understanding of the root causes of energy consumption. Trends that are becoming evident in energy consumption are expected to reveal critical information regarding the important roles different drivers will play in the future, enabling planning to identify new opportunities for energy-efficient solutions and more cost-effective renewable energy investments. The use of alternative assumptions when estimating future energy demand can lead to more reliable predictions, with major implications for energy consumption mitigation strategies. For example, if a building located in a particular neighborhood is identified as having a high potential for solar generation but the spatial dependencies predict lower energy consumption rates in the area in future, financial expenditure versus efficiency gain trade-offs can be calculated before any investment decision is made. The relationship between energy consumption and human mobility can thus be a key part of creating effective policies for urban areas.

Crucially, rapid globalization and the subsequent growth in energy consumption can no longer be sustained, as population growth has the potential to far outpace the development of new energy supplies. According to a recent International Energy Agency World Energy Outlook report, "Greater changes in the future are possible as the relation between work, home, and free time and the technologies that support these activities evolve" [47]. A better understanding of the underlying drivers of this process and its fluctuations across different populations belonging to different communities and organizations [50] will generally facilitate the identification of an urban system's reactive, recovery, and adaptive capacities across time and space. Cities are self-organizing in the sense that interactions between individuals and the built environment form self-reinforcing patterns of spatial and temporal allocations. Understanding how different urban settings and populations respond to change in a predictable fashion will also reveal the associated orders and states, thus providing useful insights that could guide future management decisions. This research is a step towards achieving these goals. Additional explorations of the functional regions to which each population travels will help to further clarify the relationship between human activities and energy consumption in urban areas, providing useful information for those charged with developing appropriate energy allocation strategies. The question of how to anticipate the growth in demand and supply energy for billions of new urban residents will require a more holistic approach to measuring energy consumption. At present, our best estimates are not adequate to deal with the major changes anticipated in energy consumption and demand. Spatial dependencies and their impact on energy consumption in response to the ongoing changes in human activities are unknowable and are, hence, often neglected in these measures. The underlying changes that will affect future demand cannot be clearly established. Energy consumption mitigation efforts that focus 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 by identifying the spatial patterns dominating energy use and their underlying determinants, a topic of considerable interest for both basic and applied research. The findings may be particularly relevant for those seeking to explain the spatial patterns and causes of energy consumption related to specific land uses and for research into the potential impact of the spatial proximity of various end use infrastructure elements.

Chapter 4

Temporal Fluctuations and Space-Time Predictions of Energy Use

Urbanization is causing a significant increase in the amount, diversity, and complexity of human activities, all of which have a substantial impact on energy consumption. Current approaches to predicting energy demand at different spatiotemporal levels are functions of the characteristics of either individual buildings or cities and their occupancy levels, or are data-driven, typically taking the form of sensor-based modeling. Nevertheless, accounting for both the spatial and temporal effects of heterogeneous human behavior patterns on buildings' energy use at the city-level remains a challenge. Here, I examine the temporal manifestation of the fluctuations of energy use driven by spatial mobility patterns of the returners urban population. I then present an urban-level spatiotemporal approach for predicting buildings' energy demand. Using a full year of individual positional records from an online social networking platform (Twitter), I introduce a multivariate autoregressive model in reduced principle component analysis (PCA) space to create monthly predictions of electricity demand that account for 88% of the energy used by buildings in the City of Chicago, generated across 801 spatial divisions through a spatial autoregressive model. This model represents an important step forward, incorporating the spatiotemporal energy use fluctuations of urban populations to create more reliable predictions of demand in future cities.

High levels of uncertainty about future energy demands impose limits on the continuing growth of cities worldwide. Urban areas, which have become the most complex built environments in human history, are rapidly expanding in terms of both their size and population [90]. However, subsequent additions to the amount and complexity of daily activities of urban populations may not be able to be sustained without an accompanying substantial increase in their energy infrastructure. Urban areas are now responsible for up to 80% of the world's total energy consumption [47, 99] and the corresponding risks involved in supplying, or failing to supply, sufficient energy resources are inevitable. Having a clear understanding of the space-time distributions of urban energy demand is thus clearly of paramount importance for both planners and city managers. We need to be able to reliably estimate how much energy will be needed at particular times and locations across a range of urban settings. Enhancing our ability to understand and manage short and long term urban energy resources is essential if our cities are to continue to thrive and develop into smarter built environments capable of accommodating the growth of technology and the corresponding fluctuating activity patterns of the urban population. Here, I examine the temporal manifestation of the fluctuations of energy use driven by the spatial mobility patterns exhibited by the city's populations and introduce a spatiotemporal approach for predicting energy demand in urban areas.

Current approaches to predicting energy consumption at different spatial levels are functions of the characteristics of buildings [15, 31, 46] or cities [23, 67] and their occupancy [67], or rely on sensor-based data-driven approaches [48]. At the city scale, Choudhary introduced a Bayesian regression model to estimate energy intensity distributions using floor area estimates for various building usages in London [23]. Mikkola and Lund [67] introduced a model for generating spatiotemporal power demand in urban areas using building and population data at the neighborhood level based on building types, their load profiles, and their share of floor area, energy intensity and electricity demand, as well as population density, and city area. At the district level, Boulaire et al. [15] proposed a statistical model based on spatial building and household characteristics in Australia. At the block (zip code) level, Howard et al.'s [46] energy prediction model is primarily based on building functions in different locations within New York City. At the building level, these efforts have tended to focus on data-driven methods and sensor-based energy modeling approaches. For example, Jain et al. [48] introduced a sensor-based forecasting model for residential buildings' energy consumption in New York City, using inputs of electricity consumption at different spatiotemporal granularities supplemented with hourly outdoor temperature data. However, a thorough review of the literature in this area has uncovered no studies exploring the predictability of urban scale energy consumption that incorporate the spatiotemporal effects arising from fluctuations in the activity patterns of the populations at the urban level.

Urban population activities are a major source of change affecting future demand and thus serve as the foundation of our spatiotemporal estimations of energy use towards more reliable predictions. Researchers have not found it easy to study the dynamics of individual activities at different spatial and temporal resolutions because the only data available was from surveys and monthly bills, and conceptual frameworks were the only measures available to assist effective decision making. Thanks to recent advances in technology, more powerful computers, and the advent of online social networks, urban population data at high spatiotemporal resolutions is now plentiful. The use of humans as sensors has made city-wide human mobility data available [109] through mobile phone signals that incorporate GPS data [13, 38, 53, 109], smart card commuting data [8], and location-embedded information from online social networks [44, 45, 64, 107, 108], all of which can be applied to provide information on the mobility behavior of urban populations. The human mobility patterns that are now visible to researchers reveal important information about the way citizens interact with their surroundings as they go about their daily lives.

As individuals move around their urban environment, they drive the energy consumption associated with their location-based activities at particular times. The essential challenge facing academic researchers is thus to find a way to anticipate future changes in human activities (human mobility) that will enable them to make reliable predictions of future urban energy demand. A growing body of research has explored the predictability of human mobility [44, 62, 63, 65, 101], and new models are continually being proposed that provide more reliable predictions of energy consumption [15, 67, 94, 106]. Studies that have focused primarily on predicting human mobility [63, 65, 85, 101] and building human mobility-based predictive models [97] have taken a number of different approaches. Although up to 93% predictability has been achieved for the movements of individuals [85, 101], changes in their predictability can arise due to unforeseen circumstances such as natural disasters [62]. McInerney et al. [65] examined the boundaries of human mobility predictability to anticipate breaks from routine using a Bayesian model, while others analyzed the travel patterns of up to 500,000 individuals using Markov chain based models to predict their visited locations, achieving an 88% theoretical maximum predictability, and introduced a mobility model for predicting individuals' locations using point of interest (POI) information [44]. Several studies of human mobility behavior have adopted a network perspective to predict the future of such networks as well as the proximity of individuals within the networks, showing great precision in anticipating future mobility topology [101]. Predictive models of human mobility have been extensively applied in recent years across applications such as traffic and travel demand predictions [4, 58], human activity predictions [97], next place locations [34], epidemics and the spread of viruses [10, 24, 71, 72], air pollution [26, 42], and transport energy consumption [42, 82, 104].

4.1 Methods

4.1.1 Data

The datasets used in this study consist of the electricity and gas consumption figures for 801 spatial divisions in Chicago, and 87,98,090 positional records accounting for human mobility within the city. The spatial level used here is an administrative boundary for Chicago, namely the most recent available Census Tract data, which represents an average population of 4000, and their corresponding electricity consumption measures. The positional record data has been collected from an online social network (Twitter) from individuals in the city of Chicago who have voluntarily publicly shared location-enabled information for their Twitter accounts and any results in this study are thus representative of this population. As yet, we lack appropriate data and analysis methods that will enable us to identify and use the full spectrum of such spatiotemporal predictions, however and this study is not immune from data availability constraints. While it does not suffer from spatial mismatches, this study inevitably had to deal with temporal mismatches (i.e. the electricity consumption data was from 2010, while the positional records accounting for human mobility were collected during 2014). The latest accessible, compatible Census Tract (2011) digital boundaries data was used for this study.

4.1.2 Radius of gyration

In order to quantify the activity patterns of the urban population through human mobility patterns radius of gyration $r_g(t)$ (Eq. 4.2) is used as an indicator for describing large-scale human mobility patterns [38]:

$$r_{cmi}(t) = \frac{1}{N_{(t)}} \sum_{i=1}^{N_{(t)}} r_i \tag{4.1}$$

$$r_{gi}(t) = \sqrt{\frac{1}{N_{(t)}} \sum_{i=1}^{N_{(t)}} (r_i - r_{cmi})^2} \tag{4.2}$$

Here, N is the total number of observations n.

The radius of gyration is calculated at two spatial and two temporal levels. First, the individual level $r_{gi}(t)$—which represents the characteristic distance traveled by a user when observed in time t [38]—is obtained per Census Tract per individual per day. Second, the Census Tract level $r_{ga}(t)$ is obtained per Census Tract over each time frame (i.e. month-by-month). Every $r_{ga}(t)$ represents the deviation of the $r_{gi}(t)s$ from the corresponding center point. This indicator is used to describe the patterns of human mobility across the Census Tracts.

4.1.3 Temporal fluctuations and spatiotemporal predictability

In order to assess the energy use attributable to individuals' urban mobility and employ human mobility as a predictor of future energy consumption, in this study I focused on the spatiotemporal predictability of energy consumption driven by intra-urban human mobility behavior of the *returners* population [74] in the City of Chicago. This population has shown to be most representative of the spatial distribution of energy use in urban settings earlier in chapter 3. I first examined whether the spatial dependencies previously found between human mobility of returners and energy use in urban areas [69] are also manifested in the form of temporal dependencies and whether temporal fluctuations in the returners' mobility still adequately represent and can explain temporal fluctuations in energy consumption. Then, the spatiotemporal predictability of energy consumption gained by examining human interactions with the urban built environment is explored through multivariate autoregressive time series and spatial regression analysis of 8,798,090 positional records collected from an online social networking platform (Twitter), over the course of 12 months (January-December, 2014) and energy consumption (electricity and gas) across 801 areas in the City of Chicago. Figure 4.1 shows a five-day cumulative distribution of positional records across the 801 Census Tract boundaries in the city. Figure 4.2 shows the distributions of these two variables ((a) energy consumption, and (b) human mobility of the returners population) in the spatial dimension over the course of the month of February, 2014.

To investigate whether there is a temporal dependency between fluctuations of the returners' mobility and energy use, I captured returners' characteristic intra-urban mobility distance across 801 spatial divisions in the City of Chicago using the radius of gyration $r_g(t)$ [17, 38, 85]. Through spatial autocorrelation statistics [32] based on a simultaneous consideration of feature locations and feature values, I first measured whether there is indeed a spatial correlation between energy consumption and their mobility variables, and, if so, whether this correlation holds true in the temporal dimension. In order to test for spatial collinearity and possible dependency structure across the 801 spatial divisions for electricity

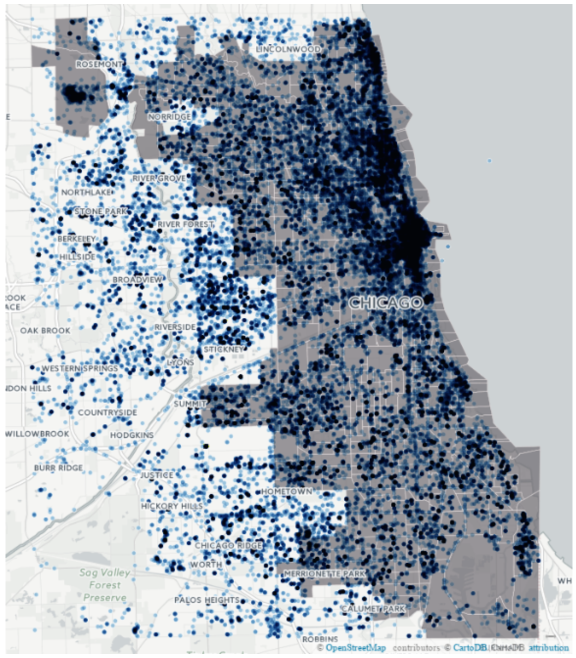


Figure 4.1: Five-day cumulative distribution of positional records for February $14 - 18^{th}$ 2014 over 801 Census Tracts.

consumption and human mobility, I performed a spatial autocorrelation analysis [32] to measure the correlations in the spatial dimension using Moran's I [70], which is also a test of independence and then went on to examine whether this dependency held true over the temporal dimension for the entire 12 months of the study.

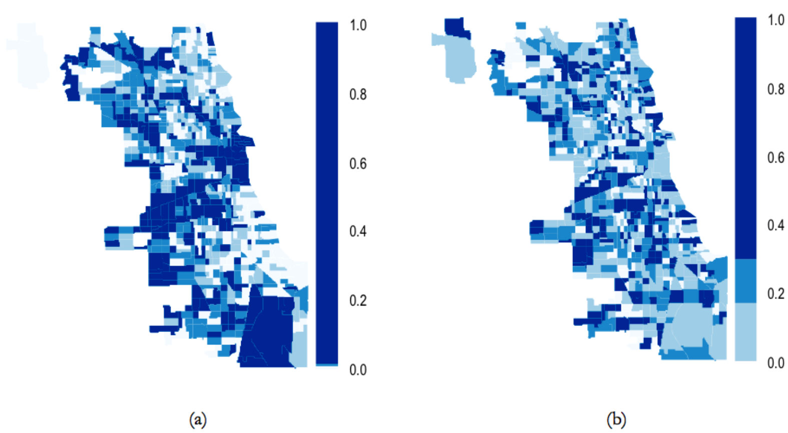


Figure 4.2: Spatial distribution of (a) electricity consumption, and (b) human mobility of returners across 801 Census Tracts, City of Chicago.

4.1.4 Multivariate Autoregressive (MAR) model in PCA space

Having accounted for spatial dependencies and the clustering distribution for both human mobility and electricity consumption across spatial divisions in a PCA space, I can examine whether a multivariate autoregressive (MAR) model (Eq. 4.3) [43] (with monthly time points per spatial division in PCA space) can be used to identify meaningful relationships between the two dimensions. MARs are linear multivariate time series models that characterize interregional dependencies across time and account for the historical influence of the variables on each other. Here, the MAR models the vector of next values for electricity consumption as a weighted linear sum one past vector values of energy consumption measurement and contains information about the process that generated it. The first model order is determined to be appropriate for this case (i.e. MAR (1)).

$$E_{(t)} = \hat{\omega} + E_{(t-1)}\hat{\beta} + \hat{\beta} \tag{4.3}$$

Where:

$\hat{\omega}$: *Vector of intercept terms.*
$E_{(t-1)}$: *Electricity consumption at time t-1.*
$\hat{\beta}$: *Vector of estimated autoregressive coefficients.*
$\hat{\beta}$: *Noise covariance matrix.*

It is important to consider an appropriate minimum sample size that adequately represents historical data for electricity and human mobility when building this statistical model. In making do with minimal temporal resolution data, the approach presented here will be representative of this limitation.

4.1.5 Spatial Autoregressive (SAR) model

To model the spatial interdependencies of the datasets across all 801 spatial divisions, I recommend a spatial autoregressive model to implicitly incorporate the spatial dependence of human mobility data into a covariance structure. According to the spatial autocorrelation results described above, due to the presence of an intrinsic spatial structure for both electricity consumption and human mobility in the city of Chicago these measures cannot be regarded as being independent of each other. 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. Based on the cross-sectional spatial data at time t for human mobility and energy consumption generated by the MAR model in PCA space, a spatial autoregressive model, namely the simultaneous autoregressive (SAR) spatial lag model shown in (Eq. 4.4) [96], which represents higher global dependency conditions can be employed. At a global scale, the SAR model implies that the state of the electricity consumption per unit of human mobility for each Census Tract in the city of Chicago is influenced by that of its neighboring Census Tracts. This model can be used to project the predictions from PCA space to cover all 801 spatial divisions using human mobility as a covariate.

$$E = \rho W E + r_{ga}\beta + \epsilon \tag{4.4}$$

Where:

E : *Vector of intercept terms.*
ρ : *Electricity consumption at time t-1.*
r_{ga} : *Vector of estimated autoregressive coefficients.*
β : *Noise covariance matrix.*
ϵ : *Noise covariance matrix.*

4.2 Findings

Tables 4.1-4.2 show the results of the global autocorrelation for both energy consumption and human mobility. Moran's I, 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 that are surrounded by other large values, ($I+$)–spatial clustering, and (I-)–spatial dispersion indicating larger values that are spatially enclosed by smaller values. Statistically significant (p-value <2.2e-16) positive values for I over the entire 12 months indicate that returners' mobility patterns in the City of Chicago follow a clustering distribution as opposed to a dispersed or random distribution. This indicates that values of human mobility or energy consumption observed in one location depend on the values observed at adjacent locations, and this dependency exists continuously throughout the course of the year. Figures 4.3-4.4 depict the Moran scatterplots for these values.

Since energy consumption exhibited a statistically significant spatial dependence over Chicago's 801 census tracts, I tested the global dependency conditions by modeling the spatial interdependencies, via an autoregressive model, thus implicitly incorporating the spatial dependence of the human mobility data into the covariance structure as a function of the number of energy meters per area. Tables 4.3 show the spatial autoregressive (SAR) model tested for this study to explicitly

Table 4.1: Spatial autocorrelations–Energy consumption, City of Chicago.

	Moran's I		
Month	Statistic	p-value	SD
January	0.077890564	4.657e-06	4.4325
February	0.0697123924	4.186e-05	3.9335
March	0.0627234439	0.0002214	3.5132
April	0.0823961291	3.144e-06	4.5165
May	0.0689312473	4.84e-05	3.8985
June	0.0725018169	2.918e-05	4.0193
July	0.0605486473	0.0003234	3.4112
August	0.0839596795	1.807e-06	4.6324
September	0.063208821	0.0002234	3.5108
October	0.0760895855	1.661e-05	4.1502
November	0.0653879581	0.0001383	3.6363
December	0.0387509133	0.01121	2.2831

examine the impact of returners mobility variables on the consumption of electricity. All spatial parameters were found to be statistically significant, as indicated by low p-values for all 12 months. This implies interdependencies for returners mobility and electricity consumption in these areas. Smaller AIC values, and relatively smaller p-values for the SAR models indicate that such a dependency exists stronger during that month of the year in comparison to others. The statistically significant spatial correlation for returners' mobility and energy consumption suggests that human mobility can be a useful spatiotemporal predictor for urban energy use. This indicates that the strength of the association between human mobility and energy consumption over time depends on spatial location, which can further be contextualized.

4.2.1 Space-time predictions of energy demand

In an ideal world, we could predict energy use for any time and location, enabling us to prepare in advance to provide sufficient resources to meet the anticipated demand. Spatiotemporal predictions pose a number of data and analysis challenges, however. Here, I introduce a spatiotemporal approach for predicting energy use in urban areas that combines space-time energy use with human mobility data and accounts for the interdependencies of their fluctuations. Spatiotemporal data are oftentimes not sufficiently accessible or cannot feasibly be collected in either the space or time dimension. Notwithstanding this condition, the data used in this study is sparse in time (monthly time intervals), but has higher resolution in space (covering a total of 801 spatial divisions within the City of Chicago). On the other hand, the human mobility data contains higher granularity in both dimensions as humans as dynamic sensors can provide data with fine-grained space-time

Table 4.2: Spatial autocorrelations–Human mobility, City of Chicago.

	Moran's I		
Month	Statistic	p-value	SD
January	0.0326270440	0.04505	1.6949
February	0.0629956317	0.0006563	3.2132
March	0.0647914579	0.0004794	3.3023
April	0.0427146003	0.01398	2.1979
May	0.066187299	0.0003722	3.3727
June	0.0588973269	0.001316	3.0077
July	0.074600221	7.434e-05	3.7933
August	0.0781581879	3.584e-0	3.9707
September	0.0350867002	0.03465	1.8165
October	0.0361323441	0.03076	1.8697
November	0.0641694623	0.0005351	3.2714
December	0.0469170094d	0.007866	2.4151

resolution. Moreover, given the presence of spatial structure for energy consumption and/or human mobility, these variables cannot simply be regarded as being independent of spatial location and are thus subject to incorporating their spatial dependencies. In order to account for the spatial dependencies across the 801 spatial divisions and balance the space-time dimensions in the predictive models, I next performed a principle component analysis (PCA) [75]. Table 4.4 summarizes the global PCA analysis, and reveals that the first six (6) components all have eigenvalues greater than or very close to unity, collectively accounting for 98% of the spatial variations in the data.

In order to account for the spatial dependencies over the time and balance the space-time dimensions of the dataset, I then generated autoregressive models in space (SAR) and time (MAR) to predict energy consumption based on previous spatiotemporal energy use data, with returners human mobility as a covariate. Using returners mobility across different parts of Chicago as a proxy indicator of energy consumption behavior I project estimations of energy use from a PCA space to spatial scales at a higher resolution than was previously possible. This allows for more reliable spatial predictions for energy consumption across the temporal dimension. Table 4.5 extends the statistical results for the multivariate autoregressive (MAR) model in PCA space.

Table 4.6 presents the statistical parameter estimations of the proposed SAR model. As indicated by the p-value lower than 0.0001, the model is a statistically significantly representation that can be used to predict electricity consumption per human mobility of the population across spatial divisions. It is important to consider an appropriate minimum sample size that adequately represents historical data for both electricity and human mobility when building such a statistical model. Given the minimal temporal resolution of the data available for this study, the results are

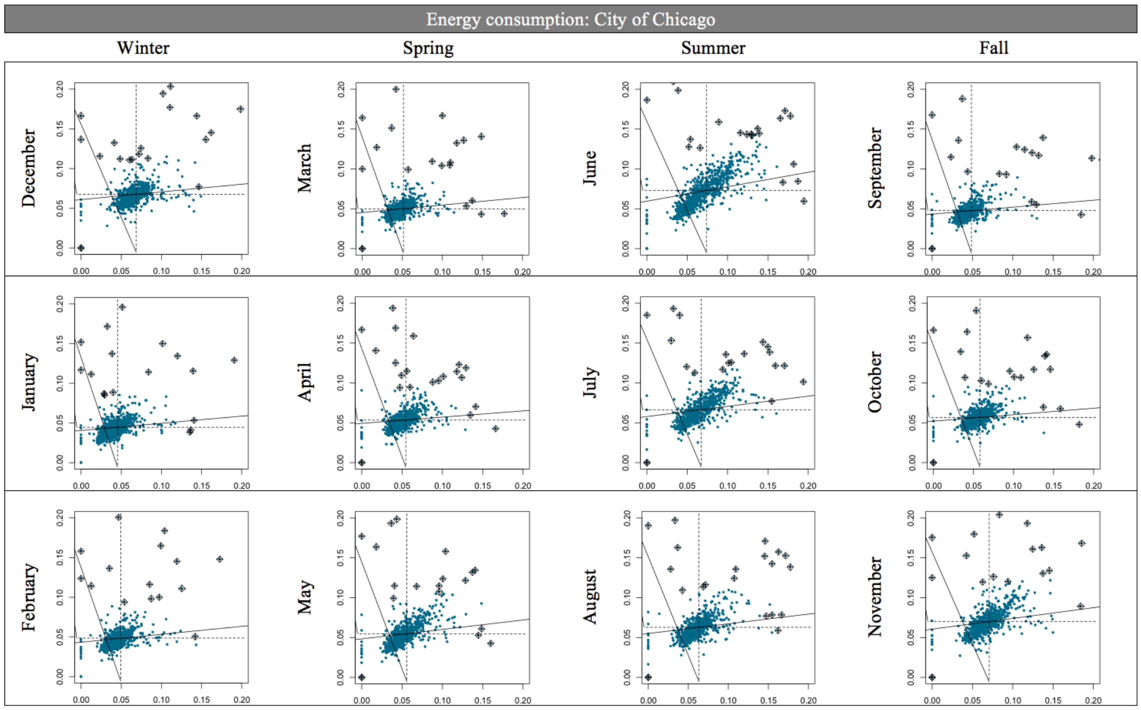


Figure 4.3: Moran scatterplots of energy consumption by month (2010)–Electricity consumption, City of Chicago.

representative of this limitation.

4.3 Discussion and Implications

Using 8,798,090 positional records gathered over the twelve (12) months of 2014 for the City of Chicago, I quantified returners populations' mobility across 801 spatial divisions of the city. Using the historical monthly energy consumption over the same period, a spatial autocorrelation analysis revealed clustering patterns and positive spatial associations for returners' mobility and energy consumption across these areas. The temporal dependencies for returners' mobility paralleled with the temporal dependencies of energy consumption in terms of structural dependency, suggesting that the intensity of temporal fluctuations in the spatial variations of human mobility may well serve to explain the fluctuating intensities in energy use at different temporal dimensions. The findings of this study confirm the temporal manifestations of human mobility-driven energy flux and support our proposed approach for the spatiotemporal prediction of energy use across urban spatial divisions. Taking into account the strength of spatial associations among and between human mobility and electricity consumption fluctuations by spatial division, I generated MAR and SAR models to predict electricity consumption in time and space in the City of Chicago. Predictive

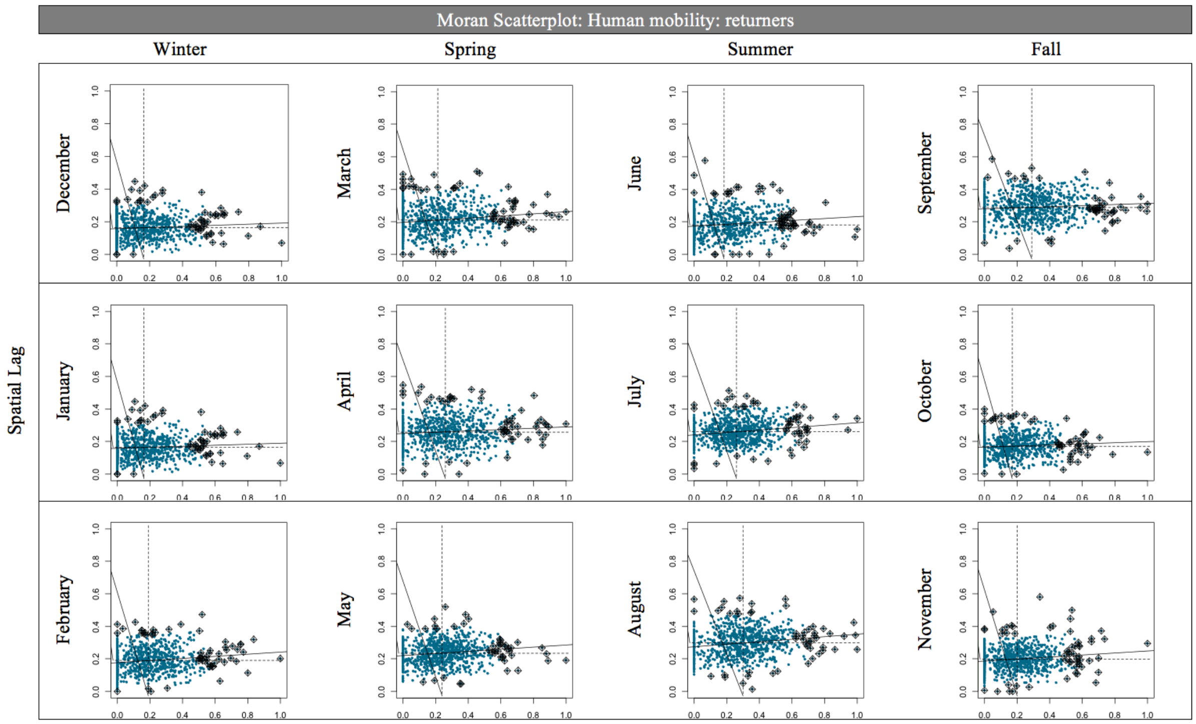


Figure 4.4: Moran scatterplots of human mobility by month (2014)–Returners population, City of Chicago.

models of urban energy use driven by human mobility intrinsically account for the human activities of an urban population, which take place at certain times and locations [107, 108]. However, our current knowledge about these patterns is based on todays population behavior and will inevitably vary under the influence of population growth and other changes in the future. Therefore, it is important to identify ways to dynamically project knowledge about urban population activities onto the relevant datasets and then use this to anticipate future energy demand. Opportunely, humans as sensors are the ideal dynamic sensors for such data collection [8, 13, 38, 64, 107, 108, 109].

This represents an important step towards incorporating the space-time fluctuations of human mobility in urban populations to create better spatiotemporal predictions of energy demand at a high resolution in both time and space dimensions. Spatiotemporal predictions of energy use based on measures of human mobility are of paramount importance, since the continuing growth in both technology and urban populations [90] is anticipated to amplify the measure and variety of human activities, thus creating ever more complex built environments in our future cities, with even greater fluctuations in energy demands across time and space. Current urban scale energy predictive approaches [15, 23, 31, 46, 48, 67] generally overlook the effects of consumer behaviors and thus will eventually fall short in terms of reliability. This study is the first attempt to use the human mobility of an urban population as an indicator of their daily activities for the spatiotemporal

Table 4.3: Spatial regression–Energy per human mobility, City of Chicago.

	Spatial Lag Model (SAR)			
Month	Statistic	p-value	*AIC*	*AIC* for Linear Model
March	0.80157	<2.22e-16	-2890.1	-2255.2
January	0.79795	<2.22e-16	-2885.6	-2273.3
May	0.80029	<2.22e-16	-2884.2	-2256.9
February	0.79995	<2.22e-16	-2875.6	-2250.1
April	0.801	<2.22e-16	-2874.8	-2243.4
August	0.79298	<2.22e-16	-2862.6	-2250.7
October	0.78998	<2.22e-16	-2862	-2260
June	0.79497	<2.22e-16	-2848.7	-2237.5
November	0.79187	<2.22e-16	-2847.5	-2243.9
July	0.77851	<2.22e-16	-2789.4	-2220.0
December	0.78378	<2.22e-16	-2787.2	-2215.5
September	0.79064	<2.22e-16	-2233.7	-2842.6

predictions of energy demand in city neighborhoods. In order 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 spatiotemporal relationship between energy consumption and human mobility is a key element for creating and managing effective energy interventions and policies for urban areas. The level of space-time demand-side diversity will dictate corresponding energy resource allocation strategies and prepare our cities for a smarter future.

A greater awareness of how individuals' move around urban open spaces and across the physical infrastructure of our urban environments (both communal and private) will enable us to build a more comprehensive understanding of how specific types of energy behavior are likely to be clustered in specific geographical spaces and temporal locations within urban areas. It will also enable us to identify the interdependencies between energy consumption, individual activities, and specific urban spatiotemporal features. These findings suggest that human mobility can indeed account for the collective energy consumption in urban areas, and further research should be considered to quantify and contextualize this relationship in predictive approaches. Future research should seek to develop a better understanding of urban activity patterns across different functional locations using human mobility data and utilize the patterns identified to develop integrated predictive models that incorporate temporal elements of activity patterns and energy consumption. The capacity to identify spatial regions with similar temporal activities will enable us to assess their energy consumption and thus quantify the drivers of spatiotemporal fluctuations in energy use in urban areas and plan accordingly. This research is an important step towards achieving this goal.

Table 4.4: Principal Component Analysis (PCA).

	Moran's I		
	SD	Proportion of Variance	Cumulative Proportion
PC1	2.4446039	0.4986314	0.4986314
PC2	2.2122267	0.40834	0.9069714
PC3	0.5479213	0.0250495	0.9320209
PC4	0.49386333	0.02035055	0.95237145
PC5	0.47931101	0.01916891	0.97154036
PC6	0.42477263	0.01505482	0.98659519
PC7	0.37373923	0.01165467	0.99824986
PC8	0.119112412	0.001183795	0.999433653
PC9	0.062677939	0.000327787	0.99976144
PC10	0.042964807	0.000154024	0.999915464
PC11	0.025552586	5.44794E-05	0.999969943
PC12	1.90E-02	3.01E-05	1.00E+00

Table 4.5: Multivariate Autoregressive (MAR) model–Energy per human mobility.

MAR	
AIC for Simple Linear Model	2250.6
AIC	2861.8
z-value	30.308
ρ	0.79274
Log Likelihood	1431.918
Approximate Std. Error	0.0081332

Table 4.6: Spatial Autoregressive (SAR) model–Energy consumption per human mobility.

SAR	
AIC for Simple Linear Model	1238.4
AIC	1851.5
z-value	20.716
ρ	0.69547
Log Likelihood	1229.744
Approximate Std. Error	0.0081405

Chapter 5

Concluding Remarks

Urban populations play an integral role in any effort to implement effective urban energy consumption measures. The increasing interdependencies between urban buildings, individuals, and required services as a result of population growth and urbanization suggest the impact of changes in human activities on energy demand may exceed the physical determinants upon which planning models are normally based. The collective combination of the population's daily activities drives and is directly linked to the energy consumption at different locations [14, 21, 78], suggesting the utility of adopting a combined building-activity-based approach to estimating urban energy consumption. Current estimates of urban energy use 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. Spatiotemporal 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.

5.1 Contributions and Implications

Taken together, the three studies presented in this dissertation contribute to and enrich our understanding of the underlying dependencies and determinants of fluctuations in urban energy systems as follows:

5.1.1 Spatiotemporal dependency

Study 1 (Chapter 2 of this dissertation) contributes to the studies on using human mobility [38] quantifying societally significant issues such as traffic and travel demand predictions [4, 58], epidemics and the spread of viruses [10, 24, 71, 72], air pollution [26, 42], and transport energy consumption [42, 82, 104] by addressing the question: Is there a spatial dependency between human mobility and energy use in urban areas? This study focuses on determining whether human mobility can be used to spatiotemporally quantify fluctuations in urban energy use. This study departs from the previous research in this area, which primarily explores the determinants of energy consumption in urban settings and the underlying drivers of its fluctuations driven by urban form, density and texture [9, 12, 28, 30, 76, 87, 100], building characteristics [6, 19, 25, 100], building age [3], and function [46], all of which proceed under the assumption that these fluctuations tend to be directly associated with the physical characteristics of the infrastructure and seldom consider any spatial effects due to the activities of different consumer populations. In this study, I provide empirical evidence supporting the existence of an underlying spatial dependency between human mobility and energy use in urban areas and demonstrate that this dependency has a temporal manifestation (see Chapter 4) that is consistently significant over the course of the year, irrespective of any seasonal or monthly effects. Thus, human mobility can be used to spatiotemporally explain the fluctuations observed in energy use in urban settings.

5.1.2 Heterogeneity and dominant predictors

Study 2 (Chapter 3 of this dissertation) complements recent studies of human mobility, exploring its heterogeneity and influence on various social phenomena [74, 79] by addressing the following questions: (a) Does a particular population's human mobility network play a dominant role in the fluctuations of energy use? and (b) Does the strength of the spatial dependencies between human mobility and energy use vary across different building types? To unpack the findings in Study 1 regarding the spatiotemporal dependencies of human mobility and energy use, I examined the effects of individuals' location-based activities that influence patterns in energy supply and demand across building types (i.e. residential and commercial buildings). This dependency represents a strong connection with residential buildings' energy use, albeit with a spatial spillover effect. I then investigated the interdependencies between human mobility networks for two distinct urban populations (the so-called returners and explorers) as an indicator of their daily activity patterns and explored how variations in human mobility networks can be used to explain fluctuations in energy use. This study shed new light on an overlooked driver of residential and commercial energy consumption and predictor of future trends, which is a topic of considerable basic and applied interest [19, 22, 23, 33, 46, 56, 83]. The findings of this study demonstrate that fluctuations in energy consumption can no longer be regarded as being independently generated at the building level or treated as arising solely as a result of individual building characteristics. Importantly, this suggests that buildings' urban spatial context must also be taken into account and that the exogenous drivers and externalities frequently linked to different types of buildings' spatial dependencies and their specific consumer populations must be reflected in energy consumption measures.

5.1.3 Spatiotemporal prediction

Study 3 (Chapter 4 of this dissertation) combines insights from the previous two studies by examining whether intra-urban human mobility can be determined as a predictor of energy use fluctuation across time and space. It also introduces a predictive approach that captures spatiotemporal variations in the determinants previously identified. This study extends the current urban scale energy predictive approaches [15, 23, 31, 46, 48, 67], which generally overlook the effects of consumer behaviors, and presents a first attempt to use the human mobility of an urban population for spatiotemporal predictions of energy use. This further enhances our understanding of space-time demand-side diversity, which will dictate corresponding energy resource allocation strategies in the future.

5.2 Limitations and Future Directions

Urban areas are undergoing a significant growth in population globally, with a commensurate increase in human activities. Given that half of all those alive today now live in urban areas, rapid urbanization and the subsequent growth in energy consumption are important challenges that we must address. The ability to identify the evolving patterns and features of temporal and spatial intra-urban mobility routines is important for predicting future energy demand patterns and protecting temporal and special energy resilience. The question remains, however, how best to anticipate the growing demand and supply energy for billions more people in these areas and whether new information on the spatiotemporal dependencies between human mobility and energy flux could be instrumental in securing energy resilience.

Given the growing amounts of data now being generated, it is no longer sufficient to merely anticipate trends; instead, we need to anticipate flux in both space and time dimensions and contextualize such variations. Research on urban scale energy predictions is so far limited, mainly because it requires broad, societally contextualized data across both space and time dimensions with high resolution. For example, the amount of information collected from online social networks (in the case of this study, Twitter) is not immune from demographic issues such as the varying tendencies of different segments of the urban population to use online social networks, as well as security issues. The individual positional record data used to approximate human mobility in this study have been collected from individuals who have voluntarily publicly shared location-enabled information for their Twitter accounts in Greater London and the City of Chicago; any results in this dissertation are thus representative of these populations. The temporal differences between human mobility data and energy consumption in both cities are based on the assumption that the mobility patterns of their urban populations are not subject to major changes year on year, and is another limitation of this study. Sustained research approaches are required that quantify and numerically represent the relationship between human mobility and energy use in spatiotemporal dimensions (i.e. having both spatial extension and temporal duration), and explore the fundamentals governing this relationship globally. Future cross-scale (i.e. spatiotemporal) and cross-urban validation studies are also encouraged using a variety of temporal and spatial scales to further explore the extent and applicability of the results of the current studies. Moreover, examining the effects of heterogeneity in human mobility as a result of the activity patterns of different urban populations may provide a valuable path for future research into the characterization of spatiotemporal dependencies with increased diversity (e.g. human mobility motifs). Further research focusing on integration with spatial proximity, the spillover effect and land use analyses could also produce useful insights.

As yet, we lack sufficient contextualized data to be able to understand the root causes of these complex relationships and develop realistic thresholds. Not only access to real world data with appropriate spatial and temporal resolutions is necessary, but we also need multidimensional analyses of this data characterized by embedded location information. Raw positional records of population and kWh energy use will be needed to build mathematically sound models. Given that individuals change their time and location designations in a heterogeneous manner, explaining the root causes of such dependencies and possible spillover effects across time and space is problematic at best. Locally and temporally contextualized data will be needed for such an interpretation to be successfully achieved. Particularly in urban settings, we require deeper discovery and understanding of the way the population interacts with the built environment and how information and influence is transferred. Access to urban scale high resolution contextualized spatiotemporal data is not yet possible, but there is a growing body of research in urban computing devoted to predicting such information from individuals' positional record data (looking, for example, at human activities [97], urban functional regions [88], and points of interest [44]). This requires both data visualization and data exploration that go beyond simple numerical models capable of capturing the spatial and temporal aspects of such interactions and instead seek to determine the space-time scaling of diffusion. Characterizing the fluctuating relationship of human mobility with energy use should help to overcome the challenges of data-driven urban discovery and allow us to eliminate erroneous assumptions by facilitating the in-depth analysis of more dimensions than is currently possible using existing dimensionality reduction methods.

It is likely that an ideal opportunity for capturing contextualized data lies in the growing domain of virtual reality. Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR)–in which reality-virtuality content coexists interactively–offer a highly effective way to simulate the spatial dimensions of urban spaces in 3D environments. By streaming reality data such as human mobility and information into these environments, we can further bring the time dimension into a contextualized virtual environment, extending the space-time domain to an additional context dimension. Such an environment, where real and simulated data are both spatiotemporally generated, creates exciting opportunities for real data analysis and contextualization, as well as testing simulated "what if" scenarios. Collectively, this will create opportunities for both realistic data visualizations in immersive experiences and data exploration beyond simple numerical models. A mixed reality platform for multi-dimensional urban data visualization and exploration can capture spatial and temporal aspects of such interactions and thus determine the space-time scaling of diffusion more accurately. The information gained by fully characterizing the fluctuating relationship between human mobility and energy use should help to overcome the challenges of data-driven urban discovery and allow us to eliminate erroneous assumptions by enabling an in-depth analysis of more dimensions than is currently possible using existing dimensionality reduction methods.

According to the UN Sustainable Cities initiative: "high density cities can bring efficiency gains and technological innovation while reducing resource and energy consumption" [91]. A possible future research project will focus on examining these efficiency balances, hopefully also uncovering appropriate policy interventions. Research areas such as urban human mobility, energy use, and virtual reality can all connect through a central focus on contextualizing the way an urban population interacts, moves, consumes resources, and transfers information and influence in order to adapt to urban spatiotemporal flux.

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Appendices

Appendix A

Chapter 2. Supplementary Material

A.1 Data

Table A.1: Data.

Data		Quantity	Temporal Scale	Spatial Scale	Organization
Digital Boundaries	LSOA*	4,835	2011	-	Greater London Authority (GLA)
	Population	Min 1,000 Max 3,000			
#Meters	Electricity	3,438,939	2014	LSOA	Dept. of Energy & Climate Change (DECC)
	Gas	3,007,392			
Positional Records		18,810,222	2014	Greater London	Twitter

* *Lower Layer Super Output Area*

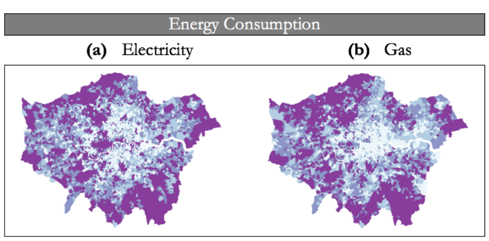


Figure A.1: Spatial distribution of energy consumption by year (2014)–Median (a) electricity, and (b) gas consumption across 4835 spatial divisions (LSOAs) in Greater London. Darker spots indicate higher values.

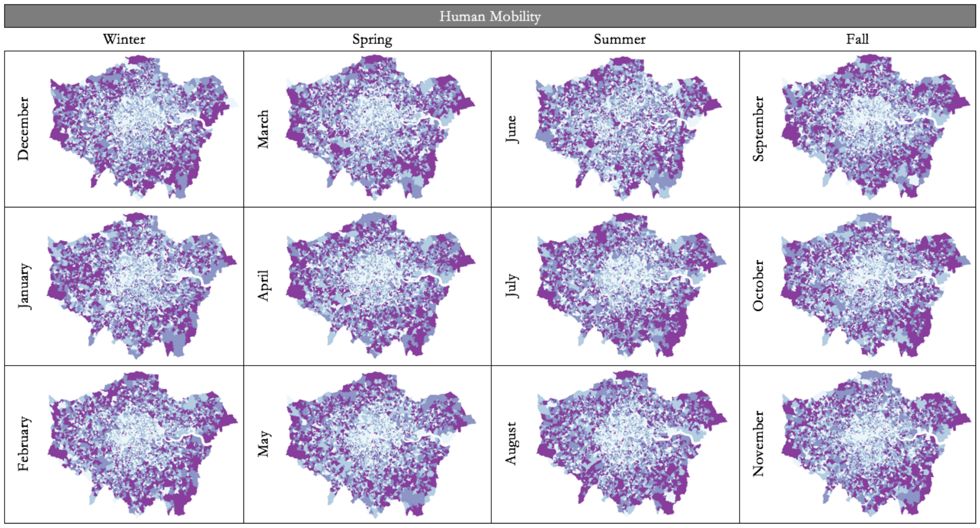


Figure A.2: Spatial distribution of human mobility by month (2014), Greater London.

Table A.2: Energy meters (a), and spatial divisions (b), Greater London boroughs*.

	Greater London Borough	(a) # Energy Meters		(b) # Spatial Divisions
		Electricity	Gas	
1	Barking and Dagenham	73547	65715	110
2	Barnet	143079	126561	211
3	Bexley	96003	88773	146
4	Brent	113459	102149	173
5	Bromley	136999	128752	197
6	Camden	101209	79540	133
7	City of London	6321	2624	6
8	Croydon	149025	137219	220
9	Ealing	130831	117851	196
10	Enfield	124747	107151	183
11	Greenwich	107660	92355	151
12	Hackney	104160	91238	144
13	Hammersmith and Fulham	83025	74856	113
14	Harringey	105760	96417	145
15	Harrow	87799	81883	137
16	Havering	101204	95200	150
17	Hillington	107953	97071	161
18	Hounslow	98414	83224	142
19	Islington	100997	87886	123
20	Kensington and Chelsea	88317	70784	103
21	Kingston upon Thames	65637	59288	98
22	Lambeth	135932	119887	178
23	Lewisham	121254	108984	169
24	Merton	82394	75957	124
25	Newham	107582	92862	164
26	Redbridge	101564	93657	161
27	Richmond upon Thames	82841	77638	115
28	Southwark	129264	102348	166
29	Sutton	80945	71314	121
30	Tower Hamlets	112518	76988	144
31	Waltham Forest	99015	92416	144
32	Wandsworth	137275	119465	179
33	Westminster	122209	89339	128

** Dept. of Energy & Climate Change (DECC).*

A.2 Spatial Autocorrelation

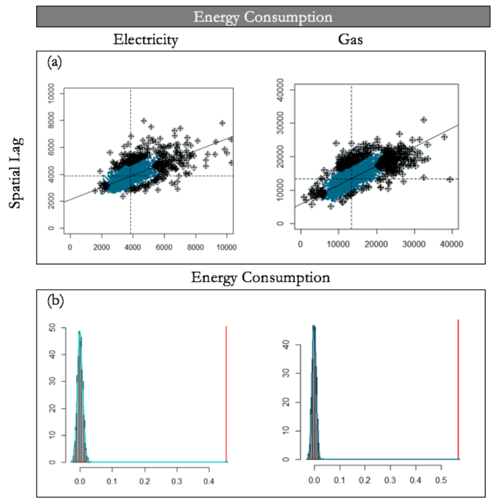


Figure A.3: Moran (a) scatterplot and (b) permutation plot by year (2014)–Energy consumption (electricity and gas), Greater London.

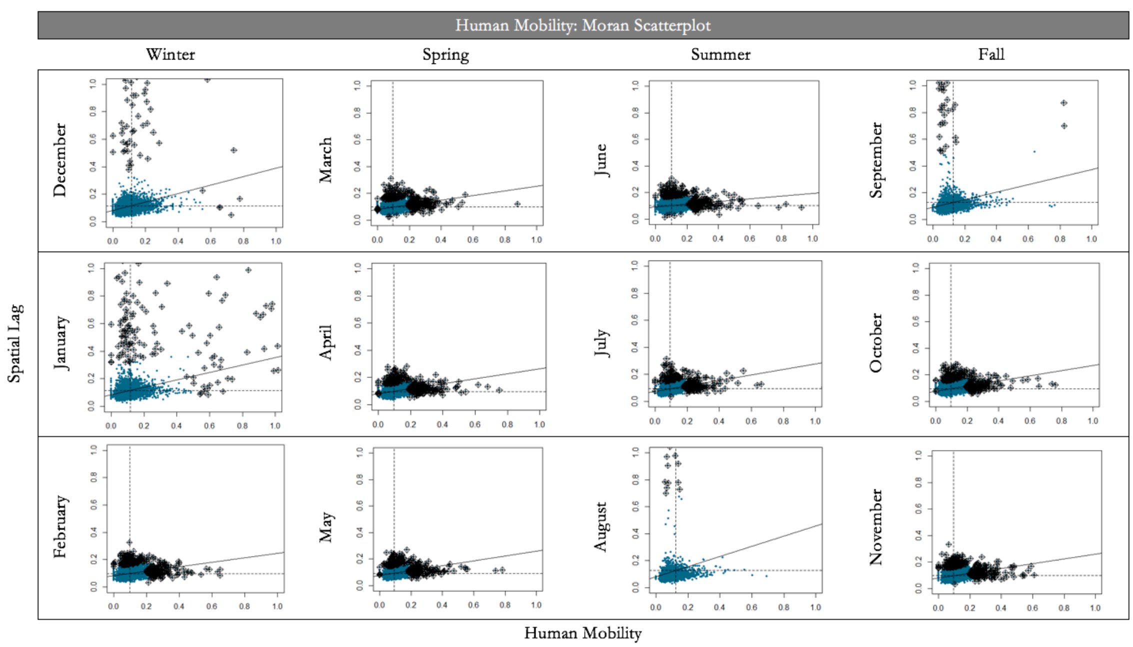


Figure A.4: Moran scatterplots of human mobility by month (2014), Greater London.

Table A.3: Spatial autocorrelation–Energy consumption.

		Statistic	*p*-value	Std.	Exp.	Var.
Electricity	*Moran's I*	4.528018e-01	< 2.2e-16	53.256	-2.068680e-04	7.235593e-05
	Geary's C	0.5603471304	< 2.2e-16	37.361	1.0	0.0001384779
Gas	*Moran's I*	5.668959e-01	< 2.2e-16	66.617	-2.068680e-04	7.247006e-05
	Geary's C	0.4290418697	< 2.2e-16	57.799	1.0	0.0000975823

Table A.4: Spatial autocorrelation–Human Mobility.

		Statistic	*p*-value	Std.	Exp.	Var.
December	*Moran's I*	0.308308172	< 2.2e-16	37.154	-0.000206868	0.000068950
	Geary's C	0.746872666	3.284e-12	6.8667	1.0	0.001358867
January	*Moran's I*	2.687373e-01	< 2.2e-16	32.076	-2.068680e-04	7.030162e-05
	Geary's C	0.6934139044	< 2.2e-16	10.367	1.0	0.0008745663
February	*Moran's I*	0.1640369366	< 2.2e-16	19.311	-0.0002068680	0.0000723364
	Geary's C	0.846590173	< 2.2e-16	12.719	1.0	0.000145476
March	*Moran's I*	1.723603e-01	< 2.2e-16	20.3	-2.068680e-04	7.226549e-05
	Geary's C	0.8326888106	< 2.2e-16	12.799	1.0	0.0001708818
April	*Moran's I*	1.843928e-01	< 2.2e-16	21.717	-2.068680e-04	7.225084e-05
	Geary's C	0.8068211034	< 2.2e-16	14.556	1.0	0.0001761315
May	*Moran's I*	1.826400e-01	< 2.2e-16	21.525	-2.068680e-04	7.215654e-05
	Geary's C	0.8072572763	< 2.2e-16	13.303	1.0	0.0002099229
June	*Moran's I*	1.032477e-01	< 2.2e-16	12.173	-2.068680e-04	7.222571e-05
	Geary's C	0.8972687134	2.174e-14	7.5501	1.0	0.0001851386
July	*Moran's I*	2.032214e-01	< 2.2e-16	23.991	-2.068680e-04	7.189822e-05
	Geary's C	0.7973517584	< 2.2e-16	11.652	1.0	0.0003024825
August	*Moran's I*	3.790858e-01	< 2.2e-16	45.485	-2.068680e-04	6.953652e-05
	Geary's C	0.664461238	< 2.2e-16	9.9	1.0	0.001148711
September	*Moran's I*	2.824235e-01	< 2.2e-16	33.681	-2.068680e-04	7.041528e-05
	Geary's C	0.7314128535	< 2.2e-16	9.3013	1.0	0.0008338389
October	*Moran's I*	1.922015e-01	< 2.2e-16	22.64	-2.068680e-04	7.222537e-05
	Geary's C	0.8000929704	< 2.2e-16	14.687	1.0	0.0001852585
November	*Moran's I*	1.789254e-01	< 2.2e-16	21.061	-2.068680e-04	7.234452e-05
	Geary's C	0.8156034681	< 2.2e-16	15.444	1.0	0.0001425644

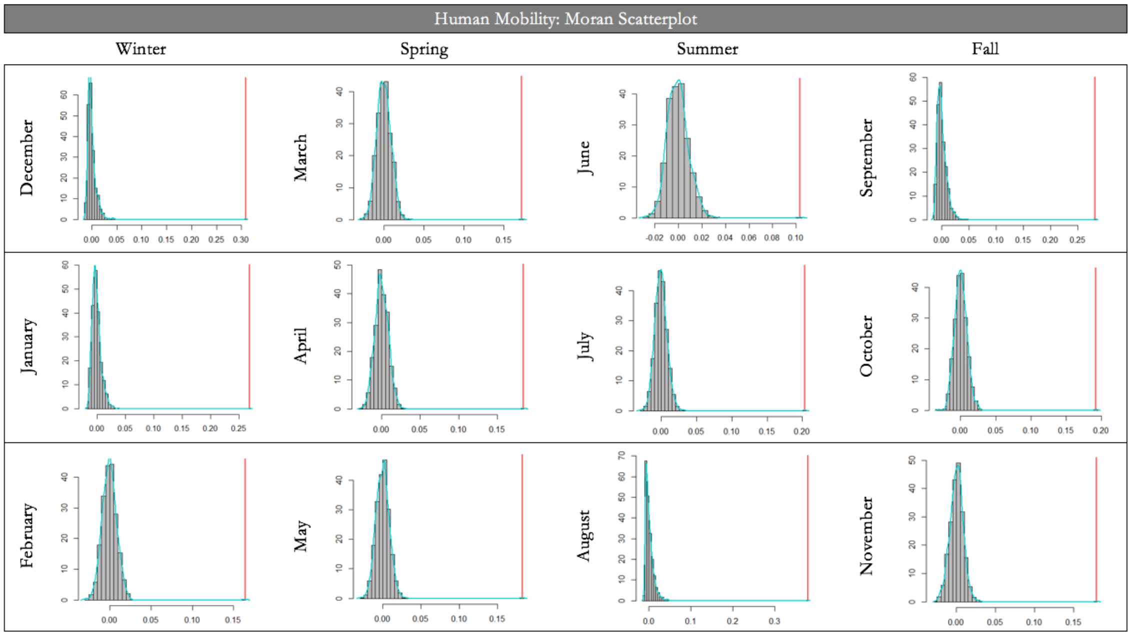


Figure A.5: Moran permutation plots of human mobility by month (2014), Greater London.

A.3 Spatial Regression

Table A.5: Spatial regression–Electricity consumption versus human mobility: Winter.

	December			January			February		
	Simple Linear Model (OLS)	**Spatial Lag Model (SAR)**	**Spatial Error Model (SEM)**	**Simple Linear Model (OLS)**	**Spatial Lag Model (SAR)**	**Spatial Error Model (SEM)**	**Simple Linear Model (OLS)**	**Spatial Lag Model (SAR)**	**Spatial Error Model (SEM)**
P-value	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	0.0617	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***
AIC	78825	76951	77044	78840	76953	77044	78801	76950	77043
R-squared[1]	0.004681	-	-	0.0005155	-	-	0.01528	-	-
Statistics	4.872	54.269	55.437	1.869	54.499	55.538	8.718	53.874	55.254
BP[2]	1.2926	1.8873	0.091264	8.1753*	3.9916	0.60269	14.185**	4.2984	0.24841
Moran's I	4.57e-01	-1.66e-02	-0.019201	4.62e-01***	-1.66e-02	-1.928e-02	4.406e-01***	-1.63e-02	-1.90e-02

p<0.05; p<0.001**; p<0.0001****
[1] *Adjusted R-squared.*
[2] *Breusch-Pagan test for heteroscedasticity.*
[3] *Moran's I for residuals.*

Table A.6: Spatial regression–Electricity consumption versus human mobility: Spring.

	March			April			May		
	OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
P-value	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2.2e-16 ***
AIC	78788	76944	77041	78797	76951	77044	78801	76951	77044
R-squared^1	0.01862	-	-	0.01684	-	-	0.01684	-	-
Statistics	9.63	53.67	55.019	9.155	53.825	56.192	8.808	53.851	55.486
BP^2	10.157**	4.3728	0.75973	13.886**	4.6953	1.0731	6.3445*	2.3556	0.13751
Moran's I	4.391e-01***	-1.64e-02	-1.88e-02	4.38e-01***	-1.65e-02	-0.0192	4.40e-01***	-0.01654	-1.92e-02

Table A.7: Spatial regression–Electricity consumption versus human mobility: Summer.

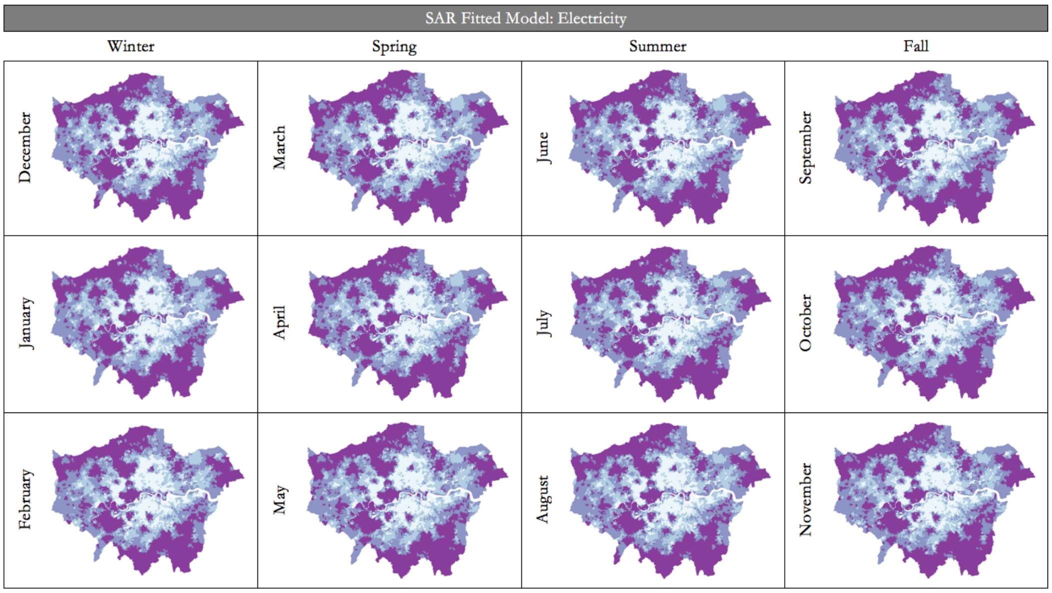
	June			July			August		
	OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
P-value	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***
AIC	78821	76951	77044	78800	76950	77044	78834	76953	77044
R-squared^1	0.005911	-	-	0.01679	-	-	0.001934	-	-
Statistics	5.454	54.18	55.45	9.14	53.807	43.878	3.22	54.455	55.528
BP^2	2.7187	1.3981	0.5995	10.077*	2.8142	0.10037	0.9741	1.0499	0.6214
Moran's I	4.54e-01***	-1.66e-02	-1.92e-02	4.39e-01***	-1.64e-02	-1.91e-02	4.59e-01***	-1.66e-02	-0.019298

Table A.8: Spatial regression–Electricity consumption versus human mobility: Fall.

	September			October			November		
	OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
P-value	<2e-16 ***	<2e-16 ***	<2e-16 ***	<2e-16 ***	<2e-16 ***	<2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2e-16 ***
AIC	78831	76949	77041	78789	76944	77039	78803	76950	77043
R-squared^1	0.001755	-	-	0.01876	-	-	0.01436	-	-
Statistics	-3.082	54.391	55.415	9.666	53.669	54.942	8.451	53.796	55.25
BP^2	5.5543*	3.186	0.91957	11.514**	2.6317	0.00061147	10.09*	1.4847	0.093808
Moran's I	4.62e-01***	-1.67e-02	-1.925e-02	4.41e-01***	-0.01598	-1.86e-02	4.23e-01***	-1.63e-02	-1.905e-02

Table A.9: Spatial regression–Gas consumption versus human mobility: Winter.

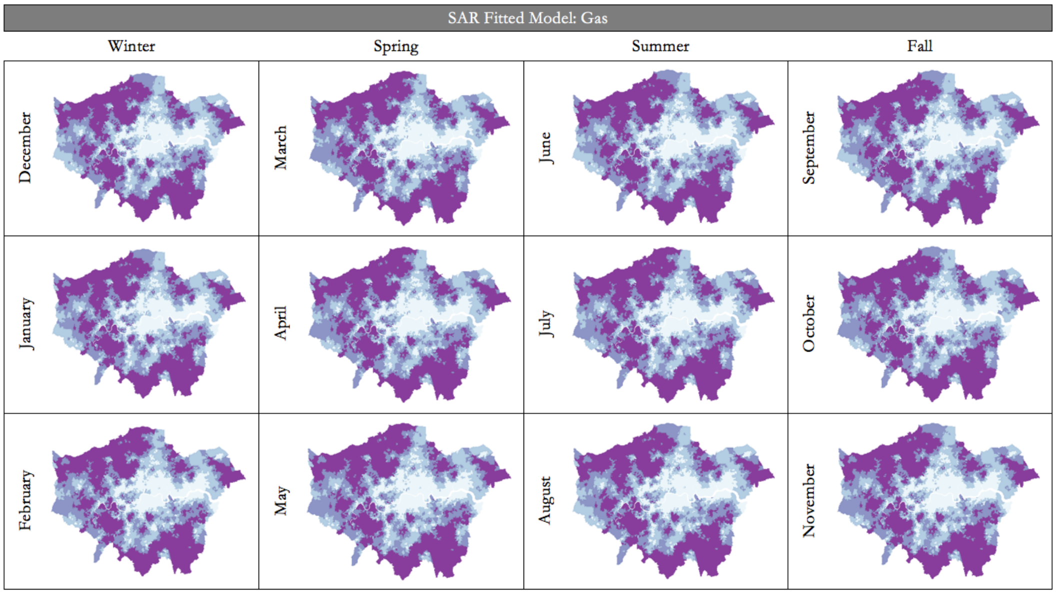
	December			January			February		
	OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
P-value	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	4.288e-08	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***
AIC	93886	90944	90946	93895	90944	90947	93788	90936	90947
R-squared^1	0.00689	-	-	0.005986	-	-	0.02797	-	-
Statistics	5.877	75.038	75.604	5.487	75.099	76.151	11.84	73.437	76.034
BP^2	0.16246	0.2323	0.0030247	1.1063	0.00028	0.004476	0.88904	10.951**	2.1066
Moran's I	5.58e-01***	-3.947e-02	-3.910e-02	5.60e-01***	-0.03918	-3.907e-02	5.27e-01***	-3.9798e-02	-3.906e-02



(a) Electricity consumption by month.

(b) Residuals for electricity consumption by month.

Figure A.6: Fitted SAR models for electricity consumption, Greater London.



(a) Gas consumption by month.

(b) Residuals for gas consumption by month.

Figure A.7: Fitted SAR models for gas consumption, Greater London.

Table A.10: Spatial regression–Gas consumption versus human mobility: Spring.

	March			April			May		
	OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
P-value	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***
AIC	93797	90929	90945	93796	90941	90945	93797	90939	90947
R-squared[1]	0.02742	-	-	0.02684	-	-	0.0266	-	-
Statistics	11.72	73.554	74.98	11.59	73.466	75.487	11.54	73.526	75.549
BP[2]	2.4996	4.7992*	0.30835	1.0206	6.2904*	0.979	0.017055	6.1036*	0.12253
Moran's I	5.32e-01***	-3.964e-02	-3.877e-02	5.26e-01***	-3.969e-02	-3.9426e-02	5.29e-01***	-3.958e-02	-3.9167e-02

Table A.11: Spatial regression–Gas consumption versus human mobility: Summer.

	June			July			August		
	OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
P-value	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***
AIC	93893	90946	90945	93786	90936	90947	93905	90946	90947
R-squared[1]	0.005216	-	-	0.02985	-	-	0.002616	-	-
Statistics	5.133	75.282	75.645	12.24	73.362	75.546	3.698	75.253	78.104
BP[2]	0.63099	1.3455	0.030219	0.011339	4.0509*	0.046681	0.27101	0.92644	0.51677
Moran's I	5.58e-01***	-3.9153e-02	-3.928e-02	5.27e-01***	-3.9654e-02	-3.908e-02	5.64e-01***	-3.9126e-02	-0.0391277

Table A.12: Spatial regression–Gas consumption versus human mobility: Fall.

	September			October			November		
	OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
P-value	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***	<2e-16 ***	<2.2e-16 ***	<2.2e-16 ***
AIC	93917	90946	90944	93795	90933	90946	93812	90937	90947
R-squared[1]	-7.265e-05	-	-	0.02684	-	-	0.02304	-	-
Statistics	0.806	75.606	75.641	11.59	73.562	75.205	10.72	73.757	76.657
BP[2]	3.386	1.2326	0.57309	0.24337	8.498*	2.2661	2.3438	8.6573*	2.7801
Moran's I	5.67e-01***	-3.89e-02	-3.909e-02	5.3e-01***	-3.959e-02	-0.03888	5.35e-01***	-3.9429e-02	-3.902e-02

Appendix B

Chapter 3. Supplementary Material

B.1 Data

Table B.1: Data–Greater London.

Data		Quantity	Temporal Scale	Spatial Scale	Organization
Digital Boundaries	MSOA*	983	2011	-	Greater London Authority (GLA)
	Population	Min 5,000 Max 15,000			
#Meters	Electricity (residential)	3,456,462	2014	MSOA	Dept. of Energy & Climate Change (DECC)
	Electricity (commercial)	370,917			
	Gas (residential)	3,001,319			
	Gas (commercial)	39,225			
Positional Records		18,996,107	2014	Greater London	Twitter

** Middle Layer Super Output Area*

Table B.2: Data–City of Chicago.

Data		Quantity	Temporal Scale	Spatial Scale	Organization
Digital Boundaries	Census Tract	801	2010	-	cityofchicago.org
	Population	Min 0 Max 10,000			
#Meters	Electricity (residential)	620,381	2010	Census Tract	cityofchicago.org
	Electricity (commercial)	24,624			
	Gas (residential)	613,614			
	Gas (commercial)	138,228			
Positional Records		87,98,090	2014	City of Chicago	Twitter

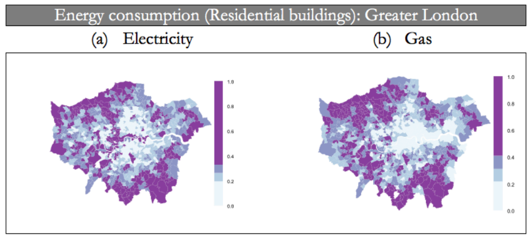


Figure B.1: Spatial distribution by year (2014)–Residential energy consumption in Greater London: (a) electricity, and (b) gas.

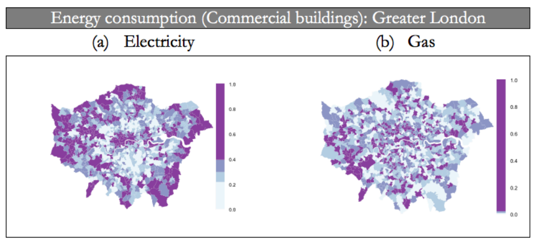


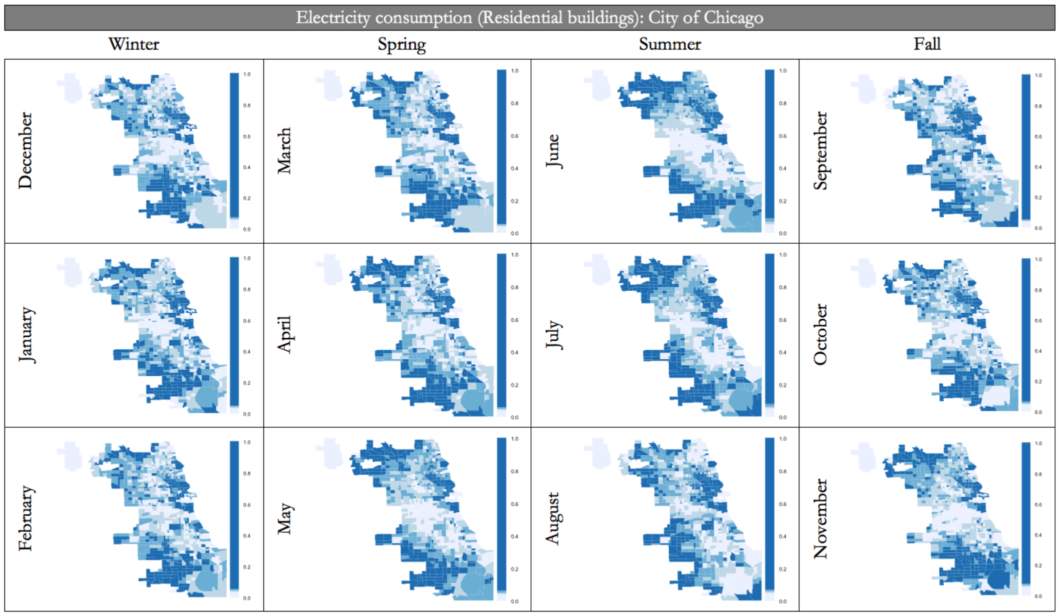
Figure B.2: Spatial distribution by year (2014)–Commercial energy consumption in Greater London: (a) electricity, and (b) gas.

Table B.3: Human mobility records, Greater London.

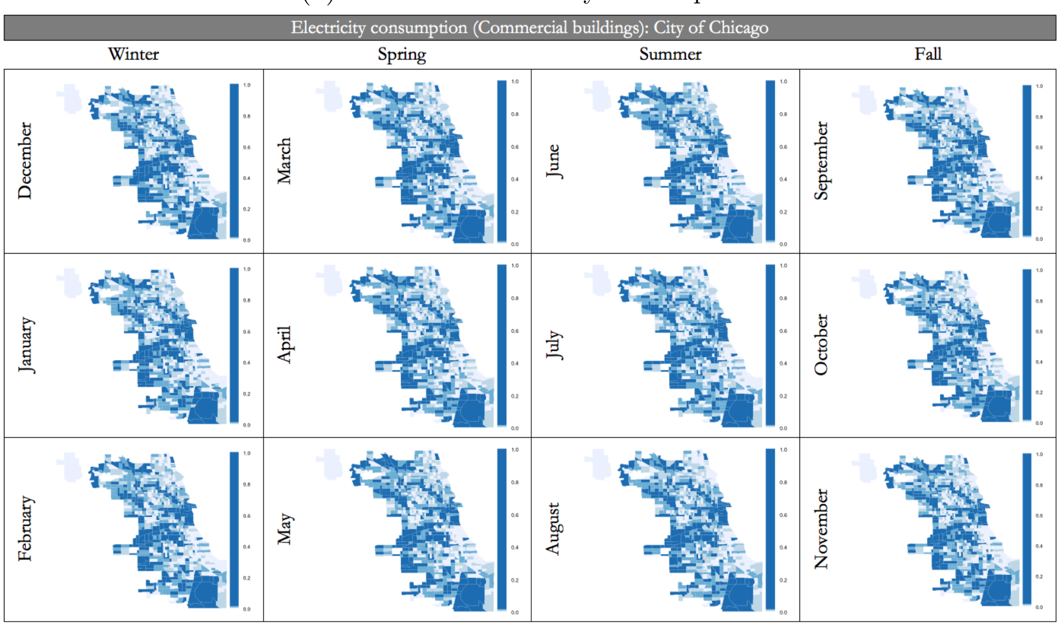
Month (2014)		(a) Positional records	(b) # Individuals visited more than one MOSA	(c) # Individuals	
				Returners	Explorers
1	January	926,854	15,008	9,500	5,508
2	February	988,685	17,425	10,893	6,532
3	March	1,011,980	17,660	10,784	6,876
4	April	1,719,756	25,454	15,240	10,214
5	May	2,305,001	32,620	19,399	13,221
6	June	666,536	11,414	7,565	3,849
7	July	2,342,541	33,265	20,061	13,204
8	August	2,367,967	31,151	18,638	12,513
9	September	2,011,132	29,312	17,871	11,441
10	October	1,676,597	24,920	15,156	9,764
11	November	1,554,680	23,509	14,395	9,114
12	December	1,394,378	19,391	11,972	7,419
Total		18,966,107	281,129	171,474	109,655

Table B.4: Human mobility records, City of Chicago.

Month (2014)		(a) Positional records	(b) # Individuals visited more than one Census Tract	(c) # Individuals	
				Returners	Explorers
1	January	417,639	4,832	3,228	1,604
2	February	414,755	5,553	3,693	1,860
3	March	458,316	6,271	3,988	2,283
4	April	825,895	9,773	6,114	3,659
5	May	1,112,019	1,2470	7,596	4,874
6	June	347,487	4,880	3,260	1,620
7	July	1,211,235	13,936	8,542	5,394
8	August	1,245,393	13,820	8,717	5,103
9	September	934,272	10,941	6,717	4,224
10	October	494,424	6,624	4,119	2,505
11	November	717,836	8,282	5,090	3,192
12	December	618,819	7,710	4,142	3,568
Total		8,798,090	105,092	65,206	39,886

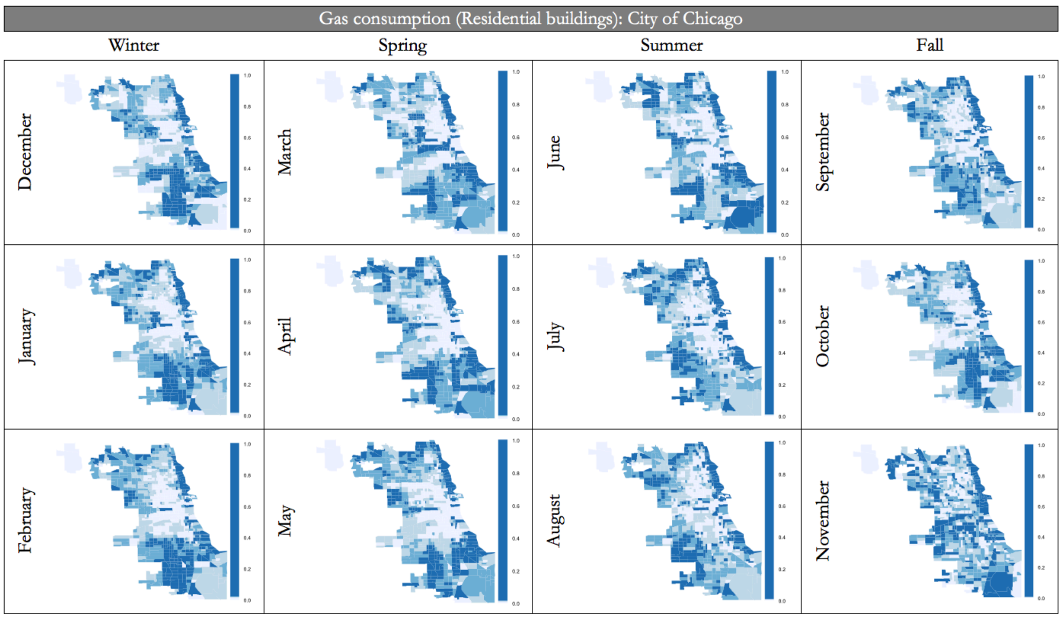


(a) Residential electricity consumption.

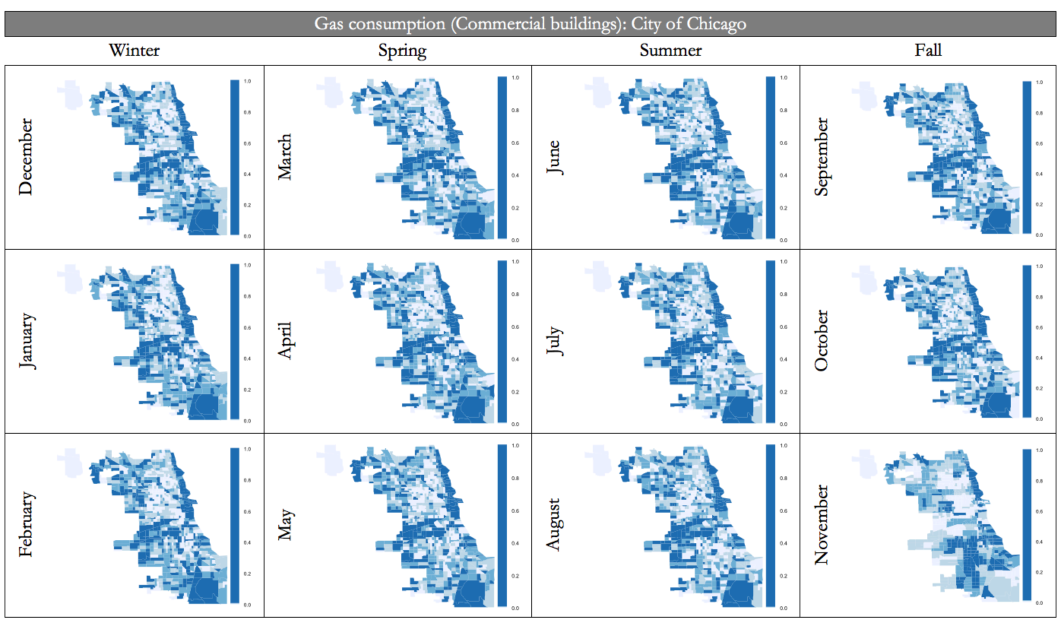


(b) Commercial electricity consumption.

Figure B.3: Spatial distribution of electricity consumption by month (2010), City of Chicago.

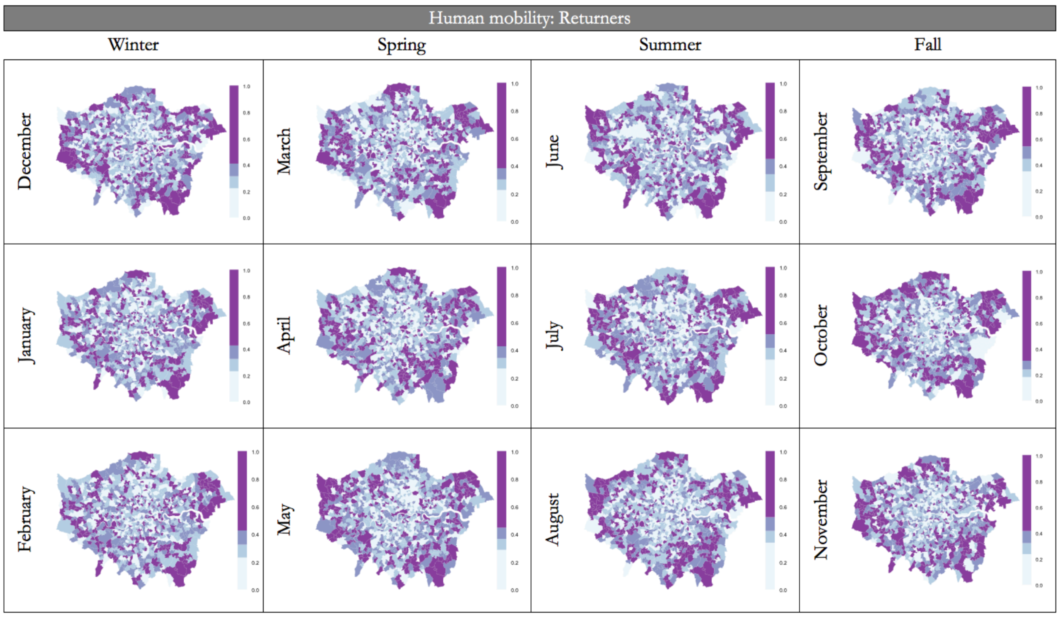


(a) Residential gas consumption.

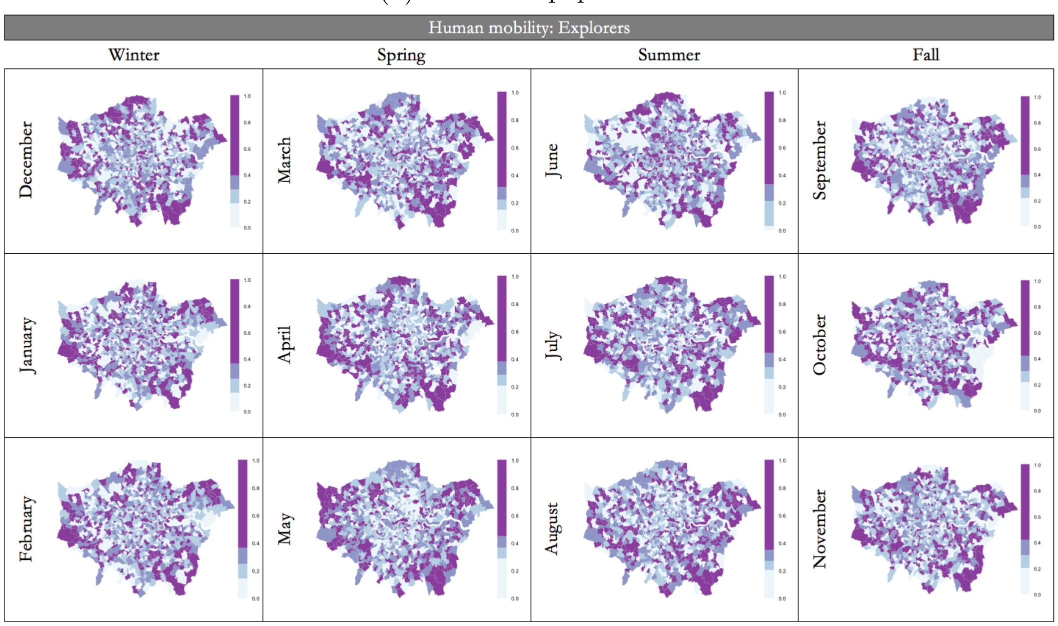


(b) Commercial gas consumption.

Figure B.4: Spatial distribution of gas consumption by month (2010), City of Chicago.

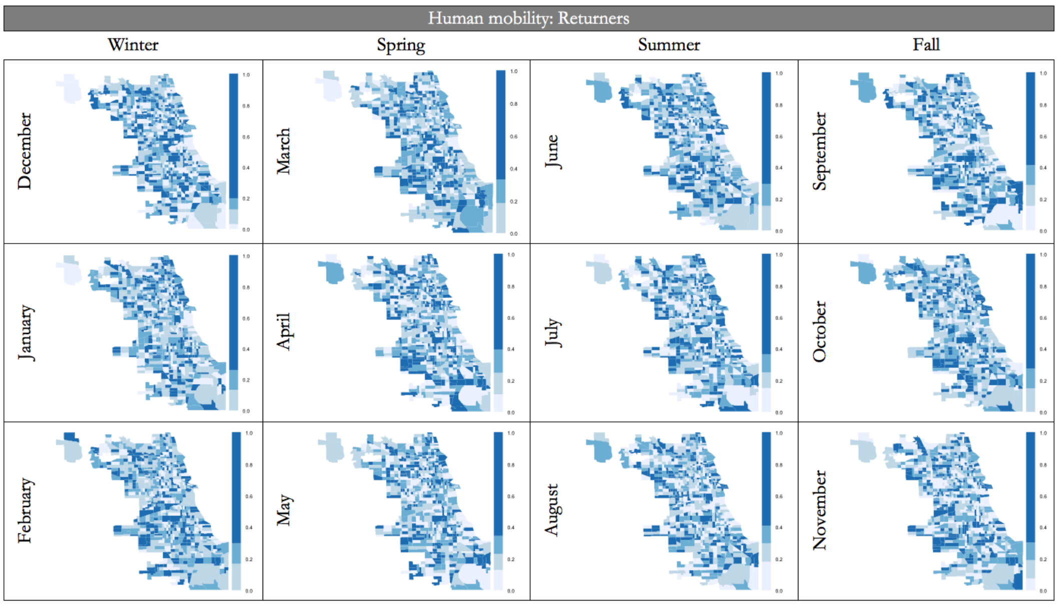


(a) Returners population.

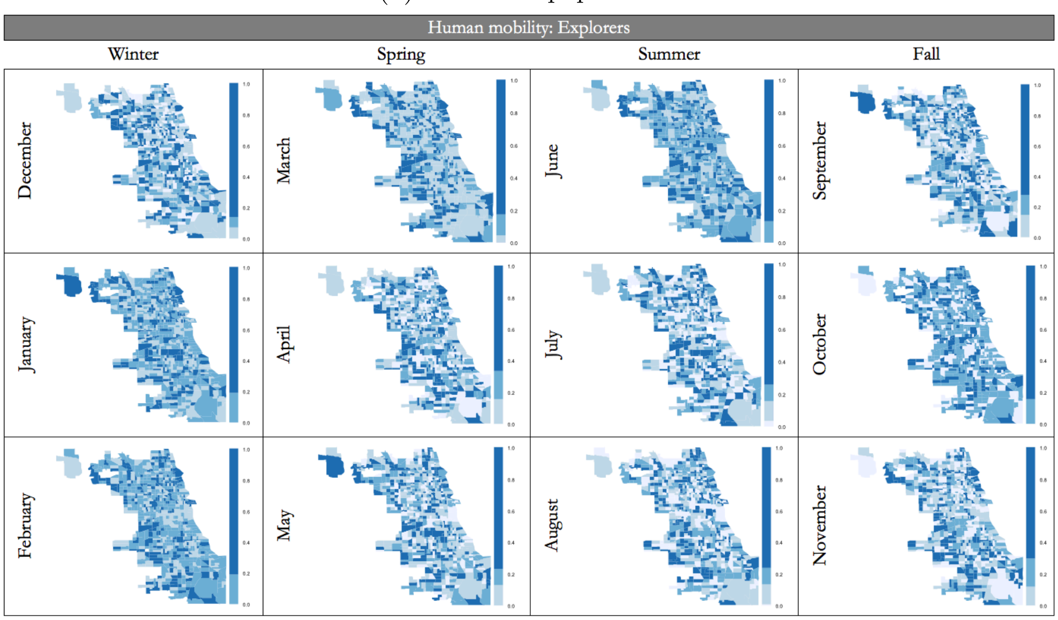


(b) Explorers population.

Figure B.5: Spatial distribution of human mobility by month (2014), Greater London.



(a) Returners population.



(b) Explorers population.

Figure B.6: Spatial distribution of human mobility by month (2014), City of Chicago.

B.2 Spatial Autocorrelation

Table B.5: Spatial autocorrelation–Residential electricity consumption, Greater London.

		Statistic	*p*-value	Std.	Exp.	Var.
Electricity	*Moran's I*	0.4656814121	< 2.2e-16	24.457	-0.0010183299	0.0003641462
Gas	*Moran's I*	0.5969151159	< 2.2e-16	31.275	-0.0010183299	0.0003655285

Table B.6: Spatial autocorrelation–Commercial electricity consumption, Greater London.

		Statistic	*p*-value	Std.	Exp.	Var.
Electricity	*Moran's I*	0.2945662471	< 2.2e-16	15.463	-0.0010183299	0.0003654126
Gas	*Moran's I*	0.01002660	0.259	0.64648	-0.00101833	0.00029189

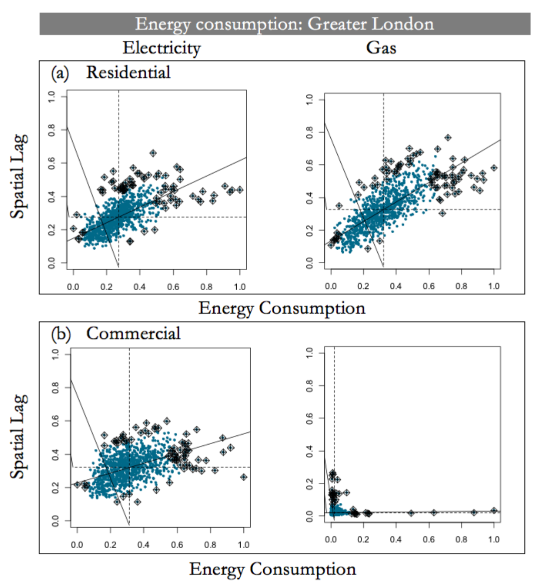


Figure B.7: Moran scatterplots of (a) residential and (b) commercial energy consumption by year (2014), Greater London.

Table B.7: Spatial autocorrelation–Residential electricity consumption, City of Chicago.

	Moran's *I*				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	0.0971466399	1.791e-09	5.9024	-0.0012500000	0.0002779093
January	0.0888722209	1.561e-08	5.5345	-0.0012500000	0.0002651588
February	0.1013927222	1.213e-10	6.3316	-0.0012500000	0.0002628054
March	0.0918113990	1.887e-09	5.8938	-0.0012500000	0.0002493119
April	0.0763240701	1.406e-06	4.684	-0.0012500000	0.0002742673
May	0.117790058	7.347e-13	7.0773	-0.001250000	0.000282908
June	0.1826303115	$< 2.2e-16$	10.157	-0.0012500000	0.0003277442
July	0.1261659819	3.099e-14	7.5038	-0.0012500000	0.0002883254
August	0.120725789	1.003e-13	7.3484	-0.001250000	0.000275527
September	0.0863208779	1.537e-09	5.9275	-0.0012500000	0.0002182575
October	0.0812910444	9.165e-08	5.2155	-0.0012500000	0.0002504637
November	0.1324275456	2.446e-15	7.8297	-0.0012500000	0.0002914952

Table B.8: Spatial autocorrelation–Commercial electricity consumption, City of Chicago.

	Moran's *I*				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	0.0387509133	0.01121	2.2831	-0.0012500000	0.0003069569
January	0.077890564	4.657e-06	4.4325	-0.001250000	0.000318783
February	0.0697123924	4.186e-05	3.9335	-0.0012500000	0.0003254569
March	0.0627234439	0.0002214	3.5132	-0.0012500000	0.0003315855
April	0.0823961291	3.144e-06	4.5165	-0.0012500000	0.0003429979
May	0.0689312473	4.84e-05	3.8985	-0.0012500000	0.0003240786
June	0.0725018169	2.918e-05	4.0193	-0.0012500000	0.0003366968
July	0.0605486473	0.0003234	3.4112	-0.0012500000	0.0003282051
August	0.0839596795	1.807e-06	4.6324	-0.0012500000	0.0003383498
September	0.063208821	0.0002234	3.5108	-0.001250000	0.000337094
October	0.0760895855	1.661e-05	4.1502	-0.0012500000	0.0003472646
November	0.0653879581	0.0001383	3.6363	-0.0012500000	0.0003358376

Table B.9: Spatial autocorrelation–Residential gas consumption, City of Chicago.

	Moran's I				
Month	Statistic	p-value	Std.	Exp.	Var.
December	5.786460e-02	8.579e-11	6.3848	-1.250000e-03	8.572164e-05
January	5.798454e-02	2.107e-10	6.2459	-1.250000e-03	8.994255e-05
February	6.576482e-02	7.841e-12	6.7414	-1.250000e-03	9.881808e-05
March	0.0577347966	2.497e-08	5.4515	-1.250000e-03	0.0001170699
April	0.0502055979	0.0001363	3.64	-1.250000e-03	0.0001998261
May	0.0340645380	0.005756	2.5267	-1.250000e-03	0.0001953376
June	0.0121956445	0.1748	0.93524	-1.250000e-03	0.0002066895
July	0.0105024592	0.1992	0.84447	-1.250000e-03	0.0001936832
August	0.0127351603	0.1564	1.0093	-1.250000e-03	0.0001919809
September	0.019480778	0.07509	1.4389	-1.250000e-03	0.000207565
October	0.0360789130	0.001286	3.0146	-1.250000e-03	0.0001533267
November	5.032477e-02	1.454e-08	5.5469	-1.250000e-03	8.645044e-05

Table B.10: Spatial autocorrelation–Commercial gas consumption, City of Chicago.

	Moran's I				
Month	Statistic	p-value	Std.	Exp.	Var.
December	0.0475495791	1.024e-06	4.7487	-0.0012500000	0.0001056044
January	0.0491187027	1.38e-06	4.6879	-0.0012500000	0.0001154441
February	0.0529940923	5.796e-07	4.8625	-0.0012500000	0.0001244478
March	0.0586310578	1.186e-06	4.7189	-0.0012500000	0.0001610276
April	0.0709373930	1.208e-06	4.715	-0.0012500000	0.0002343995
May	0.0668542797	2.436e-05	4.0617	-0.0012500000	0.0002811514
June	0.0575473795	0.000365	3.378	-0.0012500000	0.0003029599
July	0.0609264666	0.0001225	3.6675	-0.0012500000	0.0002874172
August	0.0646322249	4.548e-05	3.9135	-0.0012500000	0.0002833989
September	0.0515072845	0.0007249	3.1845	-0.0012500000	0.0002744556
October	0.0546665774	0.0001824	3.5644	-0.0012500000	0.0002460998
November	0.0516052547	5.256e-06	4.4064	-0.0012500000	0.0001438851

Table B.11: Spatial autocorrelation–Human Mobility: returners, Greater London.

	Moran's I				
Month	Statistic	p-value	Std.	Exp.	Var.
December	0.089349559	1.144e-06	4.7261	-0.001018330	0.000365607
January	0.0458433082	0.007122	2.451	-0.0010183299	0.0003655416
February	0.089349559	1.144e-06	4.7261	-0.001018330	0.000365607
March	0.1394378615	1.009e-13	7.3476	-0.0010183299	0.0003654207
April	0.0946340544	2.81e-07	5.0038	-0.0010183299	0.0003654264
May	0.2086458848	< 2.2e-16	10.968	-0.0010183299	0.0003654344
June	0.1477957232	3.634e-15	7.7797	-0.0010183299	0.0003658977
July	0.1483147076	2.869e-15	7.8096	-0.0010183299	0.0003656436
August	0.1927782381	< 2.2e-16	10.138	-0.0010183299	0.0003654482
September	0.1533081765	3.524e-16	8.0697	-0.0010183299	0.0003657359
October	0.2298976221	< 2.2e-16	12.091	-0.0010183299	0.0003647379
November	0.1332688724	1.064e-12	7.0258	-0.0010183299	0.0003653229

Table B.12: Spatial autocorrelation–Human Mobility: explorers, Greater London.

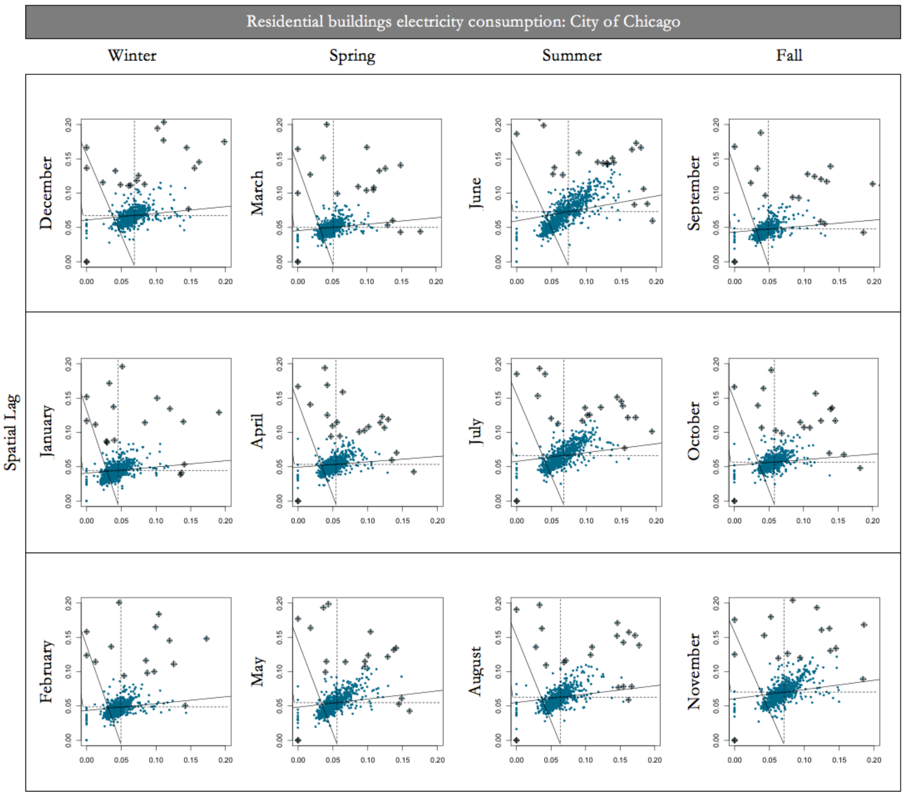
	Moran's I				
Month	Statistic	p-value	Std.	Exp.	Var.
December	0.0568457290	0.00124	3.0257	-0.0010183299	0.0003657247
January	0.0187787194	0.1503	1.0352	-0.0010183299	0.0003657377
February	0.0568457290	0.00124	3.0257	-0.0010183299	0.0003657247
March	0.0556824047	0.001503	2.967	-0.0010183299	0.0003651573
April	0.0440438554	0.009205	2.3573	-0.0010183299	0.0003654264
May	0.2086458848	< 2.2e-16	10.968	-0.0010183299	0.0003654344
June	0.039321891	0.01744	2.1098	-0.001018330	0.000365588
July	0.1050443952	1.455e-08	5.5467	-0.0010183299	0.000365637
August	0.0620730029	0.0004784	3.3029	-0.0010183299	0.0003648693
September	0.0736243344	4.728e-05	3.9041	-0.0010183299	0.0003655303
October	0.1003784824	5.722e-08	5.3022	-0.0010183299	0.0003657141
November	0.0473438331	0.005717	2.5292	-0.0010183299	0.0003656446

Table B.13: Spatial autocorrelation–Human Mobility: returners, City of Chicago.

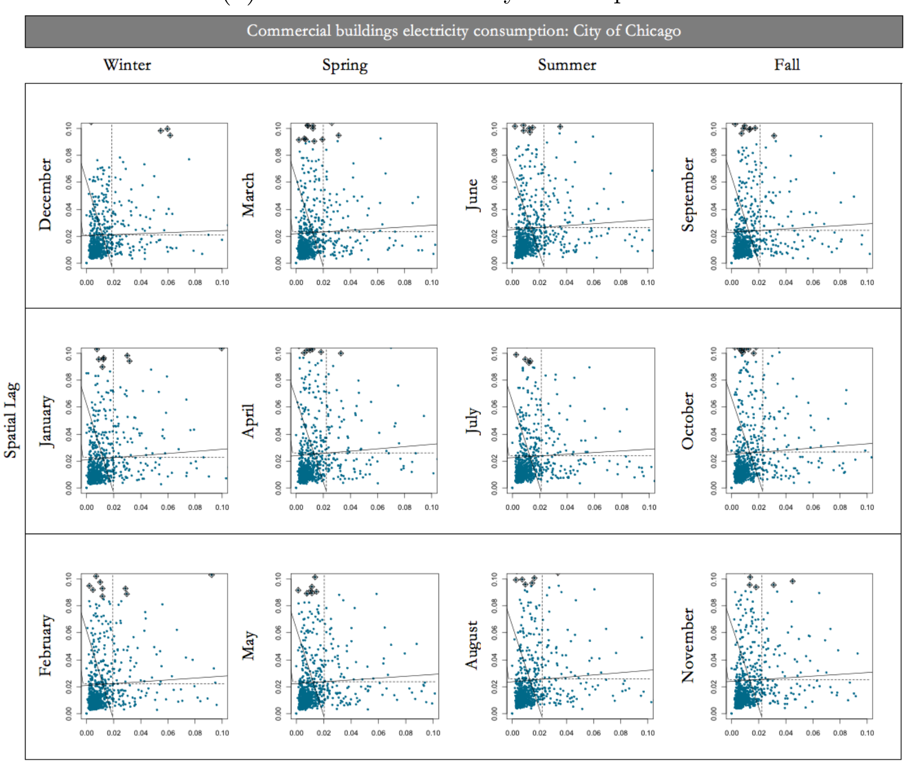
	Moran's *I*				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	0.0469170094	0.007866	2.4151	-0.0012500000	0.0003977685
January	0.0326270440	0.04505	1.6949	-0.001250000	0.0003995221
February	0.0629956317	0.0006563	3.2132	-0.0012500000	0.0006563
March	0.0647914579	0.0004794	3.3023	-0.0012500000	0.0003999407
April	0.0427146003	0.01398	2.1979	-0.0012500000	0.0004001163
May	0.066187299	0.0003722	3.3727	-0.0012500000	0.000399811
June	0.0588973269	0.001316	3.0077	-0.0012500000	0.000399756
July	0.074600221	7.434e-05	3.7933	-0.0012500000	0.000399839
August	0.0781581879	3.584e-0	3.9707	-0.0012500000	0.0003999509
September	0.0350867002	0.03465	1.8165	-0.0012500000	0.0004001576
October	0.0361323441	0.03076	1.8697	-0.0012500000	0.0003997349
November	0.0641694623	0.0005351	3.2714	-0.0012500000	0.0003998981

Table B.14: Spatial autocorrelation–Human Mobility: explorers, City of Chicago.

	Moran's *I*				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	0.0114454716	0.2617	0.63796	-0.0012500000	0.0003960126
January	0.0762326494	5.203e-05	3.8809	-0.001250000	0.0003986055
February	0.0522448772	0.003682	2.6799	-0.0012500000	0.0003984647
March	0.063742098	0.0005634	3.2568	-0.0012500000	0.000398237
April	0.0172367412	0.1776	0.92437	-0.0012500000	0.0003999705
May	0.0306151680	0.05531	1.5954	-0.0012500000	0.0003989317
June	0.0308926069	0.0531	1.6155	-0.0012500000	0.0003999193
July	0.0458434233	0.009228	2.3563	-0.0012500000	0.0003994356
August	0.0609419347	0.0009233	3.1139	-0.0012500000	0.0003989067
September	0.0400564199	0.01939	2.0665	-0.0012500000	0.0003995501
October	0.0780836438	3.435e-05	3.9808	-0.0012500000	0.0003971736
November	0.066277455	0.0003646	3.3784	-0.0012500000	0.000399527

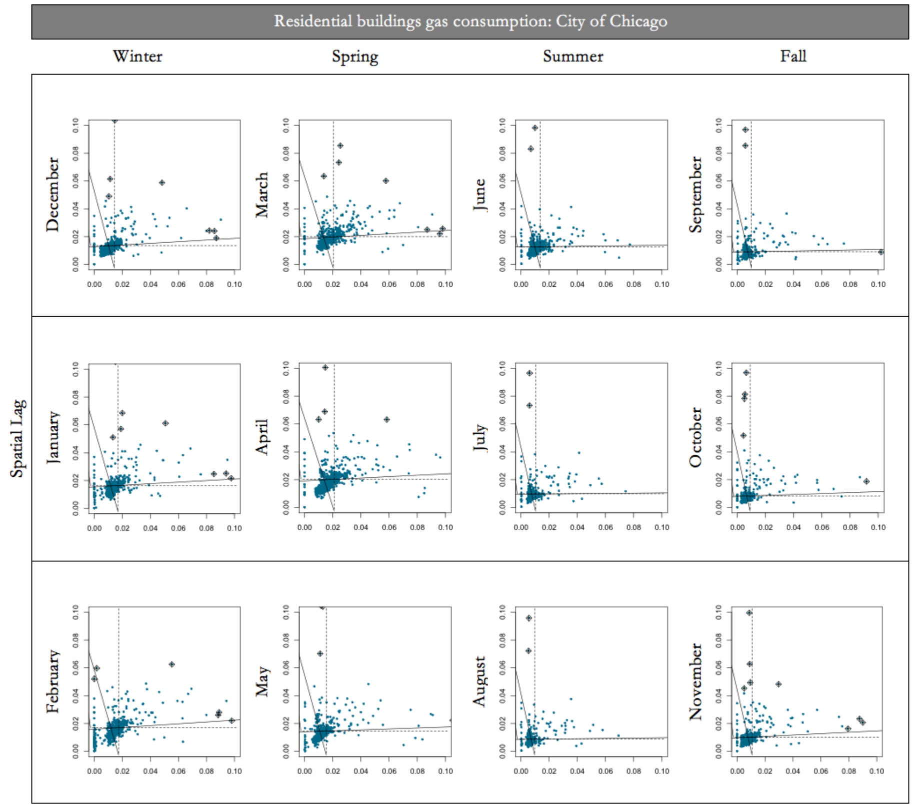


(a) Residential electricity consumption.

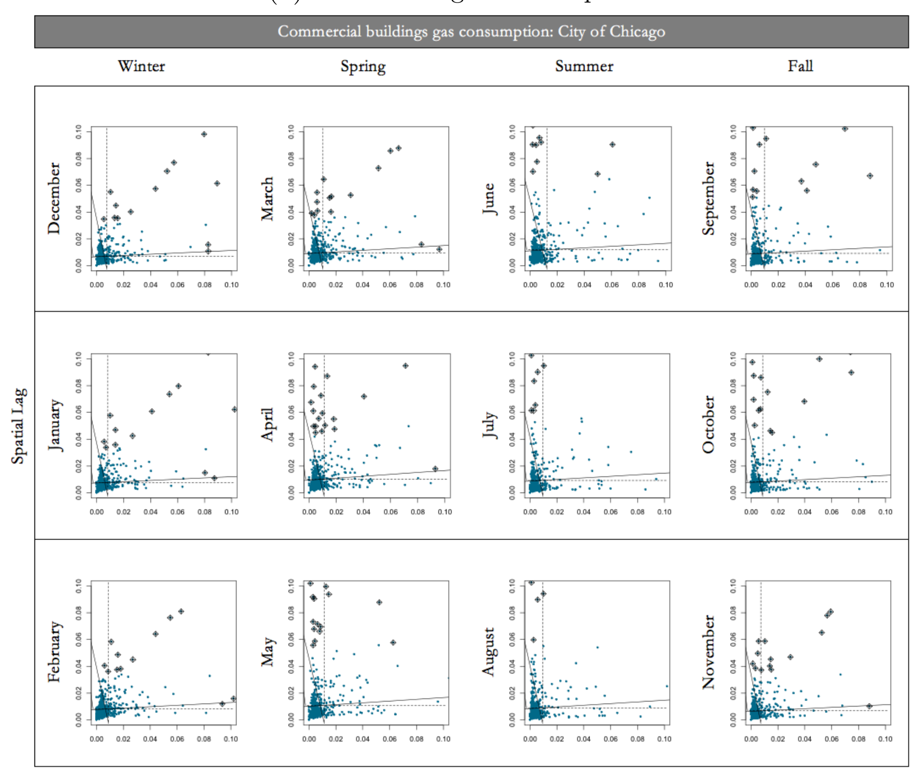


(b) Commercial electricity consumption.

Figure B.8: Moran scatterplots of electricity consumption by month (2010), City of Chicago

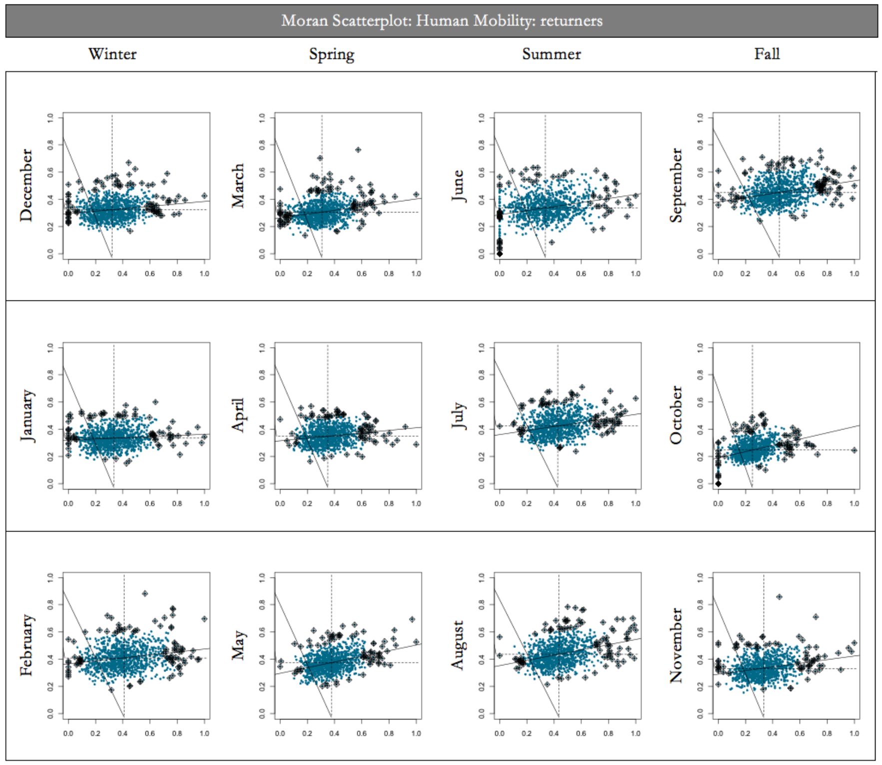


(a) Residential gas consumption.

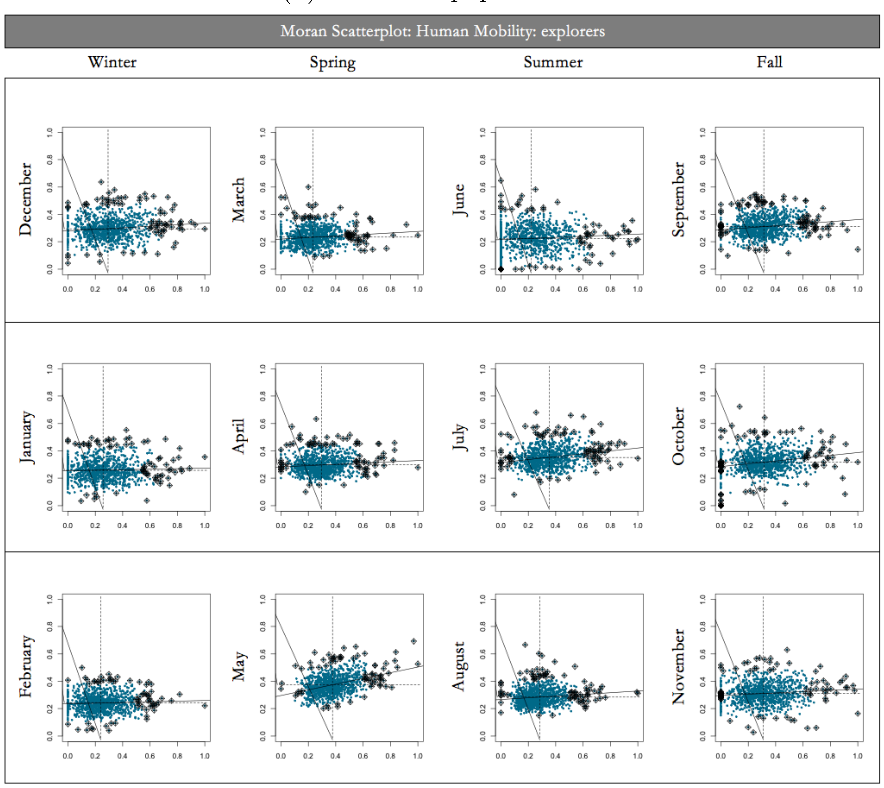


(b) Commercial gas consumption.

Figure B.9: Moran scatterplots of gas consumption by month (2010), City of Chicago.

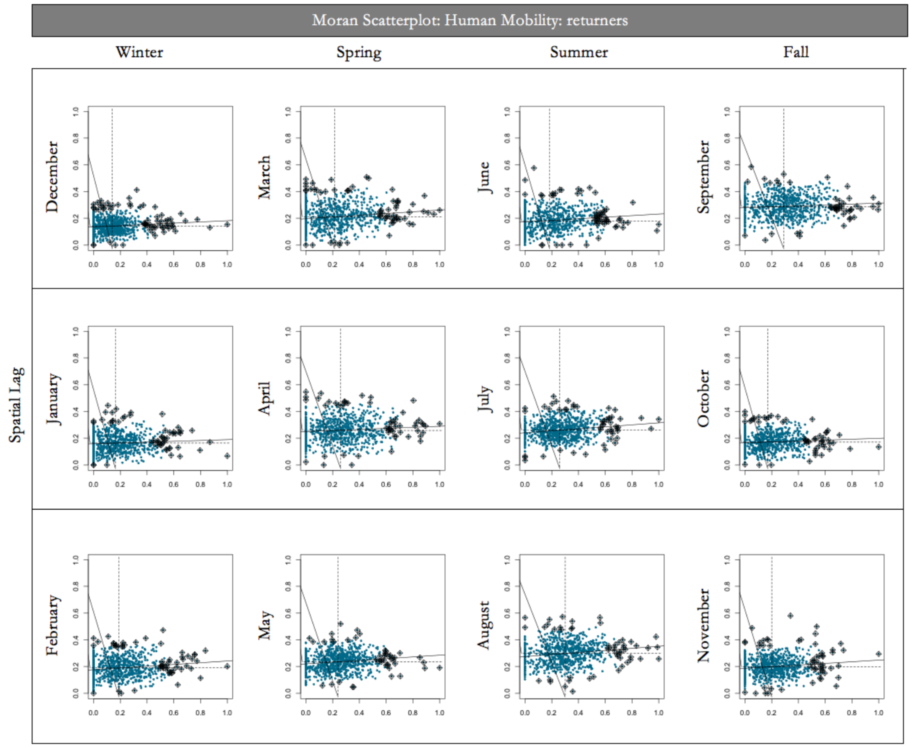


(a) Returners population.

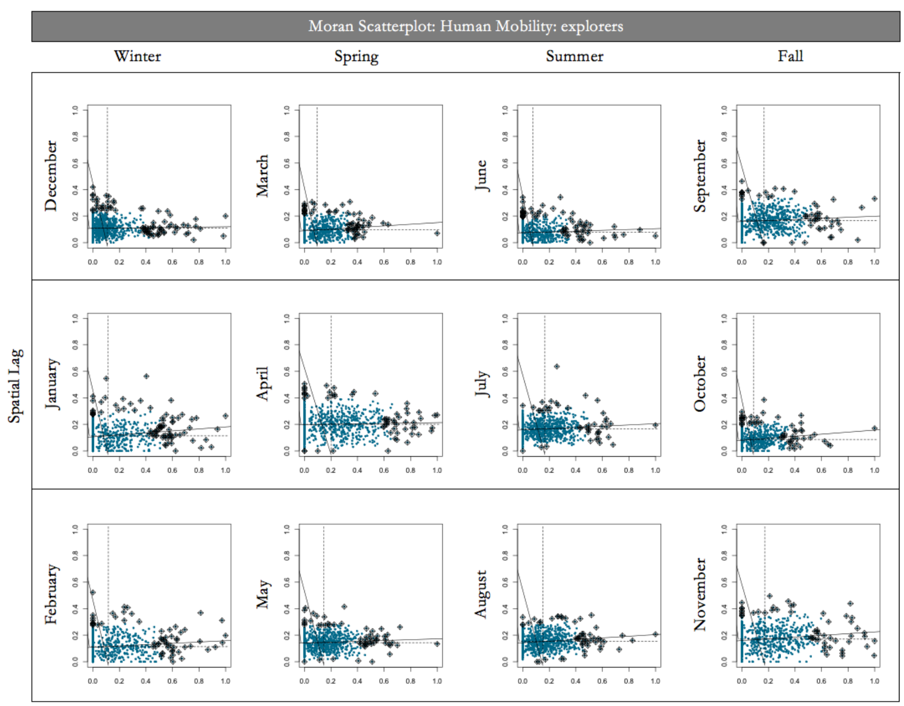


(b) Explorers population.

Figure B.10: Moran scatterplots of human mobility by month (2014), Greater London.



(a) Returners population.



(b) Explorers population.

Figure B.11: Moran scatterplots of human mobility by month (2014), City of Chicago.

B.3 Hotspot Analysis

Table B.15: Hotspots analysis–Residential energy consumption, Greater London.

		Statistic	*p*-value	Std.	Exp.	Var.
Electricity	*Getis-Ord G*	6.472315e-03	< 2.2e-16	13.083	5.840635e-03	2.331247e-09
Gas		6.804931e-03	< 2.2e-16	17.924	5.840635e-03	2.894360e-09

Table B.16: Hotspots analysis–Commercial energy consumption, Greater London.

		Statistic	*p*-value	Std.	Exp.	Var.
Electricity	*Getis-Ord G*	6.327683e-03	< 2.2e-16	10.478	5.840635e-03	2.160635e-09
Gas		6.181046e-03	0.305	0.50995	5.840635e-03	4.456140e-07

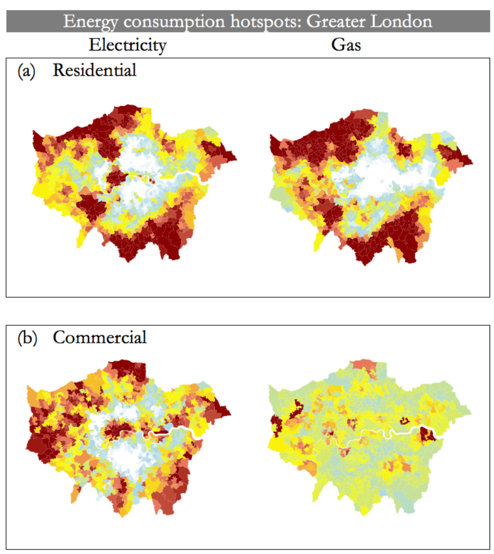
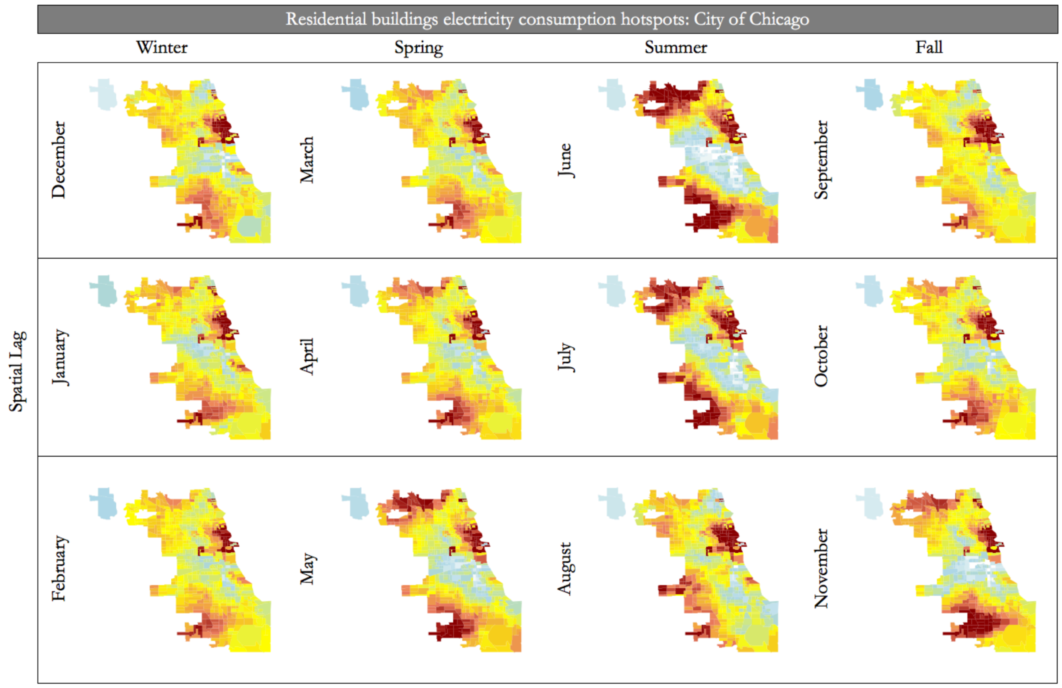
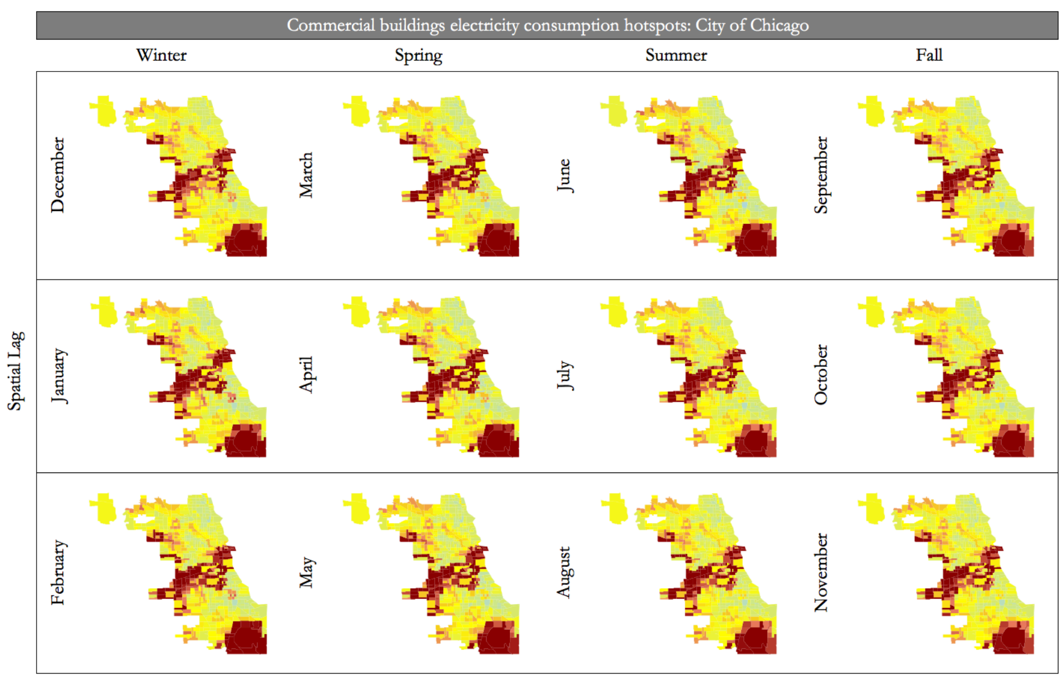


Figure B.12: Energy consumption hotspots–(a) residential and (b) commercial buildings by year (2014), Greater London.

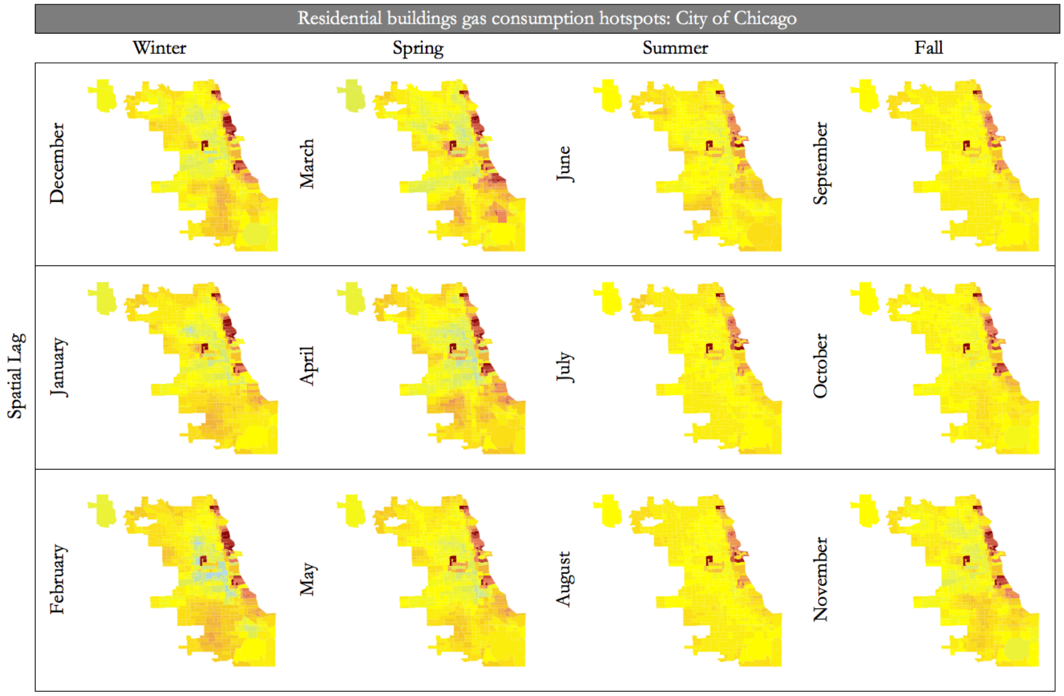


(a) Residential electricity consumption.



(b) Commercial electricity consumption.

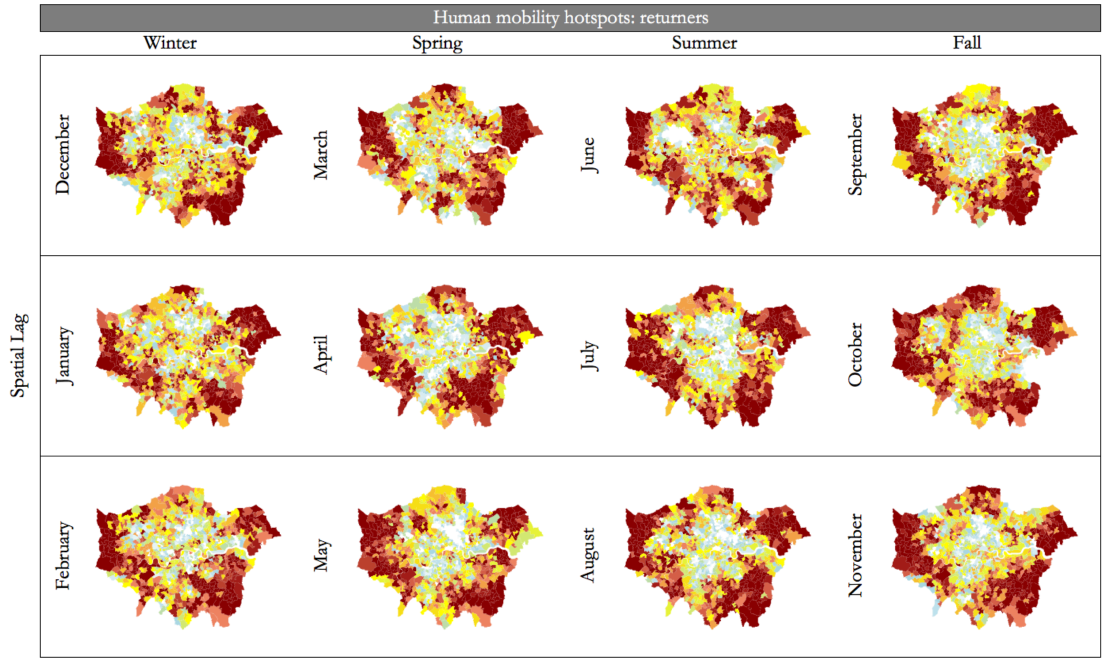
Figure B.13: Electricity consumption hotspots by month, City of Chicago.



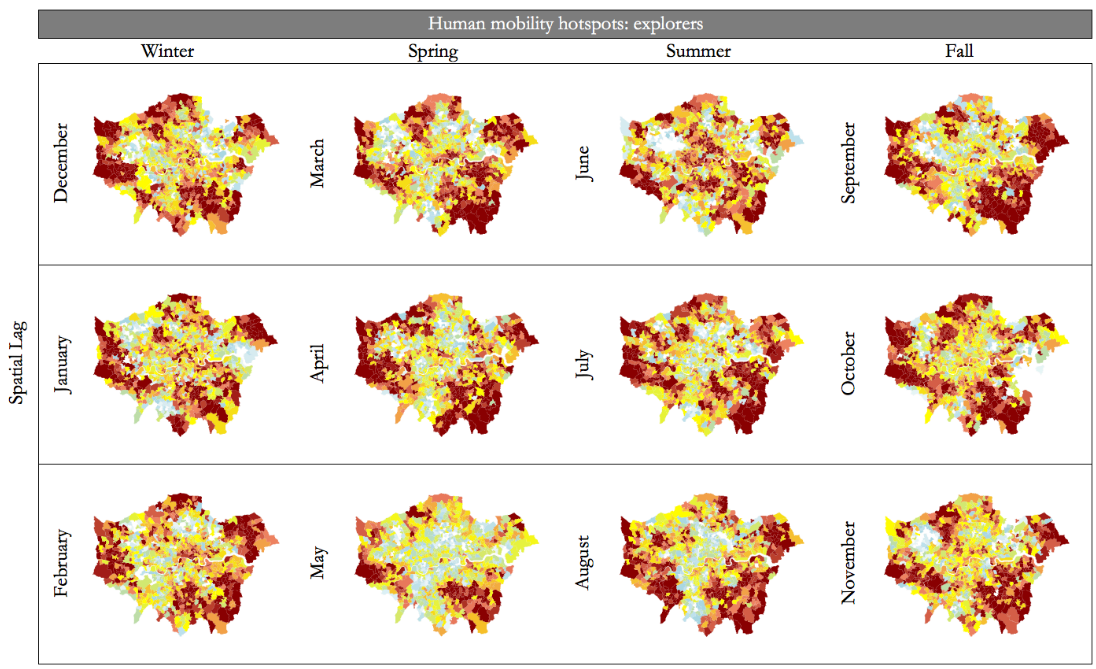
(a) Residential gas consumption.

(b) Commercial gas consumption.

Figure B.14: Gas consumption hotspots by month, City of Chicago.

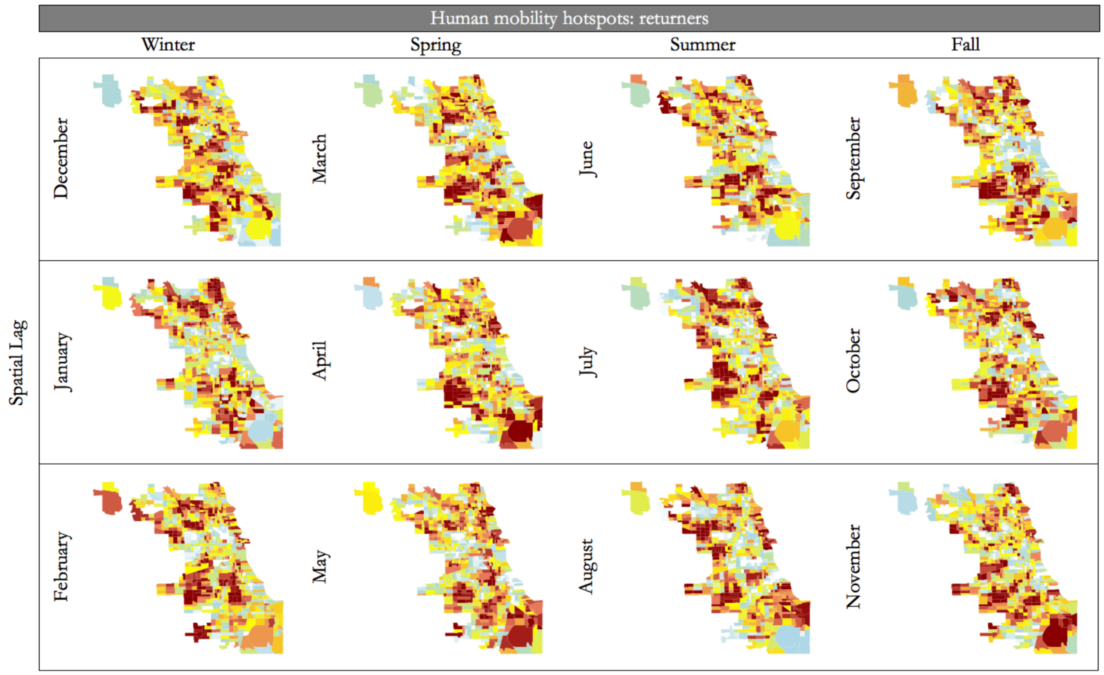


(a) Returners population.



(b) Explorers population.

Figure B.15: Human mobility hotspots by month (2014), Greater London.



(a) Returners population.

(b) Explorers population.

Figure B.16: Human mobility hotspots by month (2014), City of Chicago.

Table B.17: Hotspots analysis–Residential electricity consumption, City of Chicago.

	Getis-Ord G				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	8.427360e-03	0.06174	1.5403	8.242821e-03	1.435309e-08
January	8.602132e-03	0.03681	1.7889	8.242821e-03	4.034122e-08
February	8.659988e-03	0.01025	2.3171	8.242821e-03	3.241484e-08
March	8.535428e-03	0.03639	1.7942	8.242821e-03	2.659619e-08
April	8.363663e-03	0.228	0.74551	8.242821e-03	2.627352e-08
May	8.503765e-03	0.05362	1.6107	8.242821e-03	2.624546e-08
June	8.630438e-03	0.0021	2.8583	8.242821e-03	1.839091e-08
July	8.406331e-03	0.09864	1.2893	8.242821e-03	1.608258e-08
August	8.509386e-03	0.02074	2.0387	8.242821e-03	1.709551e-08
September	8.537374e-03	0.0334	1.8331	8.242821e-03	2.582111e-08
October	8.402191e-03	0.1245	1.1526	8.242821e-03	1.911692e-08
November	8.490956e-03	0.01894	2.0762	8.242821e-03	1.428384e-08

Table B.18: Hotspots analysis–Commercial electricity consumption, City of Chicago.

	Getis-Ord G				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	1.288325e-02	0.0002108	3.5262	8.242821e-03	1.731805e-06
January	1.535973e-02	1.787e-10	6.2716	8.242821e-03	1.287732e-06
February	1.527096e-02	5.689e-09	5.7088	8.242821e-03	1.515629e-06
March	1.492946e-02	4.8e-08	5.3341	8.242821e-03	1.571406e-06
April	1.551320e-02	3.249e-11	6.5318	8.242821e-03	1.238925e-06
May	1.462479e-02	2.227e-09	5.8664	8.242821e-03	1.183487e-06
June	1.403174e-02	8.263e-10	6.0287	8.242821e-03	9.220293e-07
July	1.428466e-02	4.945e-08	5.3287	8.242821e-03	1.285548e-06
August	1.570422e-02	3.717e-12	6.8491	8.242821e-03	1.186799e-06
September	1.468041e-02	4.598e-08	5.3419	8.242821e-03	1.452285e-06
October	1.527229e-02	1.413e-10	6.308	8.242821e-03	1.241825e-06
November	1.404237e-02	2.821e-08	5.4298	8.242821e-03	1.140841e-06

Table B.19: Hotspots analysis–Residential gas consumption, City of Chicago.

	Getis-Ord G				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	9.318378e-03	0.04709	1.6738	8.242821e-03	4.129338e-07
January	8.783438e-03	0.1387	1.0861	8.242821e-03	2.477514e-07
February	8.955118e-03	0.07304	1.4535	8.242821e-03	2.401604e-07
March	8.563190e-03	0.2206	0.77021	8.242821e-03	1.730130e-07
April	8.411621e-03	0.3831	0.29744	8.242821e-03	3.220632e-07
May	8.430668e-03	0.4251	0.18897	8.242821e-03	9.881613e-07
June	7.689465e-03	0.6499	-0.385	8.242821e-03	2.065792e-06
July	7.725959e-03	0.5986	-0.24977	8.242821e-03	4.282367e-06
August	7.957640e-03	0.5465	-0.11694	8.242821e-03	5.947210e-06
September	8.586151e-03	0.4493	0.12748	8.242821e-03	7.253536e-06
October	1.014674e-02	0.1898	0.87866	8.242821e-03	4.695164e-06
November	1.004466e-02	0.04329	1.7137	8.242821e-03	1.105455e-06

Table B.20: Hotspots analysis–Commercial gas consumption, City of Chicago.

	Getis-Ord G				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	1.448144e-02	0.002291	2.8351	8.242821e-03	4.842280e-06
January	1.376510e-02	0.002729	2.7787	8.242821e-03	3.949622e-06
February	1.345833e-02	0.002109	2.8614	8.242821e-03	3.322171e-06
March	1.282095e-02	0.00277	2.7739	8.242821e-03	2.724006e-06
April	1.450579e-02	0.0012	3.0357	8.242821e-03	4.256445e-06
May	1.618592e-02	0.001895	2.8951	8.242821e-03	7.527471e-06
June	1.666844e-02	0.003125	2.7343	8.242821e-03	9.495197e-06
July	1.995099e-02	0.001782	2.9143	8.242821e-03	1.613969e-05
August	2.121846e-02	0.001174	3.0422	8.242821e-03	1.819233e-05
September	1.835978e-02	0.00409	2.6446	8.242821e-03	1.463484e-05
October	1.730536e-02	0.00683	2.4661	8.242821e-03	1.350471e-05
November	1.609308e-02	0.002816	2.7685	8.242821e-03	8.040270e-06

Table B.21: Hotspots analysis–Human Mobility: returners, Greater London.

	Getis-Ord G				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	6.011553e-03	0.0001519	3.6121	5.840635e-03	2.239026e-09
January	5.916149e-03	0.05798	1.572	5.840635e-03	2.307560e-09
February	5.916870e-03	0.04084	1.7411	5.840635e-03	1.917295e-09
March	5.951498e-03	0.006494	2.4841	5.840635e-03	1.991715e-09
April	5.854798e-03	0.3503	0.38461	5.840635e-03	1.356117e-09
May	5.926972e-03	0.006603	2.4781	5.840635e-03	1.213787e-09
June	6.085330e-03	4.012e-05	3.9437	5.840635e-03	3.849845e-09
July	5.876885e-03	0.1398	1.0813	5.840635e-03	1.123892e-09
August	5.931657e-03	0.00463	2.6023	5.840635e-03	1.223403e-09
September	5.936146e-03	0.003242	2.7222	5.840635e-03	1.231006e-09
October	6.068089e-03	1.307e-06	4.6991	5.840635e-03	2.342931e-09
November	5.982682e-03	0.0007468	3.1759	5.840635e-03	2.000443e-09

Table B.22: Hotspots analysis–Human Mobility: explorers, Greater London.

	Getis-Ord G				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	6.011021e-03	0.005508	2.5422	5.840635e-03	4.492132e-09
January	5.939996e-03	0.102	1.2703	5.840635e-03	6.118530e-09
February	5.924753e-03	0.1109	1.2218	5.840635e-03	4.740064e-09
March	5.973160e-03	0.02481	1.9632	5.840635e-03	4.556848e-09
April	5.930210e-03	0.03669	1.7904	5.840635e-03	2.503035e-09
May	5.971599e-03	0.001896	2.8949	5.840635e-03	2.046619e-09
June	6.172151e-03	0.002451	2.8134	5.840635e-03	1.388455e-08
July	5.963225e-03	0.003163	2.7304	5.840635e-03	2.015860e-09
August	5.954498e-03	0.007587	2.4282	5.840635e-03	2.198874e-09
September	5.904742e-03	0.1059	1.2488	5.840635e-03	2.635066e-09
October	6.106967e-03	5.241e-06	4.407	5.840635e-03	3.652318e-09
November	5.925699e-03	0.08779	1.3545	5.840635e-03	3.944154e-09

Table B.23: Hotspots analysis–Human Mobility: returners, City of Chicago.

	Getis-Ord G				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	9.081090e-03	4.747e-05	3.9032	8.242821e-03	4.612397e-08
January	8.496293e-03	0.1318	1.1179	8.242821e-03	5.140761e-08
February	8.801691e-03	0.002534	2.8026	8.242821e-03	3.976383e-08
March	8.779285e-03	0.003913	2.6595	8.242821e-03	4.069035e-08
April	8.438101e-03	0.1014	1.2736	8.242821e-03	2.351105e-08
May	8.363811e-03	0.1829	0.90419	8.242821e-03	1.790527e-08
June	8.657910e-03	0.03492	1.813	8.242821e-03	5.241910e-08
July	8.567457e-03	0.003148	2.7319	8.242821e-03	1.412079e-08
August	8.400588e-03	0.08498	1.3723	8.242821e-03	1.321615e-08
September	8.285783e-03	0.374	0.32139	8.242821e-03	1.786837e-08
October	8.445906e-03	0.1554	1.0134	8.242821e-03	4.015918e-08
November	8.387221e-03	0.189	0.88163	8.242821e-03	2.682593e-08

Table B.24: Hotspots analysis–Human Mobility: explorers, City of Chicago.

	Getis-Ord G				
Month	Statistic	*p*-value	Std.	Exp.	Var.
December	8.732891e-03	0.07293	1.4543	8.242821e-03	1.135501e-07
January	9.866242e-03	0.0002814	3.4489	8.242821e-03	2.215622e-07
February	8.959008e-03	0.05636	1.5861	8.242821e-03	2.038841e-07
March	8.722084e-03	0.07412	1.4458	8.242821e-03	1.098883e-07
April	8.584896e-03	0.08998	1.3409	8.242821e-03	6.508462e-08
May	8.484917e-03	0.1353	1.1015	8.242821e-03	4.830917e-08
June	8.831153e-03	0.1248	1.1514	8.242821e-03	2.611056e-07
July	8.599385e-03	0.02741	1.9203	8.242821e-03	3.447925e-08
August	8.817467e-03	0.002353	2.8265	8.242821e-03	4.133487e-08
September	8.570310e-03	0.07761	1.4213	8.242821e-03	5.308862e-08
October	9.335205e-03	0.001523	2.963	8.242821e-03	1.359179e-07
November	8.696641e-03	0.05444	1.6033	8.242821e-03	8.012411e-08

B.4 Spatial Regression

B.4.1 Greater London

Table B.25: Spatial regression–Electricity consumption versus returners mobility: Winter.

		December			January			February		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	8.361e-08***	<2.2e-16 ***	<2e-16 ***	0.00415**	<2.2e-16 ***	<2.2e-16 ***	0.000820***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1362.4	-1737.2	-1729.8	-1341.8	-1727.3	-1725.2	-1344.8	-1725.8	-1724.1
	R-squared[1]	0.02788	-	-	0.007335	-	-	0.01035	-	-
	Statistic	5.40	0.66819	0.67378	2.873	0.67623	0.6783	3.356	0.67541	0.67911
Commercial	P-value	0.00338**	<2.2e-16 ***	<2.2e-16 ***	0.4366	<2.2e-16 ***	<2.2e-16 ***	0.1371	<2.2e-16 ***	<2e-16 ***
	AIC	-1135.1	-1291.5	-1289.5	-1127.1	-1288.2	-1288.3	-1128.7	-1288.3	-1288.3
	R-squared	0.007712	-	-	-0.0004018	-	-	0.001235	-	-
	Statistic	2.938	0.4997	0.50174	0.778	0.50562	0.50628	1.488	0.50468	0.50666

p<0.05; p<0.001**; p<0.0001***;* [1]*Adjusted R-squared.*

Table B.26: Spatial regression–Electricity consumption versus explorers mobility: Winter.

		December			January			February		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.008614**	<2.2e-16 ***	<2.2e-16 ***	0.07368	<2.2e-16 ***	<2.2e-16 ***	0.09439	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1340.5	-1725.4	-1724.1	-1336.8	-1725.3	-1724.2	-1336.4	-1725.2	-1724.5
	R-squared	0.006001	-	-	0.002241	-	-	0.001833	-	-
	Statistic	2.632	0.67688	0.67912	1.791	0.67824	0.6791	1.674	0.6784	0.67903
Commercial	P-value	0.0188*	<2.2e-16 ***	<2.2e-16 ***	0.258	<2.2e-16 ***	<2.2e-16 ***	0.862	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1132	-1290.6	-1289	-1127.7	-1288.6	-1288.3	-1126.5	-1288.8	-1289.9
	R-squared	0.004599	-	-	0.0002866	-	-	-0.0009883	-	-
	Statistic	2.353	0.50201	0.50295	1.132	0.5049	0.50537	0.174	0.50764	0.50954

Table B.27: Spatial regression–Electricity consumption versus returners mobility: Spring.

		March			April			May		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.014*	<2.2e-16 ***	<2.2e-16 ***	0.000429***	<2.2e-16 ***	<2.2e-16 ***	5.43e-09***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1339.7	-1725	-1724.1	-1346	-1726.4	-1724.2	-1367.7	-1733.4	-1726.1
	R-squared	0.005126	-	-	0.01156	-	-	0.03313	-	-
	Statistic	2.462	0.67733	0.67934	3.533	0.67478	0.67879	5.886	0.66556	0.67405
Commercial	P-value	0.000142***	<2.2e-16 ***	<2.2e-16 ***	0.3542	<2.2e-16 ***	<2.2e-16 ***	2.9e-07***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1141	0.49641	0.49789	-1127.3	-1288.4	-1289.9	-1152.8	-1299.3	-1293.5
	R-squared	0.01365	-	-	-0.0001434	-	-	0.02549	-	-
	Statistic	3.819	-1295.5	-1292	0.927	0.50735	0.51147	5.166	0.48713	0.49101

Table B.28: Spatial regression–Electricity consumption versus explorers mobility: Spring.

		March			April			May		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.2974	<2.2e-16 ***	<2.2e-16 ***	0.000126***	<2.2e-16 ***	<2.2e-16 ***	0.00175**	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1334.7	-1724.4	-1725.7	-1348.3	-1728.3	-1724.6	-1343.4	-1726.5	-1724.7
	R-squared	8.865e-05	-	-	0.01387	-	-	0.008934	-	-
	Statistic	1.043	0.68063	0.68164	3.849	0.67356	0.67766	3.139	0.67562	0.67811
Commercial	P-value	0.0112*	<2.2e-16 ***	<2.2e-16 ***	0.00074***	<2.2e-16 ***	<2.2e-16 ***	2.9e-07***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1132.9	-1292.3	-1290.7	-1137.9	-1292.6	-1289.6	-1129	-1288.3	-1288.5
	R-squared	0.00553	-	-	0.01054	-	-	0.02549	-	-
	Statistic	2.542	0.50239	0.50289	3.385	0.4977	0.50025	5.166	0.50456	0.50805

Table B.29: Spatial regression–Electricity consumption versus returners mobility: Summer.

		June			July			August		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.0137*	<2.2e-16 ***	<2.2e-16 ***	2.18e-07***	<2.2e-16 ***	<2.2e-16 ***	3.37e-07***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1339.7	-1724.4	-1724.5	-1360.5	-1729.1	-1724.6	-1359.7	-1728.2	-1724.2
	R-squared	0.005169	-	-	0.02604	-	-	0.0252	-	-
	Statistic	2.47	0.67804	0.68127	5.221	0.66909	0.67708	5.137	0.66975	-1724.2
Commercial	P-value	0.212	<2.2e-16 ***	<2.2e-16 ***	0.00743**	<2.2e-16 ***	<2.2e-16 ***	0.00186**	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1128	-1288.3	-1288.3	-1133.6	-1288.7	-1288.6	-1136.2	-1290.4	-1288.4
	R-squared	0.0005699	-	-	0.006269	-	-	0.008816	-	-
	Statistic	1.249	0.50491	0.50643	2.682	0.50197	0.51039	3.12	0.49872	0.50334

Table B.30: Spatial regression–Electricity consumption versus explorers mobility: Summer.

		June			July			August		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.308	<2.2e-16 ***	<2.2e-16 ***	0.0133*	<2.2e-16 ***	<2.2e-16 ***	0.00138**	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1334.6	-1724.5	-1724.2	-1339.8	-1725.8	-1724.2	-1343.9	-1727.7	-1725.3
	R-squared	4.105e-05	-	-	0.005223	-	-	0.009375	-	-
	Statistic	1.02	0.67911	0.67927	2.481	0.67706	0.67884	3.208	0.67538	0.67793
Commercial	P-value	0.4193	<2.2e-16 ***	<2.2e-16 ***	0.0193*	<2.2e-16 ***	<2.2e-16 ***	0.00145**	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1127.1	-1288.7	-1288.6	-1132	-1290.2	-1289	-1136.6	-1293.8	-1290.8
	R-squared	-0.0003538	-	-	0.004553	-	-	0.009284	-	-
	Statistic	-0.808	0.50558	0.50569	2.343	0.50191	0.5031	3.194	0.49961	0.50047

Table B.31: Spatial regression–Electricity consumption versus returners mobility: Fall.

		September			October			November		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	7.93e-06***	<2.2e-16 ***	<2.2e-16 ***	0.000316***	<2.2e-16 ***	<2.2e-16 ***	3.78e-08***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1353.6	-1728.5	-1725	-1346.6	-1727.8	-1725.5	-1363.9	-1736.4	-1729.4
	R-squared	0.01915	-	-	0.01214	-	-	0.0294	-	-
	Statistic	4.491	0.67159	0.67697	3.615	0.67426	0.67745	5.545	0.6673	0.67359
Commercial	P-value	0.00472**	<2.2e-16 ***	<2.2e-16 ***	0.00639**	<2.2e-16 ***	<2.2e-16 ***	3e-04***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1134.5	-1289.9	-1288.4	-1133.9	-1290.1	-1288.9	-1139.6	-1293.5	-1290.5
	R-squared	0.0071	-	-	0.006545	-	-	0.01224	-	-
	Statistic	2.832	0.50001	0.50375	2.733	0.50035	0.5025	3.629	0.49654	0.49975

Table B.32: Spatial regression–Electricity consumption versus explorers mobility: Fall.

		September			October			November		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.000171***	<2.2e-16 ***	<2.2e-16 ***	0.1883	<2.2e-16 ***	<2.2e-16 ***	0.00524**	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1347.8	-1728.4	-1724.9	-1335.3	-1724.1	-1724.8	-1341.4	-1726.2	-1724.6
	R-squared	0.0133	-	-	0.0007462	-	-	0.006905	-	-
	Statistic	3.773	0.67378	0.67731	1.317	0.67962	0.68107	2.798	0.67639	0.67835
Commercial	P-value	0.7304	<2.2e-16 ***	<2.2e-16 ***	0.1332	<2.2e-16 ***	<2.2e-16 ***	0.0962	<2.2e-16 ***	<2.2e-16 ***
	AIC	-1126.6	-1288.5	-1289.8	-1128.7	-1121.3	-1289.2	-1129.2	-1289.7	-1288.9
	R-squared	-0.0008982	-	-	0.00128	-	-	0.001803	-	-
	Statistic	0.345	0.50722	0.51022	1.503	0.50451	0.50472	1.665	0.50413	0.5042

Table B.33: Spatial regression–Gas consumption versus returners mobility: Winter.

		December			January			February		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	4.65e-05 ***	<2.2e-16 ***	<2.2e-16 ***	0.00793 **	<2.2e-16 ***	<2.2e-16 ***	9.89e-05 ***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-851.03	-1493.2	-1489.4	-841.47	-1490	-1488.4	-849.59	-1488.8	-1488.4
	R-squared	0.01577	-	-	0.006152	-	-	0.01434	-	-
	Statistic	4.091	0.77641	0.77984	2.661	0.77909	0.78059	3.909	0.77846	0.78205

Table B.34: Spatial regression–Gas consumption versus explorers mobility: Winter.

		December			January			February		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.04 *	<2.2e-16 ***	<2.2e-16 ***	0.6408	<2.2e-16 ***	<2.2e-16 ***	0.5161	<2.2e-16 ***	<2.2e-16 ***
	AIC	-838.63	-1488.2	-1488.1	-834.62	-1488	-1488.5	-834.82	-1488.1	-1488
	R-squared	0.003279	-	-	-0.0007971	-	-	-0.0005889	-	-
	Statistic	2.057	0.78141	0.78035	0.467	0.78109	0.78142	0.65	0.78091	0.78098

Table B.35: Spatial regression–Gas consumption versus returners mobility: Spring.

		March			April			May		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.0204 *	<2.2e-16 ***	<2.2e-16 ***	0.00172 **	<2.2e-16 ***	<2.2e-16 ***	6.46e-10 ***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-839.79	-1488.2	-1488.2	844.25	-1488.5	-1488.2	-872.67	-1496.2	-1490
	R-squared	0.004458	-	-	0.008958	-	-	0.03721	-	-
	Statistic	2.323	0.78032	0.78151	3.143	0.77938	0.78155	6.241	0.77086	0.77841

Table B.36: Spatial regression–Gas consumption versus explorers mobility: Spring.

		March			April			May		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.5815	<2.2e-16 ***	<2.2e-16 ***	0.0001919	<2.2e-16 ***	<2.2e-16 ***	0.0005531	<2.2e-16 ***	<2.2e-16 ***
	AIC	-834.7	-1492.1	-1494.7	-848.34	-1491	-1488.1	-846.36	-1490.8	-1488.9
	R-squared	-0.0007093	-	-	0.01308	-	-	0.01108	-	-
	Statistic	-0.551	0.78297	0.78303	3.744	0.77736	0.78057	3.465	0.77784	0.7802

Table B.37: Spatial regression–Gas consumption versus returners mobility: Summer.

		June			July			August		
		OLS	SAR	SEM	OLS	SAR	SEM	OLS	SAR	SEM
Residential	P-value	0.09787	<2.2e-16 ***	<2.2e-16 ***	7.12e-08 ***	<2.2e-16 ***	<2.2e-16 ***	4.91e-10 ***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-837.15	-1488	-1488.3	-863.5	-1490.7	-1488	-873.21	-1494	-1488.4
	R-squared	0.001774	-	-	0.02819	-	-	0.03773	-	-
	Statistic	1.657	0.78089	0.78146	5.43	0.77496	0.78099	6.285	0.77148	0.77956

Table B.38: Spatial regression–Gas consumption versus explorers mobility: Summer.

		June			July			August		
		OLS	SAR	SEM	OLS	SAR	SEM	OLS	SAR	SEM
Residential	P-value	0.7502	<2.2e-16 ***	<2.2e-16 ***	0.00971 **	<2.2e-16 ***	<2.2e-16 ***	0.0011 **	<2.2e-16 ***	<2.2e-16 ***
	AIC	-834.5	-1488.1	-1488.2	-841.1	-1488.8	-1488.1	-845.08	-1492.2	-1489.4
	R-squared	-0.0009159	-	-	0.005785	-	-	0.009799	-	-
	Statistic	-0.318	0.78118	0.78109	2.591	0.77953	0.78148	3.274	0.77804	0.78038

Table B.39: Spatial regression–Gas consumption versus returners mobility: Fall.

		September			October			November		
		OLS	SAR	SEM	OLS	SAR	SEM	OLS	SAR	SEM
Residential	P-value	1.49e-05 ***	<2.2e-16 ***	<2.2e-16 ***	0.000986 ***	<2.2e-16 ***	<2.2e-16 ***	5.03e-09 ***	<2.2e-16 ***	<2.2e-16 ***
	AIC	-853.2	-1489.7	-1488	-845.28	-1489.1	-1488	-868.66	-1501.4	-1493.1
	R-squared	0.01795	-	-	0.009999	-	-	0.03327	-	-
	Statistic	4.353	0.77718	0.78105	3.304	0.77872	0.78087	5.899	0.77135	0.77773

Table B.40: Spatial regression–Gas consumption versus explorers mobility: Fall.

		September			October			November		
		OLS	SAR	SEM	OLS	SAR	SEM	OLS	SAR	SEM
Residential	P-value	0.006 **	<2.2e-16 ***	<2.2e-16 ***	0.09825	<2.2e-16 ***	<2.2e-16 ***	0.1312	<2.2e-16 ***	<2.2e-16 ***
	AIC	-841.97	-1489	-1488	-837.14	-1488.2	-1490.4	-836.68	-1488.1	-1488.1
	R-squared	0.006659	-	-	1.655	-	-	0.001304	-	-
	Statistic	2.754	0.7793	0.78105	0.001768	0.78181	0.78307	1.511	0.7813	0.78069

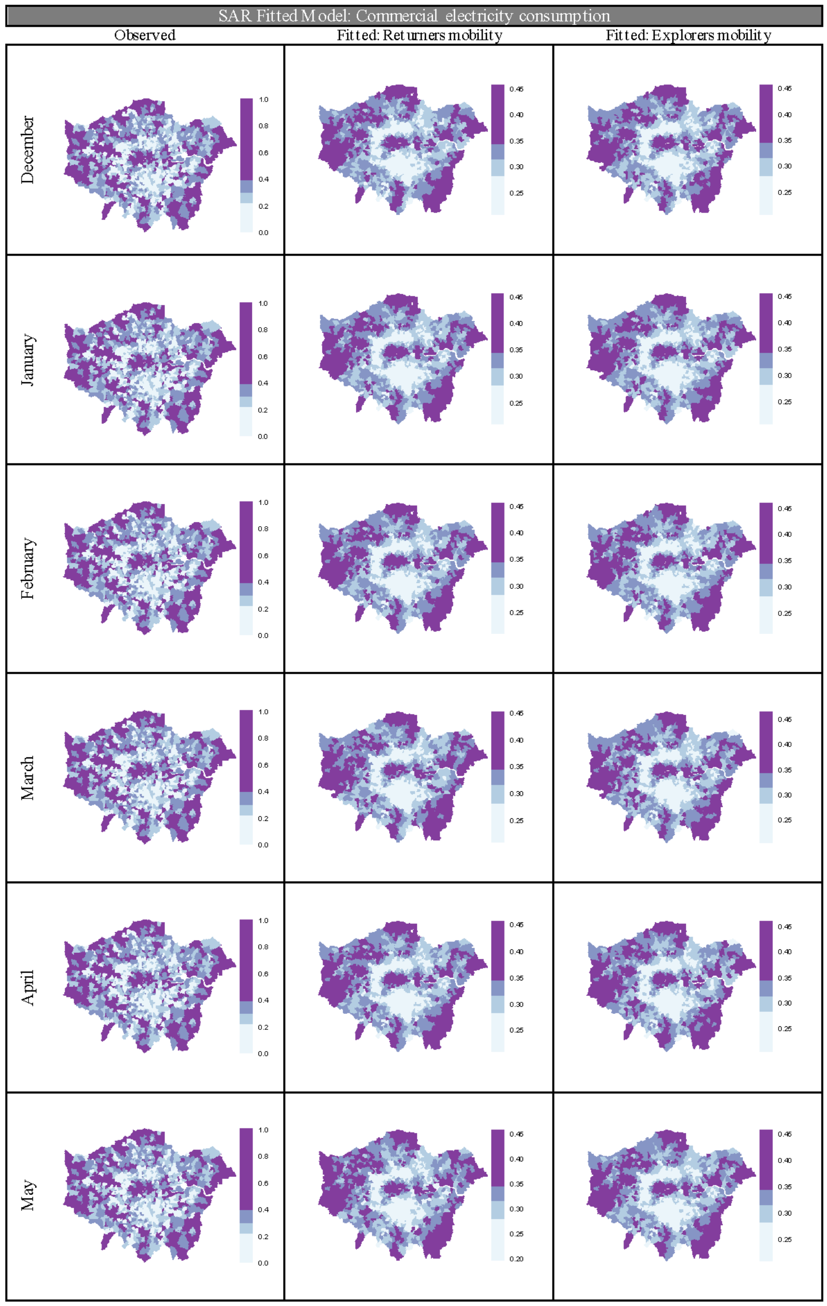


Figure B.17: Fitted SAR model–Commercial electricity, Greater London: Dec.-May.

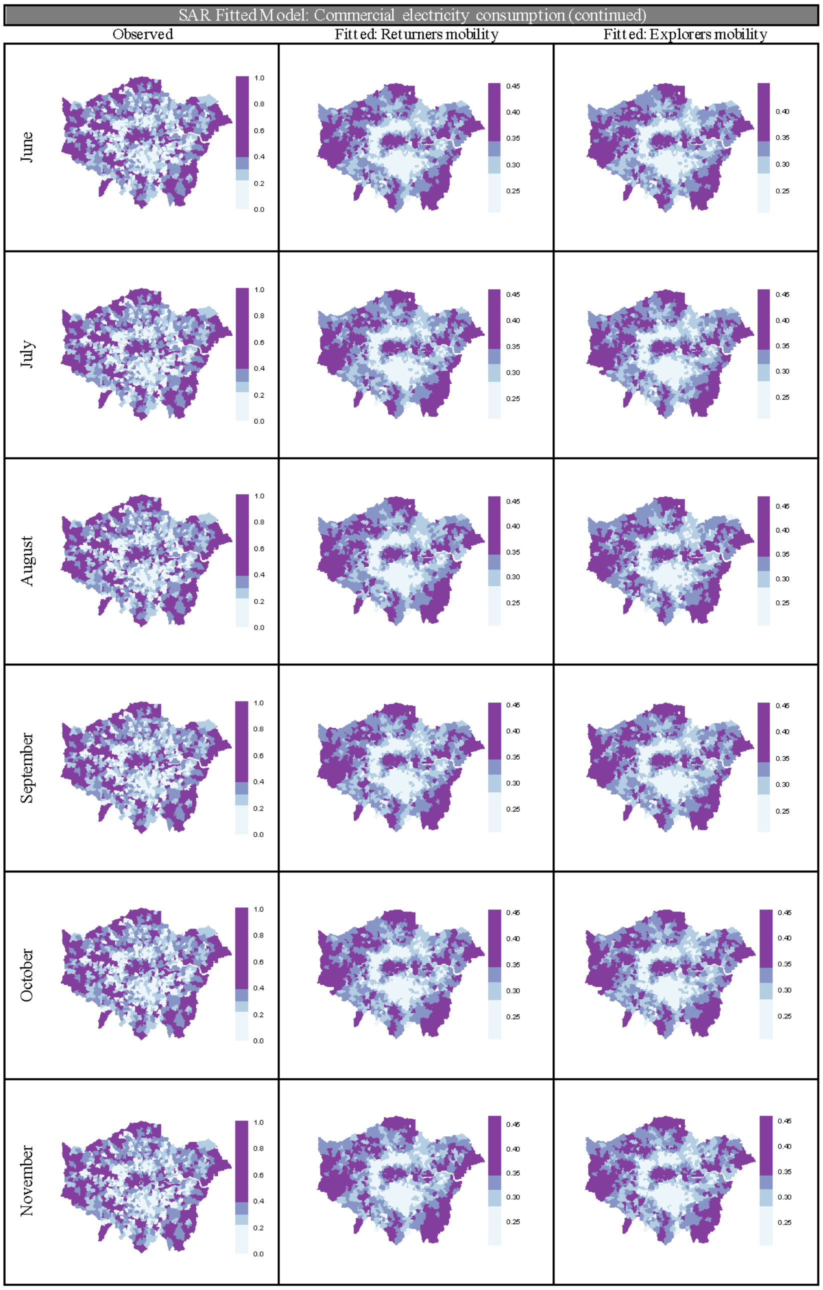


Figure B.17: Fitted SAR model–Commercial electricity, Greater London (Cont'd): June-Nov.

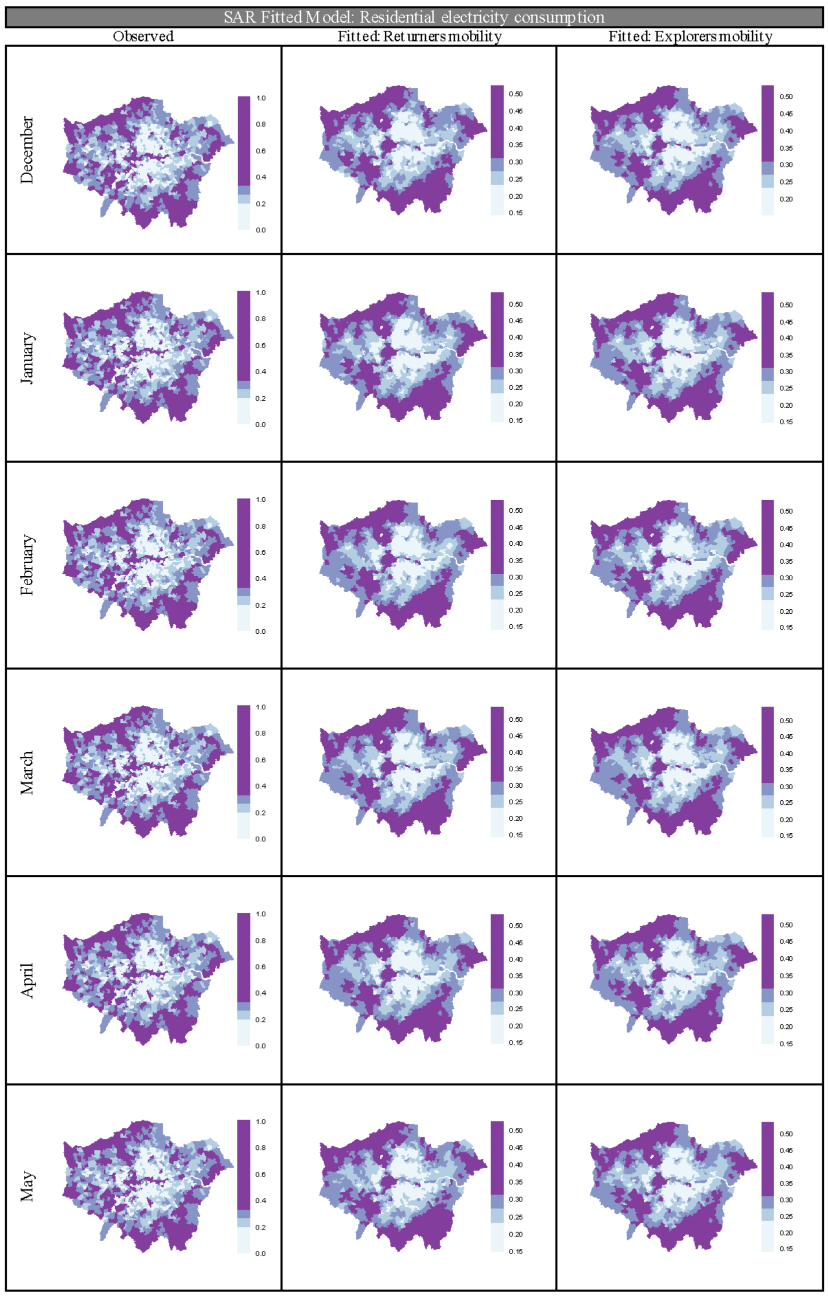


Figure B.18: Fitted SAR model–Residential electricity, Greater London: Dec.-May.

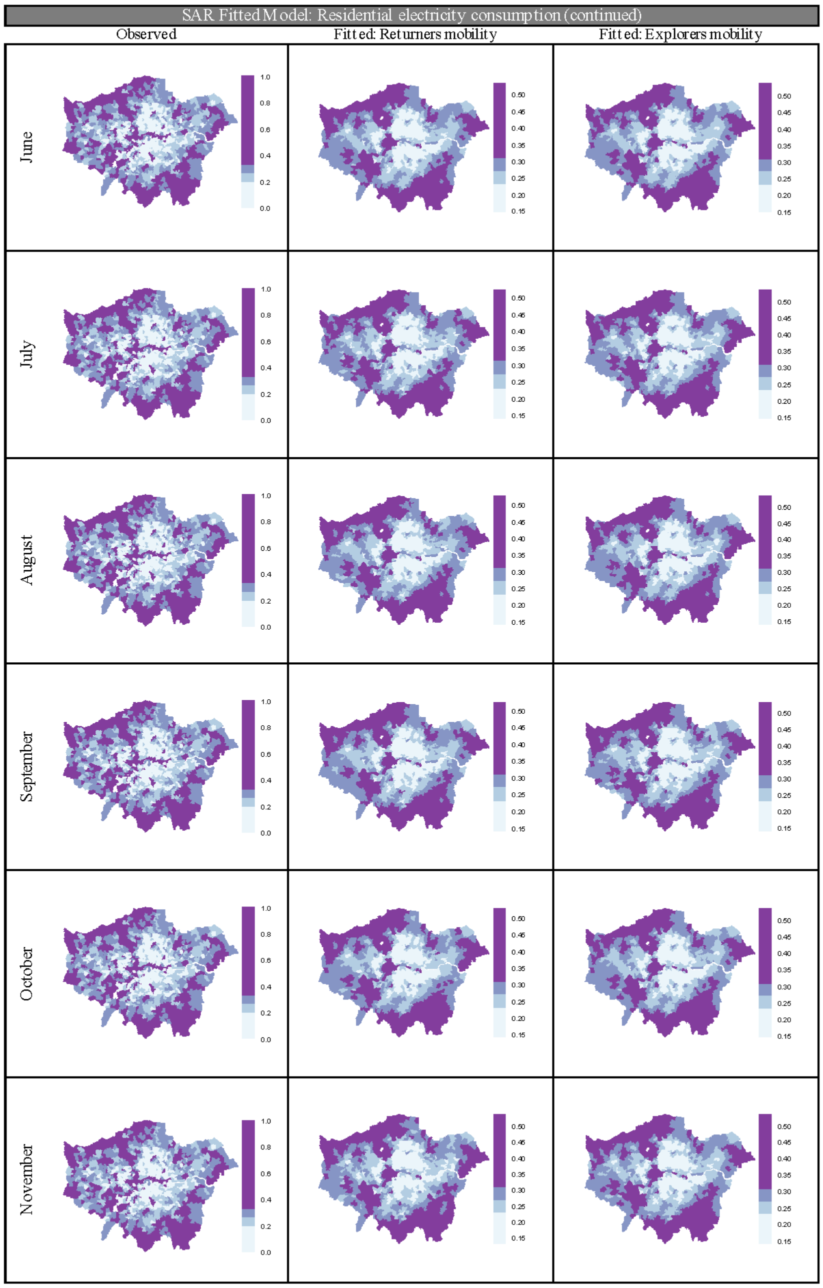


Figure B.18: Fitted SAR model–Residential electricity, Greater London (Cont'd): June-Nov.

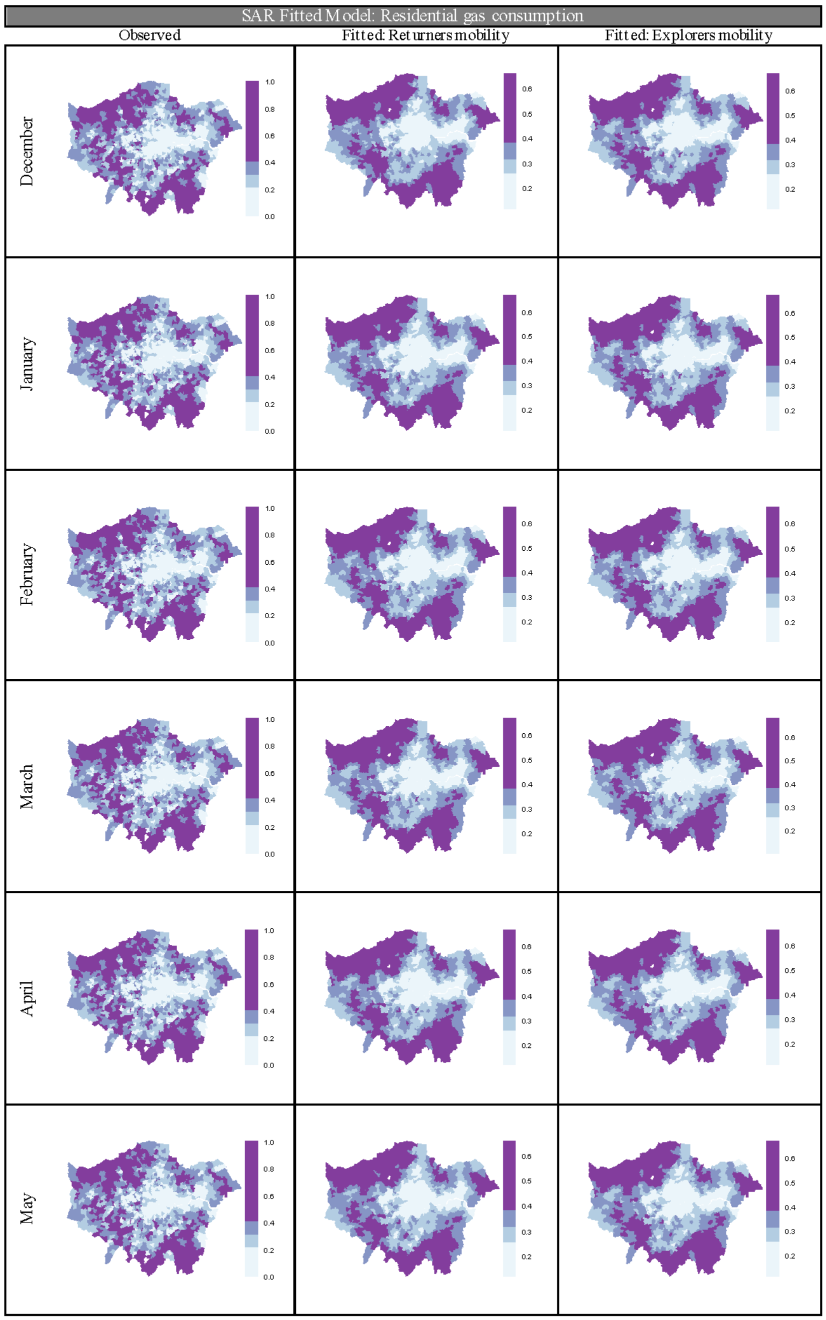


Figure B.19: Fitted SAR model–Residential gas, Greater London: Dec.-May.

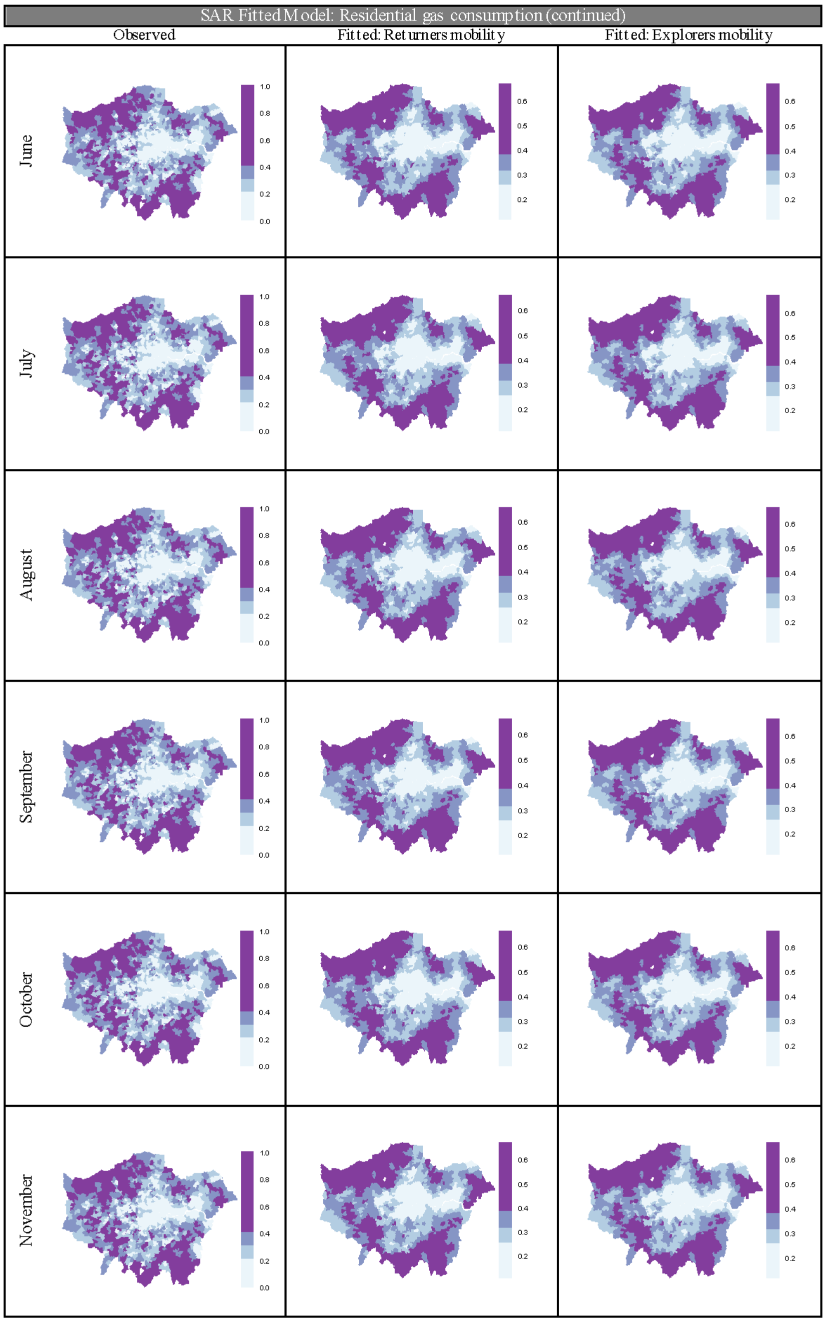


Figure B.19: Fitted SAR model–Residential gas, Greater London (Cont'd): June-Nov.

B.4.2 City of Chicago

Table B.41: Spatial regression–Electricity consumption versus returners mobility: Winter.

		December			January			February		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.5281	6.238e-06***	6.381e-06***	0.5079	2.346e-05***	2.11e-05***	0.196	1.634e-06***	1.458e-06***
	AIC	-2699.1	-2717.6	-2717.5	-2700.2	-2716.1	-2716.3	-2709	-2730	-2730.2
	R-squared[1]	-0.0007525	-	-	-0.0007021	-	-	0.0008427	-	-
	Statistic	0.631	0.25542	0.25538	-0.662	0.24333	0.24463	1.294	0.27227	0.2736
Commercial	P-value	0.8912	0.089209	0.088682	0.7765	0.0016549**	0.0016342**	0.07517	0.0041287**	0.0041344**
	AIC	-2356.4	-2357.3	-2357.3	-2431.9	-2439.8	-2439.9	-2393.1	-2399.3	-2399.3
	R-squared	-0.001228	-	-	-0.00115	-	-	0.002711	-	-
	Statistic	0.137	0.092401	0.092574	0.284	0.15622	-2439.9	1.782	0.14453	0.14499

p<0.05; p<0.001**; p<0.0001***; [1]Adjusted R-squared.*

Table B.42: Spatial regression–Electricity consumption versus explorers mobility: Winter.

		December			January			February		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.2834	6.457e-06***	7.293e-06***	0.8868	2.594e-05***	2.598e-05***	0.6087	1.911e-06***	1.921e-06***
	AIC	-2699.9	-2718.3	-2718	-2699.8	-2715.5	-2715.5	-2707.6	-2728.3	-2728.3
	R-squared	0.0001902	-	-	-0.001226	-	-	-0.000923	-	-
	Statistic	-1.073	0.25496	0.254	0.142	0.24209	0.2422	0.512	0.27067	0.27074
Commercial	P-value	09694	0.091168	0.092553	0.9791	0.00170*	0.00169*	0.7272	0.004337*	0.0043912*
	AIC	-2359.1	-2360	-2360	-2431.8	-2439.7	-2439.7	-2390	-2396.2	-2396.1
	R-squared	0.002197	-	-	-0.001251	-	-	-0.001099	-	-
	Statistic	1.662	0.091748	0.091512	-0.026	0.15584	0.15594	0.349	0.14393	0.14379

Table B.43: Spatial regression–Electricity consumption versus returners mobility: Spring.

		March			April			May		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.255	1.086e-05***	8.228e-06***	0.962	0.000202***	0.000202***	0.3575	6.101e-08***	6.533e-08***
	AIC	-2758.2	-2775.6	-2776.1	-2679.5	-2691.4	-2691.4	-2649.3	-2676.7	-2676.5
	R-squared	0.0003719	-	-	-0.001249	-	-	-0.0001904	-	-
	Statistic	-1.139	0.25333	0.25745	0.048	0.22073	0.22073	0.921	0.30037	0.30018
Commercial	P-value	0.1064	0.010988	0.010988	0.05676	0.00098**	0.00092**	0.8084	0.0055813*	0.0055709*
	AIC	-2328.9	-2333.4	-2333.4	-2260.3	-2269.2	-2269.3	-2403.7	-2409.4	-2409.4
	R-squared	0.002011	-	-	0.003289	-	-	-0.001178	-	-
	Statistic	1.616	0.1286	0.129	1.908	0.16456	0.16456	0.243	0.1376	0.13763

Table B.44: Spatial regression–Electricity consumption versus explorers mobility: Spring.

		March			April			May		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.8399	1.301e-05***	1.296e-05***	0.3714	0.000198**	0.0001886**	0.7832	5.494e-08***	5.512e-08***
	AIC	-2757	-2774	-2774	-2680.3	-2692.2	-2692.3	-2648.5	-2676.1	-2676.1
	R-squared	-0.0012	-	-	-0.0002501	-	-	-0.001157	-	-
	Statistic	0.202	0.25116	0.25122	0.894	0.22091	0.2217	0.275	0.30131	0.30137
Commercial	P-value	0.9531	0.010205*	0.010202*	0.4412	0.0010206*	0.0010729*	0.5262	0.0054632*	0.0052565*
	AIC	-2326.3	-2330.9	-2330.9	-2257.3	-2266.1	-2266	-2404.1	-2409.8	-2409.9
	R-squared	-0.001247	-	-	-0.000508	-	-	-0.0007479	-	-
	Statistic	0.059	0.13007	-2330.9	0.771	0.16297	0.16273	0.634	0.13793	0.1387

Table B.45: Spatial regression–Electricity consumption versus returners mobility: Summer.

		June			July			August		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.1526	1.554e-15***	9.99e-16***	0.4066	9.200e-09***	7.937e-09***	0.6925	1.967e-08***	1.916e-08***
	AIC	-2453.7	-2515.3	-2516.2	-2660.7	-2691.7	-2691.9	-2702.1	-2731.6	-2731.7
	R-squared	0.00131	-	-	-0.0003883	-	-	-0.001055	-	-
	Statistic	-1.432	0.40426	0.40694	-0.83	0.31419	0.3128	-0.396	0.31243	0.31265
Commercial	P-value	0.8029	0.0034119*	0.0033965*	0.9339	0.0031317*	0.012923*	0.6199	0.0007521**	0.0007474**
	AIC	-2318.7	-2325.2	-2325.3	-2331.3	-2335.5	-2335.5	-2289.5	-2298.8	-2298.8
	R-squared	-0.001173	-	-	-0.001243	-	-	-0.0009431	-	-
	Statistic	0.250	0.14593	0.146	0.083	0.12632	0.12635	-0.496	0.16665	0.16672

Table B.46: Spatial regression–Electricity consumption versus explorers mobility: Summer.

		June			July			August		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.3674	2.5535e-2***	2.776e-15***	0.5339	9.0509e-1***	8.619e-09***	0.03813*	3.702e-05***	3.427e-05***
	AIC	-2452.4	-2513.1	-2512.9	-2660.4	-2691.4	-2691.5	-2838.6	-2853.6	-2853.7
	R-squared	-0.0002335	-	-	-0.0007665	-	-	0.004125	-	-
	Statistic	-0.902	0.40145	0.40088	-0.622	0.313	0.31347	2.077	0.23969	0.24096
Commercial	P-value	0.6167	0.0035077*	0.0036076*	0.3169	0.013718*	0.014147*	0.678	0.0007168**	0.0006902**
	AIC	-2318.9	-2325.4	-2325.3	-2332.3	-2336.4	-2336.3	-2289.4	-2298.8	-2298.9
	R-squared	-0.0009375	-	-	3.65e-06	-	-	-0.001035	-	-
	Statistic	-0.501	0.14553	0.14519	1.001	0.12521	0.12492	0.415	0.16732	-2298.9

Table B.47: Spatial regression–Electricity consumption versus returners mobility: Fall.

		September			October			November		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.454	3.845e-05***	4.183e-05***	0.5796	9.798e-05***	9.611e-05***	0.9135	2.192e-09***	2.199e-09***
	AIC	-2834.8	-2849.8	-2849.6	-2766.9	-2780.1	-2780.1	-2654.6	-2688.3	-2688.3
	R-squared	-0.0005489	-	-	-0.0008668	-	-	-0.001237	-	-
	Statistic	-0.749	0.23955	0.23885	-0.554	0.22674	0.22689	-0.109	0.32304	0.32293
Commercial	P-value	0.8276	0.0092935*	0.0093466*	0.7918	0.0020159*	0.0020146*	0.7006	0.0066158**	0.0068097**
	AIC	-2280.1	-2284.9	-2284.8	-2218.1	-2225.6	-2225.6	-2294.4	-2299.7	-2299.7
	R-squared	-0.001192	-	-	-0.001164	-	-	-0.001066	-	-
	Statistic	-0.218	0.13264	0.13264	-0.264	0.1543	0.1543	-0.385	0.13783	0.13839

Table B.48: Spatial regression–Electricity consumption versus explorers mobility: Fall.

		September			October			November		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.03813*	3.702e-05***	3.427e-05***	0.9693	0.000102***	9.726e-05***	0.9422	2.222e-09***	2.227e-09***
	AIC	-2838.6	-2853.6	-2853.7	-2766.6	-2779.7	-2779.8	-2654.5	-2688.3	-2688.3
	R-squared	0.004125	-	-	-0.00125	-	-	-0.001245	-	-
	Statistic	2.077	0.23969	0.24096	-0.038	0.22639	0.22738	-0.073	0.3229	0.3229
Commercial	P-value	0.4959	0.008599**	0.0080948**	0.2702	0.0020552*	0.0020072*	0.594	0.0071568*	0.0072748*
	AIC	-2280.5	-2285.4	-2285.5	-2219.2	-2226.7	-2226.7	-2294.5	-2299.7	-2299.7
	R-squared	-0.0006704	-	-	0.000272	-	-	-0.0008953	-	-
	Statistic	0.681	0.13393	0.13505	1.103	0.15394	0.15467	-0.533	0.13697	0.13672

Table B.49: Spatial regression–Gas consumption versus returners mobility: Winter.

		December			January			February		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.6992	0.0057876*	0.0059468*	0.7408	0.0053406**	0.0051628**	0.7204	0.0017689**	0.0017566**
	AIC	-3000.5	-3006.1	-3006.1	-2999.4	-3005.2	-3005.2	-2988.7	-2996.5	-2996.5
	R-squared[1]	-0.001064	-	-	-0.001114	-	-	-0.001091	-	-
	Statistic	-0.387	0.16233	0.16203	-0.331	0.16401	0.16475	0.358	0.18249	0.18264
Commercial	P-value	0.741	0.0080963*	0.0071443*	0.4228	0.006748**	0.0062521**	0.5857	0.0038005**	0.0040032**
	AIC	-2964.5	-2969.5	-2969.8	-2952.3	-2957.6	-2957.7	-2939.9	-2946.3	-2946.2
	R-squared	-0.001115	-	-	-0.0004462	-	-	-0.0008791	-	-
	Statistic	0.331	0.17982	0.1835	-0.802	0.18291	0.18444	-0.545	0.19341	0.19248

Table B.50: Spatial regression–Gas consumption versus explorers mobility: Winter.

		December			January			February		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.4498	0.0059576*	0.0061933*	0.3956	0.0059464*	0.0062046*	0.00893	0.0020294*	0.0020914*
	AIC	-3000.9	-3006.5	-3006.4	-3000	-3005.6	-3005.5	-2995.4	-3003	-3002.9
	R-squared	-0.0005356	-	-	-0.0003469	-	-	0.007284	-	-
	Statistic	-0.756	0.16178	0.16127	0.85	0.16199	0.16137	2.621	0.17983	0.1802
Commercial	P-value	0.6756	0.0081857*	0.0076396*	0.5646	0.0069091*	0.0071677*	0.6659	0.0036631*	0.0035976*
	AIC	-2964.6	-2969.6	-2969.7	-2951.9	-2957.2	-2957.2	-2939.8	-2946.3	-2946.3
	R-squared	-0.001032	-	-	-0.0008357	-	-	-0.001018	-	-
	Statistic	0.419	0.17952	0.18128	-0.576	0.18244	0.18177	-0.432	0.19417	0.19444

Table B.51: Spatial regression–Gas consumption versus returners mobility: Spring.

		March			April			May		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.9873	0.0054991**	0.0054685**	0.9001	0.013431*	0.01347*	0.536	0.089557	0.087362
	AIC	-2965.8	-2971.5	-2971.5	-2777.1	-2781.2	-2781.2	-2757.8	-2758.6	-2758.7
	R-squared	-0.001251	-	-	-0.001232	-	-	-0.0007715	-	-
	Statistic	0.016	0.16415	0.16433	0.126	0.15003	0.15002	0.619	0.10478	0.10543
Commercial	P-value	0.9796	0.20741	0.20805	0.1932	0.0002328**	0.000215**	0.4736	0.0006897**	0.0006829**
	AIC	-2883.3	-2891.3	-2891.3	-2720.7	-2732.2	-2732.4	-2509.9	-2519.5	-2519.5
	R-squared	-0.001251	-	-	0.0008693	-	-	-0.0006077	-	-
	Statistic	0.026	0.20741	0.20805	1.302	0.23183	0.23345	-0.717	0.20966	0.20967

Table B.52: Spatial regression–Gas consumption versus explorers mobility: Spring.

		March			April			May		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	0.6015	0.0053719*	0.0049787*	0.7483	0.013571*	0.01362*	0.6157	0.086773	0.086153
	AIC	-2966.1	-2971.8	-2972	-2777.2	-2781.3	-2781.2	-2757.6	-2758.6	-2758.6
	R-squared	-0.0009096	-	-	-0.001122	-	-	-0.0009357	-	-
	Statistic	0.522	0.16612	0.16457	0.321	0.14982	0.14974	-0.502	0.10573	0.10596
Commercial	P-value	0.8049	0.0015155*	0.0013844*	0.2832	0.00025**	0.000293**	0.611	0.000756**	0.000805**
	AIC	-2883.4	-2891.	-2891.6	-2720.1	-2731.5	-2731.2	-2509.7	-2519	-2518.9
	R-squared	-0.001175	-	-	0.0001914	-	-	-0.0009271	-	-
	Statistic	-0.247	0.20847	0.21073	-1.074	0.2308	0.22876	-0.509	0.2083	0.20804

Table B.53: Spatial regression–Gas consumption versus returners mobility: Summer.

		June			July			August		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Commercial	P-value	0.4232	0.0037796*	0.0036807*	0.6166	0.0037746*	0.0038717*	0.09726	0.002685*	0.0031286*
	AIC	-2329.6	-2336	-2336	-2480.4	-2486.8	-2486.7	-2503.4	-2510.4	-2510.2
	R-squared	-0.0004477	-	-	-0.0009374	-	-	0.002191	-	-
	Statistic	-0.801	0.17641	0.17675	0.501	0.17057	0.17044	1.660	0.17398	0.1722

Table B.54: Spatial regression–Gas consumption versus explorers mobility: Summer.

		June			July			August		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Commercial	P-value	0.4101	0.004411**	0.0047161**	0.006157**	0.0036358**	0.0033885**	0.8004	0.0023216**	0.0023565**
	AIC	-2329.6	-2335.7	-2335.6	-2487.7	-2494.1	-2494.3	-2500.7	-2508	-2508
	R-squared	-0.000401	-	-	0.008113	-	-	-0.001171	-	-
	Statistic	-0.824	0.17334	0.1722	2.747	0.17065	0.17263	-0.253	0.17658	0.17658

Table B.55: Spatial regression–Gas consumption versus returners mobility: Fall.

		September			October			November		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	-	-	-	0.5728	0.075747	0.076558	0.7402	0.015176*	0.014732*
	AIC	-	-	-	-2869.6	-2870.8	-2870.8	-2993.3	-2997.2	-2997.2
	R-squared	-	-	-	-0.0008529	-	-	-0.001114	-	-
	Statistic	-	-	-	0.564	0.10855	0.10829	0.332	0.14412	0.1449
Commercial	P-value	0.8378	0.0098797*	0.0095135*	0.5145	0.0040837*	0.0042664*	0.02162*	0.0050422	0.0051207
	AIC	-2509.7	-2514.3	-2514.4	-2634	-2640.3	-2640.2	-2911.6	-2917.5	-2917.4
	R-squared	-0.001199	-	-	-0.0007189	-	-	0.005342	-	-
	Statistic	0.205	0.15884	0.15984	-0.652	0.1841	0.18313	2.301	0.18734	0.18697

Table B.56: Spatial regression–Gas consumption versus explorers mobility: Fall.

		September			October			November		
		OLS	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**	**OLS**	**SAR**	**SEM**
Residential	P-value	-	-	-	0.4269	0.067868	0.056946	0.6596	0.015367	0.01504
	AIC	-	-	-	-2870	-2871.3	-2871.6	-2993.4	-2997.2	-2997.3
	R-squared	-	-	-	-0.0004605	-	-	-0.001008	-	-
	Statistic	-	-	-	-0.795	0.11168	0.11712	0.441	0.14384	0.14436
Commercial	P-value	0.8319	0.0099325**	0.0099882**	0.8594	0.0042232**	0.0042343**	0.8918	0.0047088**	0.0044688**
	AIC	-2509.7	-2514.3	-2514.3	-2633.7	-2639.8	-2639.8	-2906.3	-2912.3	-2912.4
	R-squared	-0.001195	-	-	-0.001212	-	-	-0.001228	-	-
	Statistic	-0.212	0.15873	0.15859	0.177	0.18345	0.18345	0.136	0.18903	0.19072

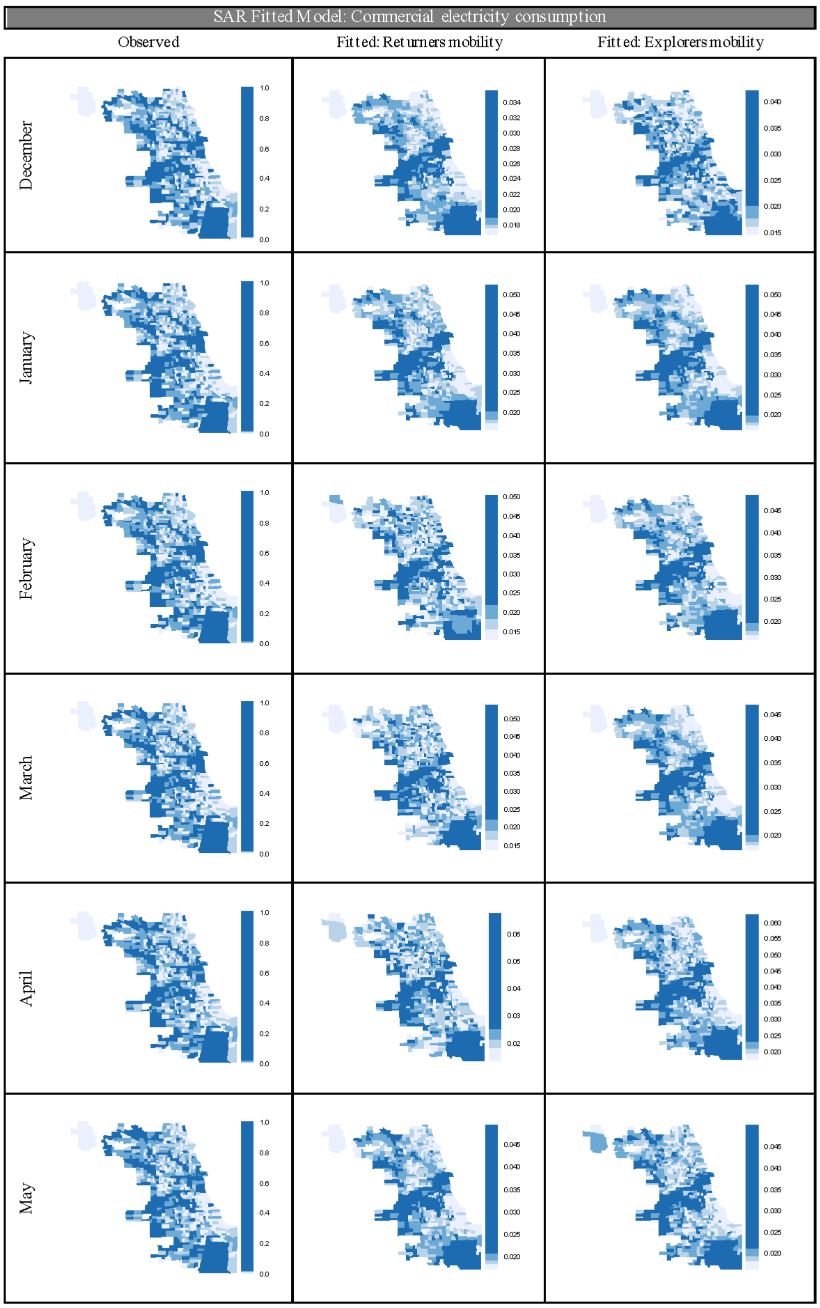


Figure B.20: Fitted SAR model–Commercial electricity, City of Chicago: Dec.-May.

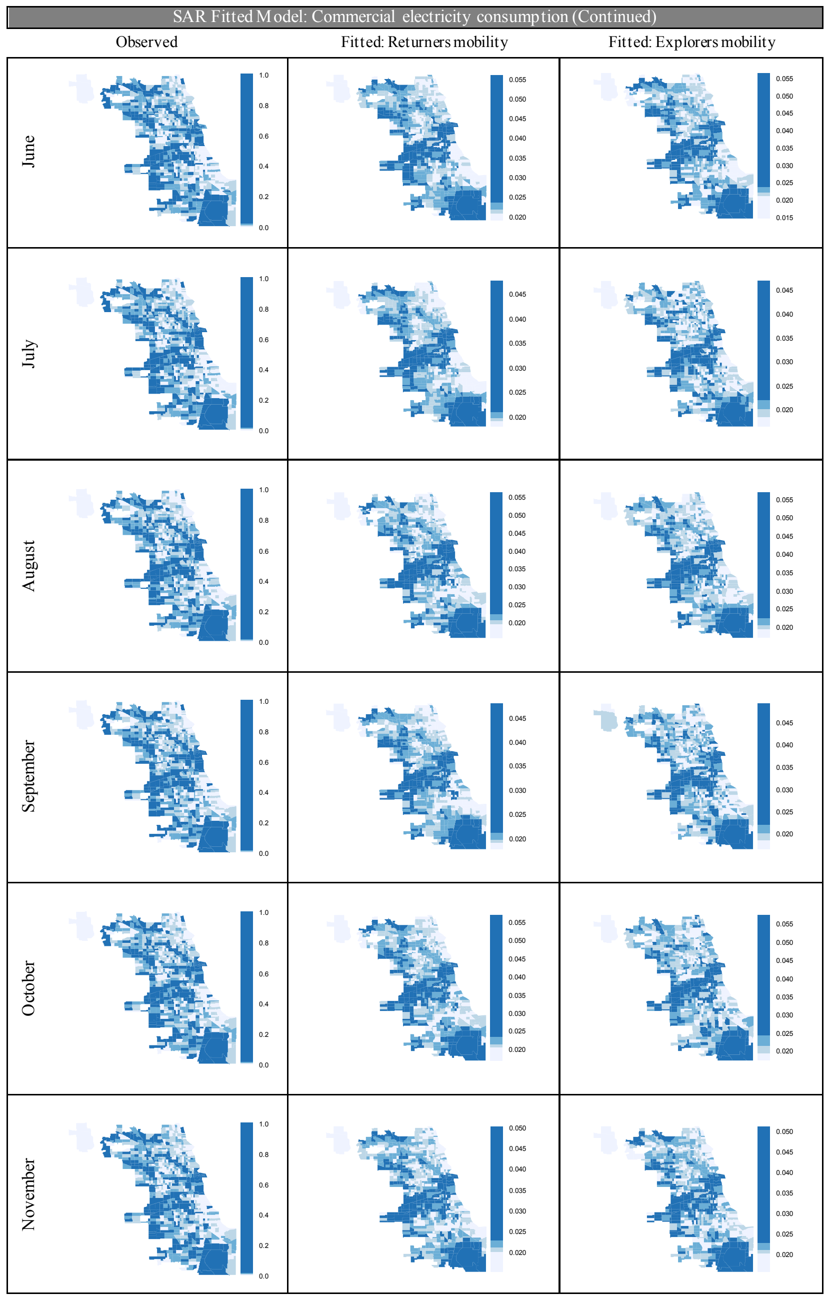


Figure B.20: Fitted SAR model–Commercial electricity, City of Chicago (Cont'd): June-Nov.

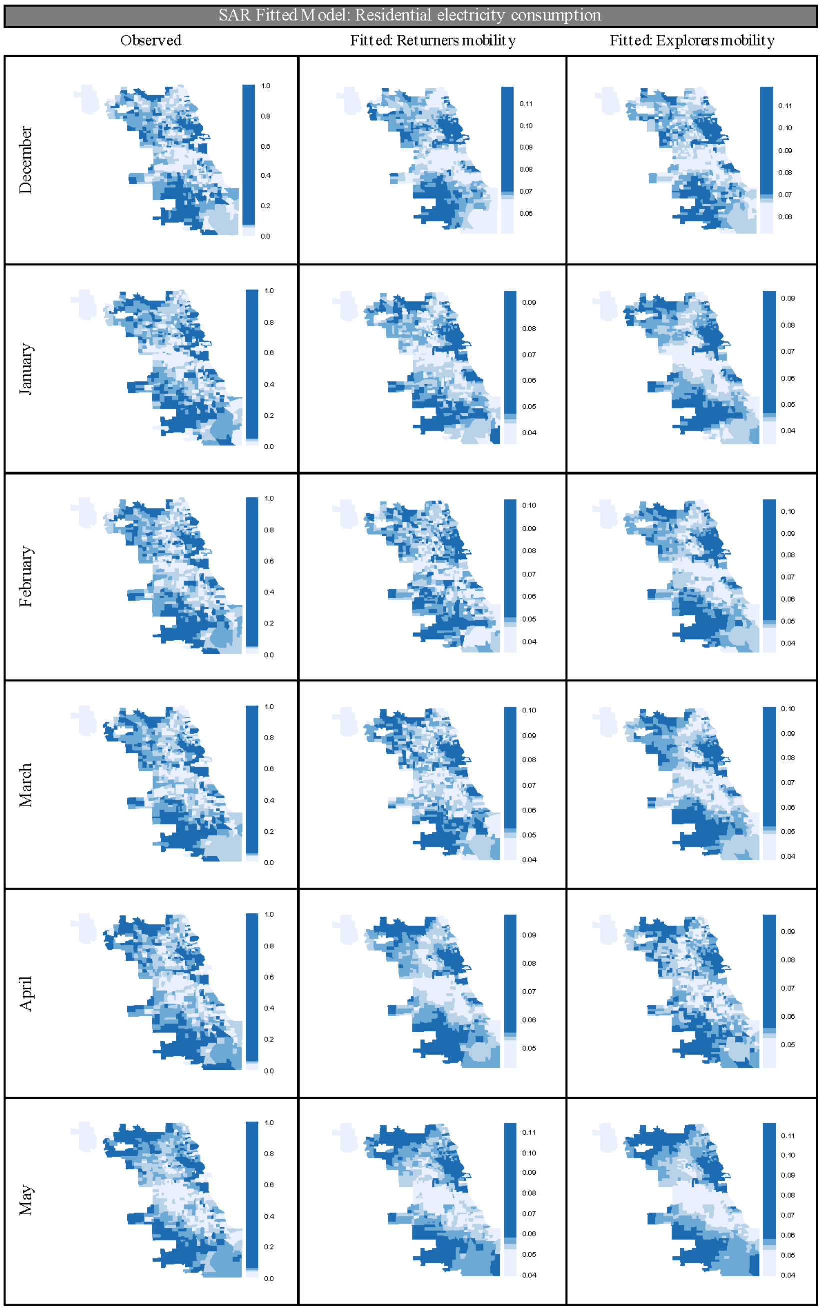


Figure B.21: Fitted SAR model–Residential electricity, City of Chicago: Dec.-May.

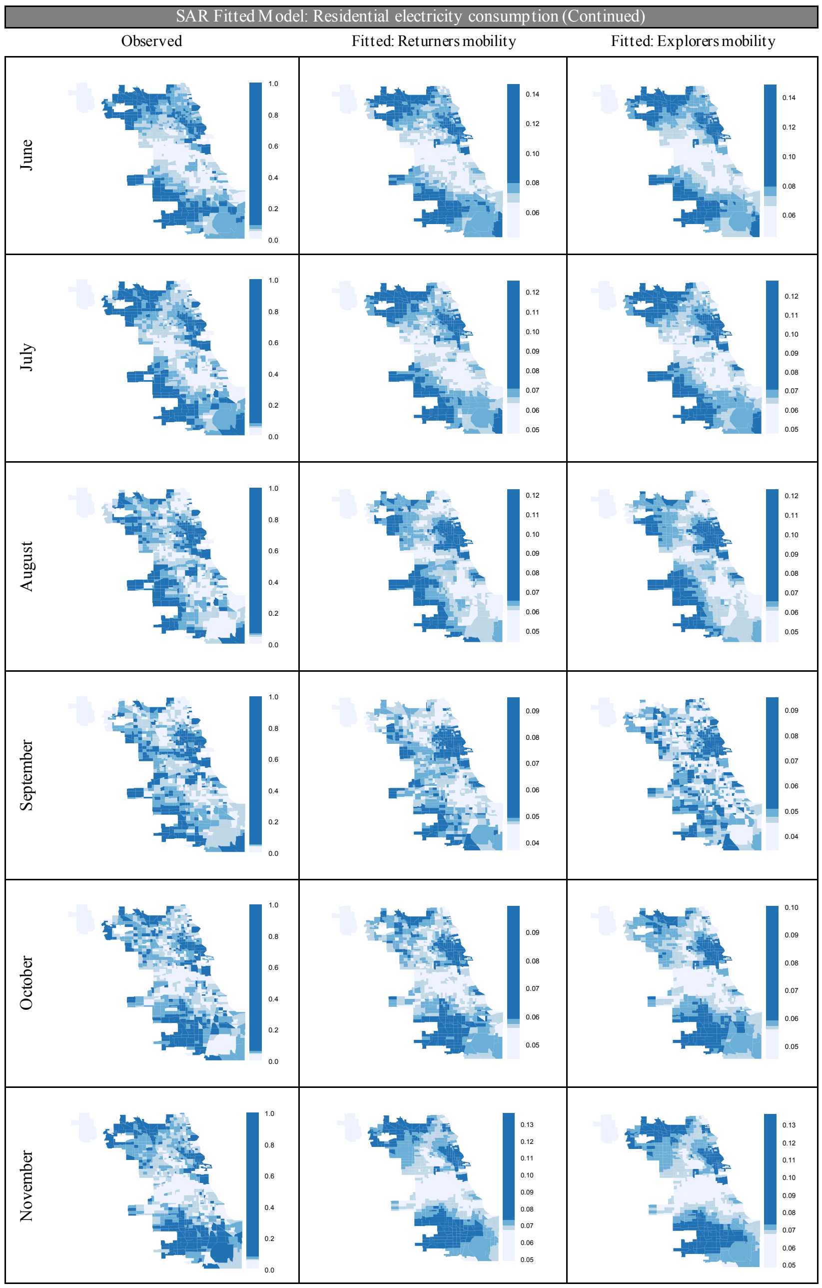


Figure B.21: Fitted SAR model–Residential electricity, City of Chicago (Cont'd): June-Nov.

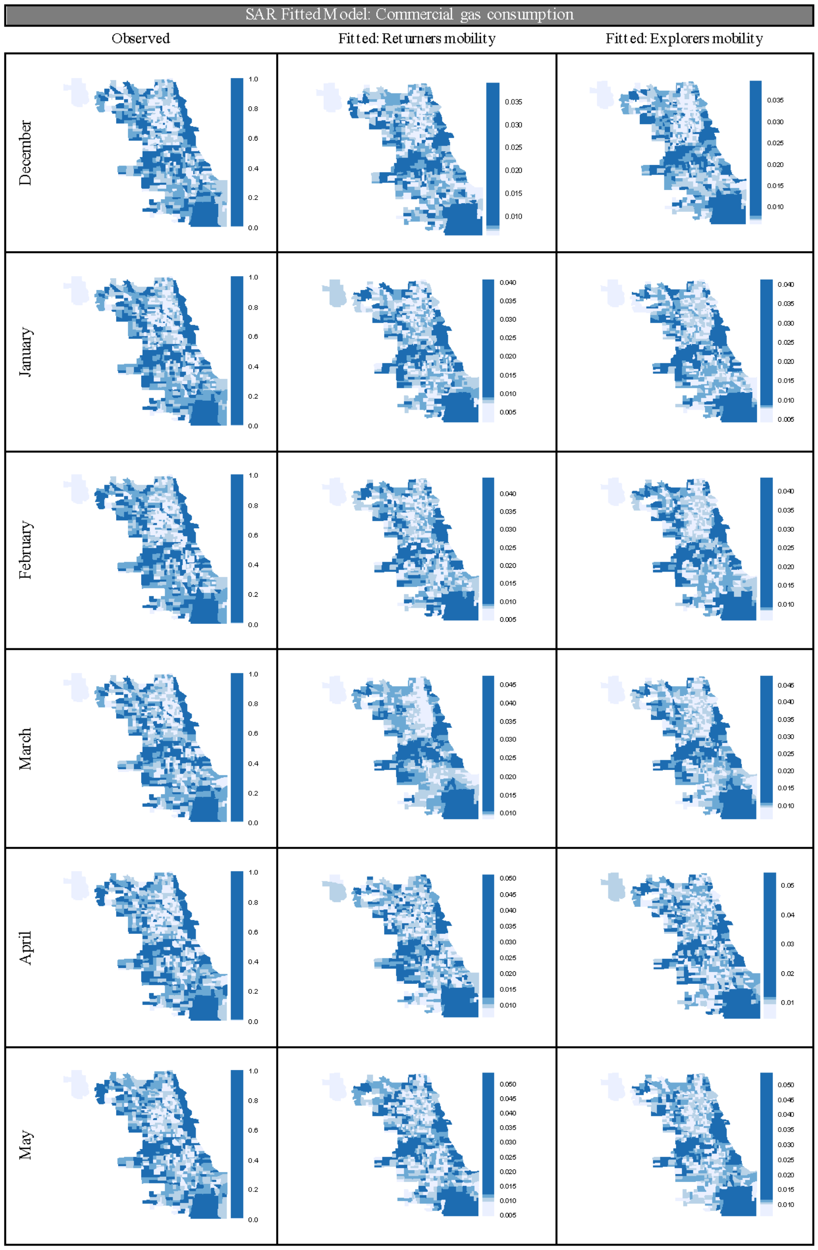


Figure B.22: Fitted SAR model–Commercial gas, City of Chicago: Dec.-May.

Figure B.22: Fitted SAR model–Commercial gas, City of Chicago (Cont'd): June-Nov.

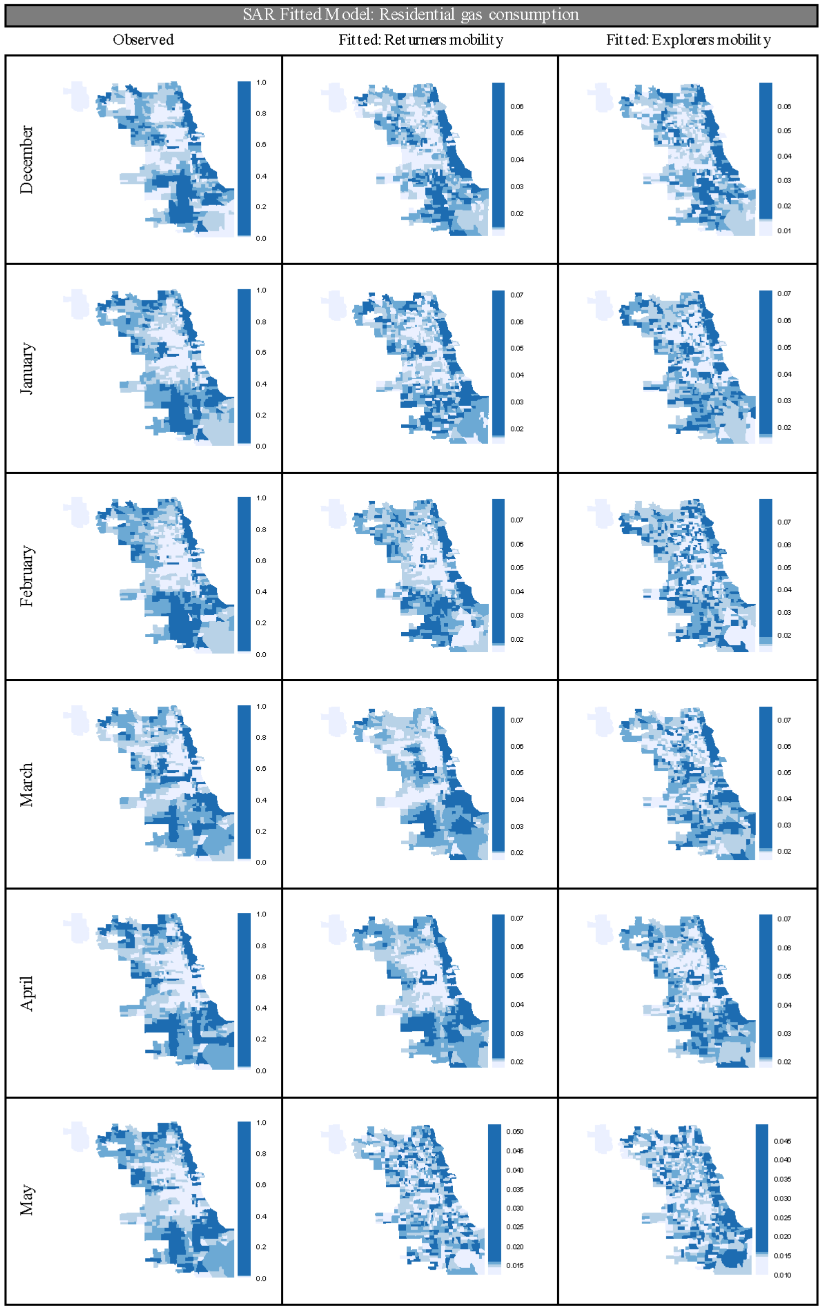


Figure B.23: Fitted SAR model–Residential gas, City of Chicago: Dec.-May.

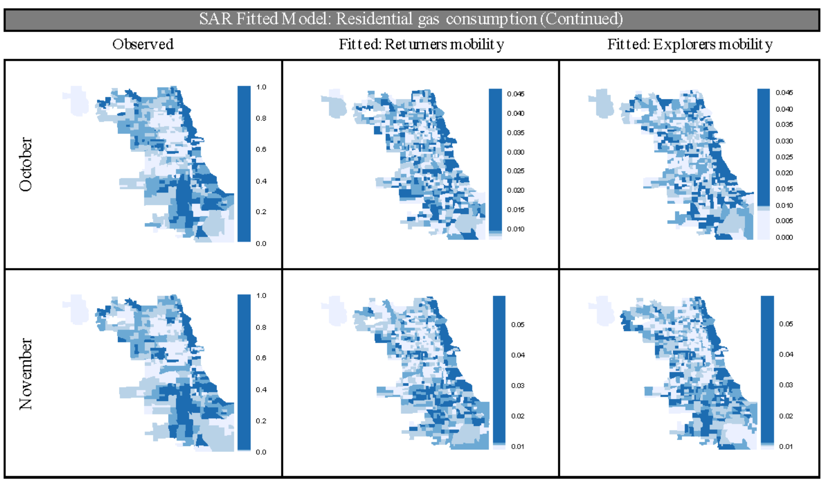


Figure B.23: Fitted SAR model–Residential gas, City of Chicago (Cont'd): Oct.-Nov.