On the Dominant Role of Returners' Human Mobility Networks on Urban Energy Consumption

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ABSTRACT

As a result of population growth and urbanization, the interdependencies between infrastructure, services, and individuals in urban areas continue to increase. Urban areas already consume up to 80% of the world's energy, and the expected population increase of nearly 70% by 2050 will drive a further rise in energy consumption. It is, therefore, vital for us to develop a better understanding of variabilities in human-related effects on buildings' energy consumption within the urban spatial context in which they exist. Intra-city trips of urban population are undertaken as a result of individuals engaging in activities across various locations. However, people exhibit variations in their daily activities and the number of locations they visit over time. Here, we investigate the spatial interdependencies between human mobility networks of two distinct populations (i.e., *returners* and *explorers*) as an indicator of their daily activity patterns, as well as gas consumption to explore how variations in human mobility networks can be used to explain spatial fluctuations in energy use. We compare 2,015,339 positional records from an online social networking platform, Twitter, with energy consumption (gas) across 983 areas in Greater London over the course of a single month (May 2014). Our findings indicate a stronger statistically significant spatial dependency between human mobility networks of the *returners* and gas consumption, indicating domination of this population in urban energy use. This suggests that spatial fluctuations in urban energy consumption are governed by the structure of human mobility networks, among other factors. These results provide a clear picture of demand-side diversity and its drivers, establishing a foundation for human mobility-based predictive models for urban energy consumption. The relationship between energy consumption and human mobility is key to creating effective policies for urban areas, leading to more reliable predictions and effective management decisions about future patterns of energy use. Our findings will be of value to urban planners, researchers and policy-makers.

Categories and Subject Descriptors

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

General Terms

Measurement, Experimentation, Human Factors.

Keywords

Energy Consumption; Human Mobility Networks; Network Dynamics; Urban Computing; Urban Energy Flux; Urban Sustainability.

UrbComp'16, August 14, 2016, San Francisco, California, USA.

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1. INTRODUCTION

Today's cities are the most complex built environments in human history, containing 54% of the world population [1], responsible for up to 80% of the world's total energy consumption [2, 3]. Given that the planet's 28 megacities are projected to increase to 41 by 2030, adding 2.5 billion residents to our urban environments [1], world energy consumption is expected to grow by as much as 56% between 2010 and 2040 [4]. The parallel rise in the scale and nature of human activities in tomorrow's urban environments [5] mean that the complex mix of operations and demands, technology adaptation, and lifestyles in future cities will be substantially different. This ever-increasing level of complexity raises serious concerns regarding the robust operation of the vital urban lifelines that supply electricity, transportation, communication, and water. There is thus a pressing need to explore how best to ensure that the expected increase in urban population, combined with the resulting additional complexities, are managed to support positive outcomes for future energy demand, efficiency and resilience. How can we make reliable predictions of future energy demand that incorporate change?

The major sources driving changes in energy demand stem from the mix of personal activities occurring at specific times and locations [6]. 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. Population growth and the shift of this population both into and within urban areas cause significant increases in the amount, diversity, and complexity of human activities, with a corresponding significant impact on energy consumption. What will the fluctuations and interdependencies between human mobility and energy consumption look like in the near and far future? This high level of uncertainty raises additional questions regarding urban energy resilience, for which our current knowledge about these patterns based on today's consumer behavior may fail to hold true in the future.

Opportunely, understanding variations in an urban population's activities can contribute to better perceptions of location-specific energy demands and its spatiotemporal fluctuations by addressing questions such as: "What are the current patterns of energy consumption as related to their stimulating urban population activities?" and "Which regions should we expect to experience increases/decreases in demand?" Understanding the distribution and patterns of urban energy consumption can be a significant indicator in managing and allocating current and future resources. Enhancing our ability to recognize and manage short and long term urban energy resilience is essential if our cities are to continue to thrive.

2. SPATIAL VARIATIONS OF URBAN ENERGY CONSUMPTION

Fluctuations in urban energy consumption have been studied in both spatial [7-10], and temporal [10-14] dimensions. It has been argued that such fluctuations are driven by urban form, density and texture [9, 15-20], building characteristics [21-24], building age [25], and function [8]; other researchers have identified population density [17], urban transport [18], climate and weather conditions [19, 21, 26], socioeconomic elements [7, 19], and individual behaviors [27] as having an effect. Some of these have identified reverse correlations with energy consumption. Ratti et al. [11] found that the surface-to-volume ratio was not representative of the total energy consumption in urban areas, instead recommending the use of the ratio of passive to non-passive zones as an indicator. Although still representative, urban texture can only explain 10% of the variations, however, which seems relatively small compared to the implications at the system and occupant behavior level [15]. A few years later, Zhang et al. [7] analyzed the spatial variations of energy consumption in China for 30 provincial capital cities utilizing parallel comparison and quantitative analysis, concluding that their different geographic features, economic development levels and local energy source availability 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. [28] 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. In a more recent study, also in Switzerland, Fonseca and Schlueter [10] took into account the spatiotemporal fluctuations of energy services in characterizing the energy consumption patterns of residential, commercial, and industrial buildings in urban settings. These researchers introduced an integrated model that incorporated spatial analysis, dynamic building energy modeling and energy mapping and then validated it against measured data. Although they did take into account elements such as the location of buildings, time, and the properties of energy services such as the power and temperature required, they failed to consider consumer aspects such as the occupant density of each neighborhood and its spatiotemporal fluctuations, both of which may be more realistic measures for demand. The main focus of their study was to understand building performance in the light of potential retrofit strategies.

Interestingly, despite its significance, all of these studies neglected to take into account activity-based variations in urban energy consumption. An individual may exhibit low consumption habits at work, but consume disproportionate amounts of energy during later hours of the day when they are at home or utilize high-energy-consuming transit modes to travel within the city. Activity-based approaches [29-31] 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 represent the extent of usage, but the movements of consumers do.

Intra-city trips are undertaken as a result of individuals' intent to engage in activities, and therefore human mobility is often used to develop a better understanding of the patterns and types of activities [32], or to identify origin-destination locations such as *home*, *work*, and *other* [33], as well as different functional locations or points of interest (POI) [34-36] in urban settings. Human mobility has been used to infer location choices and to strategize optimal accessibility to amenities under the influence of human mobility [37, 38]. 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 [7, 10, 25, 28, 39]. Researchers studying human mobility have also investigated the spatiotemporal variations of human mobility extensively [40-45], and have linked these variations to patterns of activities, or *motifs* [46-48], as well as land-use or cities' functional regions [35, 37, 49-51]. However, a thorough review of the literature revealed no attempts to integrate these variations or to seek to explain urban energy consumption in terms of patterns of individual activities, which in this context means human mobility behavior. While these spatiotemporal variations appear to have been extensively studied, the link between fluctuations in human mobility and urban energy consumption, despite its crucial role, remains elusive. Therefore, this study is designed to uncover the interdependencies that may exist between the variabilities in urban human mobility and energy consumption spatial flux.

Understanding energy consumption spatial flux across urban areas, the underlying dynamics of such fluctuations and the drivers of heterogeneity in consumption and demand is fundamental. If human mobility patterns can explain urban energy consumption patterns, is there a relationship between the spatiotemporal variations of human mobility driven by human activities as individuals visit different urban functional regions that could shed further light on the corresponding fluctuations in energy consumption?

3. HUMAN MOBILITY NETWORKS

Research has demonstrated that human mobility can account for much of the city-wide human activity observed [47, 48, 52] and thus can be used to predict urban energy consumption [53]. However, the spatiotemporal patterns of human mobility and energy consumption are not homogeneous in urban settings. Despite the fundamental laws found for human mobility and travel distance at larger scales [44, 54, 55], the distribution of the radius of gyration suggests that intra-city daily human mobility is largely heterogeneous [44, 56]: individuals exhibit variations in their daily activities, the number of locations they visit over time, and hence their daily mobility. The significance of understanding this variability in travel behavior, the analytical rationale for such an understanding and its policy implications are the subjects of a long standing debate [57]. The earliest work in this area examining the dynamics and rhythms in mobility behavior was limited to survey data [58], applying travel-activity survey data to explore spatial variability in activity-travel behavior [48]. 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 [52]. Schneider et al. [56] 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 reoccurring 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 [41] 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. The initial findings of their one week study indicated some stability in the spatial structure of the mobility patterns revealed. Louail et al. [43] also proposed a method for inferring different categories of mobility networks and their flows from origin-destination (OD) matrixes extracted from mobile phone data, in their case using data recorded in 31 Spanish cities. Louf and Barthelemy [59] took this a step further, reporting that the structure of human mobility patterns was largely governed by a variety of urban quantities, including the quantity of CO_2 emitted and the total consumption of gasoline. More recently, Pappalardo et al. [60] classified individuals into two populations with distinct mobility patterns: *returners*, and *explorers*, with the *returners* being those individuals whose mobility network is governed 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 their social interactions, as well as their role in the diffusion phenomenon. Understanding whether 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 more effective allocation of resources. Here, we explore whether one population exerts a disproportionate influence over the spatial consumption of energy in urban areas by examining the most preferred locations in their mobility networks.

4. DATA and METHODS

For this study, 2,015,339 positional records of 32,620 individuals, of whom 17,097 were identified as returners and 10,175 as explorers, along with the gas consumption of 3,040,422 building meters distributed across 983 spatial divisions were examined. These spatial divisions consist of MSOAs (middle layer super output areas), which are administrative boundaries representing a minimum population of 5,000 and an overall mean of 7,200 [61] in Greater London. Data was collected for 31 days (May, 2014). The positional records included in the study consist of those individuals with at least 3 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. The users were then classified into the two distinct populations (*returner* and *explorer*) based on their 2 (two) most frequently visited locations (Section 4.1). We then explored whether each population's mobility exhibited a meaningful spatial imprint (Section 4.2) that would serve as an indicator for energy consumption through spatial autocorrelation and regression analysis (Section 4.3). Section 5 presents our findings on the role of different human mobility networks in urban energy consumption measures and explores whether one population is predominant and its implications. The paper ends with a discussion of potentially fruitful future research directions in this area (Section 6).

4.1 Radius of Gyration

We selected the radius of gyration $r_g(t)$: *(Eq. 1)* [44] as our metric for 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 where they habitually move around in the course of their daily activities.

$$r_g = \sqrt{\frac{1}{N_{(t)}} \sum_{i=1}^{N_{(t)}} \left(r_i - r_{cm}\right)^2} \qquad (1)$$

$$r_{cm} = \frac{1}{N_{(t)}} \sum_{i=1}^{N_{(t)}} r_i \qquad (2)$$

The radius of gyration was calculated at two spatial and two 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 level $r_{ga}(t)$ represents the deviation of $r_{gi}(t)s$ from the corresponding center point *(Eq. 2)*. This indicator was then used to describe the patterns of human mobility across MSOAs. Next, we ranked the 983 MSOAs for each individual based on their frequency of visits. After identifying the two most frequently visited MSOAs for each individual, the individual level $r_{gi}(t)$ was obtained per MSOA per day. The MSOA level $r_{ga}(t)$ was then obtained per MSOA over the total time frame (in this case 31 days). At the spatial level, we calculated the weighted radius of gyration per MSOA and the total radius of gyration for each individual for the study period (May, 2014) and calculated the *M*-radius of gyration *(Eq. 3)* for each individual for the first 2 (two) most frequently visited MSOAs.

$$r_g^{(M)} = \sqrt{\frac{1}{N_M} \sum_{i=1}^{N_M} \left(r_i - r_{cm}^{(M)}\right)^2} \qquad (3)$$

$M = 1, 2$

Finally, we compared the total r_g and $r_g^{(M)}$ of each individual through a Support Vector Machine (SVM) classification such that the population was split into two distinct classes: *returners* and *explorers* [60]. *M-returners,* with $r_g^{(M)} \approx rg$, are those individuals whose characteristic travelled distance is dominated by their *M-th* most frequently visited MSOA, while the mobility network of *M-explorers*, with $r_g^{(M)} \lll rg$, spanned multiple MSOAs and could not be reduced to *M* locations. Figure 1 depicts the distribution of *returners-explorers* in terms of their total *rg* and $rg^{(2)}$ ($M = 2$, second most frequently visited MSOA).

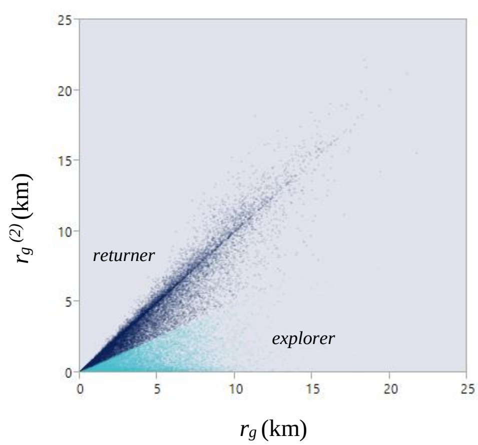


Figure 1. Recurrent vs. Overall Mobility of Populations (May 2014): *returners, explorers*.

4.2 Heterogeneity and Spatial Randomness

A spatial autocorrelation analysis was performed for energy consumption (in this case, gas) and human mobility across the 983 MSOAs in Greater London to measure the correlation among 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.4*), which ranges from -1 (most dispersed) to 1 (most clustered), describes the degree of spatial concentration or dispersion for gas and human mobility (of *returners* and *explorers*), with larger values for *I* showing clusters of larger values that are surrounded by other large values, namely (*I*+)–spatial clustering, and (*I*–)–spatial dispersion indicating larger values that are spatially enclosed by smaller values. This also provides a useful test of independence to determine whether the values of *returners* and *explorers'* human mobility or gas consumption observed in one location depend on the values observed at neighboring locations. While Moran's I represents a global spatial autocorrelation for our data, Geary's C (*Eq. 5*) was also used to examine the deviations in the responses of each observation from one another, ranging from 0 (maximum positive autocorrelation) to 2 (maximum negative autocorrelation), with 1 indicating an absence of correlation. We have used Moran's I and Geary's C here as a measure of sensitivity to extreme values of gas consumption as well as *returners* and *explorers'* human mobility in each MSOA in relation to others.

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

$$C = \frac{(N-1)\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - x_j)^2}{2(\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij})\sum_{i=1}^{n}(x_i - \bar{x})^2} \tag{5}$$

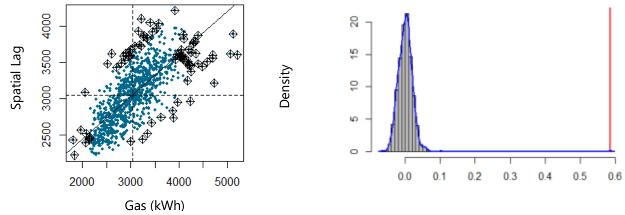
Finally, we used Getis-Ord G and Gi^* (*Eq. 6 and 7*) to perform a hotspot analysis for *returners* and *explorers*.

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{i,j} x_i x_j}{\sum_{i=1}^{n}\sum_{j=1}^{n} x_i x_j}, \forall j \neq i \tag{6}$$

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X}\sum_{j=1}^{n} w_{ij}}{S\sqrt{\frac{[n\sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2]}{n-1}}}, \tag{7}$$

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}, S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n}}$$

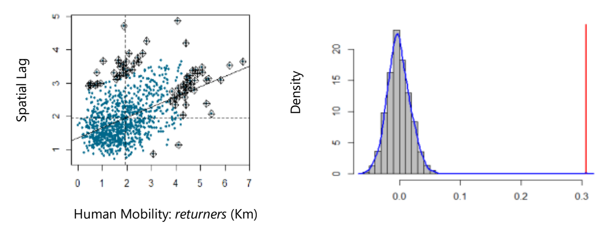
Here, n represents observations related to variable x at locations i and j, where $\bar{x}$ is the mean of the x variable, and w_{ij} are the elements of the corresponding weight matrix. As illustrated in the four quadrants of the Moran scatterplots (Figures 2-4), there are four types of spatial autocorrelation for our 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 MSOAs with low gas consumption 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. Figure 2(a) shows the Moran scatterplot for gas consumption along with its permutation test plot (Figure 2(b)), indicating the significance of Moran's I. The observed Moran's I is located in the tail of the 999 permutation sample distribution and thus has a low probability of stemming from a spatial random distribution of gas consumption (i.e., a significance level of 5%). Likewise, Figures 3 and 4 show the Moran scatterplot and permutation for the mobilities of returners and explorers, respectively. The randomness hypothesis of the mobility of both *returners* and *explorers* is rejected in favor of spatial structure.



(a) Moran Scatterplot: *Gas*   (b) Permutation Test for Moran's I – 999 permutations

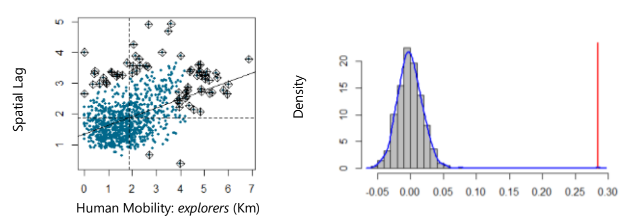
Figure 2. Spatial autocorrelation – Gas consumption

Statistically significant (*p-value* < $2.2e^{-16}$) positive values for I in human mobility as well as gas consumption indicate that these patterns in Greater London follow a clustering distribution and reject spatial randomness in favor of structure. The statistically significant results for Geary's C confirm these results, with high values of the C measures corresponding to low values of I and the two measures being inversely related. Statistical coefficients of these spatial autocorrelations are shown in Tables 2 and 3.



(a) Moran Scatterplot: *returners*   (b) Permutation Test for Moran's I – 999 permutations

Figure 3. Spatial autocorrelation – Human mobility: *returners*



(a) Moran Scatterplot: *explorers*   (b) Permutation Test for Moran's I – 999 permutations

Figure 4. Spatial autocorrelation – Human mobility: *explorers*

Table 2. Spatial autocorrelation– Moran's *I*

	Statistic(*I*)	*p*-value	Std
Gas	0.5860776	< 2.2e-16	30.7
Returners	0.3069102	< 2.2e-16	16.103
Explorers	0.2844525	< 2.2e-16	14.93

Table 3. Spatial autocorrelation– Geary's *C*

	Statistic(*C*)	*p*-value	Std
Gas	0.430018324	< 2.2e-16	27.759
Returners	0.7109341162	< 2.2e-16	13.966
Explorers	0.7002775633	< 2.2e-16	14.534

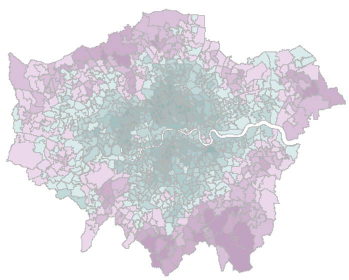


Figure 5. Gas Consumption Hotspots – Getis-Ord *Gi***

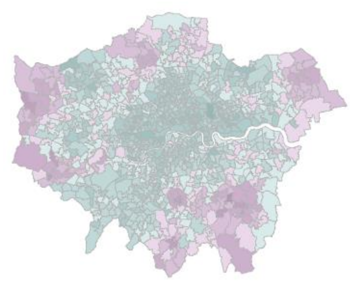


Figure 6. Returners' Mobility Hotspots – Getis-Ord *Gi***

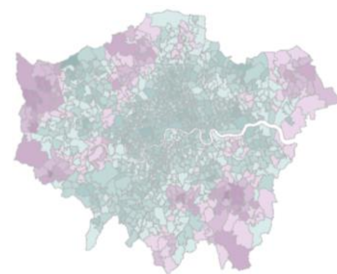


Figure 7. Explorer's Mobility Hotspots – Getis-Ord *Gi***

These results confirm that for both gas consumption and the human mobility of *returners* and *explorers*, location is relevant and provides additional information beyond just their values. To identify models that relate these observations at one location to those at other locations and determine whether there is a specific spatial correlation structure, we performed a hotspot analysis. In order to identify statistically significant hotspots (i.e., where high/low values of human mobility and gas consumption are clustered spatially), we calculated the Getis-Ord *G* and *Gi**. The results suggest a stronger relationship between hotspots of gas consumption and human mobility of *returners* than *explorers*. Table 4 shows the statistical coefficients for these analyses.

Table 4. Spatial autocorrelation – Getis-Ord *G*

	Statistic(*G*)	*p*-value	Std
Gas	5.941973e-3	1.728e-16	6.2768
Returners	6.416208e-3	< 2.2e-16	8.8668
Explorers	6.448446e-3	< 2.2e-16	9.2423

This suggests that those MSOAs with high energy consumption values are also surrounded by high human mobility of *returners*. The larger the *G*, the more intense the clustering of these high values (hotspots), indicating that hotspots of *returners'* mobility is more similarly spatially clustered to gas consumption hotspots (Figures 5-7).

4.3 Predominant Energy Consumption

Having identified a dominant role played by *returners* in the spatial imprints of gas consumption, it is of significant interest to understand the dependencies that exist between their mobility patterns and energy consumption compared to *explorers*. Albeit, the energy use 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 holds 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, does the correlation between the human mobilities of the *returners* and *explorers* and gas consumption manifest itself spatially different in urban areas? To answer this question we performed a spatial regression analysis.

5. SPATIAL EXTERNALITIES and RESILIENCE

Exploring the relationships between energy consumption and human mobility of *returners* and *explorers* in each MSOA and their neighboring values would allow us to examine the impact that one observation has on other proximate observations. Having found spatial dependencies and clustering distributions for both human mobility of *returners* and *explorers*, and gas consumption, we modeled their spatial interdependencies, by applying autoregressive models to implicitly incorporate such spatial dependence into a covariance structure. The two main autoregressive models for areal data tested 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, and examine various conditions. We also compared the results using a simple linear model, as well as developed a third model in which *returners* and *explorers* are both considered as covariants. Tables 5-7 include the statistical significance and parameters of these models.

Table 5. Spatial regression analysis results – Gas consumption per human mobility: *returners*.

	Simple Linear Model (OLS)	Spatial Lag Model (SAR)	Spatial Error Model (SEM)
***p*-value**	< 2.2e-16	< 2.22e-16	< 2.22e-16
AIC	14939	14407	14419
R-squared	0.08586	-	-
Statistics	92.14	0.73177	0.75099

As indicated by *p*-values lower than 0.0001, these models are statistically significantly representation of and can predict gas consumption per human mobility of the population. However, with respect to the AIC measures, a SAR with the least AIC value (AIC = 14,407) that incorporates data for *returners* only, is the most representative spatial model and predictor for gas consumption. The multivariate SAR that distinctly incorporates data for both *returners* and *explorers* (AIC = 14,409) has substantial evidence, while the SAR that incorporates data for *explorers* only stands last among others (AIC = 14,410) has considerably less support compared to the best model. These models explicitly test the impact of human mobility variables on energy consumption. At a global scale, they imply that the state of the gas consumption per human mobility of returners and explorers for each MSOA in Greater London is influenced by that of its neighboring MSOAs 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 gas consumption.

Table 6. Spatial regression analysis results – Gas consumption per human mobility: *explorers*.

	Simple Linear Model (OLS)	Spatial Lag Model (SAR)	Spatial Error Model (SEM)
***p*-value**	< 2.2e-16	< 2.22e-16	< 2.22e-16
AIC	14957	14410	14418
R-squared	0.06931	-	-
Statistics	73.06	0.73709	075208

Table 7. Spatial regression analysis results – Gas consumption per human mobility: *returners + explorers*.

	Simple Linear Model (OLS)	Spatial Lag Model (SAR)	Spatial Error Model (SEM)
***p*-value**	< 2.2e-16	< 2.22e-16	< 2.22e-16
AIC	14940	14409	14421
R-squared	0.08728	-	-
Statistics	46.86	0.73146	0.75092

A significant implication of these interdependencies is possible spillover effects, meaning whether fluctuations occurring in gas consumption by the human mobility of *returners* and *explorers* in one MSOA have any diffusive impact on its neighboring MSOAs. And, if yes, 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 spatial independence limitations, but the SAR models, while being 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 the gas consumption at the corresponding locations. Having such information will allow city managers and policy makers to identify hotspots and develop strategies to create bigger energy efficiency spillover effects, or to restrict unwanted or excessive energy use spillover effects. When creating such strategies, individual locations (gas consumption hotspots) 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 population), planners will be one step closer to ensuring better management and allocation of energy resources in urban areas.

6. CONCLUSIONS and FUTURE WORK

The dominance of *returners'* human mobility networks on urban energy consumption signifies the important role urban population and variations in their activities play in using current and future resources. Understanding such continuous state of flux across urban areas, their underlying dynamics and the drivers of heterogeneity in consumption and demand is thus fundamental in making demand predictions. The relationship between the spatial variations of human mobility driven by human activities of certain populations as they visit different locations and energy consumption of these locations improve our understanding of how energy demand may be distributed in an urban setting. This could shed further light on the corresponding energy allocation strategies.

Crucially, rapid globalization and the subsequent growth in energy consumption cannot be sustained as population growth has the potential to grow more rapidly than energy supplies can be increased. 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" [2]. A better understanding of the underlying drivers of this process and its fluctuations across different populations belong to different communities and organizations [62] will 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.

7. ACKNOWLEDGMENTS

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

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