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Evaluating the Spatial Reach of Energy Use Spillover Effects in Urban System Fluctuations

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EVALUATING THE SPATIAL REACH OF ENERGY USE SPILLOVER EFFECTS IN URBAN SYSTEM FLUCTUATIONS

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ABSTRACT

The rate at which we consume energy in urban areas cannot be regarded as being independently generated as a result of infrastructure characteristics, without some consideration of possible dynamic effects and externalities. Previous studies focused on identifying the endogenous and exogenous determinants of urban energy consumption have examined the spatiotemporal relationships between urban human mobility and energy use and determined an underlying spatial structure, which explains their interdependencies. However, it is not yet clear to what extent changes in endogenous and exogenous determinants identified affect this structure. In this study, we examine the spatial reach of energy use spillover effects in urban systems through statistical analysis and network-based clustering methods by considering the diffusion of energy consumption through both spatial structures (i.e. urban infrastructure and population flow) across 4,835 areas in Greater London. Integrating spatial regression models with spatially-constrained network clustering of energy use and human mobility, we compared 2,305,001 positional records from an online social networking platform, namely Twitter, with energy consumption measures using information garnered from 3,438,939 electricity meters across London over the course of a single month, May 2014. We found that there is a predominant spillover effect from the urban infrastructure and population flow on energy use, with an overall stronger effect from urban infrastructure. The results presented here provide valuable insights that will contribute to the development of a better understanding of energy use transmittal effects in urban areas as part of a complex human-infrastructure system.

KEYWORDS

Human Mobility, Spatial Constrained Clustering, Spatial Spillover Effect, Urban Energy Consumption, Urban Infrastructure.

INTRODUCTION

Urban areas already consume up to 80% of the world's energy production (EIA 2013), and the projected increase of their population to nearly 70% of the global population by 2050 will inevitably drive further increases in energy consumption (UN 2014). The rate at which we consume energy cannot be regarded as being independently a function of buildings (Boulaire et al. 2014; Farzana et al. 2014) or

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city infrastructure attributes (Choudhary 2012; Mikkola and Lund 2014). Research quantifying the underlying spatial structure for urban energy use has confirmed the presence of spatial spillover effects among neighboring units based on the statistically significant spatial dependencies that exist in relatively densely populated urban spaces (Mohammadi et al. 2017; Mohammadi and Taylor 2017). Spillover effects (Anselin 2003; Capello 2009; LeSage 2008) in an economic context are regarded as events (in this case, building energy use) that occur because of something else (here, human mobility) in different contexts. The future growth in population and urbanization will most likely increase interdependencies between infrastructure and individuals, thus further enhancing both the magnitude and spatial reach of energy use spillover effects across urban spaces. These spillover effects are not necessarily always positive as they are driven by the evolving underlying infrastructure and the intra-urban flow of population as residents move through their daily routines, instigating both desirable and unwanted energy use effects as they do so. The spatial reach of energy use spillover effects thus fluctuates across space, however, although the magnitude and extent of this spatial reach can be measured, it is not yet clear which drivers have the most significant impact on spatial reach. Here, we examine fluctuations in spatial reach and the associated energy use spillover effects in order to tease out the underlying dynamics that create energy use spillover effects with the greatest spatial reach. We conceptualize the spatial structure, in which the dynamics of the diffusion of use of energy resources take place; we examine two underlying spatial structures: urban infrastructure and population flow, and take into account the dependency of energy use on human mobility to evaluate the spatial reach of spillover effects in urban energy systems.

METHODOLOGY

DATA

The dataset used in this study consists of energy (residential electricity consumption) measures from 3,438,939 electricity meters across 33 Boroughs (BOR) (4,835 Lower Level Super Output Areas (LSOA)) in Greater London over the course of a single month, May 2014. Figure 1(a) depicts the two nested spatial divisions used in this study. Additionally, individual positional records were collected from an online social network (Twitter) across the same spatiotemporal dimensions to account for population flow.

In order to quantify the spillover effects off population flow from human mobility patterns, we have adopted the human mobility radius of gyration *(Eq. 2)* around the center of mass of the mobility of an individual *(Eq. 1)* as our metric (González et al. 2008):

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

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

Here, *N* is the total number of observations *n*.

The radius of gyration is calculated at three spatial levels. First, the individual-level $r_{gi}(t)$–which represents the characteristic distance traveled by a user when observed in time t–is obtained per Greater London BOR or LSOA per individual per day. Then, the BOR and LSOA-level human mobility radius of gyrations are obtained per each spatial division over the period of the study (i.e., month of May).
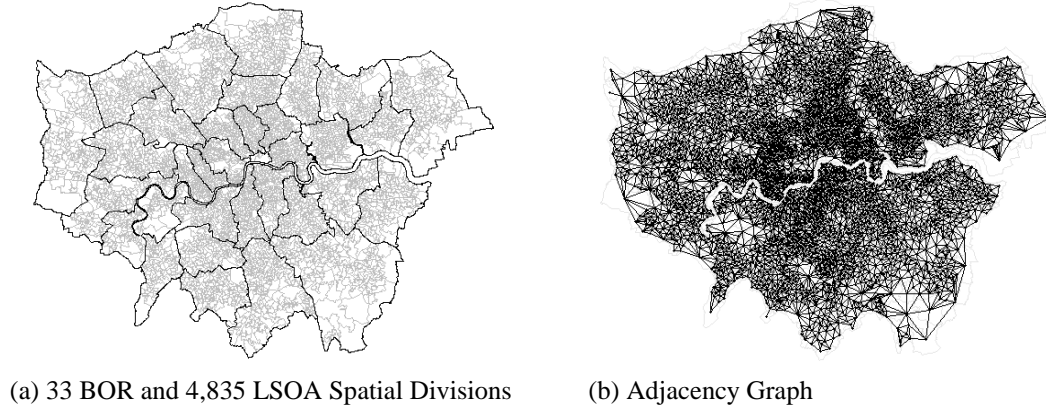

(a) 33 BOR and 4,835 LSOA Spatial Divisions   (b) Adjacency Graph

Figure 1: Greater London (a) nested spatial divisions, and (b) adjacency graph.

SPATIALLY-CONSTRAINED CLUSTERING

In order to reliably examine the spatial reach of spillover effects across LSOAs, we first partitioned the BOR-level spatial divisions into spatial clusters that are grouped in terms of both attribute similarity (i.e., contiguity) as well as spatial similarity (i.e., proximity) using the graph-based *SKATER* algorithm (Assunção et al. 2006). The contiguity is taken into account by identifying the 4,835 LSOAs as nodes of an undirected weighted or adjacency graph (Figure 1(b)) such that each LSOA is connected to its adjacent node if they share neighboring boundaries. A vector of $x_i=$ (x_{ie}, x_{im}) consisting of numerical values of energy consumption, as well as human mobility, is associated with LSOA i. The edge weight value associated with each connection measuring the dissimilarities between LSOA i and j with respect to their attribute vectors represents the distance between the two nodes in multivariate space. Higher values of the edge weights show that the corresponding LSOA pairs are farther apart in multivariate space. With the objective of minimizing the overall dissimilarity so the clusters are internally the most similar, we generated a minimum spanning tree of adjacency graph based on the aforementioned pairwise distance measures of dissimilarity across LSOAs and partitioned the graph. By partitioning the graph such that the sum of the intra-cluster square deviations is minimized, we ensure that the clusters are generated with maximized homogeneity with respect to the energy use and human mobility attributes.

Figure 2 shows the results of this clustering, spatially constrained to urban infrastructure (Figure 2(a)), and population flow (Figure 2(b)) grouped into five classes at the BOR level in Greater London.

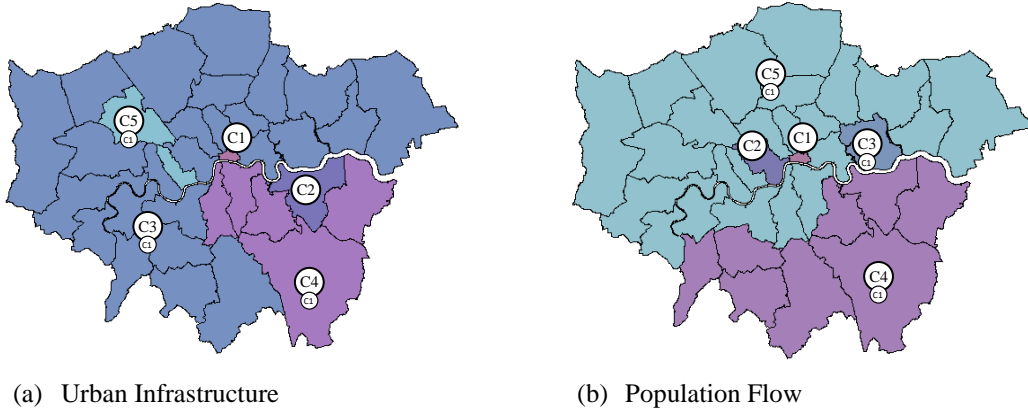(a) Urban Infrastructure   (b) Population Flow

Figure 2: Spatially constrained unsupervised clustering of Greater London Boroughs (BOR) for (a) urban infrastructure, and (b) population flow, May 2014.

SPILLOVER EFFECT

The spillover effects are examined across the spatially constrained classes identified in Figure 2 for urban infrastructure and population flow. First, the significance of an underlying spatial structure is examined through an exploratory spatial autoregressive analysis. We explore whether the spatial distribution of energy use in each clustering group is related to urban infrastructure or population flow attributes of its neighboring spatial divisions and, if so, to answer how they are associated and the extent of their direct, indirect (spillover), and total effects.

The spatial interaction and spillover effects are then measured via a Spatial Durbin Model (Anselin 1988; LeSage and Pace 2010), in which the characteristics of a cluster are simultaneously considered in the analysis *(Eq. 3)*. This model explicitly takes into account both the endogenous and exogenous interaction relationships.

$$y = \rho W y + \alpha I_n + X\beta + WX\theta + \varepsilon$$
$$\varepsilon \sim N(0, \partial^2 I_n)$$

$$(3)$$

Where, *y* is an *n×1* vector of energy use; *W* is the spatial weight matrix, where *Wy* represents the spatial lagged endogenous effects (e.g., urban infrastructure); ρ denotes the effect of *y* or spatial autoregressive coefficient. I_n is an *n×1* vector of ones associated with the intercept parameter *α*. *X* represents an *n×1* matrix of human mobility measures, which are related to the parameters *β*; *WX* reflects the spatial lagged exogenous effects (e.g., population flow); and *θ* denotes a *k×1* vector of the effects of *WX*.

FINDINGS

SPATIAL AUTOCORRELATION

Table 1 shows the results of the spatial autocorrelation for both urban infrastructure and population flow. Moran's *I*, describes the degree of spatial concentration in each case per spatially constrained cluster division. Statistically significant positive values for most of the clustered divisions indicates that the values of energy use and human

mobility in one location depend on the values observed at adjacent locations, and this dependency exists continuously throughout the course of the month (May 2014).

Table 1: Moran's *I*.

	Urban Infrastructure		Population Flow	
	I	*p-value*	*I*	*p-value*
C1	-0.21104137	0.517	-0.23733847	0.5639
C2	0.214331516	9.072e-06	0.099639711	0.01743
C3	4.378072e-01	< 2.2e-16	0.046077118	0.1261
C4	0.4857757481	< 2.2e-16	0.1579332503	< 2.2e-16
C5	0.492889834	< 2.2e-16	0.1599057663	< 2.2e-16

DIRECT AND INDIRECT (SPILLOVER) EFFECTS

Since energy use and human mobility exhibited a statistically significant spatial dependence over C2-C5 clusters in both urban infrastructure and population flow cases, we examined the spatial dependency conditions as well as direct, indirect (spillover), and total effects in each case by modeling the spatial interdependencies (Table 2). Spatial Durbin model allows for separately evaluating the direct (within LSOA) impact of an attribute (e.g., urban infrastructure, or population flow) as well as indirect (to/from neighboring LSOAs) impact on energy use (Fischer and Wang 2011; LeSage and Pace 2009). This identifies whether and to what extent change in the urban infrastructure, or population flow in one LSOA, will not only lead to the change in energy use in the same LSOA (direct impact) but also affect the energy use in other LSOAs (indirect impact) (Table 3).

Table 2: Spatial Durbin Model.

	Rho	z-value	*p*-value	Log-likelihood	AIC
Urban Infrastructure					
C1	NA	NA	NA	NA	NA
C2	0.38502	3.7835	0.00037505	-205.5207	421.04
C3	0.67721	42.482	< 2.22e-16	-4358.368	8726.7
C4	0.68648	21.975	< 2.22e-16	-1019.47	2048.9
C5	0.68324	13.111	< 2.22e-16	-330.8827	671.77
Population Flow					
C1	NA	NA	NA	NA	NA
C2	0.70838	9.8262	9.206e-13	-152.8083	315.62
C3	0.32264	2.9512	0.005132	-223.5279	457.06
C4	0.71381	28.385	< 2.22e-16	-1442.414	2894.8
C5	0.66788	39.734	< 2.22e-16	-4058.457	8126.9

The significant direct effects for both urban infrastructure and population flow clusters confirms that the attributes of surrounding LSOAs are important determinants of energy use. Four of five urban infrastructure clusters, as well as three of five population flow clusters exhibited spillover effects on energy use. For example, a one-unit increase in an exogenous variable (e.g., human mobility) in surrounding LSOAs of C2 of urban infrastructure clusters can be associated with roughly a 0.36

increase in energy use of one unit. Interestingly, this relationship within a C2 LSOA (direct effect) exhibited much a weaker spillover effect. In other words, the same increase was only related to a roughly 0.02 increase in energy use within an LSOA.

Table 3: Decomposition estimates of the direct and indirect (Spillover) effects of urban infrastructure and population flow on energy use.

	Direct Effects	Indirect Effects	Total Effects
Urban Infrastructure			
C1	NA	NA	NA
C2	0.02072484	**0.3552555**	0.3759804
C3	0.02102907	**0.2498894**	0.2709185
C4	0.02923902	**0.4017431**	0.4309821
C5	-0.05334096	**-0.0814139**	-0.1347549
Population Flow			
C1	NA	NA	NA
C2	-0.08097876	-0.0310392	-0.112018
C3	-0.193315	**-0.2701312**	-0.4634463
C4	0.01717194	**0.1649943**	0.1821662
C5	0.02770776	**0.3195341**	0.3472419

DISCUSSION

Our initial findings indicate that the spatial reach of spillover effects fluctuates across spatially-constrained clusters of urban infrastructure and population flow as a result of the underlying statistically significant spatial dependencies that arise due to energy use and human mobility. To investigate whether neighboring areas have a diffusive effect on each other and whether spatial spillovers—where changes occurring in one area have an impact on neighboring areas—exist, we performed a spatial regression analysis on the data. The spatial Durbin models used here permit the magnitude and significance of direct, indirect (spillover), and total effects to be assessed, thus showing how changes in human mobility and energy use at a particular spatial unit will be transmitted to all other locations and hence how they are likely to affect the energy consumption at those locations. Interestingly, the statistically significant values of these effects imply that the effects of human mobility and energy use in both urban infrastructure and population flow predominantly exhibit an indirect spillover effect. In smaller clusters of population flow, this effect may dissipate quite rapidly, approaching zero after a comparatively short distance; the effect decays more slowly as we move to higher order neighbors in LSOAs, however. This may indicate that urban infrastructure has a weaker direct effect on urban energy use compared to the exogenous and changing effects that take place in its surroundings. The types of spillover effects found here reflect the broader perspective needed when considering urban building energy consumption over a larger scale. These results provide a clear picture of the diverse nature of the spatial reach of energy use spillover effects and its drivers, establishing a useful foundation for localized and contextualized interventions to reduce energy consumption. Spatial dependence is the product of an underlying location-specific activity process that leads to clusters of energy use spillover effects with fluctuating spatial reach. One significant implication of this approach to identifying the drivers of spatial reach for the energy use spillover effect

in urban systems is that it becomes possible to determine how changes in energy use at each spatial unit will be diffused across neighboring locations and consequently predict how the size of this diffusion is likely to fluctuate across different spatial units. This can help city managers and policy makers identify appropriate interventions that will enable them to influence energy use at the corresponding locations by supporting positive energy efficient spillover effects with greater spatial reach and minimizing undesirable and excessive energy use spillovers, which may lead to more effective energy efficiency opportunities (Armstrong et al. 2016).

CONCLUSIONS

In our evaluation of the varying effects from endogenous and exogenous determinates of urban energy use fluctuations, we used spatially-constrained clustering and spatial regression analysis methods to determine the extent of spatial reach for urban infrastructure and population flow spillover effects. We found that exogenous effects predominantly indirectly affect energy use in both conditions. This finding may have significant implications on location-specific energy efficiency interventions, which can be achieved through targeting the underlying spatial structure by implementing interventions that focus on the influential infrastructure governing the spatial reach of the spillover effects. An alternative could be to instigate diffusion by modifying the population mobility flow, for example, by targeting influential individuals. The new approach presented here provides valuable insights that will contribute to the development of a better understanding of energy use transmittal effects in urban areas as part of a complex human-infrastructure system.

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