Energy 76 (2014) 629–640

Contents lists available at ScienceDirect

Energy

journal homepage: www.elsevier.com/locate/energy

Spatial regression analysis of domestic energy in urban areas

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ARTICLE INFO

Article history:
Received 25 February 2014
Received in revised form
9 July 2014
Accepted 17 August 2014
Available online 6 September 2014

Keywords:
Building energy
Spatial autocorrelation
Spatial regression
Urban environment
Spatial error model

ABSTRACT

One of main characteristics for building energy in urban environment is spatially distributed. Both electricity and gas per dwelling in London have positive spatial autocorrelation, which indicates that neighbourhoods tend to cluster together with similar energy use. More importantly, when applying regression analysis, the residuals from standard linear energy models may also have spatial autocorrelation, which makes statistical inference more difficult. Therefore, it is important to consider spatial effects in analysing energy consumption patterns of buildings in urban settings. This paper applies OLS (ordinary least squares) and spatial regression models to investigate the relationship between council tax evaluation bands and domestic energy consumption in London. A significant correlation was found between the number of properties in each council tax band and the corresponding energy use. Based on both statistical and theoretical analysis, the SEM (spatial error models) are more appropriate in this study than the spatial lag models. The simulation results indicate the SEM can take the spatial correlation into account by decomposing the OLS original error terms in regression analysis. The general trend is that both electricity and gas consumption per dwelling would increase from the lower to higher council tax bands.

1. Introduction

Urban areas account for approximately two thirds of global energy demand and more than half of the population lives in cities [1,2]. By 2050, it is projected to produce around 80% of global greenhouse gas emissions [1]. Moreover, the proportion of building energy is usually significantly higher compared to energy use from transportation in urban environment [3]. Hence, in order to reduce carbon emission in cities, it is necessary to understand the characteristics of urban energy consumption, especially from urban buildings.

A number of studies have been performed to analyse the patterns of energy consumption from buildings in cities using several approaches. These methods include engineering-based [4–7], machine learning [8–10], Bayesian analysis [9,11], and GIS (Geographical Information System)-based method [12–17]. Yamaguchi and Shimoda [5] developed an engineering-based simulation model to assess the impact of change of buildings on five indicators (primary energy consumption, carbon dioxide emission, sensible heat release, peak electricity demand, and water consumption). Howard et al. [8] used robust linear regression to obtain the energy use intensity of various building types in New York City. Tian et al. [9] implemented an engineering-based probabilistic model to simulate energy use in the London schools using Bayesian computation, sensitivity analysis and non-parametric regression method. Calderon et al. [12] developed a domestic energy demand model for the city and neighbourhoods of Newcastle upon Tyne (named Carbon Route Model) by applying GIS techniques. For overview of building energy analysis in cities, please refer to [18–21].

It is apparent that urban building energy is spatially distributed in cities. Therefore, it is important to analyse the characteristics of urban building energy using spatial analysis method. However, spatial analysis method is still rarely used to explore patterns of building energy in urban environment. Choudhary and Tian have applied spatial regression methods to investigate the patterns of gas consumption for London non-domestic buildings [22,23]. It should be emphasized that spatial visualization of energy data is only an initial step for spatial analysis. The key concept in spatial analysis is spatial autocorrelation [24], which means the variables in cities are associated with different geographical locations. Spatial

Abbreviations: AIC, Akaike information criterion; CT, council tax (evaluation bands from A to G); DECC, Department of Energy & Climate Change, UK; GIS, Geographical Information System; LM, Lagrange Multiplier; MSOA, middle layer super output area; OLS, ordinary least squares; ONS, Office for National Statistics, UK; R2, coefficient of determination; SEM, spatial error model; SLM, spatial lag model; VOA, Valuation Office Agency, UK.

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http://dx.doi.org/10.1016/j.energy.2014.08.057
0360-5442/

autocorrelation can be interpreted as the first law of geography, “Everything is related to everything else, but near things are more related than distant things” [24]. Thus, building energy use in different areas of a city cannot be regarded as being independent of each other in regression analysis due to spatial autocorrelation. For instance, as shown in Fig. 1, both electricity and gas consumption per dwelling in London have significant clustering patterns (discussed in detail in Section 4.1). The conventional regression method cannot capture spatial autocorrelation of energy consumption in cities that leads to non-random residuals or unstable parameters [25].

Therefore, this paper applies spatial regression method to analyse the patterns of energy use in cities by considering intrinsic spatial autocorrelation of building energy consumption. This research is focused on the relationship between council tax evaluation bands and domestic energy consumption in London. The council tax band for a property in UK can be regarded as a proxy indicator of several social economic factors, including the size, age, occupant income, and location of the dwellings (described in detail in Section 2.1) [26,27]. The social-economic characteristics have been investigated to explore the cause of the domestic energy consumption because residential energy is affected by not only building characteristics but also social-economic factors [28–32]. Moreover, the relationship between residential energy and social characteristics of dwellings is a key element for making policies in the residential sector [29].

This paper is organized as follows. Section 2 introduces the dwelling and energy data used in this paper, including council tax band, dwelling type, dwelling built periods, electricity, and gas data in the London. Section 3 describes the statistical methods used in this analysis, including spatial autocorrelation, correlation analysis, and spatial regression methods. Section 4 discusses the results using both classic least square and spatial regression methods in London dwellings.

2. Council tax bandings and domestic energy in London

Table 1 lists the data sets used in this research, including electricity/gas consumption, dwelling stock (council tax/types/ages), and digital boundaries. The spatial level applied here is MSOA (middle layer super output area) in England, which has a minimum population of 5000, with an overall mean of 7200. England has 6781 MSOAs and London has 983 MSOAs [33]. Note that there are two versions of MSOA for the years 2001 and 2011 in UK. All the analysis in this paper is based on 2001 MSOA to be compatible with the energy and dwelling data used in this research [34,35].

2.1. Dwellings by council tax band

Both the energy data and the number of dwellings in CT (council tax) bands used in the calculation are for the year 2010 [34,35]. The data for dwelling types and dwelling build periods for the year 2012 [36] are only used to explaining the characteristics of the corresponding council tax bands, which will not be used for regression analysis. The reason for the choice of the year 2012 is due to the issue of data availability for both dwelling types and dwelling build periods at London MSOA levels. Another relevant spatial scale in the London is 33 local authorities, including the 32 London borough councils and the City of London [37].

2.1.1. London dwellings in terms of council tax bands

Dwelling stock data used in this study is from UK VOA (Valuation Office Agency) [35]. A dwelling in this database is defined as a hereditament for the purposes of council tax, which is collected by UK local authorities in terms of its open market values. Based on the size, age, character, and location of properties, each dwelling is placed in one of eight valuation bands from A to H with A being the least expensive and H being the most expensive [35].

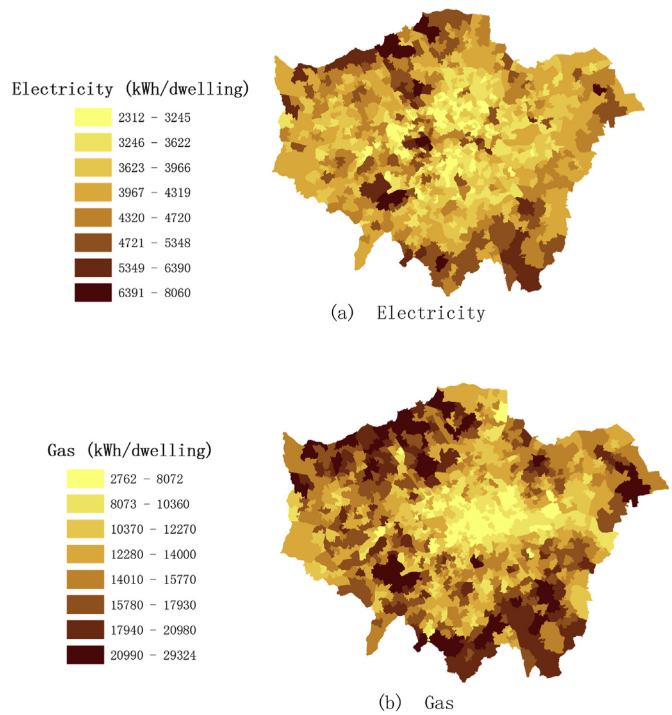

Fig. 1. Electricity and gas use (unit: kWh) per dwelling at MSOA (middle layer super output area) level in London for 2010.

Table 2 summarizes the dwelling numbers in terms of CT band for the year 2010 [35]. The total dwelling number is around 3.3 million in London. The housing is predominately bands C and D, accounting for more than half of London dwellings. The least number of chargeable dwellings is band H, only 1.7% of the total London housing.

Fig. 2 shows the spatial distributions of percentage of CT bands B and G at MSOA level [33,35]. The housing stock allocated to band B is clustered in inner eastern London. More expensive dwellings in band G are mainly in inner western London and outer London.

2.1.2. Council tax band and dwelling types

Fig. 3 shows the dwelling numbers in terms of property types [36]. The classification of dwelling types is listed in Table 3 based on UK VOA [38].

As shown in Fig. 3, around half of London's households live in flats (called apartment in North American English). Three main dwelling types are one-bedroom flat, two-bedroom flat, and three-

Table 1
Summary of data sets used in this research.

Data	Spatial scale	Year	Organisation	Reference
Electricity & gas	MSOA (middle layer super output area	2010	DECC (Department of Energy & Climate Change, UK)	[34]
Dwelling stock by council tax band	MSOA	2010	VOA (Valuation Office Agency, UK)	[35]
Digital boundaries	MSOA	2001	ONS (Office for National Statistics, UK)	[33]
Council tax property attributes (type & age)	MSOA	2012	VOA (Valuation Office Agency, UK)	[36]