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A GIS-BASED BOTTOM-UP SPACE HEATING DEMAND MODEL OF THE LONDON DOMESTIC STOCK

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ABSTRACT

This paper demonstrates a systematic approach towards exploring the impact of urban built form and the heat island effect on the levels of domestic energy consumption in London. The study combines GIS databases and a modified version of the Standard Assessment Procedure (SAP) algorithm in order to estimate the space heating demand of urban domestic energy users. The output data is aggregated to the Middle Layer Super Output Area (MLSOA) level. External air temperatures in various locations across London were predicted as part of the London Site Specific Air Temperature (LSSAT) model development. This data was used as input to the energy use calculation model. Comparison of the model output for 95 case study areas with top-down energy statistics at MLSOA level demonstrated that the model ranks areas based on their domestic energy demand with relative success.

INTRODUCTION

Predicting the baseline domestic stock energy demand at an urban scale can play a significant role in the CO_2 emission reduction strategies in the UK by identifying local level emission patterns and spatial relationships. In addition to the UK national target to cut emissions by 80% by 2050 (HMG 2008), the Mayor of London Climate Change Action Plan (MOL 2007) set the challenging target to reduce the London CO_2 emissions by 60% by 2025. London is one of the most populated cities in the developed world and one of the fastest growing cities worldwide. As of 2005, a population of 7.5 million people was occupying more than 3 million household spaces (ONS 2009). Approximately 8% of UK CO_2 emissions are produced in London, corresponding to 44 million tonnes of CO_2 annually (excluding aviation). Based on the projected rates of population and economic growth, a 15% increase in emissions is predicted, raising its annual emission rate to 51 million tonnes by 2025, if no action to tackle climate change is taken (MOL 2007).

Approximately 38% of the total of delivered energy in London is associated with domestic energy use. More than half of that amount (54%) is attributed to space heating (MOL 2007). It is well understood, therefore, that significant savings could be achieved in the domestic building sector. Importantly, the thermal performance of building envelopes is predefined largely by existing buildings. In the UK, as in most post-industrial countries, the existing building stock is characterized by long physical lifetimes and low turnover rates of approximately 1% per annum (DCLG 2006).

In the UK context, many tools have been developed as an attempt to predict the baseline energy demand of the existing domestic stock under different scenarios (Johnston et al. 2005, Shorrock and Dunster 2006, Boardman 2007, Natarajan and Levermore 2007). The main calculation algorithm integrated in the majority of the models is based on the Building Research Establishment Domestic Energy Model (BREDEM). BREDEM is the most widely used and extensively validated model for the calculation of space heating in the UK (Anderson et al. 1985). Its full version requires a large amount of data input. This data could be obtained by on-site surveys, but these tend to be costly and time-consuming. As a result, Geographic Information Systems (GIS) tools in conjunction with built-in inference databases have been commonly used in recent years in order to facilitate the acquisition of building-specific data without the need of visual inspection of the properties (Rylatt et al. 2003, Gupta et al. 2006, Jones et al. 2007).

This paper outlines the conceptual framework, the methodology and initial findings of a GIS-based domestic energy modelling approach. The research work is attached to the 'Local Urban Climate Model and its Application to the Intelligent Design of Cities' research project (LUCID 2009). The principle objective of the present study is the development of a Domestic Energy Use Urban Profiling Tool for different levels of the urban hierarchy system (i.e. local, intermediate and citywide).

METHODS

Level of data aggregation

Data relating to the plan form of dwellings was extracted from digital maps. Individual building properties were also inferred from reduced datasets as a function of the building age and type. In addition, London local temperature data was provided at a high spatial resolution by the London Site Specific Air Temperature (LSSAT) model.

It should be noted at this point, however, that the model output is restricted to an aggregated level of approximately 3,000 households rather than at the individual building level where the accuracy would be open to significant variation. Its main aim is to plot the spatial distribution of domestic heat demand across London rather than produce accurate estimates of actual energy consumption for *individual* properties. It could potentially form a flexible tool for urban modellers, planners and energy policy makers in order to investigate the effect of climate change and the heat island phenomenon on domestic energy use within a reduced level of disaggregation.

The model presented in this paper builds on previous work on GIS data extraction methods with reduced datasets. Despite the fact that data was derived from the digital maps at individual building level, the model output estimates have been aggregated to the Middle Layer Super Output Area (MLSOA) level. MLSOAs were first introduced by the Office for National Statistics (ONS) as Census output areas in 2001. They have a relatively consistent population size (minimum 5,000, mean 7,200). They are constrained by Local Authority boundaries and they are not subject to frequent border re-arrangement (ONS 2005). This level of output data aggregation was chosen in the present study for the following reasons:

(a) It is the minimum level of aggregation for which top-down London statistics are publicly available, including gas and electricity consumption data (DBERR 2009) as well as social profile data (ONS 2009).

(b) The level of inaccuracy tends to increase when aggregated building stock characteristics are assigned to individual dwelling units. As a result, the statistical interpretation of the model output would potentially be prone to the so-called 'ecological inference fallacy' (Openshaw 1984). This is a widely recognized error in ecological studies when the unit of analysis is groups of spatial entities rather than individual entities. In that case, the association that exists between variables at an aggregate level may not represent the true association that exists at an individual level.

(c) In addition, no meaningful results for individual units would be produced due to the inherent limitations of the BREDEM-type model i.e. it would be impossible to take into account individual occupant schedules and behaviour.

Therefore, it is not claimed that the model is able to predict accurately the actual energy consumption of individual dwellings. However, there is considerable value in applying such a methodology in order to capture the ranking of energy consumption of urban domestic users at an intermediate aggregated level.

Geographic data

The main GIS database used was the Greater London Area MasterMap Topography Layer, an extensively validated digital map provided by the Ordnance Survey (OS 2009). Every geographic feature in the map is represented by a polygon and a unique 16-digit code, the TOpographic IDentifier (TOID). The Topography Layer includes a rather crude land cover and land use classification system that distinguishes between natural and human surfaces, as well as residential and non-residential areas. By applying an automated script, each polygon was divided into individual properties by making use of the Address Point Layer 2, a set of points representing postal addresses and individual households in the case of multiple occupancy. It was assumed that the floor space area is equally divided between the address points contained within each polygon and that the resulting floor space area per address point is equally divided between the households contained in each address point.

The OS MasterMap Topography Layer was subsequently merged with the Cities Revealed database (Cities Revealed 2009), a commercial geographic image product. As an additional feature, the Cities Revealed Topography Layer polygons of domestic buildings are classified to 8 different age bands and 18 built form categories. The data was derived by a combination of aerial photography interpretation and on-site surveys. Height information for each polygon is also provided, based on 'Light Detection and Ranging' (LiDAR) surveys and other height data sources. Full data is currently provided only for a limited area of the OS MasterMap for London (covering the 349 MLSOAs shown in Figure 1). The results obtained from a trial run of the program in 95 MLSOAs (approximately 267,000 households) are showcased in the present paper.

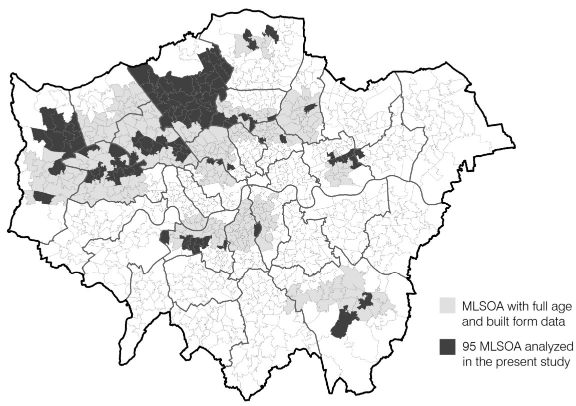

Figure 1 The Middle Layer Super Output Areas (MLSOA) data input to the model

The subset of these case study MLSOAs was selected according to the following criteria:

(a) Complete age and building type data was available for all building polygons within the MLSOA boundary.

(b) The MLSOAs were spread across the Greater London Area in order to form a representative sample of the existing domestic building stock and allow any heat island effects to be examined.

By applying a set of GIS algorithms, information on the footprint area, overall structure height, age band and built form was extracted for each polygon. In addition, the GIS processing method incorporated a series of formulae included in a model for estimating the external dimensions of UK dwellings when only a limited number of characteristics are known (Chapman 1994). BREDEM geometric data input parameters such as the average room height, the glazing ratio, the roof type and the form of the dwelling (i.e. detached, semi-detached or terraced) were thus estimated as a function of its age and building type.

An inference look-up table was built through the statistical analysis of the 2005 English House Condition Survey (EHCS) data (DCLG 2005). Ideally, this data would have been provided at Local Authority (LA) or Government Office Region (GOR) level. Unfortunately, however, the EHCS is based on a small sample of surveyed dwellings (approximately 16,600) that is aggregated to the national level. The sample would be too small at a local level to carry out any meaningful analysis. In addition, households that take part in the survey are assured anonymity and therefore no geographical indicators are released as part of the public dataset. Thus, it was not possible to extract the regional data from the database at this stage of the study. Consequently, the national level database was used. The predominant value of a series of building fabric and fuel systems characteristics was derived for each combination of age and building type. At a further stage, this data was assigned to each building polygon in the digital maps based on its age and type classification.

The London Site Specific Air Temperature Model

The input of localized data on Heating Degree Days (HDD) to the BREDEM calculation algorithm is an innovative element of the present study. This data was predicted using the London Site Specific Air Temperature (LSSAT) model (Kolokotroni et al. 2009) which comprises of a suite of Artificial Neural Network (ANN) models to predict site-specific hourly air temperature within the Greater London Area (GLA). The model was developed using a back-propagation ANN model based on hourly air temperature measurements at 77 fixed temperature stations and hourly meteorological data from Heathrow; the field measurements on which the LSSAT model is based were carried out in 80 locations (77 of which recorded sufficient data) covering eight transects as shown in Figure 2. A detailed description on measurement locations is presented in the research work done by Watkins (2002) and Kolokotroni et al. (2006). At all these locations, hourly basis data was collected for 18 months in 1999 and 2000 using Tinytalk loggers mounted on lamp posts at a height approximately 6 m above the ground. The Tinytalk was placed inside a white painted solar shield.

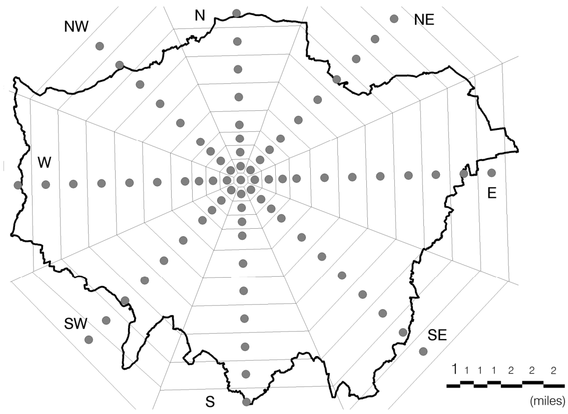

Figure 2 The eight transects of the LSSAT model in the Greater London Area

As part of the LUCID project, data was measured seven years later from the original dataset that includes new urban locations in order to test the temporal and spatial validity of the model. The LSSAT model was used to predict air temperature at the reference site (Langley Park) and one of the core sites in Central London (Montague Street) in October 1999 and 2007. This is a month that measured values are available for both sites. Heathrow meteorological station weather data required by the LSSAT model is also available for the same month. The correlation coefficient of measured and predicted temperatures are 0.97 (1999) and 0.88 (2007) for the Langley Park site and 0.94 (1999) and 0.82 (2007) for the Montague Street site. These results are as expected; the correlation between measured and predicted values is high in 1999 because this is the period used for training of the LSSAT model. The correlation in 2007 is lower for both sites, stronger for the Langley Park site, which is a rural site and therefore not affected by urban processes. It is also acceptable for the core urban site (Montague Street) which is mostly affected by urban processes.

As indicated by further analysis (Kolokotroni et al. 2009), site specific hourly air temperature prediction is within accepted range and improves considerably for average daily and monthly values. Thus, LSSAT predictions are particularly useful to calculate monthly and annual HDD. A comparison was made with HDD calculated for measured air temperature during January 2000 (these was available for 54 measurement locations, as data was missing for the rest). The correlation coefficient is 0.9988 for the 54 locations where comparison of predicted and measured HDD was possible, indicating almost perfect agreement. The annual HDDs calculated (September 1999 to August 2000) are presented in Figure 3. The calculated HDDs for Heathrow for the period considered is 1776 annual; the long-term average HDDs for Heathrow (CIBSE 2006) is 1731 annual indicating that the period examined here is not unusual.

The LSSAT model can be very useful in the calculation of HDDs for any base temperature across London using any Heathrow weather file for a specific year, design years or future climate years; such values can be used for the calculation of site-specific building heating and cooling loads.

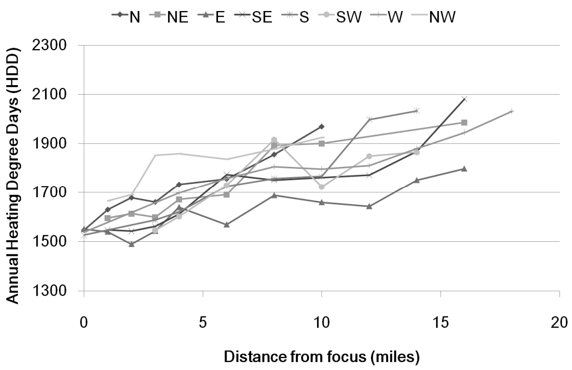

Figure 3 Predicted annual Heating Degree Days (HDD) for base temperature 15.5 ^{o}C calculated from September 1999 to August 2000, divided into the eight LSSAT transects

In the trial run of the model presented in this paper, each building polygon was assigned the localized HDD value of the nearest LSSAT measurement site. Nonetheless, it should be kept in mind that distance is not the only parameter to explain the variation in air temperature. A number of key microclimatic factors such as albedo, heat capacity and geometric characteristics of the surrounding area are expected to have a marked effect on the heat island intensity. The model will be further refined in the future in order to include these parameters.

The Parametric Domestic Energy Model

This data was finally fed into the Parametric Domestic Energy Model (Lowe et al. 2008), a modified version of the Standard Assessment Procedure (SAP) 2005 algorithm which is based on the annual version of BREDEM-9. The following modifications were made to the original spreadsheet:

(a) The default table that expresses annual HDDs as a function of base temperature contained in SAP was substituted by annual HDDs calculated for Heathrow. Hourly air temperature was provided for the period September 1999 – August 2000 from the MetOffice and subsequently the annual HDDs were calculated for the same period.

(b) An automated routine was also developed for the input of the LSSAT HDD.

The data exchange between the GIS database and the BREDEM spreadsheet was automated by a customized Dynamic Data Exchange (DDE) algorithm embedded in the model.

In order to assess the impact of the variation in external air temperature on domestic heat demand, two runs were executed: (a) one with Heathrow annual HDDs for all dwellings and (b) one with localized annual HDDs assigned at individual dwelling level. The difference between the base Heathrow HDD value and the LSSAT HDD values lies between +1012 and -307 HDDs.

Comparison with top-down data

The model output was finally compared to annual household energy consumption statistics at MLSOA level by collating a set of top-down publicly available datasets. Data on the count of dwellings, resident population, occupied household spaces, ownership type and other social characteristics (e.g. age of residents, income etc.) was provided at MLSOA level by the Office for National Statistics (ONS 2009). The annual domestic gas consumption profiles for the GLA at MLSOA level were provided from the Department for Business Enterprise and Regulatory Reform (DBERR) Regional Statistics. Data was available for the years 2004-06. Only the 2005 dataset was used (DBERR 2009) in the present study due to its high level of completeness and low percentage of unallocated data.

The comparison showed some discrepancy, for which a number of possible reasons for the discrepancy between aggregate data and the model predictions are identified:

(a) The DBERR top-down statistics are provided for the year 2005 whereas the model incorporates 1999-2000 HDD weather data. However, the average difference in the annual HDDs for the two years is approximately 10% for base temperatures between 1^{o}C and 20.5^{o}C. Therefore, the comparison between the two datasets remains valid.

(b) The DBERR data contains only gas and electricity totals at MLSOA level, whereas the BREDEM estimates are provided as primary and secondary fuel breakdowns. It was assumed that the primary fuel was gas in all the modelled households and that the primary fuel covers both space and domestic water heating demands. It is understood, however, that additional localized fuel type data (e.g. on the number of electrically heated dwellings at borough level) is needed in order to increase the accuracy of the model predictions.

DISCUSSION AND RESULT ANALYSIS

Domestic stock characteristics

A wide range of domestic dwelling types are covered in the case study MLSOAs examined. They vary from mid-war linked and step-linked two storey houses and late Victorian/Edwardian tall purpose shared discrete houses and maisonettes in semi-suburban areas such as Barnet and Brent to 4-7 storey post-war regeneration flat buildings in Camden.

Model output

As can be seen in Figure 4, the distribution of the primary fuel demand model estimates are heavily skewed to the left for both runs (Heathrow and LSSAT HDD data). As it would be expected, the use of the localized LSSAT HDD data increases the variation in the energy demand values. The domestic heat demand decreases by between 7.9% and 3.8% in urban areas such as Newham, Lambeth, Hackney, Wandsworth, Camden, Barking and Dagenham and Westminster and increases by between 7.1% and 4.0% in outer London boroughs such as Ealing, Enfield, Barnet, Hillingdon and Haringey, compared to the model output when Heathrow HDD were used for all sites. It should be noted however, that despite the fact that Heathrow is located towards the edge of the London urban heat island, it is significantly warmer that its rural surroundings. Thus, it is expected that the decrease in space heating demand due to the urban heat island phenomenon would be greater than the values presented above if a true rural reference site was used.

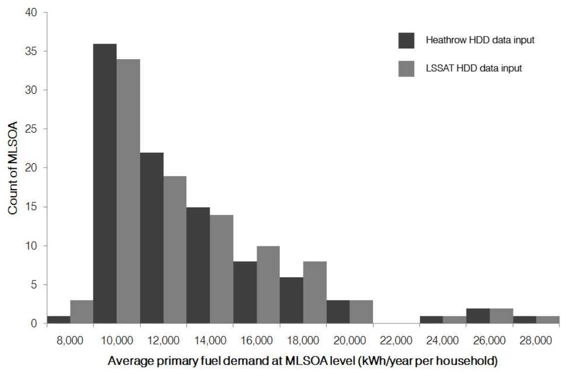

Figure 4 Distribution of primary fuel demand model predictions by using (a) Heathrow HDD data, (b) the LSSAT HDD data

The primary fuel demand for the 95 case study MLSOAs lies between 7,553 and 27,553 kWh/year per household when localized LSSAT HDD is used. The average demand is 13,113 (mean) and 11,923 (median) kWh/year per household. As can be observed there is a large number of MLSOAs clustered on the lower end of the axis and a small number of MLSOAs with average annual heat demand above 23,000 kWh/household. Approximately 1/3 of the total domestic heat demand is attributed to only 1/4 of the case study areas examined.

The highest values (between 24,000 and 27,500 kWh/year per household) were calculated for MLSOAs in Bromley, Hillingdon and Barnet. The area with the lowest domestic heat demand among the case study MLSOAs is located in Camden, followed by areas located in Hackney, Wandsworth, Barking and Dagenham and Newham with estimated energy demand below 10,000 kWh/year per household (Figure 5).

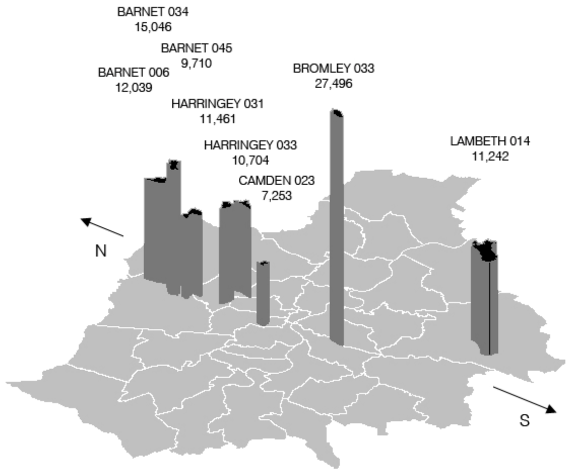

Figure 5 Primary fuel demand model predictions for MLSOAs located on the North-South transect of the Greater London Area (kWh/year per household)

Comparison with regional statistics

As can be seen in Figure 6, the model seems able to rank successfully the 95 case study MLSOAs according to their domestic heat demand. There is a good correlation between model predictions and gas regional statistics ($r(95) = 0.749$, $p = 0.000$). In addition, there is a strong correlation between the two ranking orders ($r(95) = 0.820$, $p = 0.000$).

It was observed that the outliers of the regression plot presented in Figure 6 are MLSOAs which (a) rank in the top 10% of household gas consumption (above 25,000 kWh/year per household), (b) rank in the top 20% of estimated average weekly income (above 950 pound sterling per week) and (c) feature large mid-war bungalows and single-storey detached houses located in the semi-urban areas of Barnet, Bromley and Hillingdon. Obviously, this could be partly explained by the fact that dwelling size is positively correlated with income but it might also be an indication of particular high-consumption lifestyle patterns.

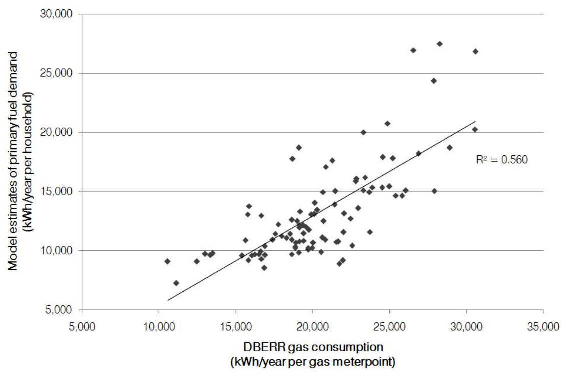

Figure 6 Comparison between DBERR gas consumption regional statistics and primary fuel demand model predictions

The heat island effect

As is illustrated in Figure 7, there seems to be a slightly positive correlation between domestic heat demand and distance from the centre of the London heat island (British Museum). However, as mentioned earlier, distance is not the only indicator of heat island intensity. Hence, additional urban morphology factors need to be co-examined in order to establish correlations with the model estimates.

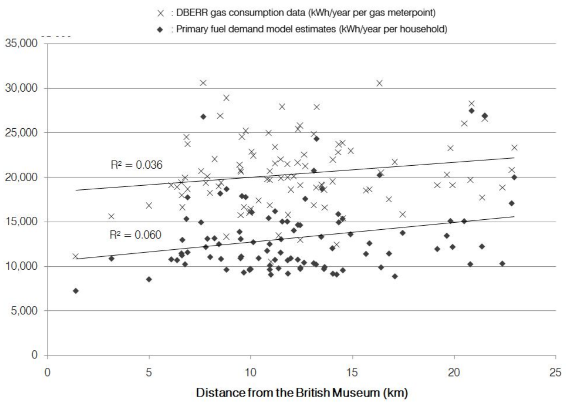

Figure 7 DBERR gas consumption regional statistics and primary fuel demand model predictions plotted against distance from the British Museum

Further research

The pilot run presented in this paper produced a set of encouraging results. Furthermore, it allowed the directions in which the model could be extended to be outlined. These could be summarized as follows:

(a) Local microclimatic features should be taken into account in addition with the building location for the assignment of HDD values at individual building level.

(b) The BREDEM-type spreadsheet currently features a limited look-up table of U-values as a function of the age of the property, based on historic UK Building Regulations energy efficiency requirements. This could be refined by making use of regional building fabric statistics as well as retrofit data and uptake rates of energy efficient measures and the replacement of elements with shorter lifecycles i.e. boilers at borough level.

(c) Future deliverables of the LSSAT model will include air temperature predictions for the year 2005 onwards. This will allow for a direct comparison between aggregate regional gas consumption statistics and the modelled domestic heat demand.

(d) Further investigation is needed on the social characteristics of the case MLSOAs in order to identify possible reasons for the observed differences between top-down/actual and modelled energy demand. This could potentially allow for the identification of individual occupant behaviour trends to be highlighted. For instance, income might prove to be a proxy for increased use of appliance related energy.

(e) In addition to the above, the methodology will be refined by making use of a monthly instead of an annual version of BREDEM and, consequently, monthly HDD predictions which will be generated by the LSSAT model.

CONCLUSION

The methodological tools and initial findings produced by a preliminary run of the heat demand-profiling tool in 95 case study MLSOAs were examined in the present paper. The heat demand estimates were decreased by up to 7.9% in central London boroughs as a result of using localized HDDs as input to the BREDEM model compared to results obtained by using Heathrow HDD data. The highest level of inconsistency between top-down statistics and modelled demand was observed for bungalows and detached houses in high income households located in semi-urban areas. At this time, it would be difficult for any definite conclusions to be drawn from such a small sample of data. Further work will produce estimates for all 349 MLSOAs for which classifications are available through an automated procedure. HDDs will be provided for the same year for which top-down energy data is also provided (e.g. 2005), in order to eliminate inconsistencies. It is also crucial that a sensitivity analysis is carried out in order to quantify the impact that different data input parameters (e.g. building form, physical properties) have on the model output.

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