Modelling Domestic Stock Energy Use and Heat-related Health Risk:
A GIS-based bottom-up modelling approach

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ABSTRACT: This paper demonstrates a systematic approach towards exploring the impact of urban built form and the combined effect of climate change and the urban heat island phenomenon on the levels of domestic energy consumption and heat-related health risk in London. The energy module of the study combines GIS databases and BREDEM-type algorithms to estimate the energy consumption of statistically derived dwelling types representative of the Middle Layer Super Output Area (MLSOA) level. External air temperature in various locations across London was predicted using the London Site Specific Air Temperature (LSSAT) model. Comparison of the model output for 10 case study areas with top-down energy statistics demonstrated that the model successfully ranks areas based on their domestic space heating demand. The health module of the model aims to investigate the urban texture factors that render domestic environments prone to higher risk of heat stress. The development and use of an epidemiological model that will feed into the health module is discussed in this paper. It is based on multi-variable analysis of deaths during heat wave and non-heat wave days in order to examine the influence on risk of heat-related mortality of local urban built form characteristics.
Keywords: domestic stock modelling, urban heat island, climate change, overheating, heat-related mortality

INTRODUCTION

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 [1]. Approximately 8% of the 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 of emissions is predicted, raising its annual emission rate to 51 million tonnes by 2025, if no action to tackle climate change is taken [2]. In addition to the UK national target to cut emissions by 80% by 2050 [3], the Mayor of London Climate Change Action Plan [2] set the challenging target to reduce the London CO_2 emissions by 60% by 2025. 38% of the total of delivered energy in London is associated with domestic energy use [2]. Thus, significant carbon savings can be achieved in the building sector. Importantly, the thermal performance of building envelopes is predefined to a large extent 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 [4]. Thereafter, predicting the baseline domestic stock energy demand at an urban scale forms a significant part of the CO_2 emission reduction strategies in the UK.

In addition, London is expected to experience an increasing risk of overheating in the future due to the combined effect of global warming-induced climate change and the intensification of the Urban Heat Island (UHI) [5, 6, 7, 8]. The temperature of the hottest summer day has increased by 5°C over the period 1977–2006. In the past, heat waves had a significant impact on the health and comfort of Londoners and have caused deaths and economic losses. An excess of 2,139 deaths were attributed to the August 2003 heat wave in England and Wales, a 17% increase to the number of summer deaths usually recorded in this region. The highest values of excess deaths were recorded in London (approximately 600) among those aged 75 and over [9]. Contrary to other climate change-induced risks (e.g. floods), heat waves are not possible to prevent and have no tightly defined physical boundaries [6]. Therefore, the development of a 'heat vulnerability index' which determines the combination of factors that make individuals and urban communities more at risk of heat stress forms an essential step of the risk identification process [6, 7].

AIMS AND OBJECTIVES

The main objective of the study presented in this paper is to outline the conceptual framework, the methodology and initial findings of a GIS-based domestic energy and summertime health risk modelling approach. The overall model comprises two modules: the Energy and the Health Module. The research work is attached to the 'Local Urban Climate Model and its Application to the Intelligent Design of Cities' (LUCID) research project [10].

The principle objective of the Energy Module of the model is the development of a Domestic Energy Use Profiling Tool for different levels of the urban hierarchy system. Data relating to the plan form of dwellings is extracted from digital maps and individual building properties are inferred from reduced datasets as a function of the building age and type. London local temperature data predictions are also provided at a high spatial resolution by the London Site Specific Air Temperature (LSSAT) model. This tool could be used by 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 output, however, will be restricted to an aggregated level of approximately 3,000 households and not at the individual dwelling level. Its main aim is to plot the spatial distribution of domestic energy demand across London rather than produce accurate estimates of actual energy consumption for individual properties.

The development of a Heat Vulnerability Index of London attempts to map the probability of urban domestic buildings to overheat and, thus, pose a heat-related risk to individuals and communities. In this current work a set of urban form factors, including builtspace ratio, green coverage ratio and urban volumetric density is analyzed at the citywide scale. This index could be of use to epidemiologists and public health policy makers attempting to quantify the variations in heat-related mortality within London and the degree to which such variation is explained by micro-variations in building and socio-demographic characteristics. As with the Energy Module, the Index aims to capture the ranking of the heat island 'hotspots' across London rather than simulate actual temperatures. The areas where heat wave mitigation strategies should be prioritised will be highlighted. As a result, the future burdens of heat-related mortality in relation to urban development could be estimated.

METHODOLOGY

The Energy Module: Many tools have attempted to predict the baseline energy performance of the existing UK domestic stock under different scenarios [11, 12, 13, 14]. The majority of the models are based on the Building Research Establishment Domestic Energy Model (BREDEM), the most widely used and extensively validated model for the calculation of space heating in the UK. The algorithms integrated in these models require a large amount of data input. On-site surveys, however, tend to be costly and time-consuming. As a result, Geographic Information Systems (GIS) tools have been extensively used in recent years in order to facilitate the calculation of the energy consumption and the carbon footprint of the UK housing stock without the need of visual inspection of the properties [15, 16, 17].

The model presented in this paper builds on previous work on GIS data extraction methods with reduced datasets. Despite the fact that data is derived from the digital maps at individual building level, the model output estimates in the present study are aggregated to the Middle Layer Super Output Area (MLSOA) level. MLSOAs are ONS Census output areas of relatively consistent population size (minimum 5,000, mean 7,200). They are constrained by Local Authority boundaries used for 2001 Census outputs and they are not subject to frequent border re-arrangement. This level of output data aggregation was chosen for two reasons: (a) Top-down energy consumption data is also available at the same level [18]. (b) The level of inaccuracy tends to increase when aggregated building stock characteristics are assigned to individual dwelling units, in addition to the inherent limitations of any BREDEM-type model (not taking into account occupant behaviour etc.). Therefore, the model does not claim that it is able to predict accurately the actual energy consumption of individual dwellings. However, there is considerable scope in applying such a methodology in order to capture the ranking of energy consumption of urban domestic users at an intermediate aggregated level.

An innovative element of this study is the input of localized data on Heating Degree Days (HDD) in each building polygon. These data were predicted using the London Site Specific Air Temperature (LSSAT) model [19] 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 77 locations covering eight transects shown in Fig. 1 [19, 20, 21]. The temporal and spatial validity of the model was tested using data measured seven years later from the original dataset which include new urban locations as part of the LUCID project. Further analysis has indicated [19] that site specific hourly air temperature prediction is within accepted range and improves considerably for average daily and monthly values. The calculated HDD for Heathrow for the period considered were 1,776 annually; the long-term average HDD for Heathrow [22] were 1,731 annually indicating that the period examined here is not unusual. Therefore, the LSSAT model can be very useful in the calculation of HDD 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 loads. Annual HDD were calculated for the period September 1999 to August 2000 for all locations. The HDD value of the nearest station was subsequently assigned to all domestic buildings in the Greater London area.

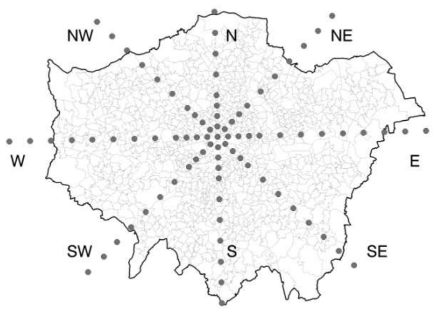

Figure 1: The eight transects of the LSSAT model in the Greater London Area.

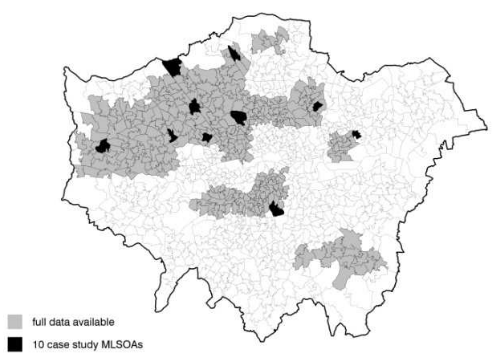

Figure 2: The Middle Layer Super Output Areas (MLSOA) data input to the model.

The main GIS database used was the Greater London Area MasterMap Topography Layer, an extensively validated digital map provided by the Ordnance Survey [23]. The Topography Layer includes a rather crude land use classification which 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/households by making use of the Address Point Layer 2, a set of points representing postal addresses together with a count of households per address point in the case of multiple occupancy. The OS MasterMap Topography Layer was subsequently merged with the Cities Revealed database [24], a commercial geographic image product. As an additional feature, the Cities Revealed Topography Layer polygons are classified to 8 different age bands and 18 built form categories. The data is 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 number of OS MasterMap chunks (covering the 350 MLSOAs shown in Fig. 2). Results for only 10 case study MLSOAs are showcased in the present paper. An attempt was made to select MLSOAs spread across the Greater London Area which are representative of the domestic building stock.

The GIS processing method incorporates a series of formulae included in a model for estimating the external dimensions of UK dwellings when only a limited number of characteristics is known [25]. BREDEM data input parameters such as the average room height, the terrace level, the glazing ratio and the main heating fuel type were estimated as a function of age and building type. Next, a 'notional' dwelling type was created for each MLSOA by averaging the building properties of the existing stock. A set of pivot tables was built by making use of the English House Condition Survey (EHCS) data [26]. For each age/type combination the predominant value for a series of building fabric characteristics was selected, and then assigned to each 'notional' building type. These data were subsequently fed into the Parametric Domestic Energy Model, a modified spreadsheet version of annual BREDEM-9/SAP [27].

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 and occupied household spaces is provided at MLSOA level by the Office for National Statistics (ONS) [1]. The annual domestic gas and electricity consumption profiles for the GLA at MLSOA level are provided from the DBERR Regional Statistics [18]. Data is available for the years 2004-06. Only the 2005 dataset was used in the present study due to its high level of completeness and low percentage of unallocated data. It is understood that this might increase the discrepancy between aggregate data and the model predictions (which are based on 1999-2000 HDD estimates).

The Health Module: The heat island phenomenon has been commonly associated to urban environments where a set of urban texture factors, such as high artificial surface coverage ratios and built density, raise the outdoor air temperatures. In addition, there is a well established relationship between outdoor temperatures and the risk of heat-related mortality [28, 29]. London death record data for the year 2003 was provided from the ONS aggregated at unit postcode level. Unfortunately, however, no local air temperature data is available at such a fine spatial resolution for the 2003 heat wave period. Thus, the method underlying the model described in this paper aims to link the urban form characteristics directly to heat-related mortality. By applying a number of customized GIS tools, a set of urban built form area markers were assigned to each unit postcode where deaths occurred during the 2003 heat wave. Land cover data was derived from the OS MasterMap Topography Layer and LiDAR height data from the Cities Revealed database. The UK unit postcodes have no geographically defined boundaries. Hence, the following area markers were generated for a circle with a radius of 250 m drawn around each unit postcode's centroid (Fig. 3): (a) builtspace ratio, (b) artificial coverage ratio, (c) green coverage ratio, (d) water coverage ratio, (e) urban volumetric density. The heat wave period analyzed (20 July – 31 August) was defined from the analysis of temperature and deaths patterns. Then, the excess number of deaths was linked to the area characteristics based on unit postcode of residence. The data was consequently normalised for a series of socioeconomic characteristics, such as age, sex and quartile of socio-economic deprivation. An epidemiological model was used to examine the association of excess deaths with these area markers by comparing the number of deaths in the heat wave period to the number of deaths during non-heat wave periods.

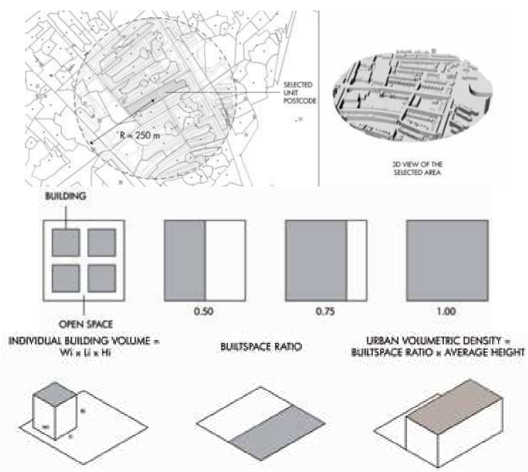

Figure 3: Definition of area built form characteristics (urban builtspace ratio and volumetric density).

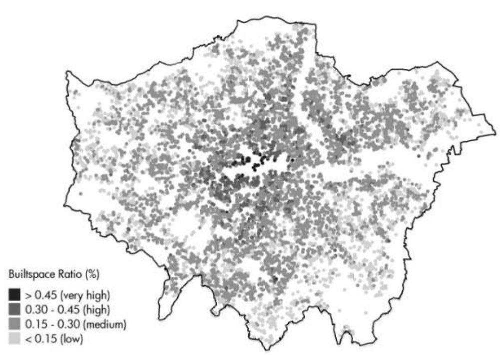

Figure 4: Builtspace ratio for London unit postcodes where deaths occurred during summer 2003.

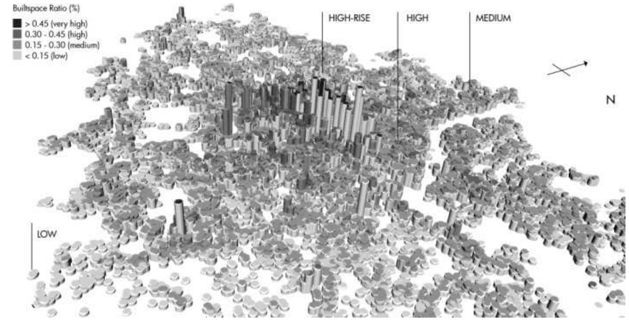

Figure 5: Urban volumetric density for London unit postcodes where deaths occurred during summer 2003.

RESULTS

Energy Module: The 'notional' typical dwellings constructed for each MLSOA cover a wide range of domestic building types. They vary from mid-war semi-detached properties of 120 m^2 on average in central MLSOAs such as Camden and Brent to larger bungalows in semi-suburban areas such as Barnet. As can be seen in Fig. 6, the model seems able to predict the baseline space heating requirement of London dwellings with ±1.5%-24% accuracy. Most importantly, it ranks successfully the 10 case study MLSOAs according to their annual household gas consumption. As is illustrated in Fig. 7, there is a good correlation between model predictions and energy regional statistics ($r(10) = 0.877$, $p = 0.01$). An apparent outlier is Southwark 031, which also happens to be characterized by the highest average floorspace area (above 200 m^2). It is also the MLSOA with the second highest estimated weekly income (15% above the average of the ten areas). No significant correlation has been established at this stage of the work between space heating demand and distance from the centre. This might be, however, an indication of additional parameters, such as local microclimatic features and the position of the locations within the GLA, that need to be taken into account [19].

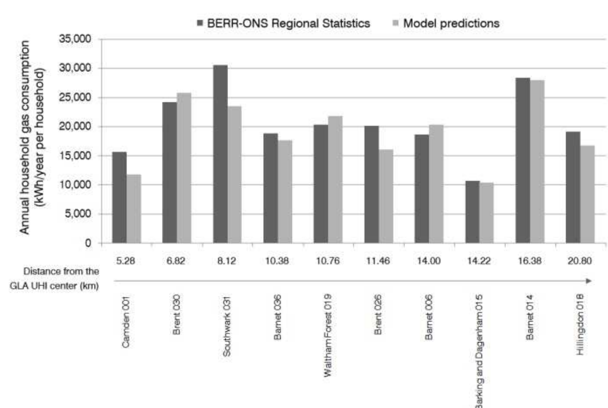

Figure 6: Comparison between the energy model output and BERR/ONS top-down statistics: Gas consumption (kWh/year per household) for the 10 case study MLSOAs ordered by distance from the London UHI centre.

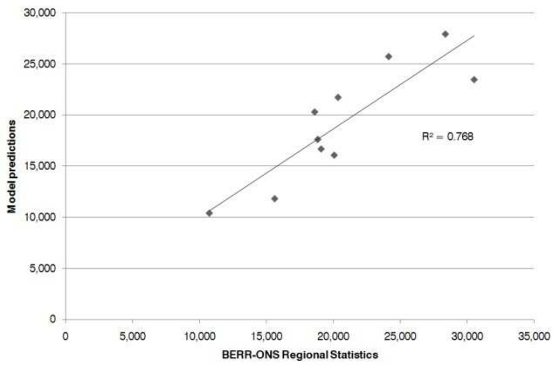

Figure 7: Regression plot of space heating demand model predictions against BERR-ONS Regional Statistics (kWh/year per household).

Overall, the heating demand of the 10 MLSOAs is reduced by 21.5% on average as a result of using the localized HDD data (heat island effect).

Health Module: The correlation matrix between the various area markers is shown in Table 1. The objective underlying the construction of this table is to identify the variables that are strongly correlated and then reduce the number of input variables by keeping only the independent ones. It was found that builtspace ratio is highly correlated with volumetric density (r = 0.8574) and artificial coverage (r = 0.8957). As expected, there is also a strong negative correlation with green coverage (r = -0.8564). This means that it would be appropriate to use only two of the area markers (i.e. builtspace ratio and water coverage) as independent variables in the epidemiological model.

Table 1: Correlation matrix of urban form area markers.

	Built space	Vol density	Artificial	Green	Water
Built space	1.0000				
Vol density	0.8574	1.0000			
Artificial	0.8957	0.7882	1.0000		
Green	-0.8564	-0.7738	-0.9715	1.0000	
Water	-0.1138	-0.0258	-0.0788	-0.1332	1.0000

A basic version of the epidemiological model was then used to estimate the heat-related relative mortality risk for the whole sample of unit postcodes where deaths occurred in the 2003 heat wave and to examine its association with builtspace ratio. There seems to be an early indication that deaths tend to increase in densely built areas of the urban heat island: The odds ratio adjusted for age, sex and quartile of socio-economic deprivation odds ratio was 1.44 (95% C.I. = 0.64-3.23).

DISCUSSION AND FURTHER RESEARCH

Testing the heat demand profiling tool in 10 case study MLSOAs produced a set of encouraging results. However, no definite conclusions can be drawn from such a small sample of data. Further work will produce estimates for all 350 MLSOAs for which classifications are available through an automated procedure. HDD 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. 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. Another important issue is that the use of such a tool presupposes that (a) there is a simple linear relationship between age and the physical properties of the building element i.e. U-values, on the one hand, and (b) the majority of the older dwellings have not been refurbished, on the other. The tool will thus be refined and incorporate information on uptake rates of energy efficient measures and the replacement of elements with shorter lifecycles i.e. boilers, in a newer version of the model.

The initial results obtained from the heat wave vulnerability study partly fit expectations regarding the possible effects of urban built form to the relative heat-related mortality risk. Further steps of the study will entail increasing the spatial resolution of the death record data. Importantly, the statistical analysis will be extended to include data for further heat waves, possibly covering the period from 1994 to 2006. The data sample could also be further adjusted to other socio-economic factors such as health status etc. Temperature and air pollution models could be integrated as additional variables to the epidemiological model, if such predictions at a high spatial resolution are made available. An important step of the study will be the acquisition of land surface temperature data from satellite imagery provided for a number of heat wave years. These data could be georeferenced and linked to both building parameters and mortality data. Last but not least, further work might include indoor climatic conditions.

CONCLUSION

This paper has presented work in progress on the development of a GIS-based energy consumption and heat vulnerability index of the Greater London Area domestic stock. Initial findings from a case study area of 10 MLSOAs, for which gas consumption was calculated based on HDD prediction using the LSSAT model, served as a demonstration of the concept of predicting the baseline domestic stock energy demand. The annual consumption estimates of statistically derived ‘average’ dwelling types for each MLSOA were compared to top-down publicly available energy and population statistics. The relative accuracy of the energy model results in this paper provides strong confirmation of the model’s ability to play a useful role in informing the process of CO_2 reduction policy making in Local Authorities. With regards to the heat vulnerability index, it appears that builtspace ratio may prove to be a proxy for heat-related mortality risk. However, taking into account that heat vulnerability is a complex phenomenon more data from other heat wave years are needed in order to determine whether any effects of urban microclimate characteristics can in fact be observed. It is expected that further work both on the energy and health aspects of the model will capture the spatial ranking of London population groups in terms of domestic energy consumption and heat-related vulnerability. These data could be visualized by using thematic maps, and thus, enable the quick identification of areas that home improvement schemes need to target.

ACKNOWLEDGEMENTS. The LUCID project is funded by an Engineering and Physical Sciences Research Council (EPSRC) grant. One of the authors (A.M.) is also supported by the Greek State Scholarship Foundation (IKY).

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