Energy Justice? A spatial analysis of variations in household direct energy consumption in the UK

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Abstract

Targets for reductions in carbon emissions and energy use are usually framed in terms of national and international percentage reductions. However, the amount of energy used by households varies greatly, with some households using considerably more than others and therefore potentially being able to make a bigger contribution towards societal reductions. Using recently released datasets from the UK Government, we present exploratory analyses of patterns of direct household energy usage from domestic gas and electricity consumption and from private motor vehicles. These analyses of the data reveal that those households with the highest domestic energy consumption may be also likely to be those that use the most energy from their motor vehicles. Whilst much work has been done around fuel poverty, our findings suggest that there may be an opposite issue around 'energy decadence', where the actions of certain households or groups within society are placing much greater strain on energy networks and environmental systems than they need. These people may also be the ones most likely to be able to afford energy efficiency measures to reduce their impacts and should therefore be a high priority in the targeting of policy interventions.

However, household energy resource isn't necessarily a simple 'good' that ought to be equally distributed. Different housing stock, accessibility of services and a wide range of other factors all lead to different energy requirements in order to attain acceptable quality of life. Using the spatial basis of the datasets, we link energy use data with a range of other data in order to try to differentiate between areas of profligate energy use and those of high energy need. The near universal coverage of these government datasets allows an entirely new geography of energy to be mapped out, opening up new possibilities for targeting interventions for energy reduction at those who can make the greatest savings, whilst ensuring that those who can't are protected from adverse effects of energy policies.

Introduction

There is an existing body of work that focusses on household energy use and carbon emissions in the UK and how these are distributed according to a range of socio-demographic and other parameters. However, due to limited datasets, to date this work has been restricted in its analysis of spatial patterns of use and emissions.

This paper seeks to build on this existing work through presenting a new methodology that can be used to gain further insight into patterns of energy use and emissions. Our work uses new datasets (to be discussed later) from the UK Government that have not yet been used for this type of analysis, along with data from the latest UK Census in 2011 to provide an up-to-date picture on the distribution of energy use and emissions.

Previous studies in the UK have tended to be based around a set of surveys, primarily the English House Condition Survey the Expenditure and Food Surveys, the UK Living Costs and Food Survey, but also including the National Travel Survey, and Air Passenger Survey (see Dresner and Ekins, 2006; Brand and Boardman, 2008; Druckman and Jackson, 2008; Thumin and White, 2008; Gough et al., 2011; Buchs and Schnepf, 2013a, 2013b and Hargreaves et al., 2013). There are two significant drawbacks to this approach. Firstly, although the sample sizes of many of these surveys are very significant (often in excess of 20,000 households in any one year), they still represent a small sample of the total 26 million UK households. Secondly, although some studies (in particular Druckman and Jackson, 2008) have used this data in combination with spatial data from the UK Census, the limited sample size means that it is difficult to undertake mapping or significant spatial analyses.

In this paper we describe two new datasets released by the UK Government that together provide both (near) universal coverage and spatial information about three key elements of household energy/carbon footprints: domestic gas and electricity usage and private car usage, and present some exploratory analyses to determine whether they can be of use in understanding socio-demographic and geographic influences on patterns of energy use. Although these datasets come with their own limitations (which will be discussed below), we believe that they can both provide a useful comparison to elements of the survey based work described above, and provide new insights of their own. After an initial description of the datasets, we then present a range of initial analyses looking at how different patterns of energy use are distributed with respect to a range of factors, including poverty and deprivation, rural and urban location, housing tenure, property type and employment status, in order to identify potential social and environmental justice issues regarding both energy consumption and potential policy interventions to reduce it.

Calculating Average Household Energy Consumption

Household Gas and Electricity Consumption Data

Since 2004 the UK Department of Energy and Climate Change (DECC) has produced data on domestic gas and electricity consumption at a sub-national level based on meter data provided by the energy supply companies (DECC, 2014). Since 2008, this data has been made available at the resolution of Lower-layer Super Output Areas (LSOAs). These are areas developed for the UK England and Wales Census with a minimum size of 1,000 residents, or 400 households, and a maximum population of 3,000 residents or 1,200 households. In total there are 34,753 LSOAs in the 2011 census in England and Wales, with an average of 1,500 residents each. Their design is intended to make them reasonably compact, and to allow significant social homogeneity within each area.

For each LSOA[1], DECC provide figures for the number of domestic meters for electricity (both standard and dual tariff) and gas, the total energy use for these, and the average energy use per meter. DECC report that, "the combined electricity and gas provide a good indication of overall annual household energy consumption in Great Britain at local authority, MSOA/IGZ and LSOA level due to the robustness of the data collection and collation process [from individual meters]" (DECC, 2014, p19). This data thus provides details of universal metered domestic energy use from gas and electricity, albeit at a cost of lack of granularity, with average household use for around 600 households. Also, whilst providing gas and electricity usage data, there is no information on use of oil, bottled gas, or solid fuel use. It is also important to take into account that gas consumption data has a weather correction factor applied to it, whilst electricity consumption is not weather corrected. This creates some potential issues regarding the comparison of gas and electricity usage related to heating, particularly when looking at the data longitudinally.

Figure 1 shows maps of gas, electricity and total domestic (i.e. gas+electricity) consumption. On the gas map, the white 'holes' where areas are not on the gas grid are particularly noticeable. Many of them appear again as blue areas of low total energy consumption in the third map where gas is replaced as a heating fuel by bottled/tanked gas, oil or solid fuels which do not appear in the DECC statistics. In some off-grid areas though

[1] Although in some areas with low numbers of meters, LSOAs are merged to add confidentiality to the data. Where LSOAs have been merged, the mean electricity/gas usage for the whole area has been allocated to each of the LSOAs.

gas may be replaced by electricity, and as this is usually used to operate storage heaters on the ‘Economy 7’ dual time tariff, future analysis of this will be undertaken. Electricity, LPG and coal are sometimes used for central heating systems, but these are rare. Currently, 83% of homes in Great Britain are heated by gas, 9.3% by electricity, 4.4% by heating oil, 1.2% by solid fuel and 0.7% by LPG (Baker, 2011). Further work will also be carried out looking at off-gas-grid areas in relation to information from the Census on the prevalence of central heating in these areas (which would tend to denote the use of oil).

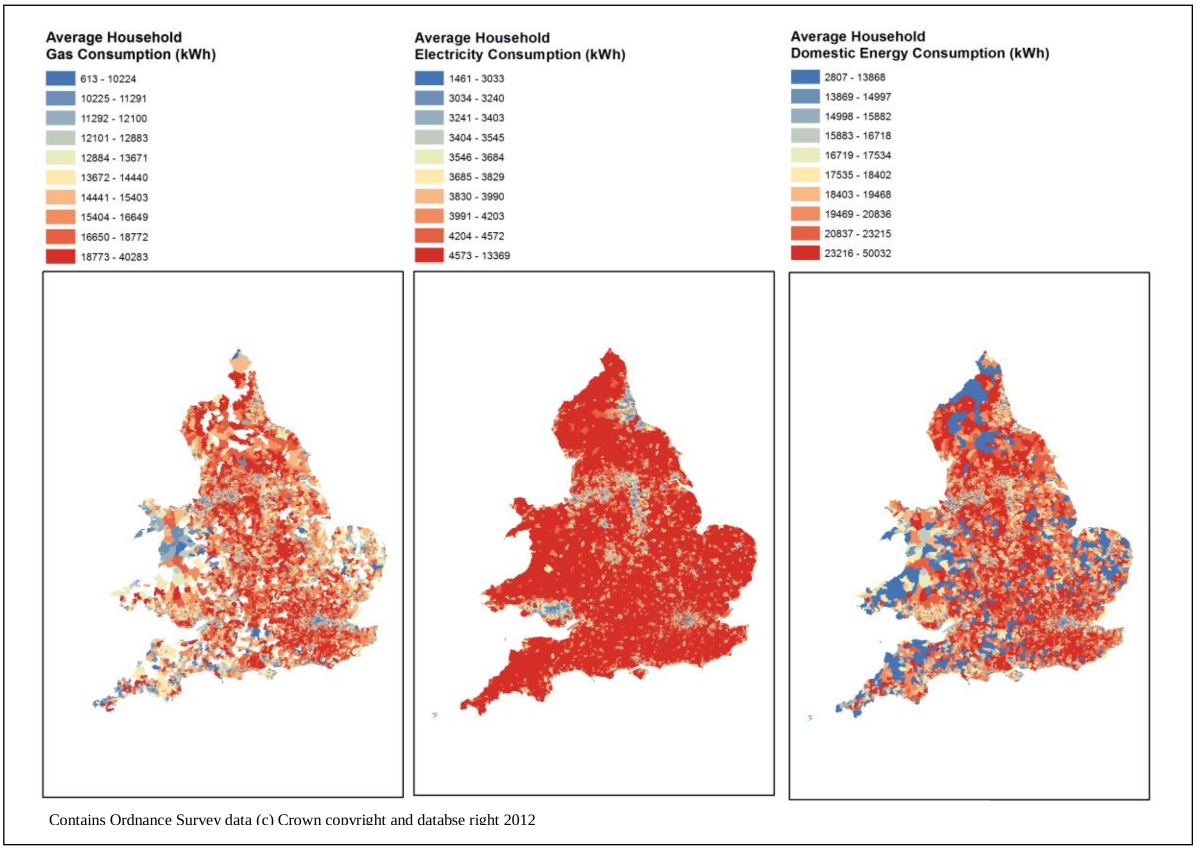

Figure 1: Mapped data for gas electricity and total domestic (gas+electricity) consumption at LSOA level

Private Car Use

In 2010, the UK Department for Transport began publishing the records from the annual vehicle roadworthiness inspections (known in the UK as ‘MOT’ tests). These tests are required for every vehicle over three years old. This data provides details of the make and model of each vehicle, engine size, fuel type, date of first registration and colour, along with the recorded mileage at each test. Using the latter, it is possible to estimate the annual mileage of each vehicle (see Wilson *et al*., 2013a, Wilson *et al*., 2013b, Cairns *et al*., 2013), and from this to then calculate the annual energy usage and air pollution and greenhouse gas emissions from each vehicle (Chatterton et al., 2013). Figure 2 shows the spatial variations in the key vehicle parameters and derived fuel and energy consumption.

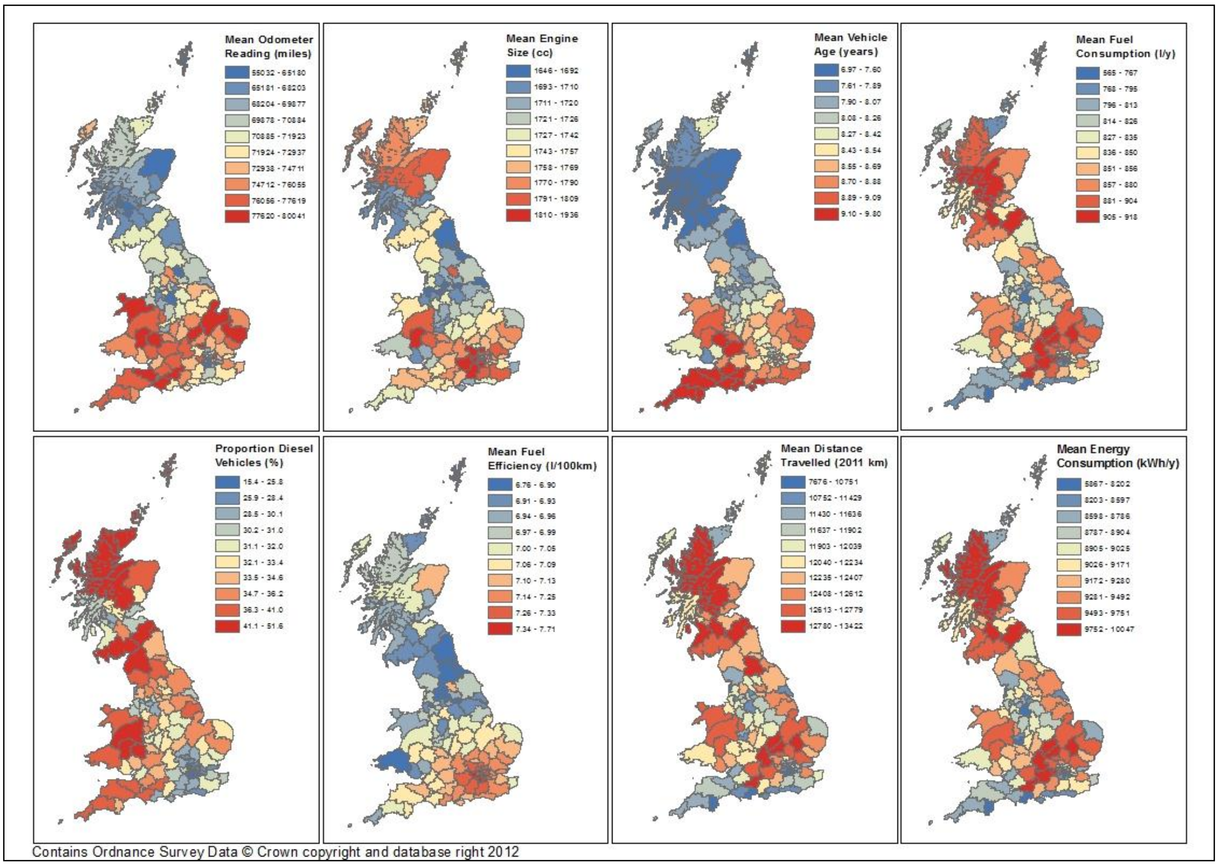

Figure 2: Spatial variations in key vehicle parameters across postcode areas

Matching the datasets

In the absence of a current ability to match individual vehicles to LSOAs, a method has been devised to estimate household emissions from private car use. Annual emissions and energy use are calculated for every vehicle within the dataset. A vehicle profile is then created for each postcode area, based on the mean emissions and energy use of all the vehicles within that area. Then, using data from the 2011 Census on the number of cars per household, a figure is calculated for each LSOA for the number of cars per household (that have access to a car). This is multiplied by the figures from the vehicle profile for the postcode area in which the LSOA centroid sits, in order to estimate the annual emissions and energy footprints for an 'average' household, to facilitate comparison with the averages for domestic gas and electricity usage from the DECC data. This can then be mapped as shown in Figure 4. Figure 3 shows the general correlations between gas and electricity usage for each LSOA, as well as between domestic energy usage (gas + electricity) and car usage. The top plots (showing a 1:1 line) show that energy use from gas consumption is generally much greater than through electricity consumption. This highlights the problem with the significant focus of many energy behaviour interventions around instant feedback using clip on electricity monitors. These only report a small fraction of actual domestic energy consumption (and even that is being rapidly decarbonised *in comparison to gas*). With increasing electrification of cooking and space heating, this also indicates that there will be a sizeable increase in domestic electricity demand (even if significant end-use efficiencies can be achieved through new technologies related to the fuel shift). Domestic energy consumption also tends to be much greater than through car usage. The lower plots, showing regression lines for gas against electricity use (R-squared = 0.40, $p<0.001$), and car against domestic use (R-squared = 0.34, $p<0.001$), indicate the tendency for energy use to increase in one domain, as it increases in another.

This is also demonstrated in Figure 5, where LSOAs have been divided into percentiles for energy use across all three domains and plotted against three axes (with energy use from car as a function of gas and electricity consumption). It is apparent from this that those households who consume the most electricity and gas, also use the most energy through private car usage. Whilst this pattern is of interest in and of itself, particularly within the context of increasing electrification of both home heating/cooking (Energy Institute, 2012) and vehicle use (OLEV, 2013), it raises questions as to whether those households represented in the elevated section of the plot might be victims of circumstance, and trapped in a position of high 'energy need' (for example poorly maintained homes in rural areas inaccessible by public transport, cycling and walking) or whether this represents a profligate use of energy where wealth and circumstance allow high energy consumption through choice (what we have termed 'energy decadence'). To make this assessment further analyses are needed.

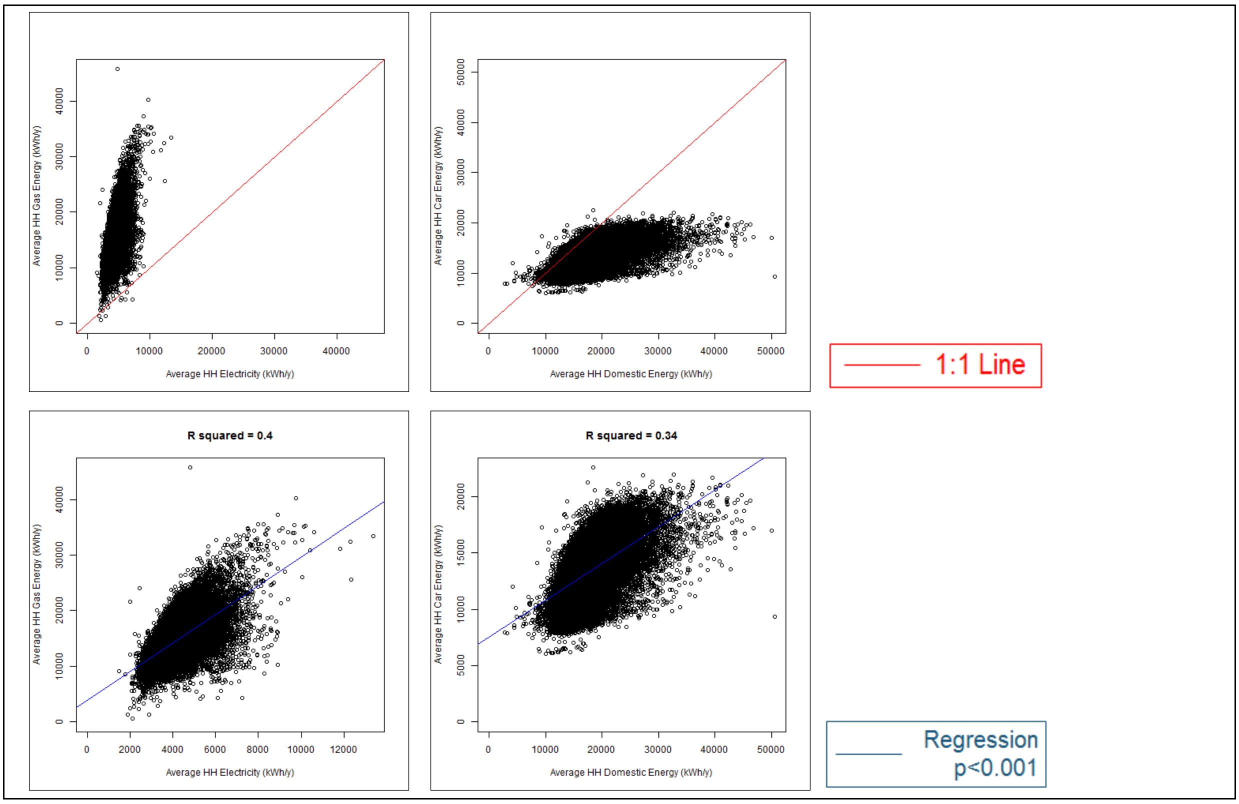

Figure 3: Relationships between gas and electricity consumption, and domestic energy and private car use

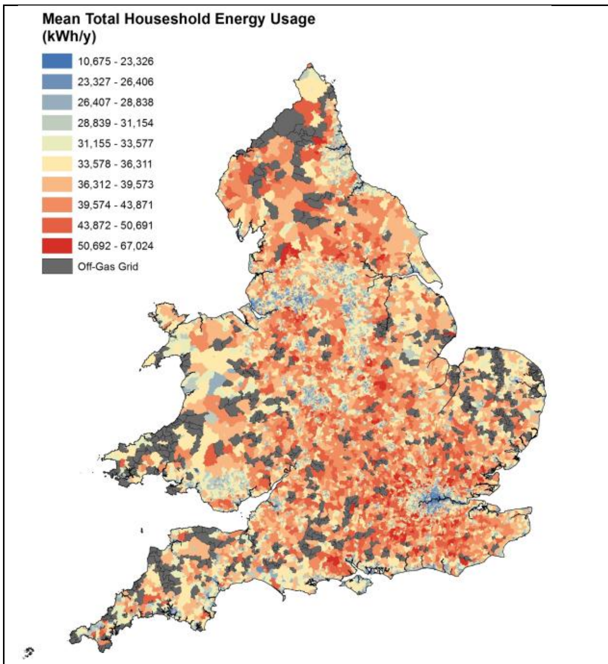

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Figure 4: Maps of energy consumption from gas, electricity and private car use

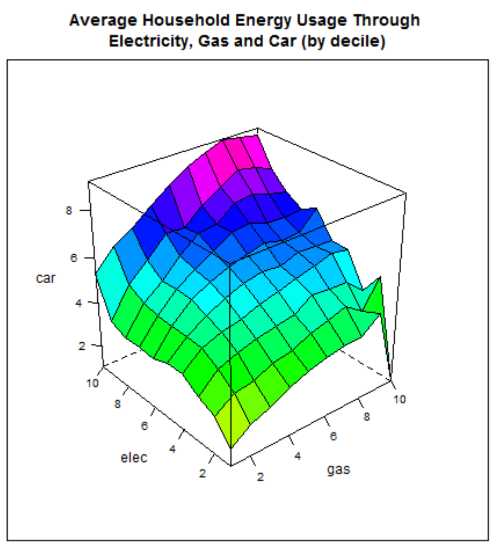

Figure 5: Energy consumption from car use in relation to gas and electricity consumption

Assessing Distributional Impacts and Justice Issues

Once average household energy usage, from gas and electricity consumption and private car use, has been estimated for each LSOA in England and Wales, it is then possible to link this to a wide range of socio-demographic and geographic information from the 2011 Census and other sources. Two sets of analyses are presented here: firstly an analysis based on the relationship between average energy use within each LSOA and the degree of poverty within that area; secondly, a deeper breakdown of the socio-demographic and geographic factors that relate to different patterns of energy usage.

A poverty analysis

Environmental justice (EJ), as a concept, began in 1982 in the US with the objection by "communities of colour" in Warren County, North Carolina to the siting of hazardous waste landfill sites in their localities (Mohai, Pellow & Roberts, 2009). Known also as environmental racism, environmental inequality and environmental injustice, the focus in the US has tended towards the unjust spatial relationships between ethnic groups and locations of industrial and waste sites, and the lack of public engagement with these minority groups. Most non-US EJ-air pollution studies have focused on socio-economic status (SES) rather than ethnicity, and may also be referred to as social justice or sustainable development studies, reflecting the greater relevance of inequity of poverty or deprivation in these areas.

Measures of poverty

Historically, poverty has been measured either indirectly, in terms of a lack of resources, e.g. income, or directly, as the consequences of that lack of resources on standards of living, e.g. deprivation. Definitions and distinctions may not be consistent over time or space and therefore it is essential that research referring to poverty metrics utilises the most appropriate measure. From a review of the previous studies on energy justice issues listed above, along with other work on social justice and air pollution (Mitchell & Dorling, 2003) and investigation of other available datasets, six potential indicators of poverty were identified that might be suitable for the study. These were:

The Breadline Britain Index (BBI90) was developed by David Gordon and Christian Pantazis in the 1990s from an individual and household level analysis of the data from the Breadline Britain survey in 1990 and allows the percentage of households in poverty ('Below the Breadline') in any area to be calculated using variables available from census data (Macgregor, 1998, p. 618) relating to factors such as housing tenure, employment, health, household composition. The values for calculating the BBI90 were applied to the latest 2011 Census data (N.B the UK Census is has been undertaken every 10 years since 1841).

Poverty and Social Exclusion (PSE99) The survey for the BBI was undertaken again in 1999 by PSE (Poverty and Social Exclusion http://www.poverty.ac.uk) to establish a new set of variables for use with the 2001 Census to reflect changing patterns of poverty. As with the BBI90, the factors derived from this survey were applied to 2011 Census data. In order to test the degree to which changes might affect the use of PSE99 with 2011 Census data as compared to 2001, the PSE99 was calculated using both 2001 data (PSE99(01)) and 2011 data (PSE99(11)) and put in the comparison. Annex 1 provides the specific factors used to calculate the PSE99 Index.

InFuse Deprivation Index (InFuse) is a per household classification of deprivation based on whether or not a household meets one or more of the following conditions (InFuse, 2014):

- **Employment:** where any member of a household, who is not a full-time student, is either unemployed or long-term sick.
- **Education:** no person in the household has level 2 education or above[2]), and no person aged 16-18 is a full-time student.
- **Health and disability:** any person in the household has general health that is 'bad' or 'very bad' or has a long term health problem.
- **Housing:** the household's accommodation is either overcrowded, , or is in a shared dwelling, or has no central heating.

[2] 5+ O Level (passes) CSEs (Grade 1)/GCSEs (Grades a*-c), School Certificate, 1 A Level/2-3 AS Levels/VCEs, Intermediate/Higher Diploma, NVQ Level 2, Intermediate GNVQ, City and Guilds Craft, BTEC First/General Diploma, or RSA Diploma Apprenticeship.

The Children in Low Income Families (CLIF) is the proportion of children living in families within the UK that are either in receipt of out-of-work benefits or in receipt of tax credits with a reported income which is less than 60 per cent of national median income (Child Poverty Unit, 2014).

Indices of Multiple Deprivation (IMD) Separate indices of deprivation are available for England from the Department for Communities and Local Government (DCLG, 2011) and in the case of Wales from the Welsh Index of Multiple Deprivation (WIMD) (Welsh Government, 2014). The indices of multiple deprivation are based on a range of types of deprivation including: income; employment; health; education; access to services; community safety; physical environment and housing. Because of differences in how these measures are calculated in England and Wales there are problems with directly comparing them, however the method described below addresses some of these.

Median Household Income (Experian) is an estimation of median household income per LSOA, estimated from modelling based on a stratified random sample of 55,000 responses to YouGov surveys (Experian, 2011).

Comparing measures of poverty

In order to decide on one indicator of poverty/deprivation for use in this study, a simple comparison was undertaken of the measures described above. So that the different measures could be compared, the LSOAs were grouped in 1 percentile bins from least deprived to most deprived (except for income which was kept reversed, i.e. higher median income implying lower levels of poverty/deprivation). All measures compared well, with significant correlations ($p<0.001$) and R-squared values greater than 0.5. All measures other than income showed R-squared values greater than 0.71 (see Figure 6).

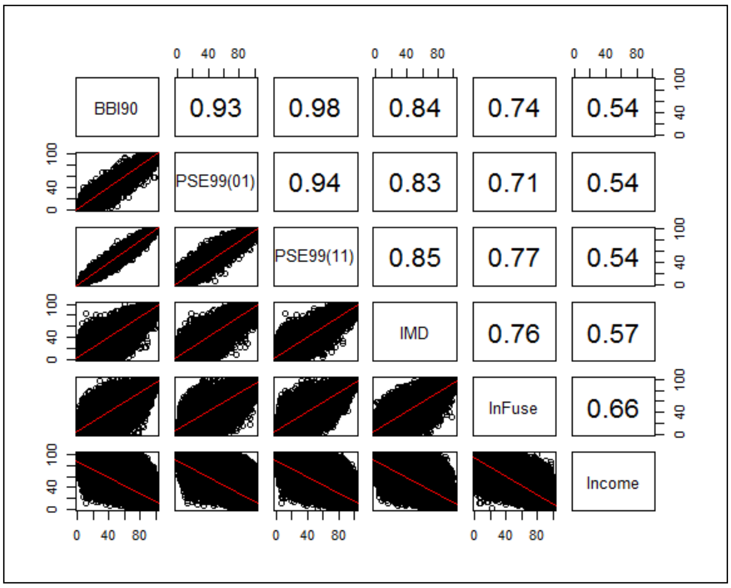

Figure 6: A comparison of available measures of poverty (R-squared values shown)

Taking a range of factors into consideration, it was decided to use the PSE99 index, calculated from the 2011 Census data as the main measure of poverty for the study. Despite caution regarding the use of factors calculated a decade apart, the strong correlation between the BBI90 and PSE99 factors suggest that this may still hold some validity. Other measures were discarded for various reasons. The CLIF was deemed to be too focussed on child poverty rather than households. The Indices of Multiple Deprivation were considered problematic due to the separate indices for England and Wales. Income was considered inappropriate due to the potentially poor correlation with wealth, and its basis on median income rather than percentage of households. The InFuse Deprivation index, while sharing many similarities with the PSE99 index, was rejected as it is not currently a generally accepted or established measure of deprivation, and no evidence was found in the literature of previous use.

Using a method established by Mitchell and Dorling (2003) in their analysis of environmental justice and air pollution, the PSE99 poverty index was used to calculate poverty based deciles, for which the mean percentage of households in poverty and mean energy usage for each energy domain (gas, electricity and car use) were calculated.. These have been plotted in Figure 7, with (very small) error bars indicating the 95% Confidence Interval. The plots indicate a very strong inverse relationship between the percentage of households in poverty and energy consumption across each domain, extending also to the totals for domestic and overall energy use.

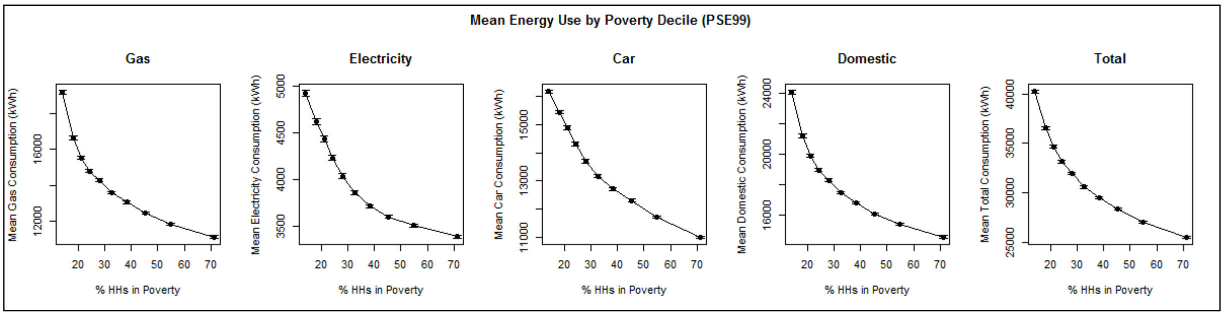

Figure 7: Analysis of energy use by type against percentage of households in poverty (PSE99)

In planned future work, the relationship between the levels of consumption of the most and least deprived percentiles will be investigated, as differences in how these vary above zero may reveal valuable information about baseline usage for each domain of energy use.

It is important to note with measures of deprivation and poverty, that the absence of poverty (i.e. fewer households in poverty) does not necessarily indicate affluence. Therefore, despite indications that higher levels of poverty are related to lower levels of energy usage, further investigation is required to identify why this might be the case. Therefore, in the following sections we investigate how a range of socio-demographic variables derived from the Census can be linked to different patterns of energy consumption.

Patterns of energy usage

In order to try to identify whether there are any particular patterns of energy use that can be typified and used for further exploration, a cluster analysis was undertaken using the figures for average household energy usage from car, gas and electricity. K-means (non-hierarchical) cluster analysis was chosen as the most appropriate method for determining clusters, and was carried out using the open source statistics program R (R Core Team, 2013). K-means cluster analysis combines data into a pre-selected number of clusters, then iteratively reassigns data to groups until data in any one group are more alike than they are to data in another group, at which point clusters are defined as distinctive. The use of K-means requires the pre-selection of the number of clusters to be identified. No standard objective selection procedure exists for K-means clustering (Hair et al., 2010). From consideration of a plot of within groups' sum of squares (Figure 9) (identifying the 'elbow' in the plot, as with a scree plot in factor analysis, which shows the point at which the marginal return of adding one more cluster is less than was the marginal return for adding the clusters prior to that (Gloukhov, 2013), and from dendograms from exploratory hierarchical clustering (Figure 8), it was decided to use five clusters for k-means analysis. Between three and eight clusters were considered, so for this exploratory analysis, five was judged to be a good starting point. The analysis that follows suggests that these clusters appear to be meaningful, but later analyses with the improved datasets will test the influence of the number of clusters chosen more rigorously.

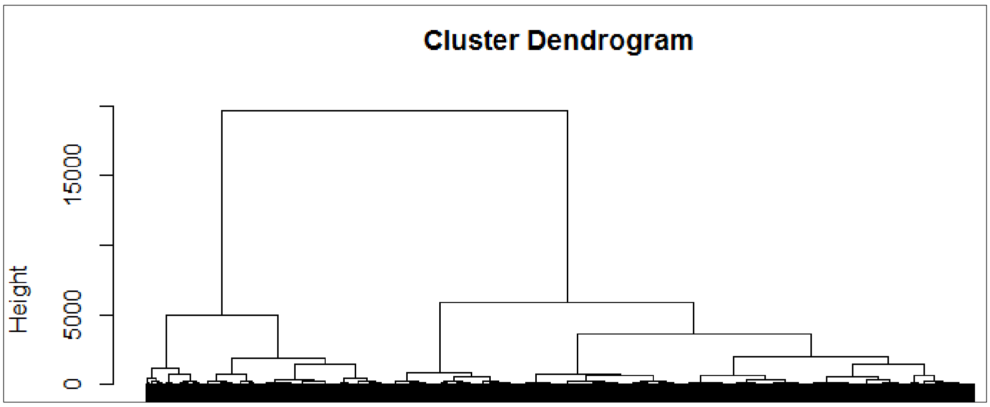

Figure 8: Dendrogram from exploratory hierarchical clustering

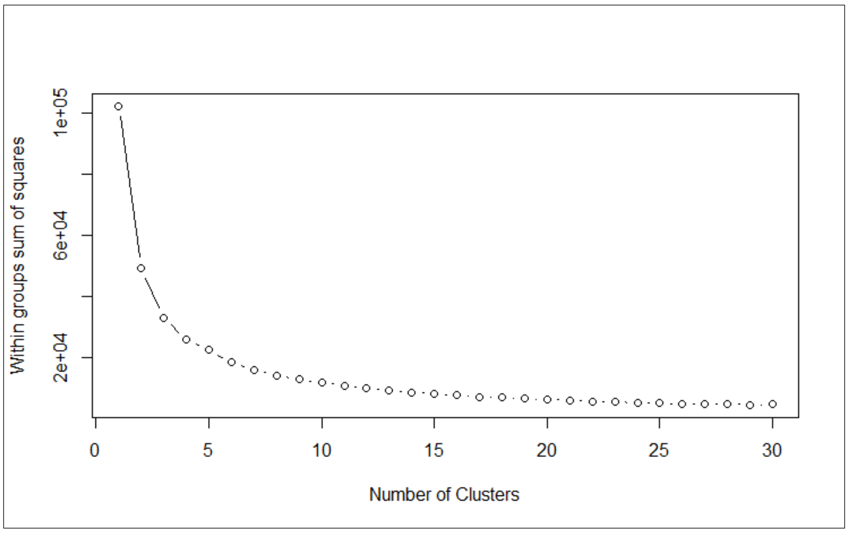

Figure 9: Within groups sum of squares plot used for deciding on number of clusters

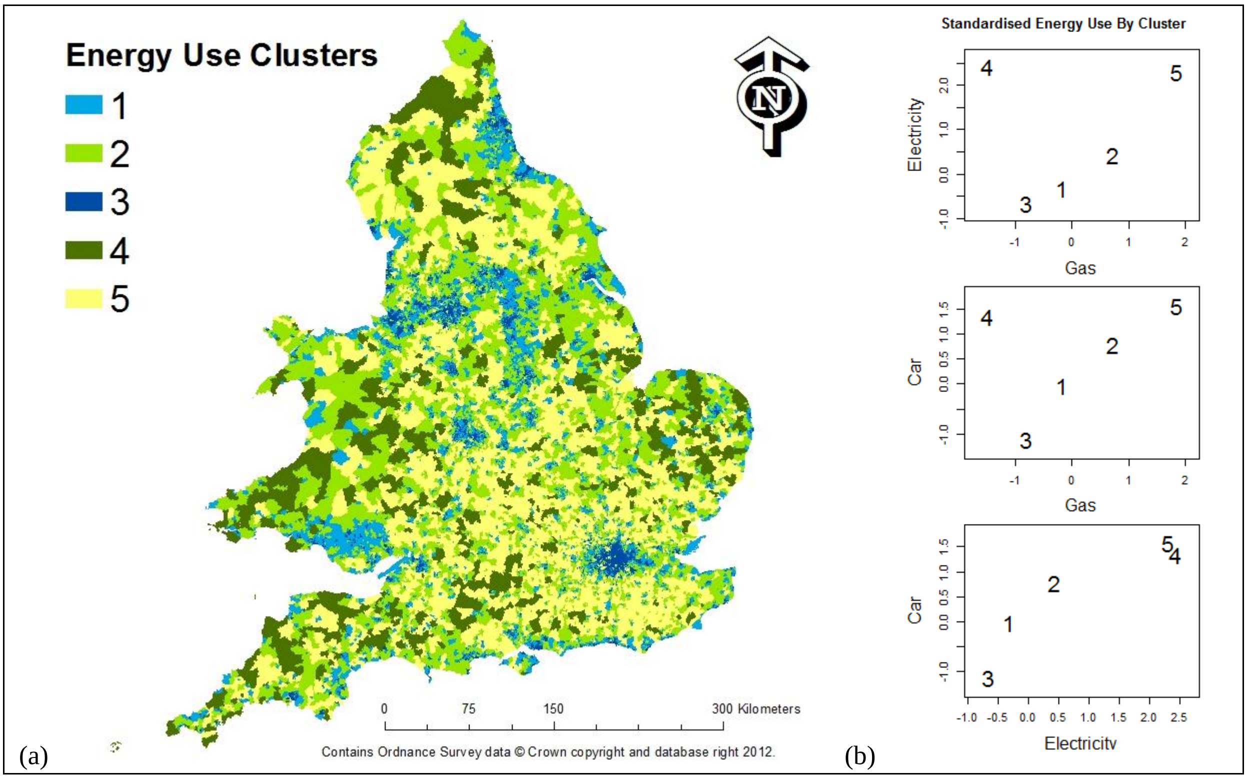

Figure 10: (a) Map showing the 5 clusters of energy use in each LSOA
(b) Mean standardised energy use for each cluster

Table 1: Patterns of energy use by cluster

	Gas	Electricity	Car
Cluster 1	Medium	Low	Medium
Cluster 2	Med-High	Med-Low	Med-High
Cluster 3	Med-Low	Low	Low
Cluster 4	Low	High	High
Cluster 5	High	High	High

Figure 10 shows a map of the five clusters, alongside plots showing a comparison of the standardised means for each of the clusters.

The five clusters show differing patterns of energy consumption (Figure 10b and Table 1):

- Cluster 1 shows medium car and gas consumption and low electricity consumption. From the map these areas appear to be predominantly suburban.
- Cluster 2 shows relatively high electricity and car consumption but relatively low gas consumption. From the map this appears to cover rural areas.
- Cluster 3 shows low car and electricity consumption but medium-low gas consumption. From the map this appears to cover urban centres.
- Cluster 4 shows high car and electricity usage, but low gas consumption. From the map this appears to cover extremely rural areas. (N.B. the data contains areas off the gas grid, and therefore low gas consumption may mean *zero* gas consumption for many households, and thus medium gas consumption may still be low.)
- Cluster 5 shows high energy usage across all 3 modes. From the map this appears to cover peri-urban/semi-rural areas.

These clusters reinforce the finding earlier relating to Figure 5, i.e. that there is a grouping that uses the most energy across all three domains. Cluster 4 is an exception to this, though as noted it may represent off-gas grid areas, predominantly in very rural areas with electric or oil/solid fuel/LPG heating and high car dependence. It is interesting to note that there are no clusters that exhibit low energy use across all three domains.

Characteristics of clusters

With the five clusters defined, further analyses have been undertaken to explore their characteristics.

Differences in Urban-Rural Characteristics between Clusters

To further investigate and confirm the apparent differences in the urban/rural nature of the clusters described above and shown in Figure 10a, data was used from the UK Office for National Statistics 2011 Rural-Urban Classification. This classifies each LSOA into one of eight classes based on settlement type. The classes are described as:

- Urban: Major Conurbation (A1)
- Urban: Minor Conurbation (B1)
- Urban: City and Town (C1)
- Urban: City and Town in a Sparse Setting (C2)
- Rural: Town and Fringe (D1)
- Rural: Town and Fringe in a Sparse Setting (D2)
- Rural: Village (E1)
- Rural: Village in a Sparse Setting (E2)

Figure 11 shows histograms for each settlement type (plus all LSOAs) showing the proportion of each settlement classification that is within each cluster. Clusters 1, 2 and 3 are predominantly urban, with Cluster 2 being very similar to the overall mix. Clusters 4 and 5 have a much greater proportion of rural areas, particularly Cluster 4 (identified as the potential off-gas grid areas) which has a high proportion of the “Village(s) in a sparse setting”.

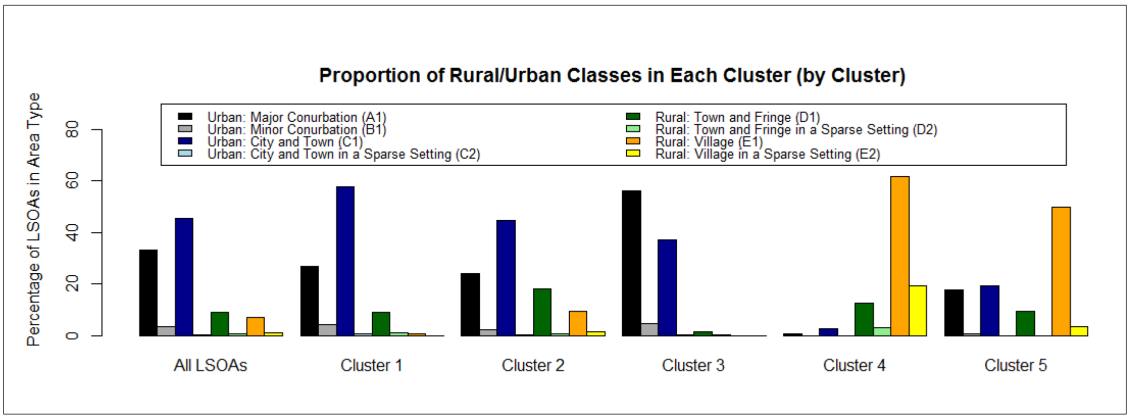

Figure 11: Proportion of Rural and Urban Classes in Each Cluster

Analysis of Variance for housing and socio demographic variables

In order to further ascertain characteristics of the clusters, a set of ANOVA calculations were undertaken for 19 variables from the census relating to housing type, and 17 socio-demographic variables, including the PSE99 measure of poverty. These were selected from the census as the main variables representing housing and economic status (ONS, 2014) once they had been reduced to avoid collinearity, and were all held to have a logical potential for affecting domestic energy or car usage in some manner. All of the variables were shown to vary significantly between one or more of the 5 clusters (indicated by a p-value <0.001). The results from these are shown in Table and Table , ranked in each group by the F ratio (the variance between groups divided by the variance within groups). The larger the F ratio, the greater the differences in the variable between clusters.

In terms of variables related to housing, detached properties and outright ownership come out as the principle two variables driving difference between the clusters. In terms of the socio-demographic characteristics, the level of poverty, as indicated by PSE99, drives the greatest difference between clusters.

Table 2: ANOVA output for housing variables (ranked by importance)

Variable	F	p
Detached Properties	9343	<0.001
Outright Ownership	6625	<0.001
Properties with Over Occupied Rooms	3362	<0.001
Mortgage on Property	3221	<0.001
Flat (in purpose built block)	2777	<0.001
Social Housing (Council)	2764	<0.001
Over Occupied Bedrooms	2763	<0.001
Terraced Housing	1974	<0.001
Social Housing (Other)	1533	<0.001
Private Rented (Landlord)	1301	<0.001
Semi-Detached Properties	1283	<0.001
Central Heating	992	<0.001
Flat in House	865	<0.001
Flat in Commercial Property	285	<0.001
Rented (Free)	800	<0.001
Unshared Properties	653	<0.001
Shared Property with 2 HHs	565	<0.001
Shared Property with 3+ HHs	471	<0.001
Shared Ownership	116	<0.001
Private Rented (Other)	27	<0.001
n = 34,753 df = 4		

Table 3: ANOVA output for socio-demographic variables (ranked by importance)

Variable	F	p
PSE99	8752	<0.001
Economically Active (Unemployed)	6013	<0.001
Economically Active (Self-employed)	5883	<0.001
Unemployed (Long-term)	5264	<0.001
Economically Inactive (Sick)	4220	<0.001
Unemployed (Never employed)	3383	<0.001
Unemployed (16 to 24)	3215	<0.001
Age (Median)	3188	<0.001
Age (Mean)	2319	<0.001
Economically Inactive (Retired)	1781	<0.001
Economically Inactive (Other)	1296	<0.001
Economically Inactive (Caring)	1203	<0.001
Unemployed (50 to 74)	1131	<0.001
Economically Active (Full-Time employed)	711	<0.001
Economically Active (Part-Time employed)	505	<0.001
Economically Active (Student)	228	<0.001
n = 34,753 df = 4		

To provide an indication of how each variable does not necessarily differ between all clusters, Table 4 shows how the means of these four variables differ across the clusters. Cluster 3 is characterised by comparatively low levels of detached housing and outright ownership, as well as very high levels of poverty and unemployment. Conversely, Clusters 4 and 5 have very high levels of detached housing, high levels of outright ownership and low levels of unemployment.

Table 4: Percentage of household types in each cluster (bold indicates extremes)

Cluster	Detached	Outright	PSE99	Economically Active (Unemployed)
1	18.7	32.1	33.7	4.2
2	38.9	40.7	21.7	2.8
3	**5.1**	**18.0**	**52.6**	**6.7**
4	**54.1**	42.6	23.1	2.6
5	**55.4**	43.7	**17.8**	2.3

Discussion and Conclusions

The exploratory studies shown here indicate a likely value in the two datasets for exploring patterns of household energy usage and their relationship to both levels of wealth, deprivation and poverty, and to physical and geographic characteristics, such as rural/urban location and housing type. The current poor spatial resolution of the vehicle test data means that it is not currently appropriate to draw hard and fast conclusions regarding the outputs of the studies and their significance, nor to compare them to other work on household energy consumption in the UK (see Introduction). However, the methods used indicate the presence of a strong relationship between levels of poverty and energy use, and that this is strongly related to patterns of housing type and tenure, as well as to age and economic status.

The inclusion of a general measure of poverty/deprivation per area has been demonstrated to be of value. Energy use across all domains has been shown to decrease significantly as the percentage of households in poverty increases Figure 7. Also, in identifying differences between the clusters, the PSE99 index outperformed all individual socio-demographic variables in terms of importance in the ANOVA analysis for socio-demographic variables (see Table 3), and was only exceeded overall by 'Detached Properties' (see Table 2).

Whilst this analysis is limited to looking at patterns of energy across areas, the fine resolution of the data at LSOA level (homogeneous areas of around 600 households), and its universal coverage[3] provide a useful comparison for previous studies. Although much greater investigation of the data is required, the early analyses presented here indicate that there are likely to be wealthy areas that have the economic means and control of their property to be able to take action to reduce their levels of energy consumption, and that identification of where these areas are could significantly improve local government attempts to target measures and interventions at these areas, where greatest savings could be made. Similarly, further analysis of data could highlight areas where energy efficiency programmes could be targeted to support those who are using excessive amounts of energy but are less able to take action themselves.

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MOT Project website http://www.abdn.ac.uk/ctr/research/currentbr-research-projects/mot/

Annex 1: Calculation of the PSE99 Index

The PSE99 was calculated by using the following parameters for each LSOA (Dorling et al., 2007):

- 57.6% of overcrowded households (more than one person per room) +
- 35.7% of households renting from local authorities or housing associations +
- 32.4% of lone-parent households +
- 30.3% of households with an unemployed Household Reference Person (HRP) +
- 18.4% of households with no car +
- 16.5% of households renting from private landlords +
- 16.1% of households with a member with a limiting long-term illness +
- 13.5% of households with no central heating or without sole use of amenities +
- 11.3% of households with HRP in a low social class (as defined under the National Statistics Socioeconomic Classification [NS-SEC] levels 6, 7 or 8: Semi-routine Occupations, Routine Occupations and Long-term Unemployed/Never Worked – see Rose and Pevalin, 2005) .

With both the BBI90 and PSE99 there have been changes throughout society since the surveys were carried out which might impact on the relevance of these, such as rises in the in-work poor and poor single young people, a fall in poverty amongst older people and changes in the housing market, especially buy-to-rent-out properties. However despite a survey being carried out to recalculate the index for 2011, a new index has not yet been calculated[4].

[4] Pers. Comm. (2014) David Gordon, Poverty and Social Exclusion