A SPATIAL TYPOLOGY OF CAR USAGE AND ITS LOCAL DETERMINANTS IN ENGLAND

Dr Ian Philips

Research Fellow

University of Leeds

Professor Jillian Anable

Professor of Transport & Energy

University of Leeds

Dr Sally Cairns

Senior Academy Fellow

Transport Research Laboratory

Paul Emmerson

Principal Transportation Officer

Transport Research Laboratory

Dr Tim Chatterton

Senior Research Fellow

University of the West of England

Abstract

This paper presents an initial classification of Middle-layer Super Output Areas (MSOAs) in England based on their car ownership, car usage and relevant local characteristics. Whilst a long lineage of widely used geodemographic classifications exist in the UK, none of these is sufficiently focused on travel behaviour and transport infrastructure to allow a useful place-based understanding of travel patterns alongside monitoring and evaluation of local transport interventions.

The analysis uses a privileged dataset which includes the characteristics of every vehicle registered in the UK in 2011, the registered keeper type and location and the annual mileage derived from annual 'MOT' tests. We present initial results in the process of developing a typology of MSOAs using cluster analysis applied to the car and mileage data alongside variables selected from a long list of variables from additional sources including the Census and DfT Accessibility statistics. The most meaningful set of variables to use as clustering variables is derived from underpinning regression models to identify the strongest determinants of car ownership and use. A clustering procedure is tested to produce a stable and meaningful set of provisional local area transport-types. We present the methodology used to create the classification, a visual profile of each local transport-area-type identified and identify the next steps required to develop and address the methodological and conceptual challenges of identifying appropriate spatial units of analysis, and change over time. This

initial classification has potential to be extended with other available datasets including, meteorological and topographical data as well as new local level measures of rail and bus provision, developed specifically for this project.   We conclude with a brief discussion of how the identification of places that are physically, socially and behaviourally similar to each other in terms of their current car usage patterns and associated determinants allows for context-appropriate policy planning, evaluation and knowledge sharing.

Keywords: Car use, Area classification, Policy evaluation

Introduction and background

In the current UK policy climate, the requirement for robust evidence to justify sustainable transport interventions is increasing (CCC, 2015). Yet, difficulties of evaluating the outcomes and impacts of transport and related interventions are well documented (Möser and Bamberg, 2008; Salon et al., 2012; Sloman et al., 2015). Key issues are lack of available data to avoid disproportionately expensive survey undertakings as well as a lack of easy-to-identify control areas. This is exacerbated by modelling and scenario efforts to assess low-carbon transport solutions tending focus largely on macro (e.g. national or at best regional) spatial scales with little ability to account for *'place based …idiosyncratic behavioural and infrastructural mitigation options that are likely to be beneficial in realising local co-benefits.'* (Creutzig, 2016: 1). This paper presents an exploratory classification of Middle-layer Super Output Areas (MSOAs) in England based on their car ownership, car usage and relevant local characteristics. MSOAs are part of the geographical hierarchy designed for reporting small area statistics in England and Wales and are generally comprised of 2000 - 6000 households. They are made of up of groups of contiguous Lower-layer Super Output Areas and we have undertaken the MSOA analysis as a precursor to an equivalent LSOA analysis.

The contribution to knowledge of the wider 'MOT project' (www.MOTproject.net) in which this paper sits is the identification of places that are physically, socially and behaviourally similar to each other in terms of their current car usage patterns and associated determinants. Classifying places in these terms will allow for context-appropriate policy planning, evaluation and knowledge sharing. A further novel element is the use of a privileged dataset developed for the underpinning 'MOT project' which includes the characteristics of every vehicle registered in the UK in 2011, various characteristics of the vehicle (age, model, fuel type etc.), the type and location of the registered keeper (at LSOA), and the annual mileage derived from annual 'MOT' tests. In this paper, our objective is to present a cluster analysis which will inform questions such as: What types of area exist in terms of motoring patterns, where are they located and what other characteristics do they tend to have in common?

Whilst a long lineage of widely used geo-demographic classifications exist in the UK, such as the Output Area Classification produced for 2001 (Vickers and Rees, 2007) and 2011 (Gale et al., 2009), none of these is sufficiently focused on travel behaviour and transport infrastructure to allow a useful place-based understanding of travel patterns alongside monitoring and evaluation of local transport interventions. UK based Geodemographic classifications include the Output Area Classification adopted by the Office for National Statistics as well as commercial classifications from Experian and Acorn. The Geodemographic classifications are 'general purpose' and the appropriateness of using these in transport applications is questioned: factors influencing travel behaviour most likely differ from factors influencing other consumer behaviours (Singleton and Longley, 2009; Bearman and Singleton, 2015), heterogeneity within zones is typically larger than between zone heterogeneity (Voas and Williamson, 2001), and Bearman and Singleton (2015) infer that seeking similarity on a specific issue can reduce this within zone heterogeneity when compared to a general purpose classification.

Area classification is not well developed within transport research. Instead, classification approaches tend to focus on grouping groups of individuals based on their attitudes, behaviours and choices (e.g. Anable, 2005 is widely cited). At the time of publication, Anable reported segmentation as little used. Confusingly both area classification and segmentation of individuals are both sometimes called 'cluster analysis' though the unit of analysis and therefore their uses differ. As of 2016 many transport behaviour studies have used attitudinal-

based segmentation of individuals (e.g. Heinen et al., 2011;Li et al., 2013; de Oña et al., 2016) behavioural-based (Julsrud, 2014; Mattioli and Anable, 2017) or a combination of the two (Molin et al., 2016). Work on area-based classifications of populations to understand travel behaviour is rarer, with a few examples emerging recently (e.g. Ralph et al., 2016). A key issue is that aggregate data for car use is provided at a coarse spatial resolution by the National Travel Survey NTS (region and national), being limited by sample sizes at smaller levels of geography. Some data such as commute distance and mode of travel to work is available through the UK census at finer resolution (Census Output Area resolution), but this provides only a partial indicator of travel behaviour. However the current state of practice in transport uses other classifications in an ad-hoc manner. Concerns have been raised (e.g. Lucas et al., 2016; Mattioli et al., 2016) that these may not be appropriate proxies for the aggregate travel behaviour in these areas. If a single variable is used as a proxy for travel behaviour, a great deal of heterogeneity is ignored e.g. there is variation within areas that are similarly urban (e.g. share similar population or population density). Another example is non-car ownership being taken as a proxy for deprivation thus ignoring the fact that a lack of car ownership can be a factor of prosperous urban living or, the corollary, a facet of car dependence / forced car ownership (Mattioli et al., 2016, 2017).

Small area classification is argued to be an effective statistical method particularly in terms of reducing risks of ecological fallacy (i.e. assuming that all small zones within a large area are the same) (Harris et al., 2005; Longley et al., 2003; Webber, 2007). The bulk of methodological developments in area clustering come from the quantitative geography sub-discipline of Geodemographics which is concerned with "the analysis of spatially referenced demographic and lifestyle data"(See and Openshaw, 2001 p269). Geodemographics has also been defined as "the analysis of people by where they live" (Sleight, 2004: p18). Data availability and GIS technologies have improved greatly over recent years making the construction of specific area classifications less onerous. (Adnan et al., 2010; Bearman and Singleton, 2015; Singleton and Longley, 2009). Drawing upon these disciplinary and methodological developments and utilising the 'MOT dataset' (described fully below), we attempt to address some of the shortcomings of current practice identified here by developing a bespoke car-use based small-area typology.

Data

In Britain, vehicles of three years old or more are subject to an annual roadworthiness inspection ('MOT test'), during which a vehicle odometer reading is taken. This information has been digitally recorded since 2006, and anonymised data was first made publicly available in 2010 (Cairns et al., 2014). The application of mathematical methods (see Wilson et al., 2013a, 2013b) allows the estimation of annual mileage rates for each vehicle, based on odometer readings. For this project, the MOT test record dataset has been enhanced through the addition of a number of new parameters recorded each time a car is newly registered or formally changes keepership so that this is captured in the Driver Vehicle Licensing Agency's (DVLA) vehicle stock tables. In particular, the DVLA data allows the linking of each vehicle to the Lower-layer Super Output Area of the registered keeper as well as a number of other vehicle characteristics (e.g. CO_2 emissions and private or a corporate keepership).

Whilst the vehicle-level data cannot be linked to the characteristics of its registered keeper for anything other than private/corporate status and LSOA location of registration, it nevertheless represents the only universal GB dataset on both car ownership and annual mileage driven. Census data provides some statistics on the number of cars a household has access to, but has one limited proxy measurement of usage (the distance to work). The NTS is limited in spatial resolution by its sample size. Neither of these datasets enables ownership or usage to be investigated in terms of a broad set of vehicle characteristics.

The data have been used for a range of travel behaviour analysis (e.g. Chatterton et al., 2015, in press, 2016). For the purposes of this paper, we have extracted data on privately owned cars (as opposed to other vehicles such as motor caravans, large passenger and small goods vehicles etc.) in England in 2011 so as to match to 2011 UK census data. Table 1 lists the variables used in the clustering analysis to follow. MSOA level data is derived from a combination of the enhanced MOT dataset, the 2011 England and Wales Census and DfT accessibility statistics. The variables fall into a number of domains relating to car ownership,

This paper is produced and circulated privately and its inclusion
in the conference does not constitute publication.

3

car use, broader travel behaviour, land use and morphology, accessibility and socio-demographic factors. Accessibility variables are used because of the link with travel behaviour (e.g. Geurs and van Wee, 2004; SEU, 2003). Land-use and morphology have long been shown to relate to travel behaviour (e.g. Ewing and Cervero, 2001; van Wee, 2011, 2002). Social and economic factors relate to car dependence and exclusion from auto-mobility (Lucas et al., 2011; Lucas, 2012).

Table 1 lists the variables used and a brief link to data sources.

Domain	Variables	Source
Car use	Miles per person per year, Gini coefficient of distribution of vehicle use across MSOA population, high mileage vehicles per person,	MOT project
Car characteristics	Vehicle age, engine size, % diesel, total particulate emissions , total CO_2 emissions	MOT project
Car ownership	Cars per person	Census
Mode share	% car commute mode share, % bike commute mode share	Census
Accessibility	Total travel time to 8 locations by car and by public transport / walk. total distance to 8 locations	DfT Accessibility statistics
Morphology and land-use	Distance to work, distance to nearest settlement of: 5000, 25000, 50000, 100000, 250000 and 500000 residents.	Derived from Ordnance Survey, census and UK Borders data
Social and demographic	% one adult households, % unemployed, % people in non-car owning households, % professional, % Intermediate occupations, % Routine / manual occupations, % work from home, % female, % children, mean income, % of population working over 31 hours per week	Census, Office for National Statistics (ONS)

Methods

The scope of the work reported here is as follows: we aim to develop an area classification based on factors associated with car ownership and use in England. Whilst we include variables which offer some context in terms of socio-demographics for example, we are not aiming to replicate the broader geodemographic classifications mentioned above. Similarly, including variables relating to non-car travel is of interest and provides context, particularly as one application of such a classification may be to monitor (changes in) modal share. However, at this stage it is not an area classification of propensity to cycle (Parkin et al., 2007,) capability to walk and cycle (Philips, 2014) or an estimate of propensity to use public transport. The principle purpose of this area classification will be as a benchmarking tool for evaluating car use and efforts to reduce it.

Having established our rationale for clustering and objective, our workflow is based on the seven step approach to clustering after Milligan, (1996). This was used by Vickers and Rees in the construction of the Output Area Classification OAC (Vickers and Rees, 2007) and the steps are as follows:

4

In Step 1 we consider the spatial units. For this exploratory work we have used MSOAs due to the availability of much of the data at this resolution. They form part of a spatial hierarchy of data dissemination units. We intend to extend this analysis to LSOAs as a follow-on task. Most variables available at MSOA are also available at LSOA. An exception is income estimates provided by the ONS at MSOA level. At LSOA level income estimates are available from an alternative source: Experian.

In Step 2 we consider the variables to be used. Over 100 potential variables were considered. Variables were processed and gathered into a single data table. All the variables were mapped and shown as histograms and output as an atlas using an R script based on code developed by Singleton, (2013) along with correlation matrices to facilitate exploratory data analysis. Regression analysis was carried out to further understand the relationship between car ownership and use (dependent variables) and the other predictor variables. As shown in Table 1, variables were selected so that each relevant domain was represented in the data.

Some studies use factor analysis to reduce the number of variables in the analysis and also in attitudinal clustering to produce latent variables which cannot be measured directly. Factor analysis can also deal with issues of collinear variables and the 'double-counting issue'. However, Mooi and Sarstedt (2010) report several problems that can occur. Variable pre-processing can lead to different results, some of the information in the original data is discarded, some variables are discarded from factors and interpretation becomes more difficult because the clusters are based on factors rather than the original variables. Another practical issue is that factor analysis adds another data processing step into the workflow.

The majority of variables used are openly available from the Census and ONS. Variables derived by the MOT project are not currently in the public domain (but work is ongoing to develop data sharing protocols which meet ethical and anonymity requirements). Brunsdon et al., (n.d.) talk of an open source geodemographic classification where all data contained are freely available. The data processing and analysis was carried out predominantly using R in order that reproducible classification can be made as is becoming common practice (Gale et al., 2009).

In Step 3 we consider variable standardisation so that the variable units do not implicitly weight the clustering. Normalizing variables between 0 and 1 is regarded as preferable to standardizing to z-scores (outliers in the latter can cause problems) (Vickers et al., 2005; Vickers and Rees, 2007).

Milligan's(1996) Steps 4 and 5 are concerned with the cluster method to be selected. There are several methods (Vickers, 2006 chapter 5 offers a good introduction). In this work the clustering process was as follows: Hierarchical clustering using Ward's method was used to generate dendograms and barcharts along with "Elbow charts" to determine the maximum and minimum number of clusters likely to produce a suitable solution. Cluster centres generated by the hierarchical clustering were then used to seed the k-means clustering algorithm. Graphical outputs, summary data and maps were generated. Hierarchical and k-means clustering are commonly used and well understood so were deemed appropriate for this exploratory classification.

Step 6 concerns the choice of number of clusters. Based on literature that has consulted users on usefulness of area classification (Vickers and Rees, 2011) and initial discussions amongst the project team, we adopted a two-tier scheme. The upper tier should contain between 5 and 8 "Supergroups" which could at a later stage be described with names and pen portraits. Each Supergroup contains a second tier of between 2 and 4 Subgroups which classify more subtle differences within each Supergroup.

Step 7 concerns validation. Basic validation has been carried out in terms of visual inspection of results and maps of clusters. However detailed statistical validation and detailed consultation and interpretation of alternative cluster solutions is beyond the scope of this exploratory stage.

Results

Figure 1 shows how a dendrogram derived from the hierarchical clustering procedure illustrates potential cluster solutions. A six cluster solution is marked in red.
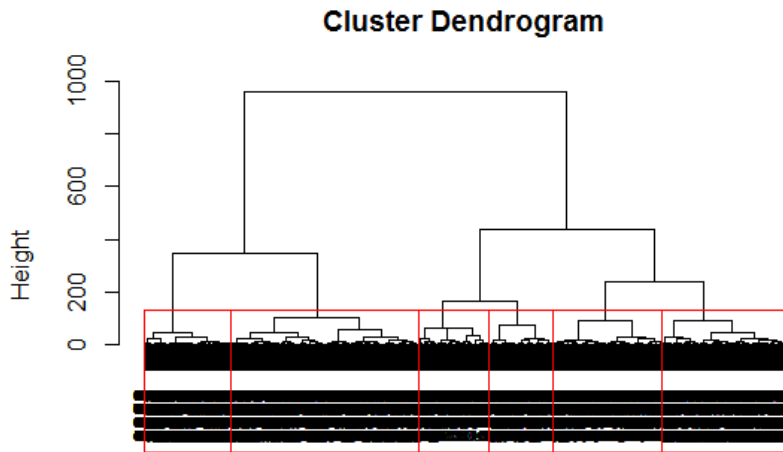
Cluster Dendrogram

Figure 1.   Dendrogram suggesting a six cluster solution

The cluster centres from the hierarchical solution seed the k-means clustering. A summary measure is given of the variance in the data explained by the clustering (the between group sum of squares / within group sum of squares). For a six cluster solution this was 53%. Whereas for a five cluster solution it was 50%. Another initial check of the outcome is shown in Figure 2 which plots the data against the first two discriminant functions to allow plotting on two axes. It provides a visual indication of the extent to which the k-means cluster solution discriminates between the different clusters. Our exploratory analysis tested four through eight cluster solutions. The six cluster solution provided a reasonable discrimination between clusters. Seven and eight cluster solutions appeared to have a less effective discrimination between clusters. A seven cluster solution provided a modest increase in the between group sum of squares / within group sum of squares ratio to 55% and represented diminishing returns compared to the increase from five to six. We acknowledge that comparing several visual pieces of information and summary measures means the analyst has to apply subjective judgement in the creation of this initial classification. As stated above Step 7 in the methodology; more detailed consultation over the most useful cluster solution would be carried out as further work.
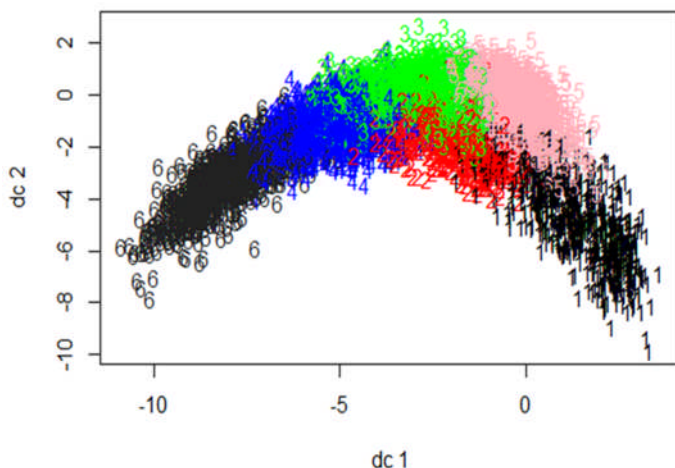

Figure 2.   Centroid plot against first two discriminant functions

Figure 3 plots the centre of each cluster for each variable. This allows interpretation of the relative characteristics of each cluster and how they differ from one another. Cluster 1 for example has the highest level of no car households and lowest level of car miles per person,

in addition to having the highest population density. Figure 3 allows the description of each cluster and could be used as the basis for writing 'pen portraits' of each cluster. At this exploratory stage however it would be imprudent to name the clusters as this may bias subsequent refinement of the clustering.
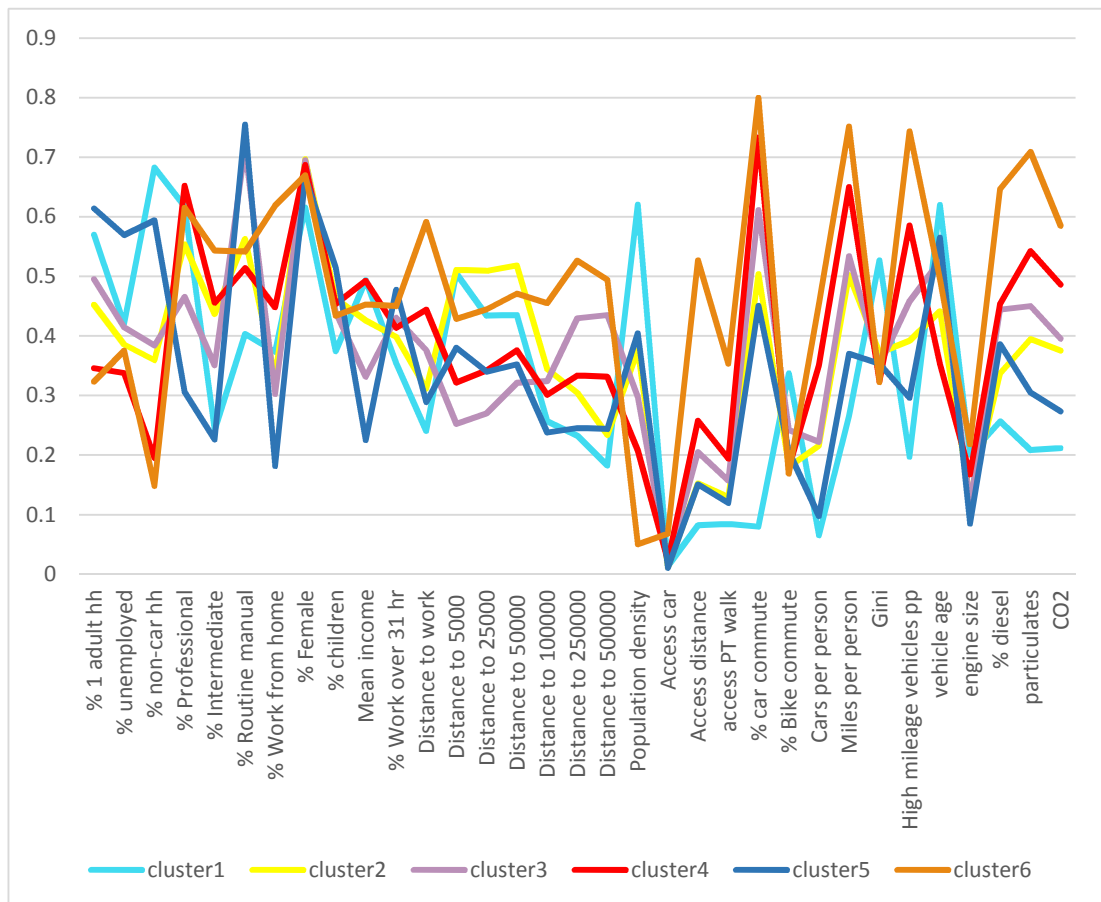

Figure 3.   Comparing the characteristics of each cluster

The potential cluster solutions were mapped to begin to understand the resulting spatial pattern, for example the 6 cluster solution is shown in Figure 4, which shows Cluster 1 is particularly associated with inner London, but also central areas of other cities. This is unsurprising given the characteristics of the cluster described above and plotted in Figure 3. Cluster 2 is dominant in outer London and suburban areas of other metropolitan areas. Cluster 6 is most commonly found in the most deeply rural areas. Some sensitivity testing will be required to ensure that the morphology and land use variables shown in Table 1 do not exert excessive influence on the clusters.
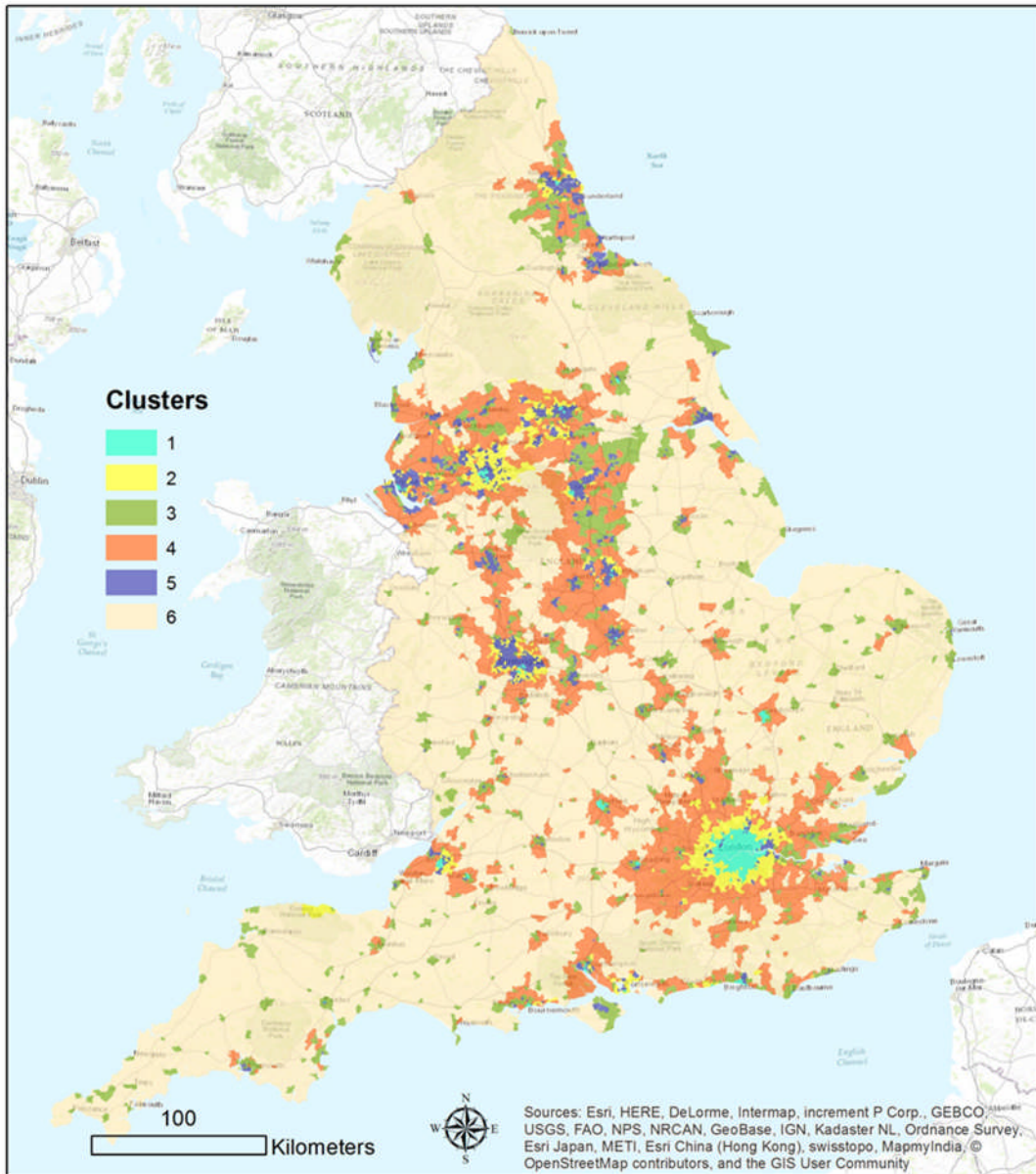
Figure 4.   Exploratory MSOA "Supergroups"

A second tier of clusters was generated to examine whether development of subgroups adds value to the classification. The data was split by Supergroup, then the construction of this second tier, like the first, used hierarchical clustering to identify potential numbers of clusters and to generate seed values for k-means clustering. As would be expected, the differences in groups were more subtle, with the differences between Subgroups often only being determined by variance on one or two variables. By way of an example, Table 2 summarises the most pronounced differences between subgroups 2.1 and 2.2. Figure 5 then maps these two Subgroups for the area classified as Supergroup 2 that dominated outer London. In simple terms, this analysis suggests that outer London could be usefully divided into at least two types of area at MSOA level in terms of car-using characteristics and the correlates of car use.

Table 2 variables with marked differences between subgroups 2.1 & 2.2

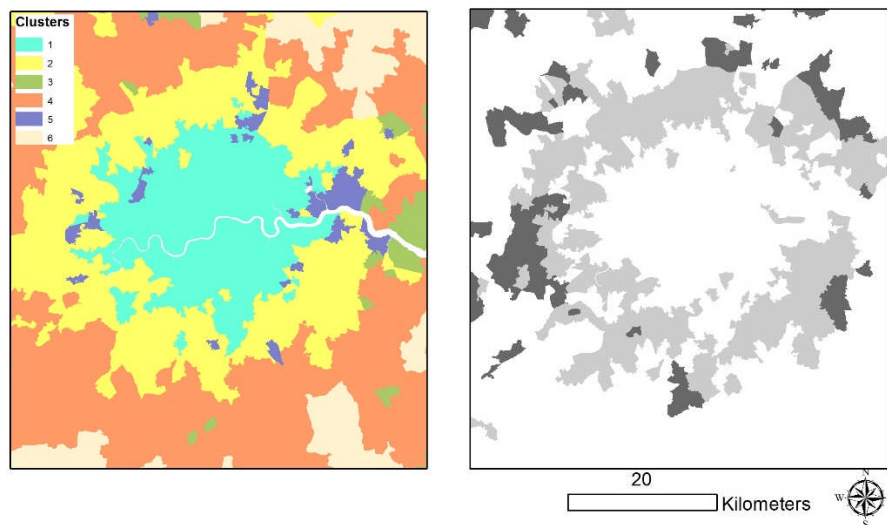| Variable	Subgroup 2.1	Subgroup 2.2
% car commute	Low	High
% professional	High	Low
% manual	Low	High
% income	High	Low

Figure 5.   Supergroups on the left and Subgroups 2.1 (dark grey) and 2.2 (light grey). Both panels show London.

The results illustrate and we acknowledge that there is an element of subjectivity in choice of cluster solution. However the visualisation tools illustrated are relatively quick to produce once reproducible R scripts are written. This means that it would be possible to discuss a range of possible solutions amongst the research team or as part of a user consultation exercise.

Conclusions and further work

This exploratory analysis has produced patterns of interest at a moderate spatial resolution. This suggests further work would be justified. Priorities would include sensitivity testing of variables in this initial classification along with testing the effects of other candidate variables (e.g. those which are significant predictor variables of car use in regression models such as public transport indicators, topographic and climate variables). We also seek early engagement with potential users. This would particularly help to refine the desired number of clusters and number of tiers, and confirm selection of further variables for inclusion. We would also wish to discuss an exploratory LSOA resolution analysis and consult with potential users over the most desirable spatial resolution. The variables used would then need to be refined to ensure that weighting of one domain (see Table 1) over another is not excessive. Extensive testing would then be required to develop a stable cluster solution. Validation testing and initial naming of upper tier clusters would lead to further user consultation before final refinement of the classification is complete.

The identification of places that are physically, socially and behaviourally similar to each other in terms of their current car usage patterns and associated determinants allows for context-appropriate policy planning, evaluation and knowledge sharing. For example, the clusters in

this exploratory stage are beginning to identify groups of areas which may be considered similar in terms of the variables in Table 1. One possible application of a refined version of this classification is to aid the selection of control areas and development of counterfactuals when monitoring and evaluating the implementation of sustainable transport interventions such as car use reduction measures. Potential value from knowledge sharing arises from this work because authorities containing similar clusters could co-design policies and interventions. Additionally, as a spatial indicator, future refinements of this classification could provide an easily communicable means of contextualising the situation at sub-district resolution which could aid policy makers in the production of locally appropriate transport policy planning.

References

Adnan, M., Longley, P.A., Singleton, A.D., Brunsdon, C., 2010. Towards Real-Time Geodemographics: Clustering Algorithm Performance for Large Multidimensional Spatial Databases: Towards Real-Time Geodemographics. Trans. GIS 14, 283–297. doi:10.1111/j.1467-9671.2010.01197.x

Anable, J., 2005. "Complacent Car Addicts" or "Aspiring Environmentalists"? Identifying travel behaviour segments using attitude theory. Transp. Policy 12, 65–78. doi:10.1016/j.tranpol.2004.11.004

Bearman, N., Singleton, A.D., 2015. TravelOAC: development of travel geodemographic classifications for England and Wales based on open data, in: GISruk 2015 Leeds. Presented at the GIS research UK, Leeds, UK.

Brunsdon, C., Charlton, M., Rigby, J., n.d. An Open Source Geodemographic Classification of Small Areas In the Republic of Ireland.

Cairns, S., Wilson, R.E., Chatterton, T., Anable, J., Notley, S., McLeod, F., 2014. Using MOT Test Data to Analyse Travel Behaviour Change - Scoping Report.

CCC, 2015. The fifth carbon budget – The next step towards a low-carbon economy. Committee on Climate Change, Holbien Place, London.

Chatterton, T., Anable, J., Cairns, S., Wilson, R.E., in press. Financial implications of car ownership and use: a social and spatial distributional analysis. Transp. Policy.

Chatterton, T., Barnes, J., Wilson, R.E., Anable, J., Cairns, S., 2015. Use of a novel dataset to explore spatial and social variations in car type, size, usage and emissions. Transp. Res. Part Transp. Environ. 39, 151–164. doi:10.1016/j.trd.2015.06.003

Chatterton, T.J., Anable, J., Barnes, J., Yeboah, G., 2016. Mapping household direct energy consumption in the United Kingdom to provide a new perspective on energy justice. Energy Res. Soc. Sci., Energy demand for mobility and domestic life: new insights from energy justice 18, 71–87. doi:10.1016/j.erss.2016.04.013

Creutzig, F., 2016. Evolving Narratives of Low-Carbon Futures in Transportation. Transp. Rev. 36, 341–360. doi:10.1080/01441647.2015.1079277

de Oña, J., de Oña, R., López, G., 2016. Transit service quality analysis using cluster analysis and decision trees: a step forward to personalized marketing in public transportation. Transportation 43, 725–747. doi:10.1007/s11116-015-9615-0

Ewing, R., Cervero, R., 2001. Travel and the Built Environment: A Synthesis. Transp. Res. Rec. J. Transp. Res. Board 1780, 87–114. doi:10.3141/1780-10

Gale, C.G., Singleton, A.D., Bates, A.G., Longley, P.A., 2009. Creating the 2011 area classification for output areas (2011 OAC). J. Spat. Inf. Sci. 2016, 1–27. doi:10.5311/JOSIS.2016.12.232

Geurs, K.T., van Wee, B., 2004. Accessibility evaluation of land-use and transport strategies: review and research directions. J. Transp. Geogr. 12, 127–140. doi:10.1016/j.jtrangeo.2003.10.005

Harris, R., Sleight, P., Webber, R., 2005. Geodemographics, GIS and neighbourhood targeting, Mastering GIS. Wiley, West Sussex, England ; Hoboken, N.J.

Heinen, E., Maat, K., Wee, B. van, 2011. The role of attitudes toward characteristics of bicycle commuting on the choice to cycle to work over various distances. Transp. Res. Part Transp. Environ. 16, 102–109. doi:10.1016/j.trd.2010.08.010

Julsrud, T.E., 2014. Activity-Based Patterns of Everyday Mobility: The Potential for Long-Term Behaviour Change Across Five Groups of Travellers. J. Environ. Policy Plan. 16, 401–417. doi:10.1080/1523908X.2013.837380

Li, Z., Wang, W., Yang, C., Ragland, D.R., 2013. Bicycle commuting market analysis using attitudinal market segmentation approach. Transp. Res. Part Policy Pract. 47, 56–68. doi:10.1016/j.tra.2012.10.017

Longley, P., Batty, M., University College, London (Eds.), 2003. Advanced spatial analysis: the CASA book of GIS. ESRI Press, Redlands, Calif.

Lucas, K., 2012. Transport and social exclusion: Where are we now? Transp. Policy 20, 105–113. doi:10.1016/j.tranpol.2012.01.013

Lucas, K., Bates, J., Moore, J., Carrasco, J.A., 2016. Modelling the relationship between travel behaviours and social disadvantage. Transp. Res. Part Policy Pract. 85, 157–173. doi:10.1016/j.tra.2016.01.008

Lucas, K., Blumenberg, E., Weinberger R., (Eds.), 2011. Auto Motives. Emerald Group Publishing Limited.

Mattioli, G., Anable, J., 2017. Gross polluters for food shopping travel: An activity-based typology. Travel Behav. Soc. 6, 19–31. doi:10.1016/j.tbs.2016.04.002

Mattioli, G., Anable, J., Vrotsou, K., 2016. Car dependent practices: Findings from a sequence pattern mining study of UK time use data. Transp. Res. Part Policy Pract. 89, 56–72. doi:10.1016/j.tra.2016.04.010

Mattioli, J., Philips, I., Anable, J., Chatterton, T., 2017. Developing an index of vulnerability to motor fuel price increases in England. Presented at the UTSG (Universities Transport Studies Group), Trinity College Dublin, p. 12.

Milligan, G., 1996. Clustering validation: results and implications for applied analyses, in: Arabie, P., Hubert, J., De Soete, G. (Eds.), Clustering and Classification. World Scientific Press, Singapore.

Molin, E., Mokhtarian, P., Kroesen, M., 2016. Multimodal travel groups and attitudes: A latent class cluster analysis of Dutch travelers. Transp. Res. Part Policy Pract. 83, 14–29. doi:10.1016/j.tra.2015.11.001

Mooi, E., Sarstedt, M., 2010. Cluster Analysis, in: A Concise Guide to Market Research. Springer Berlin Heidelberg, Berlin, Heidelberg, pp. 237–284.

Möser, G., Bamberg, S., 2008. The effectiveness of soft transport policy measures: A critical assessment and meta-analysis of empirical evidence. J. Environ. Psychol. 28, 10–26. doi:10.1016/j.jenvp.2007.09.001

Parkin, J., Wardman, M., Page, M., 2007. Estimation of the determinants of bicycle mode share for the journey to work using census data. Transportation 35, 93–109. doi:10.1007/s11116-007-9137-5

Philips, I., 2014. The potential role of walking and cycling to increase resilience of transport systems to future external shocks. (Creating an indicator of who could get to work by walking and cycling if there was no fuel for motorised transport) (phd). University of Leeds.

PHILIPS, ANABLE, CAIRNS, EMMERSON,
CHATTERTON: Spatial typology of car use

January 2017
Trinity College
Dublin
UTSG

Ralph, K., Voulgaris, C.T., Taylor, B.D., Blumenberg, E., Brown, A.E., 2016. Millennials, built form, and travel insights from a nationwide typology of U.S. neighborhoods. J. Transp. Geogr. 57, 218–226. doi:10.1016/j.jtrangeo.2016.10.007

Salon, D., Boarnet, M.G., Handy, S., Spears, S., Tal, G., 2012. How do local actions affect VMT? A critical review of the empirical evidence. Transp. Res. Part Transp. Environ. 17, 495–508. doi:10.1016/j.trd.2012.05.006

See, L., Openshaw, S., 2001. Fuzzy Geodemographic Targeting, in: Clarke, D.G., Madden, P.D.M. (Eds.), Regional Science in Business, Advances in Spatial Science. Springer Berlin Heidelberg, pp. 269–281.

SEU, 2003. Making the Connections: Final report on Transport and Social Exclusion (Social Exclusion Unit report). Office Of the Deputy Prime Minister, London.

Singleton, A.D., 2013. 2011 Census Open Atlas Project. R-Bloggers.

Singleton, A.D., Longley, P.A., 2009. Creating open source geodemographics: Refining a national classification of census output areas for applications in higher education. Pap. Reg. Sci. 88, 643–666. doi:10.1111/j.1435-5957.2008.00197.x

Sleight, P., 2004. Targeting Customers, 3rd Revised edition. ed. World Advertising Research Center.

Sloman, L., Cairns, S., Goodman, A., Hopkin, J., Taylor, I., 2015. Meta-analysis of outcomes of investment in the 12 Local Sustainable Transport Fund Large Projects: Interim Report to Department for Transport. Transport for Quality of Life and TRL.

van Wee, B., 2011. Evaluating the impact of land use on travel behaviour: the environment versus accessibility. J. Transp. Geogr. 19, 1530–1533. doi:10.1016/j.jtrangeo.2011.05.011

van Wee, B., 2002. Land use and transport: research and policy challenges. J. Transp. Geogr. 10, 259–271. doi:10.1016/S0966-6923(02)00041-8

Vickers, D., Rees, P., 2011. Ground-truthing Geodemographics. Appl. Spat. Anal. Policy 4, 3–21. doi:10.1007/s12061-009-9037-5

Vickers, D., Rees, P., 2007. Creating the UK National Statistics 2001 output area classification. J. R. Stat. Soc. Ser. A Stat. Soc. 170, 379–403. doi:10.1111/j.1467-985X.2007.00466.x

Vickers, D., Rees, P.H., Birkin, M., 2005. Creating the National classification of census Output Areas: Data, Methods and results.

Vickers, D.W., 2006. Multi-Level Integrated Classifications Based on the 2001 Census (phd). University of Leeds.

Voas, D., Williamson, P., 2001. The diversity of diversity: a critique of geodemographic classification. Area 33, 63–76. doi:10.1111/1475-4762.00009

Webber, R., 2007. The metropolitan habitus: its manifestations, locations, and consumption profiles. Environ. Plan. A 39, 182–207. doi:10.1068/a38478

Wilson, R.E., Anable, J., Cairns, S., Chatterton, T., Notley, S., Lees-Miller, J.D., 2013a. On the estimation of temporal mileage rates. Transp. Res. Part E Logist. Transp. Rev. 60, 126–139. doi:10.1016/j.tre.2013.06.004

Wilson, R.E., Cairns, S., Notley, S., Anable, J., Chatterton, T., McLeod, F., 2013b. Techniques for the inference of mileage rates from MOT data. Transp. Plan. Technol. 36, 130–143. doi:10.1080/03081060.2012.745768