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Investigating correlates of personal and freight road transport energy consumption: A case study of England

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ABSTRACT

In most countries worldwide, the transport sector is responsible for a large proportion of energy consumption, the emissions of which have adverse effects on the environment and human health. It is therefore important to understand the determinants of road transport energy consumption in an attempt to minimise these adverse effects. This paper examines the association which road transport energy consumption, for both personal and freight uses, has with a number of area-level factors, covering a host of socio-economic, built environment and travel mode choice variables. We considered England as our case study, using local authority level data. A random parameters multilevel regression model was utilised in order to accommodate the hierarchical structure of the data, with local authorities nested within major areas of England, and to address unobserved heterogeneity more fully. We paid a particular attention to understand the association between levels of active travel and road transport energy consumption, as this is less-understood. Most notably, gross disposable household income per capita had a positive association with personal road transport energy consumption, and the proportion of walking and cycling had a negative association with both personal and freight consumption. The analysis presented here may be useful in modelling the effect that anticipated changes might have on road transport energy consumption, for instance, new transport developments. In particular, local authorities may consider making a concerted effort at promoting active travel as this was found to be highly negatively associated with road transport energy consumption. As well as this, an insight into the disparity in transport energy consumption between geographical areas is provided, which may otherwise go unobserved.

1. Introduction

The transport sector has the highest oil demand compared to other major sectors (i.e., building, industry and electricity and heat) at global level, accounting for nearly 43% of world oil demand (International Energy Agency, 2022). In broad terms, the consumption of energy by road transport has negative environmental consequences both globally in terms of planetary warming, and locally in terms of air quality. In fact, road transport, is a major contributor to air pollution (Colvile et al., 2001; Bignal et al., 2007). Emissions due to the combustion of fossil fuels by motor vehicles, including a range of gaseous pollutants as well as particulate matter, have an adverse effect on the global climate and environment (Akimoto, 2003; Perera, 2018; Heydari et al., 2020) and human health (Krzyżanowski et al., 2005; Hänninen et al., 2014; Perera, 2018; Heydari et al., 2022).

Using the UK government's four-fold sectorial categorisation (services, industry, domestic and transport), and despite the drop in mobility caused by the 2020 COVID-19 pandemic, transport remains the biggest component of energy consumption according to the Department for Business, Energy and Industrial Strategy (BEIS) (BEIS, 2021a). Within the transport sector itself, road transport represented 72% of pre-pandemic energy consumption and, whilst some re-balancing between modes might be expected in future years, it seems likely that road transport will remain the dominant consumer of energy (BEIS, 2020).

Annual road transport energy consumption can be estimated as the summation of the energy consumed by all the individual vehicles that use the road network in a year. For an individual vehicle, its energy consumption depends on the characteristics of the vehicle and load, the number, length and characteristics of journeys, the traffic conditions, how the vehicle is driven and many other factors. However, as sufficient quantities of representative individual data is difficult and expensive to obtain, researchers have sought proxy measures to account for the overall quantities of energy consumed. These measures are discussed in Section 1.1.

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1.1. Literature review

1.1.1. Factors affecting road transport energy consumption

Many studies have found that economic factors affect the energy consumption of transport; examples include Gross National Product (GNP) (Murat and Ceylan, 2006), Gross Domestic Product (GDP) (Haldenbilen and Ceylan, 2005; Ceylan et al., 2008; Zhang et al., 2009; Limanond et al., 2011; Chai et al., 2016), per capita GDP (Limanond et al., 2011; Mraihi et al., 2013), income (Polemis, 2006; Barla et al., 2009; Poumanyvong et al., 2012; Modarres, 2013), price of energy (Polemis, 2006; Barla et al., 2009; Edelenbosch et al., 2020). In a study of road energy consumption in China, for instance, Chai et al. (2016) found that historically road transportation energy consumption has been inextricably linked to GDP. They observed that energy consumption rose by 0.58% for every percentage point increase in GDP and forecast that this figure would be 0.33% for every point of GDP in the future, concluding that more needs to be done by the government to check this annual increase in transport energy consumption. Limanond et al. (2011) conducted a similar study for Thailand using log-linear regression and feed-forward neural network models with variables including both GDP and per capita GDP, forecasting an increase of transport energy consumption of 237–256% from 2008 to 2030.

Other studies have noted spatial and geographic factors including population (Liddle, 2004; Haldenbilen and Ceylan, 2005; Murat and Ceylan, 2006; Ceylan et al., 2008; Barla et al., 2009; Poumanyvong et al., 2012; Chai et al., 2016), land use (e.g., urbanisation level, residential density, etc.) (Brownstone and Golob, 2009; Poumanyvong et al., 2012; Mraihi et al., 2013; Chai et al., 2016; Sodri and Garniwa, 2016), job density, and population density (Newman and Kenworthy, 1989). In a systematic investigation of countries at different stages of economic development, Poumanyvong et al. (2012) found that urbanisation, in particular, has a significant influence on road energy use, but note that this impact varies between high-, medium- and low-income countries. Such economic and spatial factors are often combined with more direct measures of transport activity such as the annual average vehicle kilometres travelled (Haldenbilen and Ceylan, 2005; Murat and Ceylan, 2006; Ceylan et al., 2008), vehicle intensity (Mraihi et al., 2013) and vehicle characteristics such as fuel type and efficiency (Wohlgemuth, 1997). Mraihi et al. (2013) used seventeen years of data from Tunisia in a decomposition analysis to find the key factors behind variation in road transport-related energy consumption, identifying vehicle intensity and vehicle fuel intensity to have been the largest contributors.

In the UK, the road transport energy consumption literature often considered economic and social factors such as income (Goodwin et al., 2004; Brand et al., 2012), price of fuel (Goodwin et al., 2004; Brand et al., 2012), population, GDP (Brand et al., 2012), household size, ageing population (Anable et al., 2012) and the proportion of walk and cycle trips (Banister et al., 1997). Brand et al. (2012), in particular, provided a comprehensive exploration of the relationship between transportation and energy demand by introducing the UK Transport Carbon Model (UKTCM). A range of factors are considered across those based on scenarios (such as economic and demographic variables) and those based on policy (such as vehicle taxes and driver behaviour). The UKTCM offers insight for policy makers as to the potential effectiveness of future energy consumption interventions and provides a useful point of reference for road energy research in the UK. For freight transport, previous research indicated that the nature of the goods carried affects its energy consumption in addition to vehicle size (Vanek and Campbell, 1999). Although GDP has often been employed in the analysis of transport energy consumption, Sorrell et al. (2012) found that its link to freight energy consumption is gradually weakening.

1.1.2. Modelling methodologies

Various methods are employed in modelling transportation energy demand. Wohlgemuth (1997) developed the International Energy Agency transport model to analyse demand elasticities in the transport sector. Murat and Ceylan (2006) used a multi-layer feed forward neural network to develop a nonlinear transport energy demand model. The decomposition analysis approach is used in the research of Mraihi et al. (2013) to analyse the relationship between contributory factors and energy consumption. The Long-range Energy Alternative Planning (LEAP) models are also applied in recent studies (Shabbir and Ahmad, 2010; Azam et al., 2016; Nieves et al., 2019; Maduekwe et al., 2020; Rivera-González et al., 2020). In addition, statistical modelling is widely used in this research area: A structural equations model is used to investigate the effects of residential density on fuel consumption (Brownstone and Golob, 2009). Vector autoregression (VAR) models and vector error correction (VEC) models have been developed to analyse the petrol and diesel demand for road transportation in Greece (Polemis, 2006). Chai et al. (2016) used both univariate and multivariate models, including exponential smoothing method (ETS) models, ARIMA models and multiple regression models to analyse and forecast the energy consumption in China. Also, for China, Zhang et al. (2009) built a partial least square regression model to predict transport energy consumption. Liddle (2004) developed Ordinary least-squares (OLS) fixed effect panel models to explain how demographic change affects per capita personal road energy use in Organization for Economic Cooperation and Development (OECD) countries. Limanond et al. (2011) performed log-linear regression models to estimate the relationship between explanatory factors (GDP and per capita GDP) and road transport energy consumption in Thailand.

Based on the UK Transport Carbon Model (UKTCM) (Brand et al., 2012), the relationship between transportation and energy demand was comprehensively explored by a set of models (transport demand model, vehicle stock model, direct energy use and emission model and life cycle and environmental impact model). As indicated by previous research, socio-technical approaches can be used to develop transport energy demand models and forecast energy demand in the UK (Anable et al., 2012; Brand et al., 2019). Decomposition analysis of energy consumption (Hammond and Norman, 2012; Sorrell et al., 2012; Reuter et al., 2017) is also a commonly used method.

1.2. The current paper

This research contributes to the road transport energy consumption literature empirically by identifying the zonal level determinants of personal and freight road transport energy usage through analysis of a comprehensive and relatively large data set. Also, it investigates whether important between-region differences could exist, for example, in the effects of these determinants on road transport energy consumption. Based on previous research, we looked for a range of explanatory factors and explored the effect they may have on both personal and freight road transport energy consumption. Whilst the broad readily-available proxy-measures are useful in estimating transport energy consumption, the diversity of measures chosen by researchers and their only partial explanation points to the potential benefit of considering further and finer-grained proxies for a more complete picture. To this end, in this study, some factors that are rarely used in previous research, such as gross disposable household income (GDHI), GDHI per capita, and unemployment rate were also considered. The paper takes into account the geographical dimensions of road transport energy consumption, which is rarely considered by previous research. As well as this, the paper investigates the association between active travel and road transport energy consumption, which is less-understood, considering spatial dimensions of active travel. Highlighting the spatial dimensions of road transport energy consumption, our research contributes empirically to the understanding of transport (and energy) geographies.

Using England as our case study, in this paper, we modelled road transport energy consumption at a local authority level for the period 2016 to 2018 (the most recent available data at the time of writing, covering a recent pre-COVID period). The local authorities are

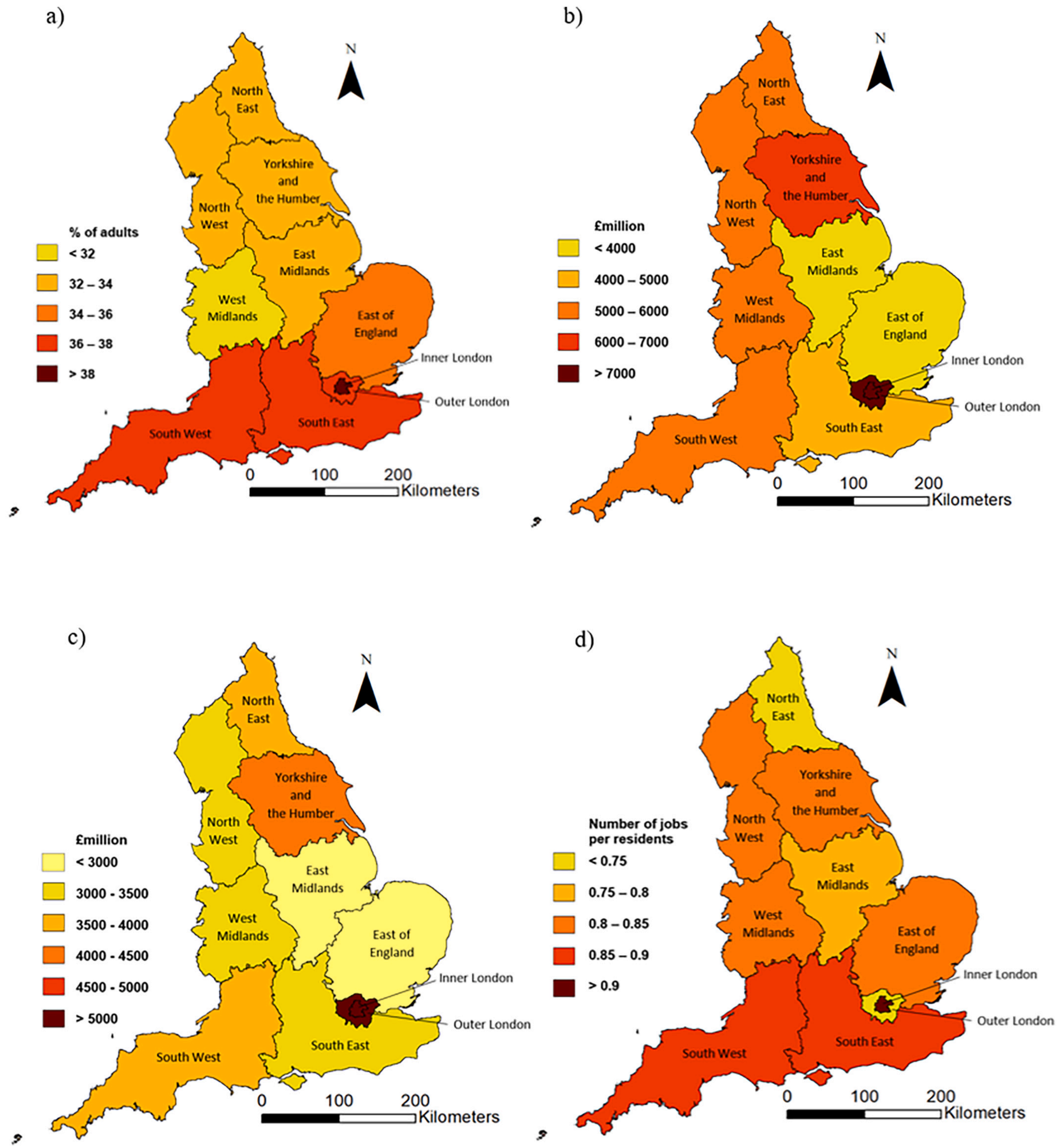

Fig. 1. Maps showing the spatial distribution of relevant explanatory variables: a) Proportion of population cycling or walking, b) GDP, c) GDHI, d) Jobs density.

Table 1
Summary statistics of the data.

Variables[1]	Year	Mean	Std. Dev.	Min	Max
Road energy consumption (personal)	2016	67,995.120	43,593.640	9078.476	359,440.600
	2017	68,191.250	43,798.820	8919.007	362,359.800
	2018	68,087.980	43,958.100	9185.923	364,162.500
Road energy consumption (freight)	2016	35,305.790	26,561.580	2526.587	189,399.700
	2017	36,017.090	27,224.210	2493.108	187,003.600
	2018	36,314.850	27,242.410	2622.755	184,443.700
Total jobs	2016	93,672.240	80,242.620	21,000.000	765,000.000
	2017	94,739.130	81,320.590	21,000.000	754,000.000
	2018	95,157.190	82,354.110	20,000.000	777,000.000
Jobs density	2016	0.841	0.291	0.400	4.420
	2017	0.847	0.290	0.420	4.330
	2018	0.848	0.289	0.390	4.290
Unemployment rate	2016	4.491	1.381	2.084	8.973
	2017	4.055	1.375	1.808	10.093
	2018	3.892	1.140	1.816	8.998
Household by combined economic activity	2016	55,578.930	38,008.890	10,600.000	337,600.000
	2017	55,740.130	38,167.940	9600.000	336,500.000
	2018	56,125.750	38,931.210	10,800.000	342,000.000
GDP	2016	5292.080	5581.193	866.000	63,413.000
	2017	5486.137	5808.559	868.000	66,918.000
	2018	5666.137	6081.792	883.000	70,937.000
Total registered vehicles	2016	100.330	69.044	26.500	762.000
	2017	101.555	70.850	26.800	800.700
	2018	102.757	71.778	27.300	796.100
Population	2016	176,098.800	118,793.600	38,949.000	1,128,077.000
	2017	177,201.500	119,621.600	39,474.000	1,137,123.000
	2018	178,345.400	120,359.100	39,697.000	1,141,374.000
Population density	2016	1827.415	2627.142	24.572	15,618.290
	2017	1838.447	2648.939	24.636	15,816.500
	2018	1852.623	2685.818	24.683	16,095.280
GDHI	2016	3547.769	2371.190	848.000	16,232.000
	2017	3627.274	2405.847	871.000	16,409.000
	2018	3809.114	2541.640	928.000	17,097.000
GDHI per capita	2016	20,512.780	6171.134	12,658.000	80,470.000
	2017	20,859.930	6162.998	12,723.000	81,531.000
	2018	21,742.340	6477.172	13,021.000	85,476.000
Employees	2016	79,787.590	71,284.000	14,874.000	700,994.000
	2017	80,812.910	72,061.900	15,079.000	694,710.000
	2018	81,123.260	73,232.000	14,776.000	716,846.000
Employment	2016	82,423.400	72,905.880	15,727.000	723,913.000
	2017	83,473.120	73,706.500	15,917.000	716,162.000
	2018	83,782.080	74,766.890	15,718.000	736,129.000
Proportion of population cycling or walking	2016	34.016	5.932	24.000	60.600
	2017	35.114	5.425	23.200	57.700
	2018	35.305	5.856	22.300	63.100

[1] See Table 2 for the description the variables.

categorised based on geographic locations and divided into ten major areas (the main regions of England). Note that there are only nine English regions, but London has been sub-divided into inner and outer London. The paper contributes to the road transport energy consumption literature methodologically by using a relatively complex statistical model. Specifically, this study adopts a random parameters multilevel approach, which accommodates the hierarchical structure of the data (i.e., local authorities nested within major areas) and addresses unobserved heterogeneity more fully compared to traditional "single-level" regression, which is commonly employed in this context. For example, multilevel models can account for spatially and non-spatially related unobservables (e.g., travel behaviour and patterns) that vary from one major area to another, improving the model fit, capturing between-area differences, and providing more reliable statistical inferences (Dupont et al., 2013). Note that multilevel modelling is extensively used in traffic safety research (Jones and Jørgensen, 2003; Yannis et al., 2007; Huang and Abdel-Aty, 2010; Dupont et al., 2013; Heydari et al., 2018) as a viable approach to accommodate the effect of groupings in crash data sets. Multilevel modelling is employed in other areas of transport such as travel demand as well (see, for example, Wang et al. (2014)). However, its use in modelling road transport energy consumption is rare if non-existent. It is anticipated that insights provided by this study could assist modelling the energy needs of proposed land use and transport developments and exploring developments which would minimise or limit total energy needs.

2. Case study

Data regarding road transport energy consumption for local authorities in England were used in this study. These data were provided by the Department for Business, Energy and Industrial Strategy (BEIS, 2021b). The database includes information relating to personal and freight road transport energy consumption for 314 English local authorities that are located in ten major areas as reported in the data: North East, North West, Yorkshire and the Humber, East Midlands, West Midlands, East of England, Greater London (including inner and outer London boroughs), South East and South West. Fig. 1 shows the spatial distribution of some select explanatory variables to provide some context to the study area. It can be noted for instance that the south of England and London seems to have the highest rates of walking and cycling as well as the highest jobs density, with the exception of outer London which is highly populated and has fewer jobs compared to Inner

Table 2
Description of the variables used for the period 2016–2018.

Variable	Definition	Unit	Source
Road energy consumption (personal)	Petrol and diesel consumption (buses, cars and motorcycles)	Tonnes of oil equivalent	(BEIS, 2021a)
Road energy consumption (freight)	Petrol and diesel consumption (heavy goods vehicles and light goods vehicles)	Tonnes of oil equivalent	(BEIS, 2021b)
Total jobs	The total number of jobs (employee jobs, self-employed, government-supported trainees and HM Forces)	Number	(Office for National Statistics, 2020c)
Jobs density	Numbers of jobs per residents aged 16–64	–	(Office for National Statistics, 2020c)
Unemployment rate	Unemployment rate for local authorities	Percent	(Office for National Statistics, 2022)
Households by combined economic activity	Including only households that contain at least one person aged 16 to 64	Number	(Office for National Statistics, 2020a)
GDP	Annual estimates of regional gross domestic product (GDP)	£million	(Office for National Statistics, 2021b)
Total registered vehicles	Licensed vehicles at the end of the year by body type	Thousand	(Driver and Vehicle Licensing Agency, 2021)
Population	Mid-year population	Persons	(Office for National Statistics, 2021a)
Population density	Mid-year population divided by the area of the local authority	People per sq. km	(Office for National Statistics, 2021a)
GDHI	Amount of money available to all of the individuals in the household sector for spending/saving after income distribution measures	£million	(Office for National Statistics, 2019)
GDHI per capita	Gross disposable household income per capita	£	(Office for National Statistics, 2019)
Employees	Number of employed residents in each local authority	Number	(Office for National Statistics, 2020b)
Employment	Sum of numbers of employees and working owners	Number	(Office for National Statistics, 2020b)
Proportion cycling or walking	Proportion of adults who do any walking/cycling for any purpose five times per week	Percentage	(Department for Transport, 2021)

Table 3
Estimation results personal road transport energy consumption.

Multiple linear regression model	Mean	Std. Err.	95% Conf. Interval	
ln((Jobs density)	−0.871	0.044	−0.958	−0.785
ln(Unemployment rate)	−0.295	0.042	−0.378	−0.212
ln(Population density)	−0.241	0.009	−0.259	−0.224
ln(GDHI per capita)	0.320	0.050	0.222	0.418
ln(Employees)	1.064	0.019	1.026	1.101
ln(Proportion of cycling or walking)	−0.847	0.064	−0.972	−0.722
Constant	0.839	0.516	−0.174	1.853
AIC	169.455			
Adjusted R-squared	0.787			
Multilevel random intercepts model	**Mean**	**Std. Err.**	**95% Conf. Interval**	
ln(Jobs density)	−0.890	0.046	−0.981	−0.800
ln(Unemployment rate)	−0.248	0.047	−0.339	−0.156
ln(Population density)	−0.231	0.010	−0.250	−0.212
ln(GDHI per capita)	0.451	0.063	0.328	0.573
ln(Employees)	1.061	0.019	1.022	1.099
ln(Proportion of cycling or walking)	−0.789	0.067	−0.919	−0.658
Constant (major area effects)	−0.772	0.713	−2.169	0.625
variance of major area effects	*0.009*	*0.006*	*0.003*	*0.032*
variance of obs. Level errors	*0.066*	*0.003*	*0.060*	*0.073*
AIC	154.006			
Multilevel random parameters model	**Mean**	**Std. Err.**	**95% Conf. Interval**	
ln(Jobs density)	−0.782	0.098	−0.974	−0.589
ln(Unemployment rate)	−0.156	0.071	−0.295	−0.018
ln(Population density)	−0.224	0.019	−0.261	−0.186
ln(GDHI per capita)	0.575	0.067	0.444	0.706
ln(Employees)	1.038	0.020	0.999	1.077
ln(Proportion of cycling or walking)	−0.732	0.066	−0.862	−0.602
Constant (major area effects)	−2.087	0.769	−3.594	−0.581
variance ln(Jobs density)	*0.067*	*0.039*	*0.021*	*0.212*
variance ln(Unemployment rate)	*0.024*	*0.021*	*0.004*	*0.138*
variance ln(Population density)	*0.003*	*0.002*	*0.001*	*0.011*
variance of major area effects	*0.036*	*0.034*	*0.006*	*0.226*
variance of obs. Level errors	*0.059*	*0.003*	*0.054*	*0.065*
AIC	118.358			

Table 4
Estimation results for freight road transport energy consumption.

Multiple linear regression model	Mean	Std. Err.	95% Conf. Interval	
ln((Jobs density)	−0.818	0.069	−0.953	−0.683
ln(Unemployment rate)	−0.147	0.059	−0.263	−0.030
ln(GDP)	1.107	0.029	1.051	1.163
ln(Population density)	−0.425	0.014	−0.454	−0.397
ln(Proportion cycling or walking)	−1.181	0.096	−1.370	−0.992
Constant	8.030	0.385	7.275	8.785
AIC	1021.770			
Adjusted R-squared	0.681			
Multilevel random intercepts model	**Mean**	**Std. Err.**	**95% Conf. Interval**	
ln(Jobs density)	−0.858	0.070	−0.996	−0.721
ln(Unemployment rate)	−0.211	0.064	−0.337	−0.085
ln(GDP)	1.117	0.029	1.060	1.175
ln(Population density)	−0.413	0.015	−0.443	−0.383
ln(Proportion of cycling or walking)	−1.058	0.103	−1.260	−0.855
Constant (major area effects)	7.506	0.430	6.664	8.348
variance of major area effects	*0.005*	*0.004*	*0.001*	*0.022*
variance of obs. Level errors	*0.176*	*0.008*	*0.161*	*0.193*
AIC	1016.985			
Multilevel random parameters model	**Mean**	**Std. Err.**	**95% Conf. Interval**	
ln(Jobs density)	−0.793	0.114	−1.016	−0.570
ln(Unemployment rate)	−0.200	0.066	−0.329	−0.070
ln(GDP)	1.115	0.030	1.056	1.173
ln(Population density)	−0.412	0.016	−0.443	−0.381
ln(Proportion cycling or walking)	−1.038	0.106	−1.246	−0.829
Constant (major area effects)	7.458	0.448	6.580	8.336
variance ln(Jobs density)	*0.065*	*0.050*	*0.014*	*0.293*
variance of major area effects	*0.013*	*0.009*	*0.003*	*0.052*
variance of obs. Level errors	*0.171*	*0.008*	*0.156*	*0.188*
AIC	1009.816			

Table 5
Average elasticity effects for random parameters multilevel models for personal and freight road transport energy consumption.

	Elasticity[1]
Personal road energy consumption	
Jobs density	−7.82
Unemployment rate	−1.56
Population density	−2.24
GDHI per capita	5.75
Employees	10.38
Proportion cycling or walking	−7.32
Freight road energy consumption	
Jobs density	−7.93
Unemployment rate	−2.00
GDP	11.15
Population density	−4.12
Proportion cycling or walking	−10.38

[1] Percentage change in the outcome variables due to a 10% increase in the explanatory variables.

London. With regard to GDP and GDHI, both Inner and Outer London appear to have high values as well as Yorkshire and the Humber, while the East of England and East Midlands have the lowest GDP and GDHI values.

The selection of explanatory variables to be analysed was guided by previous research in this area (such as those cited in literature review), the experience of the researchers, and the availability of data for England at the required areal level. Due to the lack of data for some local authorities, our final dataset contains information relating to 299 local authorities located in ten major areas (regions) of England. Note that some local authority borders were altered in April 2015 and April 2019, which leads to inconsistencies when comparing annually recorded data. To avoid the effect this would have on our analysis, we used road transport energy consumption data from 2016 to 2018. When combining the data from different sources into one coherent dataset, we matched both local authority codes and the name of the local authority to ensure accuracy.

Summary statistics of the data are provided in Table 1, which represents a combination of ten databases. Note that with respect to active travel (here, walking and cycling), we considered various data indicating the proportion of population in each area who walk, cycle, walk or cycle for any purpose and for traveling to work. Also, these data were available at different frequencies; for example, walking once per week, three times per week, and five time per week. To be concise, in Table 1 we only report the statistics relating to proportion of adults who do any walking or cycling five times per week for any purpose, which was found to be statistically important as we will see in the Section of results. Table 2 gives a description of the variables, including their definition, units and data sources. Also, since the study period includes three years of data, we created a categorical variable for year to investigate between-year differences.

3. Method

For this paper, three different statistical approaches were utilised: multiple log-linear regression, multilevel random intercepts model and multilevel random parameters model, details of each will follow. In modelling energy consumption most previous research used log-transformed data (natural log) for transport energy use/demand and explanatory variables (Liddle, 2004; Limanond et al., 2011; Poumanyvong et al., 2012; Chai et al., 2016). In this paper, the natural log transformation is applied to response variables as well as predictors variables, providing more robust models; for example, in terms of the normality of residuals. The Akaike information criterion (AIC) and the Bayesian information criterion (BIC), which are commonly used in model selection, are used in comparing different models.

3.1. Multiple log-linear regression model

A multiple log-linear regression model can be defined as follows. Let y_j represent the road transport energy consumption (personal or freight) for local authority j. Let X_j denote the vector of explanatory variables for local authority j and β be the vector of coefficients associated with X_j. Finally, let a_0 represent the constant term and ε_j denote the error term. The model can then be written as:

$$ln(y_j) = a_0 + \beta ln(X_j) + \varepsilon_j \quad (1)$$

3.2. Multilevel random intercepts log-linear model

As discussed, the dataset has two levels with local authorities nested within major areas. Therefor it is plausible to assume that there might be dependence between local authorities located in the same major areas. Multilevel regression models, also referred to as hierarchical models and mixed-effects models (StataCorp, 2021), can provide a better model fit and richer inferences than simple linear regression when analysing hierarchical data. One form which a multilevel model can take is a random intercepts model, also known as a random coefficients model and it can be written as follows. Let α_m denote the random intercepts for major areas, m, containing local authorities j. Let ε_{jm} represents a normally distributed error term at local authority level.

$$ln\ (y_{jm}) = \alpha_m + \beta ln(X_{jm}) + \varepsilon_{jm}$$

$$\alpha_m | \mu_\alpha, v_\alpha \sim normal(\mu_\alpha, v_\alpha) \quad (2)$$

$$\varepsilon_{jm} | v_\varepsilon \sim normal\ (0, v_\varepsilon)$$

As shown in eq. (2), α_m is assumed to be normally distributed with the mean μ_α and the variance v_α. In this model, β are fixed across the sample while random intercepts α_m vary between different major areas, taking into account potential between-area differences.

3.3. Multilevel random parameters log-linear model

While the effect of explanatory variables is fixed in the above-mentioned models, the random parameters (slopes) model allows the effects of these variables to vary from one major area to another. This allows us to better capture unobserved heterogeneity, which is mainly due to missing data. Given the above notation, let Z_j be explanatory variables the effects of which varies between major areas, with their respective varying coefficients γ_m.

$$ln(y_{jm}) = \alpha_m + \beta ln(X_{jm}) + \gamma_m ln(Z_{jm}) + \varepsilon_{jm}$$

$$\alpha_m | \mu_\alpha, v_\alpha \sim normal(\mu_\alpha, v_\alpha) \quad (3)$$

$$\gamma_m | \mu_\gamma, v_\gamma \sim normal(\mu_\gamma, v_\gamma)$$

$$\varepsilon_{jm} | v_\varepsilon \sim normal\ (0, v_\varepsilon)$$

Random regression parameters γ_m are assumed to be normally distributed with the mean μ_γ and the variance v_γ. Random parameters γ_m vary from one major area to another. In this way, the effect of a variable can change across spatial units (here, major areas).

4. Results and discussions

Tables 3 and 4 show the results of the three models developed for personal and freight road transport energy consumption, respectively. Statistically significant explanatory variables are reported in these

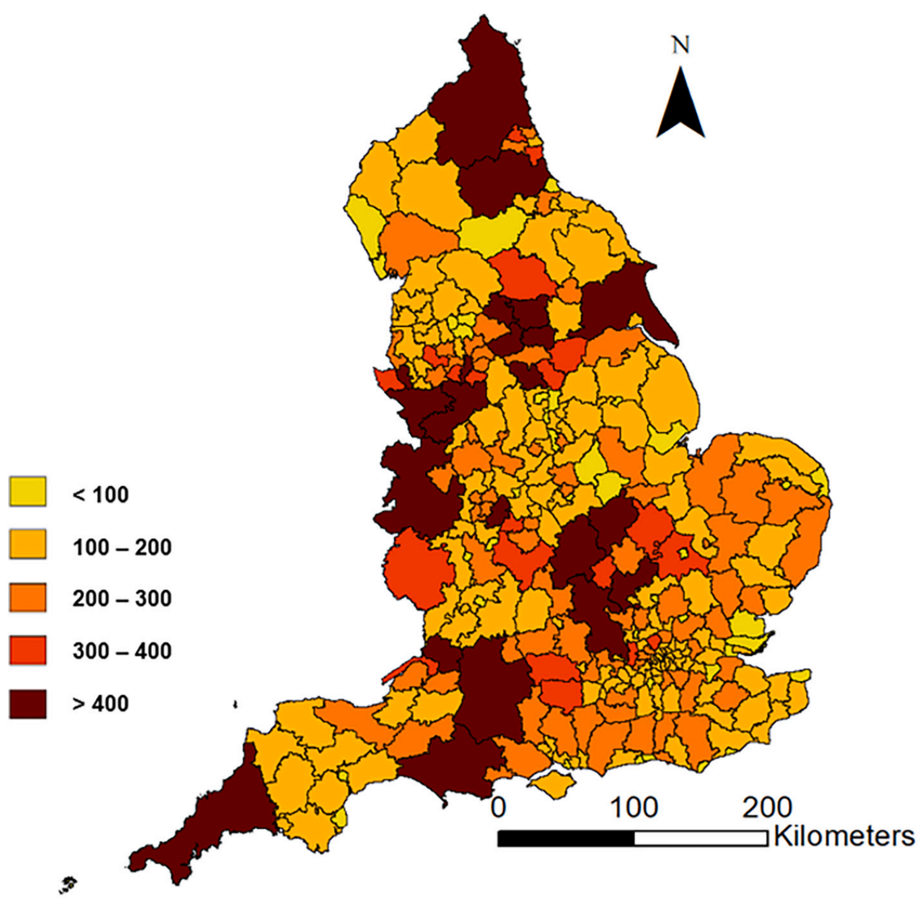

Fig. 2. Spatial distribution of expected personal road energy consumption (Tonnes of oil equivalent in 1000's) in England at local authority level over the study period.

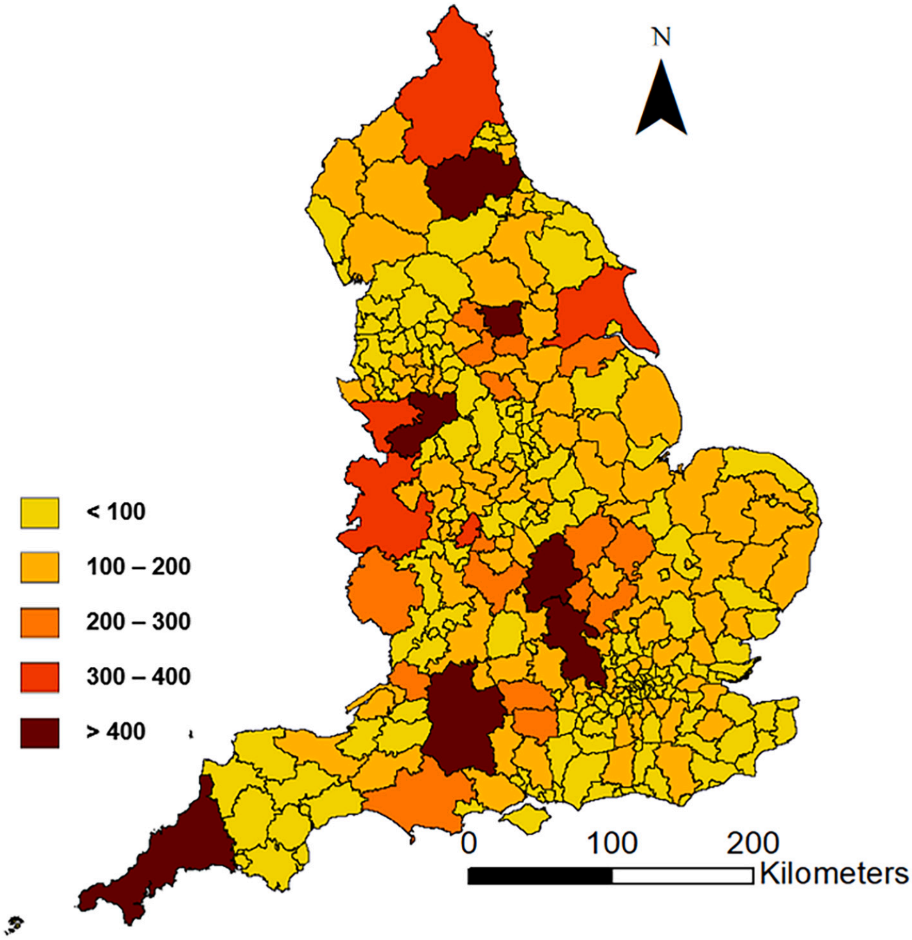

Fig. 3. Spatial distribution of expected freight road energy consumption (Tonnes of oil equivalent in 1000's) in England at local authority level over the study period.

tables. Prior to developing our models, we tested the strength of correlation between pairs of variables to avoid using highly correlated variables in the models at the same time. The adjusted R^2 values of 78.7% and 68.1% (based on the commonly used single-level models) for personal and freight energy consumption, respectively, indicate that most variability in the data is captured by the explanatory variables used in our models. The value of AIC is the lowest for the random parameters models, providing the best model fit. The categorical variable year was not found to be statistically important in our analyses.

With respect to personal road transport energy consumption, GDHI per capita and the number of employed residents were positively associated with personal energy consumption over the study period. However, jobs density, unemployment rate, population density and the proportion of adults who cycle or walk five times a week were negatively associated with personal energy consumption. Interestingly, we found that the effects of jobs density, unemployment rate and population density on personal energy consumption vary across different major areas. With respect to freight energy consumption (Table 4), GDP is positively associated with freight energy consumption while jobs density, unemployment rate, population density and the proportion of adults, who cycle or walk five times per week, are negatively associated with freight energy consumption. Also notably the effect of jobs density varies in different areas.

4.1. Policy implications

4.1.1. Elasticity effects

As the random parameters multilevel models provided the best fit, we discuss elasticity effects based on these models only. Since the dependent and independent variables are all log-transformed, the coefficients associated with the explanatory variables in the models represent average elasticities. Table 5 indicates the percentage change in transport energy consumption based on a 10% increase in the explanatory variables.

In broad terms, a 10% increase in jobs density could be expected to yield a 7.82% decrease in yearly personal energy consumption while this increase will lead to 7.93% decrease in yearly freight energy consumption. Personal energy consumption and freight energy consumption decrease by 2.24% and 4.12%, respectively, when the population density is increased by 10%. A 10% increase in the unemployment rate will result in a 1.56% reduction of personal energy consumption and a 2.00% decrease in freight energy consumption. The findings of the effects of jobs density and population density on energy consumption are in accordance with previous research (Newman and Kenworthy, 1989). Jobs density is a key parameter to evaluate land use, and population density affects how intensively urban land is used and the prevalence of city activities (Newman and Kenworthy, 1989). With this in mind, we can speculate that the growth of jobs density, unemployment rate and population density affect the way in which residents travel by influencing the local authorities' land use. This, in turn, may influence urban density; and a city with higher urban density tends to consume lower transport energy per capita (Baker and Steemers, 2003; Steemers, 2003).

A 10% increase in the proportion of adults who cycle or walk five times a week would decrease personal and freight energy consumption by 7.32% and 10.38%, respectively (note that our study does not reveal causality). This finding is in accordance with Banister et al. (1997). As

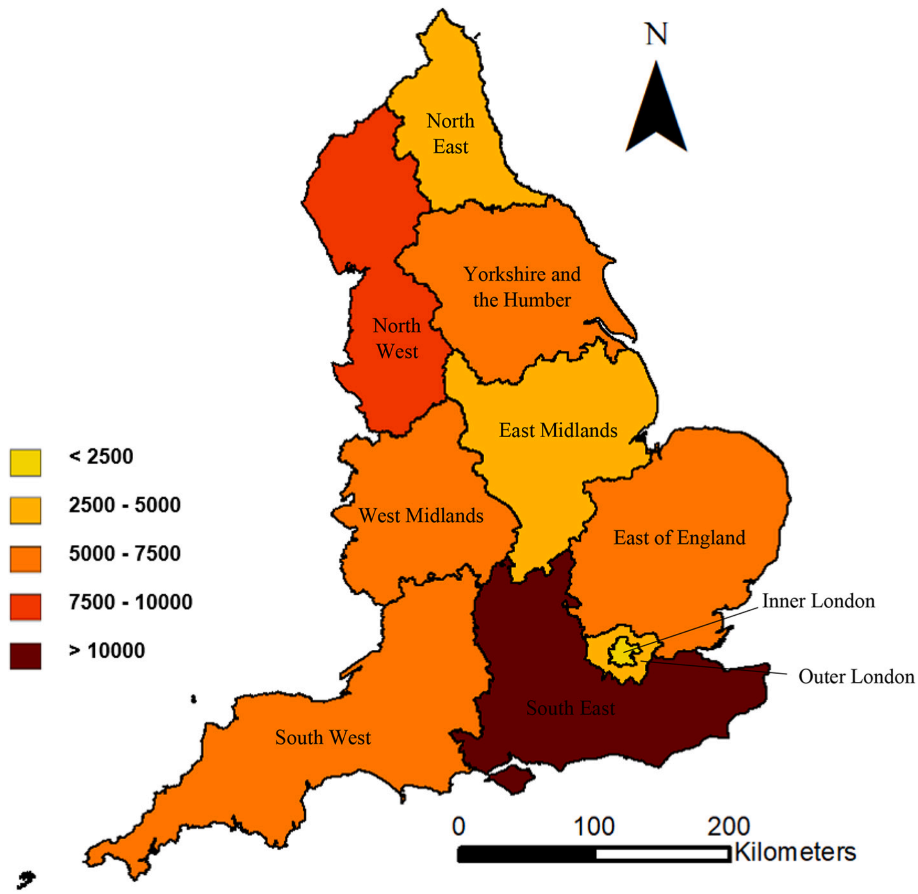

Fig. 4. Spatial distribution of expected personal road energy consumption (Tonnes of oil equivalent in 1000's) in England at major area level over the study period.

discussed by Saunders et al. (2008), walking and cycling do not consume energy for personal or freight usage. This may go some way to explaining why such active transport activity has a decreasing effect on energy consumption. Overall, a shift from motorised trips to non-motorised trips; and consequently, reduced congestion (reducing fuel by reducing idling time), and self-collection from delivery hubs or direct in-person buying and collection can partly explain this finding. Note that studies on the association between active travel and macro-level road transport energy consumption are very limited and this requires further in depth investigations to understand the underlying reasons for a relatively strong association between active travel and road transport energy consumption. Based on this finding, local authorities may consider making a concerted effort to promote the uptake of active travel.

The number of jobs held by employees is part of the number of total jobs, so it has a relationship with jobs density. In contrast to the effect of jobs density, when the number of jobs held by employees rises by 10%, the personal road transport energy consumption increases by 10.38%. This may be due to the geographical distribution of the employees. The two variables GDHI per capita and GDP are economic factors. A 10% increase in GDHI per capita would lead to a 5.75% increase in personal road transport energy consumption. Based on the study of Barla et al. (2009), a higher income will lead to higher petrol demand because of an increase in driving distance and vehicle stock. This can be used as a reference for analysing the effects of GDHI per capita. With respect to GDP, a 10% growth in GDP would result in an 11.15% increase in freight consumption. The finding of the impact of GDP on energy consumption is in line with the research of Limanond et al. (2011) and Chai et al. (2016). The growth of GDP has been shown to lead to the development of local economic activities, thereby promoting the increase of transport activities. This, in turn, leads to an increase in road transport energy consumption.

The random parameters (coefficients) models identified variation in the effects of some of the explanatory variables on road transport energy consumption in England. Based on the results of the random parameters regression, we can conclude that the effects of jobs density, unemployment rate and population density on personal energy consumption vary across major areas. Also, the effect of jobs density on freight energy consumption varies from one major area to another. This is an important finding that indicates substantial between-region differences in England in terms of road transport energy consumption. This inter-regional variability is due to unobserved/unmeasured regional attributes that have an impact on road energy consumption. For instance, such variability may be caused by a number of factors including: climate, road conditions (including the type of road infrastructure), travel behaviour and the distinctions in economic developments and land use in each area. Further in-depth investigation would be needed to understand the reasons behind the varying effects of certain explanatory variables.

While this research provides a clear picture of attribute impacts on local authority level personal and freight energy consumption in England, the following can be inferred from the results: (i) the most significant variables in terms of decrease in personal road transport energy consumption were job density and the proportion of local authority population walking or cycling, whereas the number of jobs held by employees had the highest increasing effect; (ii) the most significant variable in terms of increase in freight energy consumption was GDP while the proportion of population walking or cycling had the highest decreasing effect on freight energy consumption, followed by job density and then population density; (iii) there are differences between the determinants of personal and freight energy consumption in England as well as in the impact of the variables that appear in both models. For example, we found that, interestingly, active travel has a greater impact

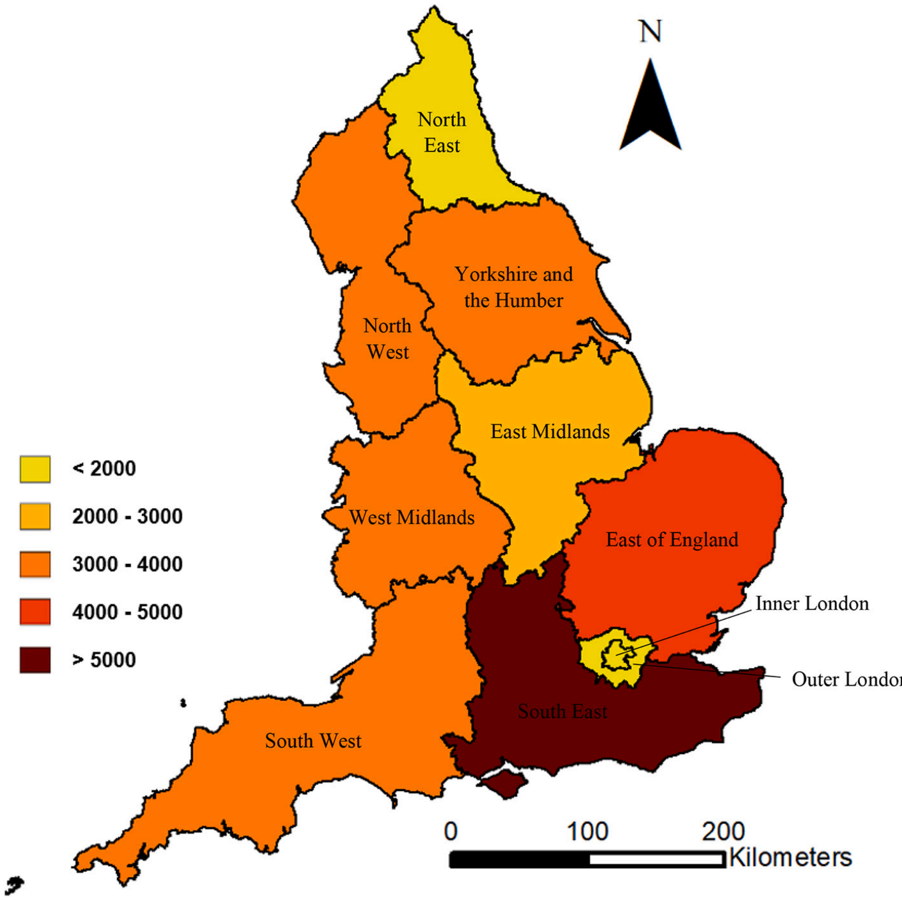

Fig. 5. Spatial distribution of expected freight road energy consumption (Tonnes of oil equivalent in 1000's) in England at major area level over the study period.

on freight energy consumption rather than personal energy consumption; and (iv) in general, the variables that explain freight energy consumption have higher elasticities.

4.1.2. Spatial distribution of expected road transport energy consumption

Figs. 2 and 3 display the spatial distribution of the expected personal and freight road transport energy consumption in England averaged over the study period. Note that expected (model based) values are statistically more reliable than observed values. A darker colour shows a higher energy consumption. For the local authorities with missing covariates, we used the observed energy consumption data. These maps may help decision makers in identifying hotspots (local authorities with highest levels of energy consumption) for which consumption reduction strategies should be prioritised. Considering the statistically important explanatory variables in our models, tailored interventions can then be applied to these hotspots, with the aim of reducing energy consumption; and consequently, emissions. As it can be inferred from Figs. 2 and 3, spatial patterns are more or less the same for both personal and freight energy consumption. That is, areas with a relatively high personal energy consumption are often high energy consumption locations with respect to freight transport as well. Figs. 4 and 5 show similar maps of expected values of personal and freight energy usage at regional level, respectively. These values were obtained by summing the expected values of the individual local authorities. With respect to personal usage, South East England has the highest road transport energy consumption followed by North West region. With respect to freight usage, South East has the highest freight road transport energy consumption followed by East England. On the other hand, Greater London, East Midlands, and North East England have the lowest personal and freight road transport energy consumption. Note that these maps are created based on absolute values of energy consumption in each region, having different characteristics, but one may normalise these by population or other measures. However, we believe no perfect measure exist and therefore we represented the maps using the absolute values.

5. Summary

This study employs multilevel random parameters regression models to investigate personal and freight road transport energy consumption in England. The dataset used in this research includes 897 observations from 2016 to 2018, containing information relating to 299 local authorities in England. While due to data availability at the time of writing, we analysed the 2016–2018 period, future research should update our analyses with the aim of understanding both short- and long-term impacts of the recent pandemic on road transport energy consumption. As we use three years of data, our results are expected to be more reliable as our analyses are not subject to unusual annual fluctuations in energy consumption. The effects of several explanatory factors on energy consumption are examined and discussed. Some of the variables (the proportion of adults who walk or cycle, GDHI and GDHI per capita) included in our analyses have rarely been used in previous studies of road transport energy use, but here we found that these are very good predictors of road transport energy consumption in England. This research contributes to the literature by being the first, to our knowledge, to analyse area-level personal and freight energy consumption separately, using a relatively complex econometric approach, a random parameters multilevel model. Our approach accounts for the hierarchical structure of the data; i.e., local authorities nested within major areas of England, accounting for dependence in the data and addressing unobserved heterogeneity more fully.

We found that road transport energy consumption is lower in local authorities with higher levels of active travel (walking or cycling). Also, we found that active travel has a higher impact on freight road transport energy consumption compared to personal road transport energy consumption. Note that our models do not reveal causality but association only. The reason why the effects of some variables vary across major areas of England is a topic for further research and subsequent exploration. The paper deepens our understanding of road transport energy consumption in England (and perhaps in similar contexts elsewhere). The developed models can be used in forecasting road transport energy consumption of the local authorities in England. Our findings could be useful for decision makers in designing low carbon transport and planning policies.

Author statement

J. Zhao: data curation, methodology, analysis, writing - original draft, writing – review & editing.

S. Heydari: data curation, methodology, analysis, writing - original draft, writing – review & editing, project administration, supervision.

M. Forrest: writing original draft, writing review/editing, visualization.

A. Stevens: writing original draft, writing review/editing.

J. Preston: writing original draft, writing review/editing.

Declaration of Competing Interest

None.

Data availability

Sources of data are stated in the paper

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