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Exploring Transport Consumption-Based Emissions: Spatial Patterns, Social Factors, Well-Being, and Policy Implications

Lena Kilian [1,*], Anne Owen [2], Andy Newing [1] and Diana Ivanova [2]

[1] School of Geography, University of Leeds, Leeds LS2 9JT, UK
[2] School of Earth and Environment, University of Leeds, Leeds LS2 9JT, UK
* Correspondence: l.kilian@leeds.ac.uk

Abstract: Recent years have seen an increased interest in demand-side mitigation of greenhouse gas emissions. Despite the oftentimes spatial nature of emissions research, links to social factors and infrastructure are often not analysed geographically. To reach substantial and lasting emission reductions without further disadvantaging vulnerable populations, the design of effective mitigation policies on the local level requires considerations of spatial and social inequalities as well as the context of well-being. Consequently, we explore spatial variations in the links between consumption-based transport emissions with infrastructural factors, such as workplace distance and public transport density, and with risk-factors of transport poverty, including income, age, ethnicity, mobility constraints in London. We find that linear models report significant spatial autocorrelation at $p \leq 0.01$ in their model residuals, indicating spatial dependency. Using geographically weighted regression models improves model fits by an adjusted R^2 value of 9–70% compared to linear models. Here, modelling flight emissions generally sees the lowest improvements, while those models modelling emissions from cars and vans see the highest improvements in model fit. We conclude that using geographically weighted regression to assess the links between social factors and emissions offers insights which global, linear models overlook. Moreover, this type of analysis enables an assessment of where, spatially, different types of policy interventions may be most effective in reducing not only emissions, but transport poverty risks. Patterns of spatial heterogeneity and policy implications of this research are discussed.

Keywords: transport footprints; geographically weighted regression; consumption-based accounting; greenhouse gas emissions; social factors

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1. Introduction

The increased involvement of local actors in climate change mitigation has meant an increased focus on local strategies [1–5]. Determining how local consumption contributes to global and national emissions is therefore important for effective, socially just greenhouse gas (GHG) reduction and resource inequality management [6–9]. With transport being one of the highest emitting sectors [10–13] and some aspects of UK road transport (including road building, infrastructure projects, congestion charging and creating low emissions zones) and airport planning being administered locally, a spatial analysis of transport can aid local climate policy makers.

Reducing transport emissions faces various challenges. Differences in incomes and access to services link emissions to social inequalities [6,10,14–21], which a focus on behaviour change can overlook. For instance, UK-based research links increased transport poverty to rural communities, lower incomes, Black, Asian, and Minority Ethnic (BAME) households, households with children, people with disabilities, and women [22,23]. Reducing and redistributing transport emissions must, therefore, also take existing inequalities and vulnerabilities into account. Furthermore, high transport emissions are driven by lock-ins [13,24,25]. Mattioli et al. [26] argue that the entanglement between the automotive industry, car-related infrastructure, political-economic relations, public transport provision, and socio-cultural factors create a lock-in and that moving away from car dependency requires consideration of all factors.

Similarly, although air travel participation of low-income households is increasing, carbon inequality remains high [27–30]. Moreover, prioritisation of economic growth, increased reliance on flights [31], disagreements about how international aviation emissions are assigned in footprint calculations, and a focus on individual responsibility [32,33] results in increased flight emissions over time and side-lines systemic changes needed for emission reductions. With policy strategies of different cities to reduce aviation emissions differing widely [34], the extent to which local policy can and does reduce aviation emissions is highly varied and often limited.

Despite evidence suggesting that energy efficiency advancements can only reduce emissions sufficiently if combined with major societal, economic, and cultural changes [35–37], transport decarbonisation discussions and policies often centre technological shifts [38–40]. Nonetheless, recent years have seen a steep increase in research published on reducing emissions through decreasing demand [41], such as avoiding flying and living car-free [42]. Moreover, research suggests that transport emissions can be effectively reduced through local policies [43–45]. In line with this, the UK's Climate Change Committee [46] aims to encourage increased use of public and active transport by 2030, through investment in local infrastructure. A spatial analysis of neighbourhood footprints can offer a perspective on how such infrastructure affects transport emissions.

Climate policy also needs to consider energy justice and well-being. Creutzig et al. [47] suggest that demand-side mitigation can positively impact different aspects of well-being. For instance, decreased commuting is linked to decreased land transport emissions [48] and increased subjective well-being [47]. Active and public transport can decrease emissions, motor vehicle crashes, and noise, while increasing greenspace can promote physical activity [49–51]. Moreover, understanding emissions through energy [52,53] and transport [54,55] justice lenses is necessary: Energy and transport access are impacted by factors such as income, age, and disability [23,56–58]. Emission reduction efforts need to consider human well-being and social factors to avoid widening inequalities.

While much research looks at the links between social factors and consumption-based emissions [10,14–17,19–21,27,59–62], the spatial aspects of consumption-based emissions are not well-studied. Although concepts of spatial justice and injustice are debated, as some argue that spatial injustices only represent social injustices [63–68], applying a spatial justice framework can be helpful in highlighting and evaluating emission inequalities. Using such a framework, Bouzarovski and Simcock [68] are able to identify various mechanisms which produce and reproduce energy poverty and vulnerability. Space is similarly important in quantitative analysis. Geographic data are generally considered to be spatially dependent, such that areas in closer geographic proximity are more likely to be more similar [69]. Ignoring spatial dependencies falsely assumes that relationships between variables are the same in all areas [70] and can overlook inconsistencies and spatial variance. Indeed, evidence from China suggests that the relationships between emissions and its predictors are spatially heterogeneous, and that employing spatial statistics can shine light on these differences [71–73].

To our knowledge, consumption-based transport emissions and their links with social factors have not been analysed spatially, in the UK. We focus on transport emissions as these have inherently spatial qualities, have the potential for local policy interventions, and as transport is one of the highest emitting sectors in the UK [74–76]. Moreover, we assess spatial factors, such as distance to workplace and public transport network density, as well as factors which increase the risk of transport poverty (where transport poverty is defined as being caused by high cost and low public transport access), including lower incomes, BAME households, households with children, people with health or mobility difficulties [22,23].

Bridging the gap between environmental economics and geographical analysis, we employ geographically weighted regression analysis, a variation of a regression analysis which embeds the spatial relationships between observations to estimate local parameters for each observation [69,73,77]. The aim of this paper is to explore whether and how relationships between social factors and transport emissions are spatially heterogenous and assess how this may impact local policy decisions. We look at emissions from the years 2015–2016 with a particular focus on London. In this paper, we first discuss the methods and data used for our analysis, results from analysis, which we split into spatial patterns of the relationships between incomes and emissions, and other social factors and emissions, as well as provide an overview of the links between emissions and well-being. Finally, we discuss our findings in the context of other research and their policy implications.

2. Materials and Methods

2.1. Neighbourhood Emissions

To estimate neighbourhood GHG emissions, we need two pieces of data: an estimate of local expenditure and product-based intensities (in $tCO_2e/£$). The multipliers incorporate both indirect emissions which occur throughout the supply chain globally and direct emissions from the burning of fuel for personal transport use (e.g., private cars).

To calculate these product-based multipliers, we first need to calculate the UK's total household GHG emissions. We conduct a multi-regional input–output (MRIO) analysis with and environmental extension to calculate indirect emissions from goods and services consumed by UK households, which occurred throughout the global supply chain. MRIO databases originate from economics but have been used by environmental economists since the 1960s due to their ability to make the link between the environmental impacts associated with the production of goods and services and final demand. The Leontief input–output model reports the economic interrelationships between industries throughout the supply chain, by documenting, in monetary units, which inputs industries consume from each other to produce their own outputs [78]. Equation (1) shows how product-level emissions ($\mathbf{p}$) can be estimated using the fundamental Leontief equation, $\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{y}$, where $\mathbf{s}$ is a vector showing direct industry emissions, $\mathbf{I}$ is the identity matrix with the same dimensions as the input–output matrix ($\mathbf{Z}$), $\mathbf{A}$ is the product of $\mathbf{Z}$ and the total industry output vector, and $\mathbf{y}$ is final demand. More details of the structure of an MRIO database can be found in the literature [78,79].

$$\mathbf{p} = \mathbf{s}(\mathbf{I} - \mathbf{A})^{-1}\hat{\mathbf{y}} \tag{1}$$

The MRIO database used to calculate product-level household emissions for the UK in the current research is the UKMRIO model from the year 2015 for 307 products and services [80–82]. The UKMRIO is an annually reported national statistic, which is constructed by the University of Leeds and follows the recommendations from Tukker et al. [83] and Eden et al. [84] for calculating consumption emissions consistent with National Accounts (see [85] for more detail). All greenhouse gases reported in the UKMRIO are converted into CO_2 equivalents and include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), hydrofluorocarbons (HFCs), perfluorocarbons (PFCs), sulphur hexafluoride (SF_6) and nitrogen trifluoride (NF_3). We estimate emissions at a Classification of Individual Consumption by Purpose (COICOP) 4 level, [86], using a UKMRIO sector to COICOP bridging table, from the UK's Office for National Statistics. After indirect emissions of UK households are calculated, direct household emissions are added to products associated with fuel burning. Direct emissions are also reported in the UKMRIO as CO_2 equivalents.

To disaggregate UK emissions subnationally, we use microdata on neighbourhood-level household expenditure. Product-level emissions estimates can be divided by total household spends for each product to produce the aforementioned carbon multipliers. The expenditure microdata used here is from the Living Costs and Food Survey (LCFS), an openly available expenditure survey recording detailed spends from 4000–6000 private households across the UK every year [87]. To increase our sample size, we combine data from 2015 and 2016 LCFS. Moreover, to reduce the effect of outliers on emission estimates, product-level household expenditures that are 3.5 standard deviations above or below the sample mean are windosirsed. To ensure that household expenditure from the LCFS matches that from the UKMRIO database [88], we adjust expenditure in the LCFS for each COICOP 4 product/service by the total spend reported in the UKMRIO.

To generate neighbourhood expenditure profiles, we follow the method used by Kilian et al. [85] to calculate neighbourhood emissions in the UK using the LCFS. This means that we use the geodemographic classification of Output Areas, the smallest census geography in the England (with a population of 100–625 people [89]), and regional information from the LCFS to generate sub-regional neighbourhood expenditure profiles. Applying the carbon multipliers to neighbourhood expenditure provides and estimate of household GHG consumption-based emissions by neighburhood. This method provides emission estimates which are comparable, for the majority of the consumption-based footprint, to estimates generated from other microdata [85]. Moreover, our selection of the method, neighbourhood size and microdata is based on suggestions by Kilian et al. [85] to ensure that data are as robust as possible.

The neighbourhood geography used in this research is Middle Layer Super Output Area (MSOA), the third smallest census geography in England, with populations of 5000–15,000 people [89] (Figure 1). To match official records, we also adjust populations from the LCFS to mid-year populations [90]. The mean number of unique households used to create an MSOA expenditure profile is 259.38 households (SD = 89.91). The distribution of sample sizes for each MSOA is shown in Figure 1: This only shows the unique observations; MSOA expenditure profiles are weighted by how often household types are present in each MSOA. Moreover, the same observation may be used to estimate emissions for multiple MSOAs, where the geodemographic neighbourhood classification indicates similar neighbourhood types in multiple MSOAs.

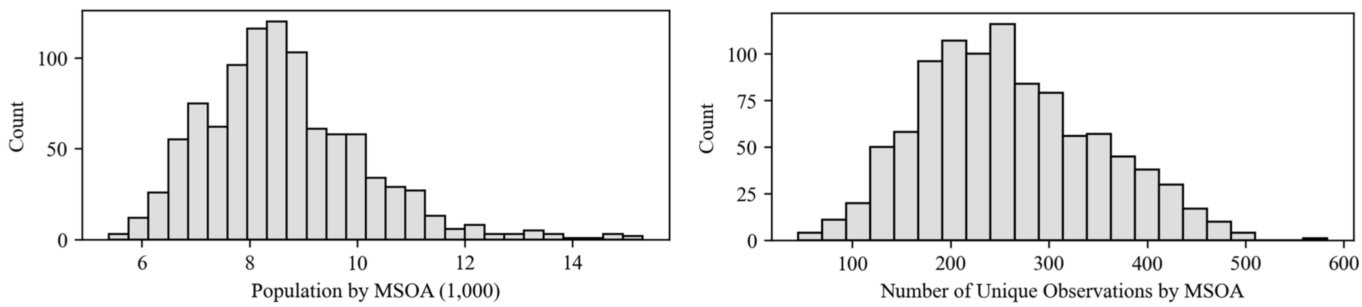

Figure 1. Histogram showing the population (**left**) and the number of unique observations (households) from LCFS (**right**) in each MSOA in London.

Using expenditure as a proxy for volume consumed is a source of uncertainty for this type of analysis [91]. We reduce this uncertainty by using data on the number of flights taken, rather than cost. We also follow Kilian et al.'s [85] recommendations to increase emission estimate robustness, including aggregating to large neighbourhoods and combining expenditure surveys from 2 years. However, using expenditure presents an issue for public transport season tickets. Here, ticket cost is not reflective of trip numbers. However, travelcard prices change with distance from central London, so prices are adjusted to the maximum distance travelable. Therefore, while we do not know the number of journeys taken, we can assume that those traveling less frequently purchase individual tickets. In other words, we assume that those buying travel cards purchase these when buying individual tickets for journeys is more expensive than buying a travel card. Thus, we assume that those buying travel cards take more journeys than those buying individual tickets, and that, therefore, prices are indicative of distance travelled, up to the travel card price.

2.2. Geographic, Census and Other Data

In this section, we summarise additional datasets we use in the current research. Descriptive statistics for all variables are shown in Table 1.

Table 1. Means and standard deviations of social and spatial factors.

	Weighted by Population		MSOA Average					
	Weekly Income (1000 GBP)	**Distance to Workplace (100 km)**	**Public Transport Density (Metric)**	**Pop. Aged ≥65 (%)**	**Pop. Aged ≤14 (%)**	**Pop. Identifying as BAME (%)**	**Pop. Limited in Day-to-Day Activities (%)**	**MSOA Population (1000)**
Mean	0.23	0.11	2.31	11.22	18.68	39.51	14.17	8.69
Std. deviation	0.08	0.02	0.77	4.12	3.88	19.35	2.68	1.54
Minimum	0.10	0.06	0.00	2.40	5.78	3.81	6.04	5.41
Maximum	0.59	0.18	4.64	27.23	34.00	93.86	22.79	15.36

2.2.1. 2011 Census

We use data from the 2011 census [92] for geography lookup tables, geographical boundaries, distance to workplace and the numbers of people aged 65 and over, 14 and younger, limited in their day-to-day activities due to long-term health problems and/or disabilities, and identifying as BAME. To ensure consistency between population data from the emission estimates and census, we adjust census data to the 2015 mid-year population [90]. Mid-year populations estimate populations for 30 June of a given year by adjusting population counts from the census with administrative data on births, deaths, and migration [93].

2.2.2. Public Transport Density

Data for 2015 public transport density are available via the London Datastore [94]. We use the Access Index measurement from the Public Transport Access Level (PTAL) indicator, which estimates public transport network density and frequency at a small area level across London. We use a log transformation on Access Index values to better represent the PTAL categories linearly [95]. How this transformed variable maps onto original PTAL categories is shown in Table 2, more information on how these categories are defined is available at the London Datastore [95]. Public transport density data are spatially divided into 100 m grid squares with 159,451 cells. For each of these, the centroid is calculated and the median transport density value of all centroids that fall within one MSOA are taken to represent the public transport density of this MSOA.

Table 2. Transformed public transport density mapping onto original PTAL category.

Original CategoryPTAL 2015	Transformed Variable Used in This Paper	
	Minimum	**Maximum**
0 (lowest)	0.00	0.00
1a	0.01	1.24
1b	1.25	1.79
2	1.80	2.40
3	2.41	2.77
4	2.78	3.03
5	3.04	3.26
6a	3.27	3.71
6b (highest)	3.72	4.64

2.2.3. Income

The income data we use are available via the UK's Office for National Statistics [96]. As data are reported as household income, we adjust them to per capita income using data on household size from the 2011 census.

2.2.4. Well-Being

We use well-being data from the London Datastore [97,98]. For data availability reasons, we use the 2013 data. These data are at ward level, which is an electoral geography larger than MSOAs. Ward boundaries for the data are from the year 2009. For this part of the analysis, therefore, we calculate ward-level emissions by generating the mean emissions from the MSOAs in each ward, weighted by MSOA population and the proportion of each MSOA's area in each ward. As research indicates that findings can depend on the definition of well-being used [99], we analyse both a well-being index score and subjective well-being. The well-being index captures life expectancy, childhood obesity, incapacity benefit claimant rate, unemployment rate, crime rate, rate of deliberate fires, GCSE point scores, unauthorised pupil absence, children in out-of-work households, public transport accessibility, access to public open spaces, and subjective well-being [97,98]. The subjective well-being score captures self-reported life satisfaction, worthwhileness, anxiety, and happiness, and is used here as transport choices have been linked to subjective well-being in the past [100–102].

2.3. Geographically Weighted Regression

Spatial data typically exhibit spatial dependency and non-stationarity. This means that more proximal locations share more similar attributes than those further apart and that processes responsible for observed phenomena can spatially vary [69,103]. Traditional regression modelling neglects these spatial differences. We therefore use geographically weighted regression (GWR) models, an extension of regular regression models. This can be expressed as shown in (2), where $\mathbf{y}$ is the dependent variable, $\mathbf{x_1}$ to $\mathbf{x_n}$ are independent variables, $\boldsymbol{\beta_0}$ is the intercept, $\boldsymbol{\beta_1}$ to $\boldsymbol{\beta_n}$ represent model coefficients, and $\boldsymbol{\varepsilon}$ is the random error term [69]. Here $\mathbf{i}$ refers to a location, in this research an MSOA-level neighbourhood. A distance weight is used to weigh data from nearer locations more strongly than data from more distant locations, resulting in local coefficients highlighting variable relationships around location $\mathbf{i}$ [69]. This is calculated using Euclidian distance. Moreover, we use an adaptive cross-validation approach to selecting the bandwidth, or number of neighbours included in each model. This means that we can find the optimal bandwidth, as a too small value can lead to large variance in local coefficients, while a too large bandwidth value can bias local estimates by including observations which are too far away [69]. This helps select a model which has a good model fit, without overfitting to the data. A more detailed description of GWR can be found in Fotheringham [69]. We use the R-package 'Gwmodel' [104] to estimate the GWR models and the distance matrix.

$$\mathbf{y_i} = \boldsymbol{\beta}_{0_\mathbf{i}} + \boldsymbol{\beta}_{1_\mathbf{i}}\mathbf{x}_{1_\mathbf{i}} + \boldsymbol{\beta}_{2_\mathbf{i}}\mathbf{x}_2 + \ldots \boldsymbol{\beta}_{\mathbf{n_i}}\mathbf{x}_{\mathbf{n_i}} + \boldsymbol{\varepsilon}_\mathbf{i} \tag{2}$$

To assess the usefulness of GWR modelling for our data, we follow recommendations by Comber et al. [70]. We do this by running both GWR and ordinary least squared linear regression (LM) models with the same variables, and comparing the fits of the two models, as well as assessing the spatial distribution of the residuals of the LM models. If residuals of LM models exhibit significant spatial clustering, they are not considered independent, thus violate assumptions of linear regression modelling. Moreover, we can compare model fits to assess which model is better able to represent the data. This allows us to evaluate whether GWR models should be used for this type of research, and if yes, where they are most able to improve on LM models.

3. Results

3.1. Descriptive Statistics and Spatial Emission Patterns

In 2015–2016, approximately 30% of London's consumption-based household emissions come from transport. As shown in Table 3, when breaking transport emissions down into various modes of transport, we find that cars have the largest footprint (M = 1.11, SD = 0.39), followed by flights (M = 0.98, SD = 0.35). It should be noted that UK flight emissions are lower between 2008 and 2018 [105] due to the 2007/08 economic crisis. Combined, emissions from flights and cars make up over 75% of the average Londoner's transport footprints. The lowest per capita emission, on the other hand, come from bus and combined transport, which includes emission from combined bus and mass rapid transit system tickets. Their combined footprint is only 0.11 tCO_2e/capita, or less than 5% of the total transport footprint. Detail on the aggregation of different COICOP 4 categories to the transport modes analysed in this paper can be found in Appendix A Table A1.

Table 3. Descriptive statistics for emissions from different transport modes in London.

	Car/Van Purchases and Motoring Oils	**Flights**	**Rail**	**Bus**	**Combined Fares**	**Other Transport**	**Total Transport**
Mean (tCO_2e/capita)	1.11	0.98	0.13	0.03	0.08	0.39	2.72
Standard deviation	0.39	0.35	0.07	0.01	0.02	0.17	0.66
Minimum (MSOA)	0.52	0.45	0.02	0.01	0.01	0.10	1.44
Maximum (MSOA)	2.26	2.40	0.47	0.06	0.16	1.29	4.47

When comparing per capita emissions of different London neighbourhoods, we find that per capita flight emissions have the largest range between London neighbourhoods (Range = 1.95 tCO_2e/capita), followed by emissions from cars (Range = 1.74 tCO_2e/capita). However, relative to magnitudes, car emissions have the smallest, albeit notable, difference where the neighbourhood with the highest emission has a per capita footprint four times that of the lowest emitting neighbourhood. For flights, it is five times as high, while for rail, bus, and combined fare emissions the highest per capita footprint is 9–21 times as high as the lowest. Thus, large carbon inequalities occur across all transport modes in London.

Spatial patterns are also evident (Figure 2). Car emissions are lower in Inner London and higher in Outer London. Contrastingly, higher rail and flight emissions are clustered mostly in Inner London. Higher bus emissions non-uniformly clustered, mostly around the southern half of Inner London and north-eastern parts of Outer London. This may be linked to reduced availability of suburban rail and mass rapid transport in some areas. Higher emissions from combined fares, on the other hand, are more present in Inner London, likely mirroring income patterns, as buses are cheaper than combined fares. Notably, some areas between the centre and outskirts indicate below median emissions from car, rail, and bus transport. This could point to areas with increased transport poverty, or with higher active transport.

3.2. Emissions and Social Factors

3.2.1. Spatial Variance in the Relationship between Income and Emissions

Regression analyses are conducted to explore the relationships between socio-demographic and spatial factors and consumption-based GHG emissions. For this, we run geographically weighted regression (GWR) models. A GWR produces two results: a 'global' model, which here is a London-wide regression model that does not consider spatial variation; and 'local' coefficients for each neighbourhood. Local coefficients represent the relationships between variables for the given and surrounding MSOAs. We also run ordinary least square regression (LM) models with the same parameters to be able to compare the model fits of a linear regression to a GWR.

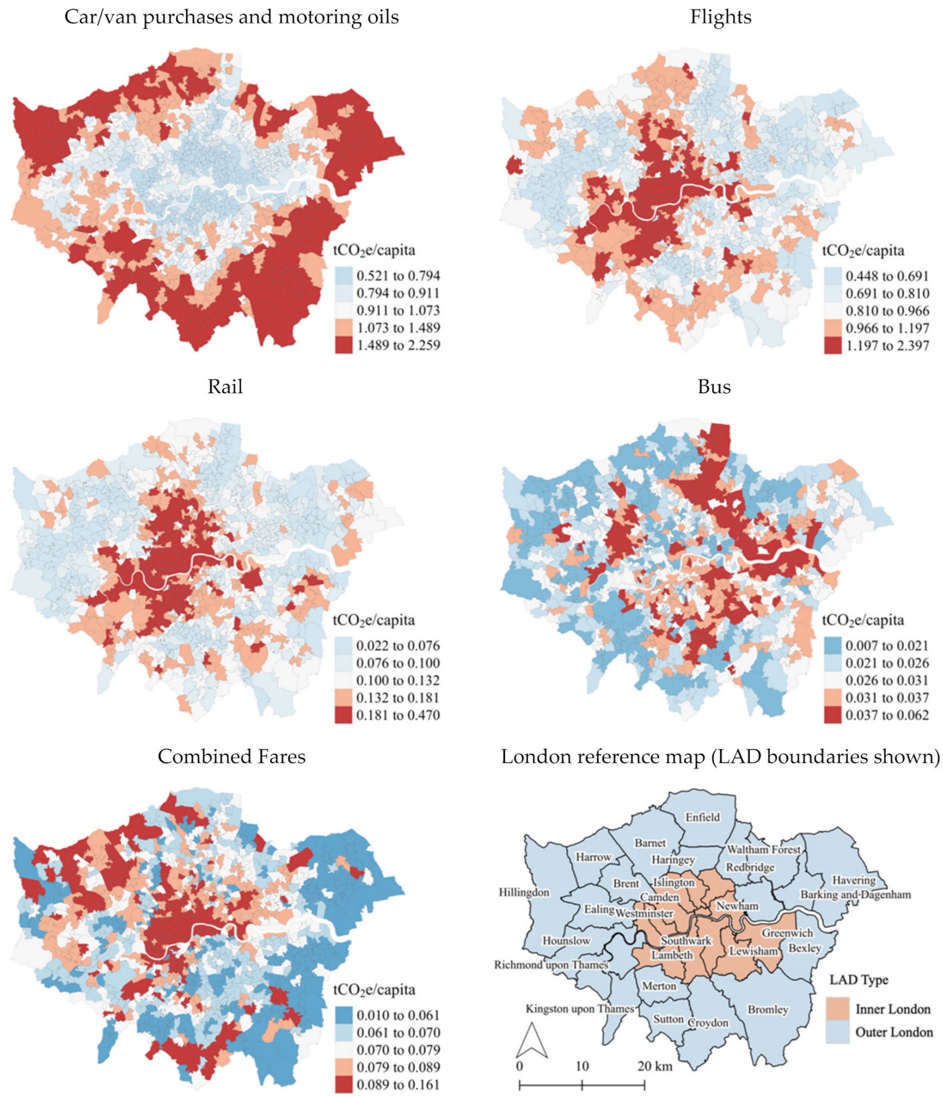

Figure 2. London's consumption-based transport emissions from 2015 to 2016 for different modes of transport. Notes: Colour ranges show quintiles. Blue neighbourhoods have below median, white neighbourhoods have close to median, red neighbourhoods have above median per capita emissions for a given transport mode.

First, we run one GWR and one LM model for each mode of transport, where we use income to predict consumption-based GHG emissions. This analysis allows us to explore spatial differences in the relationship between income and emissions. To prevent a spurious correlations by using multiple variables which are derived from common ancestors [106,107], we use total MSOA emissions and incomes, but control for MSOA populations in our models.

First, we compare the LM models to the GWR models, following suggestions by Comber et al. [70] by looking at the spatial distribution of LM residuals and model fits. The residuals of all LM models show significant spatial autocorrelation, as indicated by the Moran's *I* statistic and significance testing; Moran's $I \geq 0.50$ ($p < 0.01$). A Moran's *I* value of -1 indicates an even distribution, 0 indicates a random distribution, 1 indicates complete clustering. Thus, residuals of the LM models are significantly clustered and the use of a GWR model is advised. Next, we compare model fits of the LM and GWR models. The Akaike Information Criterion (AIC) considers both the complexity of a model, as well as its goodness of fit. This can be used to compare models, where a lower score is regarded as a better model, with less risk of over- or underfitting. Adjusted R^2 is based on the R^2 statistic, which provides a value between 0 and 1, which expressed the proportion of change in the dependent variable, which is explained by the model. Here 1 means that all change in the dependent variable is explained, while 0 means that no change in the dependent variable is explained by the model. Adjusted R^2 adjusts for the number of terms in the model and is always lower than the R^2 value of a model.

Results from our analysis are shown in Table 4. For all dependent variables, GWR has a lower AIC and a higher adjusted R^2 value, indicating that the GWR models provide a better fit for the data than the LM models. Most notable are the model improvements for the model estimating emissions from car/van purchases and motoring oils, which explains over 70% more of the change in emissions when using a GWR rather than an LM. For combined fare and bus emissions, this is around 40%, while flight and rail emissions see an improvement of 16% and 22%, respectively. As GWR models provide a better fit, we continue to assess the GWR models in more detail.

Table 4. Results from the GWR and LM models when using income as a predictor of emissions from different transport modes.

Dep. Variable (tCO_2e)	Residual Moran's I (LM)	AIC		Adjusted R^2		Global Coefficients (GWR)			Local Income Coeff. (GWR)			
		LM	GWR	LM	GWR	Income	Intercept	Pop.	1st Qu.	Med	3rd Qu.	>0 (%)
Cars/vans	0.79 **	5139	3016	0.17	0.88	1.06 **	1.55 *	0.69 **	0.42	1.59	4.35	83.2
Flights	0.54 **	3867	2817	0.73	0.89	3.84 **	−1.41 **	0.26 **	2.46	3.15	3.98	98.89
Rail	0.55 **	842	−282	0.65	0.87	0.73 **	−0.25 **	−0.01	0.46	0.62	0.81	96.26
Bus	0.51 **	−2069	−3089	0.31	0.72	−0.05 **	0.02	0.04 **	−0.11	−0.06	−0.02	17.91
C. Fares	0.56 **	−761	−1877	0.38	0.77	0.07 **	−0.07 *	0.07 **	−0.07	0.06	0.14	64.47

Notes: Single asterisk (*) indicates significance at $p < 0.05$, double asterisk (**) indicates significance at $p < 0.01$. Each line in the table shows a different model.

The global, London-wide results indicate that income significantly predicts emissions from all transport modes, $p < 0.01$. As shown in the local predictor coefficient columns, however, local, neighbourhood-level income coefficients vary. Local coefficients for income are greater than 0, and thus positively linked to emissions, for over 80% of MSOAs for emissions from cars, flights, and rail transport. In line with previous research, therefore, we find that higher incomes mostly predict higher emissions in carbon-intensive transport such as flights and cars [10,14,15,27,48,108].

Despite predominantly positive associations between income and emissions from cars and flights, our results also indicate notable differences in the strength of the associations within London. The inter quartile range of local coefficients of income to predict car emissions is 3.93, more than three times the coefficient of the global model. Similarly, the inter quartile range of local coefficients of income to predict emissions from flights is almost half as large as the global coefficient—at 1.52. These findings highlight that here spatial variance in the relationship between income and different transport emissions is strong and cannot be captured well by the global models.

Furthermore, associations between income and combined fare emissions range clearly from negative to positive (see also Figure 3). Thus, in 64.47% of MSOAs higher incomes predict higher combined fares emissions, while in the rest of London higher incomes predict lower combined fare emissions. Thus, for combined fare emissions relying on a global model can lead to misleading conclusions for local areas.

Spatial distributions of local coefficients are visualised in Figure 3. These reveal that neighbourhood clusters with negative associations between income and combined fare emissions appear mostly in Outer London. In Inner London, on the other hand, we find mostly neighbourhood clusters with negative associations between income and car emissions. Moreover, neighbourhoods with strong positive associations between car emissions and income also have the strongest negative associations between income and emissions from combined transport. This indicates that local factors other than income, such as infrastructure and workplace commute, may be important. Moreover, these findings emphasise the importance of understanding local contexts and spatial differences, as the global models can fail to capture large differences in patterns between different areas of the same city.

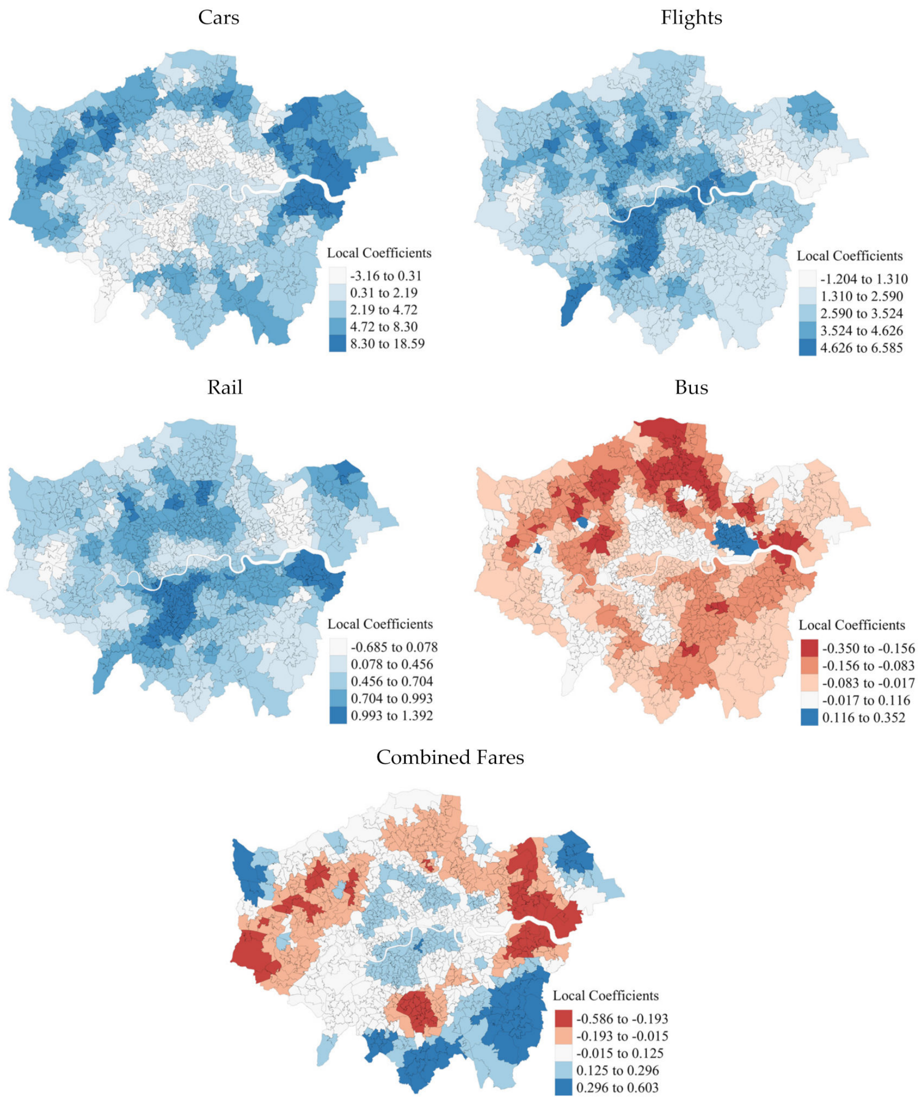

Figure 3. Spatial distributions of local coefficients of income when predicting bus and combined fare emissions. Notes: Emission estimates are from the years 2015–2016. Population is controlled for.

3.2.2. Spatial Variance in the Relationship between Other Social Factors and Emissions

In this section, we repeat a similar analysis for other social and spatial factors. We fit GWR and LM models for using other social factors to predict emissions from different transport modes. As the link between higher incomes and higher emissions is well-established, both in previous research [10,14,15,27,48] and our findings in the previous section, we control for income in all models in this section. Moreover, as spurious correlations can occur when modelling multiple variables which are derived from common ancestors [106,107], we again use total MSOA values for emissions, incomes, and other variables. As our aim is to explore the spatial variance in relationships between individual variables, and not to create a predictive model or infer causality, we run individual models for the different social factors, controlling only for population and income. This means that we model the total income from all households in one MSOA, the total emissions from all households in one MSOA, combined distance to workplace of all MSOA residents, as well as the total the numbers of people aged 65 and over, 14 and younger, limited in their day-to-day activities due to long-term health problems and/or disabilities, and identifying as BAME. To control for the effect of MSOA population, we include this as a control variable in our models.

This analysis is conducted to explore spatial variance in the relationships between different social factors and emissions when controlling for income. Social factors are chosen as they are linked to increased risk of transport poverty [22,23], or have previously been linked to increased emissions [48]. While results from this analysis cannot infer causation, they can highlight where and how such relationships are spatially heterogeneous.

Results for the model comparison indicate that the use of GWR models rather than LM models is appropriate for all models. The spatial autocorrelation tests show significant spatial clustering of residuals for all models, Moran's $I \geq 0.37$ ($p < 0.01$). Moreover, model fits indicate, again, that the GWR has a better model fit than a LM for the same data, as indicated by lower AIC, and higher adjusted R^2 values (Table 5). GWR models explain 9–69% more change in the dependent variables than LM models, varying both by transport type and independent variables. Again, models predicting emissions from cars see the greatest improvements, with adjusted R^2 values increasing by 0.18–0.69, followed by models predicting bus emissions, which see increased in adjusted R^2 values of 0.32–0.42. For flight emissions, GWRs see the smallest improvements in adjusted R^2 values across all models.

Table 5. Model fits of GWR and LM models when using different social factors as predictors of emissions from different transport modes.

Dependent Variable (tCO_2e)	Predictor Variable	Residuals' Moran's I (LM)	AIC		Adjusted R^2	
			LM	GWR	LM	GWR
Car/van purchases and motoring oils	Public Transport Density	0.49 **	4534	3072	0.55	0.88
	Pop. ltd in day-to-day act.	0.74 **	5087	3223	0.21	0.86
	Pop. aged 65 or older	0.42 **	4140	3148	0.70	0.88
	Pop. aged 14 or younger	0.77 **	5123	3184	0.18	0.87
	Pop. identifying as BAME	0.69 **	4856	3127	0.38	0.88
	Distance to workplace	0.51 **	4577	3240	0.53	0.86
Flights	Pop. ltd in day-to-day act.	0.50 **	3669	2500	0.78	0.92
	Pop. aged 65 or older	0.43 **	3542	2749	0.81	0.90
	Pop. aged 14 or younger	0.53 **	3733	2630	0.76	0.91
	Pop. identifying as BAME	0.44 **	3764	2822	0.76	0.89
Rail	Public Transport Density	0.38 **	565	−197	0.73	0.87
	Pop. ltd in day-to-day act.	0.50 **	746	−168	0.68	0.86
	Pop. aged 65 or older	0.37 **	538	−196	0.74	0.87
	Pop. aged 14 or younger	0.53 **	766	−133	0.67	0.86
	Pop. identifying as BAME	0.49 **	798	−210	0.66	0.87
	Distance to workplace	0.39 **	601	−119	0.72	0.86
Bus	Public Transport Density	0.49 **	−2107	−3047	0.34	0.71
	Pop. ltd in day-to-day act.	0.51 **	−2076	−3029	0.32	0.71
	Pop. aged 65 or older	0.49 **	−2226	−3101	0.41	0.73
	Pop. aged 14 or younger	0.51 **	−2084	−3155	0.32	0.74
	Pop. identifying as BAME	0.51 **	−2067	−2999	0.31	0.70
	Distance to workplace	0.50 **	−2076	−3024	0.32	0.70
Combined fares	Public Transport Density	0.47 **	−876	−1877	0.45	0.77
	Pop. ltd in day-to-day act.	0.52 **	−856	−1752	0.43	0.75
	Pop. aged 65 or older	0.50 **	−849	−1788	0.43	0.76
	Pop. aged 14 or younger	0.53 **	−812	−1773	0.41	0.75
	Pop. identifying as BAME	0.37 **	−1205	−1975	0.60	0.80
	Distance to workplace	0.47 **	−885	−1803	0.45	0.76

Notes: Double asterisk (**) indicates significance at $p < 0.01$. Each line in the table shows a different model.

An analysis of the coefficients confirms that spatial differences in the relationships between transport emissions and social factors occur throughout London, when controlling for income. As shown in in Table 6, the GWR analyses show, for instance, that approximately 50% of local coefficients of workplace distance are above 0 for all modes of transport, indicating high local variation. This could be due to different types of jobs and households in different areas, or differing levels of transport poverty and active transport. While our global model confirms Brand et al.'s [48] findings that workplace distance is positively linked to car emissions, locally we find spatial heterogeneity. As Figure 4 shows, both negative and positive associations between workplace distance and car emissions mostly appear in Outer London. Both trends may be linked to commuting: The negative association may be explained through better public transport connections into Central London, than within Outer London; the positive association could be linked to people in these areas working mostly outside of London. Notably clusters of positive associations are near motorways (see Appendix B Figure A1). It is also possible that journeys within Outer London have higher emissions than longer journeys into Inner London, due to rail networks mainly going into London. Future analyses of the impacts of the COVID-19 lockdowns on emissions may reveal the effects of increased localisation. Although we cannot assess why these local variations occur, it emphasises the importance of understanding local contexts.

Table 6. Geographically weighted regression coefficients when using different social factors as predictors of emissions from different transport modes. 'Predictor' refers to the variable listed in the 'Predictor Variable' column.

Dependent Variable (tCO_2e)	Predictor Variable	Global Coefficients				Local Predictor Coefficients			
		Predictor	Intercept	Population	Income	1st Qu.	Med	3rd Qu.	>0 (%)
Car/van purchases and motoring oils	Public Transport Density	−2.91 **	6.50 **	0.76 **	1.63 **	−1.71	−0.76	−0.17	15.08
	Pop. ltd in day-to-day act.	3.74 **	0.98	0.07	1.73 **	−2.35	−0.53	1.63	42.41
	Pop. aged 65 or older	7.86 **	−0.81 *	0.36 **	−0.10	0.97	3.78	5.55	83.20
	Pop. aged 14 or younger	1.70 **	1.39 *	0.25 *	1.65 **	−2.07	−0.35	1.24	41.40
	Pop. identifying as BAME	−1.46 **	−0.49	2.15 **	−1.72 **	−1.19	−0.49	0.20	31.88
	Distance to workplace	1.17 **	0.64	−0.64 **	1.51 **	−0.38	0.00	0.37	49.60
Flights	Pop. ltd in day-to-day act.	−3.63 **	−0.85 **	0.86 **	3.20 **	−4.49	−2.29	−0.81	11.44
	Pop. aged 65 or older	−2.75 **	−0.58 *	0.38 **	4.25 **	−3.52	−1.80	−0.68	12.15
	Pop. aged 14 or younger	−2.34 **	−1.20 **	0.86 **	3.04 **	−3.20	−1.67	−0.36	17.51
	Pop. identifying as BAME	0.49 **	−0.73 *	−0.23 **	4.77 **	−0.37	0.02	0.37	52.23
Rail	Public Transport Density	0.24 **	−0.66 **	−0.01	0.68 **	−0.01	0.01	0.04	63.77
	Pop. ltd in day-to-day act.	−0.56 **	−0.16 *	0.09 **	0.63 **	−0.07	0.00	0.10	50.91
	Pop. aged 65 or older	−0.58 **	−0.07	0.02 *	0.82 **	−0.18	−0.08	−0.02	19.03
	Pop. aged 14 or younger	−0.39 **	−0.21 **	0.09 **	0.60 **	−0.02	0.05	0.12	69.33
	Pop. identifying as BAME	0.07 **	−0.15 *	−0.08 **	0.86 **	−0.03	0.00	0.02	47.47
	Distance to workplace	−0.09 **	−0.17 **	0.10 **	0.69 **	−0.01	0.00	0.02	59.41
Bus	Public Transport Density	0.02 **	−0.02	0.04 **	−0.05 **	0.04	0.12	0.20	84.01
	Pop. ltd in day-to-day act.	−0.04 **	0.02	0.05 **	−0.05 **	−0.66	−0.40	−0.14	12.96
	Pop. aged 65 or older	−0.10 **	0.05 **	0.04 **	−0.03 **	−0.57	−0.33	−0.06	19.33
	Pop. aged 14 or younger	0.04 **	0.01	0.03 **	−0.03 **	−0.52	−0.31	−0.11	14.98
	Pop. identifying as BAME	0.00	0.02	0.04 **	−0.05 **	−0.15	−0.03	0.06	43.02
	Distance to workplace	0.00 **	0.02	0.04 **	−0.05 **	−0.02	0.03	0.06	66.50
Combined fares	Public Transport Density	0.07 **	−0.19 **	0.07 **	0.06 **	−0.22	−0.11	0.01	26.62
	Pop. ltd in day-to-day act.	−0.25 **	−0.03	0.11 **	0.03 **	−0.19	−0.09	0.10	36.03
	Pop. aged 65 or older	−0.15 **	−0.03	0.07 **	0.09 **	−0.19	−0.08	0.03	30.26
	Pop. aged 14 or younger	−0.14 **	−0.06	0.10 **	0.02 *	0.00	0.04	0.09	77.13
	Pop. identifying as BAME	0.09 **	0.05 *	−0.02 **	0.24 **	−0.02	0.01	0.03	59.41
	Distance to workplace	−0.03 **	−0.05	0.10 **	0.06 **	−1.71	−0.76	−0.17	15.08

Notes: Single asterisk (*) indicates significance at $p < 0.05$, double asterisk (**) indicates significance at $p < 0.01$. Each line in the table shows a different model.

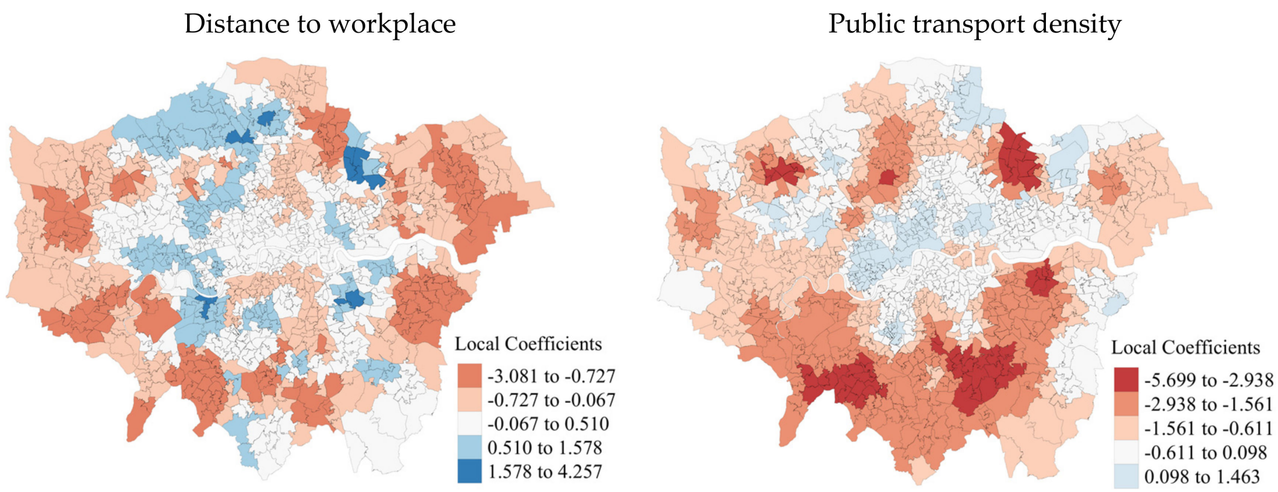

Figure 4. Spatial distributions of local coefficients of public transport density and distance to workplace when predicting emissions for cars/vans and motoring oils. Notes: Emission estimates are from the years 2015–2016. Population and income are controlled for.

Rail emissions mostly increase with public transport density, when controlling for income and population. In contrast, car emissions are mostly negatively associated with public transport density. However, the spatial variation in local coefficients (Figure 4), shows that in Outer London, and particularly in the south, this association is stronger, indicating that here public transport density is more strongly linked to reduced car emissions. This may be due to different modes of public transport being distributed unevenly throughout London but could also be linked to local attitudes, place of work, access to services, or other factors. Regardless of the reasons behind these differences, we can see that looking at the global and local coefficients may result in different policy interventions. Whereas distance to workplace is positively associated with car emissions globally, the local coefficients indicate that a positive association between these variables is only found in half the MSOAs. This means that policies aiming to reduce car emissions from workplace travel can be targeted at specific areas, namely areas where the link is strongly positive (see Figure 4).

Spatial variation between the relationships of population characteristics and emissions, when controlling for income and population, vary by transport type. For example, increases in populations limited in day-to-day activities, aged 14 or younger and aged 65 or older associated with decreased flight emissions for over two-thirds of MSOAs. On the other hand, increases in populations aged 14 or younger are linked to increased rail emissions in over two-thirds of MSOAs. Moreover, an increased population of people limited in their day-to-day activities is linked to increased rail emissions in 52% of MSOAs, indicating that the direction of this relationship is evenly varied across London.

Next, we analyse the land transport patterns of those identified by Simcock et al. [22] to be at increased risk of transport poverty. In the previous section, we report lower income to be mostly associated with bus emissions, where lower incomes are associated with higher bus emissions for over 80% of MSOAs (see Table 4), indicating that buses may be the most accessible form of motorised transport for low-income households across London. In this section (see Table 5), we find that stronger variance in local estimates occurs for the links between car-related emissions and larger populations of people identifying as BAME, limited in their day-to-day activities due to health problems or disabilities, or aged 14 or younger. This is shown by 50–60% of MSOAs being associated with increased emissions and the other ones are associated with decreased emissions, after controlling for income. This emphasises the need of understanding the contexts within which land transport emissions occur for effective and just climate policy. Transport choices can be deeply embedded in cultural, gender, and class structures [109–111], and, as Shove [112–114] points out, emissions and behaviours must be understood within the socio-cultural context in which they occur.

Moreover, larger populations identifying as BAME and 14 and younger are most commonly positively associated with increased emissions from combined fares when controlling for income. For larger populations limited in their day-to-day activities, this is for emissions from rail transport, although here positive associations only occur for around 50% of MSOAs. Thus, public transport may not only be less carbon intensive, but also more used in areas with larger populations at increased risk of transport poverty. Nonetheless, even after controlling for income, we find strong differences in different parts of London, indicating that local context matters and that global models overlook the variety of transport patterns. Moreover, this highlights specific neighbourhoods in which public transport may be more or less used indicating where further research or policy needs to asses reasons behind transport use and accessibility. This can help not only with targeting policy to reduce total transport emissions to specific areas, but also with assessing spatial differences in transport poverty.

Finally, for those aged 65 or older and those limited in day-to-day activities, accessibility needs may differ. For instance, the finding that car emissions are mostly negatively associated with a higher population of people limited in day-to-day activities points to transport and energy injustice, as this population should have higher transport energy needs due to decreased accessibility of public and active transport. Our results support previous findings that despite having increased energy needs, people with disabilities have lower energy footprints in the UK than those without disabilities [57].

3.3. Emissions and Well-Being

To assess relationships between land transport emissions and well-being, we analyse well-being index scores and subjective well-being. Here, our aim is not to assess the causal links between emissions and well-being, but to see if there are neighbourhoods in London with high well-being scores but low transport emissions.

Index scores are positively correlated to car emissions, land transport emissions, and all transport emissions (Figure 5). Income likely mediates these relationships, as the well-being index incorporates rates of incapacity benefit claimants, unemployment, and children in out-of-work households. Promisingly, transport emissions are only weakly correlated with subjective well-being, in line with previous findings [115–117].

Most importantly for this analysis, we find that 10.56% of wards have below median emissions from all transport, but a median or above median score on the well-being index (Table 7). For subjective well-being, this is higher at 24.80%. A spatial overview of this is provided in Appendix B Figure A2.

Table 7. Percentages of wards with below median emissions and median or above well-being.

	Car/Van Purchases and Motoring Oils	Land Transport	All Transport
Index Score 2013	17.60	11.68	10.56
Subjective well-being average score, 2013	27.84	25.60	24.80

While the relationship between well-being and emissions is complicated and this is not a causal analysis, our findings indicate that some areas in London have low land transport footprints, but high well-being. In other words, therefore, it is possible to have reduced emissions without negatively impacting well-being.

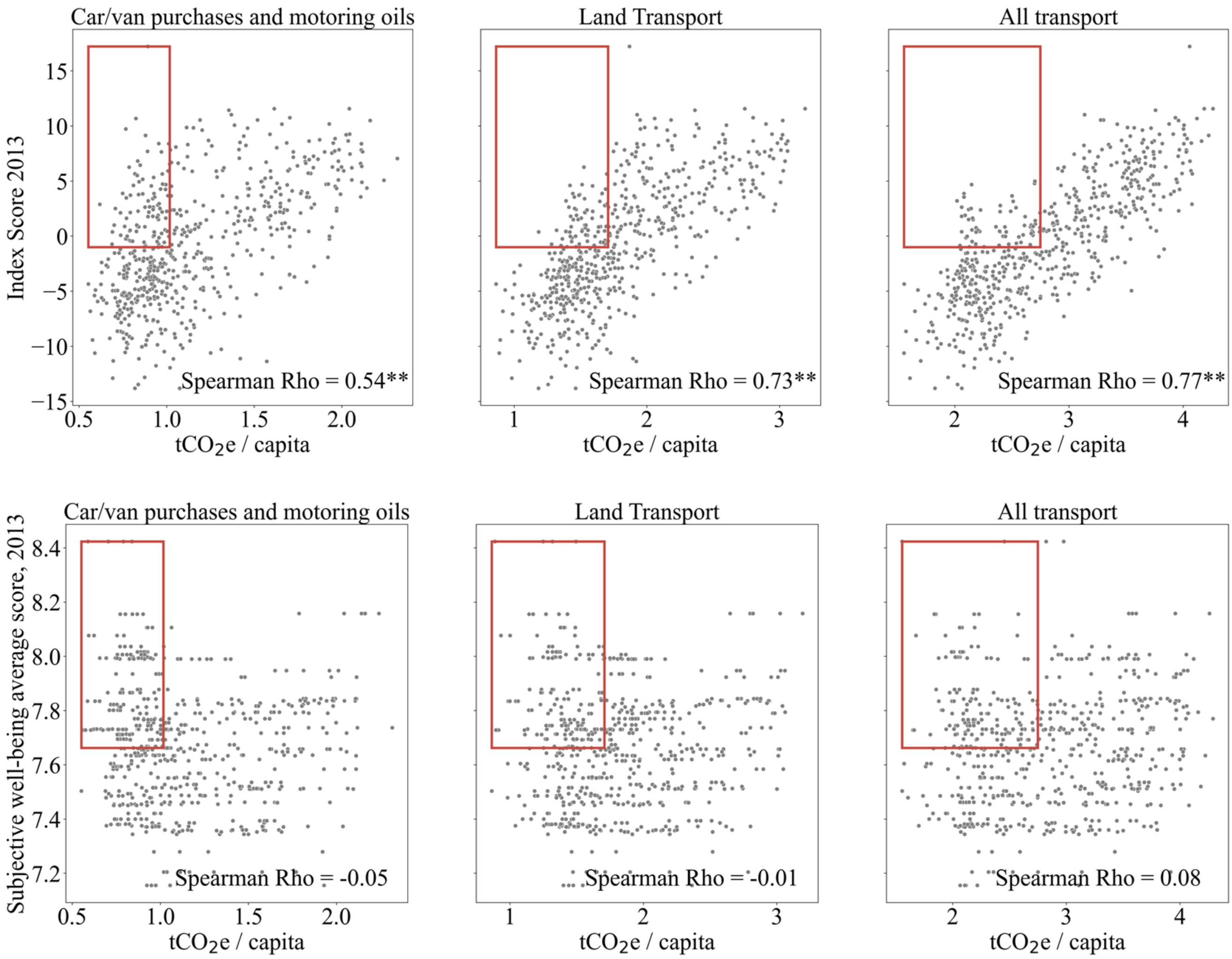

Figure 5. Scatterplots of London wards' well-being and emissions, shaded by population. Notes: Pearson's *r* values show correlation coefficients. Double asterisk (**) indicates significance at $p < 0.01$. Red boxes highlight below median emissions and above median well-being.

4. Discussion

4.1. Geographically Weighted Regression as a Tool for Emissions Analysis

In this paper, we bring together methods from industrial ecology and spatial statistics to assess if and how the relationships between transport emissions and social and spatial factors show spatial variance. Although the links between social factors and consumption-based emissions are well-studied [6,10,14–21,27,59–62], the spatial aspects of consumption-based emissions are not well-understood. Although some existing research already highlights the benefits of using spatial models for emission analyses [71–73,118], to our knowledge, this paper is the first to investigate spatial heterogeneity in the relationship between social factors and consumption-based emissions, highlighting the important contribution spatial statistics can make to the field of industrial ecology. In this paper, we find that geographically weighted regression models should be used in all tested instances of this paper, as our data exhibit spatial dependency. Thus, geographically weighted regression models are better able to model the relationships between consumption-based neighbourhood transport emissions from cars and vans, flights, rail, buses, and combined fare public transport with public transport density, distance to workplace, income, and populations limited in their day-to-day activities due to long-term health problems or disabilities, aged 14 or younger, aged 65 or older, and identifying as BAME.

For instance, in line with previous UK-based research which finds consumption-based GHG emissions to increase with income [16,17], especially transport emissions [14], we find mostly positive relationships between income and transport emissions across London. An exception to this is emissions from buses, which are mostly negatively associated with income. Despite this, our findings also indicate that both the direction and the strength of these relationships can vary. Our findings thus complement this previous research by showing that the association between income and transport emissions can vary across neighbourhoods, even within one city. Moreover, in contrast to previous research reporting a positive link between car emissions and distance to workplace [48], we find that this relationship is spatially heterogeneous, with some neighbourhoods in London having a positive and some a negative association.

We find differences in spatial heterogeneity of the relationships between higher populations of those more at risk of transport poverty and emissions from different transport modes, even after controlling for income. This links to previous research which points out that air and land travel emissions are not necessarily complementary for the same social groups [30,59,62]. For example, our results indicate that across London, increases in populations of people identifying as BAME are less frequently linked to increased car emissions that to increased flight emissions. However, in addition to previous findings, we find that even after controlling for income the relationship between higher populations of people identifying as BAME and flight emissions varies spatially both in strength and direction, indicating that consideration of spatial factors is necessary in this analysis. Similarly, we find spatial variation in the links between increased populations of those identified by Simcock et al. [22] to be at increased risk of transport poverty and different land transport emissions. Despite being more frequently linked to higher public transport emissions from rail, buses, and combined tickets, here too we find spatial variance across London. These findings highlight the importance of local and spatial contexts for understanding emissions. Regardless of whether this highlights the need for a spatial inequality lens or only points to other social inequalities which are unevenly distributed across space [63–68], our analysis underlines nuances in the relationships between emission and social factors, which global analyses overlook.

The following section discusses our findings in more detail and in light of well-being and the policy implications they may have.

4.2. Policy Implications

In the UK, transport is one of the highest emitting sectors [74–76], and thus, reducing transport emissions is important for meeting climate targets. Effectively reducing consumption-based transport emissions requires focussing on the highest-emitting categories: cars and flights.

While aviation is not part of the London Councils' [2] programmes on climate change, there is potential for local policy makers to impact aviation emissions [34], for instance, by influencing aviation infrastructure. Nationally, while the Committee on Climate Change [119] outlines demand management as flight emission reduction strategy, the UK Government focuses on growing the aviation sector and reducing emissions through future technological advancements [120]. This contrasts our and previous [42] findings that reducing aviation demand can strongly reduce emissions and that flight emissions cannot be reduced sufficiently through technological changes alone [31,121]. Moreover, although some other social drivers may play a role [59,62], flight emissions are strongly income-dependent and present a main source of carbon inequality. Continued focus on aviation growth does not challenge such patterns, which have long been pointed out by the literature on carbon lock-ins [25,26], carbon inequality [15,27,122,123], and degrowth [35,36,124].

Although we find spatial heterogeneity in the strength of the relationships between income and flight emissions, the association is positive for over 98% of London neighbourhoods. Indeed, while a geographically weighted regression model has an improved model fit compared to a linear regression model, we find flight emission models to improve the least compared to those modelling other transport modes. We conclude from this that a global model can approximate the relationship between flight and income. Thus, a widely used income-based approach to reducing emissions from aviation, such as a distance-based tax as outlined by Larsson et al. [125], may be most effective in reducing emissions from flights from a demand-side perspective.

Cars present a second large source of emissions and carbon inequality. Current strategies to reduce land transport emissions of the London Councils [126] and the Mayor of London [127] include making active transport more attractive, increasing the number of bus services, adding bus lanes, and building charging stations for electric vehicles. Here, efforts to increase bus services and reduce bus congestion should be prioritised, as buses may be more accessible to those at risk of transport poverty and as fast and dense public transport networks, particularly in Outer London, may be most effective in reducing car emissions. Investing in accessible, affordable, and fast public transport infrastructure in outer areas with high car emissions may be able to reduce car emissions as well as congestion. However, affordability also needs to be considered.

Considering links between emissions and socio-demographic characteristics differ at a neighbourhood level, approaches can also better incorporate local needs. As the relationship between workplace distance and car emissions is heterogeneously distributed across London, understanding what kind of journeys people use cars for and why people use cars is also essential when encouraging increased use of active and public transport. Investigating attitudes towards public transport could provide further insight into transport choices and how emissions can be reduced. Moreover, our findings suggest that increased public transport access in the southern outskirts of London may reduce emission more effectively than in the north, although this may be linked to having better or faster existing routes available. Other ways to reduce emissions from commuting include increased remote working [47].

Furthermore, our analysis suggests that higher public transport emissions are more often associated with those identified by Simcock et al. [22] to be at increased risk of transport poverty across different neighbourhoods. Higher bus emissions are linked to neighbourhoods with lower incomes, and higher combined fare emissions to larger populations of people aged 14 or younger and identifying as BAME, more often than emissions from other transport modes. Thus, increasing bus and mass rapid transit access and making public transport more affordable for those with lower incomes may also reduce transport inequality. This mirrors survey findings that cost is the key factor determining transport choices for 25% of Outer London commuters [128]. Despite this, spatial factors and inequalities need to be considered, as our analysis reveals spatial variation in all relationships between higher populations of groups more at risk of transport poverty and transport emissions.

Nonetheless, increasing transport access—and emissions—for those whose mobility is limited by long-term health problems or disabilities is necessary, who have lower energy footprints despite having higher energy needs [57]. Likewise, those with age-related mobility constraints may have different transport needs. Understanding reasons for lower and higher transport footprints is therefore important.

For most Londoners, however, decreased transport emissions can likely coexist with high well-being, where switching to public transport can be the key to reducing emissions. Some previous research already points to some positive impact demand-side emission mitigation efforts can have on well-being [47,49–51]. Here, our research only focuses on assessing whether areas of higher well-being and lower emissions already exist within London. Promisingly, subjective well-being does not appear to be correlated to combined fare emissions, confirming previous findings [115–117], and suggesting that switching from private to public transport does not necessarily reduce subjective well-being. Additionally, while high objective well-being is often associated with high transport emissions, some neighbourhoods in London have below average emissions while maintaining high well-being scores, showing that achieving low emissions and high well-being is possible. Consequently, investing in well-connected, convenient, and affordable bus infrastructure, in addition to making combined fares more affordable, may be key to providing low-carbon transport in a socially just way.

4.3. International Applications

In the UK, these findings are specific to London, as neither its size nor its public transport infrastructure are comparable to other cities. However, our findings may be relevant to large cities worldwide. With one in eight people globally living in megacities with more than 10 million people in 2018 [129], understanding urban transport emissions from reduction and redistribution perspectives is becoming increasingly important. Our research highlights, first, that understanding local contexts such as how existing infrastructure is being used and localised travel needs and access barriers for public transport can be key in moving from private to public transport, and, second, that methods from spatial statistics may be able to improve on more frequently used linear models when trying to understand the relationships between emissions and social factors. At the same time, high incomes have been linked to higher emissions transport internationally–particularly to higher emissions from private and air travel [10,12,14,15,18,48,122]. This mirrors our findings that reductions in flight and private transport emissions are needed to reduce the global greenhouse gas footprint. Reducing transport footprints, therefore, needs to be viewed not only from an emissions, but also an inequality lens.

4.4. Limitations

IO analysis comes with various data and analytical limitations [91,130,131], such as uncertainty from using expenditure to represent quantity. We reduce this uncertainty by using data on the number of flights taken, rather than cost. We also follow recommendations from the literature to increase emission estimate robustness [85], including aggregating to large neighbourhoods and combining expenditure surveys from 2 years; however, despite these considerations, we are generating population data from a household sample and thus introducing bias.

A further data uncertainty comes from using data from various years. Data from the census are taken from 2011, income data, emission data, and public transport data are from 2015, and well-being data from 2013. While this adds some uncertainty, we have ensured that emissions data are calculated for the last year that other data are available, such that the independent variables come chronologically before the dependent variables. Moreover, the UK census is only updated every 10 years, under the assumption that demographic changes within a smaller timeframe are relatively small. Finally, as we analyse data from 983 MSOAs, we assume that, even though some neighbourhoods may see demographic changes within the 2011–2015 time period, the majority of neighbourhoods remains constant and thus, trends are consistent between these time periods.

Moreover, this analysis is exploratory. While our relationships show correlations and predictive value, estimates do not infer causality. Future research investigating these relationships under a carefully controlled causal framework can better assess whether the associations and local variations we find here are correlational or causal.

Our findings may be linked to a further issue policy makers face: decreasing demand of one product may increase total footprints as people may consequently have more money for more carbon-intense activities [132]. Thus, understanding household emission patterns overall and not just for transport may be most useful in guiding campaigns and policies.

Finally, geographic research can suffer from various limitations. One common problem in spatial research is the Modifiable Areal Unit Problem (MAUP), which describes how where spatial boundaries are drawn influences results) [133]. While research has shown that the MAUP effect is often low for English census data and geographies, it can occur [134], and may therefore be a point of uncertainty in this research. Secondly, making inferences about individuals based on areal observation can result in ecological fallacies [135]. Thus, the findings of this paper should be interpreted at a neighbourhood level and cannot be projected onto individuals.

5. Conclusions

Understanding consumption-based emissions through a geographical lens is important for understanding the links between GHG emissions and social factors. Especially for advising a socially just transport policy, recognising spatial heterogeneity between the relationships between those at risk of transport poverty and transport emissions is invaluable. In this paper, we find that geographically weighted regression models improve on linear models, when modelling the relationships between different social factors, infrastructural factors, and consumption-based transport emissions. We conclude, therefore, that greater consideration must be given to the geographical component of consumption-based emissions when assessing their links with social factors and their social drivers. Moreover, we show how our analysis can highlight specific areas where different kinds of policy interventions may be more effective. For instance, we find that links between car emissions and distance to workplace are spatially varied, indicating that policy aiming to reduce emissions from commuting may be most effective when targeting areas of high positive links between these variables. While our current analysis is exploratory, future research could investigate this under a causal inference framework, evaluating the levels of spatial heterogeneity for social drivers of emissions. In light of local actors being increasingly involved in climate change mitigation efforts, this analysis also highlights the potential local actors have in creating context-based policies. Finally, our research highlights both consistencies and inconsistencies with previous research looking at emissions and social factors. We highlight where findings are in line with previous research and can be represented by a global model, and where local, spatial statistical approaches are needed. Bringing together industrial ecology and spatial statistics, as this paper shows, can provide new insights into consumption-based emission patterns, which are overlooked by non-geographic analysis.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Product aggregation description from COICOP 4.

COICOP 4 Code and Description	New Category
7.1.1.1 New cars/vans outright purchase	Car/van purchases and motoring oils
7.1.1.2 New cars/vans loan/HP purchase	Car/van purchases and motoring oils
7.1.2.1 Second-hand cars/vans outright purchase	Car/van purchases and motoring oils
7.1.2.2 Second-hand cars/vans loan/HP purchase	Car/van purchases and motoring oils
7.1.3.1 Outright purchase of new or second-hand motorcycles	Car/van purchases and motoring oils
7.1.3.2 Loan/HP purchase of new or second-hand motorcycles	Car/van purchases and motoring oils
7.1.3.3 Purchase of bicycles and other vehicles	Other transport
7.2.1.1 Can/van accessories and fittings	Car/van purchases and motoring oils
7.2.1.2 Car/van spare parts	Car/van purchases and motoring oils
7.2.1.3 Motorcycle accessories and spare parts	Car/van purchases and motoring oils
7.2.1.4 Bicycle accessories and spare parts	Other transport
7.2.2.1 Petrol	Car/van purchases and motoring oils
7.2.2.2 Diesel oil	Car/van purchases and motoring oils
7.2.2.3 Other motor oils	Car/van purchases and motoring oils
7.2.3.1 Car of van repairs, servicing and other work	Other transport
7.2.3.2 Motorcycle repairs and servicing	Other transport
7.2.4.1 Motoring organisation subscription	Other transport
7.2.4.2 Garage rent other costs, car washing	Other transport
7.2.4.3 Parking fees, tolls and permits	Other transport
7.2.4.4 Driving lessons	Other transport
7.2.4.5 Anti-freeze, battery water, cleaning materials	Other transport
7.3.1.1 Rail and tube season tickets	Rail
7.3.1.2 Rail and tube other than season tickets	Rail
7.3.2.1 Bus and coach season tickets	Bus
7.3.2.2 Bus and coach other than season tickets	Bus
7.3.3.1 Combined fares other than season tickets	Combined fares
7.3.3.2 Combined fares season tickets	Combined fares
7.3.4.1 Air fares within UK	Flights
7.3.4.2 Air fares international	Flights
7.3.4.3 School travel	Other transport
7.3.4.4 Taxis and hired cars with drivers	Other transport
7.3.4.5 Other personal travel and transport services	Other transport
7.3.4.6 Hire of self drive cars, vans, bicycles	Other transport
7.3.4.7 Car leasing	Car/van purchases and motoring oils
7.3.4.8 Water travel, ferries and season tickets	Other transport

Appendix B

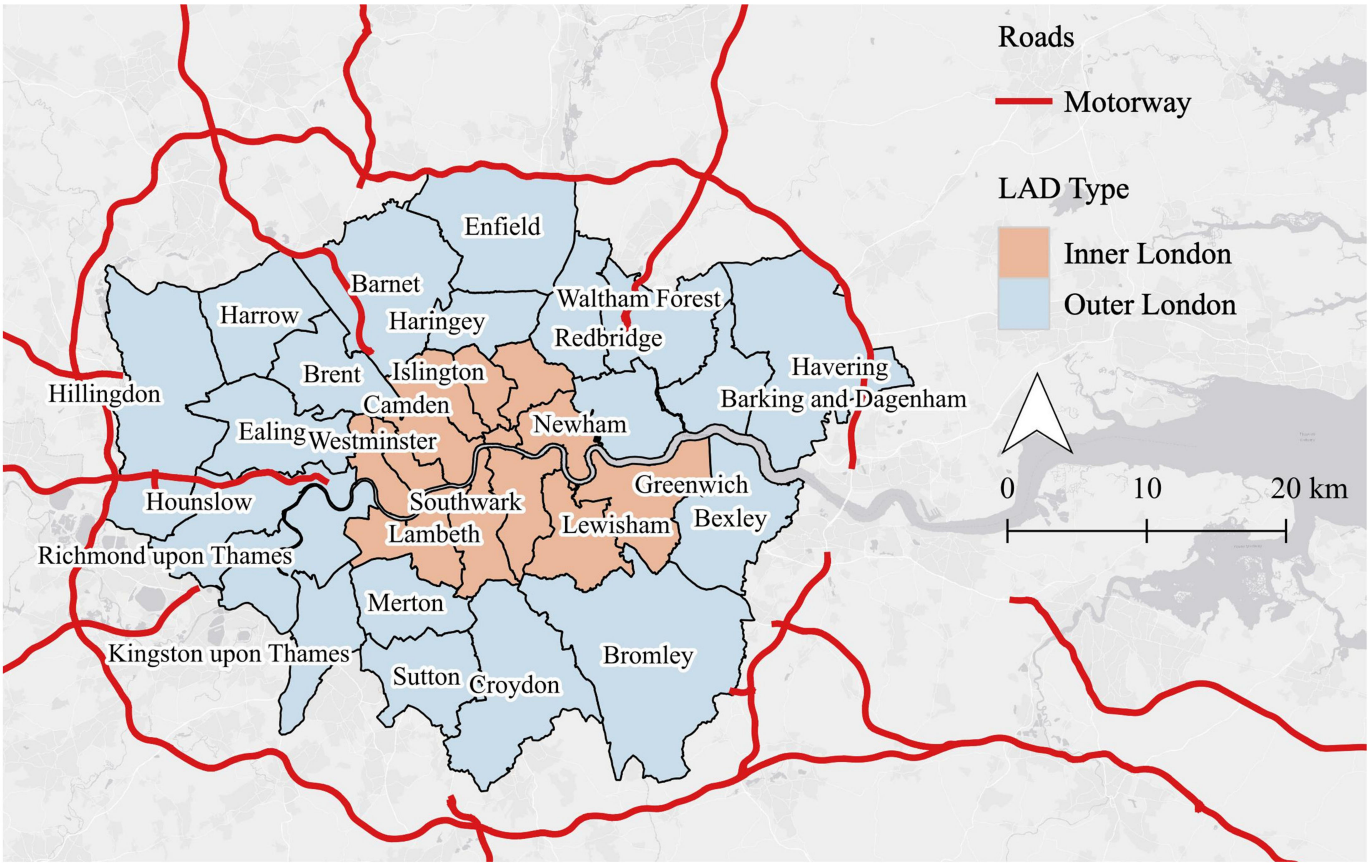

Figure A1. Map of motorways in London. Notes: Road data come from OpenStreetMap, downloaded via https://www.geofabrik.de (accessed on 14 February 2022).

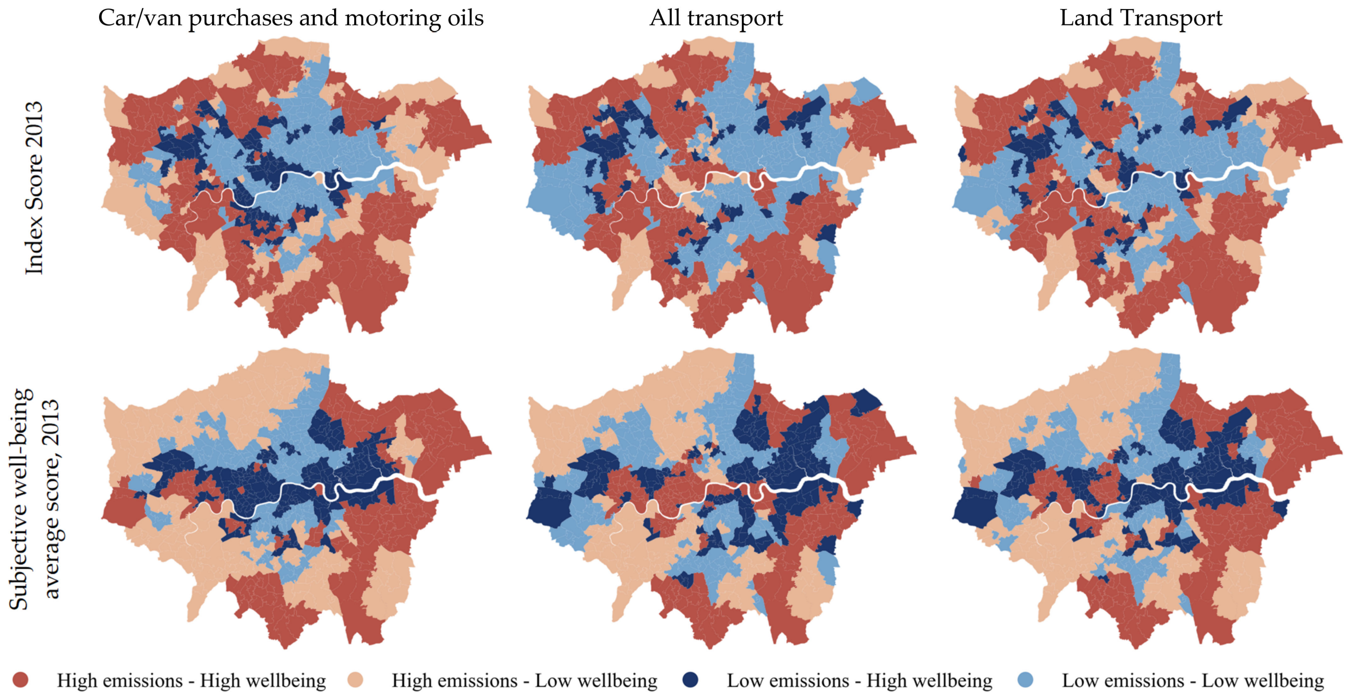

Figure A2. Maps showing spatial above and below median emission and well-being patterns.

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