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The ‘just’ management of urban air pollution? A geospatial analysis of low emission zones in Brussels and London

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ABSTRACT

The increasing evidence base and public concern on the health effects of exposure to high levels of air pollution, combined with stricter environmental legislation, are forcing local governments to take drastic measures. One of the policy instruments, the low emission zone (LEZ), specifically targets a reduction in emissions from vehicles, a key source in urban environments. It is a contested instrument, with supporters who think it is a fair “polluter pays” instrument that especially benefits more deprived communities, while opponents fear an unequal social impact on people’s accessibility and finances. This study wants to add a data-driven perspective to the discussion by simultaneously analysing the unequal exposure to air pollution and the unequal accessibility impact, in a comparative study of the LEZs in London and Brussels. The analysis combines a conventional multivariate regression analysis with a geographically weighted regression (GWR) modelling to define the local spatial variation in the relationships, which is of particular concern when considering an explicitly spatial problem and solution. The study shows that GWR is a promising method in distributional environmental justice research through identifying parts of the city where effects are more unequal, as such facilitating customized policy instruments and targeted support.

1. Introduction

Air pollution is a major international public health challenge (Health Effects Institute, 2010; Manisalidis et al., 2020) where the greatest harm often falls on the most susceptible individuals exposed to high concentrations of pollutants in urban areas (Clark et al., 2014; Hajat et al., 2015). While levels of air pollution in many European cities have fallen in recent years, challenges remain. In the UK and Belgium – the two countries covered in this study – ambient air pollution is the single greatest environmental threat to health, with an estimated 300 deaths per million per year in Belgium and 260 deaths per million per year in the UK caused by exposure to $PM_{2.5}$ alone (World Health Organization, 2016).

Increasing awareness and heightened concern about the public health impact of exposure to air pollution has led to local and regional governments adopting strict measures to reduce emissions. These interventions often focus on transport related emissions, since these directly lead to increased local pollution levels that have an evident and direct impact on public health. Some policy interventions focus on the longer term (e.g. phasing out fossil fuel cars[1]) while other measures (e.g. pedestrianization, traffic calming, traffic circulation plans and congestion charges) were typically introduced primarily to ease congestion and improve liveability in urban areas, but nevertheless also contributed to significant reductions in local air pollution - in particular congestion charges (Johansson et al., 2009; Tonne et al., 2008). Yet since the turn of the century, we have seen a new instrument gaining notable traction: the low emission zone (LEZ).[2] This instrument takes the emission standards of individual vehicles into account and restricts access to a central urban area for the most polluting vehicles, by either prohibiting them completely or charging an access fee. The aim of LEZs is to improve air quality and public health, with the reduction of traffic congestion, or the encouragement of modal change, only secondary goals. The first LEZs were implemented in Sweden in the late 1990s and only applied to heavy-duty vehicles, but since the widespread adoption of the *Umweltzone* in Germany from 2008 onwards (with Berlin and Cologne among the pioneer cities), these instruments are increasingly employed in

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[1] Norway is the most ambitious in this regard, aiming to end the sale of fossil fuel-powered cars by 2025, but also the UK has recently adjusted its ambitions, planning to ban the sale of fossil fuel-powered cars by 2030 (https://www.reuters.com/article/climate-change-britain-factbox-idINKBN27Y19F).

[2] Also known as a *Clean Air Zone* (CAZ), *Umweltzone*, *Zone de Faibles/Basses Emissions* (ZFE/ZBE), or *Zona de Bajas Emisiones* (ZBE).

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urban traffic management (Jephcote et al., 2016; Wolff & Perry, 2010) (see http://urbanaccessregulations.eu/).

In public and policy debates, LEZs have been promoted as an opportunity to exercise the "polluter pays" principle, benefiting more deprived communities that are more exposed but contribute less to air pollution.[3] At the same time, critical perspectives have also implicated LEZs in unevenly constraining spatial accessibility and placing disproportional financial burdens on disadvantaged socio-economic groups.[4] The contribution of this paper is to shed further light on these debates where the contested nature of LEZs exemplifies the tensions between dominant 'green' or environmental sustainability discourses and broader questions of social needs, welfare, and economic opportunity (Agyeman, 2013). Many quantitative studies of air pollution exposure that are rooted in an environmental justice tradition have tended to focus on the distributional (in)equalities of environmental burdens and benefits (Hajat et al., 2015). This study is an attempt to complement and extend such approaches by taking account of the complex interconnections of environmental, social and economic dimensions that underpin and shape exposure to air pollution in urban areas.

In doing so, we analyse two LEZs from a complementary environmental and transport justice perspective. The analysis first employs a conventional multivariate regression to detail global trends and interactions in underlying dimensions of exposure to air pollution. However, we recognise that such a modelling framework is prone to obscure local spatial variations, which are of particular concern when considering an explicitly spatial problem (urban air pollution) set in relation to a spatial response (LEZs). Therefore, we complement the conventional regression analysis with geographically weighted regression (GWR) to determine local spatial variations in model parameter estimates. The findings underline that GWR is a promising if underused method in distributional environmental and transport justice research.

2. Quantitative environmental justice research on urban air pollution

Environmental justice research emerged in the 1980s in the US out of concerns over the unequal spatial distribution of landfill and industrial sites and the disproportionate burden of pollution on ethnic minority populations (Bullard, 1990). Since then, the scope of research has expanded, focusing on different dimensions of social class and other forms of socio-demographic difference, scalar effects and locational differences, intended to take account of the complex landscape of environmental burden (Walker, 2012). Theoretical work has also long moved away from a purely distributional justice focus on environmental pollution, calling for a broader multidimensional conceptualization of justice, including the distribution of responsibility, procedural justice, justice as recognition, and justice as capabilities (Holifield et al., 2017; Schlosberg, 2007; Walker, 2012). At the same time, environmental justice scholarship has actively engaged with sustainability discourses, focusing on complementarities between the environmental and social dimensions of sustainability and resultant equity and justice implications (Agyeman & Evans, 2004).

Against this context, there is a notable body of quantitative environmental justice research engaging with questions on the distribution of environmental burdens in which various socio-economic indicators and geospatial techniques are employed. While many questions remain over how the interconnections of environmental, social, and economic dimensions shape exposure to air pollution in cities, there have been several major conceptual and methodological developments over the last couple of decades that we need to attend to in developing the conceptual underpinnings of our approach. First, the early "exposure-race" perspective has been extended in quantitative studies on air pollution into a "triple jeopardy" framework which recognises that lower socio-economic groups, often with compromised health due to material deprivation and psychosocial stress, not only have the highest exposure but are also most vulnerable to the impact (Laurent et al., 2007; O'Neill et al., 2003; Pearce et al., 2010).

Second, while this pattern has been established in several cities, it has been increasingly acknowledged that the relationship between air pollution exposure and deprivation is more complex than is typically assumed (Bailey et al., 2018). Studies have found a higher exposure for mid-level deprivation areas (Havard et al., 2009), a lower exposure for mid-level deprivation areas (Mitchell & Dorling, 2003) or inconsistent results depending on the city's historical socio-economic make-up and their evolution (Bailey et al., 2018; Padilla et al., 2014). Within a city, patterns are also not uniform, so clustered values can distort predictive models that do not take account of spatial dependence. Using spatial autoregressive models in addition to ordinary least square (OLS) regression models, Havard et al. (2009) found weaker coefficients even if the overall patterns of exposure remained the same. Other analyses have applied similar autoregressive models (Chakraborty, 2009; Verbeek, 2019) or corrected for spatial autocorrelation through generalized additive models (Padilla et al., 2014; Su et al., 2010). Since such models usually result in a reduction in predictive power, geographically weighted regression (GWR) has been recommended as a potentially useful, if underused technique in environmental justice research, for defining the spatial variation in model parameter estimates through locally weighted models (Bailey et al., 2018; Jephcote & Chen, 2012).

Third, the focus on exposure and vulnerability to air pollution has been expanded through studies that attend to the distribution of responsibility for urban traffic-related exposure, based on emissions and car registration data. Mitchell and Dorling (2003) demonstrated an inverse relationship between NO_2 concentrations and car ownership in the UK. However, they assumed that poorer areas with lower car ownership were likely to drive older, more polluting vehicles and as such disproportionally contribute to emissions. Recently, Barnes et al. (2019) revealed that while households in more deprived areas are indeed more likely to own older vehicles, emissions are more than offset by the longer distance driven by households living in less-deprived areas who also own higher proportions of diesel vehicles and where car ownership rates are higher (also see Jephcote et al. (2016)). Set against broader questions on the (in)equity of air pollution policies (Benmarhnia et al., 2014; Cesaroni et al., 2012; Tonne et al., 2008), we seek to contribute to the environmental and transport justice literatures by taking account of the complex interconnections of the environmental, social and economic dimensions that underpin and shape urban air pollution management, framed through the lens of low emission zones.

3. Low emission zones

Low emission zones are spatially defined urban zones, where certain vehicles are not permitted based on their emission standard. LEZs originated in Sweden in the 1990s and initially only applied to heavy duty vehicles. However, after Germany started to implement *Umweltzones* for all traffic from 2008 onward, the instrument gained popularity throughout Europe (Jephcote et al., 2016). Currently more than 250 LEZs are in force, with the majority in Germany and Italy, and prominent examples in a number of European capitals (e.g. London, Paris, Madrid, Brussels and Amsterdam). At present there are very few examples outside of Europe and all of them are in Asia, with Seoul having implemented a LEZ for all traffic in 2019 and cities like Tokyo, Hong Kong and Beijing maintaining a LEZ for heavy duty vehicles.

The relatively widespread adoption of LEZs reflects a number of factors. On the one hand, there has been an understanding of the need to tackle traffic-related peak level emissions of air pollutants in cities – in particular black carbon (BC) and nitrogen dioxide (NO_2) – on health

[3] https://airqualitynews.com/2019/01/10/khans-new-ulez-set-to-benefit-poorest-londoners-the-most/.

[4] https://www.standard.co.uk/comment/comment/shaun-bailey-expanded-ulez-will-hurt-poorer-londoners-a4123776.html.

Table 1
Descriptive statistics.

Greater Brussels, census wards (n = 1186)[a]	Min	Max	Mean	SD	Moran's I
Median household income (€)	13,420	45,683	24,803	5,924	0.58**
Average annual NO_2 concentration (μg/m^3)	13.13	61.77	24.90	6.47	0.89**
Non-compliant cars (proportion of all cars)[b]	0.17	0.40	0.23	0.06	(0.89**)
Average additional travel time by public transport (min)	10.98	78.16	31.40	11.06	0.89**
Population (sum = 1,637,613)	*21*	*8,344*	*1,381*	*1,242*	–
Area (km^2) (sum = 549.94)	*0.011*	*13.754*	*0.464*	*0.837*	–
Greater London, MSOA (n = 983)	**Min**	**Max**	**Mean**	**SD**	**Moran's I**
Average equivalent household income (£)	25,900	67,100	38,293	6,203	0.59**
Average annual NO_2 concentration (μg/m^3)	24.74	51.70	36.03	4.89	0.94**
Non-compliant cars (proportion of all cars)	0.24	0.51	0.41	0.04	0.65**
Average additional travel time by public transport (min)	−3.16	67.38	19.39	8.93	0.68**
Population (sum = 8,961,989)	*5,341*	*26,513*	*9,117*	*2,022*	–
Area (km^2) (sum = 1,573.51)	0.294	22.448	1.601	1.861	–

[a] Several census wards were removed from the data set because no income data were available due to the very low number of taxpayers (n = 113) or because the census ward consists of a hospital or university campus leading to problematic income data (n = 4).
[b] Data were only available at municipal level and municipal proportions were assumed to be similar across the municipal territory.

grounds. At the same time, the EU Clean Air Directive – among the strictest of global legislations targeting air pollution – has incentivised political and policy action. When first introduced, the Directive only mandated cities to model and monitor pollutants, draw up action plans and inform the population of pollution levels but since 2008 it has introduced stiff financial penalties if certain air pollution limits are exceeded (Wolff & Perry, 2010). Since many European cities were found to be violating the directive, it might not be a coincidence that the implementation of LEZs started to take off at the same time. It is also important to situate the implementation of LEZs in a longer transition towards sustainable urban mobility, with less space for private cars and more support for active travel, public transport and shared mobility solutions (Banister, 2008).

While it is still too early to make a thorough evaluation of the impact of LEZs on local air quality given the recent implementation of most zones and the challenge of accounting for gradual tightening of restrictions, several studies nevertheless point to improvements in air quality within LEZs (Holman et al., 2015). When set in this light, it is perhaps unsurprising that several LEZs are the subject of discussions over their potential expansion beyond their current extents (e.g. in London, Paris, and Ghent). Yet although only a handful of LEZs have actually ever been abolished, of which Rotterdam's is perhaps the most notable[5], in various cities LEZs have proven highly contentious, with heated public debates focusing on their effectiveness, desirability, and fairness.[6]

Set against this context, if we interpret social justice as a fair and equitable distribution of social, environmental and economic resources, with the imperative to address those who are least advantaged (Rawls, 2001), LEZs demonstrate that the pursuit of social justice is complicated by the uneven distribution of two resources – air quality and accessibility – which are mutually dependent. On the one hand, access to a clean and a healthy environment – including clean air – is regarded as a fundamental human right (Boyd, 2012), leading to an increasing number of court cases forcing governments to act. The potential unequal exposure to air pollution, with more deprived areas being more exposed, is generally invoked as a social justice argument in favour of the implementation of LEZs (Müller & Le Petit, 2019). On the other hand, by limiting transport options to improve air quality, LEZs could constrain accessibility to the detriment of social inclusion (Farrington, 2007; Kenyon et al., 2002). Here the potential for LEZs to unevenly impact accessibility, with more deprived areas being more affected than less deprived areas, is invoked as a social justice argument against the implementation of LEZs, or in favour of mitigation policies instead. At the same time, LEZs "confine" the problem of urban air pollution to something manageable with fixed borders, while the transport impacts of the plan, as well as the impacts of air pollution, go beyond these boundaries. Ultimately, where and how the boundaries of these zones are drawn, and which rules and exemptions apply, has direct implications for determining who "wins" and who "loses" across a range of political, social, economic, ecological and cultural domains. These reflections raise three research questions to which we turn in the remainder of the paper:

- RQ1: How is air pollution distributed across the city and what is the relationship with socio-economic patterns?
- RQ2: What are the spatial impacts of low emission zones on accessibility in urban areas and how do these relate to socio-economic patterns?
- RQ3: How do patterns of air pollution and accessibility relate to the LEZ boundaries and what lessons might be drawn about the implementation of LEZs?

4. Methodology

To explore these three research questions this study focuses on two prominent low emission zones in two European capitals: Brussels and London. Similarities and differences in the spatial patterns of environmental, social and transport equity are examined with geographically weighted regression (GWR), providing an innovative exploration of the justice and fairness of low emission zones in the context of air pollution burdens and accessibility.

4.1. Study areas

Brussels and London are two cities where LEZs have been implemented in direct response to air pollution concerns. In Brussels the LEZ follows the boundaries of the Brussels Capital Region, one of the three Regions of Belgium that have their own legislative and executive organs. However, because the Brussels metropolitan area extends far beyond the regional boundary and there is no official definition of it, we expand the study area to the Brussels Periphery (or Brussels Rim), a group of 19 suburban Flemish municipalities that encircle the Capital Region. This "Greater Brussels" area covers about 550 km^2 and has a population of

[5] Rotterdam's LEZ was abolished on 1st January 2020, four years after its implementation, because the number of polluting diesel cars had fallen sharply. Instead, parking regulations to discourage older cars from entering the city centre were adopted.
[6] Examples: https://www.wired.co.uk/article/taxi-cabs-sadiq-khan-uber-gilet-jaunes-strike-congestion (London), https://cities-today.com/madrids-low-emissions-zone-to-be-scrapped/(Madrid), https://www.birminghammail.co.uk/news/midlands-news/birmingham-clean-air-zone-protesters-20454807 (Birmingham).

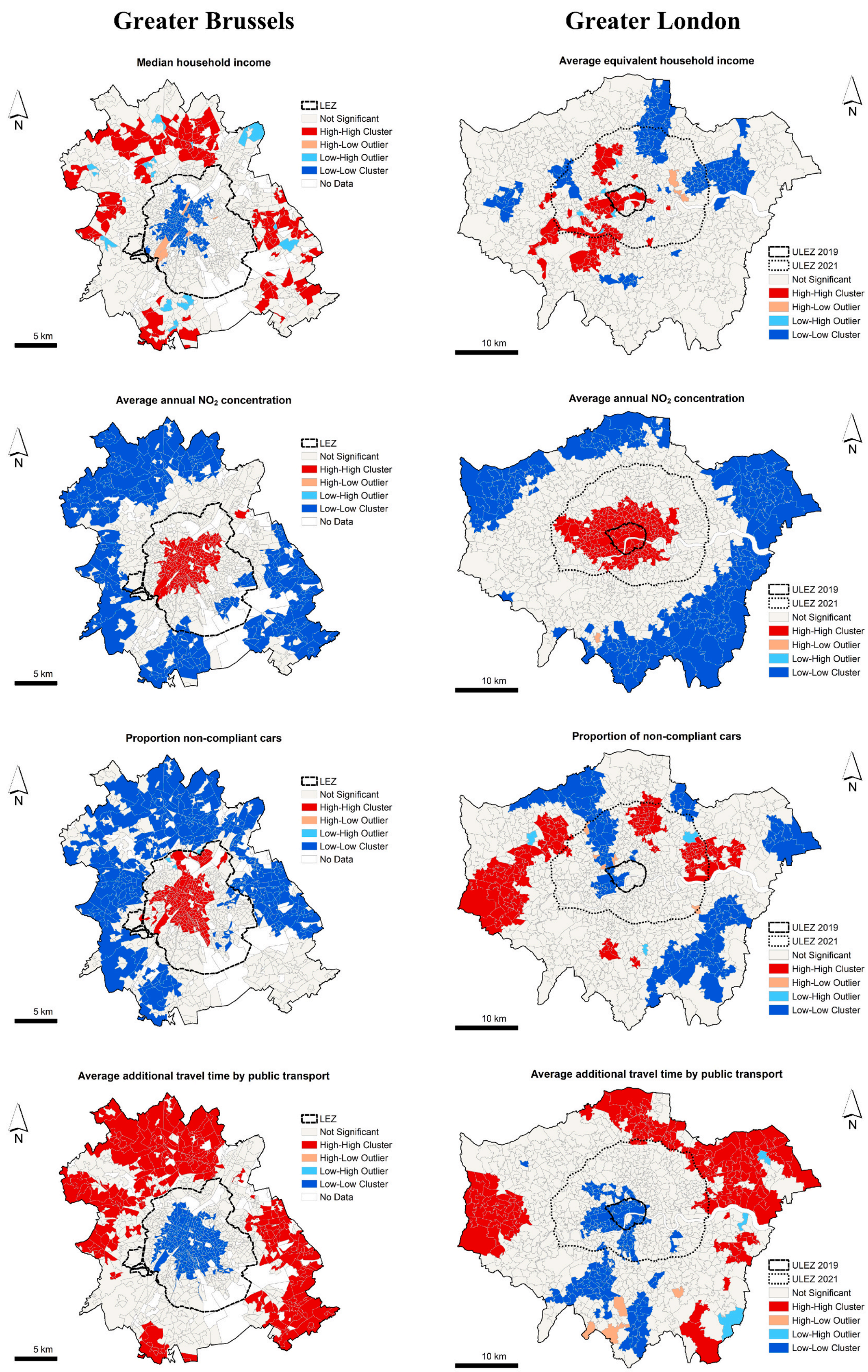

Fig. 1. Local Moran's I cluster and outlier analysis for the four key variables, with LEZ boundaries added for spatial reference.

over 1.6 million (see Table 1 and Fig. 1). In London the initial ULEZ consisted of a small central area spatially bounded by several busy urban roads. The ULEZ expansion in October 2021 led to a 19-fold increase of ULEZ area. However, this still excludes large parts of the Greater London Region and so we adopt the regional boundaries to define our second study area. This region is considerably larger and more populated than Greater Brussels, covering about 1,573 km^2 with a population of almost 9 million, making the region also twice as densely populated (see Table 1 and Fig. 1). The benefit of adopting study areas that are more spatially extensive than the LEZs themselves is that it allows us to mitigate "edge effects", where air pollution burdens and accessibility impacts are likely to transcend the boundaries of the LEZs (Su et al., 2010).

4.2. Data

The first step in the data collection was to establish the spatial resolution for both cities, considering computational feasibility and analytical comparability. Census wards were chosen for Greater Brussels (n = 1,303) and Middle Layer Super Output Areas (MSOAs) were chosen for Greater London (n = 983) (Table 1). On average, London's MSOAs are considerably larger (1.60 km^2) and more populated (n = 9,117) than Brussels' census wards (0.46 km^2 and n = 1,381).[7]

Socio-economic status was operationalized through the indicator of household income since other indicators – such as the often-used UK Index of Multiple Deprivation – are not available or replicable for both cities.

Both London and Brussels have robust air quality monitoring and modelling systems and produce regularly updated ground-level concentration maps based on dispersion modelling of emissions. For both cities we used the most recent data on average annual NO_2 concentrations. NO_2 concentration levels are generally accepted as a proxy for traffic-related air pollution, showing more spatial variation than other modelled pollutants (Goodman et al., 2011), while also being subject to some of the most significant (legal) limits on urban air pollution, adopted by the WHO and the European Commission. Instead of calculating area-averaged NO_2 concentration values, the spatial distribution of both air pollution and population within MSOAs and census wards was accounted for by calculating average *address-based* exposure. By including all addresses – residential, commercial, public services – this indicator accounts to some extent for local spatial differences in density of activity and exposure levels.

To measure the potential accessibility impact of the low emission zones two indicators were calculated: (1) the percentage of non-compliant cars, showing in which areas the low emission zone has a heavier direct burden on households; and (2) the quality of public transport provision, indicating in which areas a modal shift from private to public transport is easier to make, alleviating the impact of the low emission zone. There are many ways to measure public transport accessibility and quality (Handy, 2020). Because the focus of this study is on the feasibility of a shift from car to public transport, it was decided to compare the average travel time by public transport to a set of random points within the LEZ with the average travel time by car, for each spatial unit (an approach based on the operationalization of accessibility in da Schio et al. (2019)).

More detail on data collection and calculation of key variables can be found in Appendix A.

4.3. Methods

The first step in the methodology involved calculating descriptive statistics and Pearson correlation coefficients. In the correlation analysis the focus was on determining the association between exposure to air pollution and income (RQ-1), and between the accessibility impact of the LEZ and income (RQ-2). Here correlations were calculated for the whole urban region, but also for the subset of census wards or MSOAs that are located within or outside the LEZ boundaries. This was intended as an initial diagnostic of association in the variables across the urban regions and critically, to shed an initial light on the locational implications of the LEZ boundaries (RQ-3).

Next, the four key variables (income, air pollution, non-compliant cars, and additional travel time by public transport) were analysed for global spatial autocorrelation with the univariate global Moran's I statistic. Local spatial patterns in the four indicators were then measured using the local indicators of spatial association (LISA), a suite of statistics used to decompose global spatial autocorrelation in order to measure the degree to which spatial units are similar in terms of attributes and location to the areas surrounding it (Anselin, 1995). Following testing, for both the local and global Moran's I calculations, first order queen contiguity was adopted as the chosen spatial weights, together with row standardisation.

Ordinary least square (OLS) regression models were then calculated to establish global trends and relationships between the variables in both cities. We calculated two models: an environmental justice-based model (OLS-1) on the association between exposure to air pollution and household income and a transport justice-based model (OLS-2) on the association between non-compliant car ownership, public transport accessibility and household income. Since population size varies across census wards and MSOAs, a cross-validation analysis was carried out in which spatial units were weighted based on their share in the total population.

The global OLS models assume uniform relationships between income and each explanatory variable, thus failing to explore local or regional variations in regression model coefficients and goodness-of-fit. Therefore, the same dependent and independent variables from the global models were employed to develop geographically weighted regression (GWR) models, that allow the regression coefficients to vary across space continuously (GWR-1 and GWR-2). GWR models were based on an adaptive kernel, a bisquare weighting scheme, and optimum bandwidth selection based on the number of neighbours and the lowest AICc (corrected Akaike Information Criterion), with condition numbers below 30 to prevent multicollinearity (Fotheringham et al., 2003). The use of adaptive kernels is in line with other studies at small area level that dealt with areas of variable size and identified an improved model performance when following this approach (Gilbert & Chakraborty, 2011; Jephcote & Chen, 2012). GWR models are particularly useful in studying local spatial variation in the strength and direction of associations between variables and thus local coefficient estimates of the models are mapped and analysed. IBM SPSS Statistics 27 was used for statistical analysis and ArcMap 10.7.1 was used for geospatial analysis.

5. Results

5.1. Descriptive statistics

The overview in Table 1 shows that standard deviations for the four key variables are comparable for Greater London and Greater Brussels. Income, air pollution and the proportion of non-compliant cars are on average higher in London than in Brussels.[8] Also the quality of public transport is generally better in London (i.e. less additional travel time), with London even including several MSOAs where the average travel time by public transport is shorter than the average travel time by car (i.e. negative additional travel time). This is notable given that calculated travel times by public transport virtually always include a section travelled on foot to get to and from a station or stop, while car travel times assume the availability of a car from origin to destination.

[7] Population data for 2019 provided by the Office for National Statistics and the Belgian Statistical Office.

[8] An exchange rate of £1.00 = €1.10 was assumed (06/07/2020).

Table 2
Correlation analysis of key associations.

Pearson correlation coefficients	Greater Brussels			Greater London			
	ALL (n = 1186)	within LEZ (n = 655)	outside LEZ (n = 531)	ALL (n = 983)	within ULEZ 2019 (n = 23)	within ULEZ 2021expansion (n = 400)	outside ULEZ 2021 (n = 560)
Income & Air pollution	−0.669**	−0.479**	−0.418**	0.228**	0.261	0.254**	0.117**
Income & Non-compliant cars	−0.611**	−0.465**	0.104*	−0.538**	−0.306	−0.630**	−0.485**
Income & Additional travel time by public transport	0.664**	0.412**	0.307**	−0.386**	−0.355	−0.341**	−0.426**

The results of the bivariate Pearson correlation analysis, presented in Table 2, are notable in several ways. First, while the association between income and air pollution is negative in Brussels, with lower income areas having generally higher levels of air pollution, the association is positive (though very weak) in London. The equally strong negative association within and outside the LEZ in Brussels shows that environmental inequity is an issue across the wider urban region. Second, lower income census wards are associated with higher public transport quality in Brussels, while in London it is higher income MSOAs that generally seem to benefit from better public transport connectivity. Less surprising is the negative association between income and the percentage of non-compliant cars in both cities, except for the census wards outside of the Brussels LEZ.

5.2. Spatial autocorrelation analysis

As a first step in the geospatial analysis, indicators for global spatial autocorrelation were calculated for each variable, in the form of Global Moran's I (Table 1). All variables show significant positive spatial autocorrelation, which means they are spatially clustered. Subsequently, patterns of spatial clustering were further explored through an analysis of Local Indicators of Spatial Association using the Local Moran's I statistical test (Fig. 1). Census wards and MSOAs shown in dark red are areas with high values surrounded by areas with equally high values, indicating a positive cluster. Likewise, dark blue coloured areas indicate a negative cluster. Census wards and MSOAs shown in light red or light blue represent spatial outliers, with high values surrounded by low values or vice versa. Areas coloured in grey represent non-significant spatial patterns, while Brussels' census wards coloured in white were excluded from the analysis.

For household income, in Greater Brussels (left) a concentric pattern was found, with low-income clusters in the city centre (within the LEZ), and high-income clusters in the suburban area (outside the LEZ). In Greater London (right) the pattern is more dispersed, with high- and low-income clusters scattered within and outside the expanded ULEZ, though with the initial ULEZ being part of a high-income cluster. For air pollution, a largely concentric pattern was found in both cities, with a central large cluster of high air pollution, and clusters of low air pollution at the edges of the urban agglomeration. However, in Greater Brussels several low air pollution clusters also fall within the LEZ, and one isolated high air pollution cluster just outside it, showing that the Brussels' LEZ boundaries correspond less with the spatial patterns of air pollution. For the proportion of non-compliant cars, a concentric pattern can be found again in Greater Brussels, with high proportions of non-compliant cars within and low proportions outside the LEZ. In Greater London the spatial pattern is again more dispersed, with high- and low-proportion clusters scattered across the region. Finally, for public transport accessibility again a concentric pattern was found for Greater Brussels, with clusters of high accessibility (less additional travel time) within the LEZ and clusters of low accessibility (more additional travel time) outside the LEZ. In Greater London the most central area also has high public transport accessibility, but additionally there are large clusters in the southwest of the urban region and even outside of the expanded ULEZ boundary with a high accessibility. Conversely, clusters of low public transport accessibility are mainly found in the northeast and the west of Greater London, largely outside of the expanded ULEZ but straddling the north-eastern boundary.

5.3. OLS and GWR models

The results of the OLS and GWR models for Greater Brussels are presented in Table 3. The adjusted R-squared values suggest a moderate goodness-of-fit for both OLS models. In line with the correlation analysis, the highly significant coefficients of the OLS regression models provide strong evidence for a global inverse relationship between exposure to air pollution and household income and between the proportion of non-compliant cars and household income, and a global direct relationship between the additional travel time by public transport and household income. Population-weighted models (not shown) gave similar, slightly stronger results and the unweighted models were thus considered robust for differences in population size of census wards. However, as shown by the highly significant Moran's I of the residuals for both models, spatial autocorrelation needs to be accounted for in the modelling framework. Therefore, alternative GWR models were calculated, that show an improvement in the model fit, as indicated by higher adjusted R-squared values and lower values for the Residual Sum of Squares (RSS), AICc, and Moran's I of the residuals. While the mean values of the GWR local coefficient estimates correspond well with the OLS coefficients, their wide range indicates that the relationship between air pollution and income is not inverse across the whole territory, and for both non-compliant cars and public transport quality for some parts of the study area coefficient values around zero indicate no clear relationship with income.

Table 4 presents the summary statistics for the OLS and GWR models for Greater London. The significant coefficients of the OLS models provide evidence for a global direct relationship between exposure to air pollution and household income and between the proportion of non-compliant cars and household income, and a global inverse relationship between the additional travel time by public transport and household income. Interestingly, the OLS coefficients obtained for air pollution and public transport accessibility in Greater London contrast sharply with those for Greater Brussels. While lower-income areas are globally associated with higher air pollution exposure and better public transport provision in Greater Brussels, they are associated with slightly lower air pollution exposure and worse public transport provision in Greater London. Closer inspection of the table shows that the goodness-of-fit of the second model (OLS-4) is in line with the respective model for Brussels, but the air pollution model (OLS-3) has a very low adjusted R-squared value and thus a bad model fit with a lot of local variation. Population-weighted models (not shown) gave similar results, showing that the unweighted models are robust for differences in population size of MSOAs. The GWR models for Greater London provide strong evidence

Table 3
OLS and GWR models for Greater Brussels (**p < 0.05).

	Greater Brussels (n = 1186)					
	OLS-1		GWR-1 (86 nearest neighbours)			
Dependent variable: Median household income (1,000 €)	β	SE	Mean β	Min β	Max β	SD β
Intercept	40.038**	0.509	33.053	0.319	59.890	10.039
Annual NO_2 concentration (μg/m^3)	−0.612**	0.020	−0.380	−1.679	0.578	0.312
Adjusted R^2	0.447	–	0.566	–	–	–
RSS	22,999	–	16,723	–	–	–
AICc	6,888	–	6,645	–	–	–
Moran's I (residuals)	0.23**	–	0.05**	–	–	–
	OLS-2		GWR-2 (419 nearest neighbours)			
Dependent variable: Median household income (1,000 €)	β	SE	Mean β	Min β	Max β	SD β
Intercept	23.479**	1.001	21.540	13.145	31.530	4.528
Non-compliant cars (percentage)	−0.281**	0.027	−0.220	−0.535	−0.009	0.099
Add. travel time by public transport (min)	0.248**	0.015	0.248	−0.034	0.380	0.081
Adjusted R^2	0.489	–	0.540	–	–	–
RSS	21,233	–	18,710	–	–	–
AICc	6,795	–	6,679	–	–	–
Moran's I (residuals)	0.21**	–	0.12**	–	–	–

Table 4
OLS and GWR models for Greater London (**p < 0.05).

	Greater London (n = 983)					
	OLS-3		GWR-3 (248 nearest neighbours)			
Dependent variable: Average household income (1,000 £)	β	SE	Mean β	Min β	Max β	SD β
Intercept	27.858**	1.433	29.090	4.472	52.879	10.135
Annual NO_2 concentration (μg/m^3)	0.290**	0.039	0.241	−0.465	0.876	0.279
Adjusted R^2	0.051	–	0.287	–	–	–
RSS	35,813	–	26,322	–	–	–
AICc	6,330	–	6,059	–	–	–
Moran's I (residuals)	0.57**	–	0.42**	–	–	–
	OLS-4		GWR-4 (946 nearest neighbours)			
Dependent variable: Average household income (1,000 £)	β	SE	Mean β	Min β	Max β	SD β
Intercept	77.866**	1.706	82.097	76.490	86.503	2.250
Non-compliant cars (percentage)	−0.859**	0.042	−0.956	−1.051	−0.851	0.046
Add. travel time by public transport (min)	−0.239**	0.017	−0.250	−0.292	−0.189	0.027
Adjusted R^2	0.406	–	0.457	–	–	–
RSS	22,415	–	20,385	–	–	–
AICc	5,871	–	5,785	–	–	–
Moran's I (residuals)	0.44**	–	0.38**	–	–	–

of an improvement in the fit of the OLS regression models, demonstrated by an increase in the adjusted R-squared value and substantial decreases in the RSS and AICc, but with the air pollution model still showing a weak fit. The spatial autocorrelation of the residuals has decreased but is still high, indicating that the GWR models are not as good at explaining spatial income differences as in Greater Brussels. Closer inspection of the table shows that all local coefficients for the proportion of non-compliant cars and public transport provision are negative and cover a limited range. On the other hand, the relationship between air pollution and income shows more variation and is not direct across the whole territory.

5.4. Spatial distribution of GWR local coefficient estimates

Since the local coefficients represent the strength and direction of the association between dependent and independent variables in a local area (Fig. 2), they are a useful diagnostic for environmental and transport justice considerations. For ease of interpretation, blue colours are used to represent "'positive inequality" distributions and red colours for "negative inequality" distributions. For air pollution (top row) this means that blue areas represent parts of the urban region where there is a direct relationship between household income and air pollution (higher exposure levels for higher-income areas), and red areas represent an inverse relationship. For the proportion of non-compliant cars (middle row) there is consistent negative inequality across both urban regions, with a higher proportion of non-compliant cars in lower-income areas and vice versa. For additional travel time by public transport (bottom row) blue areas are areas with a direct relationship (longer additional travel times for higher-income census wards or MSOAs), and red areas are areas with an inverse relationship. The strength of these relationships is visualised through darker and lighter colours.

The air pollution map for Greater Brussels (top left) shows a concentric ring around the city centre where the unequal exposure to air pollution is highest. This is the most problematic area in terms of environmental justice, with lower-income census wards greatly disadvantaged in terms of air pollution exposure compared to nearby higher-

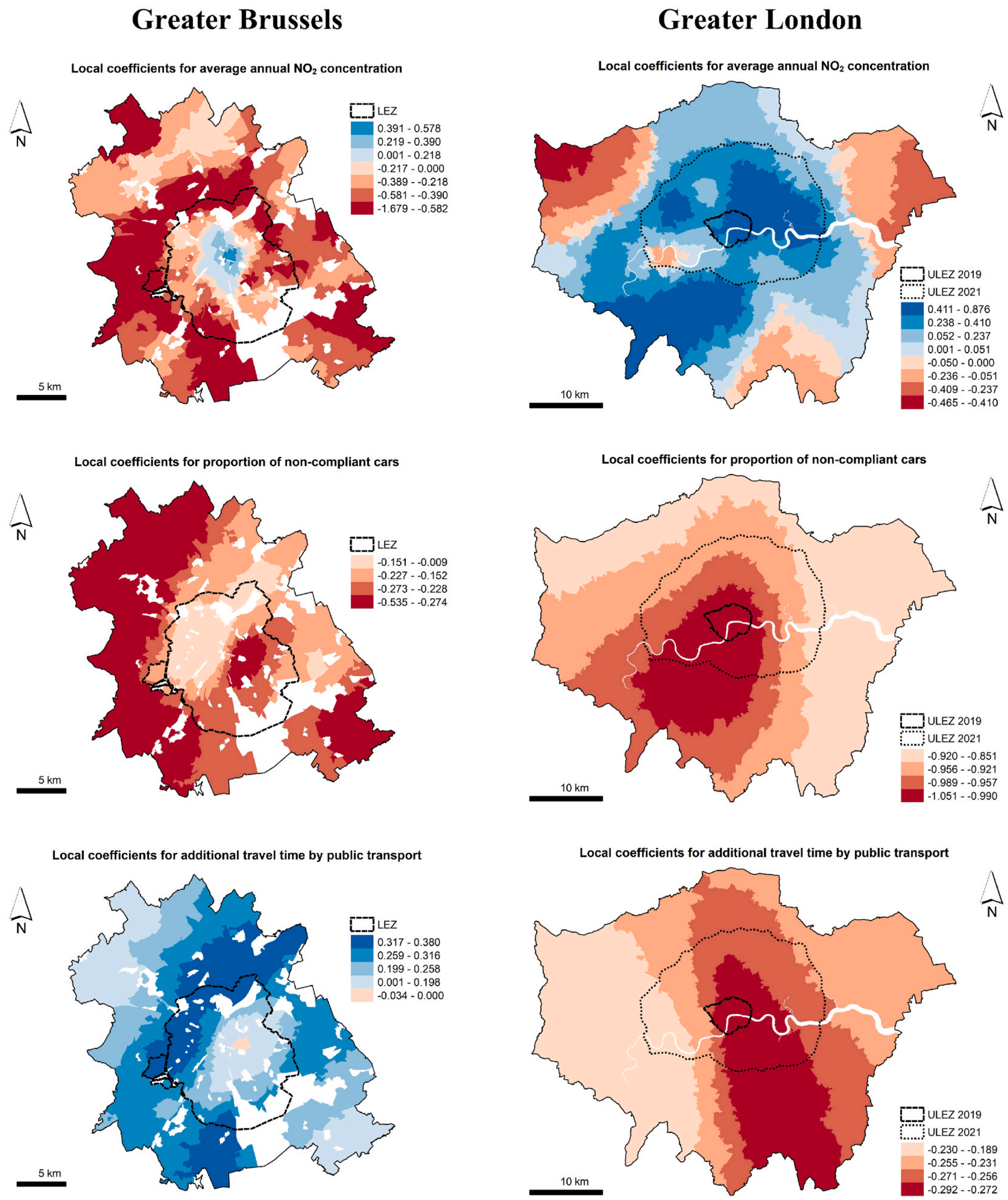

Fig. 2. Local coefficient estimates of the GWR models, with boundaries of the low emission zones added for spatial reference.

income census wards. In the city centre there is a much weaker or even positive association between income and air pollution, which means that high- and low-income census wards bear a similar level of exposure. The second map (middle left) reveals that the inverse relation between household income and the proportion of non-compliant cars is strongest in the western and southern part of the Brussels periphery, and in the eastern part of the city centre. However, coefficients do not noticeably vary. The coefficients for public transport quality (bottom left) show that the north-western and southern edge of the city have a "positive inequality" in public transport provision, with better public transport for lower-income census wards.

For Greater London, the air pollution map (top right) offers a noticeably different picture. A large part of Greater London is characterized by a positive relationship between income and air pollution, with three distinct areas where this association is most pronounced. It means that lower-income MSOAs in large parts of Greater London have a relatively lower exposure to air pollution than nearby higher-income MSOAs. Only at the edges of Greater London this relationship is inverted. For the proportion of non-compliant cars (middle right) and the provision of public transport (bottom right) a very local GWR model could not be fitted because of multicollinearity issues. Therefore, the local coefficient estimates maps are relatively smoothed out, with small variations in coefficient strength. It shows that across the Greater London territory the relation between income and non-compliant cars or public transport provision is quite robust and representing "negative inequality" at MSOA level.

6. Discussion

This study set out to take account of the complex interconnections of environmental, social and economic dimensions that underpin and shape exposure to air pollution in urban areas, framed through a complementary environmental and transport justice perspective. The first question focused on establishing the relationship between the spatial patterns of air pollution and socio-economic status in Greater Brussels and Greater London. Very different socio-spatial realities were revealed in both cities, running counter to the often taken-for-granted assumption that more deprived areas have a higher exposure to air pollution. While in Greater Brussels the relationship is inverse and strong, with lower-income census wards bearing higher levels of exposure to air pollution, in London there is generally a slightly higher exposure to air pollution for higher income MSOAs than for lower income MSOAs. These results confirm those of previous studies (Bailey et al., 2018; Padilla et al., 2014) who also found complex and peculiar patterns depending on city's socio-economic make-up and evolution. However, they seem to contradict the findings of other studies in London that found a higher exposure to NO_2 for more deprived areas by applying the Index of Multiple Deprivation at LSOA level (Logika Consultants, 2021; Tonne et al., 2008). The use of an estimated average income indicator in this study presents a much narrower view on deprivation, and the pragmatic choice for the MSOA level might have masked differences at a more local level.

The second research question focused on the spatial distribution of the accessibility impact of the LEZ policy and its relationship with socio-economic patterns. It was again found that the assumption that lower-income areas were the hardest hit does not universally hold true. While our results demonstrate that proportions of non-compliant vehicles are generally higher in lower-income areas in both cities, in Greater Brussels poorer census wards seem to have generally better public transport provision, while higher-income MSOAs have better public transport provision in Greater London.

These global associations reflect trends across the whole territory of both urban regions. However, such as patial, global models, are prone to obscure significant local spatial variation, which is of particular concern when considering an explicitly spatial problem (air pollution) and spatial solution (low emission zones). Our analysis shows that GWR models can be particularly relevant in spatial research on urban inequalities, as they help identify those parts of the city where inequalities are most pronounced, allowing for locally adapted policies. In the current study, GWR models allow us to give a tentative answer to our third research question and cast a critical lens on the spatial boundaries of both low emission zones.

- In Brussels, the environmental justice argument in favour of the implementation of the low emission zone largely holds. The most polluted areas of the urban region are indeed situated within the LEZ, and across the Greater Brussels region there is a clear inverse association between exposure to air pollution and household income, with the poorest census wards bearing the heaviest burden overall. The social justice argument against the implementation of a LEZ only partially holds; more deprived areas generally have a higher proportion of non-compliant cars, but also better public transport. Our work suggests that the current LEZ is underbounded by excluding the urban fringe around the Brussels Capital Region. The strongest argument is provided by the GWR local coefficient map that finds the most unequal exposures to air pollution in a concentric ring around the city centre, partially outside the LEZ.
- A different picture emerges for London, where the environmental justice argument in favour of the low emission zone is weaker. While the most polluted areas are within the expanded ULEZ, a weak direct association between income and air pollution was found at MSOA level, instead of an inverse one. The weak association and the contradictory results of other studies make it difficult to draw firm conclusions, though it is without doubt that Greater London - with a scattered pattern of high- and low-income MSOAs across the most polluted areas of the city - does not resemble a concentric pattern like Greater Brussels. In addition, the social justice argument against the implementation of the ULEZ is stronger than in Brussels. Not only do lower-income MSOAs have a higher proportion of non-compliant cars, they are also characterized by poorer public transport quality.

A more detailed analysis of the LISA and GWR maps points to the most problematic areas in the 2021 ULEZ expansion. An area that stands out is the north-eastern part of the expanded ULEZ, marked by clusters of low income, a high proportion of non-compliant cars, and weak public transport links. The social impact of the ULEZ expansion could be significant here, and the gains to be made in terms of air quality relatively small. A second area of concern are the low-income outskirts of Greater London, which have poorer public transport access to places within the expanded ULEZ and a high proportion of non-compliant cars. The impact on these areas will depend on their functional relationship with places within the expanded ULEZ, especially in terms of commuting.

GWR is a promising if underused method in distributional environmental and transport justice research and while the merits of the approach were demonstrated in this study, the generalisability and significance of the findings are subject to certain limitations. The GWR model only reveals trends and although it offers more granularity than a global OLS model, there are still many isolated areas that do not fit the GWR local patterns – especially in London. This might also be caused by the pragmatic choice to work with MSOAs, which could have smoothed out differences at a more local level like LSOAs or wards. The application of GWR in a multiscalar framework would be an obvious extension for future research, as a means of accounting for variation in associations between variables across scales. This approach could be used to support the development of policy measures where a clear sense of the scale at which interventions are likely to have the most benefit is needed. The four variables used in this study also have their limitations. Household income is only one indicator of socio-economic status and deprivation, with other studies using different indicators such as the Index of Multiple Deprivation, based on a combination of factors including employment, education, health and crime (McLennan et al., 2019). Moreover, owning a property can make a significant difference in someone's socio-economic status, particularly in London that is suffering from a major housing crisis (Edwards, 2016). The indicator of air pollution should also be interpreted with caution, since it is largely based on modelling static exposure instead of measuring the real exposure of an individual throughout the day (Dhondt et al., 2012). As for the non-compliant cars variable, data are provided at aggregated level, which means it is impossible to know who exactly owns these cars. When there is an association between local deprivation and percentage of non-compliant cars, it is uncertain if it is the poorer part of the population that owns these cars (ecological fallacy). Finally, the indicator that was developed for public transport accessibility was limited in terms of the random selection of destination points, not reflecting concentrations of employment, education, shopping or cultural facilities; the use of centroids, which are not necessarily the most accessible points; and the calculation of travel durations in July 2020 during the COVID19 pandemic, with reduced public transport availability, though assumedly with equal effect across the urban agglomeration.

Author statement

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Appendix A

The different key variables used in the analysis were calculated as follows.

Household income

For Brussels, household income data were obtained through the Belgian Statistical Office, who provide annual fiscal income data based on households' tax return. The latest available data were used, i.e. median net household income based on the 2017 tax return. For London, household income data were obtained through the Office for National Statistics (ONS) and as a variable the modelled estimates for the mean equivalent net household income for 2018 were used.

Air pollution

For Brussels, average annual NO_2 concentration data is available on a 10m × 10m grid surface for 2018, obtained through the Belgian Interregional Environment Agency, whose air quality maps are based on the ATMO-street model developed by the Flemish Institute of Technology. This dispersion model takes into account the regional and urban background but also captures so called street canyon effects into one single air quality map (see https://vito.be/en/atmo-street). For London, average annual NO_2 concentration data for 2016 were obtained through the London Atmospheric Emissions Inventory (LAEI) developed by King's College London, publicly accessible on the London Datastore. The LAEI is considered the primary authority for air pollution levels in London with annual average NO_2 concentrations calculated on a 20m × 20m grid surface. The model uses emissions data from all sources in an atmospheric dispersion model to estimate ground level concentrations of NO_2, but in contrast to the Brussels model does not take the effect of street canyons into account. To calculate average *address-based* exposure address point data sets were used. For Greater Brussels, CRAB (Centraal Referentieadressenbestand) address points (2020) provided by Informatie Vlaanderen were used for census wards falling in the Flemish Region, and UrbIS address points (2020) provided by Irisnet Brussel were used for census wards falling in the Brussels Capital Region. For Greater London, instead of individual addresses, ONS Postcode Points (2020) were used, each combining around 15 addresses. The exposure indicator was calculated through adding the rasterized air pollution data to each address or postcode point using bilinear interpolation in ArcMap 10.7.1, and subsequently averaging these values at census ward and MSOA level. By including all addresses – residential, commercial, public services – this indicator accounts to some extent for local spatial differences in density of activity and air pollution exposure levels.

Non-compliant cars

Recent spatial data for 2020 on the percentage of registered cars not meeting the LEZ emission standards was supplied by the Belgian Department of Vehicle Registration (DIV) for Greater Brussels and by the Vehicle Statistics Team of the Department of Transport (based on DVLA data) for Greater London although the DIV car register was only available at municipal level. For Greater Brussels the 2022 LEZ emission standards were used (Euro 2 for petrol cars, Euro 5 for diesel cars). For Greater London the current ULEZ emission standards were used, which will stay in place for several more years (Euro 4 for petrol cars, Euro 6 for diesel cars).

Public transport quality

The centroids of census wards and MSOAs were used as origins while destination points were defined as a set of random locations within the boundaries of the – expanded, in the case of Greater London – low emission zone (10 for Brussels, and 15 for London). Average travel time between the centroids and all destination points was calculated using the Google Directions API, with timestamp July 06, 2020 at 08:00 and API requests written in Python. For car travel time, the duration in traffic is based on historical data. For public transport travel time, the duration is based on official timetables. As a final indicator of public transport quality, we calculated the 'additional travel time by public transport' by subtracting the average travel time by car from the average travel time by public transport.

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