

Mapping Ambient Vulnerabilities: Commuters' exposure to air pollution

A preliminary study

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Abstract

Exposure to air pollution from ambient environments has become a major public health concern across the Global North, especially in increasingly urbanised areas with higher traffic and fewer green spaces. The highest exposure to air pollution typically occurs during people's commutes and travel across urban landscapes; however, our understanding of the extent and disproportionate exposure across populations remains limited, as granular pollution exposure research is resource-intensive. This paper bridges this gap by conducting a large-scale simulation of commuters' exposure to air pollution using network routing and granular air pollution estimates. This allows for a) assessment of commuting time commitments by populations across England and b) estimation of air pollution exposure that populations in different local authorities and regions face in their daily movements through the city. By linking these estimates with demographic, socio-economic and other contextual variables, we explore the distributions of air pollution exposure and time commitments in the context of spatial inequalities and spatial justice. The outputs allow for neighbourhood comparison of population pollution exposure through commuting, highlighting patterns that do not completely align with the expectations from the literature. The resultant data product can be used to underpin greater equitability in urban and transport policy-making.

Keywords: air pollution, commuter, spatial justice, inequalities

Introduction

Long- and short-term exposure to pollutants such as nitrogen dioxide (NO₂) and fine particulate matter (PM_{2.5}) has been consistently linked to adverse health outcomes, including respiratory and cardiovascular disease, reduced life expectancy, and increased mortality (Royal College of Physicians of London, 2016). Although outdoor air quality in the United Kingdom has improved, particularly in urban areas with high traffic and dense populations, air pollution remains a persistent concern. As urban populations grow and daily mobility remains integral to modern life, understanding how people are exposed to pollution in everyday environments is increasingly important (Steinle et al. 2013).

In the UK today, air pollution is recognised as the most significant environmental risk. Under the UK Clean Air Strategy (DEFRA 2019), the government aims to reduce population exposure below WHO PM_{2.5} limits in at least 50% of currently non-compliant areas. The strategy identifies transport as a major emissions source and prioritises three interventions: limiting emissions (e.g., electric vehicle uptake), strengthening emissions standards and enforcement, and encouraging behavioural change such as walking and cycling. These measures are already visible through electric vehicle adoption, Low Traffic Neighbourhoods (LTNs), and Low Emission Zones (LEZs).

In the UK, commuting represents a particularly important component of population's daily exposure. Roughly two in three economically active people in UK travel to work, however, the mode of travel is skewed. While 15% of people use public transport, and similarly 15% people use active travel (either walk or cycle), 69% use motorised vehicles such as a car or motorbike (Department for Transport 2022). The majority of economically active people (84%) travel to

work through a main road network, spending roughly 27 min (on average) doing both: contributing to and experiencing increased air pollution exposure. There are, however, spatial differences in these patterns: car use accounts for 80% of commuting in Wales compared to only 30% in London, suggesting that the transport-related exposure is likely to be unevenly distributed across the population, and particular places. Despite this, much of the large-scale research informing such policies is based on studies at fixed locations.

Over the past two decades, GPS-enabled devices have enabled researchers to track individuals in space and time and assess exposure during daily movement. Evidence shows exposure is often highest during commuting (Knibbs et al. 2011; Steinle et al. 2015), and that transport mode and route significantly shape pollution intake (Cepeda et al. 2017; Rafiepourgatabi et al. 2021). Even for pedestrians, exposure can be higher at crossroads and intersections (Rafiepourgatabi et al. 2021). Time of day is especially influential, with peak-hour exposure several times higher than off-peak levels (Miao et al. 2015), suggesting a significant contribution to individuals' pollution exposure through commonality of their daily travel patterns.

This growing body of evidence highlights the importance of mobility in personal pollution exposure and reveals new grounds for both theoretical and applied research. Indeed, recent theoretical work from (Walker et al. 2022) has drawn from Lefebvre's philosophy and describes air pollution exposure as rhythmic: structured not only by where people live, but also by how, when and how long they move through urban spaces. Moreover, the research suggests the presence of inequalities within this "exposure on move" as individuals with less control over their time and mobility might be more likely to travel in *disadvantaged* times and spaces. They might be more likely to travel in peak times, rely on more exposed transport modes and in general spend more time travelling, leading to higher cumulative exposure and a higher likelihood of long-term health problems. Despite this, at larger spatial scales the air pollution research has been mainly focused on estimation of exposure risks at locations rather. These approaches largely ignore the mobility dimension of exposure and overlook daily movement patterns. As a result, pollution exposure is systematically underestimated, reinforcing policy blind spots (Kenis and Loopmans 2022).

This study takes the first step toward building this research agenda by developing a simulation of population exposure "on the move," drawing on big data, census-based information on daily mobility patterns, and available computational resources. By exploring the feasibility of estimating mobility-related air pollution exposure across England, the study contributes to broader debates on spatial inequality, environmental justice, and the distributional impacts of transport systems.

Data and Method

A wide range of approaches has been developed to model human exposure to air pollution, varying substantially in spatial and temporal resolution, pollutants considered, and incorporation of human activity patterns (Dias and Tchepel 2018). Quantifying exposure is challenging due to the high spatio-temporal variability of both pollution concentrations and human behaviour (Steinle et al. 2013), meaning most studies face limitations in temporal extent, spatial coverage, and pollutant capture.

Where high-resolution measurements are unavailable, researchers rely on microenvironment-based approaches, which assign pollutant concentrations to relatively homogeneous spaces and calculate individual exposure as a function of time spent in each (Duan 1982; Steinle et al. 2013). This study adopts that approach to enable simulations with both large spatial extent and high granularity, simulating individual-level journeys through urban environments to quantify

population exposure within Output Areas. Until indirect data collection via personal devices becomes viable, we leverage existing knowledge of environmental patterns and population movement through network-analysis and high-performance computing (Figure 1).

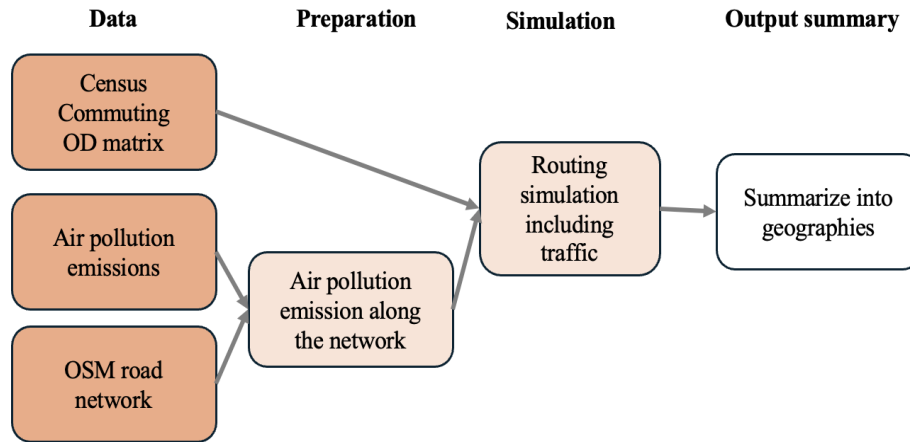


Figure 1 Simplified pipeline. The analysis process consists of three main steps: Data preparation, simulation, and summary of results.

The most comprehensive and reliable data on air pollution in the UK is provided by the UK National Atmospheric Emissions Inventory (NAEI). The NAEI is a modelled, raster-based dataset that offers spatio-temporal information on annual emissions for all major pollutants and serves as the core evidence base for understanding air pollution in the UK. The dataset is available at a 1 km spatial resolution and provides a yearly estimate of air pollution within each grid cell. To estimate pollution exposure at the road level, we overlay the NAEI emissions raster with the OpenStreetMap (OSM) road network. This allows us to derive road-specific emission estimates and summarise pollution emissions for each subsection of the road network. These estimates are then combined with road characteristics, enabling the pre-calculation of exposure per minute of travel for each road segment (Eq.1).

$$Exposure_i = Emission_i \times \frac{Length_i}{Maximum\ speed_i} \quad (1)$$

$$Exposure_{O-pop} = \sum_{d \in D} w_{O,d} \sum_{i \in r_{O,d}} Exposure_i \quad (2)$$

Here, the per-minute air pollution exposure for a road segment i is calculated as the pollution emission associated with the segment multiplied by the time required to traverse it. Travel time is approximated as the length of the road segment divided by its maximum permitted speed. While this results in spatially and temporally homogenous estimation of air pollution exposure, the ‘Travel time’ variable remains crucial: it can be refined in future to account for peak time traffic for example. These steps are necessary to reduce the computational complexity of the task and are essential for preserving resources in large-scale simulations.

To represent daily population mobility patterns, we use the Output Area (OA) level Origin-Destination Workplace data from the 2021 Census in England and Wales. This dataset captures commuting flows of the economically active population. Although the 2021 Census was conducted during the COVID-19 pandemic and may therefore contain some anomalies related to commuter mobility, it remains the most comprehensive and reliable source of information on population daily mobility available at present.

Routing and shortest-path algorithms are implemented using the Pandana Python package (Groh et al. 2021) to simulate daily commuting journeys for populations in each OA. Specifically, we generate unique routes from each origin OA to all destination OAs and weight each route by the number of individuals undertaking that journey. Exposure is calculated for each route and aggregated to the origin OA, yielding an estimate of total commuting-related pollution exposure for the population residing in each area. Here, total exposure for the population residing in origin O is calculated as the sum of exposures across all road segments i along each route r between origin O and destination d , weighted by the number of people ($w_{O,d}$) undertaking each journey.

Due to the computational demands of England's full road network, the country was divided into regional subgraphs processed separately, which required excluding cross-regional journeys and leads to some underestimation of exposure for cross-border commuters; a limitation to be resolved by migrating the workflow to a high-performance computer.

Results & Conclusion

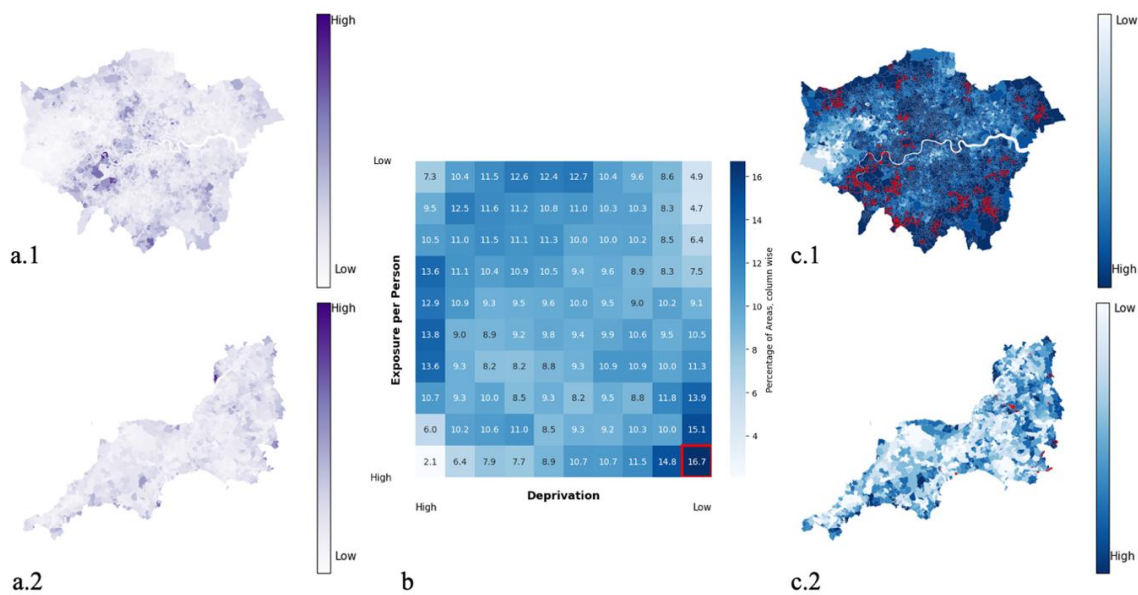


Figure 2 shows preliminary simulation results. Subfigure a shows estimated PM_{2.5} exposure per commuter journey in London (a.1) and the South West (a.2). Subfigure b shows a heatmap of area counts across deprivation and exposure deciles for England. Subfigure c shows exposure deciles in London (c.1) and the South West (c.2), with areas of lowest deprivation but highest exposure highlighted in red.

The main limitation of this simulation is its reliance on NAEI modelled emission maps. Although modelled emissions provide some indication of potential pollution concentrations, they cannot be directly interpreted as such, meaning estimates cannot be compared against UK or WHO guideline limits. However, under the assumption that emissions are intrinsically linked to concentrations at a given location, they still allow us to examine spatial and temporal dynamics and their relationships with other variables.

In London, estimates show higher commuting exposure in South and South-East London, though the top 10% of high-exposure areas are distributed across the entire city, suggesting Londoners are disproportionately exposed to PM_{2.5} emissions during commutes compared to the rest of England. In other regions, such as the South West, higher exposure areas appear to cluster around motorways or away from major urban cores, implying that longer or motorway-adjacent commutes contribute to greater PM_{2.5} exposure.

Literature suggests that populations with less control over their time and resources face higher pollution exposure due to unfavourable commutes and reliance on public transport. Testing this against deprivation levels (Figure 2b) reveals a more complex picture. While the most deprived 10% of areas do face relatively higher commuter exposure, areas in the upper 40% of deprivation are generally associated with lower PM_{2.5} exposure, and higher-exposure areas tend to be less deprived. The highest concentration of areas combining top 10% pollution exposure with bottom 10% deprivation is found in London (Figures 2c and 2d), suggesting the city behaves differently from the rest of England and warrants further investigation.

Overall, while there are some limitations to our approach, it allows us to build a better understanding of population pollution exposure "on the move" across regions and whole countries. This is a crucial step in bridging the gap between granular air pollution research and scalable mapping, allowing for multiscale comparison of population vulnerabilities and feeding into a broader discussion about inequalities in the UK.

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