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Impact of COVID-19 lockdown on NO_2 and $PM_{2.5}$ exposure inequalities in London, UK

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Abstract

Amid the COVID-19 pandemic, a nationwide lockdown was imposed in the United Kingdom (UK) on 23rd March 2020. These sudden control measures led to radical changes in human activities in the Greater London Area (GLA). During this lockdown, transportation use was significantly reduced and non-key workers were required to work from home. This study aims to understand how population exposure to $PM_{2.5}$ and NO_2 changed spatially and temporally across London, in different microenvironments, following the lockdown period relative to the previous three-year average in the same calendar period. Our research shows that population exposure to NO_2 declined significantly (52.3% ±6.1%), while population exposure to $PM_{2.5}$ showed a smaller relative reduction (15.7% ±4.1%). Changes in population activity had the strongest relative influence on exposure levels during morning rush hours, when prior to the lockdown a large percentage of people would normally commute or be at the workplace. In particular, a very high exposure decrease was observed for both pollutants (approximately 66% for NO_2 and 19% for $PM_{2.5}$) at 08:00am, consistent with the radical changes in population commuting. The infiltration of outdoor air pollution into housing modifies the degree of exposure change both temporally and spatially. Moreover, this study shows that the impacts on air pollution exposure vary across groups with different socioeconomic status (SES), with a disproportionate positive effect on the areas of the city home to more economically deprived communities.

Keywords

COVID-19; Lockdown measures; Population activity; Population-weighted exposure change; Concentration change; Socioeconomic inequalities

1. Introduction

Ambient air pollution levels are strongly associated with human activities, such as transportation, and can have significant population health impacts; in the UK, for example, air pollution is thought to contribute 28,000 to 36,000 excess deaths a year (PHE, 2019). On 23rd March 2020, the UK government imposed a nationwide lockdown due to increasing transmission of coronavirus, which subsequently led to radical changes in human activities including the transportation and time-activity behaviours of the population. The COVID-19 lockdown offers a unique natural experiment to evaluate and quantify the impact of rapid changes in people's activity patterns and emissions on air pollution and subsequent population exposure.

Numerous studies have already evaluated the impact of COVID-19 lockdowns on outdoor air quality worldwide (Muhammad et al., 2020). The vast majority of these studies show that radical shutdown measures in big cities led to lower and less variable outdoor concentrations of urban air pollutants (Gruener et al., 2020; Zhao et al., 2020; Mahata et al., 2020; Sharma et al., 2020; Mbandi et al., 2020). However, most of these studies focus solely on the reduction of outdoor *concentrations*, and a relative few studies have assessed the impact of lockdowns on population *exposure* to urban air pollution (Williams, 2020; Zhu et al., 2020). This is important, as exposure to outdoor air pollution also occurs in non-outdoor microenvironments (MEs) due to the infiltration of polluted air; for example, housing is thought to significantly modify population exposures (Taylor et al., 2014).

Exposure is also dependent on the time-activity profiles of the population. In cities under lockdown, much of the population radically changed their daily activities, including working from home instead of their usual workplace and by avoiding all unnecessary travel. For example, the lockdown led to a greater than 70% decrease in public and private transportation in London, likely reducing exposure to outdoor generated air pollution (Williams, 2020). Therefore, to assess spatial and temporal changes in exposure during the lockdown, key factors such as changes in population activity patterns and concentrations in different microenvironments, where people spent their daily time (for example at home, workplaces, in transit, and outdoors) need to be considered.

In addition, there may be important differences in exposure between population groups. Socioeconomic inequalities in concentration and exposure to outdoor pollution are well established (Tonne et al., 2018; Shiels et al., 2017; Stringhini et al., 2017; Rivas et al., 2017; Rotko et al., 2001 and 2000) and there is emerging evidence of similar disparities indoors (Ferguson et al., 2020). Several studies have shown a strong connection between communities of either lower or higher socioeconomic position and increased concentrations and exposure to urban air pollution (Hajat et al., 2015). In US, several studies have shown that deprived areas experience higher levels of outdoor pollution exposures (Su et al., 2012; Gray et al., 2013; Hajat et al., 2015). In London and other big cities, it has been suggested socioeconomic inequalities in outdoor levels of traffic-related air pollution are driven by differences in road traffic volume, which affects the amount of emissions (Tonne et al., 2018; Brook and King, 2017; Pandilla et al., 2014). Therefore, changes in road traffic following the lockdown provide a unique natural experiment opportunity to investigate exposure disparities across socioeconomic groups, with potential changes in outdoor generated air pollution resulting in differences in exposure changes across different such groups.

In this study, we seek to 1) understand how the COVID-19 lockdown changed population-level outdoor air pollution exposures, and 2) evaluate whether changes in exposures varied across socioeconomic groups and explore the role of traffic-related pollution on exposure inequalities.

To achieve this, we aim to quantify and illustrate the spatio-temporal change in population exposure to outdoor-generated air pollution in London during the lockdown period relative to previous years for the same period. By accounting for the spatial and temporal variability of outdoor air pollution, dwelling Indoor-Outdoor (I/O) ratios (the proportion of outdoor air pollution that infiltrates indoors), and changes in diurnal population activity patterns, we assess the impact of the lockdown on the population exposure levels. Moreover, we also evaluate socioeconomic differences in exposure reduction. Understanding the spatial and temporal distribution of air pollution across different MEs, and subsequent exposure inequalities, is important to develop policies to reduce inequalities and improve sustainable development.

2. Material and methods

2.1 Study period and air quality data

Lockdown measures were applied to the Greater London Area (GLA), UK, on March 23rd, 2020. To examine the impact on short-term air quality, a one-month period (23 March to 22 April) in 2020 was compared against the same calendar period, averaged from 2017-2019. The hourly monitoring data for two major traffic-related air pollutants (NO_2 and $PM_{2.5}$) were obtained from the London Air Quality Network (LAQN) (King's College London). For NO_2, 98 monitoring sites were included, whereas for $PM_{2.5}$ only 21 monitoring sites were available for the study period. Average hourly concentrations for each hour of the study period were calculated for each monitoring site. The Voronoi Neighbor Averaging (VNA) tool in QGIS was used to spatially interpolate hourly data between monitoring sites, estimating hourly outdoor concentrations pre and post-lockdown at Lower-Super Output Area (LSOA) level (a census unit with an average of 1500 residents).

2.2 Microenvironments and infiltration of outdoor pollutants

Four different MEs have been considered in this work:

(i) The home;

(ii) Work, assuming that all individuals work inside buildings;

(iii) Transport, including public or private transportation (i.e., bus, private car/taxi and train) to travel; and

(iv) Outdoors, including people who are walking or cycling.

We only consider exposure to outdoor-generated pollution. Estimates of indoor pollution from indoor sources are highly uncertain and have not been considered in this study due to a lack of data. The infiltration of outdoor NO_2 and $PM_{2.5}$ into the home ME was considered using previously derived hourly I/O ratios across GLA for the same calendar period (Taylor et al, 2014). This data includes the hourly average I/O ratios of 1.5 million London dwelling (covering approximately 46% of London dwellings), and accounts for seasonal wind pressures and summertime window opening; here we use hourly average dwelling I/O ratios for April to represent the lockdown period, averaged by LSOA (Figure S1). For both pollutants, central London shows the lowest I/O ratios, likely due to the newer building stock and the large number of flats in multi-dwelling buildings, where the available surface for infiltration is considerably smaller. The average I/O ratio in the GLA ranges from 0.40 to 0.63 for $PM_{2.5}$ and 0.15-0.40 for NO_2. The I/O ratio is likely to significantly modify population exposure to outdoor air pollution due to the extended amount of time that people spent at home during the lockdown period.

The spatially and temporally resolved I/O ratios provided by Taylor et al. (2014) have been derived only for domestic buildings and are not representative of commercial areas and workplaces. Thus, for the workplace, we have selected representative values according to the available literature. For $PM_{2.5}$, we selected an average value of 0.60 (Singh et al., 2020; Soares et al., 2014; Hanninen et al., 2011) and for NO_2, we chose to use an average value of 0.68 (Hu and Zhao, 2020, Kornartit et al., 2010).

For outdoor air pollution exposure in the transportation ME, we calculated the in-vehicle concentration using a mass balance equation (Smith et al., 2016). The same input values as Smith et al. (2016) were used except for the outdoor concentrations which were updated. As in Smith et al. (2016), the surface area of each commuter was derived as per Song et al. (2009).

2.3 London population data and activity

The spatial distribution of the London population was derived from 2011 census data from the Office of National Statistics (ONS, 2012), representing 95% of households, and was assumed to be the same in both the baseline and study periods. The spatial distribution of the population was considered during daytime (defined as the period from 7:00am to 19:00) population (Figure S2a in SI) and night-time (defined as the period from 20:00 to 06:00am) population (Figure S2b in SI). The Census usual resident population was used for the night-time period and the workday population for the daytime period. As expected, under normal circumstances the daytime population density is much higher in Inner London due to much of the population commuting into the city centre, whereas the night-time distribution is much more uniform across the GLA.

2.3.1. Pre-COVID

For the pre-COVID-19 period, we analyzed the amount of people at home, at work, in transportation and outdoors using Census and London Travel Demand Survey (LTDS, 2011) data. We used the Census workplace population (the number of people in each LSOA that were in their workplace during a usual weekday) to calculate the percentage of people normally at work. From the LTDS, the total number of trips per hour of a weekday, and the number of average trips per person were used to calculate the number of people that use public transportation each hour. As there was no data on the movements of populations in each LSOA, the temporal variation of the percentage of people in each ME was estimated using the LTDS data and the daytime and night-time population distributions. LTDS also provides data on the number of people commuting at each hour, defined as travelling between the home and workplace. Thus, at each hour the respective number of commuters was subtracted from the workplace population.

The diurnal variation of the population activity in the four MEs is presented in Figure 1A. During the morning and afternoon rush hours, the percentage of people in the transportation ME peaks. During daytime, more than 30% of people are either at work or in transportation, while at the night after 22:00 more than 90% of the population are at home. In this study, children were included in the home population.

2.3.2. COVID Lockdown

For the COVID-19 period, changes in population daily movements between MEs were obtained from App Maps and Google statistics. Google statistics used the median value of each day of the week in January 2020 (i.e., 5-week period from 3 January until 5 February) as baseline, while App Maps used 13 January 2020. Both datasets show significant changes in population travel and working behavior after March 23rd, with transportation reduced by more than 70%, and more than 75% of the working population remaining at home. The remaining population at work during the lockdown period likely consists largely of key workers, who continued going to their workplace. The data also shows that less than 1% of the total population are outside at most hours of the day. This data was used alongside spatial distribution of the usual resident (night-time) population in order to estimate the variation of the percentage of the population in each ME during the COVID-19 period (Figure 1B).

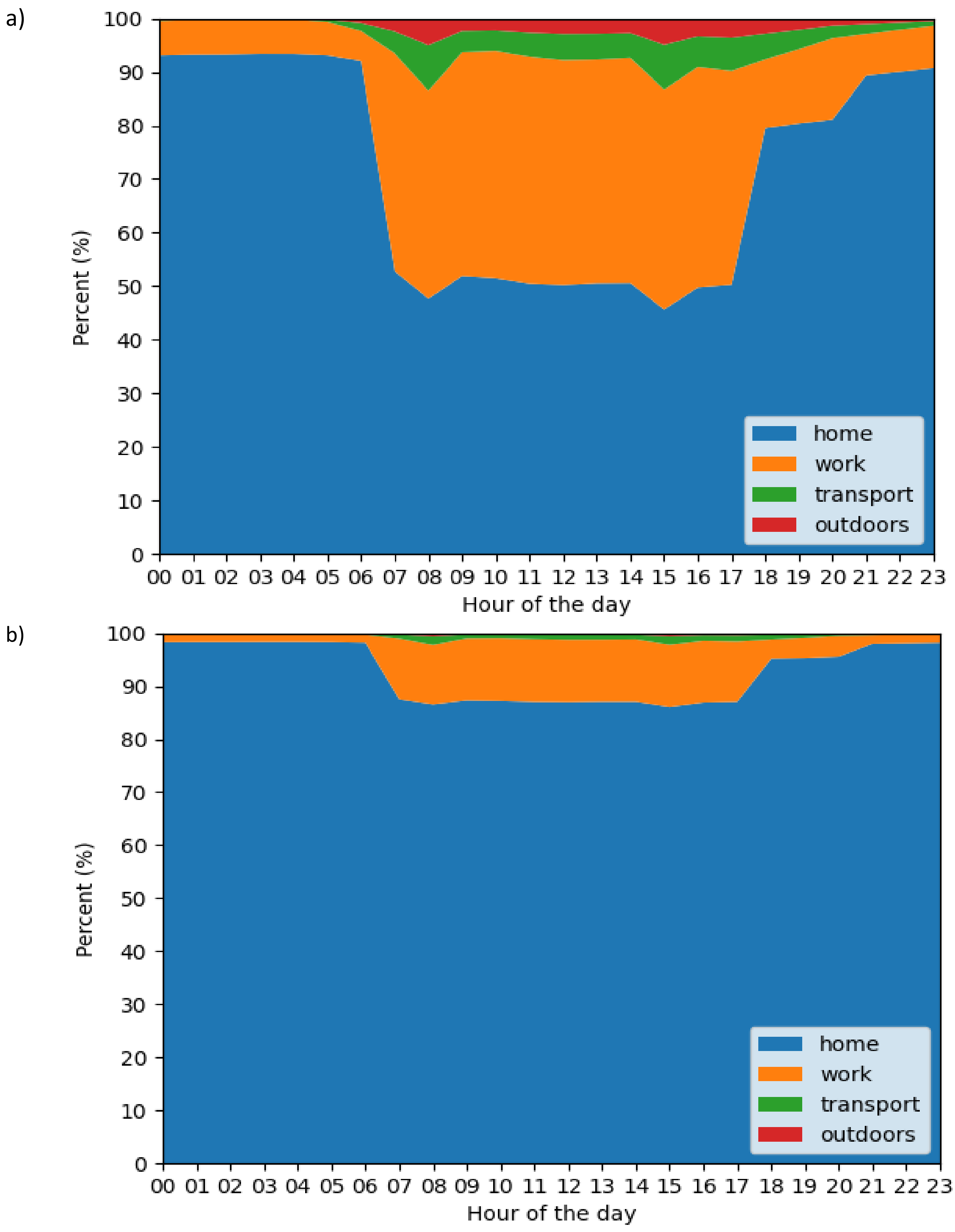


Figure 1: Diurnal variation of the percentage of people in each ME: a) during the pre-COVID-19 period and b) during the COVID-19 period (first lockdown).

2.4 Population-weighted exposure

The population-weighted mean exposure (PE) is estimated from the concentration level in each ME and the amount of people that spent time in those MEs. The PE was calculated as:

$$PE = \frac{\sum_{i=1}^{n} C_{i,t,j} \times P_{i,t,j}}{P_T} \quad (1)$$

Where PE is the population weighted mean exposure for a population, n is the number of the populated geographical units (here LSOAs); *C* and *P* are the mean concentration of the pollutant and the number of people, respectively, for LSOA *i*, microenvironment *j and* hour *t* of the day; and P_T is the respective total population.

2.5 Socioeconomic analysis

To compare concentration and exposure across socioeconomic status (SES), we used LSOA – level deprivation data from the 2019 Index of Multiple Deprivation (IMD). The IMD is an overall relative measure of deprivation constructed by combining seven domains of social and economic deprivation (i.e.,' Income Deprivation', 'Employment Deprivation', 'Education, Skills and Training Deprivation', 'Health Deprivation', 'Crime', 'Barriers to Housing and Services' and 'Living Environment Deprivation'). The IMD was linked to population exposure in each LSOA based on the usual resident population distribution.

We then examined the statistical relationship between the IMD and the average change of concentration and exposure to $PM_{2.5}$ and NO_2 at LSOA-level using Spearman's correlation. Our goal was to show the strength of association between the time-averaged air pollution reductions and SES. Spearman's correlation was chosen for the statistical analysis because it is considered as a suitable technique to correlate ordinal variables, such as the ranked IMD data, and has been previously used to correlate UK IMD data with different environmental exposures (Tonne et al., 2018).

3. Results

3.1 Spatial and temporal change in air pollution concentration and exposure

3.1.1 Spatial distribution of concentrations and exposure reduction

Hourly average outdoor concentrations changed significantly following the COVID-19 lockdown. Before the lockdown, the three-year London average (2017 - 2019) NO_2 and $PM_{2.5}$ concentrations from 23 March to 23 April were 45.1 µg/m^3 and 18.2 µg/m^3, respectively. After implementation of lockdown measures, the average outdoor concentrations of NO_2 and $PM_{2.5}$ during the same period were 26.7 µg/m^3 and 15.7 µg/m^3 (Table 1), respectively, representing a decrease of 40.9% ±6% for NO_2 and 13.9% ±4% for $PM_{2.5}$.

As changes in outdoor concentrations of NO_2 and $PM_{2.5}$ due to COVID-19 shutdown have been presented and analyzed by several studies, we focus here on changes in population-weighted exposure across different environments. We estimate that transportation was the most highly polluted ME during the lockdown with an average exposure of 22.1 µg/m^3 for NO_2 and 13.1 µg/m^3 for $PM_{2.5}$, while the average workplace concentration was 17.1 µg/m^3 for NO_2 and 9.4 µg/m^3 for $PM_{2.5}$. The home ME had the lowest NO_2 and $PM_{2.5}$ concentrations with 7 µg/m^3 and 8.6 µg/m^3, respectively.

Table 1: Total exposure and concentrations before (2017-19) and during the lockdown period (2020).

MEs	2017-19		2020	
	NO_2 (µg/m^3)	$PM_{2.5}$ (µg/m^3)	NO_2 (µg/m^3)	$PM_{2.5}$ (µg/m^3)
Outdoor	45.1	18.2	26.7	15.7
Transportation	37.4	15.1	22.1	13.1
Work	28.9	10.9	17.1	9.4
Home	11.9	9.9	7	8.6
Total Exposure concentration	16.2	10.3	7.7	8.7

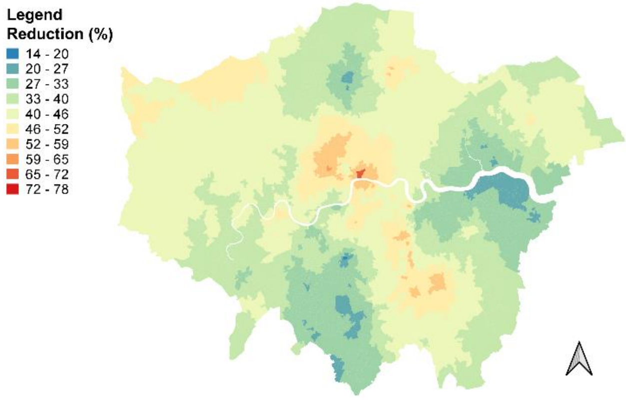
Population and time-weighted exposure is impacted by population activity patterns, I/O ratios and outdoor concentration. The indoor levels of outdoor air pollution are directly affected by the I/O ratios of dwellings, thus modifying exposures to outdoor air pollution. Here, we found that the average population-weighted mean exposure decreased following lockdown from 16.2 µg/m^3 to 7.7 µg/m^3 (a 52.3% reduction) for NO_2, and from 10.3 µg/m^3 to 8.7 µg/m^3 (a 15.7% reduction) for $PM_{2.5}$. The fact that a much higher percentage of people were spending their daytime inside their homes (an increase from 50% to 90%), has led to a greater reduction in exposure during the lockdown due to the protective role of housing on outdoor air pollution exposures (Smith et al., 2016).

Figures 2a and 3a show the concentration and exposure change across London. For NO_2, the greatest exposure reductions (55 to 71%) were observed in Inner London (Figure 2a). $PM_{2.5}$ showed the greatest reductions (28% to 32%) in East and West areas of Inner London (Figure 3a). Relatively few areas in West London showed only minor reductions in exposure (<2%). The spatial variation of exposure reduction is also in-part due to changes in the distribution of the population across London and the I/O ratios of the dwellings where they spend their time. The large decrease in exposure in Central London was due to various factors, particularly the more uniform distribution of the population during the lockdown, when the population was not concentrated in central London during working hours (Figure S2). Additionally, the lower average I/O ratios of dwellings (Figure S1) and the greater reduction in outdoor concentrations (Figures 2 and 3) also contributed to reduced exposure. In contrast, some areas in western London, which showed higher I/O ratios (particularly $PM_{2.5}$) and low reductions in outdoor pollution show comparatively low decreases in overall exposure levels.

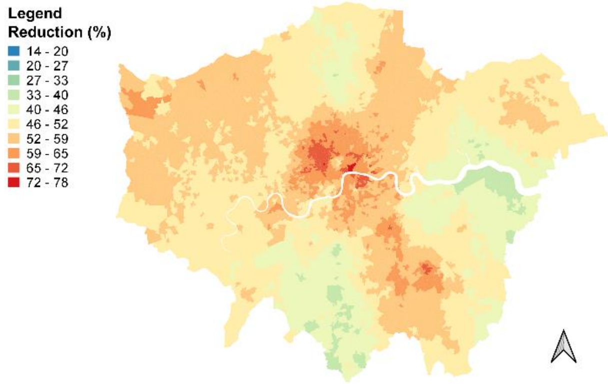
3.1.2 Temporal change in air pollution concentration and exposure

Figure 4 describes the average hourly reduction in concentration and population exposure to NO_2 and $PM_{2.5}$ during the lockdown. As expected, there is little difference between the concentration (Figure 4a) and exposure (Figure 4b) reduction during most hours of the day for both pollutants. However, during morning during rush hours the percent reduction fluctuates differently for both pollutants, which reveals the strong impact of the change in population activity on exposure. Both pollutants show the greatest exposure decrease during morning and evening peak rush hours. During those two time periods, the lowest percentage of people are inside the home relative to other hours of the day (Figure 1) pre-COVID-19, and thus we expect to observe the most significant changes after lockdown measures at these times. In particular, there was the greatest reduction in population exposure for NO_2 (66.1% ±5.1%) and $PM_{2.5}$ (19.2% ±3.9%) at 08:00am.

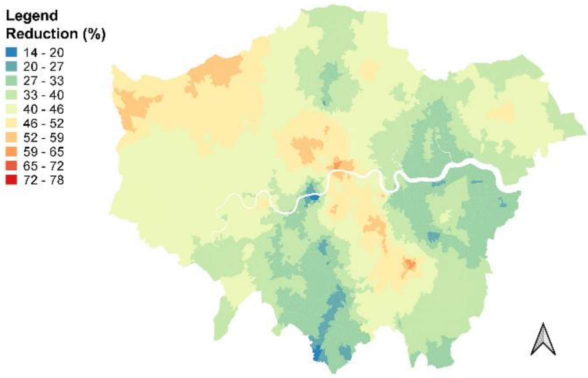
The spatial distribution of the concentration and exposure reduction at the time of the greatest hourly decrease (i.e., 08:00am) is illustrated on Figures 2b and 3b. NO_2 exposures show the highest percent reduction (>65%) in Inner and Northwest London, while $PM_{2.5}$ exposure is reduced more in the Northeast, South, and parts of Inner London. Because NO_2 is strongly related to traffic, the most traffic congested areas of London, such as central London, show the highest exposure change. $PM_{2.5}$ shows a slightly different and more uniform distribution of exposure reduction, due to factors discussed in section 3.1.1.



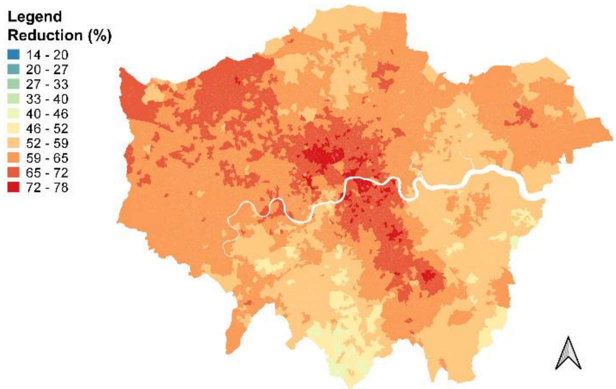
a) Average reduction of NO_2 concentration



b) Average reduction of NO_2 exposure

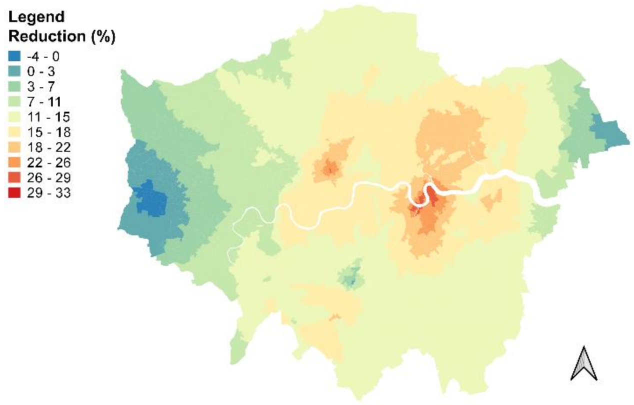


c) Reduction of NO_2 concentration at 08:00am

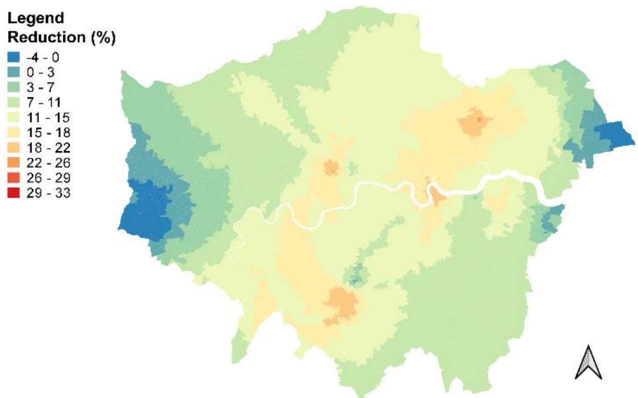


d) Reduction of NO_2 exposure at 08:00am

Figure 2: Maps a) and b) illustrate the spatial distribution of average NO_2 concentration and exposure reduction (%) during the lockdown period across London. Maps c) and d) illustrate the spatial distribution of average NO_2 concentration and exposure reduction (%) at 08:00am.



a) Average reduction of $PM_{2.5}$ concentration   b) Average reduction of $PM_{2.5}$ exposure



c) Reduction of $PM_{2.5}$ concentration at 08:00am   d) Reduction of $PM_{2.5}$ exposure at 08:00am

Figure 3: Maps a) and b) illustrate the spatial distribution of average $PM_{2.5}$ concentration and exposure reduction (%) during the lockdown period across London. Maps c) and d) illustrate the spatial distribution of average $PM_{2.5}$ concentration and exposure reduction (%) at 08:00am.

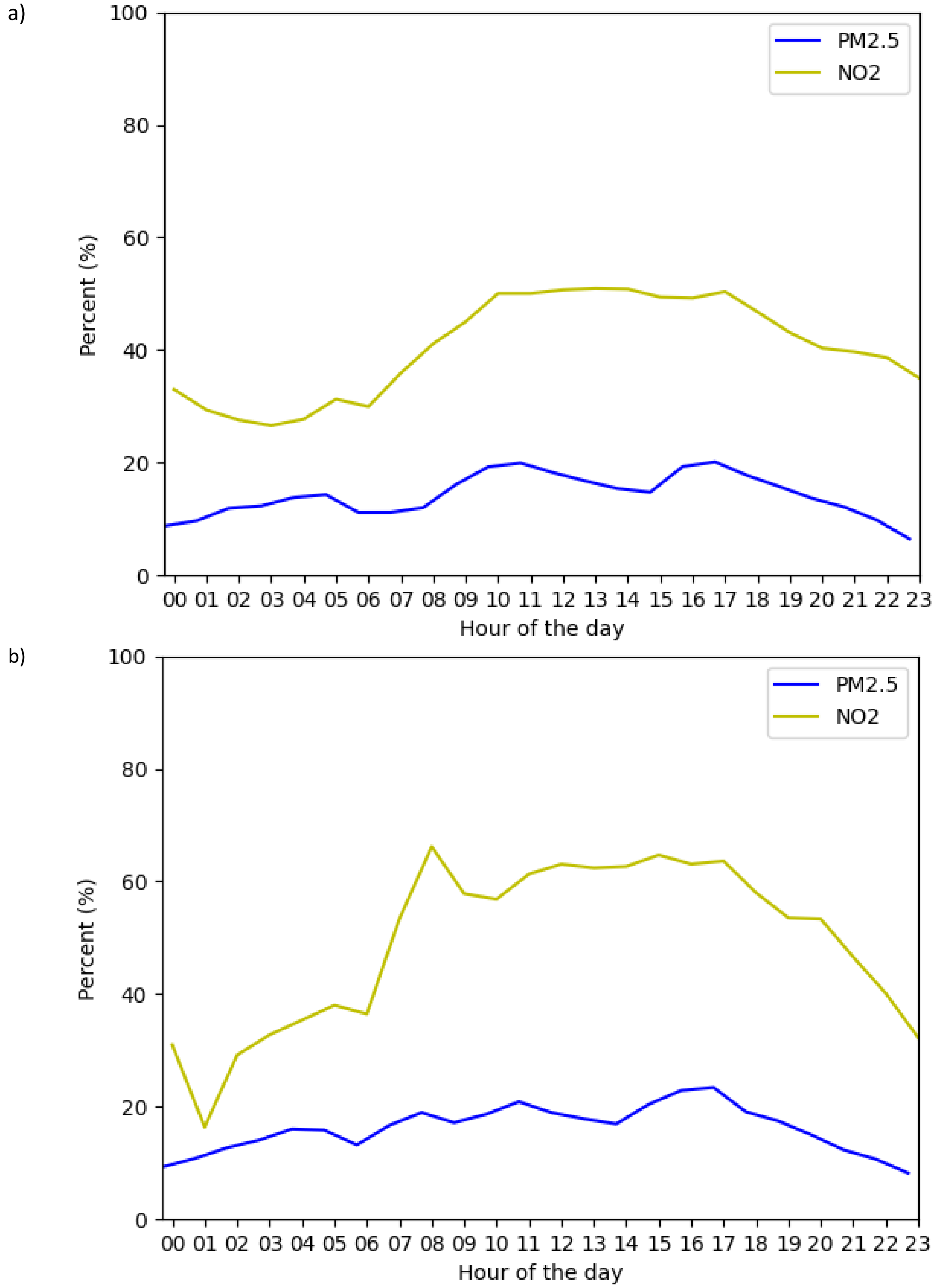


Figure 4: Average diurnal a) concentration reduction (%) and b) exposure reduction (%) during the lockdown period (yellow represents NO_2 and blue $PM_{2.5}$).

3.2 Socioeconomic Status

Air pollution concentration and exposure data are summarized to illustrate the differences between IMD classifications. Figures 5 and 6 present $PM_{2.5}$ and NO_2 concentrations and exposure differences between the two examined periods across each deprivation decile. For $PM_{2.5}$, the concentration and exposure differences in the most deprived LSOAs (deciles 1, 2, and 3) demonstrate the lowest variability, while the LSOAs with moderate deprivation (i.e., deciles 4,5,6) show the largest variability. For NO_2, LSOAs in IMD decile 2 show the highest average and the greatest variability for both concentration and exposure difference, while the least deprived LSOAs (i.e., decile 10) show the lowest variability and slightly lower average difference (8.6 μg/m^3) compared to the most deprived (8.9 μg/m^3). The magnitude of the variability in each IMD decile is likely influenced by the corresponding spatial variation of I/O ratios and outdoor concentrations among the LSOAs of each decile. The smaller variability across the deprivation deciles observed for $PM_{2.5}$ reductions relative to NO_2 may be explained by the less variable particle concentrations across London (Williams, 2020). Moreover, the reductions in concentration also indicate that highly deprived populations in London are disproportionately impacted by air pollution from traffic sources. For both pollutants, the results demonstrate a negative relationship between deprivation deciles and the average exposure and concentration difference during the study period (Table 2). Therefore, disadvantaged areas were associated with higher reduction of concentration and exposure to $PM_{2.5}$ and NO_2. Only a very weak association was found for NO_2 with correlations of -0.11 and -0.05 for concentration and exposure, whereas the $PM_{2.5}$ concentration and exposure difference were more strongly correlated with IMD. All correlations are statistically significant (p-value <0.05). This study provides evidence of weak associations, but in the direction of the predictions of several previous studies that suggest a great concentrations or exposure in the most deprived areas (Tonne et al., 2018; Brook and King, 2017; Pandilla et al., 2014).

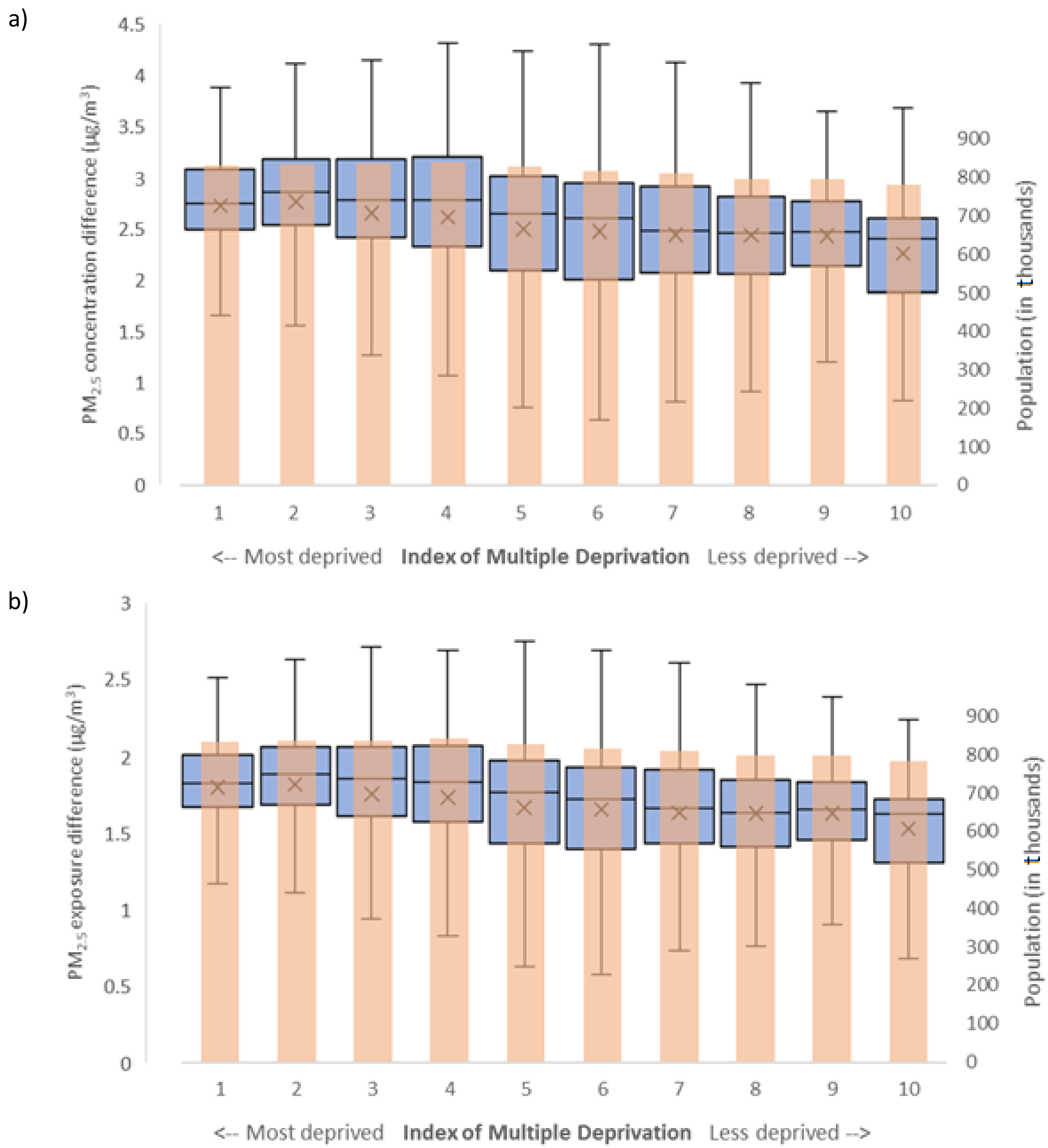


Figure 5: a) Variation of $PM_{2.5}$ concentration difference and the total population of all LSOAs in each decile, b) Variation of $PM_{2.5}$ exposure difference and the total population of all LSOAs in each decile.

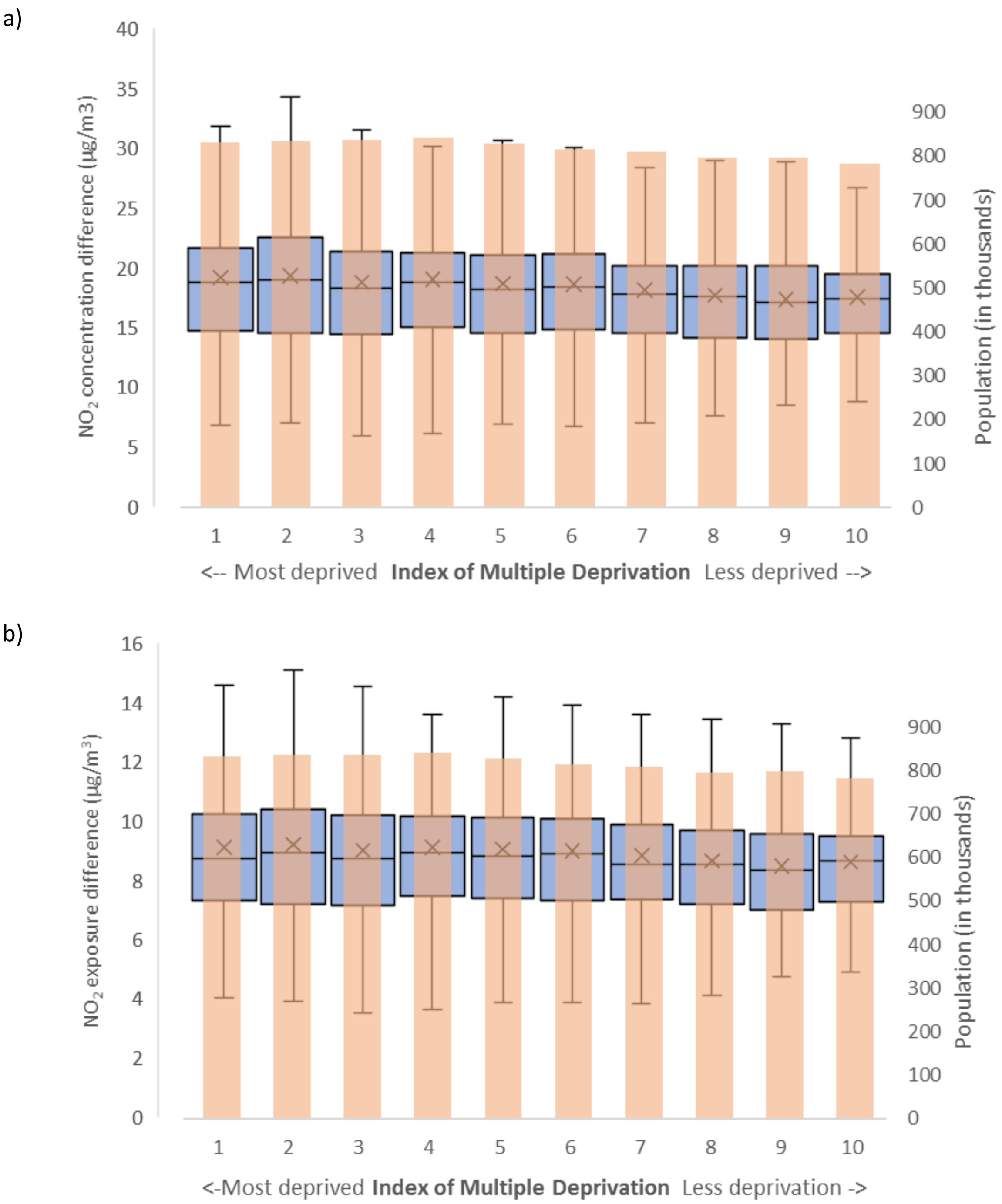


Figure 6: a) Variation of NO_2 concentration difference and the number of people in each decile; b) Variation of NO_2 exposure and the number of people in each decile.

Table 2: Spearman's correlation coefficient between deprivation index (IMD) and air pollution concentration (exposure) difference.

	Concentration		Exposure	
	NO_2	$PM_{2.5}$	NO_2	$PM_{2.5}$
IMD	-0.11*	-0.25*	-0.05**	-0.26*

*p-value <0.001, **p-value<0.05

4. Discussion

Lockdown measures in different parts of the world due to the COVID-19 outbreak have provided an opportunity to evaluate the human impact on the urban environment. In this work, we evaluate the relationship between population exposure and time-activity patterns, including the time spent indoors. We found a high average percent reduction in NO_2 exposure (52.3% ±6.1%) with the greatest decrease in Inner London, while $PM_{2.5}$ exposure showed a considerably lower average percent reduction (15.7% ±4.1%). The very high reductions in exposure to both pollutants during the morning rush hours show the strong influence of changes in population commuting. By linking population SES and exposure change, we demonstrate variation in air pollution exposure reduction following lockdown across IMD deciles, and provide evidence supporting the conclusion that deprived communities in London are disproportionately affected by road transport pollution.

Numerous prior research studies have investigated and evaluated the influence of coronavirus on air quality globally, and several approaches can be broadly identified. According to recent literature, reductions in NO_2 and $PM_{2.5}$ concentrations during the lockdown ranged from 10% to greater than 50% worldwide (Wu et al., 2021; Gruener et al., 2020; Zhao et al., 2020; Williams, 2020; Fonseca et al., 2020; Brook and King, 2020) with the highest emission reductions observed during morning rush hours. Here, we estimate an average reduction of approximately 50% and 16% for NO_2 and $PM_{2.5}$, respectively. The radical changes in population activity and the significant change in the spatial distribution of the population are likely to have significantly contributed to this reduction in emissions. As with other studies, we estimated the greatest exposure reductions during morning rush hours and during the evening peak hours, particularly at 08:00am when there was the greatest reduction in population exposure for NO_2 (66.1% ±5.1%) and $PM_{2.5}$ (19.2% ±3.9%). The steep decrease in air pollution exposure levels during rush hours reflects the importance of the temporal variation of population activity and spatio-temporal variation of the domestic I/O ratios. Conversely, during night hours and early morning hours, the reduction in exposure was much lower. As the number of night workers is much lower than the number of day or evening workers and over 90% of the population was at home during night or early morning, only minor changes were observed to the population activity patterns at these times.

Many large cities around the world demonstrated lower outdoor concentrations of air pollution during the quarantine measures, improving air quality (Arregoces et al., 2021; Kumar et al., 2020). However, it is worth noting that some studies show higher $PM_{2.5}$ concentrations in several locations (Daniella Rodriguez-Urrego and Leonardo Rodriguez-Urrego, 2020) relative to the pre-covid period, and the effect of the lockdown on some pollutants might be still questionable. A direct comparison between studies is frustrated by the different periods and sites considered, and the methodologies used to quantify the changes. In the UK, a selection of studies have investigated the impact of the shutdown on the concentration of urban pollutants (Williams, 2020; Fonseca et al., 2020). However, there is little research on how changes in population exposure are distributed across urban areas, accounting for the spatial and temporal variability of the exposures in different MEs. Our novel approach includes hourly average I/O ratios of more than 1.5 million dwellings - averaged by LSOA - and estimates an average population exposure reduction of 66% and 19% for NO_2 and $PM_{2.5}$. For NO_2, the highest reduction was observed in Central, Northwest and Southeast London and for $PM_{2.5}$ in the West and East of Inner London. For both concentration and exposure, NO_2 show notably higher reductions than $PM_{2.5}$ post lockdown. This is likely due to a significant decrease in traffic-rated emissions in London, meaning pollutants that are strongly related to traffic emissions, such as NO_2, are more significantly affected. On the other hand, for outdoor $PM_{2.5}$, the contribution of local transport emissions is smaller than for NO_2 (Reis et al., 2018) and particulate pollution may be influenced by other factors (for example, local meteorology, transboundary transport, resuspension and the use of fireplaces).

Health studies have suggested that lower SES populations are more likely to suffer premature mortality from air pollution exposure than higher SES populations (Krewski et al. 2000a, b). Multiple studies have been conducted in large cities and metropolitan areas around the world associating the SES with the air pollution concentration and exposure. Most of them demonstrate high associations between the most deprived areas and high outdoor (Sarmadi et al., 2020; Cakmak et al., 2016; Pinault et al., 2016; Pandilla et al., 2014; Gray et al., 2013) and indoor concentrations (Ferguson et al., 2020). Here, we provide new information about the impact of lockdown measures on people across different IMD groups. Results indicate negative associations between the reductions of concentration and exposure during the lockdown period and the area-level deprivation status, where $PM_{2.5}$ is more strongly correlated than NO_2. Several studies conducted in large urban areas have presented similar outcomes (Pandilla et al., 2014). In London, Brook and King (2017) predicted that reductions in exposure to NO_2 would be higher for areas that fall within IMD decile 1 (most deprived) after the implementation of air pollution reduction measures. Furthermore, Tonne et al. (2018) analyzed the relationship between SES and outdoor air pollution, finding an exposure different of 0 to 1.9 $\mu g/m^3$ between the highest and lowest household income groups, and greater reductions in air pollution in the least advantaged areas after the activation of the Congestion Charging Zone in London.

The main strengths of our study are the large dataset, including population information at LSOA-level, travel behavior from a representative sample of the London population and the large spatio-temporal variability of the I/O ratios for dwellings. The indoor environment is protective of exposure to outdoor air pollutants and that is usually reflected in much lower exposures when Home MEs have been taken into account. Amid the pandemic lockdown measures, when more than 90% of the population had to stay at their home during the daytime, the incorporation of the spatial and temporal distribution of domestic I/O ratios when estimating the population-weighted exposure significantly modifies the magnitude and distribution of the exposure change.

This study contains several limitations. The limitations are the quality of the derived air pollution data and the absence of meteorological effects. Because our study is based on recent measurements, most of the available concentrations for 2020 have not yet been fully ratified by the LAQN. However, in order to reduce the uncertainty and improve the quality of our data, we did not include any negative or unusually extreme hourly values to our analysis. A few monitoring sites did not provide 100% of the data for the whole study period and some hourly readings were missing (or not included). No sites provided less than 70% of the data (Lang et al. 2019; King's College London, 2015). Temporal and spatial variability of air pollution concentrations are subject to changes in emissions and meteorology, which may impact the exposure levels (Bujin et al., 2020). NO_2 levels can be directly linked to the reduction of transport emissions due to its strong relation to traffic (He et al., 2020a; He et al., 2020b). However, transboundary transport of PM and precursors from mainland European sources and the associated meteorology play an important role in PM concentrations in London. Thus, post-COVID-19 concentrations might be different than pre-COVID-19 due to reasons that are not directly related to lockdown. The wind conditions during 2020 have been exceptional in many ways across the UK (Carslaw, 2020). Moreover, the lockdown period also coincides with the period of the year where there is an increased frequency of $PM_{2.5}$ episodes in Europe (Air Quality Expert Group, 2020). Therefore, the lack of accounting for weather conditions in our assessment is likely to have affected our results and some reductions may have been over-estimated. However, our approach of averaging the same calendar period of the previous years might have the benefit of reducing meteorological variability. Another limitation is that exposure to other urban air pollutants was not considered, mostly due to data inavailability. In this study we focused on the two most important major air pollutants for London's air quality (https://www.london.gov.uk/). Many air pollutants have common sources, and air pollution reduction strategies that take advantage of these common sources may achieve economies of scale that control strategies that target one pollutant at a time cannot. Moreover, pollutants can also be connected by similar precursors or chemical reactions once in the atmosphere. Thus, control strategies that target one pollutant may affect others, perhaps in unintended ways. A much denser network of monitoring stations was available for the NO_2 compared to $PM_{2.5}$. As the concentration of air pollution can change across small distances, the denser network can lead to higher prediction accuracy. In this work, roadside and urban background sites were included, with roadside sites mostly located within Inner London. The denser NO_2 monitoring network and the smaller distances between the sites were able to provide adequate coverage of background sites for non-traffic locations. However, the interpolation of roadside measurements, especially for the less dense $PM_{2.5}$ network, may have led to an overestimation of the impacts of reduced traffic by interpolating to non-traffic areas. The surrounding urban environment can significantly influence pollutant transport and concentration, and to account for this, high-skilled urban modelling accounting for complex urban morphology is required. However, this kind of advanced modelling was not feasible for this study, but could be incorporated to future studies. Moreover, schools and commercial buildings were assumed to have same values as home microenvironment and children were included in the home population. Finally, the average workplace I/O ratio used in this study was assumed from several European cities (Soares et al., 2014; Hanninen et al., 2011; Hanninen et al., 2004). Data on I/O ratios in commercial buildings, and for different type of workplaces are scarce. Therefore, it was assumed that the values demonstrated in Europe were also representative for London.

This work utilized Google Statistics and App Maps to determine differences in travel patterns. Both App Maps and Google statistics are based on data sent from users' devices and users that opt-in to location history for their account, respectively. Consequently, those data sources contain limitations in terms of their representativeness of the overall population. Apple Maps has no demographic information about its users, making it difficult determine data representativeness. In the calculations, Google statistics includes only data from users that use their Google account and have opted-in to Location History. Those data also have to meet Google's privacy threshold. Consequently, this location data may not represent the exact behaviour of the wider population. As described in methodology section, the IMD is based on seven main domains. The 'Living Environment' domain contributes approximately 9% to the production of the overall index and measures the quality of the local environment and the indicators fall into two sub-domains. The 'indoors' and the 'outdoors', which consists of two elements: air quality and road accidents. However, the already included 'air quality' element is not likely to have affected our calculations, because here we examined the associations between the IMD and the reduction of concentration and exposure. Other studies have already used IMD to investigate SES inequalities in air pollution (Sheridan et al., 2019; Tonne et al., 2018; Brooks and King, 2017).

Some segments of the working population – so-called essential or key workers - had to continue to travel to work in their original workplace during the lockdown period. When estimating the population-weighted exposure, we assumed that all SES groups are equally likely to stay at home during lockdown, however many essential workers are likely to be low SES individuals. Their total exposure to air pollution may still decrease due to the reduction in outdoor concentration, however the change in their exposure to air pollution would be different from other working groups because their daily activity during the lockdown would be the same as the pre-COVID-19 period. Due to the unavailability of data, essential workers could not be linked with the IMD analysis to investigate how this may impact exposure differences between IMD groups. By using the workplace population for the work ME, and by applying the mean percent reduction for the population that continued going to workplaces during the shutdown, we assume that the percentage of population in work ME during post-COVID-19 period (28%) represents essential workers. This percentage is consistent with the ONS estimate that essential workers are approximately 29.5% of London's workforce (ONS, 2020). While further work is required to understand uncertainties in travel and work patterns of low-SES essential workers, these results allow us to conclude that the lockdown provided significant exposure reductions to low-income communities in London.

5. Conclusions

The implementation of stay-at-home measures due to the global outbreak of COVID-19 has offered a unique opportunity to assess the effect of the rapid changes in population activity patterns on air pollution concentration and population exposure. This study quantified and analyzed spatial and temporal changes in population-weighted mean exposure to air pollution of outdoor origin between the COVID-19 lockdown period and previous 3-year average during the same calendar period. Subsequently, we evaluated socioeconomic variation across the distribution of exposure change. We demonstrate that changes in diurnal population activity and outdoor concentrations have reduced exposure to air pollution, predominately during the morning rush hours. The average exposure to NO_2 showed a greater than 50% reduction, which was consistent with the remarkable decrease in traffic levels, a major source of NO_2. For $PM_{2.5}$, the 16% decrease in average exposure could not be linked directly to the reduction in urban traffic, because other factors, such as meteorological conditions, may have affected the magnitude of the change in the outdoor concentrations. While there were not large inequalities in how the exposure change was distributed among people with different SES, our results provided useful evidence about the strength of association between the concentration and exposure reduction, and the impact on the most and the least deprived areas.

By quantifying exposure reduction, and accounting for the significance of the time spent indoors and the spatio-temporal variability of average dwelling I/O ratios, this study offers insight into the effectiveness of extreme traffic-control measures on reducing the outdoor pollution and the exposure. Although these measures are extreme and highly unlikely to be adopted under normal conditions, this natural experiment offers the opportunity to assess the influence of some key elements (e.g., population activity, important indoor MEs) on population exposure, using largely real-world data. The estimated exposure reductions may provide best-case estimates of the degree to which more realistic control strategies for stationary and mobile urban sources, such technological (e.g., new-source certifications, retrofits of existing vehicles, etc.) or non-technological (e.g., management of transportation, etc.) may reduce exposures. The analysis of the SES inequalities across the distribution of the exposure reduction also demonstrates the importance of developing strategies that can reduce existing exposure inequalities.

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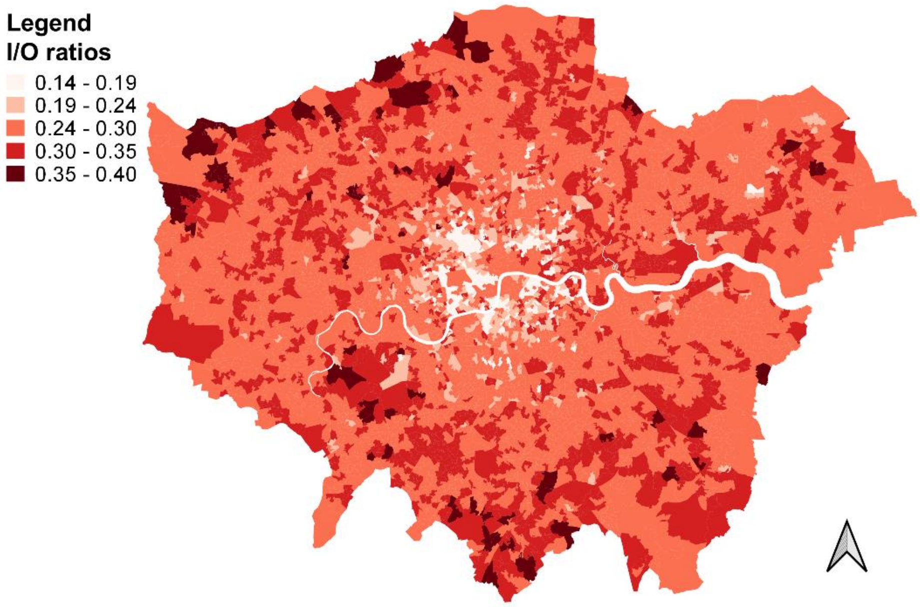
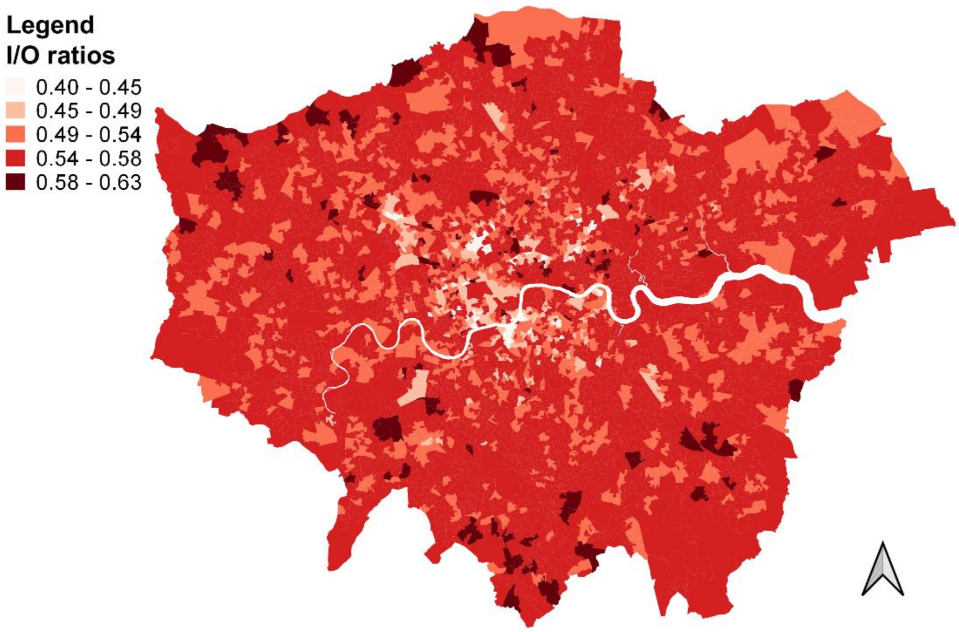
Supplementary material

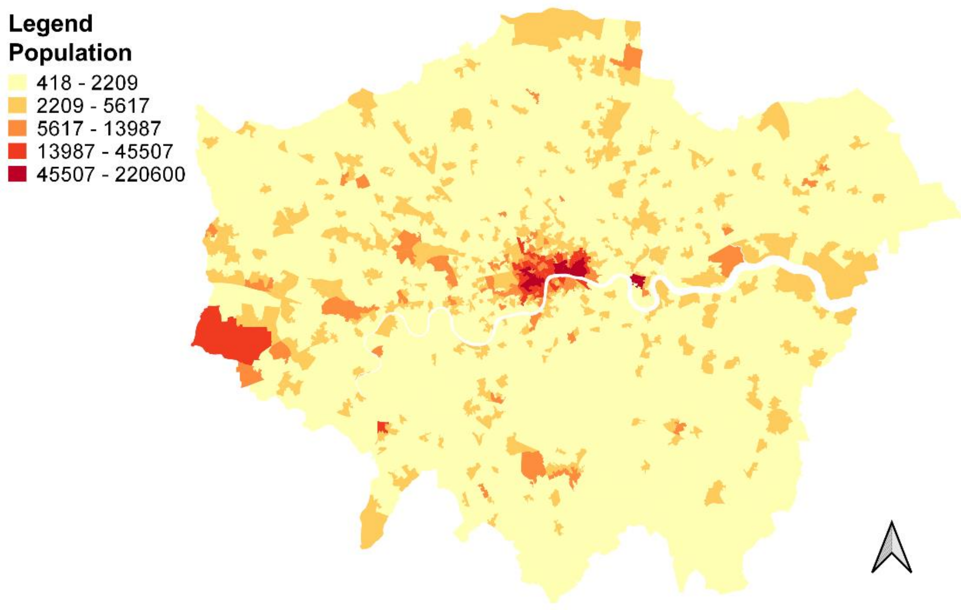


a) NO_2

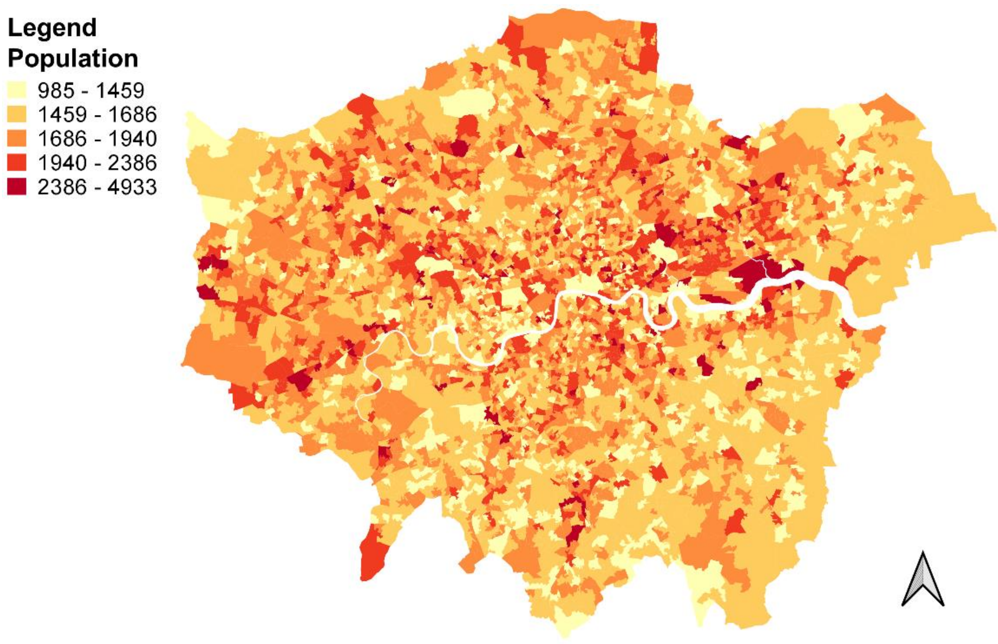


b) $PM_{2.5}$

Figure S1: Spatial variability of 24h average indoor/outdoor (I/O) ratios.



a) Daytime



b) Night-time

Figure S2: The spatial distribution of LSOA population in London: a) during daytime (defined as the period between 07:00am and 19:00), and b) during nighttime (defined as the period between 20:00 and 06:00am).