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1 **Impact of COVID-19 lockdown on NO₂ and PM_{2.5} exposure inequalities in**
2 **London, UK**

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Vasilis Kazakos¹, Jonathon Taylor², Zhiwen Luo*¹

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¹School of Built Environment, University of Reading, Reading, UK

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²Faculty of Built Environment, Tampere University, Tampere, Finland

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*Author of correspondence:

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Dr Zhiwen Luo, School of the Built Environment, University of Reading, United Kingdom

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Email : z.luo@reading.ac.uk

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12 **Abstract**

13 Amid the COVID-19 pandemic, a nationwide lockdown was imposed in the United Kingdom (UK) on
14 23rd March 2020. These sudden control measures led to radical changes in human activities in the
15 Greater London Area (GLA). During this lockdown, transportation use was significantly reduced and
16 non-key workers were required to work from home. This study aims to understand how population
17 exposure to PM_{2.5} and NO₂ changed spatially and temporally across London, in different
18 microenvironments, following the lockdown period relative to the previous three-year average in
19 the same calendar period. Our research shows that population exposure to NO₂ declined
20 significantly (52.3% ±6.1%), while population exposure to PM_{2.5} showed a smaller relative reduction
21 (15.7% ±4.1%). Changes in population activity had the strongest relative influence on exposure levels
22 during morning rush hours, when prior to the lockdown a large percentage of people would
23 normally commute or be at the workplace. In particular, a very high exposure decrease was
24 observed for both pollutants (approximately 66% for NO₂ and 19% for PM_{2.5}) at 08:00am, consistent
25 with the radical changes in population commuting. The infiltration of outdoor air pollution into
26 housing modifies the degree of exposure change both temporally and spatially. Moreover, this
27 study shows that the impacts on air pollution exposure vary across groups with different
28 socioeconomic status (SES), with a disproportionate positive effect on the areas of the city home to
29 more economically deprived communities.

30

31 **Keywords**

32 COVID-19; Lockdown measures; Population activity; Population-weighted exposure change;

33 Concentration change; Socioeconomic inequalities

34 1. Introduction

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

43 Numerous studies have already evaluated the impact of COVID-19 lockdowns on outdoor air quality
44 worldwide (Muhammad et al., 2020). The vast majority of these studies show that radical shutdown
45 measures in big cities led to lower and less variable outdoor concentrations of urban air pollutants
46 (Gruener et al., 2020; Zhao et al., 2020; Mahata et al., 2020; Sharma et al., 2020; Mbandi et al.,
47 2020). However, most of these studies focus solely on the reduction of outdoor *concentrations*, and
48 a relative few studies have assessed the impact of lockdowns on population *exposure* to urban air
49 pollution (Williams, 2020; Zhu et al., 2020). This is important, as exposure to outdoor air pollution
50 also occurs in non-outdoor microenvironments (MEs) due to the infiltration of polluted air; for
51 example, housing is thought to significantly modify population exposures (Taylor et al., 2014).

52 Exposure is also dependent on the time-activity profiles of the population. In cities under lockdown,
53 much of the population radically changed their daily activities, including working from home instead
54 of their usual workplace and by avoiding all unnecessary travel. For example, the lockdown led to a
55 greater than 70% decrease in public and private transportation in London, likely reducing exposure
56 to outdoor generated air pollution (Williams, 2020). Therefore, to assess spatial and temporal
57 changes in exposure during the lockdown, key factors such as changes in population activity patterns

58 and concentrations in different microenvironments, where people spent their daily time (for
59 example at home, workplaces, in transit, and outdoors) need to be considered.

60 In addition, there may be important differences in exposure between population groups.

61 Socioeconomic inequalities in concentration and exposure to outdoor pollution are well established

62 (Tonne et al., 2018; Shiels et al., 2017; Stringhini et al., 2017; Rivas et al., 2017; Rotko et al., 2001

63 and 2000) and there is emerging evidence of similar disparities indoors (Ferguson et al., 2020).

64 Several studies have shown a strong connection between communities of either lower or higher

65 socioeconomic position and increased concentrations and exposure to urban air pollution (Hajat et

66 al., 2015). In US, several studies have shown that deprived areas experience higher levels of outdoor

67 pollution exposures (Su et al., 2012; Gray et al., 2013; Hajat et al., 2015). In London and other big

68 cities, it has been suggested socioeconomic inequalities in outdoor levels of traffic-related air

69 pollution are driven by differences in road traffic volume, which affects the amount of emissions

70 (Tonne et al., 2018; Brook and King, 2017; Pandilla et al., 2014). Therefore, changes in road traffic

71 following the lockdown provide a unique natural experiment opportunity to investigate exposure

72 disparities across socioeconomic groups, with potential changes in outdoor generated air pollution

73 resulting in differences in exposure changes across different such groups.

74 In this study, we seek to 1) understand how the COVID-19 lockdown changed population-level

75 outdoor air pollution exposures, and 2) evaluate whether changes in exposures varied across

76 socioeconomic groups and explore the role of traffic-related pollution on exposure inequalities.

77 To achieve this, we aim to quantify and illustrate the spatio-temporal change in population

78 exposure to outdoor-generated air pollution in London during the lockdown period relative to

79 previous years for the same period. By accounting for the spatial and temporal variability of outdoor

80 air pollution, dwelling Indoor-Outdoor (I/O) ratios (the proportion of outdoor air pollution that

81 infiltrates indoors), and changes in diurnal population activity patterns, we assess the impact of the

82 lockdown on the population exposure levels. Moreover, we also evaluate socioeconomic differences

83 in exposure reduction. Understanding the spatial and temporal distribution of air pollution across
84 different MEs, and subsequent exposure inequalities, is important to develop policies to reduce
85 inequalities and improve sustainable development.

86

87 **2. Material and methods**

88 **2.1 Study period and air quality data**

89 Lockdown measures were applied to the Greater London Area (GLA), UK, on March 23rd, 2020. To
90 examine the impact on short-term air quality, a one-month period (23 March to 22 April) in 2020
91 was compared against the same calendar period, averaged from 2017-2019. The hourly monitoring
92 data for two major traffic-related air pollutants (NO₂ and PM_{2.5}) were obtained from the London Air
93 Quality Network (LAQN) (King's College London). For NO₂, 98 monitoring sites were included,
94 whereas for PM_{2.5} only 21 monitoring sites were available for the study period. Average hourly
95 concentrations for each hour of the study period were calculated for each monitoring site. The
96 Voronoi Neighbor Averaging (VNA) tool in QGIS was used to spatially interpolate hourly data
97 between monitoring sites, estimating hourly outdoor concentrations pre and post-lockdown at
98 Lower-Super Output Area (LSOA) level (a census unit with an average of 1500 residents).

99

100 **2.2 Microenvironments and infiltration of outdoor pollutants**

101 Four different MEs have been considered in this work:

- 102 (i) The home;
- 103 (ii) Work, assuming that all individuals work inside buildings;
- 104 (iii) Transport, including public or private transportation (i.e., bus, private car/taxi and train)
- 105 to travel; and

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

107 We only consider exposure to outdoor-generated pollution. Estimates of indoor pollution from
108 indoor sources are highly uncertain and have not been considered in this study due to a lack of data.
109 The infiltration of outdoor NO_2 and $\text{PM}_{2.5}$ into the home ME was considered using previously derived
110 hourly I/O ratios across GLA for the same calendar period (Taylor et al, 2014). This data includes the
111 hourly average I/O ratios of 1.5 million London dwelling (covering approximately 46% of London
112 dwellings), and accounts for seasonal wind pressures and summertime window opening; here we
113 use hourly average dwelling I/O ratios for April to represent the lockdown period, averaged by LSOA
114 (Figure S1). For both pollutants, central London shows the lowest I/O ratios, likely due to the newer
115 building stock and the large number of flats in multi-dwelling buildings, where the available surface
116 for infiltration is considerably smaller. The average I/O ratio in the GLA ranges from 0.40 to 0.63 for
117 $\text{PM}_{2.5}$ and 0.15-0.40 for NO_2 . The I/O ratio is likely to significantly modify population exposure to
118 outdoor air pollution due to the extended amount of time that people spent at home during the
119 lockdown period.

120 The spatially and temporally resolved I/O ratios provided by Taylor et al. (2014) have been derived
121 only for domestic buildings and are not representative of commercial areas and workplaces. Thus,
122 for the workplace, we have selected representative values according to the available literature. For
123 $\text{PM}_{2.5}$, we selected an average value of 0.60 (Singh et al., 2020; Soares et al., 2014; Hanninen et al.,
124 2011) and for NO_2 , we chose to use an average value of 0.68 (Hu and Zhao, 2020, Kornartit et al.,
125 2010).

126 For outdoor air pollution exposure in the transportation ME, we calculated the in-vehicle
127 concentration using a mass balance equation (Smith et al., 2016). The same input values as Smith et
128 al. (2016) were used except for the outdoor concentrations which were updated. As in Smith et al.
129 (2016), the surface area of each commuter was derived as per Song et al. (2009).

130

131 **2.3 London population data and activity**

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

141

142 **2.3.1. Pre-COVID**

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

154 The diurnal variation of the population activity in the four MEs is presented in Figure 1A. During the
155 morning and afternoon rush hours, the percentage of people in the transportation ME peaks. During

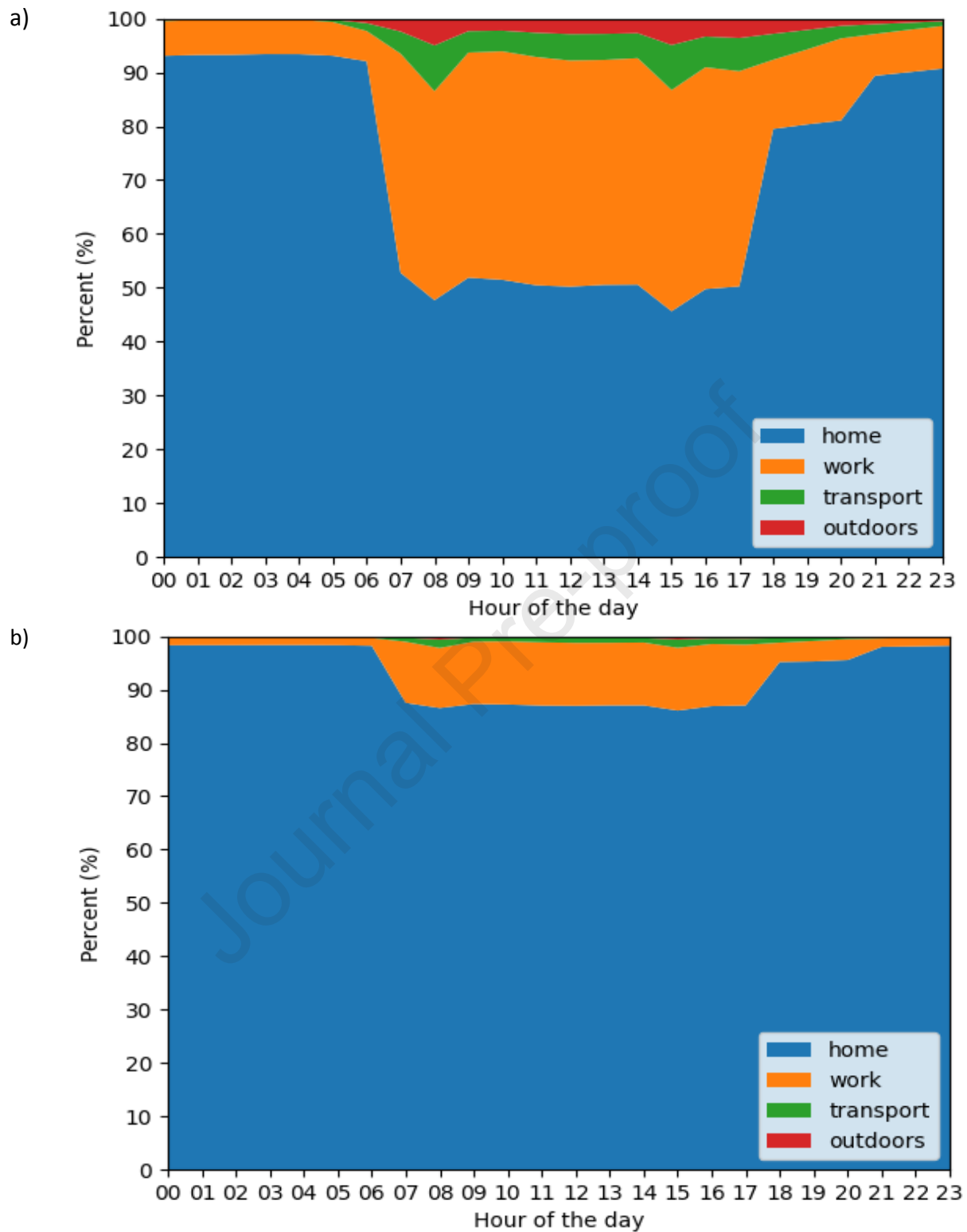
156 daytime, more than 30% of people are either at work or in transportation, while at the night after
157 22:00 more than 90% of the population are at home. In this study, children were included in the
158 home population.

159

160 **2.3.2. COVID Lockdown**

161 For the COVID-19 period, changes in population daily movements between MEs were obtained from
162 App Maps and Google statistics. Google statistics used the median value of each day of the week in
163 January 2020 (i.e., 5-week period from 3 January until 5 February) as baseline, while App Maps used
164 13 January 2020. Both datasets show significant changes in population travel and working behavior
165 after March 23rd, with transportation reduced by more than 70%, and more than 75% of the working
166 population remaining at home. The remaining population at work during the lockdown period likely
167 consists largely of key workers, who continued going to their workplace. The data also shows that
168 less than 1% of the total population are outside at most hours of the day. This data was used
169 alongside spatial distribution of the usual resident (night-time) population in order to estimate the
170 variation of the percentage of the population in each ME during the COVID-19 period (Figure 1B).

171



172

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

174 during the COVID-19 period (first lockdown).

175

176 2.4 Population-weighted exposure

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

$$179 \quad PE = \frac{\sum_{i=1}^n C_{i,t,j} \times P_{i,t,j}}{P_T} \quad (1)$$

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

184

185 2.5 Socioeconomic analysis

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

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

199

200 3. Results

201 3.1 Spatial and temporal change in air pollution concentration and exposure

202 3.1.1 Spatial distribution of concentrations and exposure reduction

203 Hourly average outdoor concentrations changed significantly following the COVID-19 lockdown.
 204 Before the lockdown, the three-year London average (2017 - 2019) NO₂ and PM_{2.5} concentrations
 205 from 23 March to 23 April were 45.1 µg/m³ and 18.2 µg/m³, respectively. After implementation of
 206 lockdown measures, the average outdoor concentrations of NO₂ and PM_{2.5} during the same period
 207 were 26.7 µg/m³ and 15.7 µg/m³ (Table 1), respectively, representing a decrease of 40.9% ±6% for
 208 NO₂ and 13.9% ±4% for PM_{2.5}.

209 As changes in outdoor concentrations of NO₂ and PM_{2.5} due to COVID-19 shutdown have been
 210 presented and analyzed by several studies, we focus here on changes in population-weighted
 211 exposure across different environments. We estimate that transportation was the most highly
 212 polluted ME during the lockdown with an average exposure of 22.1 µg/m³ for NO₂ and 13.1 µg/m³
 213 for PM_{2.5}, while the average workplace concentration was 17.1 µg/m³ for NO₂ and 9.4 µg/m³ for
 214 PM_{2.5}. The home ME had the lowest NO₂ and PM_{2.5} concentrations with 7 µg/m³ and 8.6 µg/m³,
 215 respectively.

216

217 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

218

219 Population and time-weighted exposure is impacted by population activity patterns, I/O ratios and
220 outdoor concentration. The indoor levels of outdoor air pollution are directly affected by the I/O
221 ratios of dwellings, thus modifying exposures to outdoor air pollution. Here, we found that the
222 average population-weighted mean exposure decreased following lockdown from 16.2 $\mu\text{g}/\text{m}^3$ to 7.7
223 $\mu\text{g}/\text{m}^3$ (a 52.3% reduction) for NO_2 , and from 10.3 $\mu\text{g}/\text{m}^3$ to 8.7 $\mu\text{g}/\text{m}^3$ (a 15.7% reduction) for $\text{PM}_{2.5}$.
224 The fact that a much higher percentage of people were spending their daytime inside their homes
225 (an increase from 50% to 90%), has led to a greater reduction in exposure during the lockdown due
226 to the protective role of housing on outdoor air pollution exposures (Smith et al., 2016).

227 Figures 2a and 3a show the concentration and exposure change across London. For NO_2 , the greatest
228 exposure reductions (55 to 71%) were observed in Inner London (Figure 2a). $\text{PM}_{2.5}$ showed the
229 greatest reductions (28% to 32%) in East and West areas of Inner London (Figure 3a). Relatively few
230 areas in West London showed only minor reductions in exposure (<2%). The spatial variation of
231 exposure reduction is also in-part due to changes in the distribution of the population across London
232 and the I/O ratios of the dwellings where they spend their time. The large decrease in exposure in
233 Central London was due to various factors, particularly the more uniform distribution of the
234 population during the lockdown, when the population was not concentrated in central London
235 during working hours (Figure S2). Additionally, the lower average I/O ratios of dwellings (Figure S1)
236 and the greater reduction in outdoor concentrations (Figures 2 and 3) also contributed to reduced
237 exposure. In contrast, some areas in western London, which showed higher I/O ratios (particularly
238 $\text{PM}_{2.5}$) and low reductions in outdoor pollution show comparatively low decreases in overall
239 exposure levels.

240

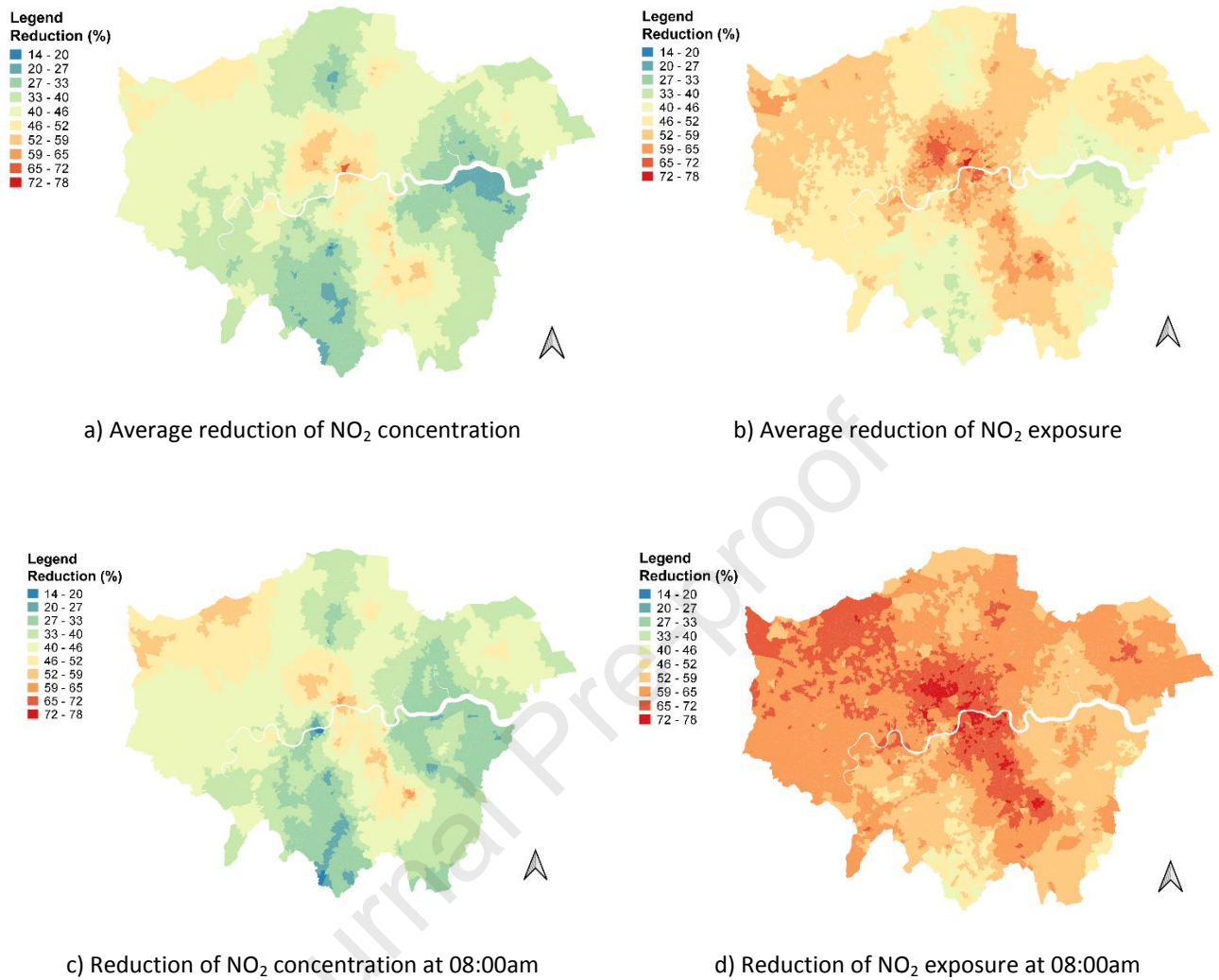
241 **3.1.2 Temporal change in air pollution concentration and exposure**

242 Figure 4 describes the average hourly reduction in concentration and population exposure to NO₂
243 and PM_{2.5} during the lockdown. As expected, there is little difference between the concentration
244 (Figure 4a) and exposure (Figure 4b) reduction during most hours of the day for both pollutants.
245 However, during morning during rush hours the percent reduction fluctuates differently for both
246 pollutants, which reveals the strong impact of the change in population activity on exposure. Both
247 pollutants show the greatest exposure decrease during morning and evening peak rush hours.
248 During those two time periods, the lowest percentage of people are inside the home relative to
249 other hours of the day (Figure 1) pre-COVID-19, and thus we expect to observe the most significant
250 changes after lockdown measures at these times. In particular, there was the greatest reduction in
251 population exposure for NO₂ (66.1% ±5.1%) and PM_{2.5} (19.2% ±3.9%) at 08:00am.

252 The spatial distribution of the concentration and exposure reduction at the time of the greatest
253 hourly decrease (i.e., 08:00am) is illustrated on Figures 2b and 3b. NO₂ exposures show the highest
254 percent reduction (>65%) in Inner and Northwest London, while PM_{2.5} exposure is reduced more in
255 the Northeast, South, and parts of Inner London. Because NO₂ is strongly related to traffic, the most
256 traffic congested areas of London, such as central London, show the highest exposure change. PM_{2.5}
257 shows a slightly different and more uniform distribution of exposure reduction, due to factors
258 discussed in section 3.1.1.

259

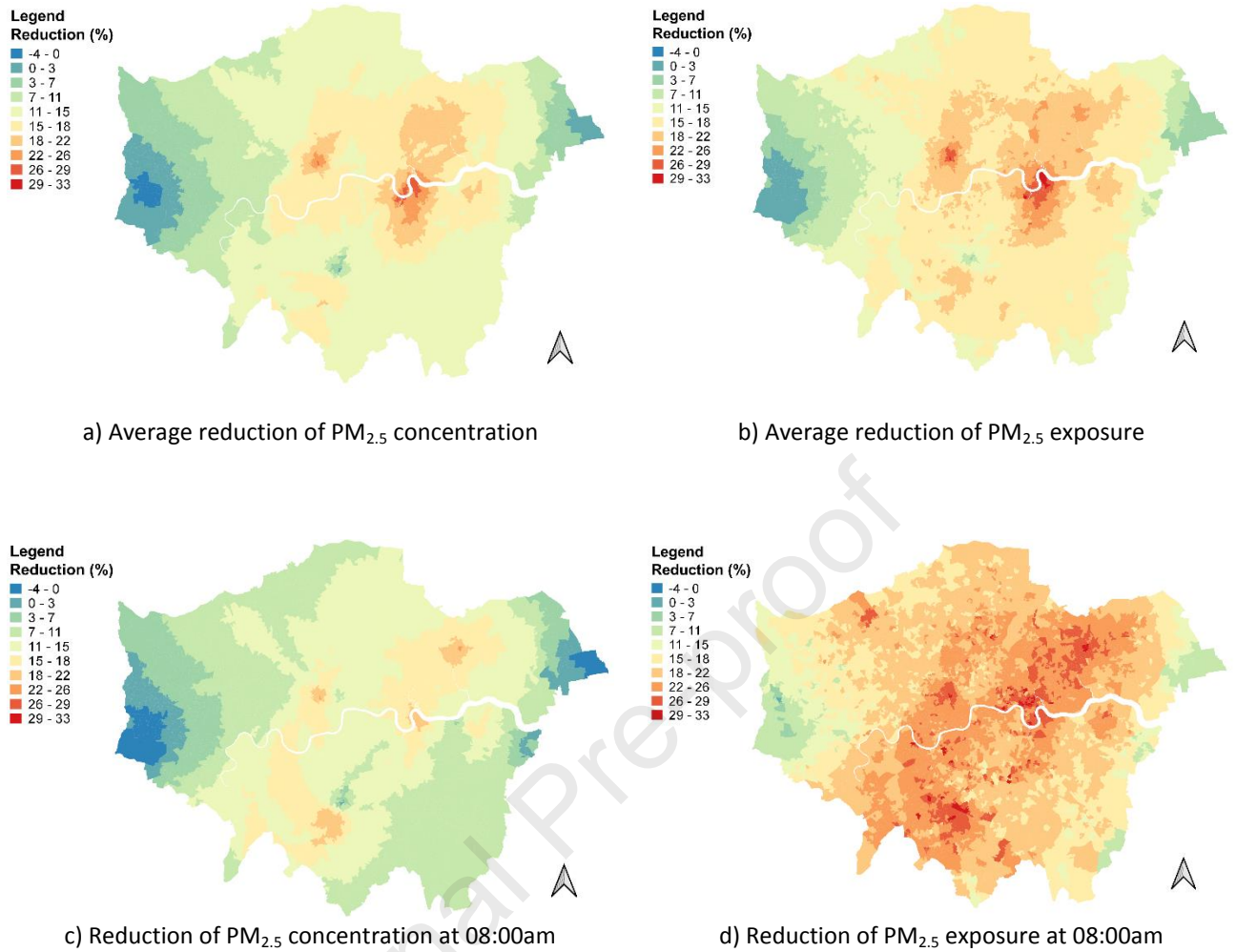
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261

262 Figure 2: Maps a) and b) illustrate the spatial distribution of average NO₂ concentration and exposure
 263 reduction (%) during the lockdown period across London. Maps c) and d) illustrate the spatial distribution of
 264 average NO₂ concentration and exposure reduction (%) at 08:00am.

265



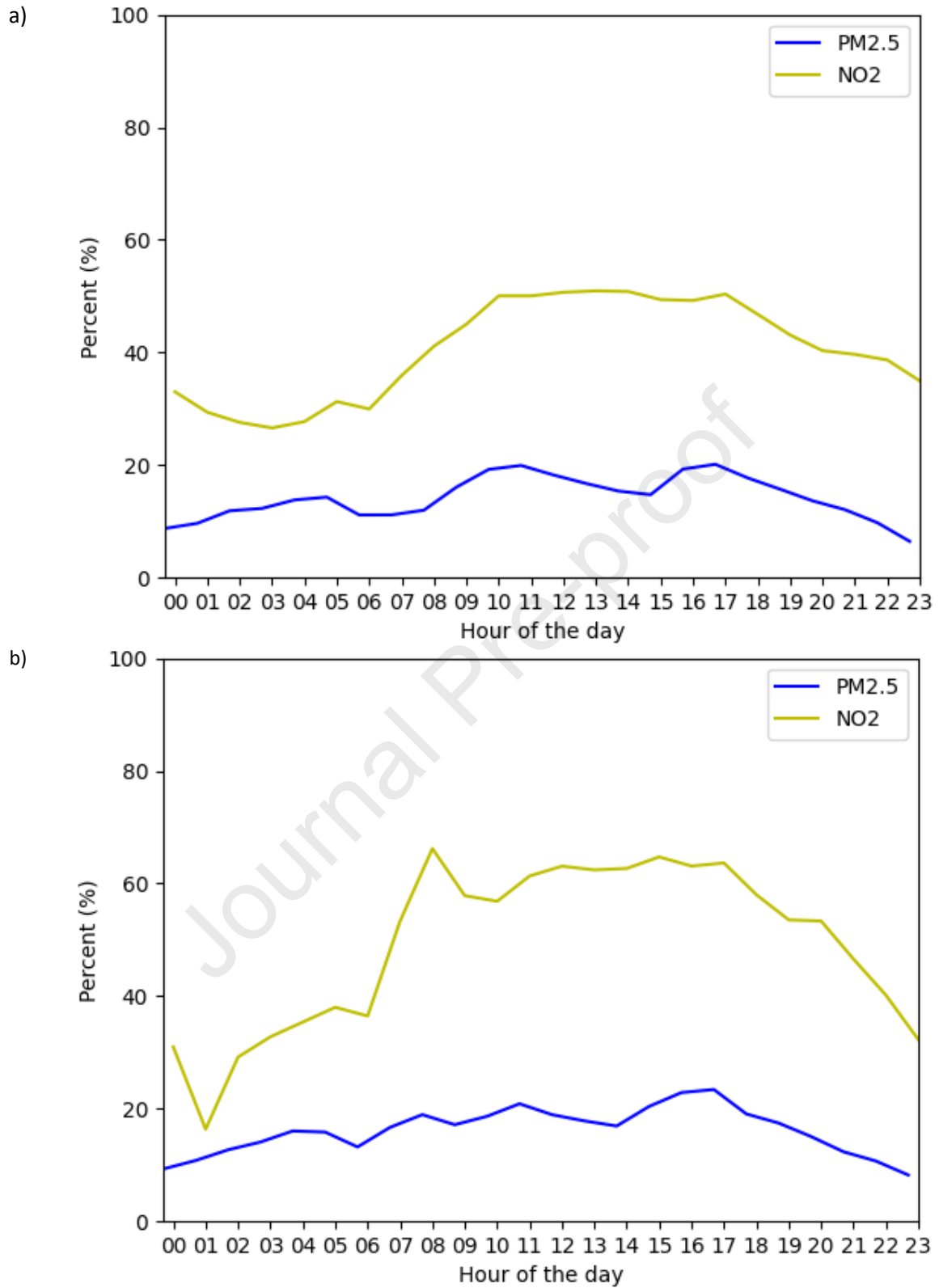
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267 Figure 3: Maps a) and b) illustrate the spatial distribution of average PM_{2.5} concentration and exposure

268 reduction (%) during the lockdown period across London. Maps c) and d) illustrate the spatial distribution of

269 average PM_{2.5} concentration and exposure reduction (%) at 08:00am.

270



271

272 Figure 4: Average diurnal a) concentration reduction (%) and b) exposure reduction (%) during the lockdown

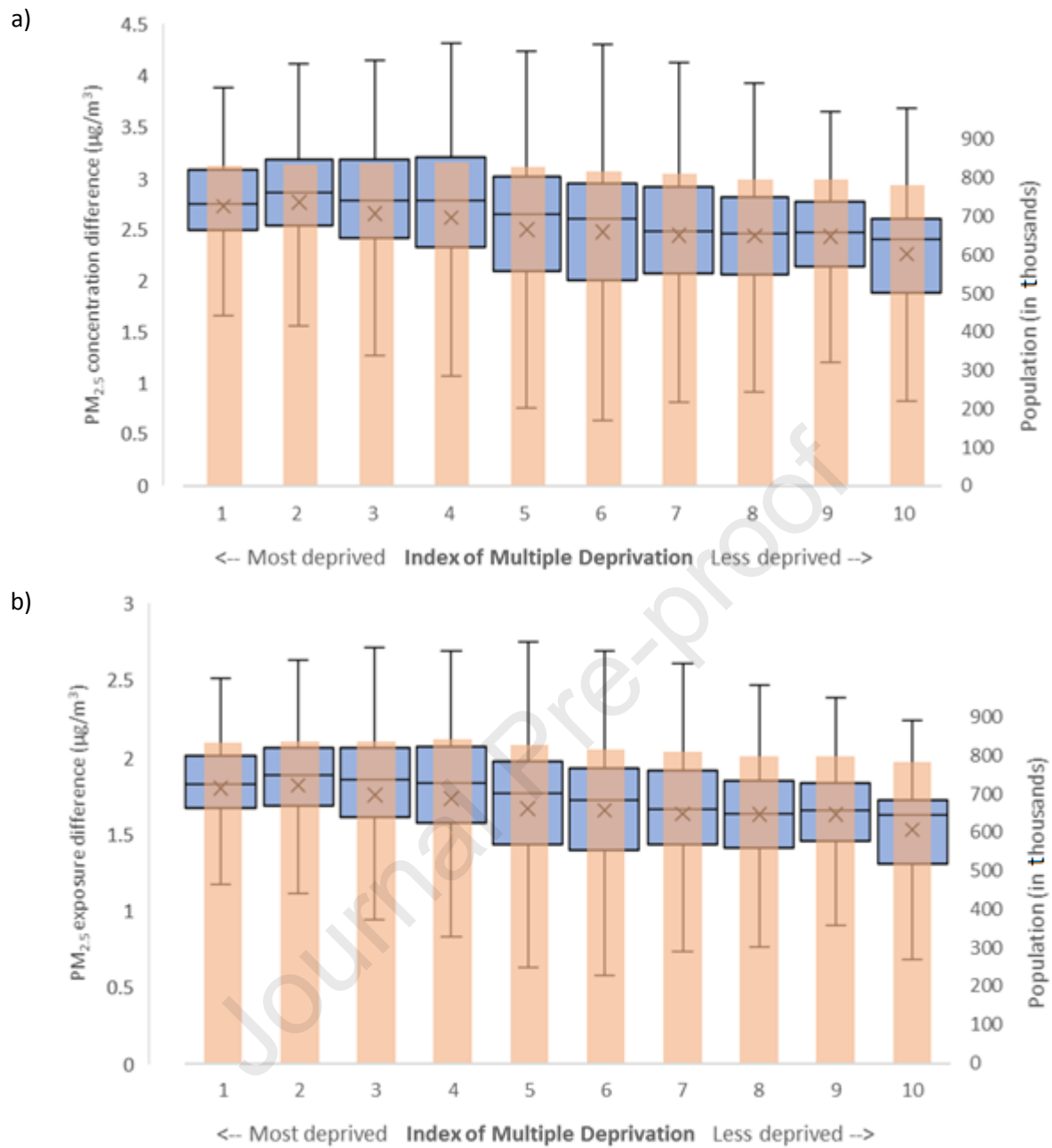
273 period (yellow represents NO₂ and blue PM_{2.5}).

274

275 3.2 Socioeconomic Status

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

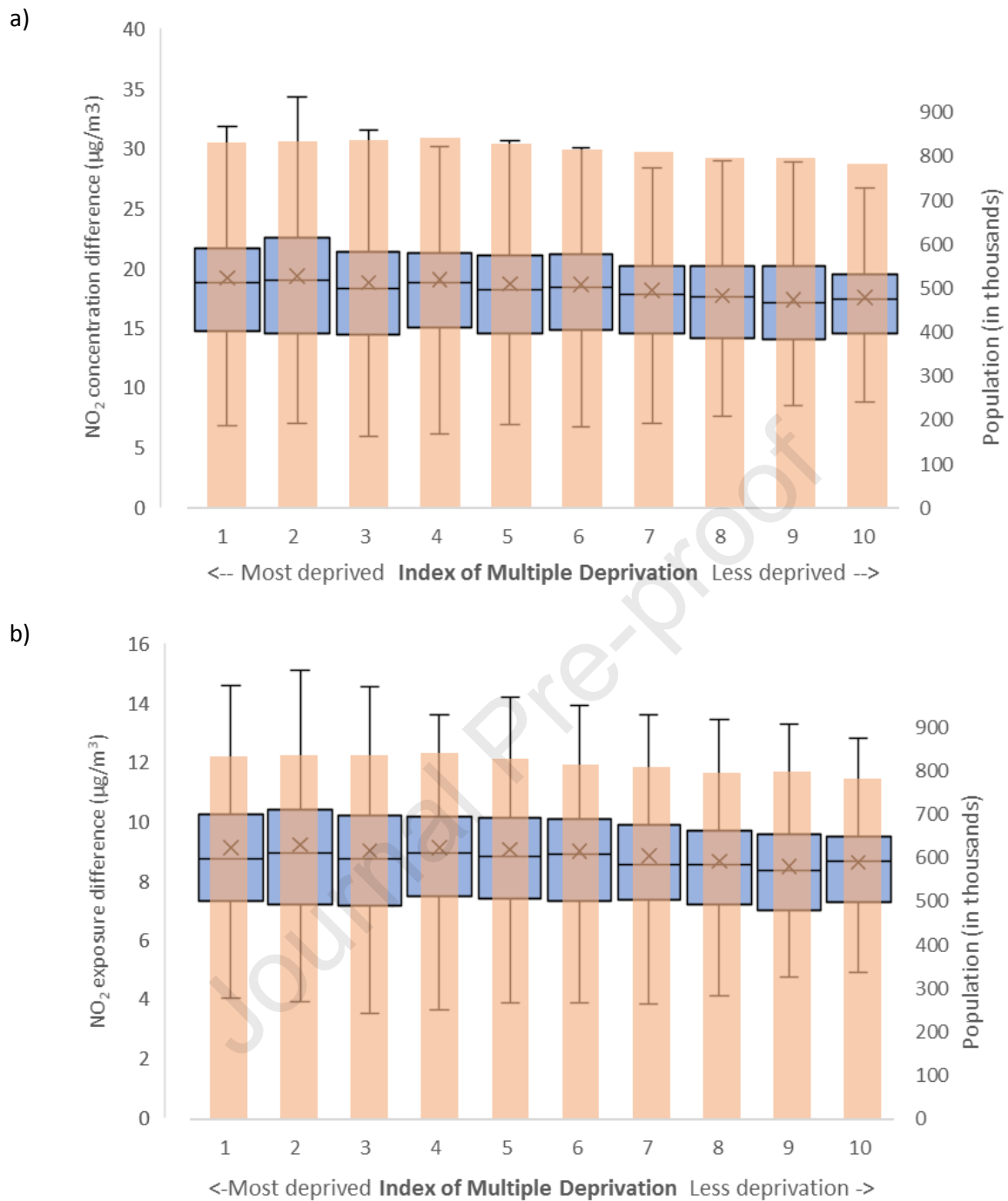
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300

301 Figure 5: a) Variation of PM_{2.5} concentration difference and the total population of all LSOAs in each decile, b)302 Variation of PM_{2.5} exposure difference and the total population of all LSOAs in each decile.

303



304

305 Figure 6: a) Variation of NO₂ concentration difference and the number of people in each decile; b) Variation of306 NO₂ exposure and the number of people in each decile.

307

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

	Concentration		Exposure	
	NO ₂	PM _{2.5}	NO ₂	PM _{2.5}
IMD	-0.11*	-0.25*	-0.05**	-0.26*

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

311

312 4. Discussion

313 Lockdown measures in different parts of the world due to the COVID-19 outbreak have provided an
 314 opportunity to evaluate the human impact on the urban environment. In this work, we evaluate the
 315 relationship between population exposure and time-activity patterns, including the time spent
 316 indoors. We found a high average percent reduction in NO₂ exposure (52.3% ±6.1%) with the
 317 greatest decrease in Inner London, while PM_{2.5} exposure showed a considerably lower average
 318 percent reduction (15.7% ±4.1%). The very high reductions in exposure to both pollutants during the
 319 morning rush hours show the strong influence of changes in population commuting. By linking
 320 population SES and exposure change, we demonstrate variation in air pollution exposure reduction
 321 following lockdown across IMD deciles, and provide evidence supporting the conclusion that
 322 deprived communities in London are disproportionately affected by road transport pollution.

323 Numerous prior research studies have investigated and evaluated the influence of coronavirus on air
 324 quality globally, and several approaches can be broadly identified. According to recent literature,
 325 reductions in NO₂ and PM_{2.5} concentrations during the lockdown ranged from 10% to greater than
 326 50% worldwide (Wu et al., 2021; Gruener et al., 2020; Zhao et al., 2020; Williams, 2020; Fonseca et
 327 al., 2020; Brook and King, 2020) with the highest emission reductions observed during morning rush
 328 hours. Here, we estimate an average reduction of approximately 50% and 16% for NO₂ and PM_{2.5},
 329 respectively. The radical changes in population activity and the significant change in the spatial
 330 distribution of the population are likely to have significantly contributed to this reduction in

331 emissions. As with other studies, we estimated the greatest exposure reductions during morning
332 rush hours and during the evening peak hours, particularly at 08:00am when there was the greatest
333 reduction in population exposure for NO₂ (66.1% ±5.1%) and PM_{2.5} (19.2% ±3.9%). The steep
334 decrease in air pollution exposure levels during rush hours reflects the importance of the temporal
335 variation of population activity and spatio-temporal variation of the domestic I/O ratios. Conversely,
336 during night hours and early morning hours, the reduction in exposure was much lower. As the
337 number of night workers is much lower than the number of day or evening workers and over 90% of
338 the population was at home during night or early morning, only minor changes were observed to the
339 population activity patterns at these times.

340 Many large cities around the world demonstrated lower outdoor concentrations of air pollution
341 during the quarantine measures, improving air quality (Arregoces et al., 2021; Kumar et al., 2020).
342 However, it is worth noting that some studies show higher PM_{2.5} concentrations in several locations
343 (Daniella Rodriguez-Urrego and Leonardo Rodriguez-Urrego, 2020) relative to the pre-covid period,
344 and the effect of the lockdown on some pollutants might be still questionable. A direct comparison
345 between studies is frustrated by the different periods and sites considered, and the methodologies
346 used to quantify the changes. In the UK, a selection of studies have investigated the impact of the
347 shutdown on the concentration of urban pollutants (Williams, 2020; Fonseca et al., 2020). However,
348 there is little research on how changes in population exposure are distributed across urban areas,
349 accounting for the spatial and temporal variability of the exposures in different MEs. Our novel
350 approach includes hourly average I/O ratios of more than 1.5 million dwellings - averaged by LSOA -
351 and estimates an average population exposure reduction of 66% and 19% for NO₂ and PM_{2.5}. For
352 NO₂, the highest reduction was observed in Central, Northwest and Southeast London and for PM_{2.5}
353 in the West and East of Inner London. For both concentration and exposure, NO₂ show notably
354 higher reductions than PM_{2.5} post lockdown. This is likely due to a significant decrease in traffic-rated
355 emissions in London, meaning pollutants that are strongly related to traffic emissions, such as NO₂,
356 are more significantly affected. On the other hand, for outdoor PM_{2.5}, the contribution of local

357 transport emissions is smaller than for NO₂ (Reis et al., 2018) and particulate pollution may be
358 influenced by other factors (for example, local meteorology, transboundary transport, resuspension
359 and the use of fireplaces).

360 Health studies have suggested that lower SES populations are more likely to suffer premature
361 mortality from air pollution exposure than higher SES populations (Krewski et al. 2000a, b). Multiple
362 studies have been conducted in large cities and metropolitan areas around the world associating the
363 SES with the air pollution concentration and exposure. Most of them demonstrate high associations
364 between the most deprived areas and high outdoor (Sarmadi et al., 2020; Cakmak et al., 2016;
365 Pinault et al., 2016; Pandilla et al., 2014; Gray et al., 2013) and indoor concentrations (Ferguson et
366 al., 2020). Here, we provide new information about the impact of lockdown measures on people
367 across different IMD groups. Results indicate negative associations between the reductions of
368 concentration and exposure during the lockdown period and the area-level deprivation status,
369 where PM_{2.5} is more strongly correlated than NO₂. Several studies conducted in large urban areas
370 have presented similar outcomes (Pandilla et al., 2014). In London, Brook and King (2017) predicted
371 that reductions in exposure to NO₂ would be higher for areas that fall within IMD decile 1 (most
372 deprived) after the implementation of air pollution reduction measures. Furthermore, Tonne et al.
373 (2018) analyzed the relationship between SES and outdoor air pollution, finding an exposure
374 different of 0 to 1.9 µg/m³ between the highest and lowest household income groups, and greater
375 reductions in air pollution in the least advantaged areas after the activation of the Congestion
376 Charging Zone in London.

377 The main strengths of our study are the large dataset, including population information at LSOA-
378 level, travel behavior from a representative sample of the London population and the large spatio-
379 temporal variability of the I/O ratios for dwellings. The indoor environment is protective of exposure
380 to outdoor air pollutants and that is usually reflected in much lower exposures when Home MEs
381 have been taken into account. Amid the pandemic lockdown measures, when more than 90% of the

382 population had to stay at their home during the daytime, the incorporation of the spatial and
383 temporal distribution of domestic I/O ratios when estimating the population-weighted exposure
384 significantly modifies the magnitude and distribution of the exposure change.

385 This study contains several limitations. The limitations are the quality of the derived air pollution
386 data and the absence of meteorological effects. Because our study is based on recent
387 measurements, most of the available concentrations for 2020 have not yet been fully ratified by the
388 LAQN. However, in order to reduce the uncertainty and improve the quality of our data, we did not
389 include any negative or unusually extreme hourly values to our analysis. A few monitoring sites did
390 not provide 100% of the data for the whole study period and some hourly readings were missing (or
391 not included). No sites provided less than 70% of the data (Lang et al. 2019; King's College London,
392 2015). Temporal and spatial variability of air pollution concentrations are subject to changes in
393 emissions and meteorology, which may impact the exposure levels (Bujin et al., 2020). NO₂ levels
394 can be directly linked to the reduction of transport emissions due to its strong relation to traffic (He
395 et al., 2020a; He et al., 2020b). However, transboundary transport of PM and precursors from
396 mainland European sources and the associated meteorology play an important role in PM
397 concentrations in London. Thus, post-COVID-19 concentrations might be different than pre-COVID-
398 19 due to reasons that are not directly related to lockdown. The wind conditions during 2020 have
399 been exceptional in many ways across the UK (Carslaw, 2020). Moreover, the lockdown period also
400 coincides with the period of the year where there is an increased frequency of PM_{2.5} episodes in
401 Europe (Air Quality Expert Group, 2020). Therefore, the lack of accounting for weather conditions in
402 our assessment is likely to have affected our results and some reductions may have been over-
403 estimated. However, our approach of averaging the same calendar period of the previous years
404 might have the benefit of reducing meteorological variability. Another limitation is that exposure to
405 other urban air pollutants was not considered, mostly due to data inavailability. In this study we
406 focused on the two most important major air pollutants for London's air quality
407 (<https://www.london.gov.uk/>). Many air pollutants have common sources, and air pollution

408 reduction strategies that take advantage of these common sources may achieve economies of scale
409 that control strategies that target one pollutant at a time cannot. Moreover, pollutants can also be
410 connected by similar precursors or chemical reactions once in the atmosphere. Thus, control
411 strategies that target one pollutant may affect others, perhaps in unintended ways. A much denser
412 network of monitoring stations was available for the NO_2 compared to $\text{PM}_{2.5}$. As the concentration of
413 air pollution can change across small distances, the denser network can lead to higher prediction
414 accuracy. In this work, roadside and urban background sites were included, with roadside sites
415 mostly located within Inner London. The denser NO_2 monitoring network and the smaller distances
416 between the sites were able to provide adequate coverage of background sites for non-traffic
417 locations. However, the interpolation of roadside measurements, especially for the less dense $\text{PM}_{2.5}$
418 network, may have led to an overestimation of the impacts of reduced traffic by interpolating to
419 non-traffic areas. The surrounding urban environment can significantly influence pollutant transport
420 and concentration, and to account for this, high-skilled urban modelling accounting for complex
421 urban morphology is required. However, this kind of advanced modelling was not feasible for this
422 study, but could be incorporated to future studies. Moreover, schools and commercial buildings
423 were assumed to have same values as home microenvironment and children were included in the
424 home population. Finally, the average workplace I/O ratio used in this study was assumed from
425 several European cities (Soares et al., 2014; Hanninen et al., 2011; Hanninen et al., 2004). Data on
426 I/O ratios in commercial buildings, and for different type of workplaces are scarce. Therefore, it was
427 assumed that the values demonstrated in Europe were also representative for London.

428 This work utilized Google Statistics and App Maps to determine differences in travel patterns. Both
429 App Maps and Google statistics are based on data sent from users' devices and users that opt-in to
430 location history for their account, respectively. Consequently, those data sources contain limitations
431 in terms of their representativeness of the overall population. Apple Maps has no demographic
432 information about its users, making it difficult to determine data representativeness. In the
433 calculations, Google statistics includes only data from users that use their Google account and have

434 opted-in to Location History. Those data also have to meet Google's privacy threshold.
435 Consequently, this location data may not represent the exact behaviour of the wider population. As
436 described in methodology section, the IMD is based on seven main domains. The 'Living
437 Environment' domain contributes approximately 9% to the production of the overall index and
438 measures the quality of the local environment and the indicators fall into two sub-domains. The
439 'indoors' and the 'outdoors', which consists of two elements: air quality and road accidents.
440 However, the already included 'air quality' element is not likely to have affected our calculations,
441 because here we examined the associations between the IMD and the reduction of concentration
442 and exposure. Other studies have already used IMD to investigate SES inequalities in air pollution
443 (Sheridan et al., 2019; Tonne et al., 2018; Brooks and King, 2017).

444 Some segments of the working population – so-called essential or key workers - had to continue to
445 travel to work in their original workplace during the lockdown period. When estimating the
446 population-weighted exposure, we assumed that all SES groups are equally likely to stay at home
447 during lockdown, however many essential workers are likely to be low SES individuals. Their total
448 exposure to air pollution may still decrease due to the reduction in outdoor concentration, however
449 the change in their exposure to air pollution would be different from other working groups because
450 their daily activity during the lockdown would be the same as the pre-COVID-19 period. Due to the
451 unavailability of data, essential workers could not be linked with the IMD analysis to investigate how
452 this may impact exposure differences between IMD groups. By using the workplace population for
453 the work ME, and by applying the mean percent reduction for the population that continued going
454 to workplaces during the shutdown, we assume that the percentage of population in work ME
455 during post-COVID-19 period (28%) represents essential workers. This percentage is consistent with
456 the ONS estimate that essential workers are approximately 29.5% of London's workforce (ONS,
457 2020). While further work is required to understand uncertainties in travel and work patterns of low-
458 SES essential workers, these results allow us to conclude that the lockdown provided significant
459 exposure reductions to low-income communities in London.

460

461 **5. Conclusions**

462 The implementation of stay-at-home measures due to the global outbreak of COVID-19 has offered a
463 unique opportunity to assess the effect of the rapid changes in population activity patterns on air
464 pollution concentration and population exposure. This study quantified and analyzed spatial and
465 temporal changes in population-weighted mean exposure to air pollution of outdoor origin between
466 the COVID-19 lockdown period and previous 3-year average during the same calendar period.

467 Subsequently, we evaluated socioeconomic variation across the distribution of exposure change. We
468 demonstrate that changes in diurnal population activity and outdoor concentrations have reduced
469 exposure to air pollution, predominately during the morning rush hours. The average exposure to
470 NO₂ showed a greater than 50% reduction, which was consistent with the remarkable decrease in
471 traffic levels, a major source of NO₂. For PM_{2.5}, the 16% decrease in average exposure could not be
472 linked directly to the reduction in urban traffic, because other factors, such as meteorological
473 conditions, may have affected the magnitude of the change in the outdoor concentrations. While
474 there were not large inequalities in how the exposure change was distributed among people with
475 different SES, our results provided useful evidence about the strength of association between the
476 concentration and exposure reduction, and the impact on the most and the least deprived areas.

477 By quantifying exposure reduction, and accounting for the significance of the time spent indoors and
478 the spatio-temporal variability of average dwelling I/O ratios, this study offers insight into the
479 effectiveness of extreme traffic-control measures on reducing the outdoor pollution and the
480 exposure. Although these measures are extreme and highly unlikely to be adopted under normal
481 conditions, this natural experiment offers the opportunity to assess the influence of some key
482 elements (e.g., population activity, important indoor MEs) on population exposure, using largely
483 real-world data. The estimated exposure reductions may provide best-case estimates of the degree
484 to which more realistic control strategies for stationary and mobile urban sources, such

485 technological (e.g., new-source certifications, retrofits of existing vehicles, etc.) or non-technological
 486 (e.g., management of transportation, etc.) may reduce exposures. The analysis of the SES
 487 inequalities across the distribution of the exposure reduction also demonstrates the importance of
 488 developing strategies that can reduce existing exposure inequalities.

489

490 6. References

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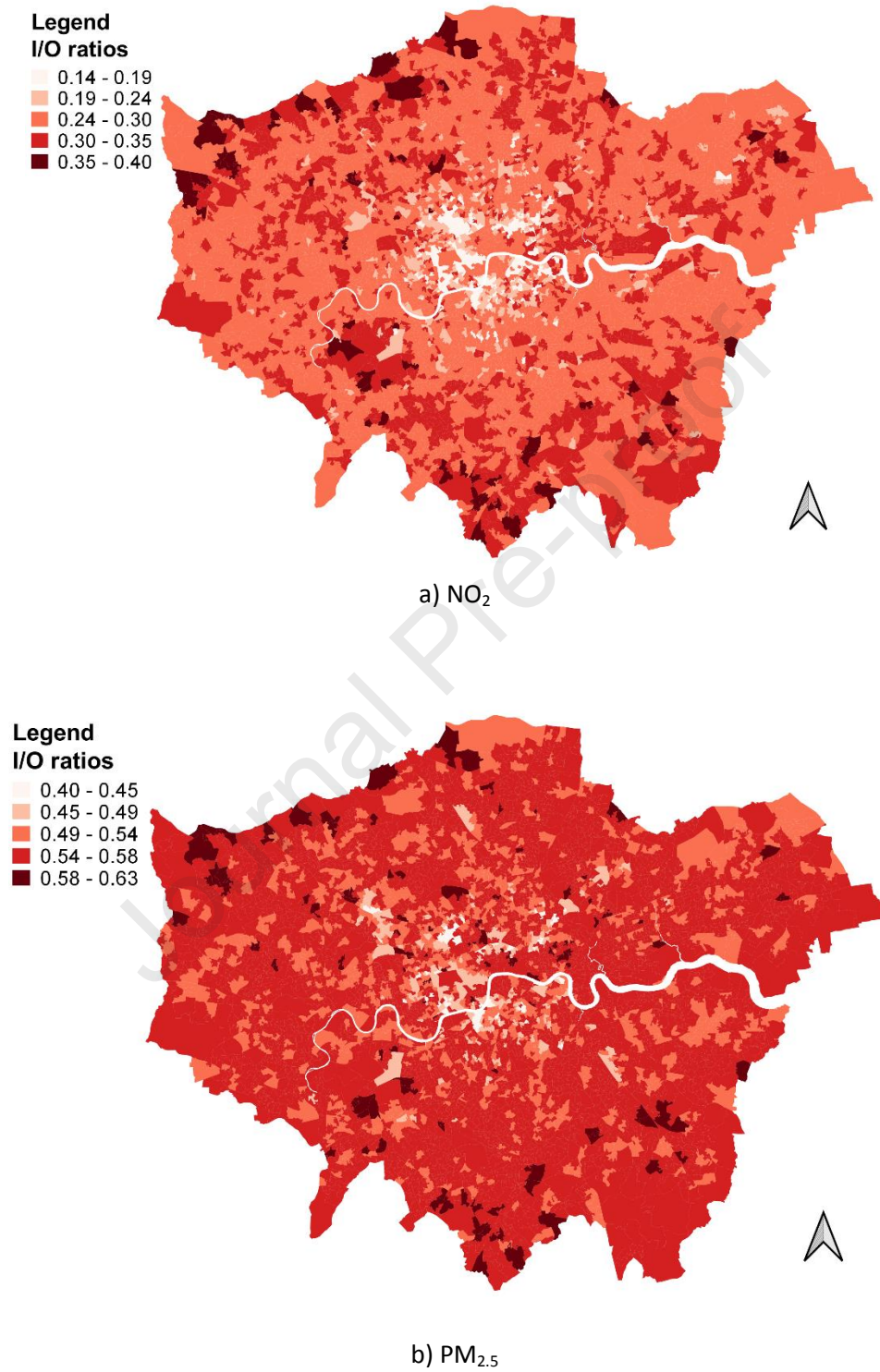
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668 **Supplementary material**

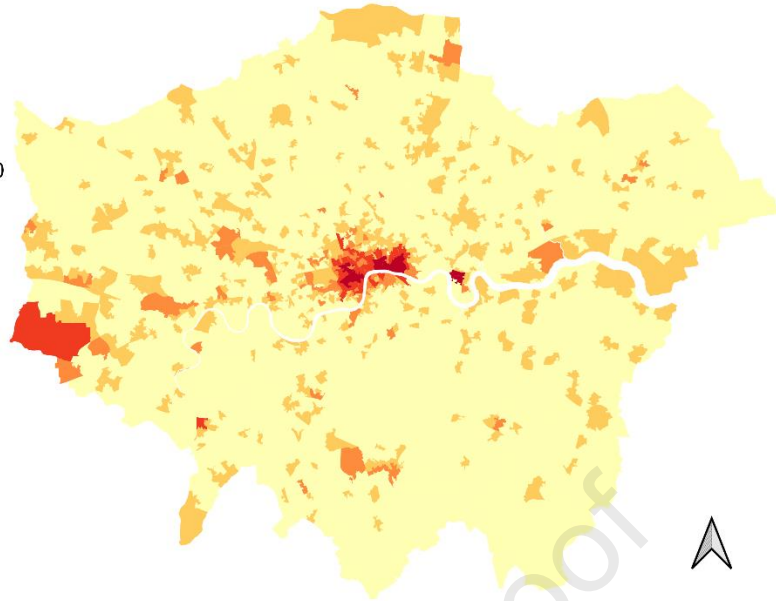
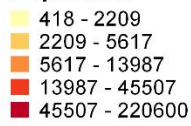
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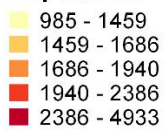
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Figure S1: Spatial variability of 24h average indoor/outdoor (I/O) ratios.

**Legend
Population**

a) Daytime

**Legend
Population**

b) Night-time

672

673

674 Figure S2: The spatial distribution of LSOA population in London: a) during daytime (defined as the period

675 between 07:00am and 19:00), and b) during nighttime (defined as the period between 20:00 and 06:00am).

Highlights

- Spatio-temporal change in PM_{2.5} and NO₂ exposure during the lockdown is quantified.
- The average exposure reduction was 66% for NO₂ and 19% for PM_{2.5}.
- The exposure during morning rush hour is considerably reduced for both pollutants.
- Association between the SES and exposure reduction is presented.
- The impact on the most and the least deprived areas is demonstrated.

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Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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