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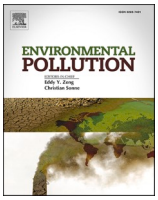

Impacts of emergency health protection measures upon air quality, traffic and public health: evidence from Oxford, UK☆

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ABSTRACT

Emergency responses to the COVID-19 pandemic led to major changes in travel behaviours and economic activities in 2020. Machine learning provides a reliable approach for assessing the contribution of these changes to air quality. This study investigates impacts of health protection measures upon air pollution and traffic emissions and estimates health and economic impacts arising from these changes during two national 'lockdown' periods in Oxford, UK. Air quality improvements were most marked during the first lockdown with reductions in observed NO_2 concentrations of 38% (SD ± 24.0%) at roadside and 17% (SD ± 5.4%) at urban background locations. Observed changes in $PM_{2.5}$, PM_{10} and O_3 concentrations were not significant during first or second lockdown. Deweathering and detrending analyses revealed a 22% (SD ± 4.4%) reduction in roadside NO_2 and 2% (SD ± 7.1%) at urban background with no significant changes in the second lockdown. Deweathered-detrended $PM_{2.5}$ and O_3 concentration changes were not significant, but PM_{10} increased in the second lockdown only. City centre traffic volume reduced by 69% and 38% in the first and second lockdown periods. Buses and passenger cars were the major contributors to NO_2 emissions, with relative reductions of 56% and 77% respectively during the first lockdown, and less pronounced changes in the second lockdown. While car and bus NO_2 emissions decreased during both lockdown periods, the overall contribution from buses increased relative to cars in the second lockdown. Sustained NO_2 emissions reduction consistent with the first lockdown could prevent 48 lost life-years among the city population, with economic benefits of up to £2.5 million. Our findings highlight the critical importance of decoupling emissions changes from meteorological influences to avoid overestimation of lockdown impacts and indicate targeted emissions control measures will be the most effective strategy for achieving air quality and public health benefits in this setting.

1. Introduction

In March 2020, COVID-19 disease caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2) was declared a global pandemic by the World Health Organization (WHO) (WHO, 2020). As of September 28, 2021, approximately 7.7 million confirmed COVID-19 cases and 158664 deaths have occurred in the UK (PHE, 2021). In early 2020 emergency public health actions intended to contain and control COVID-19 were implemented successively in multiple countries worldwide, resulting in radical changes in social and economic activity and transportation patterns with major implications for urban air quality (Berman and Ebisu, 2020; He et al., 2020; Mahato et al., 2020; Sung and Monschauer, 2020).

The UK was significantly affected by the COVID-19 pandemic during 2020, with repeated emergency public health measures implemented at both national and regional levels (WHO, 2021; Davies et al., 2020).

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Within the first phase of emergency health protection measures in England (23rd March–15th June 2020), specific legislation was enacted (with supporting guidance) restricting people to only leave their homes for very limited reasons (UKHSA, 2021). These emergency 'lockdown' measures led to major reductions in demand for all forms of transport, both nationally and internationally (Sung and Monschauer, 2020). In response to an increase in COVID-19 cases a second national lockdown was implemented from 5th November to 2nd December 2020, including similar travel restrictions to the first lockdown period, but with schools and universities remaining open under restricted operations (PMO, 2020). Following a subsequent resurgence in cases during the Christmas and New Year period a third national lockdown was implemented from January 5, 2021 (UKHSA, 2021).

Air pollution is a major global public health concern, responsible for approximately 7 million early deaths each year worldwide (WHO, 2016). It is estimated that exposure to poor air quality contributes up to 6 months loss in life expectancy among those living in the UK (COMEAP, 2010). Emerging evidence has suggested that poor air quality may be associated with increased COVID-19 related disease severity and mortality although it remains unclear to what extent these observed differences are due to individual and area level confounding factors (Benmarhnia, 2020; Fattorini and Regoli, 2020; Konstantinoudis et al., 2021; Magazzino et al., 2020; Ogen, 2020; Sasidharan et al., 2020; Wu et al., 2020).

Several studies of the early pandemic phase reported substantial changes in anthropogenic activities and associated short-term air quality improvements in multiple cities worldwide, including Delhi, Barcelona, New York, London and Wuhan (Mahato et al., 2020; Baldasano, 2020; Zangari et al., 2020; Jephcote et al., 2020; Lian et al., 2020). However, more recent analyses undertaken by Shi et al. (2021), applying a novel machine learning deweathering technique, indicated smaller than expected changes in the concentrations of major air pollutants such as nitrogen dioxide (NO_2) and particulate matter (PM) in major cities around the world. The study clearly highlighted the impact of meteorological variations which can mask the impact of changes in emissions upon observed air quality concentrations and highlighted the need for sophisticated analyses to quantify lockdown impacts.

In the UK, several studies have been performed to understand regional and national changes in ambient air quality during COVID-19 lockdown periods in 2020 (Higham et al., 2020; Jephcote et al., 2020; Shi et al., 2021; Wyche et al., 2020). However, most existing research regarding UK lockdown impacts has focused upon short-term air quality changes in major conurbations, with few authors assessing impacts in the towns and cities in which approximately 45% of the UK population live (ONS, 2020). Further, only a limited number of studies have integrated localised traffic information to identify impacts of changing travel patterns upon vehicle fleet characteristics, real-world emissions, and air pollutant concentrations, thereby generating relevant health impact scenarios (Baldasano, J.M., 2020; Jephcote et al., 2020; Vega et al., 2021).

To address this knowledge gap, the present study evaluates impacts of two national COVID-19 lockdown periods upon ambient air pollutant concentrations, traffic volume and vehicle emissions in Oxford, UK, applying a deweathering technique (Shi et al., 2021). In addition, we estimate health and economic benefits which could be achieved if a lockdown scenario were sustained; thereby generating insights into the most effective air pollution mitigation measures in this context.

2. Data and methods

2.1. The study area

Oxford is a compact historic university city 68 m above sea level with a temperate climate (mean annual temperature 10.3 °C, mean annual cumulative rainfall 708 mm) and area approx. 46 km^2 (OP, 2021). The diverse population of approximately 152000 residents is recognised to be highly transient, including approximately 34000 students enrolled at two universities (ONS, 2020). It is the main employment site serving the wider Oxfordshire region with an estimated 46000 people typically commuting into the city for work on a daily basis prior to the COVID-19 pandemic (OCC, 2018). As with many UK cities Oxford has recognised air quality challenges, with transport identified as the main source of NO_2 emissions (Ricardo, 2020). Oxford City Council declared the whole city an Air Quality Management Area (AQMA) in 2010 and initiated an Air Quality Action Plan (AQAP) in 2013. A key AQAP measure was the implementation of a bus-based central Low Emission Zone (LEZ) from 2014 requiring all buses operating in the LEZ area to meet Euro V emissions standards. More recently this was updated to require a minimum Euro VI standard by December 2021 (OCC, 2020). Data from the two regulatory air quality monitoring locations in Oxford indicated overall mean NO_2 concentrations reduced by 29% during the period 2009–2019 (Abreu, 2020). However, in 2019 annual mean NO_2 concentrations remained above legal limits in six central locations including the Oxford City Roadside Automatic Urban and Rural Network (AURN) site (Abreu, 2020). More recently, the City and County Councils jointly committed to future introduction of a central Zero Emissions Zone (ZEZ) (OCC, 2021), and adopted a local annual mean NO_2 target of 30 μg m^{-3} to be achieved by 2025 (Abreu, 2021b). However, the available epidemiological evidence suggests that no threshold for effects of NO_2 exposure exists, with evidence of adverse disease outcomes associated with exposure to annual mean NO_2 concentrations as low as 5 μg m^{-3} (COMEAP, 2018).

2.2. Data sources

2.2.1. Air pollutant and meteorological data

Hourly gaseous and particulate concentrations specifically NO_2, NO_x, Ozone (O_3), $PM_{2.5}$ (PM with aerodynamic diameter less than 2.5 μm) and PM_{10} (PM with aerodynamic diameter less than 10 μm) data were obtained for 11 years (2010–2020) to provide the long-term air quality trends for Oxford City. However, to evaluate the lockdown benefits and understand the changes in air quality during 2020, we used the most recent five years (2016–2020) of hourly measured data for key gaseous and particulate concentrations. Air pollutant data were obtained from the UK Department for Environment, Food and Rural Affairs (Defra) Automatic Urban and Rural Network (AURN) (Defra, 2021) sites in Oxford City; an urban background site at St Ebbe's located within air-conditioned housing within the grounds of St Ebbe's School, and Oxford Centre Roadside located at St Aldate's in the city centre. It should be noted that the archived roadside location does not capture PM and O_3 data and therefore data for these pollutants were available at the urban background site only. Hourly meteorological variables (i.e., air temperature, wind speed, wind direction, relative humidity, atmospheric pressure, total cloud cover, planetary boundary layer height, surface net solar radiation) were obtained for Oxford from the ERA5 reanalysis dataset via the Copernicus Climate Change Service (C3S) Climate Data Store (CDS) (Hersbach et al., 2018) for the time period 2016–2020.

2.2.2. HYSPLIT model data sources

The Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model (Stein et al., 2015) was used to calculate 72-h back trajectories (defined as categorical variables) arriving at an altitude of 100 m for the study area following Shi et al. (2021). Meteorological data from National Centers for Environmental Prediction (NCEP) and the National Center for Atmospheric Research (NCAR) reanalysis dataset were used to run the HYSPLIT model. Back trajectory air masses were clustered using the 'trajCluster' function within the "openair" package in R (Carslaw and Ropkins, 2012). Clusters were determined as those best representing the dataset when using the 'Euclid' method within the 'trajCluster' function. This method uses the Euclidian distance between each pair of trajectories to generate the distance matrix which determines similarity (or dissimilarity) between back trajectories used as

the basis for clustering (Wilks, 2011).

2.2.3. Traffic and vehicle emissions data

Traffic data for a central Oxford location was obtained from a Vivacity Labs (VL) roadside motion detection sensor managed by Oxfordshire County Council (Vivacity, 2021a). VL sensors obtain camera images and apply motion and shape detection algorithms to detect and classify transport modes and urban movement including classified counts, vehicle path, journey time and speed. Daily vehicle counts (from January 1, 2020) categorised by vehicle type (car, motorbike, bus, Light Goods Vehicle (LGV), Ordinary Goods Vehicle (OGV)) were extracted for the VL sensor located at the main arterial traffic route at Oxford High Street, approximately 200 m from the St Aldate's roadside AURN site. Data for the Oxford City bus fleet engine types (2020) was provided directly by city transport operators (e.g., Oxford Bus Company, Stagecoach, and Thames Travel).

2.2.4. Demographic, health and economic data

Demographic data for health impact assessment was obtained from the Office for National Statistics (ONS) including mid-2019 population estimates (ONS, 2020) population size (152000), and district (city) level annual mortality rate (ONS, 2019). Air quality data for city-wide health impact assessment at baseline was obtained from the network of 71 diffusion tubes maintained by Oxford City Council, with annual mean NO_2 concentrations (2019) extracted from the Air Quality Annual Status Report 2019 (Abreu, 2020).

2.3. Methods

2.3.1. Estimation of lockdown impacts using deweathering technique

Machine learning techniques can be applied to quantify the contributions of emissions and meteorological factors to observed short-term changes in air quality during the COVID-19 lockdown periods. To quantify these changes in Oxford City, we apply a random forest (RF) algorithm-based weather normalization technique, following Shi et al. (2021) and Grange and Carslaw (2019). This approach enables calculation of 'deweathered' (weather-normalized) concentrations, reflecting air pollutant concentrations under average meteorological conditions, thereby quantifying the contribution of emissions changes during the study period. The RF model can well reproduce air pollutant concentrations with high model performance and has been widely used in several studies (Dai et al., 2021; Grange et al., 2018; Shi et al., 2021). The 'rmweather' package in the R programming tool was used for RF modelling and weather normalization in this study (Grange and Carslaw, 2019). Explanatory variables in the model include meteorological variables (air temperature, wind-speed, wind-direction, relative humidity, atmospheric pressure, total cloud cover, planetary boundary layer height, and surface net solar radiation), air mass clusters, and time variables (Unix-time, hour of the day, weekday and day of the year). Deweathered air pollutant concentrations at hourly intervals were calculated by averaging 1000 predictions (Grange et al., 2018) from the meteorological variables (excluding all time variables), resampled at random from the entire dataset during the study period. We considered it necessary to retain the weekly and seasonal cycles as weather-normalized concentrations should be consistent with emission cycles.

Changes in deweathered concentrations before and after lockdown began are on their own insufficient to identify the lockdown impact, because of possible emission changes in the business-as-usual (BAU) scenario. Thus, it is necessary to subtract the deweathered change in the BAU scenario (e.g., 2016–2019) from that in 2020, to obtain the detrended change that is attributable to lockdown-associated emissions changes only. We therefore utilized hourly pollutant concentrations data for the five-year period 2016–2020 to estimate deweathered and detrended concentrations of air pollutants during 2020, in comparison to 2016–2019. Further detailed information of the weather normalization technique and model utilized in this study can be found in Shi et al. (2021).

2.3.2. Calculation of percentage change in air pollutant concentrations

The percentage change (P) in the observed, deweathered concentrations of air pollutants was derived using equation (1), following Shi et al. (2021).

$$P = \frac{(C_i - C)}{C} \times 100 \quad (1)$$

where C_i is the mean concentration of the air pollutant (observed or deweathered) on the ith day (8th to 35th day after lockdown start date). C is the mean concentration of the air pollutant (observed or deweathered) in pre-lockdown period (2nd and 3rd weeks before lockdown start date). We utilized the past five years (2016–2020) data to calculate percentage changes in observed and deweathered concentrations in 2020, compared to 2016–2019 (Table 1).

In addition, for each air pollutant we calculated the 'detrended' percentage change ($P^* = P_{2020} - P_{2016–2019}$) (Table 1) through Monte Carlo simulations (n = 10000) in RStudio (Allaire, 2012), using normal distribution of percentage changes in deweathered pollutant concentrations. Here, P_{2020} and $P_{2016–2019}$ denote the percentage changes in deweathered pollutant concentrations in 2020 and the mean concentrations for 2016–2019, respectively.

2.3.3. Estimation of lockdown impacts on the on-road emissions by vehicle types

An emissions estimation was conducted to explore the impacts of the lockdown periods upon vehicle exhaust emissions by vehicle types. Daily total exhaust emissions of vehicle type p are estimated by the following equation:

$$E_p = EF_p \times AC_p \times DT_p \quad (2)$$

where $E_p(g)$, $EF_p(g/km)$, AC_p, and $DT_p(km)$ are daily total exhaust emission of vehicle type p, the exhaust emission factor of vehicle type p, the total daily activity of vehicle type p, i.e. the number of vehicles of type p that travel on a certain day in the studied location, and distance travelled by vehicle type p, respectively. Here, p represents either car, OGV, HGV, motorbike, or bus. The required activity data were obtained from the Vivacity sensor run by Oxfordshire County Council (Vivacity, 2021a). The emission factor of vehicle type p is estimated by the following equation:

$$EF_p = \frac{\sum_{i=1}^{6} \alpha_i EF_{p,i}}{\sum_{i=1}^{6} \alpha_i} \quad (3)$$

where $EF_{p,i}(g/km)$, and α_i are the emission factor of vehicle type p with the emission standard i, and the contribution of vehicle type p with emission standard i to the total population of vehicle type p. The emission standard i accounts for Euro 1/I to Euro 6/VI. Euro 1–6 refers to the legislation for light-duty vehicles and Euro I-VI refers to the legislation for heavy-duty vehicles. α_i is determined through the fleet composition of each area. The fleet composition of Oxford City was previously reported by Hitchcock et al. (2017) and updated with local bus fleet data provided by local operators. The fleet composition is based on fuel types (diesel or petrol) and was estimated using the method described by Osei et al. (2021). Real-world emission factors for different vehicle types with different emission standards ($EF_{p,i}$) were obtained from a dataset measured by the Emission Detecting and Reporting (EDAR) system during five UK city campaigns. EDAR is a vehicle remote sensing system which is deployed adjacent to roads and measures the real-world EFs of moving vehicles (Ghaffarpasand et al., 2020; Ropkins et al., 2017). The EDAR campaigns occurred from 2016 to 2018 and captured vehicles with different emission standards up to the present-day Euro 6/VI standards. It was assumed that the same distance was travelled for all observed vehicles to assess the contribution of different vehicle classes

to local exhaust emissions. This assumption is appropriate for the estimation of emissions at a single roadside location, such as that used in this study, where the roadside concentrations will be dominated by the local traffic sources. It is assumed that all observed vehicles travel approximately the same distance within the area local to the measurement, i.e., all vehicles travel the same distance down the same road where the traffic monitoring is located.

2.3.4. Estimation of health and economic impacts due to changes in air quality

A health impact estimation was performed to assess reductions in attributable mortality, life years saved and associated economic benefits attributable to NO_2 exposure reduction for a specified lockdown scenario. For this purpose, dwellings in the city were classified into three exposure zones: Zone 1: within 25 m of centre lines of main roads (near roadside); Zone 2: 26–50 m from centre lines of major roads (far roadside); Zone 3: >50 m from centre lines of major roads (urban background). Annual mean NO_2 concentrations measured at multiple (n = 71) diffusion tube sites and AURN sites (n = 3) in 2019 were used to calculate a mean annual NO_2 concentration representative of each respective exposure zone. Due to a limited number of diffusion tube sites in Zone 2, the Zone 2 value was calculated by applying a 10 μg m^{-3} dispersion/dilution factor to the Zone 1 mean value, based on the sample sites where data were available. The dispersion/dilution factor was obtained from locations in the city where both a roadside (Zone 1) and a near roadside (Zone 2) diffusion tube monitoring site were available in close proximity and therefore used to estimate the likely general relationship between NO_2 concentrations in Zone 1 compared with Zone 2. The estimated 2019 annual mean NO_2 concentrations in each exposure zone were Zone 1: 31.7 μg m^{-3}; Zone 2: 21.7 μg m^{-3} and Zone 3: 20 μg m^{-3}, respectively. Using GIS mapping ('Select by location' tool in ArcMap 10.6.1) a total of 61711 addressable residential properties were identified in the National Land and Property Gazetteer (NLPG) layer and multiplied by the mean city household size of 2.47 (Geoplace, 2014) to estimate the population size within each respective zone: Zone 1: 11961 (8%); Zone 2: 14072 (9%); Zone 3: 126467 (83%); total population 152000. All-cause mortality attributable to NO_2 exposure among those adults aged 30 years or over residing within each exposure zone was estimated using a standard concentration-response function of 1.0095 (95% CI 1.006,1.013) per 10 μg m^{-3} increase in annual mean NO_2 concentration (COMEAP, 2018), applied to 2019 city population mortality rates (0.00857) (ONS, 2020).

To estimate the economic impacts arising from air pollution exposure, the recommended approach in the UK converts attributable mortality into life years lost (COMEAP, 2012). A 10.67 multiplier was used to convert each death in Oxford into total life years lost (PHE, 2014, Table 4, Column 3). So, for each premature death caused by air pollution in the Oxford area that person would have been expected to live for 10.67 additional years. Each life year lost was costed by applying a standard £27630 Value of Life Years lost (VOLY), updated to 2019 prices using HM Treasury GDP deflators, giving a value of £38527 per life year lost (Chilton et al., 2004; Treasury, 2021).

3. Results

3.1. Observed air quality changes in Oxford during 2020

To understand the effect of lockdown measures on air quality, it is important to first understand the air quality patterns and trends of recent previous years. The temporal trends of monthly mean

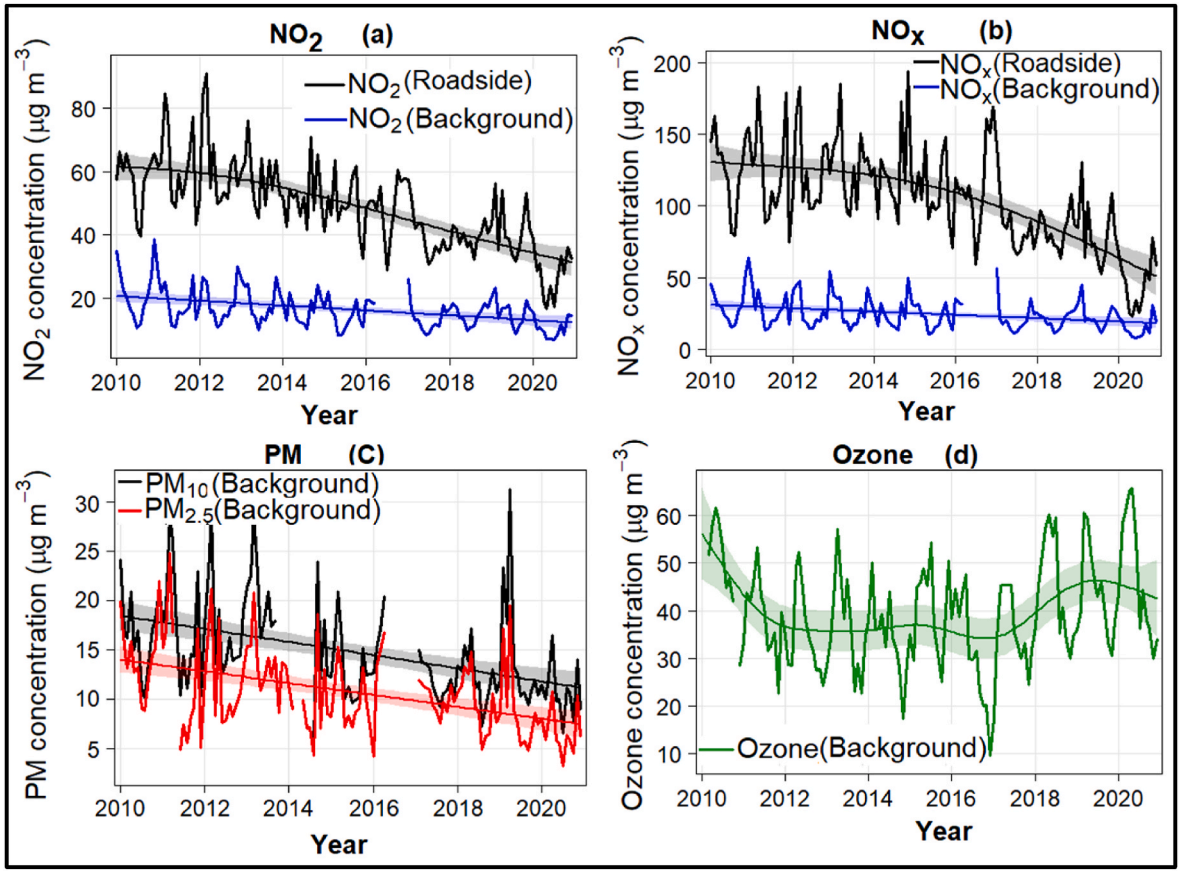

Fig. 1. Time series of monthly mean ambient air pollutant concentrations in Oxford City from 2010 to 2020. The shaded lines represent the smooth fit line at the 95% confidence interval.

concentrations of key ambient air pollutant (NO_2, NO_x, $PM_{2.5}$, PM_{10} and O_3) in Oxford city over the previous decade are shown in Fig. 1. Focusing upon the previous five years (2016–2020), a clear change in ambient air pollutant concentrations can be observed with reductions in roadside NO_2 and NO_x, and background PM_{10} and $PM_{2.5}$ concentrations (Fig. 1). To assess the changes in Oxford ambient air quality during 2020 in comparison to previous years (2016–2019), the mean monthly concentrations of NO_2, NO_x, $PM_{2.5}$, PM_{10} and O_3 at the urban background site and NO_2 and NO_x at the roadside site are presented in Fig. 2. All monthly mean pollutant concentrations were of lower magnitude during January and February 2020 (pre-lockdown) in comparison to monthly mean concentrations over the previous four-year period (2016–2019). During the first national lockdown period (23rd March–15th June 2020) observed monthly mean concentrations of NO_2 and NO_x reduced by about 47% and 63% (at roadside) and 36% and 40% (at urban background) respectively in comparison to the monthly means over the previous four-year period (2016–2019) (Fig. 2 and S1) – a greater difference than that observed during the pre-lockdown period in early 2020. Less marked changes in NO_2 and NO_x concentrations were observed at both roadside (approx. 26% and 31%, respectively) and urban background (approx. 21% and +1%, respectively) locations during the second national lockdown period (5th November–1st December 2020), relative to the mean of the previous four-year period (2016–2019). The annual cycle for $PM_{2.5}$ and PM_{10} concentrations during 2020 was not observed to change relative to previous years. Given the below mean pollutant concentrations during the pre-

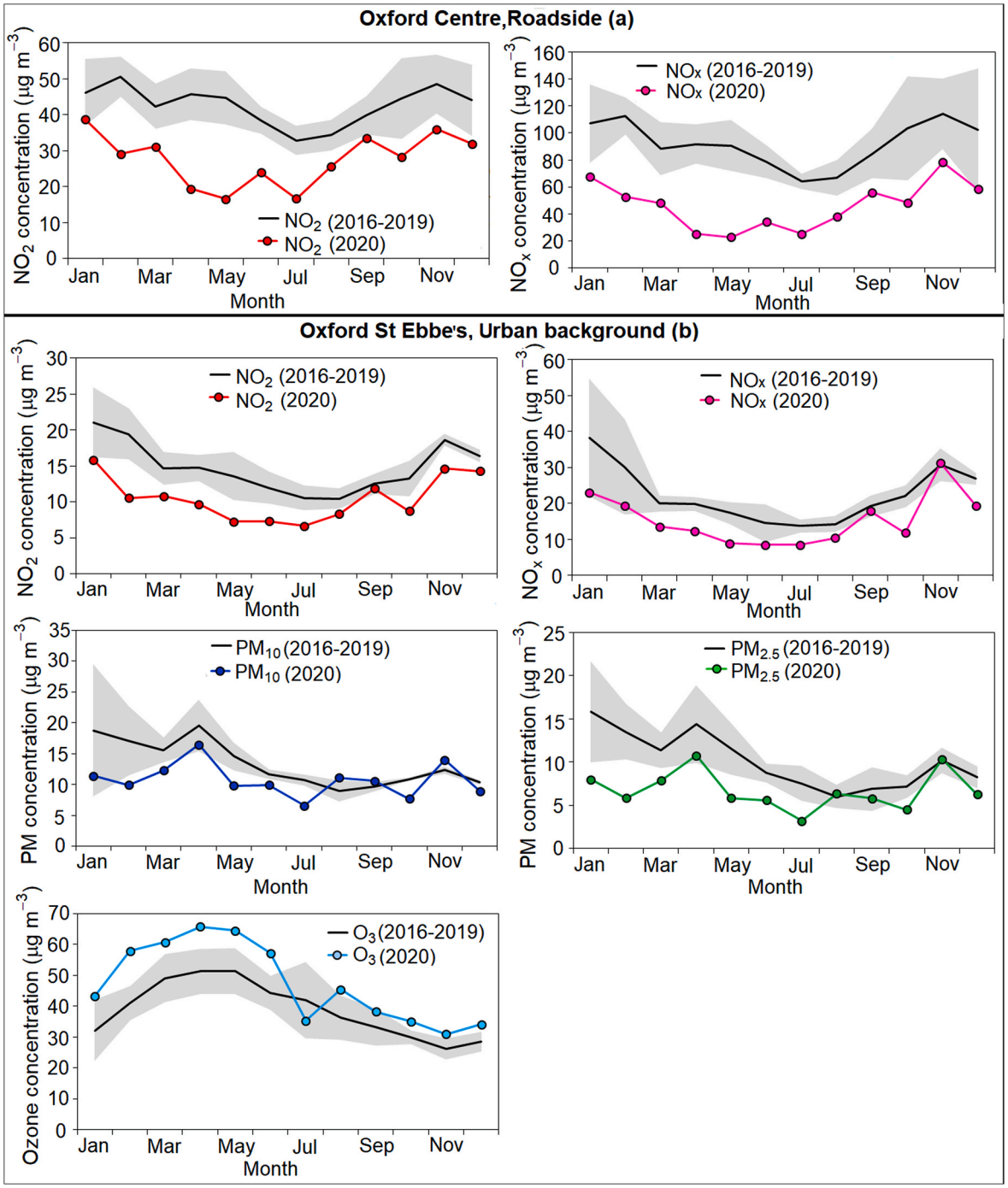

Fig. 2. Mean monthly annual cycle for key air pollutants (NO_2, NO_x, $PM_{2.5}$, PM_{10} and O_3) at Oxford a) roadside (St Aldate's) and b) urban background site (St Ebbe's) during 2020, compared to four-year mean (2016–2019). The shaded areas represent the 95% confidence interval.

lockdown period and influence of seasonal trends, it is evident that direct comparisons of observed pollutant concentrations can lead to inaccurate conclusions regarding the impact of lockdown measures. It is therefore essential to uncouple observed values from meteorological and seasonal influences to understand the actual changes associated with COVID-19 restrictions.

In contrast to changes in mean monthly NO_2, NO_x and PM concentrations, O_3 (a secondary pollutant) concentrations measured at the urban background site were higher in 2020 as compared to the previous four-year mean (2016–2019) (Fig. 2 and S1). The increased O_3 concentrations during the early part of the year most likely reflect synoptic weather during 2020. Overall changes in observed monthly mean gases and particulate pollutants concentrations were more pronounced during the first as compared to the second lockdown period, where a seasonal variation in pollutant concentrations was also evident.

This section presents the analysis of hourly diurnal changes in pollutant (NO_2, NO_x, $PM_{2.5}$, PM_{10} and O_3) concentrations during 2020 in comparison to the previous four years (2016–2019). A clear change in NO_2 and NO_x hourly patterns was seen at the roadside location in 2020, compared to the four-year mean (2016–2019), whereas similar hourly

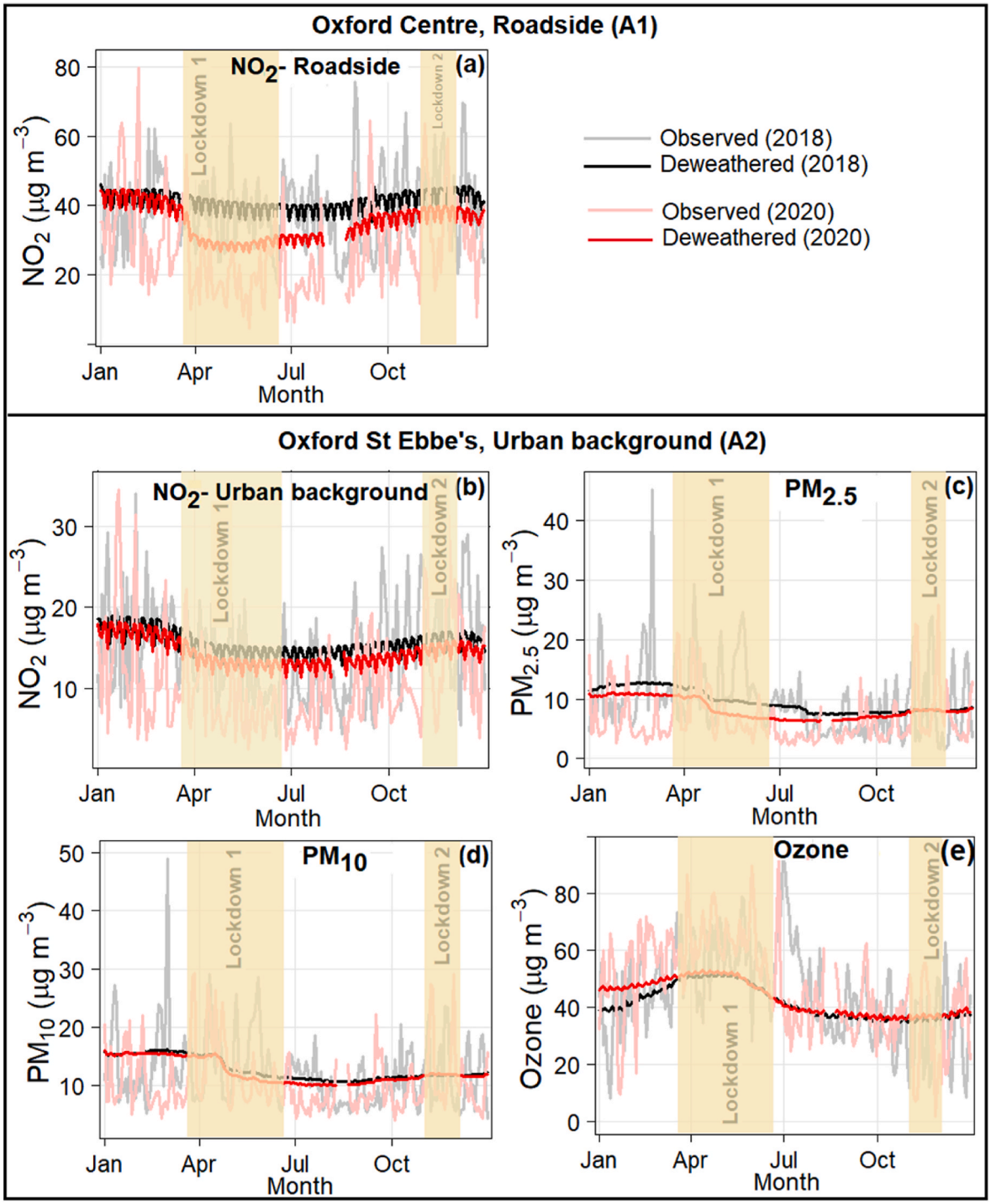

Fig. 3. Observed (light lines) and deweathered (dark lines) daily pollutant concentrations at A1) Roadside and A2) Urban background locations in 2020 versus 2018. Light yellow shades show the UK national lockdown periods. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

patterns with relatively lower values were observed in NO_2, NO_x, $PM_{2.5}$ and PM_{10} at the urban background site (see Supplementary Figure S2). The roadside location showed significant lower magnitude concentrations of NO_2 and NO_x in 2020 compared to 2016–2019, suggesting changes in diurnal traffic volume and the renewal of the vehicular fleet. In contrast to NO_2, NO_x and PM, increased concentrations of O_3 were observed at the urban background site with similar hourly patterns for both COVID-19 year (2020) and previous years (2016–2019).

These results need to be considered in the context of weather effects because meteorology can moderate the link between emissions and pollution concentrations and thus the real observed air quality levels. To this end, we proceed to apply machine learning deweathering technique to estimate lockdown related air quality impacts which may be attributed to actual changes in pollutant emissions.

3.2. *Evaluating changes in pollutant concentrations due to national lockdowns using deweathering machine learning technique*

Fig. 3 shows the time series of daily observed and deweathered concentrations of air pollutants in 2020 versus 2018 (as an example year) in Oxford City. For readability of the figure, we only plotted data in 2018 as reference levels. Clear changes can be seen in observed and deweathered NO_2 concentrations at the roadside location during the first national lockdown, while no significant changes were observed during second lockdown and smaller changes were noted at the urban background location. Deweathered concentrations showed the similar pattern to the observed values but with different magnitude. Smaller changes (distinct from 2018) were identified in both observed and deweathered PM concentrations at urban background locations after

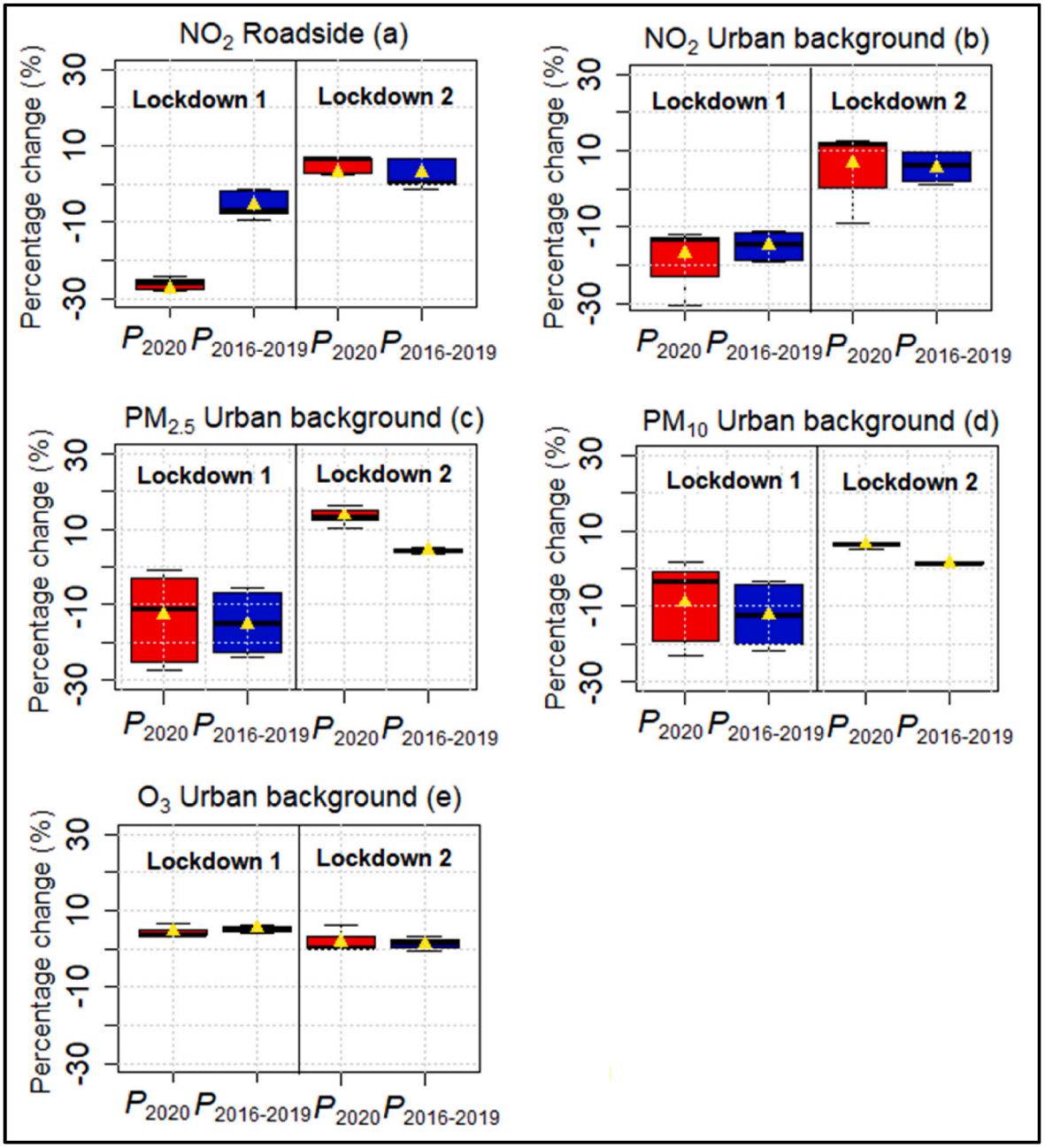

Fig. 4. Box plots of percentage change in deweathered concentrations of air pollutants in 2020 versus 2016–2019. These box plots include median along with upper and lower quartiles, and the yellow marker shows the mean value. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

Table 1
Percentage changes in observed, deweathered and detrended concentrations of ambient air pollutants during national lockdown periods in 2020 versus 2016–2019 (roadside and urban background AURN sites), where uncertainties are at 1 standard deviation (±1σ) of the mean.

Pollutants		Lockdown 1			Lockdown 2	
	P_{2020}	$P_{2016–2019}$	P*	P_{2020}	$P_{2016–2019}$	P*
NO_2 (Obs)-Roadside	−38.1 ± 24.0	20.2 ± 55.0	−58.2 ± 60.1	17.6 ± 50.2	12.5 ± 21.0	5.7 ± 54.5
NO_2 (DeW) -Roadside	−28.2 ± 4.1	−6.0 ± 1.5	−22.2 ± 4.4	2.7 ± 8.0	2.6 ± 1.3	0.2 ± 8.1
NO_2 (Obs)-Urban background	−16.5 ± 5.4	7.0 ± 81.3	−22.6 ± 81.9	89.9 ± 94.1	32.1 ± 28.7	57.4 ± 99.0
NO_2 (DeW)-Urban background	−18.0 ± 6.6	−16.0 ± 2.3	−2.0 ± 7.1	6.7 ± 8.3	5.4 ± 1.3	1.4 ± 8.4
O_3 (Obs)-Urban background	11.0 ± 19.0	13.4 ± 26.5	−3.1 ± 32.7	−29.6 ± 48.5	−4.0 ± 3.3	−26.5 ± 49.1
O_3 (DeW)-Urban background	4.2 ± 1.0	5.3 ± 2.5	−1.1 ± 2.7	1.7 ± 2.2	1.2 ± 0.5	0.5 ± 2.3
$PM_{2.5}$ (Obs)-Urban background	98.3 ± 105.3	46.2 ± 105.3	52.5 ± 146.8	101.7 ± 140.7	24.6 ± 36.0	76.2 ± 143.6
$PM_{2.5}$ (DeW)-Urban background	−12.9 ± 10.6	−15.48 ± 7.5	2.7 ± 10.7	13.5 ± 1.6	4.5 ± 2.1	9.1 ± 16.0
PM_{10} (Obs)-Urban background	83.1 ± 85.0	14.0 ± 16.1	69.1 ± 86.6	54.8 ± 88.6	3.0 ± 18.0	52.0 ± 19.0
PM_{10} (DeW)-Urban background	−9.1 ± 9.5	−12.5 ± 7.8	3.2 ± 12.2	6.3 ± 0.5	1.3 ± 0.7	5.0 ± 0.9

Dew- Deweathered, Obs- Observed, P- Percentage change and P* - Detrended percentage change ($P^* = P_{2020} - P_{2016–2019}$), calculated using Monte Carlo simulations (n = 10,000) based on the normal distribution of P_{2020} and $P_{2016–2019}$.

both first and second lockdowns in 2020. In contrast, similar increases in both observed and deweathered O_3 concentrations were noted at the urban background location during the first lockdown, in comparison to 2018.

We used deweathered and detrended data to evaluate the impact of national lockdown measures on Oxford's ambient air quality in 2020 versus 2016–2019 by decoupling the effect of emission changes from meteorology. We found that deweathered NO_2 concentrations in 2016–2019 were reduced significantly during the first lockdown period at both roadside ($P_{2016–2019} = -6.0 \pm 1.5\%$) and urban background ($P_{2016–2019} = -16.0 \pm 2.3\%$) locations, but always a lesser reduction than the equivalent lockdown calendar period in 2020 ($P_{2020} = -28.2 \pm 4.1\%$ and $P_{2020} = -18.0 \pm 6.6\%$ respectively) (Fig. 4 and Table 1). However, during the second lockdown period, a similar increase (within a range of uncertainty) in deweathered NO_2 concentrations was noted in 2016–2019 and 2020 at both roadside ($P_{2016–2019} = 2.6 \pm 1.3\%$ and $P_{2020} = 2.7 \pm 8.0\%$ respectively) and urban background ($P_{2016–2019} = 5.4 \pm 1.3\%$ and $P_{2020} = 6.7 \pm 8.3\%$ respectively) (Fig. 4 and Table 1). Furthermore, it is noted that the deweathered percentage change in urban NO_2 in Oxford during the first lockdown (−18.0 ± 6.6%), was comparable to that reported in London (−18.2 ± 6.0%) by Shi et al. (2021). Unfavourable meteorological effects during the first lockdown contributed to approximately +1.4% and +111.2% in observed percentage changes in urban NO_2 and $PM_{2.5}$ before and after lockdown began in Oxford, respectively, which are slightly smaller than +8.1% in urban NO_2 and +144.3% in urban $PM_{2.5}$ identified in London (Shi et al., 2021). In contrast to NO_2, PM changes in deweathered concentrations in 2020 were much less marked in comparison to 2016–2019 reflecting the more complex interactions of PM sources (emission and secondary formation) and transport, although deweathered PM_{10} concentration increased during the second lockdown period ($P_{2016–2019} = 1.3 \pm 0.7\%$ and $P_{2020} = 6.3 \pm 0.5\%$ respectively) (Fig. 4 and Table 1).

The detrended results also showed a significant reduction in NO_2 concentrations during the first lockdown period at both roadside ($P^* = -22.2 \pm 4.4\%$) and urban background ($P^* = -2.0 \pm 7.1\%$) locations, but with a smaller reduction than the corresponding deweathered concentrations (Table 1). Moreover, increases in deweathered O_3 concentrations at the urban background location were of the same magnitude in 2016–2019 and 2020 during both first ($P_{2016–2019} = 5.3 \pm 2.5\%$ and $P_{2020} = 4.2 \pm 1.0\%$ respectively) and second lockdown periods ($P_{2016–2019} = 1.2 \pm 0.5\%$ and $P_{2020} = 1.7 \pm 2.2\%$ respectively), where the detrended percentage changes were always smaller than the corresponding deweathered changes (Fig. 4 and Table 1). There were no significant changes in detrended NO_2 concentrations at either roadside or urban background locations in the second lockdown period and changes in detrended $PM_{2.5}$ and O_3 concentrations at the background site were not significant in either lockdown period. However, a significant increase in detrended PM_{10} concentration was identified at urban background location in the second lockdown period only ($P^* = +5.0 \pm 0.9\%$).

3.3. Lockdown impacts upon vehicle activity and estimation of on-road emissions changes by vehicle class

Daily traffic count data by vehicle class for Oxford High Street are presented in Table S1 and Fig. 5. Pre-pandemic mean daily traffic counts were 7709 vehicles per day (range 1514–8705), of which approximately 61% were passenger cars. A rapid reduction in daily volumes of all vehicle types was observed during first two weeks of March 2020 following escalation of the England Chief Medical Officer (CMO) advice regarding risk to public health on 12th March 2020 (PMO, 2020) with an overall traffic volume reduction of 69% and 38% in the first and second lockdown periods respectively. It is notable that the percentage reduction in the volume of cars and buses was much higher in the first compared to the second lockdown period (Fig. 5 and Table S1).

The relative magnitude of changes in traffic volume is broadly consistent with the large change in (deweathered, detrended) roadside NO_2 observed during the first lockdown and the smaller (statistically not significant) changes in (deweathered, detrended) roadside NO_2 during lockdown 2 (Fig. 5). However, these traffic trends do not reveal which types of vehicles contributed the most to pollutant concentrations during the respective lockdown periods. To this end, we calculate the estimated on-road emissions at the studied location by vehicle class during the lockdown periods.

The relative NO_2 emission of different vehicle classes in the study location are illustrated in Fig. 6. It should be noted that the emission of vehicles has been normalized according to the mean emission throughout pre-lockdown status. Substantial drops are observed in the NO_2 emission of buses and cars which reduced by 56% and 77% respectively during the first lockdown. Although there are some reductions in the relative NO_2 emissions of LGVs and OGVs these are not significant when compared to those arising from cars and buses. These reductions are mainly attributed to the lockdown measures and reduction of human activities, including travel for work and leisure purposes for that period. The second lockdown had lesser effects upon travel demand and therefore the NO_2 emission of buses and cars, which reduced by 5% and 37% respectively. Meanwhile, the impact of the second lockdown period upon the NO_2 emission of LGVs and OGVs was not significant. The contribution of different vehicle classes to the local fleet NO_2 emissions is illustrated in Fig. 7. The dominant contribution of buses to overall emissions is attributed to the high volume of bus transport at the studied area, shown in Figs. 5 and 7 and higher NO_2 emissions from the heavy-duty engines used in buses and OGVs compared to light-duty vehicles. High NO_2 emission of heavy diesel engines have been evidenced by many previous investigators, see for example (Ghaffarpasand et al., 2021; Rosero et al., 2021).

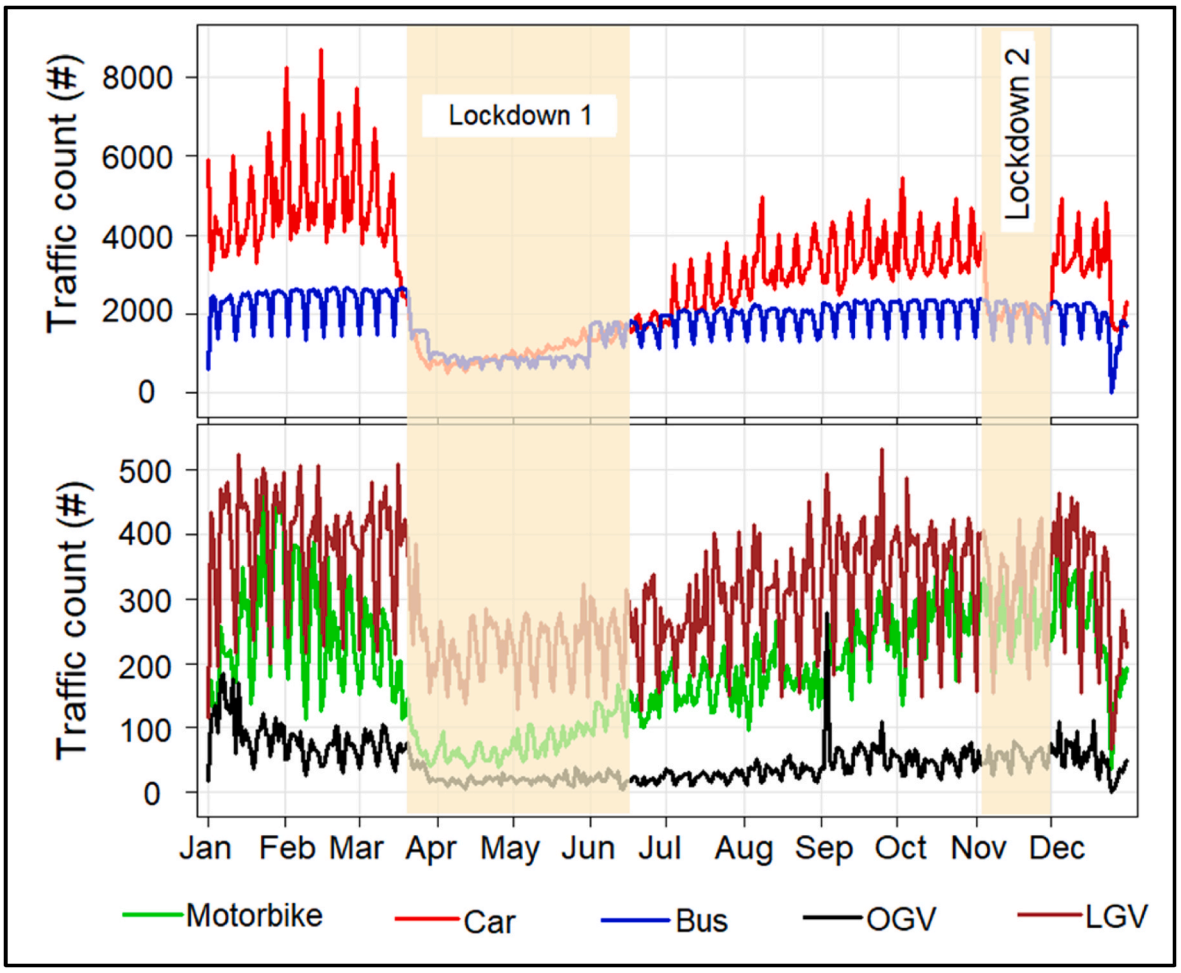

Fig. 5. Time-series of daily traffic count by vehicle type at Oxford Roadside (Oxford High Street) (1st Jan–31st Dec 2020), where OGV = Ordinary Goods Vehicles (includes both Class 1 and Class 2) and LGV = Light Goods Vehicles.

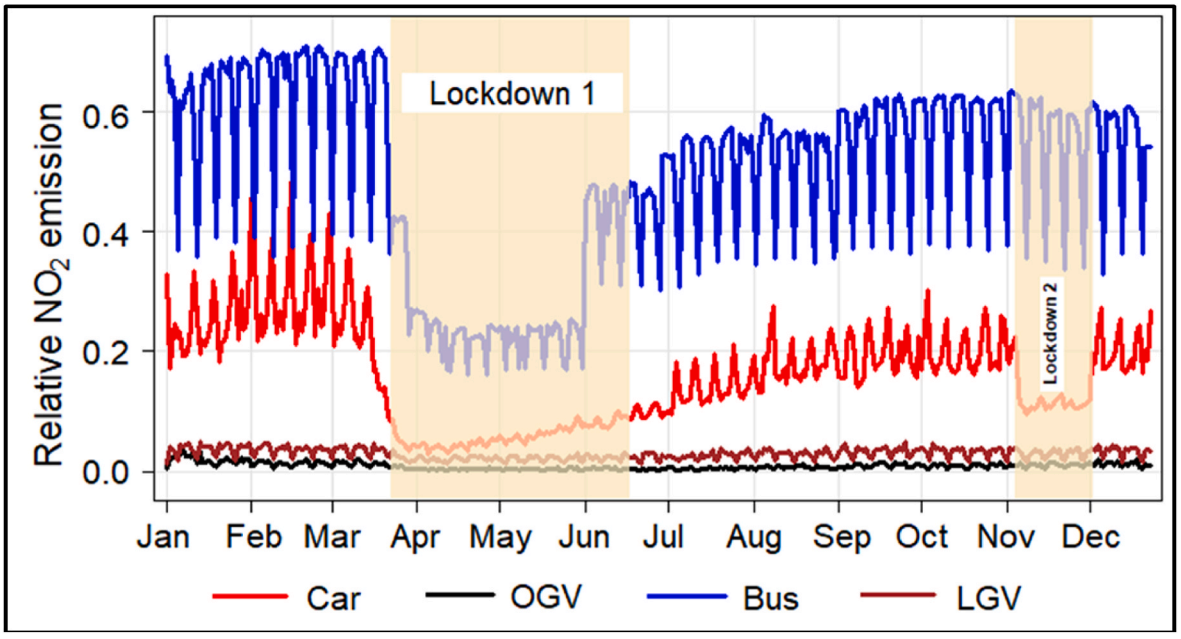

Fig. 6. Relative NO_2 emission by vehicle type at the studied location in 2020.

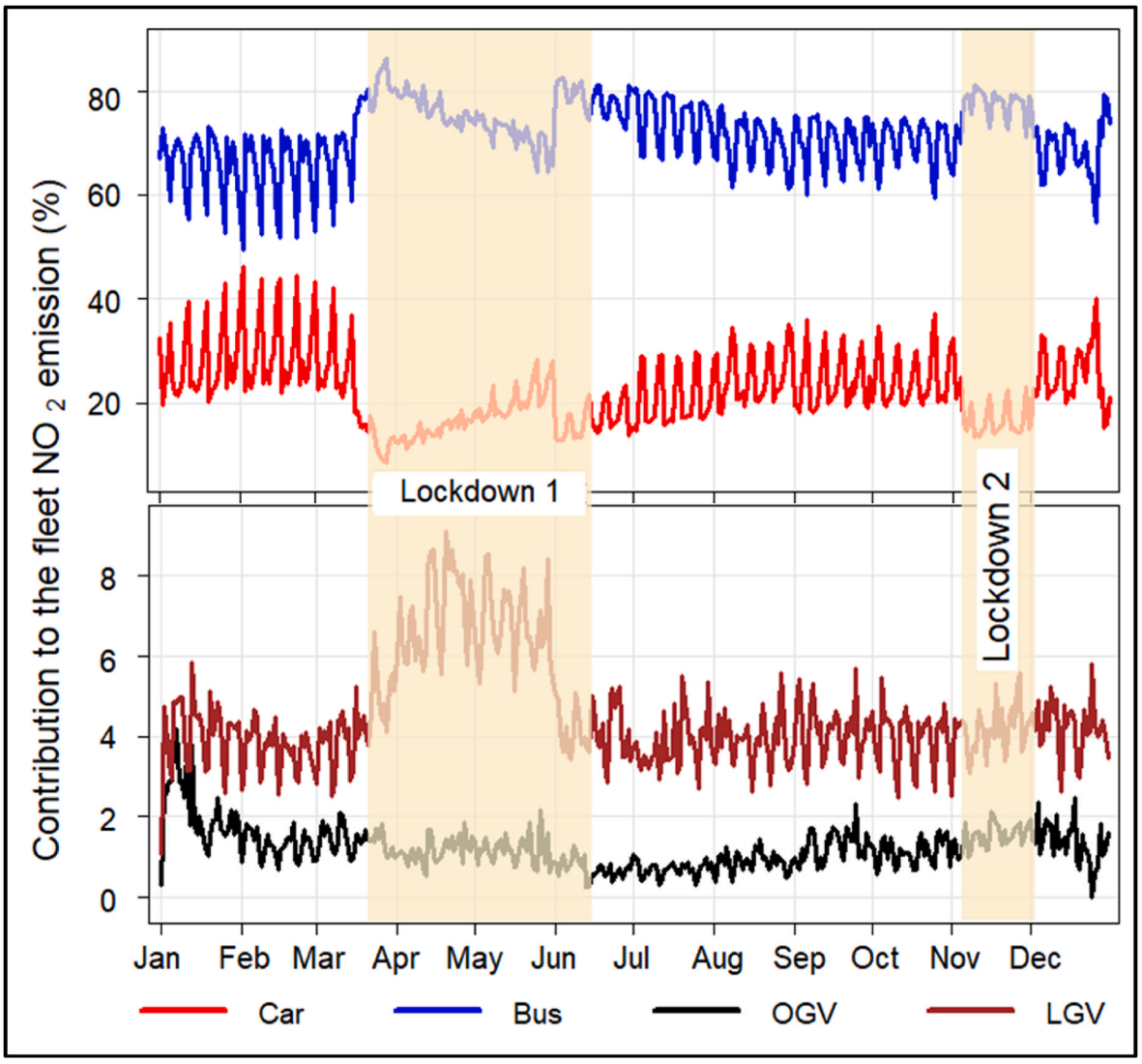

Fig. 7. Contribution of different vehicle types to the NO_2 fleet emissions at the studied area in 2020.

Overall, a significant drop in traffic volume did not translate into an equivalent large reduction in (deweathered, detrended) NO_2 concentrations, suggesting emissions control policies would be more effective by targeting the high emitters (e.g., most polluting vehicles) rather than overall reductions in overall passenger vehicle traffic volume.

3.4. Estimation of health impacts and economic benefits associated with air quality changes attributed to COVID-19 lockdown scenarios

Having established the actual changes in air quality associated with emissions changes we consider the potential health benefits arising if this scenario were maintained across the city. We focus only on the reduction in NO_2 concentrations in the first lockdown period due to the significant decrease in deweathered and detrended NO_2 roadside concentrations as described previously. We consider health and economic implications for city residents by exposure zone status if equivalent NO_2 reductions were to be sustained on an annual basis (Table 2). Accordingly, we would predict 5 deaths each year could be prevented at a city level, reflecting 48 lost life years averted at a total economic benefit of £1.83 million (£1.16–2.52 million) compared to 2019 baseline. The greatest relative health and economic gains achieved by this scenario would be experienced by those living at near roadside locations, with 7 lost life years averted at additional economic benefit £0.28 million, compared to far roadside (4 life years, £0.12 million) or urban background (5 life years, £0.17 million) sub-populations.

It is important to note that here we are modelling lives saved as a result of reduction in a single pollutant only (NO_2) and we do not consider impacts of PM or O_3 concentration changes. We also assume a linear mortality response for the reduction in NO_2 (with no minimum safe threshold for human health) and a consistent level of reduction over the complete lockdown period. Finally, it is beyond scope of this current analysis to consider the wider public health impacts of restricted economic activities or lockdown measures.

4. Discussion

We have examined impacts of the COVID-19 pandemic and associated emergency public health lockdown interventions upon ambient air quality and traffic volume in Oxford during 2020. Our analyses reveal the importance of deweathering and de-trending approaches for understanding the real-world air quality impacts of such measures – notably reductions in vehicle movements and emissions – to inform future air urban quality management strategies in small and medium-sized UK cities.

Table 2
Attributable mortality, lost life years and value of life years lost (VOLYs) attributable to NO_2 annual mean concentrations consistent with lockdown 1 scenario, by population exposure zone status (near roadside/far roadside/urban background).

	NO_2 annual mean concentration[a] (2019) μg m^{-3}	City Population (2019)	Annual deaths attributable to NO_2 exposure[b,c] N (95% CI)	Associated total lost life years[d] N (95% CI)	Value of life years lost[e] £M (95% CI)
City					
Baseline scenario	29.7	152000	37 (23–50)	393.3 (248.4–538.2)	15.15 (9.57–20.74)
Lockdown 1 Scenario	26.1	152000	32 (20–44)	345.6 (218.3–473.0)	13.32 (8.41–18.22)
Zone 1: Near Roadside					
Baseline scenario	31.7	11961	3 (2–4)	32.9 (20.8–45.1)	1.26 (0.80–1.74)
Lockdown 1 scenario	24.7	11961	2 (2–3)	25.6 (16.2–35.1)	0.98 (0.62–1.35)
Zone 2: Far roadside					
Baseline scenario	21.7	14072	2 (2–3)	26.5 (16.7–36.3)	1.02 (0.65–1.40)
Lockdown 1 scenario	19.313	14072	2 (1–3)	23.6 (14.9–32.3)	0.90 (0.57–1.24)
Zone 3: Urban background					
Baseline scenario	20	126467	21 (13–28)	219.7 (138.7–300.6)	8.46 (5.3–11.6)
Lockdown 1 scenario	19.6	126467	20 (13–28)	215.3 (135.9–294.6)	8.29 (5.2–11.3)

[a] Mean value across zone-specific NO_2 monitoring locations (2019).
[b] Reduced NO_2 mortality coefficient: 1.0095 (1.006–1.013) per 10 μg m^{-3} NO_2.
[c] Mortality rate: 0.00857 (ONS, 2019).
[d] Life-years lost multiplier: 10.667.
[e] Value of life years lost: £38,527 (updated from 2004 costs).

Analyses commissioned by Defra indicated relatively high (59%) reductions in observed roadside NO_2 concentrations in Oxford during the first lockdown, ranking as the third highest city-level reduction (below Glasgow and Warrington) (Carslaw, 2020). However, this previous investigation was undertaken for 23rd March to 3rd May 2020 only and did not account for seasonal trends. The Oxford City Council 2020 Annual Air Quality Annual Status Report identified a 29% reduction in observed NO_2 concentrations during 2020 compared to the previous 10 years (2009–2019) (Abreu, 2021a); a finding broadly consistent with our own observed results. However, ours is the first study to apply a deweathering approach in this context and our results indicate that actual lockdown related impacts were much less marked than those reported previously with observed NO_2 reductions in the first lockdown period of 38% and 17% at roadside and urban background sites corresponding to deweathered and detrended values of 22% (SD ± 4.4%) and 2% (SD ± 7.1%) respectively. Notably, pre-pandemic observed pollutant concentrations for NO_2, $PM_{2.5}$, PM_{10} and O_3 were already below the previous four-year mean concentrations in spring 2020, likely to be due to prevailing meteorological conditions and (or) impacts of recent policy interventions (i.e., LEZ related Euro VI bus upgrades). During the second lockdown period, deweathering and detrending analyses revealed no significant change in NO_2 at roadside (0.2 ± 8.1%) suggesting that an overall 38% reduction in traffic flow does not achieve NO_2 exposure reductions at this location. Observed particulate concentrations exhibited considerable variability, however we identified a significant increase in PM_{10} during the second lockdown (5.0 ± 0.9%). Our results also suggest that increases in O_3 were not as pronounced in this setting as those originally reported in other UK cities (AQER, 2020).

Analyses of dynamic traffic data for the lockdown periods broadly reflect national trends of COVID-19 restrictions upon vehicle movements (Vivacity, 2021b) and are consistent with the 35% reduction in vehicle volume from 23rd March–31st December 2020 reported by Oxford City Council, and operator reported changes in bus service levels. We identify buses and cars as the dominant source of NO_2 emissions, with OGVs (including HGVs) having a relatively minor contribution, as reported previously (Abreu, 2021a; Ricardo, 2020). While the emissions of cars and buses decreased during both lockdown periods, buses increased their overall contribution to local emissions, replacing the overall contribution of cars in the second lockdown (Ricardo, 2020). These patterns may reflect the dominance of the educational sectors in the city, with university, college and campus operations highly restricted during the initial pandemic phase, but remaining largely operational during the second lockdown period. Decreases in activity levels from other combustion sources, such as power plants and industry may have contributed to the decline in NO_2 emissions, but the relatively small and non-significant (deweathered, detrended) decline in NO_2 concentrations at the urban background site suggests these were not substantial for this location. In this study we did not consider the influences of driving behaviour such as mean speeds or acceleration events upon NO_2 emissions (Leach et al., 2020); research which considers these factors could provide further relevant insights at the studied location.

Identifying the impacts of lockdown measures upon $PM_{2.5}$ and PM_{10} concentrations is more complex due to the wider range of emissions sources, contribution of secondary formation and influences of regional, national and international long-range sources. It has been estimated previously that domestic combustion contributes to 66% and 48% of local $PM_{2.5}$ and PM_{10} emissions in the city and domestic emissions may have increased during lockdown periods due to changes in time activity patterns. However, the increase in PM_{10} during the second lockdown may also be associated with resumption of highway works and construction activities in the city centre. The relatively small change in observed O_3 concentration for urban background is consistent with recent model simulations which predict substantive changes in O_3 concentrations within city centers, due to reductions in NO titration, but much smaller changes in surface O_3 regionally or at background sites (1.5–2.2 ppb, for emissions reductions of 20–45%, respectively (Potts et al., 2021).

Health benefits associated with air quality improvements consistent with the first lockdown period translate to marginal population level mortality benefits across the city due to the relatively small population living in roadside locations, but may deliver major economic savings, estimated here at £1.16–2.52 million. There are many reasons to consider that our economic estimates are likely to be an underestimate. Firstly, we consider residential locations only and therefore do not capture benefits arising from reduced roadside NO_2 exposure experienced during commuting and leisure activities. We do not include additional morbidity benefits of reduced air pollutant exposure, including avoided primary care consultations and emergency hospital admissions. Further it is beyond the scope of the present study to

consider broader benefits associated with traffic reduction such as reduced road traffic injuries, increased physical activity levels, reduced noise pollution, improved mental health and quality of life. Finally, the VOLY approach to costing is typically conservative; the UK government (DfT, 2021) adopts a value of £1.56 million for the Value of a Statistical Life (VSL) (£1.62 million in 2019 prices) which would generate economic savings of approximately 4–5 times those reported here.

Strengths of our methodological approach include use of four complete years of data for detrending analyses, therefore impacts arising from specific weather-related events will be small. In comparison to previous studies (Jephcote et al., 2020; Lee et al., 2020; Potts et al., 2021; Ropkins and Tate, 2021), this study applied a robust methodology with good performance to estimate air quality changes attributable to the lockdown, which ruled out the impacts of meteorology and pre-existing emission changes due to long-term trends. In addition, the availability of vehicle data and emission estimates provide information upon transport related activity occurring at the transition stages into respective lockdown periods.

Overall, NO_2 concentrations in Oxford have reduced year-on-year over the last decade with the transport sector identified as responsible for 68% of total NO_2 emissions (Carslaw, 2020; Abreu, 2021b; Ricardo, 2020). Air quality improvements prior to the COVID-19 pandemic were attributed to introduction of bus-based emissions restrictions from 2014 and cleaner vehicle fleet evolution, reflecting national trends. The city is also recognised as the first in the UK to formally adopt a NO_2 annual mean objective of 30 μg m^{-3}. Modelling suggests this target will be achieved if all measures within Oxford City Council's most recent AQAP are delivered, including 30 priority actions to be undertaken by the local authority and partners (Abreu, 2021b). Key planned interventions include emissions control restrictions (e.g., a central ZEZ), proposals for a series of point filters for private motor vehicles (bus gates) and implementation of a Workplace Parking Levy (WPL). Our current findings provide insights regarding the potential impacts of transport policy measures of relevance to other similar sized UK cities; traffic reduction consistent with the first lockdown would achieve 34 μg m^{-3} annual mean (roadside) NO_2 concentration, with minimal change at urban background sites. Therefore, further targeted emissions control measures will be necessary to achieve local target compliance and to deliver major public health gains, notably given the limited city population residing at roadside locations. We also note the historic Oxford High Street is a location where passenger vehicles are already restricted and is a major central bus route, and therefore emissions contributions at this location are likely to be proportionately higher from public transport sources compared to other UK cities. Further, traffic reduction had minimal impact upon PM concentrations, with indication of PM_{10} increase during the second lockdown, suggesting additional measures tackling a wider range of emissions sources will be necessary to reduce PM exposure among the city population. Overall, our findings strongly reinforce the need for a holistic air quality strategy addressing a broad range of pollutants.

It is also evident from our analyses that failure to adequately account for the respective influences of meteorology and seasonal trends is likely to overestimate air quality benefits arising from emergency public health measures implemented during lockdown periods. The methodology described may also be applied to evaluate future emissions trends and relevant interventions, enabling robust scientific assessment of changes attributable to transport and air quality policy measures in this context.

5. Conclusions

Emissions changes arising from altered patterns of economic activity and travel behaviours during the COVID-19 national lockdown periods have led to complex changes in air pollutant concentrations in this city centre setting. Our novel analysis indicates that observed NO_2 reductions of 38% at roadside and 17% at urban background locations reflect actual emissions reductions of 22% and 2% respectively. This work emphasises the need for rigorous evaluation of urban air quality interventions in the context of meteorological influences and long-term trends. Achieving a 70% reduction in city centre traffic volume would deliver some public health benefits; however PM concentrations would not reduce and targeted emissions control measures may be more effective. Further research focusing upon population health, economic and climate co-benefits arising from such interventions would be valuable to inform transport policy decisions in similar small and medium sized UK cities.

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Data availability

Datasets used in this study are obtained from publicly available data sources:

Air quality data: https://uk-air.defra.gov.uk/data/

Meteorological variables data: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels?tab=overview.

Demographic data for health impact assessment: https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland

https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/bulletins/deathsregistrationsummarytables/2019.

Credit author statement

Ajit Singh: Conceptualization, Methodology, Formal analysis, Data curation, Data Formal analysis, Data visualisation, Writing – original draft, Writing – review & editing Suzanne E. Bartington: Funding acquisition; Investigation; Methodology Conceptualization, Supervision, Writing – original draft, Writing – review & editing; Congbo Song: Methodology, Data Formal analysis, Writing – original draft; Omid Ghaffarpasand: Methodology, Data Formal analysis, Writing – original draft Martin Kraftl: Methodology, Data curation, Data Formal analysis; Zongbo Shi: Methodology, Supervision, Writing – review & editing Francis D. Pope: Funding acquisition; Methodology, Supervision Writing - review & editing Brian Stacey: Funding acquisition, Validation, Resources; James Hall: Data curation, Data Formal analysis, Writing – original draft; G. Neil Thomas: Funding acquisition; Writing – review & editing William J. Bloss: Validation, Supervision Writing - review & editing Felix C.P. Leach: Funding acquisition; Investigation; Methodology, Conceptualization, Supervision; Writing – review & editing

Declaration of competing interest

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2021.118584.

References

Abreu, P., 2020. 2019 Air Quality Annual Status Report (ASR). Oxford City Council, Oxford, United Kingdom. https://www.oxford.gov.uk/downloads/file/7334/air_quality_annual_status_report_2019.

Abreu, P., 2021a. 2020 Air Quality Annual Status Report. Oxford City Council, Oxford, United Kingdom, ASR2020. https://www.oxford.gov.uk/downloads/file/7612/air_quality_annual_status_report_2020.

Abreu, P., 2021b. Oxford City Council Air Quality Action Plan 2021-2025. Oxford City Council, Oxford, United Kingdom. https://www.oxford.gov.uk/downloads/file/7428/air_quality_action_plan_2021-2025.

Allaire, J., 2012. RStudio: integrated development environment for R. Boston, MA 770 (394), 165–171. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.651.1157&rep=rep1&type=pdf#page=14.

AQER, 2020. Assessing the Effectiveness of Interventions on Air Quality. Department for Environment, Food and Rural Affairs (DEFRA). https://uk-air.defra.gov.uk/library/reports?report_id=1004.

Baldasano, J.M., 2020. COVID-19 lockdown effects on air quality by NO2 in the cities of Barcelona and Madrid (Spain). Sci. Total Environ. 741, 140353. https://doi.org/10.1016/j.scitotenv.2020.140353.

Benmarhnia, T., 2020. Linkages between air pollution and the health burden from COVID-19: methodological challenges and opportunities. Am. J. Epidemiol. 189 (11), 1238–1243. https://doi.org/10.1093/aje/kwaa148.

Berman, J.D., Ebisu, K., 2020. Changes in US air pollution during the COVID-19 pandemic. Sci. Total Environ. 739, 139864. https://doi.org/10.1016/j.scitotenv.2020.139864.

Carslaw, D., 2020. Blog Update on COVID-19 and Changes in Air Pollution. Ricardo, United Kingdom. https://ee.ricardo.com/news/blog-update-on-covid-19-and-changes-in-air-pollution.

Carslaw, D.C., Ropkins, K., 2012. Openair—an R package for air quality data analysis. Environ. Model. Software 27, 52–61. https://doi.org/10.1016/j.envsoft.2011.09.008.

Chilton, S., Covey, J., Jones-Lee, M., Loomes, G., Metcalf, H., 2004. Valuation of Health Benefits Associated with Reductions in Air Pollution. Department for Environment, Food and Rural Affairs (Defra), London, United Kingdom. https://webarchive.nationalarchives.gov.uk/ukgwa/20051125120000/http://www.defra.gov.uk/environment/airquality/airpoll_health/index.htm.

Comeap, 2010. The Mortality Effects of Long-Term Exposure to Particulate Air Pollution in the United Kingdom: A Report by the Committee on the Medical Effects of Air Pollutants. Health Protection Agency, London, United Kingdom. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/304641/COMEAP_mortality_effects_of_long_term_exposure.pdf.

Comeap, 2012. Statement on Estimating the Mortality Burden of Particulate Air Pollution at the Local Level. Committee on the Medical Effects of Air Pollutants. Public Health England (PHE). http://www.comeap.org.uk/documents/statements. (Accessed 9 July 2021).

Comeap, 2018. Associations of Long-Term Average Concentrations of Nitrogen Dioxide with Mortality: A Report by the Committee on the Medical Effects of Air Pollutants. Health Protection Agency, London, United Kingdom. https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/734799/COMEAP_NO2_Report.pdf.

Dai, Q., Hou, L., Liu, B., Zhang, Y., Song, C., Shi, Z., Hopke, P.K., Feng, Y., 2021. Spring festival and COVID-19 lockdown: disentangling PM sources in major Chinese cities. Geophys. Res. Lett. 48 (11) https://doi.org/10.1029/2021GL093403 e2021GL093403.

Davies, N.G., Barnard, R.C., Jarvis, C.I., Russell, T.W., Semple, M.G., Jit, M., Edmunds, W.J., 2020. Association of tiered restrictions and a second lockdown with COVID-19 deaths and hospital admissions in England: a modelling study. Lancet Infect. Dis. 21 (4), 482–492. https://doi.org/10.1016/S1473-3099(20)30984-1.

Defra, 2021. UK Air Information. https://uk-air.defra.gov.uk/. (Accessed 1 June 2021).

DfT, 2021. Transport Analysis Guidance (TAG). Department for Transport, London, United Kingdom. https://www.gov.uk/government/publications/tag-data-book.

Fattorini, D., Regoli, F., 2020. Role of the chronic air pollution levels in the Covid-19 outbreak risk in Italy. Environ. Pollut. 264, 114732. https://doi.org/10.1016/j.envpol.2020.114732.

Geoplace, 2014. National Land and Property Gazetteer. London, United Kingdom. https://data.gov.uk/dataset/9231ef97-a965-4d91-97c4-482d33de459a/national-land-and-property-gazetteer.

Ghaffarpasand, O., Beddows, D.C.S., Ropkins, K., Pope, F.D., 2020. Real-world assessment of vehicle air pollutant emissions subset by vehicle type, fuel and EURO class: New findings from the recent UK EDAR field campaigns, and implications for emissions restricted zones. Sci. Total Environ. 734, 139416. https://doi.org/10.1016/j.scitotenv.2020.139416.

Ghaffarpasand, O., Talaie, M.R., Ahmadikia, H., Khozani, A.T., Shalamzari, M.D., Majidi, S., 2021. Real-world assessment of urban bus transport in a medium-sized city of the Middle East: driving behavior, emission performance, and fuel consumption. Atmospheric Pollution Research 12 (3), 113–124. https://doi.org/10.1016/j.apr.2021.02.004.

Grange, S.K., Carslaw, D.C., 2019. Using meteorological normalisation to detect interventions in air quality time series. Sci. Total Environ. 653, 578–588. https://doi.org/10.1016/j.scitotenv.2018.10.344.

Grange, S.K., Carslaw, D.C., Lewis, A.C., Boleti, E., Hueglin, C., 2018. Random forest meteorological normalisation models for Swiss PM10 trend analysis. Atmos. Chem. Phys. 18 (9), 6223–6239. https://doi.org/10.5194/acp-18-6223-2018.

He, G., Pan, Y., Tanaka, T., 2020. The short-term impacts of COVID-19 lockdown on urban air pollution in China. Nature Sustainability 3 (12), 1005–1011. https://doi.org/10.1038/s41893-020-0581-y.

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., Schepers, D., Simmons, A., Soci, C., Dee, D., Thépaut, J.-N., 2018. ERA5 Hourly Data on Single Levels from 1979 to Present. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). https://doi.org/10.24381/cds.adbb2d47. (Accessed 3 August 2021).

Higham, J., Ramírez, C.A., Green, M., Morse, A., 2020. UK COVID-19 lockdown: 100 days of air pollution reduction? Air Quality, Atmosphere & Health 14 (3), 325–332. https://doi.org/10.1007/s11869-020-00937-0.

Hitchcock, G., Birchby, D., Bouvet, C., Clarke, D., 2017. Oxford Zero Emission Zone Feasibility and Implementation Study. Oxford City Council and Oxfordshire County Council, Harwell, United Kingdom. https://www.oxford.gov.uk/downloads/file/4019/zero_emission_zone_feasibility_study_october_2017.

Jephcote, C., Hansell, A.L., Adams, K., Gulliver, J., 2020. Changes in air quality during COVID-19 'lockdown' in the United Kingdom. Environ. Pollut. 272, 116011. https://doi.org/10.1016/j.envpol.2020.116011.

Konstantinoudis, G., Padellini, T., Bennett, J., Davies, B., Ezzati, M., Blangiardo, M., 2021. Long-term exposure to air-pollution and COVID-19 mortality in England: a hierarchical spatial analysis. Environ. Int. 146, 106316. https://doi.org/10.1016/j.envint.2020.106316.

Leach, F.C.P., Peckham, M.S., Hammond, M.J., 2020. Identifying NOx hotspots in transient urban driving of two diesel buses and a diesel car. Atmosphere 11 (4), 355. https://doi.org/10.3390/atmos11040355.

Lee, J.D., Drysdale, W.S., Finch, D.P., Wilde, S.E., Palmer, P.I., 2020. UK surface NO2 levels dropped by 42% during the COVID-19 lockdown: impact on surface O3. Atmos. Chem. Phys. 20 (24), 15743–15759. https://doi.org/10.5194/acp-20-15743-2020.

Lian, X., Huang, J., Huang, R., Liu, C., Wang, L., Zhang, T., 2020. Impact of city lockdown on the air quality of COVID-19-hit of Wuhan city. Sci. Total Environ. 742, 140556. https://doi.org/10.1016/j.scitotenv.2020.140556.

Magazzino, C., Mele, M., Schneider, N., 2020. The relationship between air pollution and COVID-19-related deaths: an application to three French cities. Appl. Energy 279, 115835. https://doi.org/10.1016/j.apenergy.2020.115835.

Mahato, S., Pal, S., Ghosh, K.G., 2020. Effect of lockdown amid COVID-19 pandemic on air quality of the megacity Delhi, India. Sci. Total Environ. 730, 139086. https://doi.org/10.1016/j.scitotenv.2020.139086.

OCC, 2018. Oxford Profile 2018 Key Facts Oxford City Council. Oxford, United Kingdom. https://www.oxford.gov.uk/downloads/file/5021/oxford_profile_2018.

OCC, 2020. Updates to Emission Standards for Hackney Carriages and Timeline for Buses for the Oxford Zero Emission Zone Following Coronavirus Pandemic. https://www.oxford.gov.uk/news/article/1413/updates. (Accessed 9 July 2021).

OCC, 2021. Background to the Oxford Zero Emission Zone (ZEZ) about Oxford. https://www.oxford.gov.uk/info/20299/air_quality_projects/1305/oxford_zero_emission_zone_zez. (Accessed 9 July 2021).

Ogen, Y., 2020. Assessing nitrogen dioxide (NO2) levels as a contributing factor to the coronavirus (COVID-19) fatality rate. Sci. Total Environ. 726, 138605. https://doi.org/10.1016/j.scitotenv.2020.139853.

ONS, 2020. Population Estimates for the UK, England and Wales, Scotland and Northern Ireland: Mid-2019, Using April 2019 Local Authority District Codes. Office for National Statistics, Fareham,United Kingdom. https://www.ons.gov.uk/peoplepopulationandcommunity/populationandmigration/populationestimates/datasets/populationestimatesforukenglandandwalesscotlandandnorthernireland.

OP, A.M., 2021. AM Online Projects. Oxford, United Kingdom. https://en.climate-data.org/europe/united-kingdom/england/oxford-22/. (Accessed 9 July 2021).

Osei, L.K., Ghaffarpasand, O., Pope, F.D., 2021. Real-world contribution of electrification and replacement scenarios to the fleet emissions in west midland boroughs, UK. Atmosphere 12 (3), 332. https://doi.org/10.3390/atmos12030332.

PHE, 2014. Estimating Local Mortality Burdens Associated with Particulate Air Pollution. Public Health England, United Kingdom. PHE-CRCE-010. https://www.gov.uk/government/publications/estimating-local-mortality-burdens-associated-with-particulate-air-pollution.

PHE, 2021. The Official UK Government Website for Data and Insights on Coronavirus (COVID-19). https://coronavirus.data.gov.uk/. (Accessed 28 September 2021).

PMO, 2020. Prime Minister's Statement on Coronavirus (COVID-19): 5 November 2020. Prime Minister's Office, 10 Downing Street. https://www.gov.uk/government/speeches/prime-ministers-statement-on-coronavirus-covid-19-5-november-2020. (Accessed 8 August 2021).

Potts, D.A., Marais, E.A., Boesch, H., Pope, R.J., Lee, J., Drysdale, W., Chipperfield, M.P., Kerridge, B., Siddans, R., Moore, D.P., Remedios, J., 2021. Diagnosing air quality changes in the UK during the COVID-19 lockdown using TROPOMI and GEOS-Chem. Environ. Res. Lett. 16 (5), 054031 https://doi.org/10.1088/1748-9326/abde5d.

Ricardo, E.E., 2020. Oxford Source Apportionment Study. Ricardo Energy & Environment, Harwell, United Kingdom. Issue Number 4, ED 13208100. https://www.oxford.gov.uk/download/downloads/id/7320/oxford_source_apportionment_study.pdf.

Ropkins, K., Tate, J.E., 2021. Early observations on the impact of the COVID-19 lockdown on air quality trends across the UK. Sci. Total Environ. 754, 142374. https://doi.org/10.1016/j.scitotenv.2020.142374.

Ropkins, K., DeFries, T.H., Pope, F., Green, D.C., Kemper, J., Kishan, S., Fuller, G.W., Li, H., Sidebottom, J., Crilley, L.R., Kramer, L., Bloss, W.J., Stewart Hager, J., 2017. Evaluation of EDAR vehicle emissions remote sensing technology. Sci. Total Environ. 609, 1464–1474. https://doi.org/10.1016/j.scitotenv.2017.07.137.

Rosero, F., Fonseca, N., López, J.-M., Casanova, J., 2021. Effects of passenger load, road grade, and congestion level on real-world fuel consumption and emissions from compressed natural gas and diesel urban buses. Appl. Energy 282, 116195. https://doi.org/10.1016/j.apenergy.2020.116195.

Sasidharan, M., Singh, A., Torbaghan, M.E., Parlikad, A.K., 2020. A vulnerability-based approach to human-mobility reduction for countering COVID-19 transmission in London while considering local air quality. Sci. Total Environ. 741, 140515. https://doi.org/10.1016/j.scitotenv.2020.140515.

Shi, Z., Song, C., Liu, B., Lu, G., Xu, J., Van Vu, T., Elliott, R.J.R., Li, W., Bloss, W.J., Harrison, R.M., 2021. Abrupt but smaller than expected changes in surface air quality attributable to COVID-19 lockdowns. Science Advances 7 (3), eabd6696. https://doi.org/10.1126/sciadv.abd6696.

Stein, A.F., Draxler, R.R., Rolph, G.D., Stunder, B.J.B., Cohen, M.D., Ngan, F., 2015. NOAA's HYSPLIT atmospheric transport and dispersion modeling system. Bull. Am. Meteorol. Soc. 96 (12), 2059–2077. https://doi.org/10.1175/BAMS-D-14-00110.1.

Sung, J., Monschauer, Y., 2020. Changes in Transport Behaviour during the Covid-19 Crisis. International Energy Agency (IEA), Paris, France. https://www.iea.org/articles/changes-in-transport-behaviour-during-the-covid-19-crisis.

Treasury, H.M., 2021. GDP Deflators at Market Prices, and Money GDP. Her Majesty's (HM) Treasury Press Office, London, United Kingdom. https://www.gov.uk/government/collections/gdp-deflators-at-market-prices-and-money-gdp. (Accessed 30 September 2021).

UKHSA, 2021. Coronavirus (COVID-19). UK Health Security Agency (UKHSA). https://www.gov.uk/coronavirus. (Accessed 9 July 2021).

Vega, E., Namdeo, A., Bramwell, L., Miquelajauregui, Y., Resendiz-Martinez, C.G., Jaimes-Palomera, M., Luna-Falfan, F., Terrazas-Ahumada, A., Maji, K.J., Entwistle, J., Enríquez, J.C.N., Mejia, J.M., Portas, A., Hayes, L., McNally, R., 2021. Changes in air quality in Mexico City, London and Delhi in response to various stages and levels of lockdowns and easing of restrictions during COVID-19 pandemic. Environ. Pollut. 285, 117664. https://doi.org/10.1016/j.envpol.2021.117664.

Vivacity, 2021a. Improving Traffic Insights with Artificial Intelligence: Traffic Data. https://vivacitylabs.com/. (Accessed 9 July 2021).

Vivacity, 2021b. New Insights into Urban Air Pollution through Novel Road Traffic and Vehicle Emission Remote Sensing Data. https://vivacitylabs.com/new-insights-into-urban-air-pollution-through-novel-road-traffic-and-vehicle-emission-remote-sensing-data.

WHO, 2016. Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease. World Health Organization, Geneva, Switzerland. https://www.who.int/publications/i/item/9789241511353.

WHO, 2020. WHO Director-General's Opening Remarks at the Media Briefing on COVID-19 - 11 March 2020. World Health Organization. https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19—11-march-2020.

WHO, 2021. WHO Coronavirus (COVID-19) Dashboard Overview Data Table. https://coronavirus.data.gov.uk/. (Accessed 9 July 2021).

Wilks, D.S., 2011. Statistical Methods in the Atmospheric Sciences, third ed. Academic Press, Oxford; Waltham, MA https://www.elsevier.com/books/statistical-methods-in-the-atmospheric-sciences/wilks/978-0-12-385022-5.

Wu, X., Nethery, R., Sabath, M., Braun, D., Dominici, F., 2020. Air pollution and COVID-19 mortality in the United States: strengths and limitations of an ecological regression analysis. Science advances 6 (45), eabd4049. https://doi.org/10.1126/sciadv.abd4049.

Wyche, K., Nichols, M., Parfitt, H., Beckett, P., Gregg, D., Smallbone, K., Monks, P., 2020. Changes in ambient air quality and atmospheric composition and reactivity in the South East of the UK as a result of the COVID-19 lockdown. Sci. Total Environ. 755, 142526. https://doi.org/10.1016/j.scitotenv.2020.142526.

Zangari, S., Hill, D.T., Charette, A.T., Mirowsky, J.E., 2020. Air quality changes in New York City during the COVID-19 pandemic. Sci. Total Environ. 742, 140496. https://doi.org/10.1016/j.scitotenv.2020.140496.