Traffic-Related Air Pollution Reduction at UK Schools During the Covid-19 Lockdown

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Abstract

Elevated urban Nitrogen Dioxide (NO_2) is a consequence of road traffic and other fossil-fuel combustion sources, and the road transport sector provides a significant contribution to UK NO_2 emissions. The inhalation of traffic-related air pollution, including NO_2, can cause a range of problems to human health. Due to their developing organs, children are particularly susceptible to the negative effects of air pollution inhalation. Accordingly, schools and associated travel behaviours present an important area of study for the reduction of child exposure to these harmful pollutants.

COVID-19 reached the UK in late January, 2020. On the 23rd of March that year, the UK government announced a nationwide stay-at-home order, or lockdown, banning all non-essential travel and contact with people outside of their own homes. The lockdown was accompanied by the closure of schools, public facilities, amenities, businesses and places of worship.

The current study aims to assess the significance of nationwide NO_2 reductions at schools in England as a consequence of the lockdown in order to highlight the benefits of associated behavioural changes within the context of schools in England and potential child exposure. NO_2 data were collected from all AURN (Automatic Urban and Rural Network) monitoring sites within 500 metres of nurseries, primary schools, secondary schools and colleges in

England. A significant reduction of mean NO_2 concentrations was observed in the first month of the UK lockdown at background (-35.13%) and traffic (-40.82%) sites.

Whilst lockdown restrictions are undoubtedly unsustainable, the study results demonstrate the possible reductions of NO_2 at schools in England and potential reductions of child exposure that are achievable when public behaviours shift towards active travel, work from home policies and generally lower use of polluting vehicles.

Keywords: COVID-19; Lockdown; NO_2; Nitrogen Dioxide; Schools; England

1.0 Introduction

Elevated urban Nitrogen Oxides (NO_X) are a consequence of road traffic and other fossil-fuel combustion sources. The road transport sector accounts for a significant proportion of UK NO_X emissions, contributing 31% (NAEI, 2020). The inhalation of traffic-related air pollution, including Nitrogen Dioxide (NO_2), a component of NO_X, can cause a range of problems to human health. Short-term exposure to these concentrations can lead to the aggravation of existing respiratory problems (Esposito et al., 2014; Goldizen et al., 2016; Searing & Rabinovitch, 2011), and increased cases of hospitalisation (Kampa & Castanas, 2008). Long-term exposure has been linked to further issues, including greater susceptibility to infections of the respiratory system (Ryan et al., 2013). Children have been identified as a vulnerable group due to their developing organs, making them particularly susceptible to the negative effects of NO_2 (Guarnieri & Balmes, 2014; WHO, 2018). Accordingly, schools and associated travel present an important area of study for the reduction of child exposure to harmful traffic-related pollutants.

COVID-19 reached the UK in late January 2020. On the 23rd of March the same year, the UK government announced a nationwide stay-at-home order, or lockdown, which banned all non-essential travel and contact with people outside of their own homes (Iacobucci, 2020). This was accompanied by the closure of schools, public facilities, amenities, businesses and places of worship. Whilst forecasts predicted the negative financial consequences of a prolonged lockdown, the considerable effects of population confinement and travel restrictions on air pollution reduction were promptly highlighted (Berman & Keita, 2020; Dutheil et al., 2020).

The current study aims to assess and highlight the benefits of these behavioural changes within the context of schools in England, to demonstrate the child exposure reductions that are possible when public behaviours shift towards active travel, work from home policies and generally lower use of polluting vehicles. The study does not seek to estimate actual reductions in child exposure for the study periods, due to children's absence from schools during the lockdown period.

It is not the intention of the current research to attribute pollutant reductions to specific behavioural changes as a consequence of lockdown measures, nor does it seek to quantify the influence of other factors, such as pollutant transportation. This study acknowledges that a deeper analysis is required to accurately ascertain this information. However, the effects of the lockdown measures on air pollution provide a unique opportunity to assess the reductions that are possible due to the associated behavioural change, and to determine further policies for the reduction of child exposure to these harmful pollutants.

1.1 Research Question

The study aim can be summarised in the following statement:

- To assess the significance of nationwide NO_2 reductions at schools in England as a consequence of the lockdown in order to highlight the benefits of associated behavioural changes within the context of schools in England and potential child exposure.

Accordingly, the aforementioned study approach can be summarised in the following research question:

- To what extent did traffic-related air pollution reduce around schools in England during the first month of the UK lockdown in 2020?

2.0 Methods

Air quality data were collected from background and traffic monitoring sites within 500 metres of schools in England. The data was analysed using R (Version 3.6.3) in R Studio (Version 1.3.1093) to determine the significance of difference between the lockdown period and the same time period for the five previous years, and to adjust the data for meteorological influence.

2.1 Site Selection

Using ArcGIS Pro (Ver 2.4.0, Esri Inc.), school locations in England were plotted with Automatic Urban and Rural Network (AURN) air quality monitoring sites. AURN monitors are sited according to specific requirements (Directive 2008/50/EC) and are defined in terms of background sites that are representative of general urban population exposure, and traffic sites located within 10 metres from the kerbside and at least 25 metres from major junctions. Background sites are located so that recorded pollution levels are not significantly influenced by any single source and are representative of several square kilometres. Traffic sites are located so that recorded pollution levels are predominantly determined by nearby traffic emissions, and are representative of air quality for a street segment greater than 100 metres

(Defra, 2020a). All AURN site information, including historical data, is made freely available by Defra (Defra, 2020b).

A Geographical Information System (GIS) was used to identify all AURN sites in England within 500 metres of an educational establishment for use as representative of pollution levels and exposure. The locations of all AURN sites are made available by Defra and are searchable by location (Defra, 2020c). The 500-metre distance is supported by studies that have suggested exposure to NO_2 within 500 metres of the source is potentially hazardous to human health (Zhou & Levy, 2007). Educational establishments included nurseries, primary schools, secondary schools and colleges. The list was classified by AURN site type and all valid urban background and traffic sites were selected for further analysis and comparison. Using the Openair package in R Studio, data for all selected AURN sites were collected for the years 2015 to 2020. The data included the site names, NO_2 concentration readings for the 5-year period, and modelled temperature, wind speed and wind direction (Defra, 2020d).

2.2 Data Preparation

The first month of the lockdown period was considered appropriate for the scope of the investigation. This time period is representative of the time that lockdown measures were more closely followed by the general public (Sibley et al., 2020). Longer time periods would incur the effects of too many variables, including 'crisis fatigue' (Aras & Yorulmazlar, 2020), and a general easing of attitudes and compliance with the measures (Jackson et al., 2020), due to the public becoming accustomed to the impositions and more willing to contravene the restrictions. To prepare the datasets for analysis the sites were categorised into background and traffic groups, and time periods were selected within each category. Time periods were specified as 'Historical' (23rd of March to 23rd of April, each year from 2015 to 2019, as a combined average) and 'Lockdown' (23rd of March to 23rd of April, 2020). Weekend data were removed and weekday data retained to better represent the days children attend school. Datasets were also created for each site category for weekdays between January and August, 2020, for time series analysis.

2.3 Analysis

Descriptive statistics were calculated for the data and the normality of the data was checked by visual inspection. To confirm the data distribution, the Anderson Darling test was conducted. The data did not follow a normal distribution so a Mann-Whitney U test was used to determine the significance of difference in background and traffic NO_2 concentrations between the Lockdown and Historical periods. Time variation data was plotted for pollutant concentrations at background and traffic sites before and after the lockdown measures (from January to August, 2020) to assess the pollutant reduction as a consequence of the restrictions.

2.4 Adjustment for Meteorological Influence

A persistent issue when analysing air pollution levels is the role of the weather, which can affect changes in concentrations. The general weather of 2020 was relatively mild when compared to the average temperature, and the start of the year was particularly windy. These weather events may potentially impact the recorded reduction of concentrations as a consequence of lockdown measures (Grange et al., 2020). Due to the central role played by meteorology in affecting atmospheric pollutant concentrations, the consideration of air pollutant trends can be problematic. Because of the difficulties in determining whether concentration changes are due to emissions or meteorology, it is imperative to ensure an adequate understanding of the role of weather in the recorded pollution levels and observed reduction (Carslaw, 2020; Grange et al., 2020). All functions used in the procedure for metrological adjustments are part of the Openair package for R. A segment of data (January to August, 2020) was selected for background and traffic sites to perform initial model viability testing with the commonly-used covariates of wind speed, wind direction, air temperature, hour, weekday, week and NO_2. The testMod function was then used to build and test models to derive the most appropriate. Variables including 'hour' 'month' and 'weekday' were used as proxies for the determination of variation (Carslaw, 2020).

Once it was established that a suitable model could be developed, the buildMod function was applied to the background and traffic data. Partial dependencies were plotted using the resultant datasets and the plotALLPD function. The interaction between wind speed and air temperature was then considered using the plot2Way function on the modelled data. Meteorological averaging utilises the model to perform multiple predictions with random meteorological condition sampling (using the metSim function). The resulting trends were then plotted for the period between January and August, 2020, to provide a before-and-after picture of the lockdown period, and the subsequent return to business-as-usual.

3.0 Results

This section presents the results of the data analyses. Time periods are displayed as *Historical* (23^{rd} of March to 23^{rd} of April, each year from 2015 to 2019) and *Lockdown* (23^{rd} of March to 23^{rd} of April, 2020).

3.1 Statistical Analysis

3.1.1 Descriptive Statistics

Descriptive statistics for background and traffic sites are shown in Table 1. The Lockdown NO_2 concentrations for background sites were M = 15.75 (µg/m^3), SD = 12.98. This was lower than the Historical concentrations M = 24.28 (µg/m^3), SD = 17.67. The Lockdown NO_2 concentrations for traffic sites were M = 22.82 (µg/m^3), SD = 16.37, which was also lower than the Historical concentrations M = 38.56 ($\mu g/m^3$), SD = 27.00. The mean NO_2 reductions during Lockdown compared to the Historical period were 8.53 ($\mu g/m^3$), or 35.13%, and 15.74 ($\mu g/m^3$) or 40.82%, at background and traffic sites, respectively.

Table 1 Descriptive statistics for lockdown and historical periods at background and traffic sites.

	Lockdown NO_2 ($\mu g/m^3$)		Historical NO_2 ($\mu g/m^3$)	
	Background	Traffic	Background	Traffic
Count	28057	20267	115206	83738
Mean	15.75	22.82	24.28	38.56
Standard Deviation	12.98	16.37	17.67	27
Median	11.67	18.43	19.57	32.53
Standard Error	0.08	0.11	0.05	0.09

The standard deviations around the means appear substantial, although the coefficient of variation (CV) in all cases is <1 (CV= standard deviation/mean). The medians in all cases are less than the mean values, indicating the data is skewed to the right. This comparison introduces a considerable disparity in the number of counts in each sample used for the calculations. However, all standard errors are low, indicating a greater likelihood that the sample mean is close to the population mean.

3.1.2 Normality Tests

The Anderson-Darling test was conducted and the outcome confirmed the non-normal distribution of the background (AD = 4933.2, p = < 2.2e-16) and traffic (AD = 1154.8, p = < 2.2e-16) concentration data.

3.1.3 Tests of Difference

The 2-group Wilcoxon Rank Sum Test was used to test the difference between lockdown and historical concentrations. The following null hypothesis was used:

H_0 There is no difference in NO_2 concentrations between the first month of lockdown and the same time period in previous years.

The Wilcoxon Test indicated that a significant difference existed between the Historical and Lockdown periods for background (p = < 2.2e-16) and traffic (p = < 2.2e-16) sites, and the null hypothesis was rejected.

3.2 Time-Series Analysis

Having determined the significance of the NO_2 reduction during the Lockdown period when compared to the Historical time period, the NO_2 trend was plotted for January to August, 2020 to visualise the concentration reduction (Figure 1).

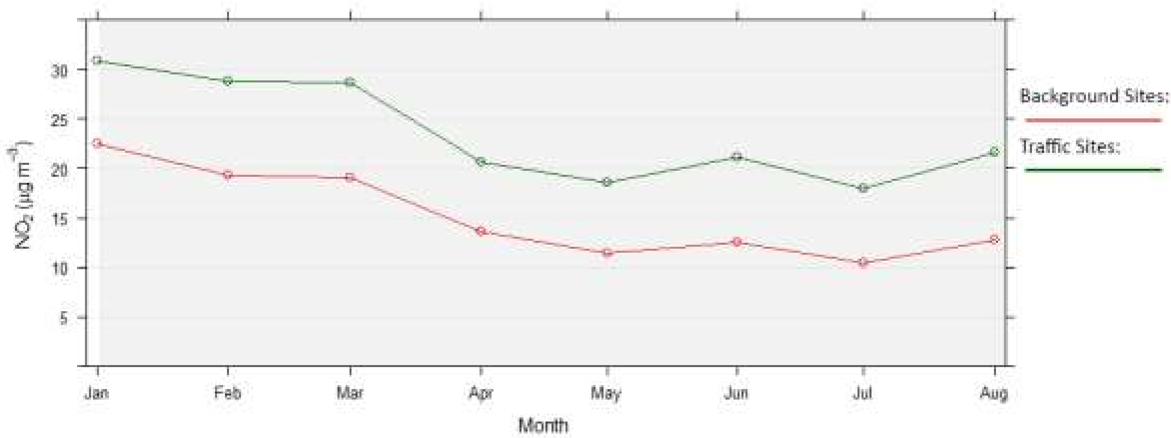

Figure 1 Smooth trend plot for NO_2 ($\mu g/m^3$) at background and traffic sites between January and August, 2020.

Time variation analyses of NO_2 concentrations were plotted for January to August, 2020 (Figures 2 and 3). The pre-lockdown period (January 1st to March 22rd, 2020) of this study spans approximately three months, and the post-lockdown period (April 23rd to August 31st,

2020) spans approximately four months. NO_2 concentrations appear to follow a similar diurnal pattern, although they are clearly reduced following the implementation of the lockdown measures. Daily concentration patterns are also evident with morning and afternoon peaks corresponding to peak traffic times. The time variation plots clearly show NO_2 reductions as a consequence of the measures, with diurnal variation for all days showing lower levels.

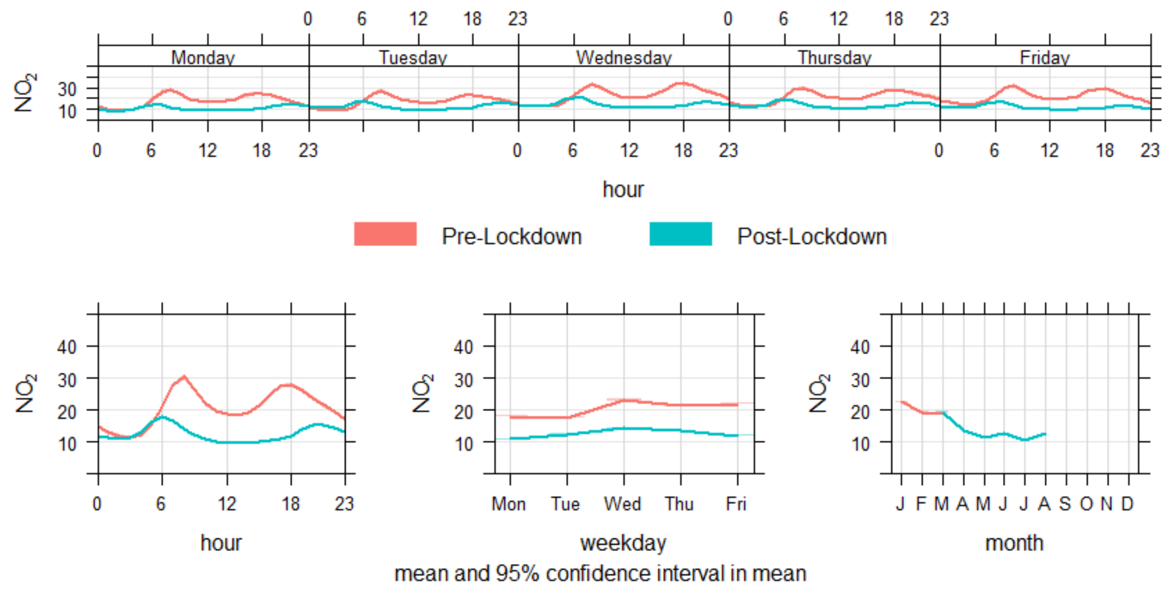

Figure 2 Time variation of NO_2 ($\mu g/m^3$) during pre- and post-lockdown periods for background sites between January and August, 2020 (Confidence Interval is represented by line width).

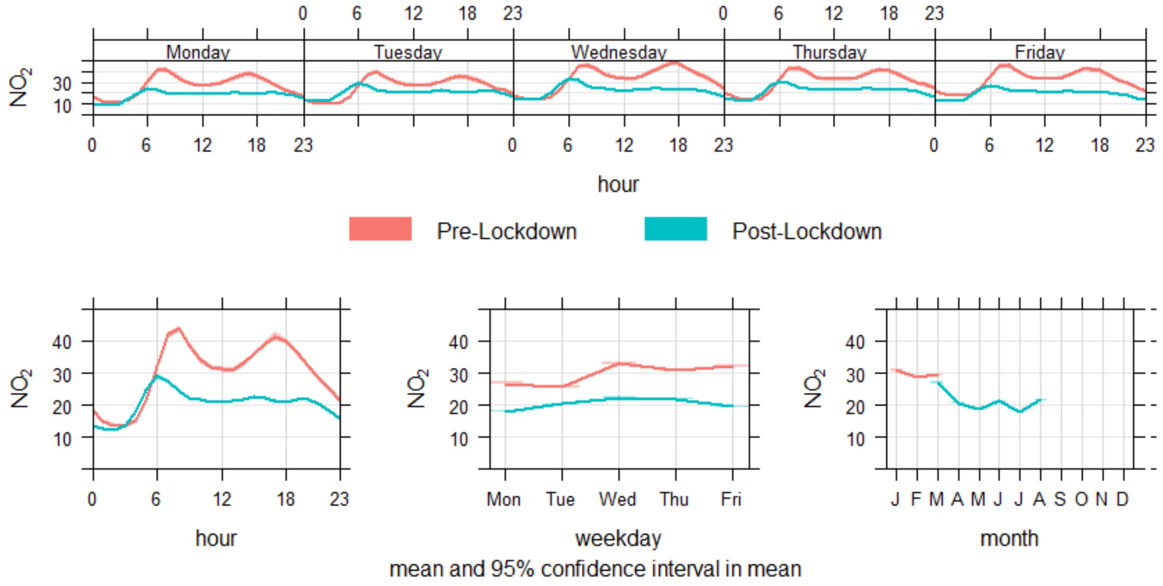

Figure 3 Time variation of NO_2 (μg/m^3) during pre- and post-lockdown periods for traffic sites between January and August, 2020 (Confidence Interval is represented by line width).

Descriptive statistics were also produced for the pre- and post-lockdown periods in 2020 (see Table 2). For the pre-lockdown period, mean NO_2 concentrations (μg/m^3) at background sites were 20.49 (SD = 17.05, SE = 0.06), and at traffic sites mean NO_2 concentrations were 29.83 (SD = 22.81, SE = 0.10). For the post-lockdown period, mean NO_2 concentrations (μg/m^3) at background sites were 11.74 (SD = 12.98, SE = 0.08), and at traffic sites mean NO_2 concentrations were 19.8 (SD = 14.92, SE = 0.05).

Table 2 Mean NO_2 (μg/m^3) comparisons pre-, during, and post- lockdown at background and traffic sites.

	Pre-lockdown		Lockdown		Post-lockdown	
	Background	Traffic	Background	Traffic	Background	Traffic
Count	70098	49296	28057	20267	107998	77073
Mean	20.49	29.83	15.75	22.82	11.74	19.8
Standard Deviation	17.05	22.81	12.98	16.37	9.53	14.92
Median	15.23	24.66	11.67	18.43	9.08	16.15
Standard Error	0.06	0.10	0.08	0.12	0.03	0.05

3.3 Meteorological Adjustment

The outcomes of the testMod function were suitably low and the root mean squared was sufficient to provide confidence in the model, with -1% for background sites and 1.8% for traffic sites. The two-way interactions between wind speed and air temperature indicate that, particularly at background sites, NO_2 concentrations were higher when atmospheric conditions were stable with low temperatures and low wind speeds (Figures 4 and 5). The plots also indicate thatNO_2 concentrations tend be higher with higher temperatures. This is likely due to greater available ground-level O_3 for conversion of NO to NO_2.

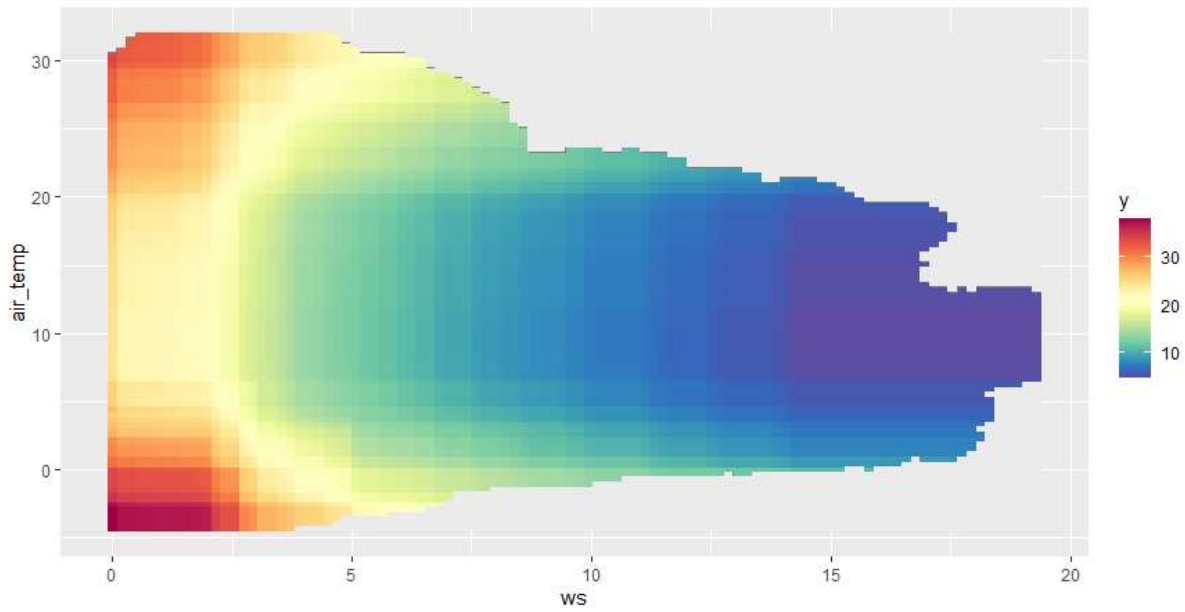

Figure 4 Modelled two-way interactions between wind speed and air temperature on NO_2 (µg/m^3) (y) at background sites.

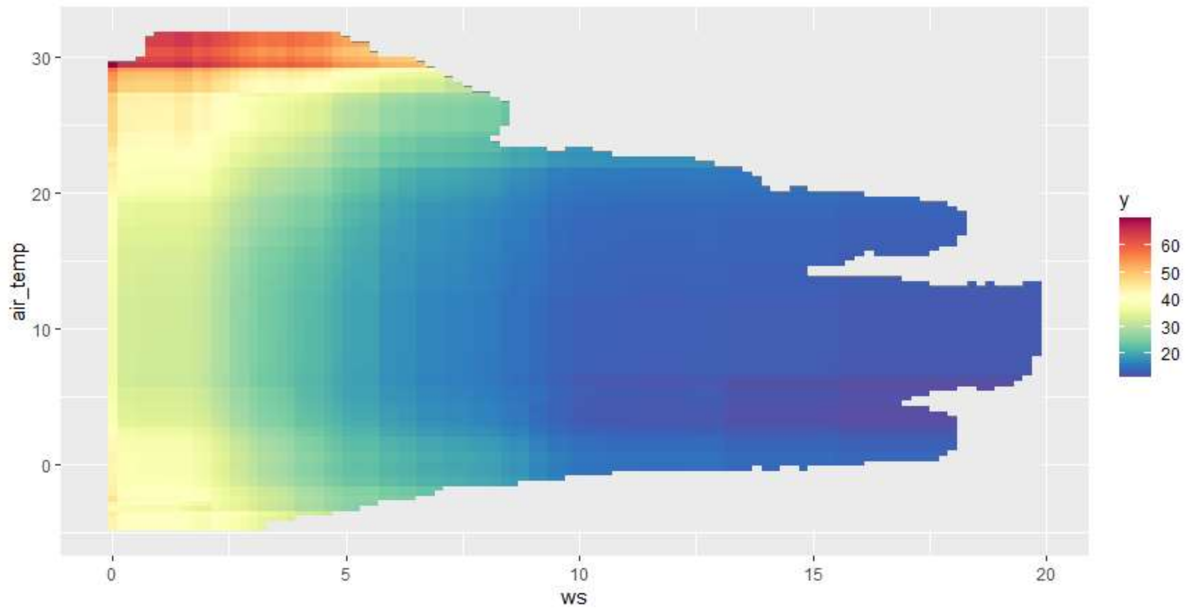

Figure 5 Modelled two-way interactions between wind speed and air temperature on NO_2 ($\mu g/m^3$) (y) at traffic sites.

A comparison between the meteorologically adjusted predicted NO_2 concentrations and the recorded data for the month following the lockdown measures (23rd March to 23rd April, 2020) is shown in Table 3.

Table 3 Comparison of recorded (observed) and meteorologically adjusted (predicted) mean data.

	Background		Traffic	
NO_2 ($\mu g/m^3$)	Observed	Predicted	Observed	Predicted
Count	28057	576	20267	576
Mean	15.75	14.18	22.82	20.93
Standard Deviation	12.98	2.39	16.37	3.52
Median	11.67	13.53	18.43	19.89
Standard Error	0.08	0.1	0.11	0.15

For the lockdown period, meteorologically adjusted predictions of NO_2 concentrations for background sites (M = 14.18, SE = 0.1) are lower than recorded concentrations (M = 15.75, SE = 0.08). Meteorologically adjusted predictions of NO_2 concentrations for traffic sites (M = 20.93, SE = 0.15) are lower than recorded concentrations (M = 22.82, SE = 0.11).

The meteorological adjustments for NO_2 are representative of the potential effect of weather on recorded background and traffic concentrations, reducing levels by 9.97% and 8.28%, respectively.

4.0 Discussion

The analysis provides an overview of the air pollution changes as a consequence of the COVID-19 lockdown, and the reductions of NO_2 in the vicinity of schools in England. A significant reduction of NO_2 took place following the stay-at-home order on March 23rd and the trends indicated a sustained reduction of NO_2 at background and traffic sites for several months following the announcement.

Both traffic and background site data indicated significant reductions on schooldays. Around schools in England, NO_2 concentration reductions during lockdown when compared to the five-year historical mean for background and traffic sites ranged between 35.13% and 40.85%. Once the data was adjusted for meteorological influence, the potential reductions increased, although the range narrowed to between 41.60% and 45.75 %. The general trends show a steep decline of NO_2 concentrations at both background and traffic sites at the start of the lockdown measures.

Temporal trends for both site groups were similar, although a sharper reduction was visible at the traffic sites, indicating a lag between the traffic and background sites. This behaviour is to be expected when considering pollution from traffic sites, which are characteristically proximal to road sources, and background sites, which are further from those sources, and will take longer to be affected by any related changes. For the same reason, it is also understandable that diurnal traffic would not affect background sites as much as those near roadsides.

The lockdown NO_2 concentration means showed a reduction of 4.74 μg/m^3 for background sites and 7.01 μg/m^3 for traffic sites when compared to the pre-lockdown period. This trend continued into the post-lockdown period, with further respective reductions for background and traffic sites of 4.01 μg/m^3 and 3.02 μg/m^3, although an increase is observable towards the end of the period as restrictions become more relaxed. Analyses of the reduction support arguments for lower levels of traffic around schools to reduce potential child exposure to air pollutants. Policies that encourage active travel and discourage unnecessary vehicular use during peak traffic times can lower air pollution in the vicinity of schools when children are on the school run, but can also improve air quality for all of those who must travel at these particularly polluted periods of each day.

Improvements to traffic management can help to reduce pollution at the most congested periods of the day, which is particularly relevant for the reduction of child exposure to pollutants during peak traffic periods on weekday mornings. Indeed, policies and interventions that encourage active travel will be further benefitted by more general reductions in peak traffic and accompanying pollution. The study results support the position of research relating to measures for improved management of traffic, including school travel planning (Cairns et al., 2008), promotion of active travel (McDonald et al., 2014; Smith et al., 2015), walking school buses (Dirks et al., 2016), improved workplace travel initiatives and planning (Macmillan et al., 2013), improvements to public transport, school buses and related incentives (Schraufnagel et al., 2019), carpooling and car-sharing (Hasan et al., 2016), teleworking (Giovanis, 2018) and anti-idling campaigns (Eghbalnia et al., 2013; Ryan et al., 2013). The results indicate that practices such as working from home, active travel, and a reduction of non-essential travel can help to maintain these reductions outside of the lockdown, and the discouragement of driving to school during peak traffic times can also assist in the reduction of child exposure to harmful pollutants.

5.0 Conclusion

Due to their sensitivity, developing physiology and regular exposure to heavy traffic, children are an at-risk group who are particularly susceptible and vulnerable to high concentrations of traffic-related air pollution. Schools and associated travel present areas of interest for the reduction of traffic-related air pollution and the mitigation of child exposure. The current study has demonstrated that the measures taken as part of the UK stay-at-home order, such as teleworking, the reduction of non-essential travel and the removal of traffic related to school runs, have significantly reduced air pollution in the vicinity of schools in England. Limitations of the current study include the focus on NO_2 and schools in England. Future research should investigate the interactions between other traffic-related pollutants, including the effects of meteorology, and in different regions of the UK.

In order to maintain the pollution reductions highlighted in the current study, it is essential to develop and implement effective behavioural strategies towards the reduction of peak traffic. Whilst this can be partly achieved by a reduction of school-related traffic, it is also important to develop broader strategies to reduce overall levels of traffic to ensure that child exposure in active travel at peak times remains low.

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References

Aras, B., Yorulmazlar, E., 2020. The Day After Covid-19: Capacity, Governance and Order. Istanbul Policy Center. Sabanci University. Retrieved from: https://ipc.sabanciuniv.edu/Content/Images/CKeditorImages/20200717-00070919.pdf (accessed 11 December 2020).

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

Cairns, S., Sloman, L., Newson, C., Anable, J., Kirkbride, A., Goodwin, P., 2008. Smarter Choices: Assessing the Potential to Achieve Traffic Reduction Using 'Soft Measures'. Transport Reviews, 28(5), pp. 593-618. https://doi.org/10.1080/01441640801892504.

Carslaw, D., 2020. Deweather: An R package to remove meteorological variation from air quality data. GitHub. https://github.com/davidcarslaw/deweather (accessed 11 December 2020).

Defra. 2020a. Site Environment Types. Monitoring Networks. Department for Environment Food & Rural Affairs. https://uk-air.defra.gov.uk/networks/site-types (accessed 11 December 2020).

Defra. 2020b. Data Selector. Department for Environment Food & Rural Affairs. https://uk-air.defra.gov.uk/data/data_selector (accessed 12 February 2021).

Defra. 2020c. Interactive Monitoring Networks Map. Department for Environment Food & Rural Affairs. https://uk-air.defra.gov.uk/interactive-map (accessed 12 February 2021).

Defra. 2020d. Automatic Urban and Rural Network (AURN). Automatic Networks. Department for Environment Food & Rural Affairs. https://uk-air.defra.gov.uk/networks/network-info?view=aurn (accessed 11 December 2020).

Directive 2008/50/EC, Annex III and VIII-ozone. https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex%3A32008L0050 (accessed 11 December 2020).

Dirks, K. N., Wang, J. Y., Khan, A., Rushton, C., 2016. Air pollution exposure in relation to the commute to school: a Bradford UK case study. International journal of environmental research and public health, 13(11), pp. 1064. https://doi.org/10.3390/ijerph13111064.

Dutheil, F., Baker, J. S., Navel, V., 2020. COVID-19 as a factor influencing air pollution?. Environmental Pollution. 263, Part A. https://doi.org/10.1016/j.envpol.2020.114466.

Eghbalnia, C., Sharkey, K., Garland-Porter, D., Alam, M., Crumpton, M., Jones, C., Ryan, P., 2013. A Community-Based Participatory Research Partnership to Reduce Vehicle Idling Near Public Schools. Journal of Environmental Health, 75(9), pp. 14-9. PMID: 23734527.

Esposito, S., Tenconi, R., Lelii, M., Preti, V., Nazzari, E., Consolo, S., Patria, M. F., 2014. Possible molecular mechanisms linking air pollution and asthma in children. BMC pulmonary medicine, 14(1), pp. 31. https://doi.org/10.1186/1471-2466-14-31.

Giovanis, E., 2018. The relationship between teleworking, traffic and air pollution. Atmospheric Pollution Research, 9(1), pp. 1-14. https://doi.org/10.1016/j.apr.2017.06.004.

Goldizen, F. C., Sly, P. D., Knibbs, L. D., 2016. Respiratory effects of air pollution on children. Pediatric pulmonology, 51(1), pp. 94-108. https://doi.org/10.1002/ppul.23262.

Grange, S. K., Lee, J. D., Drysdale, W. S., Lewis, A. C., Hueglin, C., Emmenegger, L., Carslaw, D. C., 2020. COVID-19 lockdowns highlight a risk of increasing ozone pollution in

European urban areas, Atmos. Chem. Phys. Discuss., in review, 2020. https://doi.org/10.5194/acp-2020-1171.

Guarnieri, M., & Balmes, J. R., 2014. Outdoor air pollution and asthma. The Lancet, 383(9928), pp. 1581-1592. https://doi.org/10.1016/S0140-6736(14)60617-6.

Hasan, R., Bhatti, A. H., Hayat, M. S., Gebreyohannes, H. M., Ali, S. I., Syed, A. J., 2016. Smart peer carpooling system. In: 2016 3rd MEC International Conference on Big Data and Smart City (ICBDSC), March 2016, pp. 1-6. IEEE. https://doi.org/10.1109/ICBDSC.2016.7460384.

Iacobucci, G., 2020. Covid-19: UK lockdown is “crucial” to saving lives, say doctors and scientists. BMJ 2020; 368:m1204. https://doi.org/10.1136/bmj.m1204.

Jackson, J., Posch, C., Bradford, B., Hobson, Z., Kyprianides, A., Yesberg, J., 2020. The lockdown and social norms: Why the UK is complying by consent rather than compulsion. LSE Blogs (April 27). https://blogs.lse.ac.uk/politicsandpolicy/lockdownsocial-norms (accessed 11 December 2020).

Kampa, M., Castanas, E., 2008. Human health effects of air pollution. Environmental Pollution., 151(2), pp. 362-367. https://doi.org/10.1016/j.envpol.2007.06.012.

Macmillan, A. K., Hosking, J., Connor, J. L., Bullen, C., Ameratunga, S., 2013. A Cochrane systematic review of the effectiveness of organisational travel plans: Improving the evidence base for transport decisions. Transport policy, 29, pp. 249-256. https://doi.org/10.1016/j.tranpol.2012.06.019.

McDonald, N. C., Steiner, R. L., Lee, C., Rhoulac Smith, T., Zhu, X., Yang, Y., 2014. Impact of the safe routes to school program on walking and bicycling. Journal of the American Planning Association, 80(2), pp. 153-167. https://doi.org/10.1080/01944363.2014.956654.

NAEI (2020). Overview of air pollutants. Pollutant Information: Nitrogen Oxides. National Atmospheric Emissions Inventory, UK. https://naei.beis.gov.uk/overview/pollutants?pollutant_id=6 (accessed 11 December 2020).

Ryan, P. H., Reponen, T., Simmons, M., Yermakov, M., Sharkey, K., Garland-Porter, D., Eghbalnia, C., Grinshpun, S. A., 2013. The impact of an anti-idling campaign on outdoor air quality at four urban schools. Environmental Science: Processes & Impacts, 15(11), pp. 2030-2037. https://doi.org/10.1039/c3em00377a.

Schraufnagel, D.E.; Balmes, J.; Cowl, C.T.; De Matteis, S.; Jung, S.-H.; Mortimer, K.; Perez-Padilla, R.; Rice, M.B.; Riojas-Rodroguez, H.; Sood, A., 2018. Air pollution and non-communicable diseases: A review by the forum of international respiratory societies' environmental committee. Part 2: Air pollution and organ systems. Chest 2018, 155, pp. 417–426. https://doi.org/10.1016/j.chest.2018.10.041.

Searing, D. A., Rabinovitch, N., 2011. Environmental pollution and lung effects in children. Current opinion in pediatrics, 23(3), pp. 314-318. https://doi.org/10.1097/mop.0b013e3283461926.

Sibley, C. G., Greaves, L. M., Satherley, N., Wilson, M. S., Overall, N. C., Milojev, P., Bulbulia, J., Osborne, D., Milfont, T. L., Houkamau, C. A., Duck, I. M., Vickers-Jones, R., Barlow, F. K., 2020. Effects of the COVID-19 pandemic and nationwide lockdown on trust, attitudes toward government, and well-being. American Psychologist. https://doi.org/10.1037/amp0000662

Smith, L., Norgate, S. H., Cherrett, T., Davies, N., Winstanley, C., Harding, M., 2015. Walking school buses as a form of active transportation for children—a review of the evidence. Journal of school health, 85(3), pp. 197-210. https://doi.org/10.1111/josh.12239.

WHO. 2018. Air pollution and child health: prescribing clean air. WHO/CED/PHE/18.01. Retrieved from: http://www.who.int/ceh/publications/Advance-copy-Oct24_18150_Air-Pollution-and-Child-Health-merged-compressed.pdf (accessed 11 December 2020).

Zhou, Y., Levy, J.I., 2007. Factors influencing the spatial extent of mobile source air pollution impacts: a meta-analysis. BMC Public Health, 7:89. https://doi.org/10.1186/1471-2458-7-89.