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Comparing different approaches for assessing the impact of COVID-19 lockdown on urban air quality in Reading, UK

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Abstract

Many studies investigated the impact of COVID-19 lockdown on urban air quality, but their adopted approaches have varied and there is no consensus as to which approach should be used. In this paper we compare three of the main approaches and assess their performance using both estimated and measured data from several air quality monitoring stations (AQMS) in Reading, Berkshire UK. The approaches are: (1) Sequential approach - comparing pre-lockdown and lockdown periods 2020; (2) Parallel approach - comparing 2019 and 2020 for the equivalent time of the lockdown period; and (3) Machine learning modelling approach - predicting pollution levels for the lockdown period using business as usual (BAU) scenario and comparing with the observations. The parallel and machine learning approaches resulted in relative higher reductions and both showed strong correlation (0.97) and less error with each other. The sequential approach showed less reduction in NO and NOx, showed positive gain in PM_{10} and NO_2 at most of the sites and demonstrated weak correlation with the other two approaches, and is not recommended for such analysis. Overall, the sequential approach showed -14, +4, -32, and +56 % change, the parallel approach showed -46, -43, -43 and +7 % change, and the machine learning approach showed -47, -44, -38 and +5 % change in NOx, NO_2, NO and PM_{10} concentrations, respectively. The pollution roses demonstrated that the UK received easterly polluted winds from the central and eastern Europe, promoting secondary particulates and O_3 formation during the lockdown. Changes in pollutant concentrations vary both in space and time according to the approach used, environment type of the monitoring site and the data type (e.g., deweathered vs. raw data). Therefore, the reported results (here or elsewhere) should be viewed in light of these factors before making any conclusion.

Keywords: air quality, COVID-19, deweathering, lockdown, intervention, generalised additive model.

1. Introduction

Following the COVID-19 pandemic over 4 million people were infected and more than 120 thousand people died in the UK (GOV_UK, 2021). The first case of COVID-19 in the UK was confirmed in January 2020 and the number of cases increased rapidly to March 2020. As a result the UK Government had no option but to declare a national lockdown in the country on 23rd March 2020 (Air Quality Expert Group (AQEG), 2020). Educational institutes were shut down, people were asked to work from home where possible and to stay indoors, except for certain reasons, and, as a result, the economy slowed down and energy consumption decreased, particularly from reduced road traffic, rail services and aviation (Jephcote et al., 2021). These 'lockdown' measures also reduced air pollutants and greenhouse gas emissions significantly, which was also highlighted widely in a variety of media channels (e.g., Dixon, 2020; Quinio and Enenkel, 2020), which reported a reduction in atmospheric pollutant concentrations. COVID-19 lockdown therefore acted as a natural country- or even global-scale intervention on air quality conditions.

Numerous studies (e.g., Dacre et al., 2020; Solberg et al., 2021; Jephcote et al., 2021) were published investigating the impact of COVID-19 lockdown on air quality in different countries around the world. Jephcote et al. (2021) analysed data from 129 air quality monitoring stations (AQMS), which are part of the UK Automatic Urban and Rural Network (AURN) operated by DEFRA. This is probably one of the most comprehensive analyses in the UK which quantified changes in air quality during the lockdown period. This study found there was a mean reduction of 38.3 % in NO_2 concentrations and a 16.5 % reduction in $PM_{2.5}$ concentrations in the UK. The reduction in pollutant concentrations was greater at urban traffic sites but more modest at background sites. In contrast, mean O_3 levels increased by 7.6 % with the largest increase at urban traffic (roadside) sites due to reduction in the emissions of NO, which act as a 'scavenger' for O_3.

Dacre et al., (2020) and Solberg et al. (2021) focused only on NO_2 concentrations during the lockdown period using statistical modelling approaches. Dacre et al. (2020) limited their study to the UK and analysed NO_2 data from 142 AURN sites, whereas Solberg et al. (2021) used NO_2 data from over 2000 AQMS from across the Europe including UK. Dacre et al. (2020) reported relatively less reductions in NO_2 concentrations: a 27% mean reduction at urban traffic and 14 % at urban background sites. In contrast, Solberg et al. (2021) estimated 60 %, 51 %, 51 %, 47 % and 43 % reduction in NO_2 concentrations in Spain, Italy, France, Portugal and United Kingdom, respectively. The study reported relatively moderate reduction in NO_2 in the eastern European countries, e.g., 22% and 23 % in Poland and Hungary. Moreover, Shi et al. (2020) analysed the data of NO_2, O_3 and $PM_{2.5}$ from selected cities around the world, including London, to investigate the effect of lockdown measures on these pollutants. According to their findings, NO_2 concentrations showed a 52 % reduction in raw data and an 18 % reduction in deweathered data in London. Due to prevailing weather conditions an episode of $PM_{2.5}$ was experienced in London during the lockdown period. $PM_{2.5}$ concentrations showed significant gains at the roadside (+107.6 %), in an urban background context (+152.9 %) and in more rural sites (+164.5%) in London during the lockdown period (Shi et al., 2020). However, deweathered $PM_{2.5}$ concentrations demonstrated much gentler change while O_3 concentrations showed positive gain at all monitoring sites including London (Shi et al., 2021).

Researchers have employed different approaches for quantifying the effect of COVID-19 lockdown on air pollution. The most common approaches are:

1. Comparing pre-lockdown with the lockdown period. This approach compares observed concentrations of pollutants for the pre-lockdown period with the lockdown period (e.g., Rodríguez-Urrego and Rodríguez-Urrego, 2020; Tobias et al., 2020). We have referred to this technique as a 'sequential approach' in this study.
2. Comparing the lockdown period in 2020 with the equivalent period in previous years (Sicard et al., 2020; Sharma et al., 2020; Shi et al., 2021). This technique has been referred to as the 'parallel approach' in this study. This and the previous method are probably the most common and simple techniques used for this type of analysis.
3. Comparing measured and estimated concentrations for the lockdown period. The estimated concentrations are predicted using different machine learning approaches, such as multiple linear regression, random forest, boosted regression trees and generalised additive model (e.g., Lovric et al., 2020; Solberg et al., 2021; Liu et al., 2021; Jephcote et al., 2021, Ropkins and Tate, 2021).
4. Estimations of chemical transport modelling (CTM) are compared with measured concentrations for the lockdown period. Examples of CTM are the Community Multi-scale Air Quality Model (Wang et al., 2020), NASA GEOS-CF Model (Keller et al.,

2020), WRF-CHIMERE Model (Dumka et al., 2020), and GEOS–Chem Model (Wang et al., 2021).

5. Using air pollutant data derived from satellite maps (e.g., Solberg et al., 2021; Venter et al., 2020; Liu et al., 2020). The last two approaches i.e. chemical transport modelling and using satellite data have not been explored further in this paper.

The techniques using ground-based observations (e.g., NO_2, O_3, PM_{10} and $PM_{2.5}$) are generally considered more reliable and accurate than the techniques using either model estimated or satellite retrieved data. However, the air quality monitoring sites are sparse and machine learning techniques are necessary to support the measured data in terms of spatiotemporal coverage and resolution The statistical and machine learning approaches do not need emission data and models can be trained specifically for each monitoring site using the measured air quality data (e.g., Solberg et al., 2021; Dacre et al., 2020). However, the pollutants data need to be normalised for the effect of meteorology. CTM models require detailed emission, meteorology and geographical information. The changes in emission during the lockdown vary from city to city and country to country and are difficult to obtain with good accuracy (Solberg et al., 2021).

Employing different techniques could result in the amount of change in pollutant concentrations recorded during the lockdown period varying significantly from one study to another even within the same area. For example, authors using different methods analysed the same NO_2 data from the UK AURN and arrived at different results during the lockdown period. Dacre et al. (2020) using multiple linear regression estimated -19, -14 and +20 % change, whereas Jephcote et al. (2021) using boosted regression tree method estimated -38, -36 and -44 % change in NO_2 at urban traffic, urban background and rural sites, respectively across the UK. Similarly, Lee (2020) using parallel method estimated -45 and -38 % change, whereas Murrells (2020) using deweather package estimated -37 and -25 % reduction in NO_2 at urban traffic and urban background sites, respectively across the UK.

This comparison of previous studies shows that different approaches lead to different results. Therefore, here we intend to compare three of these approaches (sequential, parallel and machine-learning modelling), which are the most widely used for determining the impacts of lockdown on air quality. The purpose is to analyse how and why the results of these approaches often vary and which approach could potentially provide more 'realistic' results. The performance of the three approaches are compared using both measured (raw) and deweathered data in a case study urban area (Reading, UK) and the results are discussed in the light of the prevailing weather conditions and emissions changes.

2. Methodology

This study quantifies the effect of COVID-19 lockdown intervention on air quality (AQ) in Reading, Berkshire, United Kingdom. In this paper, the focus is on the first lockdown period (23 March to 10 May 2020). AQ data came from four air quality monitoring stations (AQMS) in Reading, which are described in section 2.1. The measurements of several meteorological parameters are used for deweathering AQ data and estimating pollutant levels using a Business As Usual (BAU) scenario for the lockdown period. Meteorological data are described in section 2.2. Deweathering and modelling techniques are described in section 2.3. This study compares three approaches for quantifying the effect of COVID-19 lockdown on AQ. Statistical software and the three research approaches used in this study are described in section 2.4.

2.1 Air quality monitoring network

Data were obtained from four reference AQMS (Figure 1) in the Reading area. Two of the AQMS (London Rd and Newtown) are part of the UK Automatic Urban and Rural Network (AURN) operated by DEFRA, and the other two AQMS (Oxford Rd and Caversham Rd) are operated by Reading Borough Council (RBC) (Table 1). Pollutant concentrations measured by all four AQMS are NO, NO_2, NOx and PM_{10}. In addition, $PM_{2.5}$ and O_3 are monitored at the Newtown AQMS only. Data for these pollutants were available for the study period. According to DEFRA classification London Rd, Oxford Rd and Caversham Rd are classified as urban traffic (roadside), whereas Newtown site is classified as urban background site. Air quality England has classified London Rd as a rural AQMS. In the light of this difference, we will see in later sections that London Rd site behaves differently from the other two roadside sites.

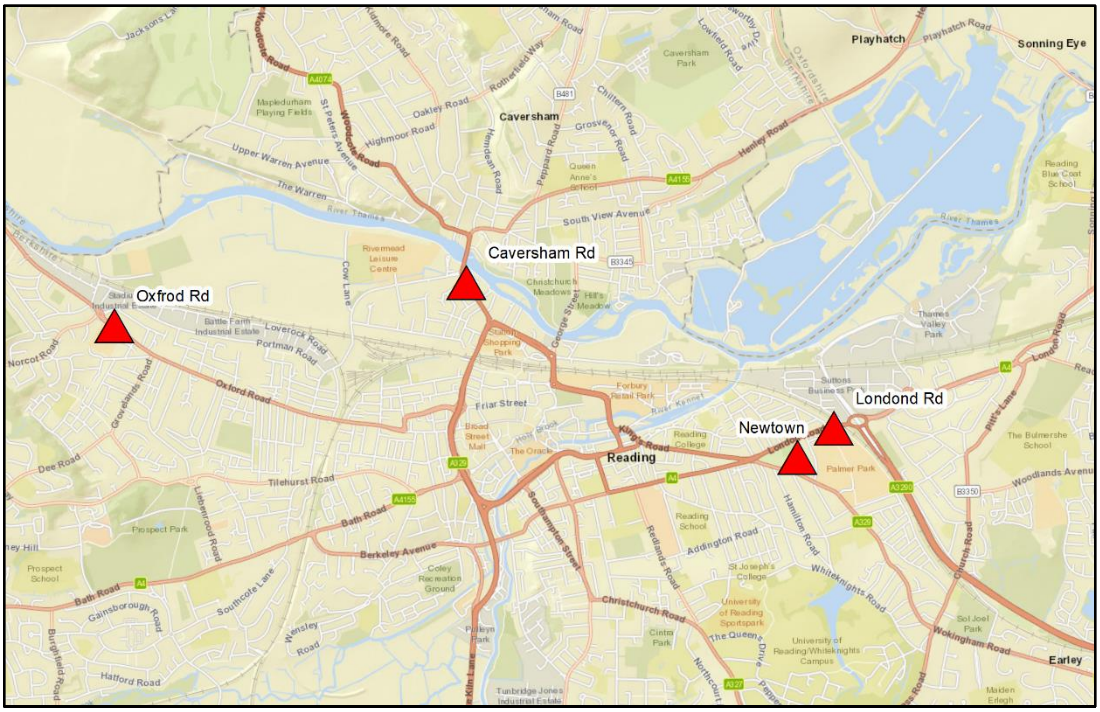


Figure 1. Air Quality Monitoring Network (AQMN) in Reading, where Newtown and London Rd are AURN sites run by DEFRA, whereas Oxford Rd and Caversham Rd sites are run by Reading Borough Council (RBC).

Table 1. Air quality monitoring stations and mean concentrations of pollutants during the lockdown period. RBC = Reading Borough Council, and AURN = automatic urban and rural network.

Site	Site type	Operated by	Pollutants measured
London Rd	Rural/Urban Traffic*	AURN	NO, NO_2, NO_x, PM_{10}
Oxford Rd	Urban Traffic	RBC	
Caversham Rd	Urban Traffic	RBC	
Newtown	Urban Background	AURN	NO, NO_2, NO_x, PM_{10}, $PM_{2.5}$, O_3

*DEFRA has classified this site as an urban traffic site, whereas Air Quality England has classified it as a rural site (Air Quality England, 2021; DEFRA, 2021).

2.2 Meteorological data

Meteorological data from the Met Office high-resolution weather prediction model are available at all AURN sites. However, the meteorological data are not available at the AQMS run by the local authorities, for example RBC. Therefore, estimated meteorological data were not available at Caversham and Oxford Rd sites. As an alternative source, meteorological data were available at the University of Reading Atmospheric Observatory (URAO) for the study period. The Met office weather prediction available at the two AURN sites and the URAO measured weather data were analysed and compared to decide which dataset should be used in the deweathering and machine learning modelling analysis. Correlation analysis and machine learning analysis showed that meteorological data from URAO had a stronger association with measured pollutant concentrations. Therefore, it was decided that the meteorological data from the URAO should be used in this study for two reasons: (a) the measured parameters at URAO had generally stronger correlation with the air pollutants, (b) data for more meteorological parameters e.g., relative humidity and atmospheric pressure were also available at the URAO. Meteorological parameters used were temperature, wind speed, wind direction, atmospheric pressure and relative humidity. In this paper we used relative humidity and not absolute humidity because relative humidity is preferred by most of the researchers (e.g., Jephcote et al., 2021; Solberg et al., 2021, Shi et al., 2021; Collivignarelli et al., 2020) who analysed the relationship between air quality and meteorological conditions during the lockdown period.

2.3 Generalised Additive Model development and deweathering of air quality data

Changes in weather conditions can mask the association between pollutant emissions and atmospheric concentrations, so it is vital to remove the effect of meteorology on AQ to understand the reduction or gain in air pollution concentrations caused by changes in emissions. Removing the effect of variation in weather conditions on air pollutant concentration is referred to as 'deweathering' AQ data, 'weather normalisation', 'weather decoupling' or 'adjusting for meteorological conditions'. To deweather AQ data, researchers have preferred to use different interpretable machine learning techniques such as Boosted Regression Trees (TRB) (e.g., Carslaw, 2018; Jephcote et al., 2021), random forest (Grange et al., 2018; Shi et al., 2021), and generalised additive modelling (Solberg et al., 2021; Ropkins and Tate, 2021; Carslaw et al., 2007). In this paper, a generalised additive model (GAM) was employed, which is considered to be an interpretable supervised machine learning technique that can provide functional association between each predictor and the predictand variables. This is in contrast to the other uninterpretable or less interpretable machine learning techniques that tend to produce 'black-box' results (Solberg et al., 2021). GAM has already been described in detail by several authors (e.g., Solberg et al., 2021; Carslaw et al., 2007 and the relevant references therein).

To deweather the AQ data using GAM, we used temperature, wind speed, wind direction, atmospheric pressure and relative humidity data provided by URAO. In addition, hour of the day, day of the month and week of the year were used as predictors to account for temporal variations. Models were fitted on an 80 % training dataset and cross-validated on a 20% testing dataset, both randomly selected. Models demonstrating satisfactory performance on cross-validation were then applied to deweather the whole datasets. Separate models were developed for 2018-2019 and 2020. For predicting BAU scenario, the GAM model was trained and validated using 2018 and 2019 data and then used to predict the lockdown period from 24 March to 10 May 2020.

For evaluating the models performance, predicted and measured concentrations were compared and several statistical metrics were calculated. The metrics used in this study were: correlation coefficients (r), factor of two (Fac2), root mean squared error (RMSE), mean absolute error (MAE) and mean biased error (MBE). MAE and RMSE show the size of the average error, however they do not provide information whether the model is over predicting or under predicting as these are based on absolute value of the difference. On the other hand, MBE describes the direction of the error bias, where a negative value of MBE shows that predicted values are smaller than the observed values i.e model is under predicting. FAC2 is the percentage of the predictions within a factor of two of the observed values, and correlation coefficient shows the linear association between predicted and observed values. The GAM model is presented in equations 1 and 2 and the values of these metrics for both fitted (using training dataset) and cross-validated (using testing dataset) models are provided in Table 2.

$$Y = s_1(X_1) + s_2(X_2) + \ldots + s_n(X_n) \qquad (1)$$

Where Y is the predictand (response variable) and s_i is the smoothing parameter associated with the predictors or explanatory variables (Xi) of the model. According to equation 1, the GAM model, using NO_2 as an example of the predictands , can be written as shown in equation 2:

$$[NO_2] = s_1(rh) + s_2(ws) + s_3(wd) + s_4(p) + s_5(temp) + s_6(hr) + s_7(day) + s_8(wk) \qquad (2)$$

Where rh, ws, wd, p, temp, hr, day, wk are relative humidity, wind speed, wind direction, atmospheric pressure, temperature, hour of the day, day of the month and week of the year, respectively.

Table 2. GAM validation in terms of statistical metrics calculated by comparing the predictions of both fitted and cross-validated models with observed concentrations.

Site	Modelled pollutant	Model	r	Fac2	RMSE	MAE	MBE	n
London Rd	NO_2	FM	0.79	0.84	11.64	8.81	1.72e-13	13416
		CV	0.79	0.84	11.50	8.75	0.53	3351
	NO	FM	0.68	0.44	22.81	14.14	-.178e-13	13416
		CV	0.67	0.44	21.13	13.67	1.17	3351
	NOx	FM	0.73	0.64	42.78	28.21	-4.08e-13	13416
		CV	0.73	0.65	40.36	27.42	2.32	3351
	PM_{10}	FM	0.55	0.78	9.60	6.98	-6.01e-13	12854
		CV	0.54	0.78	9.29	6.84	0.28	3220
Oxford Rd	NO_2	FM	0.75	0.84	11.43	8.55	-2.41e-12	13638
		CV	0.74	0.83	11.32	8.46	0.17	3394
	NO	FM	0.65	0.51	23.46	14.15	-2.29e-12	13638
		CV	0.65	0.50	23.39	13.90	0.26	3394
	NOx	FM	0.69	0.70	43.14	27.67	-6.16e-12	13638
		CV	0.69	0.70	42.77	27.06	0.57	3394
	PM_{10}	FM	0.54	0.88	10.84	7.47	3.73e-12	13662
		CV	0.54	0.87	10.84	7.50	-0.01	3414
Caversham Rd	NO_2	FM	0.73	0.84	17.54	12.42	-1.22e-11	13507
		CV	0.73	0.85	17.63	12.15	-0.22	3387
	NO	FM	0.69	0.55	22.66	15.34	-2.29e-12	13528
		CV	0.69	0.56	22.85	15.37	-0.11	3393
	NOx	FM	0.73	0.75	45.52	32.32	-6.92e-12	13507
		CV	0.74	0.75	45.83	32.33	-0.42	3387
	PM_{10}	FM	0.49	0.87	12.35	8.01	9.53e-13	13229
		CV	0.45	0.87	13.34	8.25	-0.10	3316
Newtown	NO_2	FM	0.80	0.93	9.04	6.67	-1.43e-11	10911
		CV	0.80	0.93	9.00	6.65	0.17	2705
	NO	FM	0.62	0.30	14.52	7.32	-5.55e-12	10911
		CV	0.66	0.30	13.30	7.30	0.02	2705
	NOx	FM	0.73	0.79	26.08	14.72	-2.87e11	10911
		CV	0.75	0.78	24.31	14.63	0.21	2705
	PM_{10}	FM	0.58	0.73	7.73	5.65	1.09e-12	9052
		CV	0.56	0.74	7.81	5.62	0.02	2231
	$PM_{2.5}$	FM	0.64	0.65	6.48	4.59	-2.94e-12	9119
		CV	0.64	0.69	6.26	4.44	0.13	2246
	O_3	FM	0.88	0.84	12.56	9.77	1.54e-11	11209
		CV	0.88	0.84	12.77	9.95	0.02	2772

Note: FM, CV, r, Fac2, RMSE, MAE, MBE and n are fitted model, cross validated model, correlation coefficient, factor of two, root mean squared error, mean absolute error, mean biased error and the number of observations, respectively.

2.4 Three approaches to estimate the impact of lockdown on air quality

The novelty of this study is that it applies and compares three different approaches for extracting the effect of COVID-19 lockdown intervention on air pollutant concentrations. Furthermore, in this study both raw and deweathered data were used. The three approaches are:

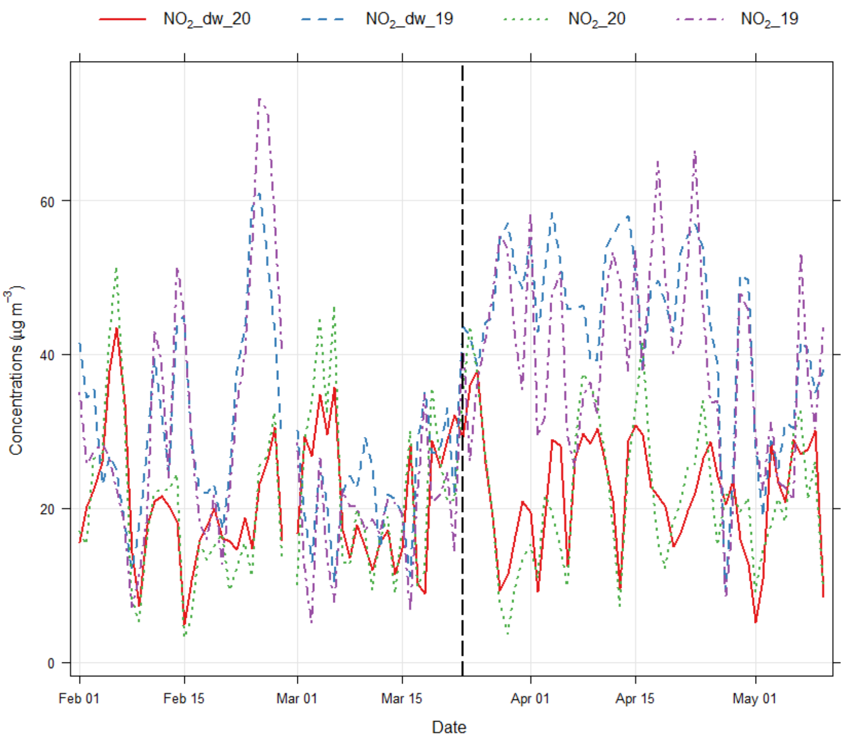
1. Sequential approach - Comparing pre-lockdown and lockdown periods in 2020. The period from 1 February to 23 March was considered as pre-lockdown, the period from 24 March to 10 May was considered as lockdown, and the period from 11 May to 30 June was considered as post lockdown period.
2. Parallel approach - Comparing 2019 and 2020 for equivalent months of the lockdown period. In this case, the lockdown period (24 March to 10 May) of 2020 was compared with the equivalent time period in 2019. Air pollutant levels have a decreasing trend over the last decade or so in the UK, as a result pollutant levels were significantly higher in 2010 than in 2019. Therefore, averaging air quality data over a longer period of time have the issue of long term trend which needs to be removed before comparing it with 2020, which will make the analysis more complicated. In contrast, difference between two consecutive years will be much lower and can be ignored. Therefore, in this study we did not consider average of the past several years (e.g., 2010 to 2019) and simply compared 2019 with 2020.
3. Machine learning modelling approach - Predicting pollution levels for the lockdown period using business as usual (BAU) scenario and comparing predicted and observed concentrations for the same period. Models were trained and validated on 2018 and 2019 and applied to predict pollutant levels for the lockdown period (24 March to 10 May 2020). The difference between the predicted and observed concentrations was considered as the change (reduction/gain) in pollutant levels due the lockdown measures.

R programming language (R Core Team, 2020) and several of its packages were used for data analysis, mainly ‘openair’ (Carslaw, 2019) and ‘mgcv’ (Wood, 2020). Openair – package was used for general data analysis and producing various visualisations, whereas mgcv-package was used for training/fitting, cross-validating and evaluating the goodness-of-fit of GAM. The ‘mgcv-package’ was also used for deweathering the AQ data.

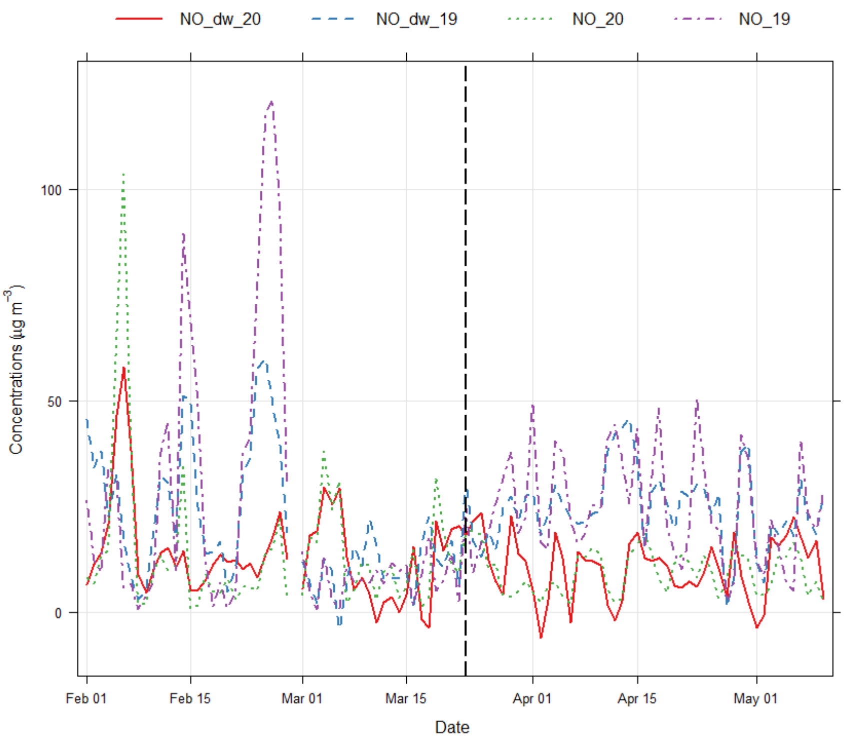
3 Results and discussion

Here, we first present a general picture of the pollutant levels during the pre-lockdown and lockdown period for both year 2019 and 2020 using both raw and adjusted data. Figure 2 presents the daily concentrations of NO, NO_2 and PM_{10} for the pre-lockdown and lockdown periods for both 2019 and 2020 at Caversham site, used as an example. The black vertical line (23rd March) is a separation line between the pre-lockdown and lockdown periods. Figure 2 shows how the levels of pollutants change during these periods including the transition period. Levels of both deweathered and raw NO and NO_2 have increased during the equivalent lockdown period in 2019, whereas they have decreased in the lockdown period 2020. The difference in NO_2 concentrations between 2019 and 2020 during the lockdown period is evident. However, in contrast the levels of PM_{10} seem to have increased during the mid of April for both years and there seem to be no impact of the lockdown on PM10 levels. Increase in PM_{10} levels during the lockdown period has been discussed later.

The changes in air pollutant levels during the lockdown period are presented in three sections (3.1, 3.2 and 3.3) according to the three approaches used for analysing the effect of lockdown measures on air quality.



NO2_dw_20
NO2_dw_19
NO2_20
NO2_19
Concentrations (µg m-3)
Date
Feb 01
Feb 15
Mar 01
Mar 15
Apr 01
Apr 15
May 01
0
20
40
60



NO_dw_20
NO_dw_19
NO_20
NO_19
Concentrations (µg m-3)
Date
Feb 01
Feb 15
Mar 01
Mar 15
Apr 01
Apr 15
May 01
0
50
100

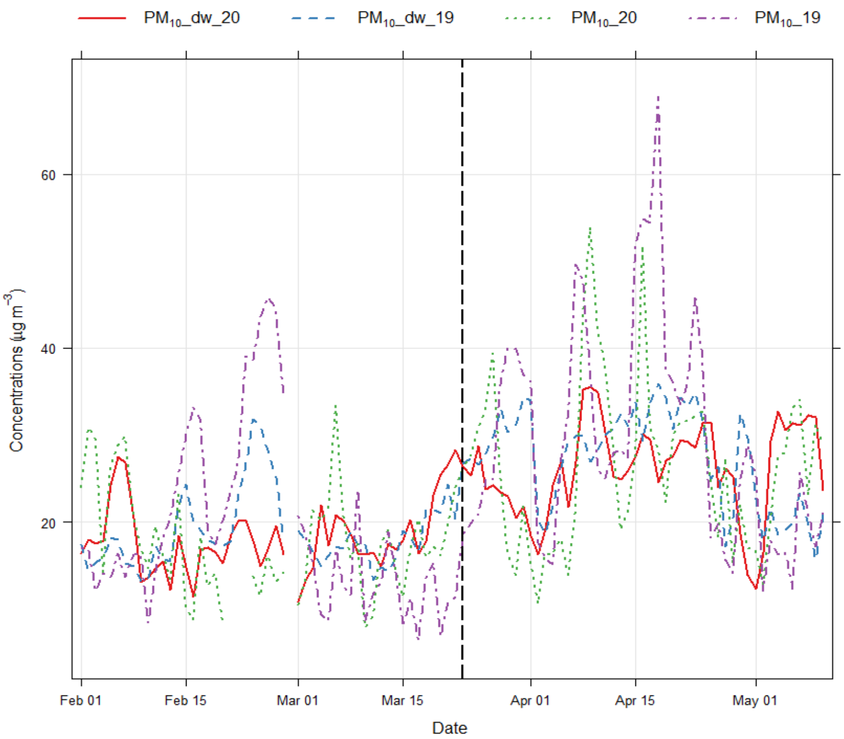


Figure 2. Comparing the levels of raw and deweathered NO, NO_2 and PM_{10} for the pre-lockdown and lockdown periods for both year 2019 and 2020 at Caversham Rd site. The black vertical line (23rd March) separate pre-lockdown and lockdown period.

3.1 Sequential approach

Data from all four AQMS were downloaded and deweathered using the GAM supervised machine learning technique. Both raw and deweathered concentrations of different pollutants were compared for the pre-lockdown and lockdown periods.

Both raw and deweathered concentrations of NOx and NO have *decreased*, whereas that of PM_{10} have *increased* at all four sites during the lockdown period. Concentrations of NO_2 have increased at three out of four sites. However, O_3 and $PM_{2.5}$ were only monitored at Newtown site, where both have shown positive gain in their concentrations (Table 3). Figure 3 shows that the reduction in pollutant concentrations is different during different days of the week. Interestingly, at weekends there has been a greater reduction in pollutants than during weekdays. Both raw and deweathered data show the same weekly pattern. However, reductions in deweathered data are relatively less than in the raw data. Figure 4 shows how the change in NO_2 and O_3 varied on different days of the week, confirming the opposite trend in NO_2 and O_3 concentrations. O_3 concentrations have shown the highest gain at the weekend due to the O_3 weekend effect, whereas NO_2 concentrations have shown the largest reduction. The inverse correlation between O_3 and NOx is a well-known fact (Jenkins, 2004; Munir et al., 2013). It should be noted that Newtown is an urban background site, therefore it is not as affected by a reduction in road traffic as much as roadside monitoring stations. The temporal changes in pollutant concentrations also varied at different sites (Figure 3 vs. Figure 4).

It should be noted that air pollutant emissions change substantially from one season to another in the UK (Shi et al., 2021), therefore comparison of pollutant concentrations during different months of the year may lead to biased results. As a result, the sequential approach, which directly compares the pre-lockdown and lockdown period, may produce unreliable results. This is the reason that although road traffic flows have experienced significant reductions (up to 70 %), the concentrations of some pollutants (e.g., PM_{10} and NO_2) have increased. This method, therefore, is not recommended for extracting the effect of lockdown on air pollutant concentrations. When the differences were averaged for all AQMS, the percentage (%) averaged changes in raw and deweathered concentrations of NOx, NO_2, NO and PM_{10} were -17.82, 4.17, -38.99, 61.14 and -9.18, -4.56, -27.42, 55.84, respectively.

Table 3. Comparing pre-lockdown and lockdown concentrations of different pollutants at all four sites. Pollutants with 'dw' show deweathered concentrations and 'diff' stands for difference.

Site	Pollutant	Lockdown	Pre-lockdown	Diff	%Diff
London Rd	NOx	33.49	43.29	-9.80	-22.64
	NO_2	20.59	20.97	-0.38	-1.80
	NO	8.41	14.56	-6.15	-42.22
	PM_{10}	27.86	17.98	9.87	54.90
	NOx_dw	34.53	42.09	-7.56	-17.96
	NO_2_dw	20.82	20.85	-0.02	-0.11
	NO_dw	8.94	13.87	-4.93	-35.54
	PM_{10}_dw	26.96	18.26	8.70	47.66
Newtown	NOx	24.65	25.80	-1.15	-4.47
	NO_2	17.58	16.29	1.30	7.95
	NO	4.60	6.20	-1.60	-25.76
	O_3	65.21	54.04	11.17	20.67
	PM_{10}	23.42	13.05	10.37	79.48
	$PM_{2.5}$	14.91	7.52	7.39	98.31
	NOx_dw	24.35	25.20	-0.85	-3.37
	NO_2_dw	17.29	16.54	0.76	4.57
	NO_dw	4.58	5.66	-1.07	-18.95
	O_3_dw	63.93	53.01	10.92	20.60
	PM_{10}_dw	22.57	13.38	9.19	68.67
	$PM_{2.5}$_dw	14.16	8.00	6.16	77.07
Oxford Rd	NOx	31.79	46.74	-14.95	-31.99
	NO_2	20.15	19.42	0.74	3.80
	NO	7.59	17.82	-10.23	-57.42
	PM_{10}	24.76	16.56	8.21	49.56
	NOx_dw	33.19	45.34	-12.15	-26.80
	NO_2_dw	20.33	19.28	1.05	5.44
	NO_dw	8.30	17.06	-8.75	-51.31
	PM_{10}_dw	23.93	16.50	7.43	45.05
Caversham Rd	NOx	36.07	41.07	-5.00	-12.18
	NO_2	21.74	20.37	1.37	6.71
	NO	9.37	13.50	-4.13	-30.56
	PM_{10}	26.43	16.45	9.97	60.60
	NOx_dw	37.96	40.58	-2.62	-6.46
	NO_2_dw	21.99	20.50	1.49	7.27
	NO_dw	10.35	13.18	-2.83	-21.48
	PM_{10}_dw	26.10	16.12	9.99	61.97

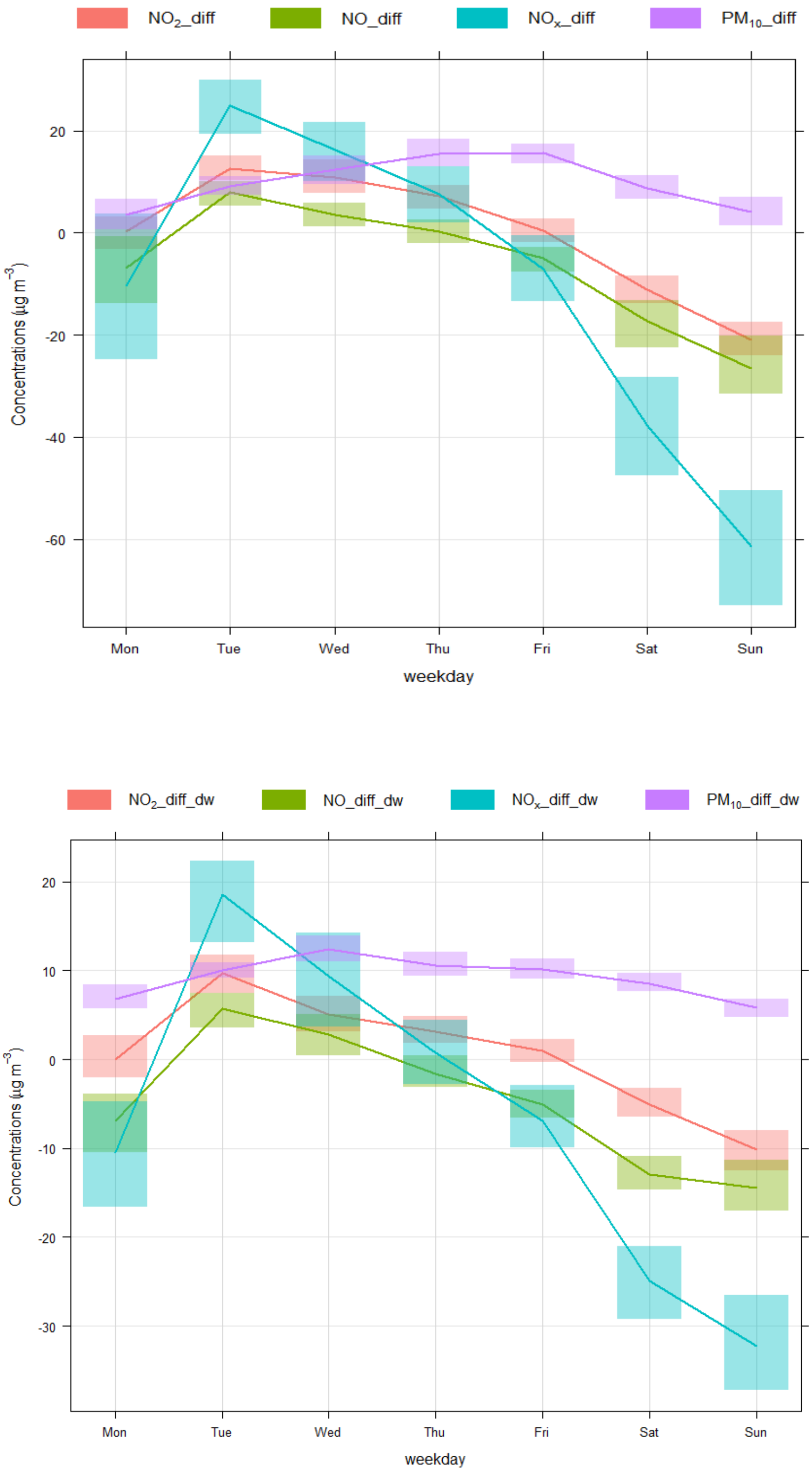


Figure 3. Showing difference in pollutant concentrations between lockdown and pre-lockdown period at London Rd monitoring site. Upper-panel shows raw and bottom-panel shows deweathered concentrations.

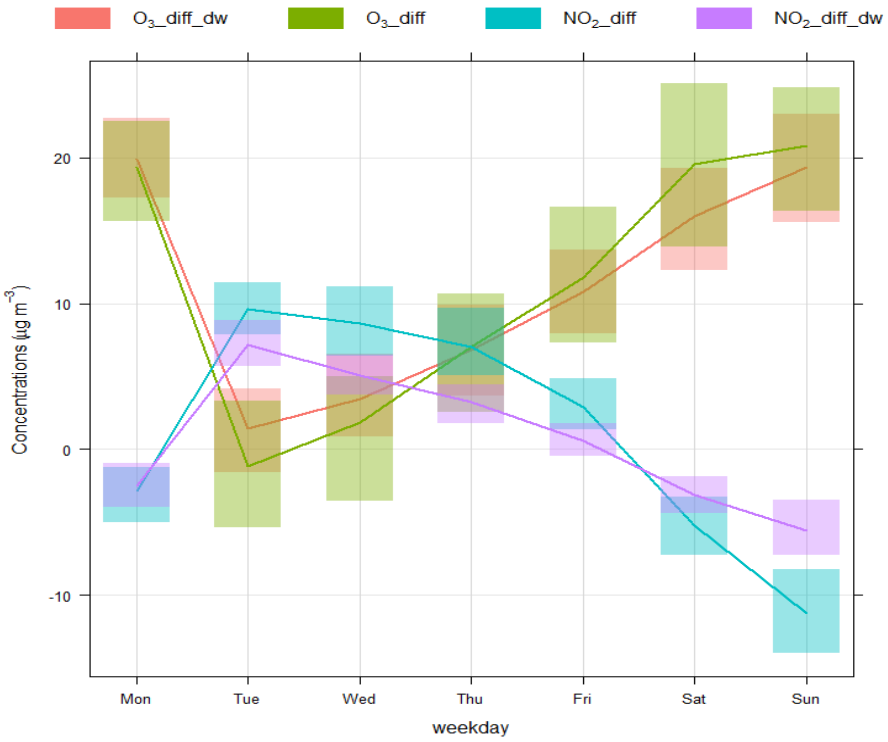


Figure 4. Difference in O_3 and NO_2 concentrations between lockdown and pre-lockdown period at Newtown monitoring site. 'Diff' and 'dw' stand for difference and deweathered, respectively.

3.2 Parallel approach

The differences in pollutant concentrations between 2020 and 2019 for both raw and deweathered data for the lockdown period are shown in Table 4. According to this approach, NOx, NO and NO_2 concentrations showed reductions in both raw and deweathered data at all four sites. However, PM_{10} concentration showed reduction only at Oxford Rd and Caversham Rd site. O_3 and $PM_{2.5}$ demonstrated positive gain at Newtown site. The change in pollutant concentrations during different days of the week at London Rd site is shown in Figure 5. NOx, NO_2 and NO showed the lowest change on Tuesday and the highest on Sunday for the raw data, whereas the results showed the highest change on Saturday and the lowest on Monday for the deweathered data. PM_{10} showed no reduction on any day, except on Monday and Tuesday for the raw data at the London Rd site. Newtown is an urban background site, where pollutant levels are not directly affected by the traffic flow, therefore pollutants have shown less reductions compared to the urban traffic sites. Figure 6 depicts changes in the levels of NOx, NO_2, O_3 and $PM_{2.5}$ and demonstrates as to how changes in pollutant levels vary during different hours of day at Newtown and Oxford Rd sites. The highest changes in NOx, NO_2 and O_3 levels are shown just after the evening peak hours (6 pm) and the lowest just before midday. The O_3 data demonstrated opposite diurnal trend to NOx, which is expected because of their mutual chemical reaction. At oxford Rd site highest differences are shown just after 6 pm, similar to the Newtown site (Figure 6).

Table 4. Comparing the concentrations of different pollutants during 2020 and 2019 for the lockdown period (24 March to 10 May) at all four sites. Pollutants with 'dw' show deweathered concentrations. 'Diff' and '%Diff' stand for difference and percent difference, respectively.

Sites	Pollutant	2020	2019	Diff	%Diff
London Rd	NOx	33.49	62.67	-29.18	-46.56
	NO_2	20.59	34.81	-14.22	-40.84
	NO	8.41	18.17	-9.76	-53.71
	PM_{10}	27.86	25.91	1.94	7.50
	NOx_dw	34.53	66.68	-32.15	-48.21
	NO_2_dw	20.82	34.96	-14.14	-40.44
	NO_dw	8.94	20.70	-11.77	-56.83
	PM_{10}_dw	26.96	23.60	3.36	14.24
Newtown	NOx	24.65	36.64	-12.00	-32.74
	NO_2	17.58	30.45	-12.86	-42.25
	NO	4.04	4.60	-0.57	-14.04
	O_3	65.21	56.28	8.93	15.86
	PM_{10}	23.42	14.75	8.67	58.78
	$PM_{2.5}$	14.91	11.35	3.56	31.37
	NOx_dw	24.35	38.93	-14.58	-37.45
	NO_2_dw	17.29	31.91	-14.62	-45.81
	NO_dw	4.53	4.58	-0.06	-1.25
	O_3_dw	63.93	55.10	8.83	16.03
	PM_{10}_dw	22.57	17.27	5.31	30.73
	$PM_{2.5}$_dw	14.16	13.13	1.03	7.85
Oxford Rd	NOx	31.79	56.88	-25.09	-44.12
	NO_2	20.15	31.71	-11.56	-36.45
	NO	7.59	16.42	-8.83	-53.78
	PM_{10}	24.76	28.81	-4.05	-14.05
	NOx_dw	33.19	60.82	-27.63	-45.44
	NO_2_dw	20.33	32.46	-12.13	-37.37
	NO_dw	8.30	18.49	-10.18	-55.07
	PM_{10}_dw	23.93	27.62	-3.69	-13.36
Caversham Rd	NOx	77.73	36.07	-41.66	-53.60
	NO_2	39.83	21.74	-18.09	-45.41
	NO	24.72	9.37	-15.35	-62.08
	PM_{10}	29.62	26.43	-3.19	-10.78
	NOx_dw	81.53	37.96	-43.58	-53.45
	NO_2_dw	43.95	21.99	-21.97	-49.98
	NO_dw	24.47	10.35	-14.12	-57.71
	PM_{10}_dw	27.33	26.10	-1.23	-4.49

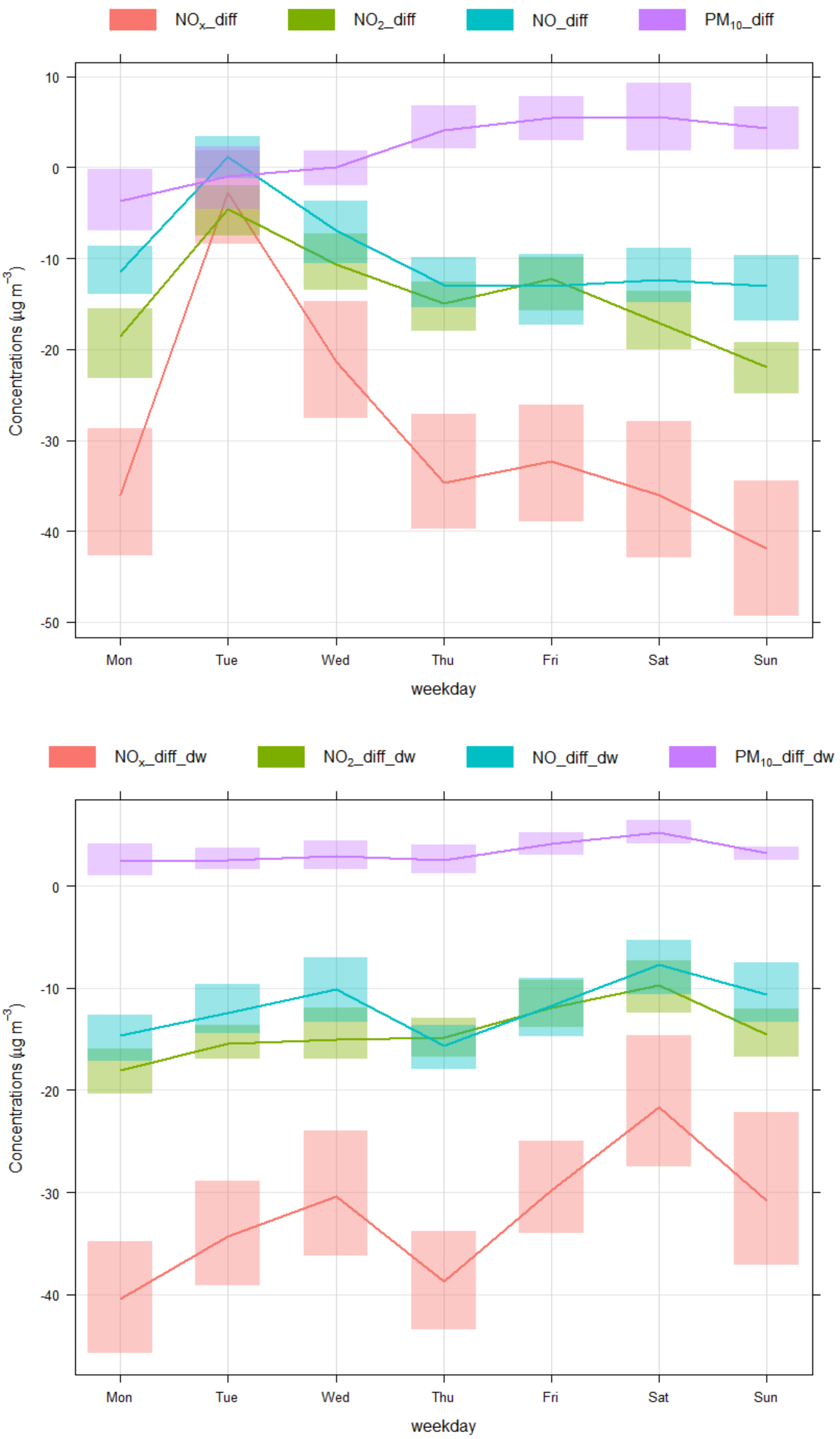


Figure 5. Difference in pollutant concentrations between 2020 and 2019 for the lockdown (24 March to 10 May) period at London Rd monitoring site. Upper-panel shows raw and bottom-

panel shows deweathered concentrations. Pollutant with ‘diff’ and ‘dw’ stand for difference and deweathered concentrations, respectively.

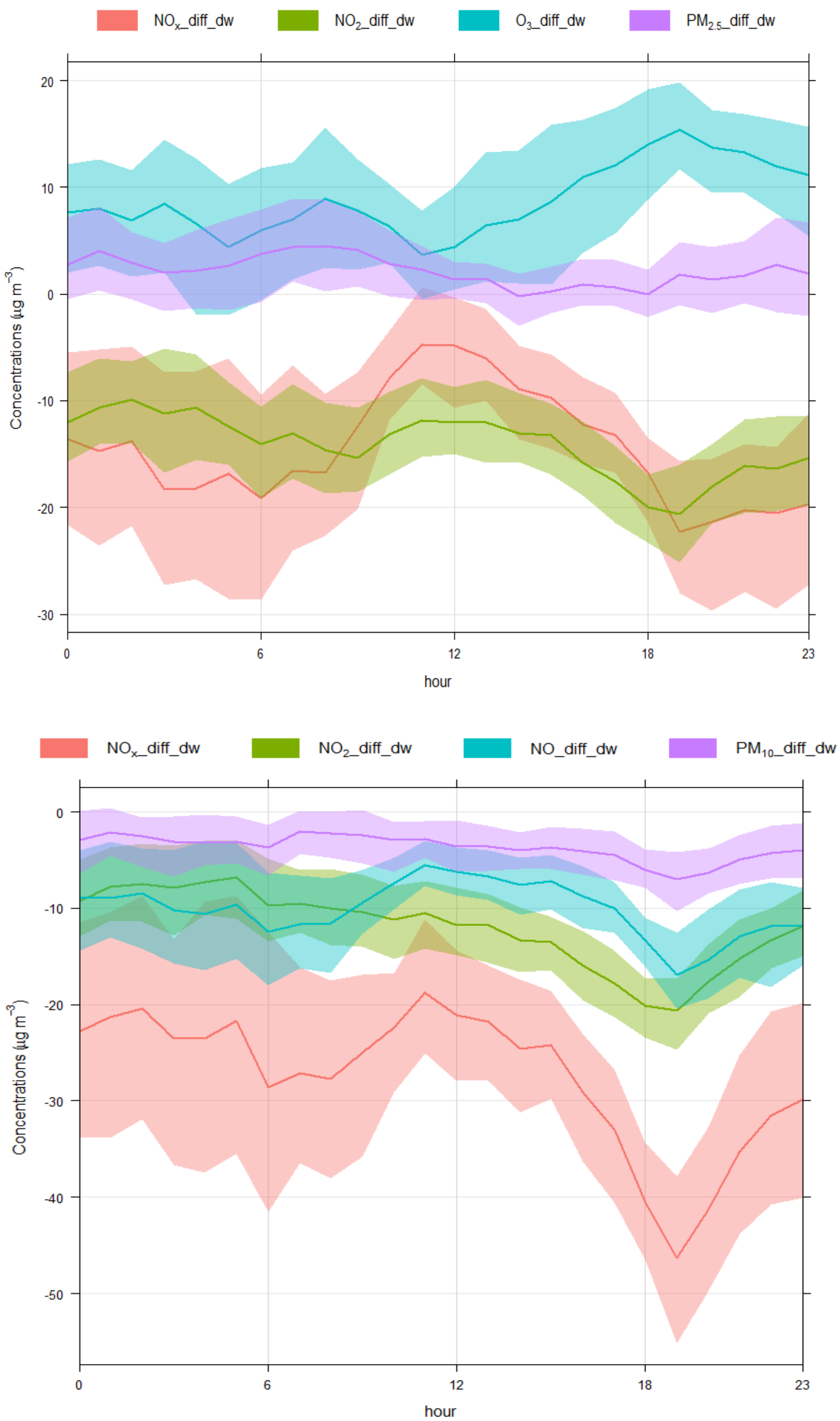


Figure 6. Diurnal cycles of change in pollutant concentrations between 2020 and 2019 for the lockdown period at Newtown (upper-panel) and Oxford Rd (lower-panel) sites. Pollutant with ‘diff’ and ‘dw’ stand for difference and deweathered concentrations, respectively.

3.3 Machine learning modelling Approach

In this section GAM was used to predict the concentrations of air pollutants for the lockdown period 2020 using the BAU scenario. Basically, the model predictions show the concentrations which would have been experienced if there had been no lockdown. The model was trained using 2018 and 2019 air pollutants and meteorological data and then used to make a prediction at each site for the lockdown period of 2020. The difference in observed and predicted concentrations is regarded as the reduction/gain due to the lockdown intervention.

At London Rd the difference between modelled BAU scenario and observed concentration is shown in Table 5, where NOx, NO_2 and NO concentrations demonstrated reductions whereas PM_{10} demonstrated gain during the lockdown period. The highest reduction was shown by NO (-58.55 %), followed by NOx (-49.81 %). The reduction shown by BAU scenario is relatively greater than the other approaches. The difference between the BAU scenario and observed concentrations is also shown in Figure 7. At the Newtown site only NOx and NO_2 showed a reduction, while all other pollutants showed gains in their concentrations during the lockdown period. The highest gain was shown by PM_{10} (32.47 %) and the highest reduction by NO_2 (-43.56 %) (Table 5). At other sites, NO demonstrated the highest reduction, although, at the Newtown site, which is a background site, NO demonstrated a positive gain. The difference between BAU and observed concentrations are depicted in Figure 7. At the Oxford Rd site all pollutants demonstrated reductions during the lockdown period according to BAU scenario. Highest reduction is shown by NO (-56.50%), followed by NOx (-46.62 %) (Table 5). The lowest reduction is shown by PM_{10} (-14.97 %). Figure 7 shows the difference between BAU and observed concentrations in all four pollutants in the form of boxplot. At the Caversham site all four pollutants showed a reduction (Table 5) during the lockdown period. The highest reduction is shown by NO (-63.49 %) and lowest by PM_{10} (-8.99 %).

Table 5. Observed and BAU concentrations and their difference (diff) and percent difference (% Diff) for the lockdown period 2020 at all four sites.

Site	Pollutant	Observed	BAU	Diff	%Diff
London Rd	NOx	33.49	66.73	-33.24	-49.81
	NO_2	20.59	35.64	-15.05	-42.22
	NO	8.41	20.29	-11.88	-58.55
	PM_{10}	27.86	24.64	3.21	13.03
Newtown	NOx	24.65	36.88	-12.23	-33.16
	NO_2	17.58	31.15	-13.57	-43.56
	NO	4.60	3.69	0.92	24.93
	O_3	65.21	63.44	1.77	2.79
	PM_{10}	23.42	17.68	5.74	32.47
	$PM_{2.5}$	14.91	13.20	1.71	12.95
Oxford Rd	NOx	31.79	59.55	-27.76	-46.62
	NO_2	20.15	32.75	-12.59	-38.44
	NO	7.59	17.45	-9.86	-56.50
	PM_{10}	24.76	29.12	-4.36	-14.97
Caversham Rd	NOx	36.07	83.49	-47.42	-56.80
	NO_2	21.74	44.05	-22.31	-50.65
	NO	9.37	25.69	-16.31	-63.49
	PM_{10}	26.43	29.04	-2.61	-8.99

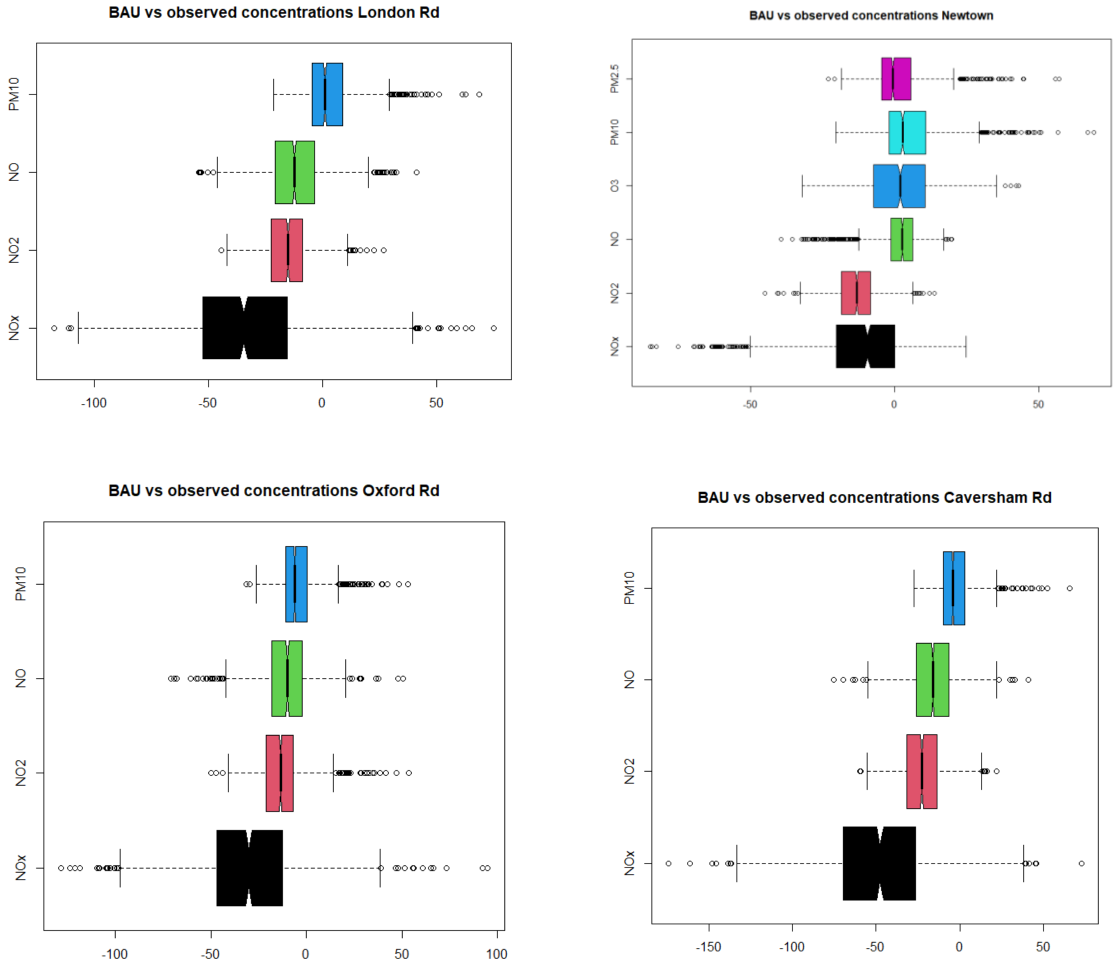


Figure 7. Boxplot showing the difference between observed and BAU scenario for the lockdown period 2020 at all four sites.

3.4 Discussion

3.4.1 Comparison among different approaches

Overall, the sequential approach detected less reductions in pollutant concentrations compared with the other two approaches. Furthermore, the sequential approach calculated positive gains in several pollutants which showed a reduction using the other two approaches. For example, the sequential approach showed gains in NO_2 and PM_{10} concentrations, in contrast to the other approaches that showed a significant reduction. Furthermore, all three approaches demonstrated positive gains in O_3, $PM_{2.5}$ and PM_{10} at the Newtown site, although the gain calculated by the sequential approach was considerably higher than the other two approaches. The difference between the results of the sequential and other approaches is clearly shown in Figure 8. The parallel and modelling approaches demonstrated little differences between them, with generally the modelling approach resulting in slightly larger changes. When correlation coefficients were calculated between the changes estimated by the different approaches for all pollutants and all sites, parallel vs. modelling approaches showed the strongest correlation (0.97), followed by sequential vs. parallel (0.79), whereas the weakest correlation was found between sequential vs modelling (0.72). RMSE values were 7.44, 41.63 and 43.48, and MBE were 0.02, -35.24 and -35.22 for parallel vs. modelling, parallel vs. sequential and modelling vs. sequential, respectively. Parallel vs. modelling demonstrated stronger correlation and less error, compared to the sequential vs. any of the other two approaches. Therefore, it can be concluded from this research that the parallel and modelling approaches are more suitable for extracting the effect of lockdown or any other traffic management intervention on air pollutant levels.

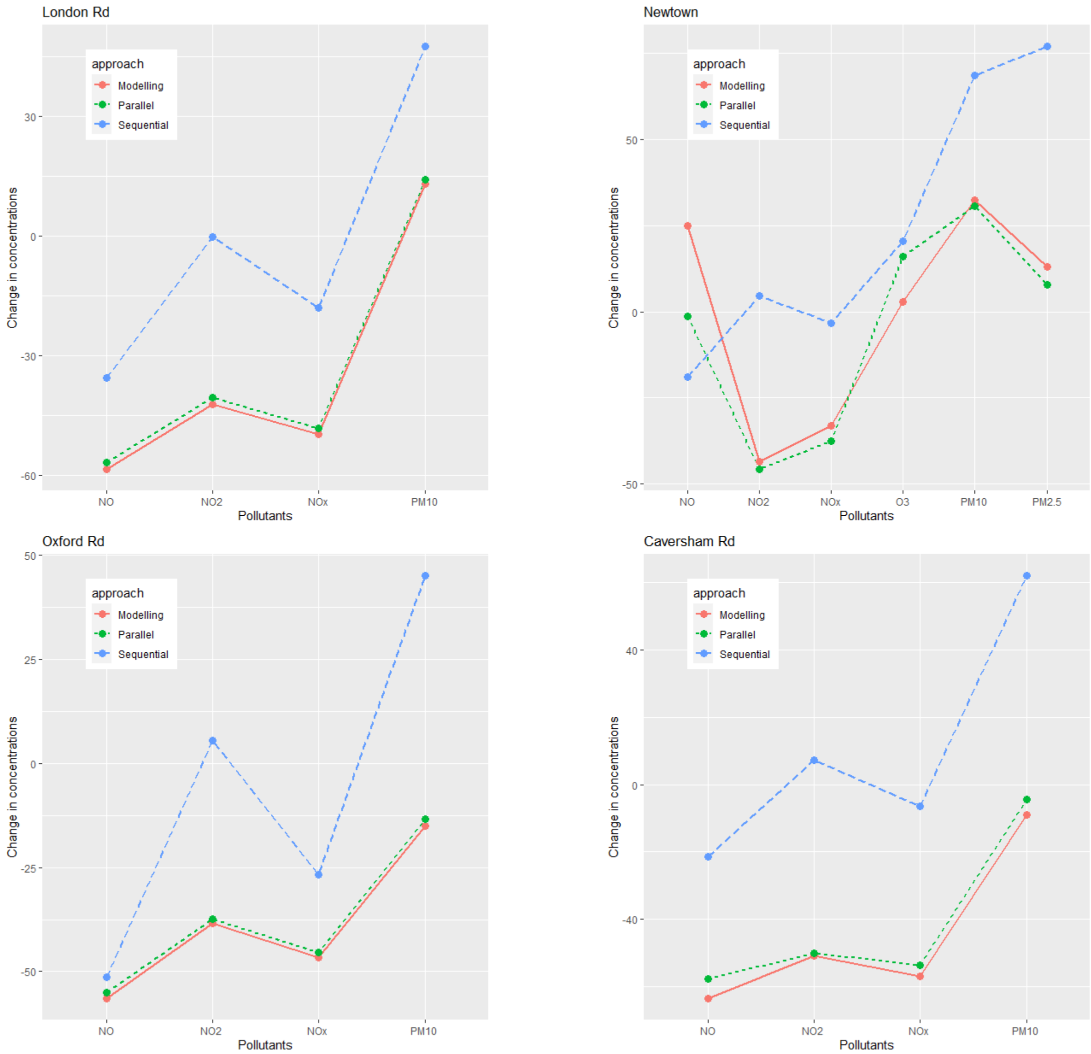


Figure 8. Comparing change in the concentrations of air pollutants at the four monitoring sites calculated by the three approaches: Modelling, Parallel and Sequential.

Air pollutant levels demonstrate a typical annual cycle in the UK and experience significant changes from one month to another, therefore seasonal variations could have affected the results of the sequential approach. Furthermore, it is reported that during the pre-lockdown period the wind direction was predominantly south-westerly, advecting clean Atlantic air over the UK, whereas during the lockdown period the wind was predominantly easterly and north-easterly resulting in the advection of air laden with emissions from Europe over the UK (Dacre et al., 2020), which resulted in high concentrations of PM_{10}, $PM_{2.5}$, NO_2 and O_3 during the lockdown period. Using meteorology data from URAO our analysis showed similar results (Figure 9), which reconfirms that wind direction, temperature and relative humidity were considerably different during pre-lockdown and lockdown periods. The effect of meteorology was more prominent in the sequential approach. To minimise this effect, we used parallel and modelling approaches and deweathered the pollutant data. Deweathered and raw concentrations generally demonstrated a similar pattern, although the magnitude in change varied. Deweathered concentrations of NO_2, NO and NOx decreased at all sites, however, PM_{10} levels only decreased at the roadside sites and increased at the urban background site according to parallel and modelling approaches. The sequential approach demonstrated a gain in PM_{10} concentrations at all sites, most probably due to the meteorological conditions favourable for secondary particulate formations and advection of polluted airmasses from the central and eastern Europe during the lockdown period. Shi et al. (2021) reported that in several megacities around the world (e.g., Beijing, Paris, and London) pollution events of particulate matter were observed after the lockdowns began. This shows that short-term variabilities in pollutant concentrations are more controlled by meteorological variations rather than by changes in emissions (Shi et al., 2021). Therefore, it is vital to consider changes in pollutant concentrations in the light of changes in meteorological conditions.

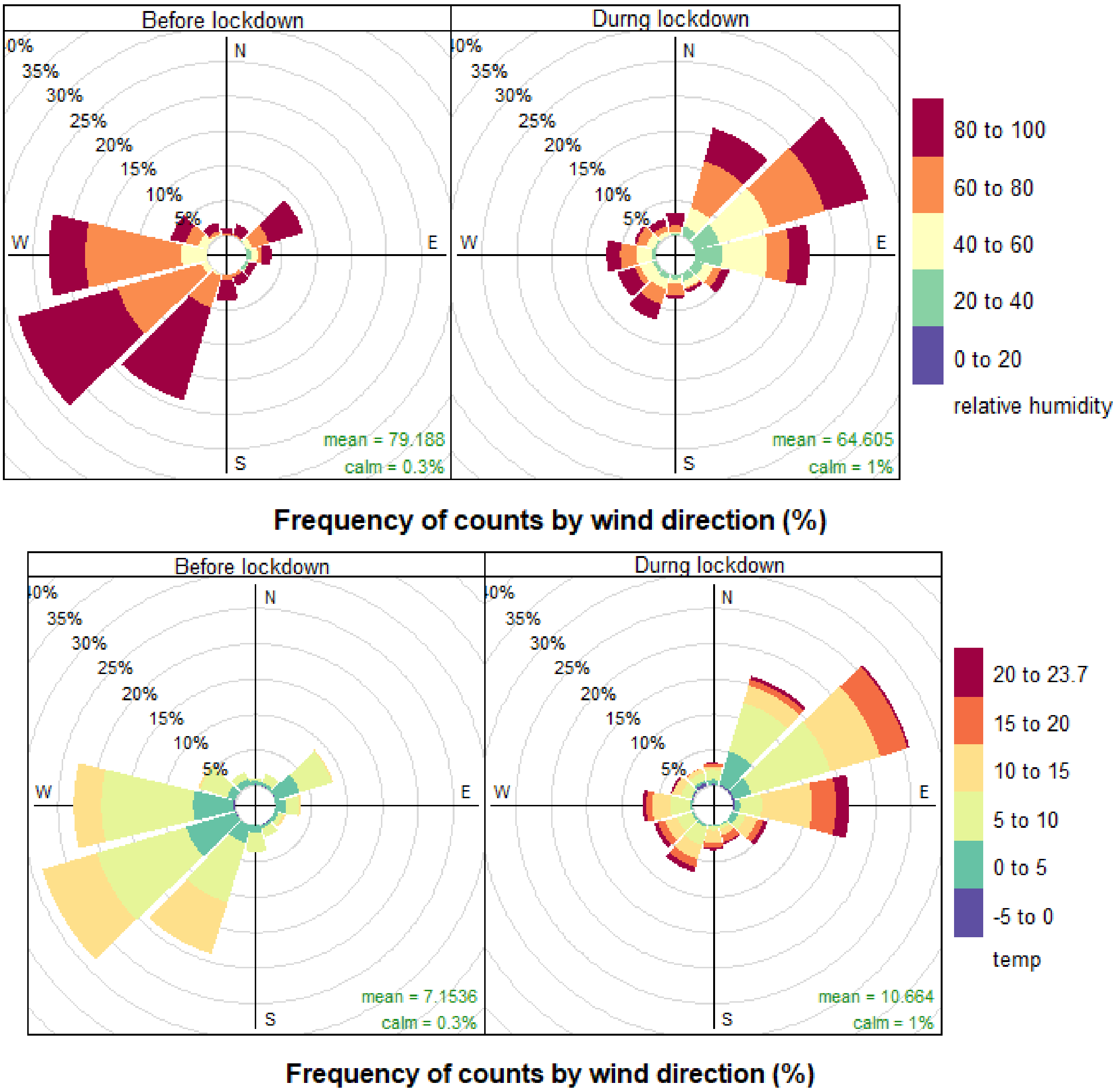


Figure 9. Pollution rose showing wind speed and wind direction for pre-lockdown and during lockdown. The levels of relative humidity and temperature are shown in upper and lower panels, respectively.

There is a considerable site to site variability in the change in pollutant concentrations during the lockdown period. If we disregard the sequential approach generally NO, NO_2 and NOx have decreased at all sites, whereas PM_{10} have increased at London Rd and Newtown sites and decreased at Oxford Rd and Caversham Rd sites. The spatial differences are due to the nature of the sites in terms of their distance to roads and other emission sources. Newtown is an urban background site, whereas Oxford Rd and Caversham Rd are urban traffic sites, and London Rd is classified as a rural site by the air quality England (Air Quality England, 2021) and as an urban traffic by DEFRA (DEFRA, 2021). The setting of the site are more like a rural site, this is perhaps the reason that London Rd site has behaved differently from the other two urban traffic sites. London Rd site demonstrated less reduction compared to Oxford Rd and Caversham Rd sites, where all pollutants have demonstrated a reduction according to the parallel and modelling approaches. At the rural and urban background sites measurements are more representative of large areas, and hence pollutant concentrations are dominated by the regional advection of pollutants. In contrast, urban traffic sites are more representative of the local emissions and therefore are directly influenced by reduction in local emissions (e.g., Shi et al., 2021; Dacre et al., 2020). The regional advection of pollutants has affected the sequential approach more as it compares different seasons of the same year.

3.4.2 Comparison with previous studies

Other studies have showed similar findings to the current research. For example, Jephcote et al. (2021) reported reductions in NO_2, NOx and $PM_{2.5}$ concentrations, and positive gains in O_3 concentrations during the lockdown period. Jephcote et al. (2021) reported greater reductions at urban traffic than at background and rural sites. On average, according to the same study NO_2 demonstrated 47.9, 36.7 and 23.9 % reductions, NOx showed 57.3, 37.8 and 18.6 % reductions, $PM_{2.5}$ demonstrated 18.1, 17.3 and 2.6 % reductions, and O_3 demonstrated 34.1, 7.4 and 0.1 % gains at urban traffic, urban background and rural sites, respectively. However, in addition to the environmental type of the sites, the changes varied spatially in the UK, depending on whether the site was situated in the north, south, east or west of the country. It is worth mentioning that Jephcote et al. (2021) used only wind speed, wind direction and temperature data to train their model, whereas in this study in addition, we also used relative humidity and atmospheric pressure data. Furthermore, the current study also had the benefit of using measured meteorological data in contrast to the modelled meteorology used by Jephcote et al. (2021) and Dacre et al. (2020). In further support for the current findings, Shi et al., (2021), Lovric et al. (2020) and Dacre et al. (2020) also reported reductions in NO_2 and $PM_{2.5}$ concentrations and positive gains in O_3 concentrations during the lockdown period. Using a GAM model, Solberg et al. (2021) evaluated the impact of lockdown on NO_2 concentration in Europe and reported significant differences in NO_2 reduction between different European countries. According to their analysis Spain, France, Italy, UK and Portugal experienced significantly more reductions in NO_2 concentrations than the eastern European countries, for example Poland and Hungary.

According to all previous studies and this current study O_3 demonstrated gains during the lockdown periods. O_3 concentrations in the atmosphere are controlled by several processes (Munir et al., 2014), mainly: (1) O_3 titration by NOx species, especially on the roadside sites; (2) Local photochemical O_3 formation; (3) O_3 rich-air advection either horizontally (regional O_3 transportation) or vertically (stratospheric-tropospheric O_3 exchange); and (4) dry deposition. NOx is invariably negatively correlated with O_3, therefore any reduction in NOx concentrations will lead to increase in atmospheric O_3 (Jenkin, 2004; Munir et al., 2013). During the lockdown period reductions in road traffic caused reductions in NOx concentrations, which in turn decreased titration of O_3 and its concentrations went up. Secondly, the UK experienced warm sunny weather conditions during the lockdown period (Dacre et al., 2020; Jephcote et al., 2021), leading to enhanced photochemical O_3 formation. Furthermore, easterly wind during the lockdown period advected air rich in O_3 and its precursors from central and eastern Europe, which increased O_3 levels in the UK. Furthermore, dry warm conditions encourage the release of biogenic volatile organic compounds (BVOC) from the vegetations, which act as precursors for O_3 formations and might have contributed in the positive gain of O_3 concentrations during the lockdown period (Fitzkyet al., 2019). As a result, in such conditions, plants close their stomata resulting in reduction of O_3 dry deposition (Fitzkyet al., 2019).

During the lockdown period road traffic counts on A-roads and motorways were reduced by 69% compared with the equivalent period in 2019 (Jephcote et al., 2021). There was 74% reduction in light vehicles and a 35% reduction in heavy goods vehicles and mostly the same pattern existed across all the UK regions (Jephcote et al., 2021). This resulted in a reduction of the emissions of primary pollutants, leading to reductions in atmospheric concentrations, as expected. However, the reduction in pollutant concentration is not linear to the reduction in emissions. In other words, the reduction in traffic flow is much greater than the reduction in pollutant concentrations. This is mainly due the effect of meteorological conditions that sometimes mask the variations due to reduction in emissions (discussed in section 3.4.1).

Although this study considers only a limited area and analyses data from only four air quality monitoring stations we believe that this case study highlights the importance of comparing the three approaches in a single urban area: readers interested in a UK wide analysis are referred to Jephcote et al. (2021) and Dacre et al. (2020). Our aim was to present a methodological approach, rather than covering a wide range of AQMS. We provided a detailed discussion of the main reasons behind the changes in pollution concentrations so that the readers understand why pollutants have behaved in a certain manner.

It is important to mention that a number of local authorities (LAs) around the UK (including Leeds, Bristol, Sheffield and Greater Manchester) have announced delays or have abandoned the implementation of Clean Air Zones (CAZs), thinking perhaps that CAZs are not required immediately because COVID-19 lockdown has done the job and the fact that LAs are stretched financially and resources wise during the pandemic (Air Quality News, 2020; Quinio and Enenkel, 2020). But this might not be the case and pollutants levels might get back to the pre-lockdown levels quickly when the lockdown measures are removed (Quinio and Enenkel, 2020). Therefore, the following suggestion might be useful:

(a) Policy interventions are required to make people change their behaviour as they did during the lockdown period.
(b) CAZs should be implemented in all large cities as were planned before the COVID-19 pandemic.
(c) Reducing road traffic will cause reduction in NO_2 pollution but perhaps this will not address the issue of particulate matter such as $PM_{2.5}$, which is predominantly emitted by other emission sources, e.g., point sources and residential sources. More work and policy interventions are required to manage $PM_{2.5}$ emissions.
(d) More work is required to understand the effect of COVID-19 lockdown on indoor air pollution, especially as more people are working from home now.
(e) International policies and collaborations are required to address the issue of transboundary air pollutants, e.g., ground level O_3.

4 Conclusion

Air quality improved (at least in the ‘short term) as a result of COVID-19 lockdown, especially the improvement is more prominent in NOx, NO and NO_2 concentrations. In the Reading case study PM_{10} levels have decreased at roadside and increased at background sites according to parallel and modelling approaches. PM_{10}, $PM_{2.5}$ and O_3 levels have increased at background site, most probably due to polluted air advection from the central and eastern Europe and due to warmer weather conditions conducive to photochemical formation of the secondary particulate matter and O_3.

In this study three approaches were compared for quantifying the impact of lockdown measures on air pollution levels, which resulted in different amounts of changes in pollution levels:

1. Sequential approach - comparing pre-lockdown and lockdown period showed less reduction in pollutant concentrations and showed positive gain in PM_{10} at all sites.
2. Parallel approach - comparing 2019 and 2020 for the equivalent period showed more reduction than the sequential approach and slightly less reduction than the modelling BAU scenario, showing strong correlation with the modelling approach (r-value 0.97).
3. Machine learning modelling - comparing BAU scenario and measured values showed more reduction than the other two approaches.

Different approaches result in different changes for the lockdown period so it is important to understand which approach has been used for quantifying the impact of an intervention and whether the data have been normalised for changes in meteorology or not. The sequential approach compared different months of the same year, which differ in terms of emissions and therefore probably resulted in less change as compared to the other approaches. Therefore, parallel and modelling approaches are recommended for such intervention analysis, which resulted in realistic reduction in air pollution levels and showed strong correlation with each other. On average, road traffic decreased by about 70 %, however, reductions in pollutant concentrations are much less (ranging from 30 to 55 %). This probably shows the complexity of the atmospheric system and the role of weather conditions in controlling the air quality dynamic.

The uniqueness of this study is that using air quality and meteorology data from four sites in Reading, it compares three approaches for analysing the effect of COVID-19 on air quality. These approaches can also be used for evaluating the effect of any short-term intervention (e.g., smart traffic management interventions) on air quality. This study uses measured meteorology data, in contrast to some other studies which used estimated meteorological data. Furthermore, in addition to average change, it is shown how the changes vary across different days of the week and hours of the day. Finally, after the COVID-19 pandemic air pollution levels will probably increase again and reach the levels observed before the lockdown period, therefore efforts at local, national and international levels are required to manage behaviour, introduce policy interventions and reduce emissions to address the issue of air pollution effectively and more sustainably.

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Author contributions

Said Munir: Conceptualization; Data curation; Methodology; Formal analysis; Validation; Visualization; Roles/Writing - original draft. Zhiwen Luo: Conceptualization; Funding acquisition; Investigation; Methodology; Project administration; Supervision; Writing - review & editing. Tim Dixon: Funding acquisition; 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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