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Short Communication

Early observations on the impact of the COVID-19 lockdown on air quality trends across the UK

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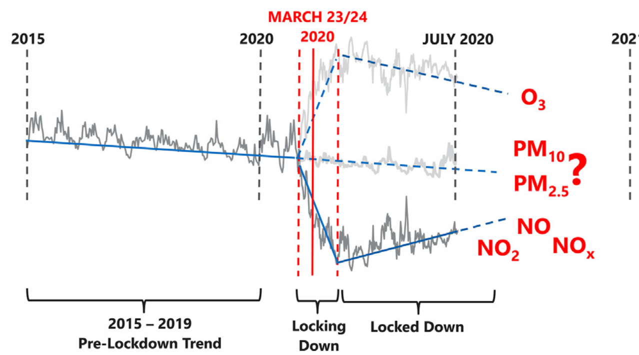
HIGHLIGHTS

- Lockdown air pollutant levels across UK analysed using break-point/segment methods.
- NO, NO_2 and NO_x decreased (on average) 32% to 50% at roadsides on lockdown.
- O_3 concentrations increased by (on average) 20% on lockdown.
- Change-points indicate lockdown not a major source of change for UK particulates.
- While locked down NO, NO_2 and NO_x gradually increase as vehicles return to roads.

GRAPHICAL ABSTRACT



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ABSTRACT

UK government implemented national lockdown in response to COVID-19 on the 23–26 March 2020. As elsewhere in Europe and Internationally, associated restrictions initially limited individual mobility and workplace activity to essential services and travel, and significant air quality benefits were widely anticipated. Here, break-point/segment methods are applied to air pollutant time-series from the first half of 2020 to provide an independent estimate of the timings of discrete changes in NO, NO_2, NO_x, O_3, PM_{10} and $PM_{2.5}$ time-series from Automatic Urban Rural Network (AURN) monitoring stations across the UK. NO, NO_2 and NO_x all exhibit abrupt decreases at the time the UK locked down of (on average) 7.6 to 17 $\mu g \cdot m^{-3}$ (or 32 to 50%) at Urban Traffic stations and 4 to 5.7 $\mu g \cdot m^{-3}$ (or 26 to 46%) at Urban Background stations. However, after the initial abrupt reduction, gradual increases were then observed through lockdown. This suggests that the return of vehicles to the road during early lockdown has already offset much of the air quality improvement seen when locking down (provisional estimate 50 to 70% by 01 July). While locking down O_3 increased (7 to 7.4 $\mu g \cdot m^{-3}$ or 14 to 17% at Urban stations) broadly in line with NO_2 reductions, but later changes suggest significant non-lockdown contributions to O_3 during the months that followed. Increases of similar magnitudes were observed for both PM_{10} (5.9 to 6.3 $\mu g \cdot m^{-3}$) and $PM_{2.5}$ (3.9 to 5.0 $\mu g \cdot m^{-3}$) at both Rural and Urban stations alike, but the distribution of changes suggests the lockdown was not an obvious direct source of changes in levels of either of these species during this period, and that more complex contributions, e.g. from resuspension and secondary aerosol, may be more likely major drivers for these changes.

1. Introduction

Since its outbreak in late 2019, COVID-19 has spread rapidly across the globe, infecting most populations (WHO, 2020). The first UK cases were confirmed at the end of January 2020, and, as in most countries,

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numbers of cases and deaths increased quickly over the following days, weeks and months (data.gov.uk, 2020). During February and early March, UK Government issued warnings and advice designed to reduce infection rates amongst the UK population, and Government, emergency services and businesses all began ringfencing resources, suspending non-essential services and restructuring in preparation for unprecedented disruption (see e.g. UK DHSC, 2020; NHS England, 2020; Nicola et al., 2020). However, it was not until 23–26 March when both cases and death rates peaked at about 5000 and 900 per day, respectively, (data.gov.uk, 2020) that UK Government announced an official lockdown (GOV.UK, 2020a) and brought into force mandatory restrictions on the majority of UK non-essential UK travel (PH England, 2020). These months and those that followed have obviously been challenging, few if any of us remain unaffected, and the demands placed on frontline medical practitioners have been unprecedented and their response heroic, but with death and cases numbers in decline and restrictions being lifted (GOV.UK, 2020b), we begin a transition out of lockdown.

We naturally look forward to better circumstances, but also have to ask ourselves if we can, should or want to return to exactly the lives we had before or if, building on the experiences of recent times, we would rather aim for a 'new normal' (see e.g. Budd and Ison, 2020; Zeegen et al., 2020). For example, although few would ever describe COVID-19 as anything but a tragedy, many in the air quality research community have highlighted the associated travel and work restrictions and their impact on vehicle use and manufacturing work, emissions and air quality an experience which, however fleeting they may one day seem, we should actively seek to learn from in our on-going efforts to reduce pollution (Monks, 2020; Muhammad et al., 2020; Winfree and Zietsman, 2020). The very earliest comments on lockdown and air quality were understandably crude estimates limited by data availability. But subsequent modelling (see e.g. Menut et al., 2020), satellite observation (Bauwens et al., 2020; Muhammad et al., 2020) and monitoring data (see e.g. Bao and Zhang, 2020; Cadotte, 2020; Collivignarelli et al., 2020; Tobías et al., 2020) studies from areas that were earlier affected and/or earlier to implement lockdowns all reported substantial associated reductions in pollutant levels, many of the order of 25–55% and 15–30% for NO_2 and PM_{10}, respectively.

Here, we present break-point/segment analysis on air quality data from the UK Department for Environment, Food and Rural Affairs (Defra) Automatic Urban and Rural Network (AURN) (https://uk-air.defra.gov.uk/) using methods and software developed as part of an on-going Defra/Ipsos MORI/University of Leeds research project (2018–2022) to evaluate and track the impact of air quality plans. Early findings from this work were submitted to Defra's Call for Evidence on 'Estimation of changes in air pollution emissions, concentrations and exposure during the COVID-19 outbreak in the UK' (UK Defra, 2020) but here we extend the analysis to comment on air quality trends as lockdown restrictions on movement lessened through to the end of June 2020. One of the unique features of this approach is that the break-point step does not assume event dates, but instead uses changes in linear regression properties in a data-series over time to identify likely points-of-changes, so provides a more independent measure of events and their timescales than a classical 'before and after' analysis. Acknowledging the complexities of air quality data, we also apply deseasonalisation and deweathering procedures to the pollutant time-series prior to analysis to reduce the influence of other sources of air quality variance, and methods based on Theil-Sen regression to characterize pre-existing air pollutant trends going into lockdown, because the lockdown should not be considered an event that occurred in isolation. This combination of methods demonstrates that there were both on-going changes in air quality happening ahead of lockdown and upon which lockdown-related change is superimposed and, for some airborne species, some major changes over the timescales of lockdown that are not obviously lockdown-related.

2. Materials and methods

All analyses reported here were carried out using R (R Core Team, 2020) and R software packages. All of these are freely available from CRAN (https://cran.r-project.org/) or GitHub (https://github.com/) archives, except 'AQEval' which, although currently pre-release, should be available shortly.

1-Hour resolution 01 January 2015 to 30 June 2020 air pollutant (NO, NO_2, NO_x, O_3, PM_{10} and $PM_{2.5}$) time-series from monitoring stations classified as 'Urban Traffic', 'Urban Background' and 'Rural Background' were downloaded from the Defra AURN online archives using openair (Carslaw and Ropkins, 2012) function importAURN. Although the archive includes data from over 300 monitoring stations, not all stations monitor all species and not all were operating throughout the analysis period. As a result, UK AURN coverage for this study ranged from up to 153 stations for NO, NO_2 and NO_x to 75 for O_3. (See Fig. S1 and Table S1 in Supporting information.) [NB: We say 'up to' here because not all analyses (Theil-sen, break-point and break-segment) could be conducted on all data from all stations.] AURN data is routinely ratified within 6 months of collection, so while pre-2020 data discussed here has been ratified, results reported for 2020 are in the process of being ratified, and any associated observations should be regarded as early observations based on unratified data. As part of the pre-processing of the 2020 data, some data sets were identified which contained atypically high NO_x values over periods when neither NO or NO_2 were reported, see e.g. Fig. S2 in Supporting information. These 'high NO_x but no NO or NO_2' regions were assumed to be pre-ratification artefacts (e.g. an instrument, calibration or logging issue) and excluded prior to analysis.

For each AURN monitoring station, a nearby meteorological station in the National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Database (ISD (https://www.ncdc.noaa.gov/isd) was identified that had >90% data capture for 1-hour resolution wind speed, wind direction and air temperature data for the same period, and this data was downloaded and paired with the pollutant time-series measurements using worldmet (Carslaw, 2019) and dplyr (Wickham et al., 2020) methods, respectively. The AQEval function isolateContribution was then used to deseasonalise and deweather (dSW) air pollutant time-series in these merged AURN/worldmet datasets. Here, a relatively crude dSW was applied and variance associated with hour-of-day, day-of-year, wind-speed and direction and air temperature by Generalized Additive Model (GAM; Wood, 2019) subtracted from the ambient pollutant time-series to reduce the influence of meteorological and seasonal contributions.

01 January 2015 to 31 December 2019 dSW time-series (or part thereof if incomplete but sufficient for analysis) were then analysed using Theil-Sen regression (Theil, 1950; Sen, 1968) as implemented by the openair TheilSen function to characterize general air quality trends prior to lockdown. The method is applied at 1-month resolution and provides a non-parametric measurement of trends on 'a median of slopes of pairs of points with different x-values' estimate of slope, and bootstrap estimate of uncertainty (https://davidcarslaw.github.io/openair/reference/TheilSen.html).

01 January to 30 June 2020 dSW time-series (or part thereof if incomplete but sufficient for analysis) were then analysed using quantBreakPoints and quantBreakSegments functions in AQEval. These applied 'strucchange' break-point detection methods of Zeileis and colleagues (Zeileis et al., 2002, 2003): applying a rolling-window approach to compare the linear regression properties across a time-series and assigning points of likely change based on the hypothesis that a change exists wherever the surrounding data is significantly better explained by two discrete models rather than one general model. Then using these identified break-points and their confidence intervals as the starting points to iteratively fit and build change-segment descriptions of the time-series using the segmented methods of Muggeo (2003, 2008, 2017). We propose that this combination of break-points and segments, here referred to as break-segments, provides a more realistic

characterization of air quality time-series change than either break-point or segmented approaches in isolation (Ropkins et al., in preparation). Here, break-point testing was applied to 2020 time-series at 4-hour resolution using a time-window of 10% of the supplied time-series, nominally about 18 days but depending on data-capture/availability, and restricted segment iteration to prevent fitted segments 'wandering' away from break-points.

2020 Automatic Traffic Count (ATC) data was also provided by Leeds City Council for a site on Headingley Lane (A660) for the purposes of comparison with air quality data from the nearby AURN Headingley Roadside monitoring station. There was insufficient ATC data for dSW, so the ATC data were analysed at 1-day resolution to minimize variance associated with daily traffic flow patterns.

3. Results

Using NO_2 data from the Leeds Headingley Roadside AURN station as an example, Fig. 1 demonstrates the effects of the different steps of this analysis. Fig. 1 Top Left and Right compares the full (01 January 2015 to 30 June 2020) NO_2 time-series before and after dSW. Here, the most apparent effect is the removal of cyclic yearly trends associated with seasonality and meteorological parameters that have broadly yearly cyclic trends, e.g. air temperature. However, there is also a general reduction in the scatter of the data and an enhancement of other features, e.g. the general decrease 2015 to 2020 and the concentration drop in 2020. Fig. 1 Middle and Bottom compare the Theil-Sen analysis of 01 January 2015 to 31 December 2019 data and the break-point testing of 01 January to 30 June 2020, without (Left) and with (Right) dSW, respectively. Here, (as in most cases with pronounced trends) dSW does not modify the slope prediction significantly, −3.3 with dSW versus −3.26 without dSW, but it does significantly improve the 95% confidence intervals, −3.78 to −2.83 with- dSW versus −4.5 to −1.78 without dSW. In locations where concentrations are lower and/or trends are less obvious, differences can be more pronounced, but in general Theil-Sen predictions with dSW tended to be within the confidence intervals estimated for the associated without dSW case (see also Fig. S3 in

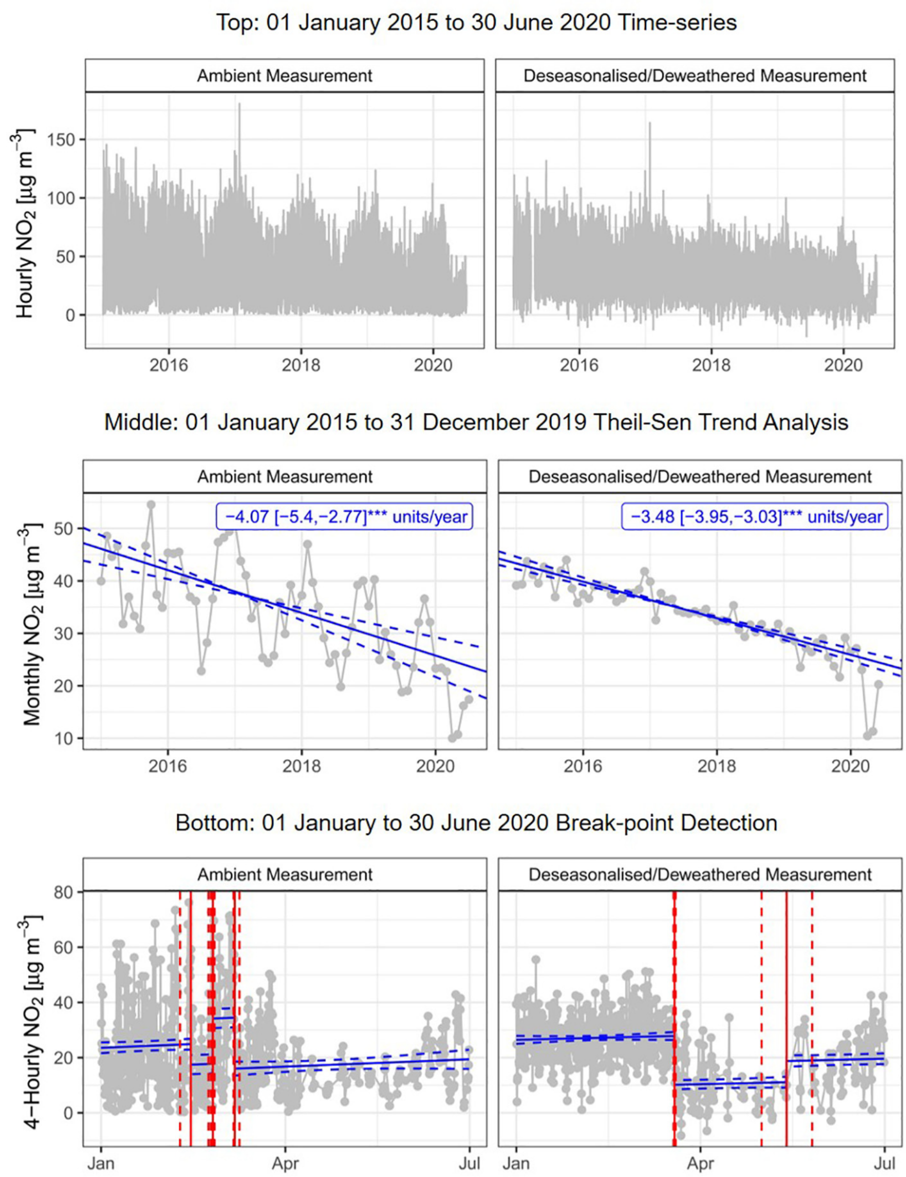

Fig. 1. Effect of deseasonalisation and deweathering (dSW) on NO_2 data from the AURN Headingley Roadside air quality monitoring station: Top the full time-series before (Left) and after (Right) dSW; Middle Theil-sen analysis of the January 2015 to 31 December 2019 time-series without (Left) and with (Right) prior dSW; and, Bottom break-point detection of the 01 January to 30 June 2019 time-series without (Left) and with (Right) prior dSW. (Data in grey; predicted trends in blue; and, break-points in red; solid lines are predictions and dashed lines are associated 95% confidence intervals.)

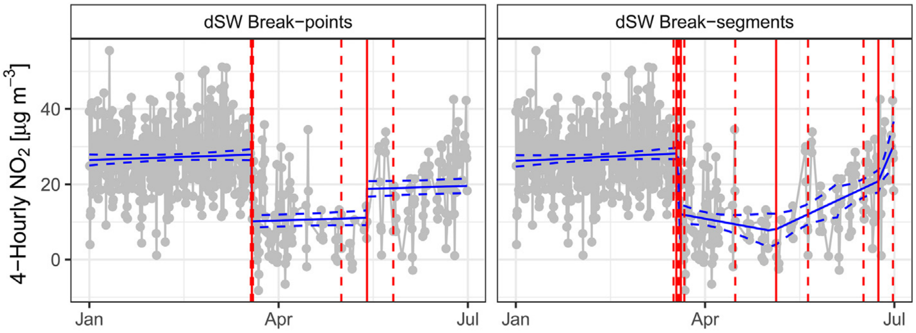

Fig. 2. Break-point (Left) and Break-segment (Right) models of deseasonalised and deweathered (dSW) 01 January to 30 June 2019 NO_2 data from the AURN Headingley Roadside air quality monitoring station. (Data in grey; predicted trends in blue; and, break-points in red; solid lines are predictions and dashed lines are associated 95% confidence intervals.)

Supporting information). Although change-points were highly visible in some ambient time-series, and dSW was not strictly required for data from some AURN stations where NO_2 levels were highest, e.g. London Marylebone, the benefits of dSW were apparent at lower levels, including some cases where changes appear relatively obvious on visual inspection. With the Headingley NO_2 dataset presented here, for example, three potential break-points are reported when the methods are applied to the without dSW data, but not one in late March when arguably the most distinct change happens. Furthermore, the observed pattern, several roughly regularly spaced break-points, appears to be characteristic of cases when the method 'trips' on a reoccurring frequency pattern (e.g., a weekly or monthly cycle). Consistent with this interpretation, break-point detection of the dSW data identifies a main break-point in late March (where visual inspection would most likely place the main change in the ambient time-series) and a second smaller, and less confidentially located (indicated by much wider confidence intervals) break-point in May.

Fig. 2 shows the outcome of remodelling these break-points as break-segments. Here, the earlier larger and more confidently located break-point seen in late March produces a segment with a steep slope and short duration, while the later smaller and less confidently located break-point in May produces a much shallower and broader segment. Closer inspection of the break-segment assignments and data (Fig. 2 Right) suggest that the methods may have assigned the end of main break-segment slightly early, resulting in an under-estimate of the magnitude of the late March change. Arguably, fit parameters could have been 'fine-tuned' to provide a closer alignment but rather than introduce a subjective element, we choose to present the analysis 'as is' with the caveat that we may underestimate changes slightly as part of this preliminary analysis.

Fig. 3 presents break-point and break-segment models generated for traffic volume data from a nearby ATC for the same time period as Fig. 2. Here, the main feature of both break-point and break-segment models is again a sharp drop in late March. While this is undoubtedly the main response to the UK lockdown, both analyses identify several other change-events indicating that even the changes in traffic volumes on lockdown were not strictly isolated events. Firstly, here (and in many other traffic data time-series) there is an increase in traffic volumes in early January, most likely associated with the return to work after the winter holidays. Although associated traffic volume changes were smaller than those seen going into lockdown, they were of the order of 5–10% of those seen 20–26 March, so not insignificant. Next, the lockdown event itself was not a switch - *one day cars on the road, the next none*. Here, in Headingly for example, the 'response' started early, with a less pronounced decrease in traffic over the weeks before the official lockdown, perhaps reflecting government advice on non-essential journeys and public uncertainty about traveling more generally at the time. Similarly, traffic flows never actually stopped but tailed away reaching a low of about 300 vehicles hour^{-1} (and ca. 30% of that in the month before lockdown) but then started increasing at end of March/start of April, and continued increasing through May and June, as vehicles returned to the roads.

While we defer to those better placed to comment on national trends in traffic data, the limited traffic data we have seen also indicates that while the main changes in traffic volumes clearly align with the official lockdown, the rate at which vehicle demand fell both prior to lockdown and while locking down, the proportion of vehicle which came off the road, and rate at which vehicles returned to road during the latter part of the lockdown, all most inevitably varied by location.

Break-point/segment trends determined for all UK AURN stations studied 01 January to 30 June 2020 are summarized for NO, NO_2, NO_x, O_3, PM_{10} and $PM_{2.5}$ in the Fig. 4 density plots.

Here, the higher densities, shown as red and orange regions, indicate times when similar changes are seen at multiple sites across the UK.

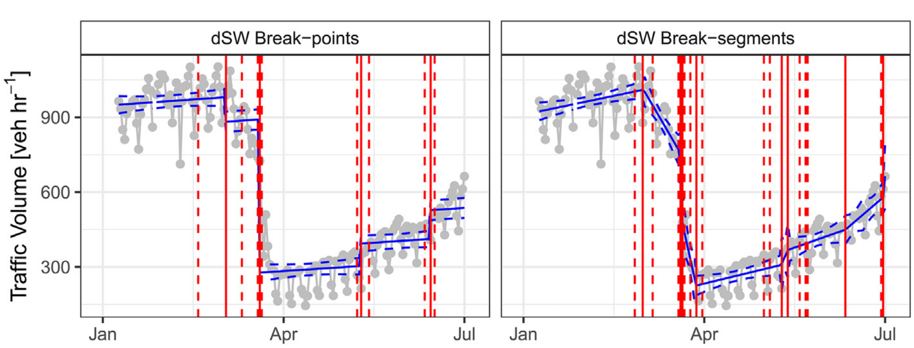

Fig. 3. Break-point (Left) and Break-segment (Right) models of 01 January to 30 June 2019 traffic volume data from a Leeds City Council ATC at a location near to the Headingley AURN station NO_2 data was taken from for Figs. 1 and 2. (Data in grey; predicted trends in blue; and, break-points in red; solid lines are predictions and dashed lines are associated 95% confidence intervals.)

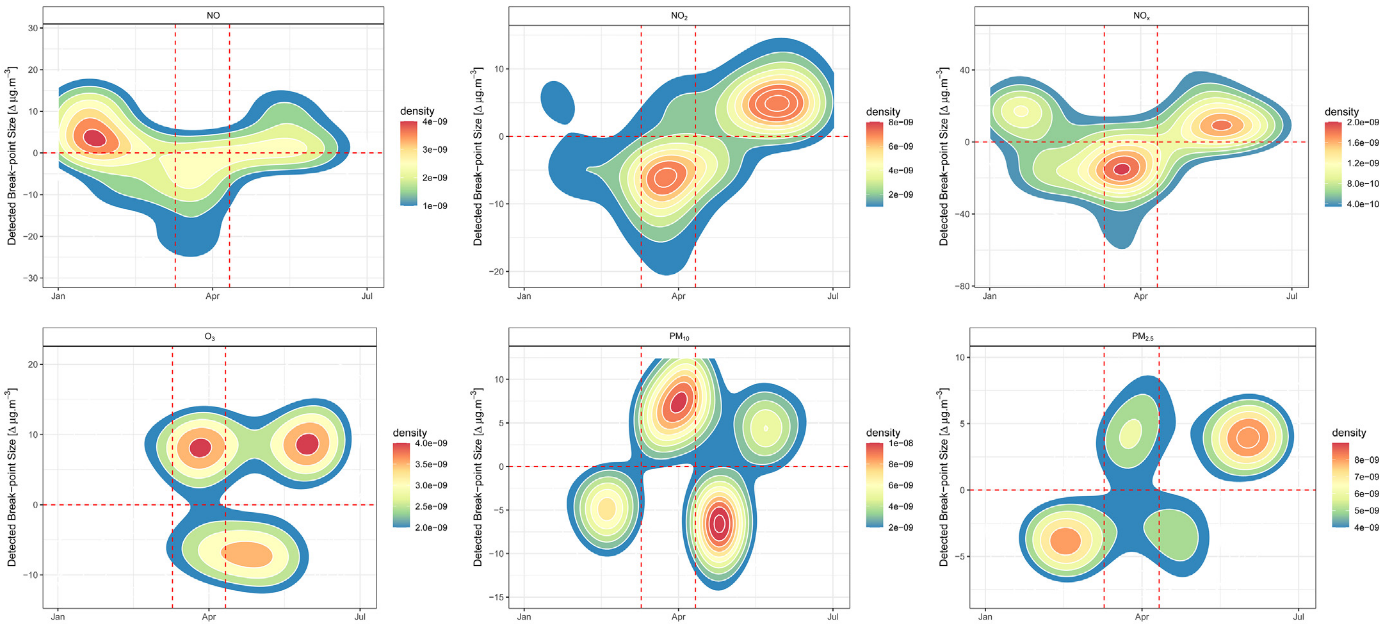

Fig. 4. Density plots of NO, NO_2, NO_x, O_3, PM_{10} and $PM_{2.5}$ break-point/segment events detected 01 January to 30 June 2020 at UK AURN monitoring stations. Here, the horizontal red dashed line indicates the 'no change' boundary for detected events, above increases and below decreases; and the two vertical red dashed lines indicate 10 March 2020 and 11 April 2020, the dates assigned to start and end of the period referred to as locking down in this study.

Most density plots include high density regions towards the end of March, typically in the time period 10 March 2020 to 10 April 2020 indicated by the red vertical dashed lines in Fig. 4. This is slightly wider than the time-range for the lockdown-related changes in road vehicle numbers reported for Headingley in Fig. 3, but, given both potential regional differences in responses (most notably slightly later and/or less rapid responses) and an estimated measurement time-accuracy of ca. $\pm$10 days for the break-point/segment methods when applied to 6 month time-series of air quality data, we assign this as the time period when we would expect to see the full range of changes associated with start of the lockdown across the UK. Hereafter, we refer to this period (10 March to 10 April 2020) as 'locking down' and the remainder of the studied period (11 April to 30 June 2020) as 'locked down'. [NB: One of the intensions going forward is to further characterize the lockdown, e.g. locked down before and after 13 May 2020 restriction easing, once we have sufficient data.]

NO, NO_2, NO_x, O_3, PM_{10} and $PM_{2.5}$ break-point/segment changes detected while locking down and when locked down are summarized for Rural Background, Urban Background and Urban Traffic AURN stations across the UK in Table 1 (and Fig. S4), along with average yearly changes for the period 01 January 2015 to 31 December 2019 determined using Theil-Sen regression. Results for individual stations are also provided in the Supporting information as Figs. S5 to S10.

Of the species studied, NO_2 exhibits arguably the break-point/segment density plot distribution closest to that expected for a classical before-and-after response to lockdown. In Fig. 4, the largest and most commonly observed NO_2 changes are decreases seen while locking down and then increases while locked down, aligning with the expected changes in on-road vehicle numbers across the UK during these time periods. The largest NO_2 decreases while locking down (Table 1; ca. −7.6 µg m^{-3}, −32%) and NO_2 increases while locked down (Table 1; ca. 5 µg m^{-3}, 33%) were observed at Urban Traffic sites. Some of the largest NO_2 reductions when locking down were observed at London Marylebone Road and Camden Kerbside (both Greater London), Oxford Centre Roadside (South East), Glasgow Kerbside (Central Scotland) and Leeds Headingley Kerbside (Yorkshire and Humberside), of the order of −20 to −33 µg m^{-3} (Fig. S6). By comparison, NO_2 trends were less pronounced at Urban Background and Rural Background AURN stations, consistent with a traffic-related source driving this change. It was also noted that atypical changes, e.g. increases while locking down, tended to be seen most commonly at Rural Background and Urban Background AURN stations, and at AURN stations in South East and South West zones, although the reason for this latter observation is less clear at this stage.

Although similar trends are seen for NO at several AURN stations, lockdown related changes were less frequently identified when compared to NO_2 (compare break-point/segment numbers in Figs. S6 and S5), and the most commonly seen NO changes were in January (compare NO_2 and NO in Fig. 4) at the time when vehicle numbers were expecting to be increasing as the public return to work after the winter holidays. This is consistent with a NO-dominated response to changing vehicle numbers in January when O_3 levels were lower and an NO_2-dominated response to changing vehicle numbers while locking down in late March. As a result, perhaps counter-intuitively, lockdown-related changes appear more distinct for NO_2 by comparison to NO_x (~NO + NO_2). However, for both NO and NO_x, there is clear evidence of changes that break-point/segment methods independently associate with the different stages of lockdown (Table 1; at Urban Traffic AURN Stations, ca. −9.68 µg m^{-3} or −49.9% and ca. −17.1 µg m^{-3} or −38.2% for NO and NO_x, respectively, while locking down; and, ca. 6.06 µg m^{-3} or 50.1% and ca. 9.0 µg m^{-3} or 34.2% for NO and NO_x, respectively, while locked down), and which, as with NO_2, are more pronounced at Urban Traffic AURN stations, as would be expected for a vehicle emissions driven air quality change.

The behaviours of O_3, PM_{10} and $PM_{2.5}$ were, however, much less readily attributed to an isolated response to either the lockdown specifically or on-road vehicle numbers.

O_3 levels typically increased at both Urban Traffic and Urban Background AURN Stations while locking down. Although average NO/NO_2/NO_x and O_3 measurements are not strictly directly comparable because NO, NO_2 and NO_x monitoring tends to be more common at Urban Traffic stations and O_3 monitoring more common at Rural Background stations, there is a reasonably reciprocal relationship between O_3 and NO_2 changes at most sites while locking down. Compare, for example, −4.3 µg m^{-3} versus 1.8 µg m^{-3}, 7.0 µg m^{-3} versus −4.2 µg m^{-3} and 7.4 µg m^{-3} versus −7.6 µg m^{-3} for O_3 and NO_2 at Rural Background,

Table 1
Overall (absolute and percent) trends for NO, NO_2, NO_x, O_3, PM_{10} and $PM_{2.5}$ at UK AURN sites: for each site, Average Yearly Change (pre-2020) are the average annual change as determined by Theil-Sen analysis for the period 01 January 2015 to 31 December 2019, and Change Locking Down and Change while Locked Down are determined as the net sum of changes due for break-points/segments detected during the periods 10 March to 10 April 2020 and 11 April to 30 June 2020, respectively. Results are reported as site type median with 5% and 95% quantiles in parentheses.

Species	Change	Average yearly change (pre-2020) [μg m^{-3} yr^{-1}]			Change locking down (10 March 10 April 2020) [μg m^{-3}]			Change while locked down (11 April to 30 June 2020) [μg m^{-3}]		
		Rural Background	Urban Background	Urban Traffic	Rural Background	Urban Background	Urban Traffic	Rural Background	Urban Background	Urban Traffic
NO	Absolute	−0.07 [−0.37, 0.03]	−0.35 [−1.27, 0.51]	−1.55 [−6.39, 0.38]	0.41 [−0.36, 0.8]	−3.9 [−7.37, 0.54]	−9.68 [−32.96, −4.34]	−0.42 [−0.76, 0.25]	1.37 [−2.5, 13.26]	6.06 [2.28, 13.51]
	Percent	−6.91 [−16.57, 4.41]	−5.72 [−11.3, 10.59]	−5.88 [−11.48, 2.24]	80.8 [−42.58, 156.88][a]	−45.79 [−59.39, 46.08]	−49.85 [−79.29, −29.88]	−36.12 [−61.93, 55.28]	26.26 [−45.62, 516.38][a]	50.1 [17.07, 107.49]
NO_2	Absolute	−0.19 [−0.85, 0.25]	−0.74 [−2.6, 0.04]	−1.48 [−3.74, −0.1]	1.76 [−1.35, 5.19]	−4.16 [−7.88, 4.55]	−7.58 [−20.32, 2.14]	1.49 [−2.81, 3.05]	3.06 [−6.1, 6.71]	4.99 [−7.47, 13.52]
	Percent	−3.41 [−8.38, 5.06]	−3.31 [−7.94, 0.27]	−4.35 [−8.04, −0.36]	39.61 [−126.86, 158.09][a]	−25.62 [−39, 36.7]	−32.17 [−54.87, 10.54]	25.46 [−29.34, 186.37]	20.61 [−37.73, 45.09]	31.37 [−33.15, 98]
NO_x	Absolute	−0.27 [−1.32, −0.04]	−1.26 [−4.61, 0.36]	−3.3 [−13.17, 0.56]	1.37 [−1.32, 4.74]	−5.66 [−15.39, 8.66]	−17.14 [−48.25, −5.27]	0.93 [−4.27, 2.34]	3.19 [−6.37, 9.54]	8.95 [2.12, 32.54]
	Percent	−3.31 [−9.62, −0.17]	−4.13 [−9.25, 0.81]	−5.29 [−10.04, 0.95]	40.21 [−68.57, 109.27][a]	−28 [−42.63, 47.29]	−38.19 [−67.83, −17.42]	10.96 [−32.01, 829.57]	21.27 [−27.35, 42.62]	34.17 [5.52, 91.26]
O_3	Absolute	0.48 [−1.62, 2.12]	0.66 [−2.05, 1.95]	1.37 [−0.56, 3.71]	−4.3 [−10.21, 11.59]	6.96 [−6.35, 10.12]	7.39 [6.3, 12.62]	4.25 [−8.53, 12.44]	1.89 [−7.76, 13.98]	ca. −6.82[b]
	Percent	0.84 [−3.06, 3.65]	1.46 [−3.81, 5.12]	8.34 [−1.52, 16]	−7.44 [−16.43, 20.81]	13.91 [−11.99, 22.07]	17.46 [16.37, 49.13]	6.77 [−13.66, 21.88]	3.55 [−15.04, 28.7]	ca. −17.24[b]
PM_{10}	Absolute	−0.26 [−1.02, 0.28]	−0.13 [−1.9, 1.04]	−0.25 [−1.51, 1.06]	5.81 [1.71, 11.37]	6.16 [−0.71, 10.52]	6.26 [−3.62, 11.16]	−3.52 [−7.3, −1.64]	−2.06 [−9.55, 4.22]	−2.09 [−10.37, 5.35]
	Percent	−2.68 [−6.71, 4.85]	−0.95 [−10.88, 8.95]	−1.15 [−7.69, 6.15]	73.05 [28.4, 118.68][a]	61.28 [−6.23, 98.39]	47.81 [−25.28, 80.89]	−25.91 [−33.31, −22.33]	−12.39 [−41.25, 27.25]	−13.08 [−38.01, 44.3]
$PM_{2.5}$	Absolute	−0.43 [−0.85, 0.33]	−0.22 [−1.1, 0.34]	−0.43 [−0.87, 0.38]	3.94 [1.55, 7.04]	4.79 [1.47, 6.94]	5 [0.59, 8.49]	−1.08 [−1.86, 2.24]	0.46 [−6.45, 4.72]	0.18 [−6.7, 4.5]
	Percent	−5.73 [−12.09, 11.51]	−2.08 [−9.55, 4.11]	−3.05 [−7.41, 4.44]	80.46 [47.26, 114.1]	90.73 [30.92, 143]	84.81 [25.85, 134.99]	−14.19 [−22.35, 80.9]	5.51 [−43.27, 50.06]	2.46 [−45.19, 92.96]

Notes: For Average Yearly Change/Theil-Sen analyses, percent changes are calculated relative to mid-point concentration for available data time-range; For both lockdown related changes/Break-point/segment analyses, percent changes are calculated relative to concentration prior to first detected change in that time period. As a result, percent changes locking down and while locked down should not be compared directly because each is calculated relative to its start-point. (From example, a 50% reduction from 100 μg m^{-3} followed by a 50% increase from there does not return levels to 100 μg m^{-3}: 100 μg m^{-3} − 50% = 50 μg m^{-3}; then 50 μg m^{-3} + 50% = 75 μg m^{-3}.)

[a] Considered less reliable because large uncertainty associated with change, start-point concentration or combination.

[b] Median change reported without 5% and 95% quantiles as ESTIMATE ONLY because insufficient measurements for quantile calculation.

Urban Background and Urban Traffic AURN stations, respectively, in Table 1 or trends in Fig. S3 Left. This is consistent with reduced O_3 quenching (O_3 + NO → O_2 + NO_2, etc.) in areas where NO_x levels have decreased, and, lockdown-related trends reported elsewhere (e.g. Collivignarelli et al., 2020, in Italy and Tobías et al., 2020, in Spain). However, although O_3 decreased in the weeks that followed, again in reasonable alignment with the increases in NO_2 as vehicles return to the road while the UK was locked down, there were also large increases in O_3 levels at many AURN stations in May/June, most likely driven by warmer weather rather than an association with either the lockdown or vehicle-related NO/NO_2, so suggesting at least two potential sources for O_3 changes observed.

The association between a change in on-road vehicle numbers, emission rates and airborne pollution levels would be expected to be less distinct for particulates by comparison to gaseous species like NO, NO_2 and NO_2 because non-traffic-related sources tend to be larger particulate contributors even at roadsides (see e.g. Jones et al., 2019) and the main traffic sources are more complex (exhaust, brake and tyre wear, road dust resuspension compared with exhaust alone) (Hester and Harrison, 2016). In addition, bus services were not stopped in most areas during the UK lockdown, and these are potentially a major airborne particle source, either because of tail-pipe emissions from buses not equipped with diesel particle filters (see e.g. Smit et al., 2019) or higher levels of particle resuspension associated with the large frontal area of the vehicle class more generally. However, if PM_{10} and $PM_{2.5}$ levels were affected by lockdown, the expected effect would be a decrease during lockdown, similar to the observed for NO_2, and similar to trends reported by others elsewhere (Bao and Zhang, 2020; Collivignarelli et al., 2020; Tobías et al., 2020). By contrast, pronounced increases were observed for both PM_{10} and $PM_{2.5}$ while locking down. Furthermore, these increases were highly similar at all three site types (Table 1; On average, PM_{10} 5.8, 6.2 and 6.3 μg m^{-3} and $PM_{2.5}$ 3.9, 4.8 and 5 μg m^{-3} at Rural Background, Urban Background and Urban Traffic AURN Stations, respectively) and part of pattern of changes (a decrease prior to lockdown followed by an increase while locking down and then a further increase and decrease while locked down) that was highly inconsistent with vehicle-related particulate emissions being their major contributor. Elsewhere others have identified secondary aerosols and regional pollution as potential confounders for lockdown-related particulate impact assessment (e.g. Tobías et al., 2020). These, meteorological processes (e.g. rain washout and resuspension) or other as-yet-accounted-for phenomena could be sources for the observed changes. Although this analysis provides no specific insights regarding the sources of particulate changes during the lockdown, it does clearly demonstrate that associated break-point/segment trends are distinctly different from those seen for NO, NO_2 and NO_x, and distinctly different to what would be expected as a response to lockdown.

In addition, Theil-Sen regression of trends 01 January 2015 to 31 December 2019 clearly show that NO, NO_2, NO_x, PM_{10} and $PM_{2.5}$ levels were typically all decreasing and O_3 levels were typically increasing year-on-year across the UK prior to lockdown (Table 1 and Figs. S4–S10), and in some cases these yearly changes were of the order of 10 to 25% of the magnitude of the changes observed while locking down.

Since this work was undertaken, the UK Air Quality Expert Group (AQEG) has published their own report based on Defra's Call for Evidence (AQEG, 2020). Although early work from this study was submitted to that call, it is worth briefly commenting on other findings reported there and published elsewhere e.g. Lee et al. (2020) and Forster et al. (2020), and the relevance of this extension to work reported to the Call in May 2020. All work points to similar interpretations for NO, NO_2, NO_x and O_3 trends about lockdown, and AQEG (2020) highlighted the complex nature of particulate trends and the challenges in their interpretation. Arguably, this approach, which uses break-point/segmentation methods to identify dates of likely discrete change rather than enforcing a 23/24th March 2020 change-point, provides unique evidence regarding the nature of change observed at the time. The profiles estimated for the UK (Fig. 4), also, perhaps, suggest options for 'unpicking' what is and is not lockdown-related change for species like O_3 and particulates where multiple contributions are highly likely to be contributing on relevant time-scales and at similar or greater magnitudes. Also, with regards the extension of the analysis into June (and potentially in future onwards), it is also worth highlighting the important of starting to treat the lockdown as series of events or more strictly stages, e.g. 'locking down', 'while locked down' (maybe also 'easing restrictions'), and 'coming out of lock down'. The lockdown and each of these stages are all likely to be dynamic events rather than static regions, and the greatest insights regarding the interaction of traffic and air quality will come from treating data from lockdown accordingly. Break-point/segmentation is certainly one of the tools worth considering as part of this process.

4. Conclusions

The current analysis should be regarded as provisional. Firstly, the analysis reported here is data that is not yet fully ratified, so potentially subject to revision, and the analysis employs break-point/segment methods that are in-development, and include some elements, e.g. the matching of air quality and meteorological data sources, that may be subject to further refinement. But, also equally importantly, the lockdown is itself an event in progress, and any study of impacts will, unavoidably, be provisional until there is sufficient data for the characterization of baselines both before and after the lockdown.

However, these caveats acknowledged, the current analysis provides provisional estimates of the magnitude of the air quality impact of the lockdown across the UK and break-point segment evidence on the very different change profiles observed for NO, NO_2, NO_x, O_3, PM_{10} and $PM_{2.5}$ in the UK that may help to inform other on-going efforts to characterize this highly unique event:

- NO, NO_2, and NO_x all exhibits trends highly consistent with airborne species impacted the UK lockdown, e.g. an abrupt decrease while locking down, on average NO −9.7 μg m^{-3} (−50%), NO_2–7.6 μg m^{-3} (−32%) and NO_x −17.1 μg m^{-3} (−38%) at AURN Urban Traffic monitoring stations, and a more gradual increase while locked down associated with the return to the road of vehicle during this period, on average NO 6.1 μg m^{-3}, NO_2 5 μg m^{-3} and NO_x 9 μg m^{-3} at AURN Urban Traffic monitoring stations. This suggests that by the end of studied period (30 June 2020) a significant proportion, provisionally estimated at ca. 50–70%, of the air quality benefits observed while locking down had already been offset by the return of vehicles to the roads.
- Although few UK Urban Traffic AURN Stations monitor O_3, O_3 levels increased on average 7.4 μg m^{-3} (17%) and 7.0 μg m^{-3} (14%) at these and Urban Background AURN Stations, respectively. These changes were broadly consistent with NO_2 reductions, supporting the assignment of this as an associated event. However, later changes during lockdown were less consistent trends while locked down, suggesting additional sources (most likely warm weather events) also make significant contributions to O_3 levels during this period.
- Observed trends for both PM_{10} and $PM_{2.5}$ were highly inconsistent with an air quality response to the lockdown. Across the UK, irrespectively of AURN site type, increases were observed for both species while locking down (PM_{10} 5.9 μg m^{-3} to 6.3 μg m^{-3} and $PM_{2.5}$ 3.9 μg m^{-3} to 5.0 μg m^{-3}) and trends both before and after were distinctly different to those expected for a lockdown response, indicating that the lockdown was not the major source (or not a direct source) of the most pronounced changes in levels of either of these species during this period.

Theil-Sen regression of the period 01 January 2015 to 31 December 2019 also indicated general year-on-year deductions for NO, NO_2, NO_x, PM_{10} and $PM_{2.5}$ and increases for O_3, prior to lockdown, and highlighting the limitations of 'same-time-last-year' studies that do not take into account underlying air quality trends.

Likewise, the identification of similar magnitude events not associated with lockdown, e.g. NO-dominated events associated with changes in on-road vehicle numbers in early January and O_3 events in May/June, and a highly uncertain association between PM_{10} and PM_{10} changes and the lockdown, also all highlight the potential limitations of studies that treat the lockdown as an event that happened in isolation.

However, perhaps the most important observation is that even for species like NO_2 that appears, in the UK at least, to exhibit a well isolated response to locking down, the period while locked down was not a stable baseline. Numbers of vehicles on the roads were changing during this time. As a result, even in the most ideal cases, studies that apply a conventional 'before-and-after' model selected periods before lockdown and in lockdown need, like this work, to be considered provisional estimates of the impact of the lockdown. Arguably, this situation is unlikely to change until we can robustly characterize both pre- and post-lockdown baselines and look critically at all the potential sources of air quality change about lockdown.

CRediT authorship contribution statement

Karl Ropkins: Conceptualization, Investigation, Resources, Formal analysis, Writing - original draft. **James Tate:** Conceptualization, Investigation, Resources, Writing - original draft.

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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The views and opinions expressed herein by the authors are their own and do not necessarily reflect those of UK Government or any agency thereof.

Appendix A. Supplementary data

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