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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, NO₂ and NOₓ decreased (on average) 32% to 50% at roadsides on lockdown.
• O₃ 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, NO₂ and NOₓ gradually increase as vehicles return to roads.

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, NO₂, NOₓ, O₃, PM₁₀ and PM₂.₅ time-series from Automatic Urban Rural Network (AURN) monitoring stations across the UK. NO, NO₂ and NOₓ all exhibit abrupt decreases at the time the UK locked down of (on average) 7.6 to 17 μg·m⁻³ (or 32 to 50%) at Urban Traffic stations and 4 to 5.7 μg·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 O₃ increased (7 to 7.4 μg·m⁻³ or 14 to 17% at Urban stations) broadly in line with NO₂ reductions, but later changes suggest significant non-lockdown contributions to O₃ during the months that followed. Increases of similar magnitudes were observed for both PM₁₀ (5.9 to 6.3 μg·m⁻³) and PM₂.₅ (3.9 to 5.0 μg·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.

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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 of countries,
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 Isson, 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; Tobias 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 NOx and PM10, 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-change, 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, NO2, NOx, O3, PM10 and PM2.5) 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, NOx and NO2 to 75 for O3. (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 unratted data. As part of the pre-processing of the 2020 data, some data sets were identified which contained atypically high NOx values over periods when neither NO or NO2 were reported, see e.g. Fig S2 in Supporting Information. These ‘high NOx’ but no NO or NO2’ 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 used to estimate of slope, and build change-segment descriptions (quantBreakPoints and quantBreakSegments functions in AQEval). The AQEval function isolateChange 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 ‘struchange’ break-point detection methods of Zelieis and colleagues (Zelieis 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\textsubscript{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\textsubscript{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\textsubscript{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.)
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 NO₂ 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 NO₂ 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 ‘triips’ 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 confidently 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 Headingley 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, NO₂, NOₓ, O₃, PM₁₀ and PM₂.₅ 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.
Some of the largest NO2 reductions when locking down were commonly observed NO2 changes are decreases seen while locking down and then increases while locked down, aligned with the expected changes in on-road vehicle numbers. The largest NO2 decreases while locking down and then increases while locked 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 NO2 (compare break-point/segment numbers in Figs. S6 and S5), and the most commonly seen NO changes were in January (compare NO2 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 O3 levels were lower and an NO2-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 NO2 by comparison to NOx (NO + NO2). However, for both NO and NOx, 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 NOx, 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 NOx, respectively, while locked down), and which, as with NO2, are more pronounced at Urban Traffic AURN stations, as would be expected for a vehicle emissions driven air quality change.

The behaviours of O3, PM10 and PM2.5 were, however, much less readily attributed to an isolated response to either the lockdown specifically or on-road vehicle numbers.

O3 levels typically increased at both Urban Traffic and Urban Background AURN stations while locking down. Although average NO/NO2/NOx and O3 measurements are not strictly directly comparable because NO, NO2 and NOx monitoring tends to be more common at Urban Background stations and O3 monitoring more common at Rural Background, the largest NO2 decreases while locking down were decreases seen while locking down and then increases while locked down, aligning with the expected changes in on-road vehicle numbers 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.
Urban Background and Urban Traffic AURN stations, respectively, in Table 1 or trends in Fig. S3 Left. This is consistent with reduced NO quenching (O$_3$ + NO $\rightarrow$ 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 Tobias et al., 2020, in Spain). However, although O$_3$ decreased in the weeks that followed, again in reasonable alignment with the increases in NO$_x$ 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$_x$, 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$_x$ and NO$_2$ because non-traffic-related sources tend to be larger particulate contributors even at road sides (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$_x$ and similar to trends reported by others elsewhere (Bao and Zhang, 2020; Collivignarelli et al., 2020; Tobias et al., 2020). By contrast, pronounced increases were observed for both PM$_{10}$ and PM$_{2.5}$ while lockdown 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 lockdown 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. Tobias 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$_x$, NO$_3$ and O$_3$ and distinctly different to what would be expected as a response to lockdown.

In addition, Thel-Sen regression of trends 01 January 2015 to 31 December 2019 reveals 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, NO2, NOx and O3 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 O3 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/segmentation 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, NO2, NOx, O3, PM10 and PM2.5 in the UK that may help to inform other on-going efforts to characterize this highly unique event:

• NO, NO2, and NOx 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%), NO2 = 7.6 µg m⁻³ (−32%) and NOx = 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 vehicles during this period, on average NO = 6.1 µg m⁻³, NO2 = 5 µg m⁻³ and NOx = 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 O3, O3 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 NOx 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 O3 levels during this period.
• Observed trends for both PM10 and PM2.5 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 (PM10 = 5.9 µg m⁻³ to 6.3 µg m⁻³ and PM2.5 = 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, NO2, NOx, PM10 and PM2.5 and increases for O3 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 O3 events in May/June, and a highly uncertain association between PM10 and PM2.5 changes and the lockdown, also 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 NO2 that appears, in the UK at least, to exhibit a well isolated response to lockdown, 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.

**Acknowledgements**

The AQEval package used in the present work is an in-development element of on-going work funded by the Department for Environment, Food and Rural Affairs (Defra). The authors gratefully acknowledge contributions and input from colleagues at University of Leeds, Defra, IPSOS Mori, as part of that work. The authors gratefully acknowledge the support of Leeds City Council, including provision of traffic data, as well as the work of the R Core Team and their many collaborators in developing and maintaining the open-source statistical language R and associated packages (http://www.r-project.org/). We also gratefully acknowledge, comments, advice and suggestions from those involved in the peer-review process.

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**

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2020.142374.
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