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Early Observations on the impact of the COVID-19 Lockdown on Air Quality Trends across the UK

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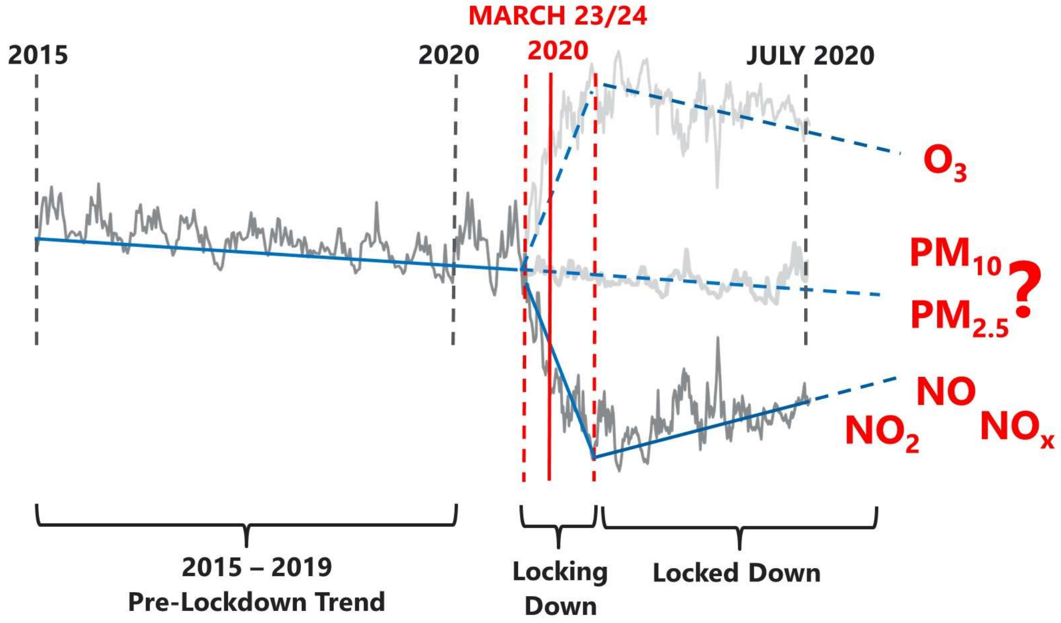
Highlights:

- 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:



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 $\mu g.m^{-3}$ (or 32 to 50%) at Urban Traffic stations and 4 to 5.7 $\mu g.m^{-3}$ (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 $\mu g.m^{-3}$ 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 $\mu g.m^{-3}$) and $PM_{2.5}$ (3.9 to 5.0 $\mu g.m^{-3}$) 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.

Keywords: COVID-19; Lockdown; NO_2; NO_x; O_3; Particulate Matter.

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; Nicola et al., 2020). However, it was not until 23-26 March when both cases and death rates peaked at about 5,000 and 900 per day, respectively, (data.gov.uk, 2020) that UK Government announced an official lockdown (GOV.UK, 2020a) an 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 & 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 & 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 & 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 & 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 Figure 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. Figure 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 prep*). 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.

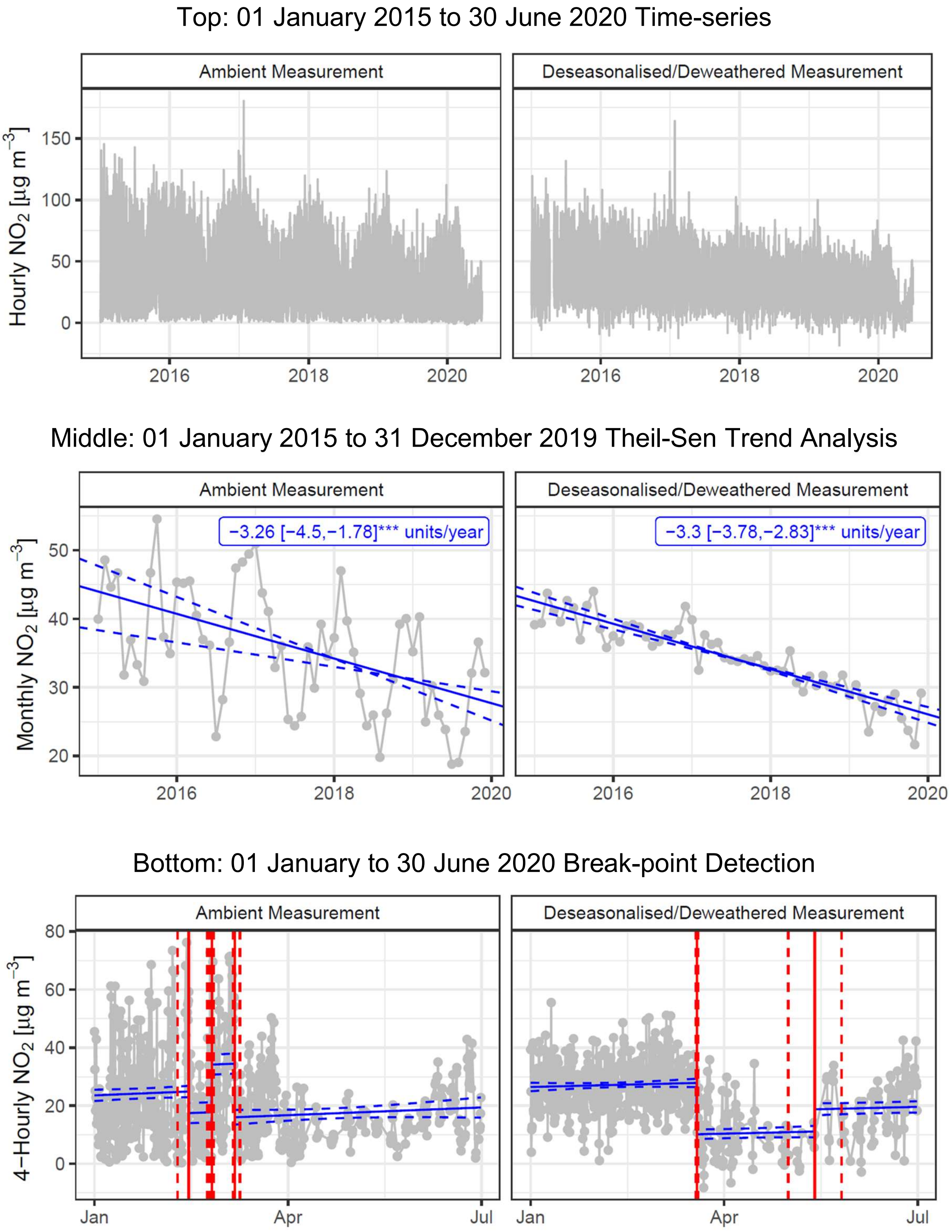
2020 Automatic Traffic Count (ATC) data was also provided by Leeds City Council for a site on Headingley Lane (A660) for the purposes of comparison with air quality data from the nearby AURN Headingley Roadside monitoring station. There was insufficient ATC data for dSW, so the ATC data were analysed 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, Figure 1 demonstrates the effects of the different steps of this analysis. Figure 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. Figure 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 Figure S3 in 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.

Figure 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 (Figure 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.

Figure 3 presents break-point and break-segment models generated for traffic volume data from a nearby ATC for the same time period as Figure 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.


Top: 01 January 2015 to 30 June 2020 Time-series

Middle: 01 January 2015 to 31 December 2019 Theil-Sen Trend Analysis

Bottom: 01 January to 30 June 2020 Break-point Detection

Figure 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.)

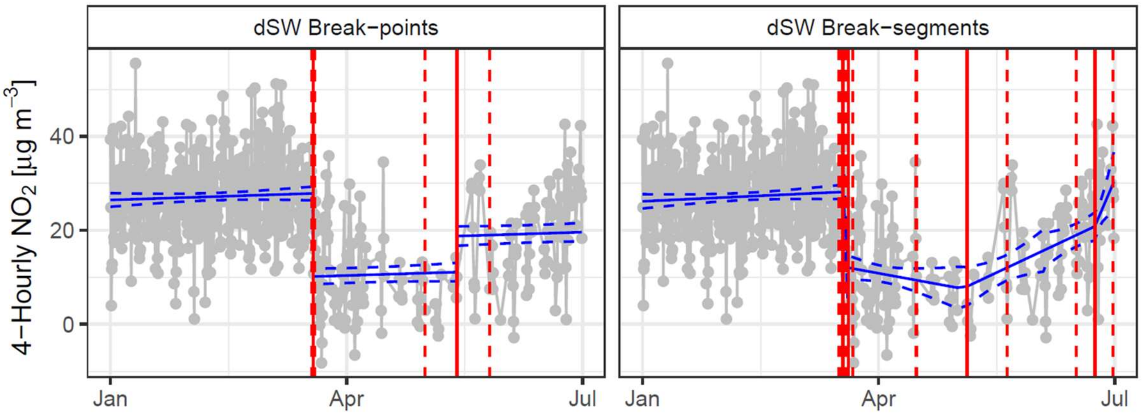


Figure 2: Break-point (Left) and Break-segment (Right) models of deseasonalised and deweathered (dSW) 01 January to 30 June 2019 NO$_2$ data from the AURN Headingley Roadside air quality monitoring station. (Data in grey; predicted trends in blue; and, break-points in red; solid lines are predictions and dashed lines are associated 95% confidence intervals.)

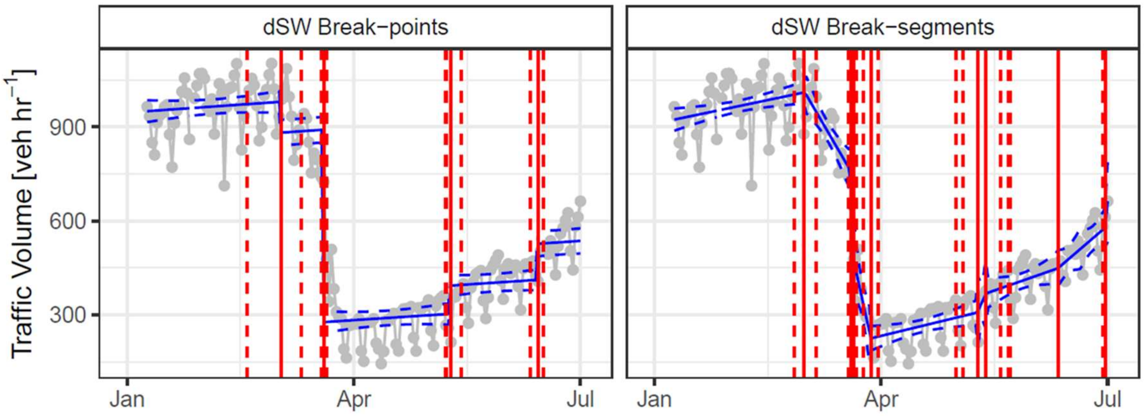


Figure 3: Break-point (Left) and Break-segment (Right) models of 01 January to 30 June 2019 traffic volume data from a Leeds City Council ATC at a location near to the Headingley AURN station NO$_2$ data was taken from for Figures 1 and 2. (Data in grey; predicted trends in blue; and, break-points in red; solid lines are predictions and dashed lines are associated 95% confidence intervals.)

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 Figure 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. 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 Figure 4. This is slightly wider than the time-range for the lockdown-related changes in road vehicle numbers reported for Headingley in Figure 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.* ± 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 characterise 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 Figure 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 Figures 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 Figure 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} (Figure 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 Figures S6 and S5), and the most commonly seen NO changes were in January (compare NO_2 and NO in Figure 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 $\mu g\ m^{-3}$ or -49.9% and *ca.* -17.1 $\mu g\ m^{-3}$ or -38.2% for NO and NO_x, respectively, while locking down; and, ca. 6.06 $\mu g\ m^{-3}$ or 50.1% and *ca.* 9.0 $\mu g\ m^{-3}$ 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 $\mu g\ m^{-3}$ versus 1.8 $\mu g\ m^{-3}$, 7.0 $\mu g\ m^{-3}$ versus -4.2 $\mu g\ m^{-3}$ and 7.4 $\mu g\ m^{-3}$ versus -7.6 $\mu g\ m^{-3}$ for O_3 and NO_2 at Rural Background, Urban Background and Urban Traffic AURN stations, respectively, in Table 1 or trends in Figure S3 Left. This is consistent with reduced O_3 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 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 & 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 & 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 Figures S4-S10), and in some cases these yearly changes were of the order of 10 to 25% of the magnitude of the changes observed whilst 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 (Figure 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.

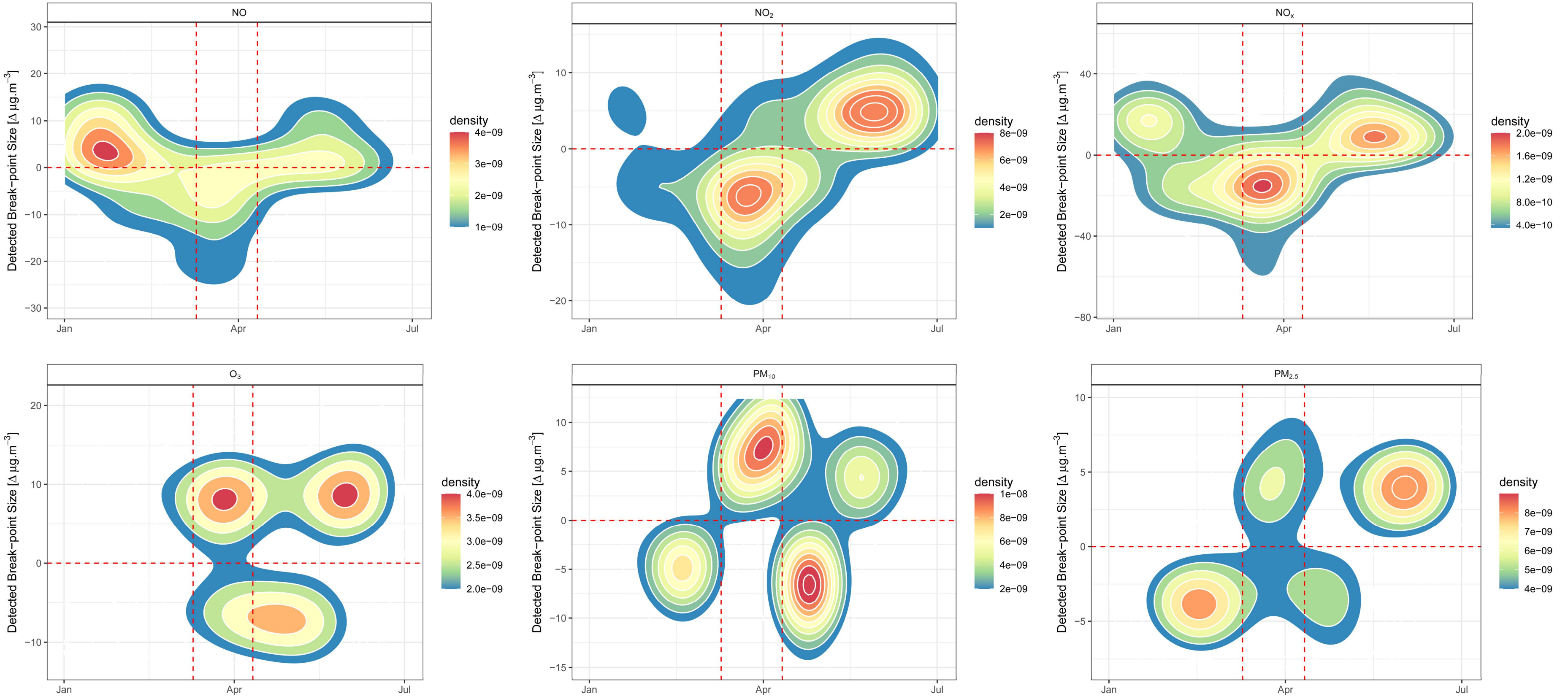


Figure 4: Density plots of NO, NO$_2$, NO$_x$, O$_3$, PM$_{10}$ and PM$_{2.5}$ break-point/segment events detected 01 January to 30 June 2020 at UK AURN monitoring stations. Here, the horizontal red dashed line indicates the ‘no change’ boundary for detected events, above increases and below decreases; 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.

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.

		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}]**		
Species	**Change**	**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]*	-45.79 [-59.39, 46.08]	-49.85 [-79.29, -29.88]	-36.12 [-61.93, 55.28]	26.26 [-45.62, 516.38]*	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]*	-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]*	-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**
	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**
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]*	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}.)

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

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

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.

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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Short Communication: Early Detection of the impact of theCOVID-19 Lockdown on Air Quality Trends across the UK

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Supporting Information:

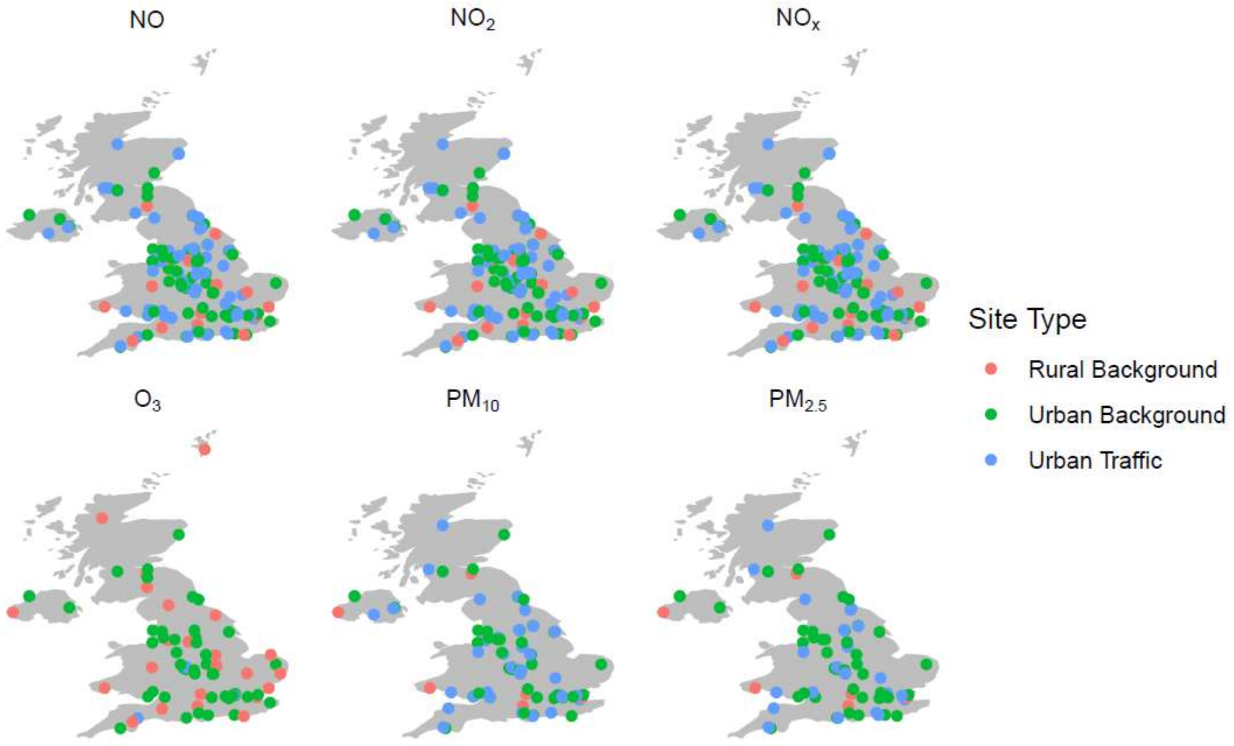

Figure S1: UK AURN Monitoring Stations with NO, NO_2, NO_x, O_3, PM_{10} or $PM_{2.5}$ data available between 01 January 2015 and 30 June 2020.

Table S1: Counts by site type of UK AURN Monitoring Stations with NO, NO_2, NO_x, O_3, PM_{10} or $PM_{2.5}$ data available between 01 January 2015 and 30 June 2020.

	Species					
Site Type	**NO**	**NO_2**	**NO_x**	**O_3**	**PM_{10}**	**$PM_{2.5}$**
Rural Background	16	16	16	24	6	6
Urban Background	67	67	67	47	43	47
Urban Traffic	70	70	70	4	39	27
Total	**153**	**153**	**153**	**75**	**88**	**80**

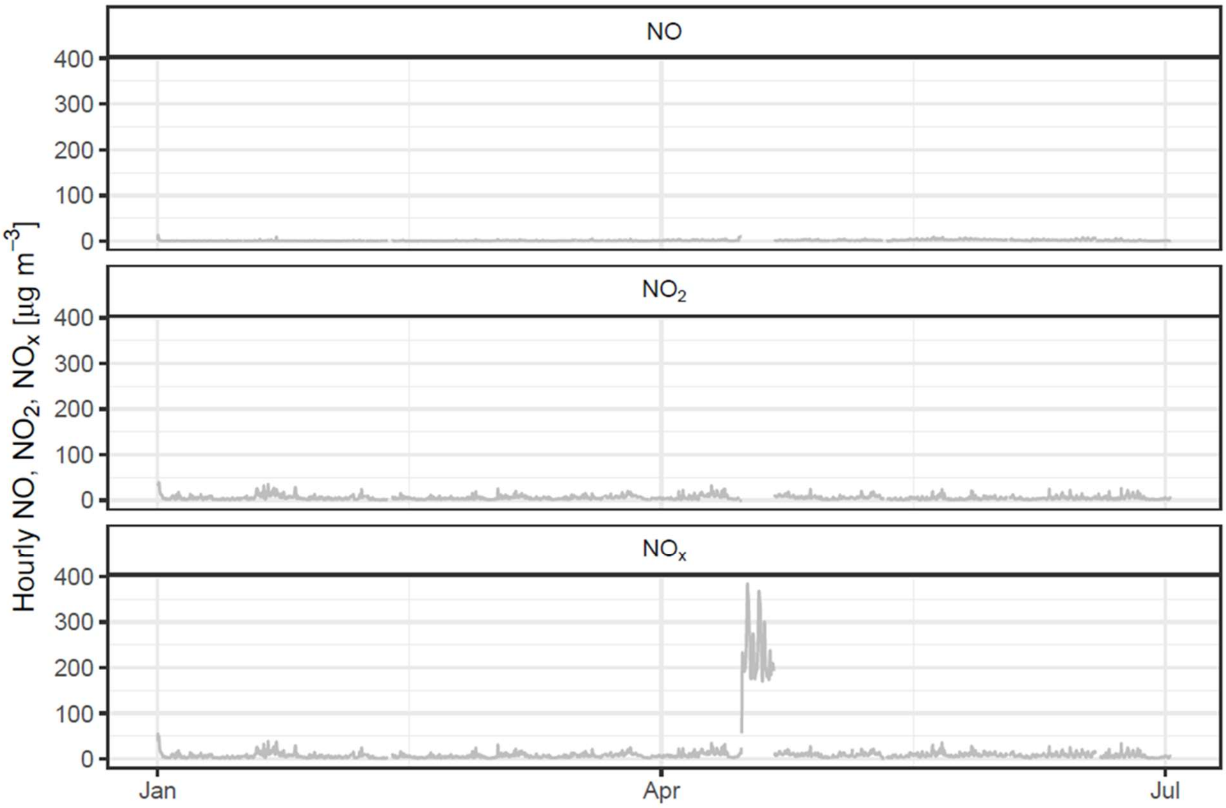

Figure S2: 2020 time-series for AURN NO, NO_2 and NO_x data from Lullington Health (AURN CODE LH, Rural Background, South East Zone) showing atypically high feature in NOx mid to late April and assumed to be a pre-ratification artefact.

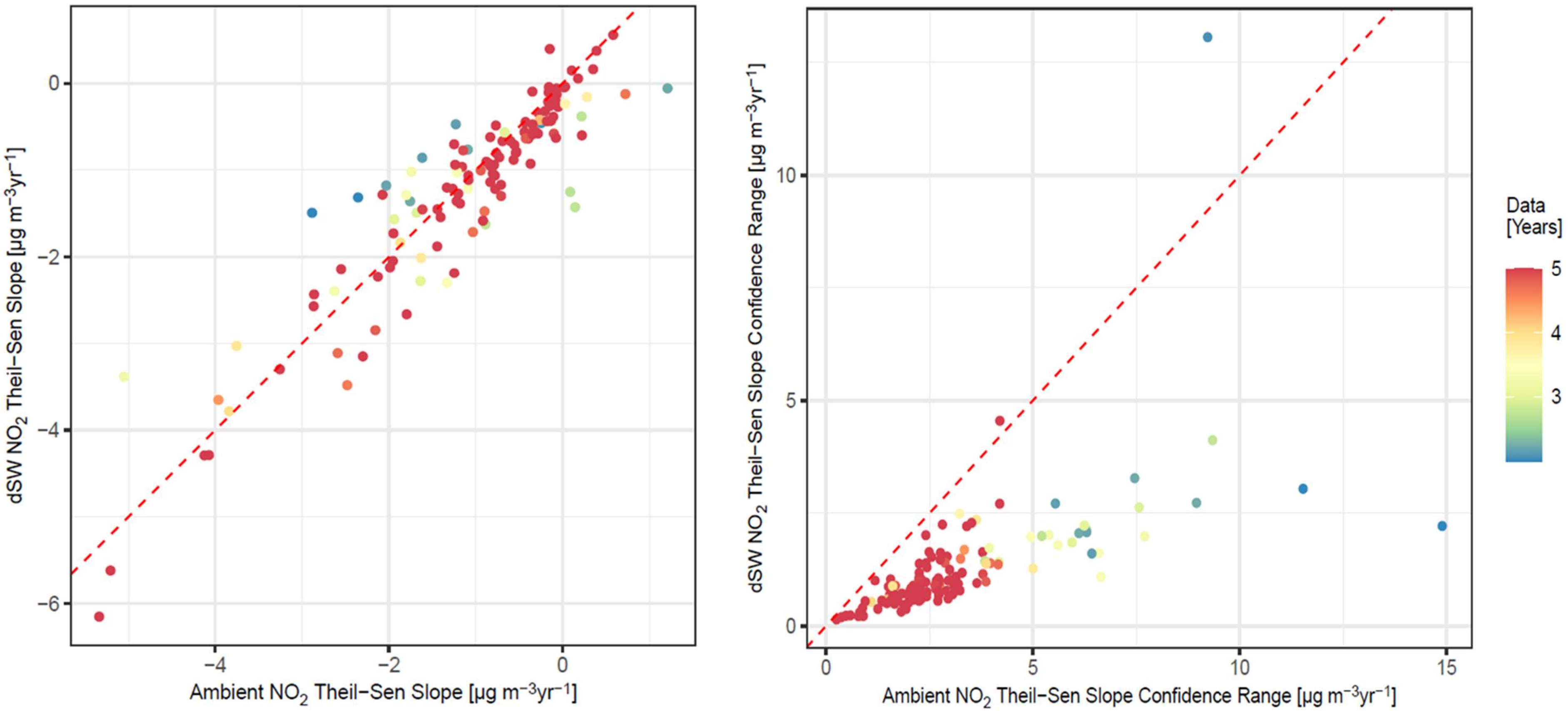

Figure S3: Comparison of Theil-Sen analysis of ambient and deseasonalised and deweathered (dSW) NO_2 data from the period 01 January 2015 to 31 December 2019: Left Theil-Sen analysis slopes for 1-month average data; and, Right Theil-Sen slope confidence range (upper – lower 95% confidence interval). In both cases, the data is colour-coded according to available time range, and the Y=X is included as a dashed red line for reference. Please Note: The near proximity of most points to Y=X in S3 Left indicating that estimated Theil-Sen trends where generally similar with or without dSW, and that the majority of data in S3 Right is below Y=X demonstrating that confidence intervals were typically smaller when dSW is applied.

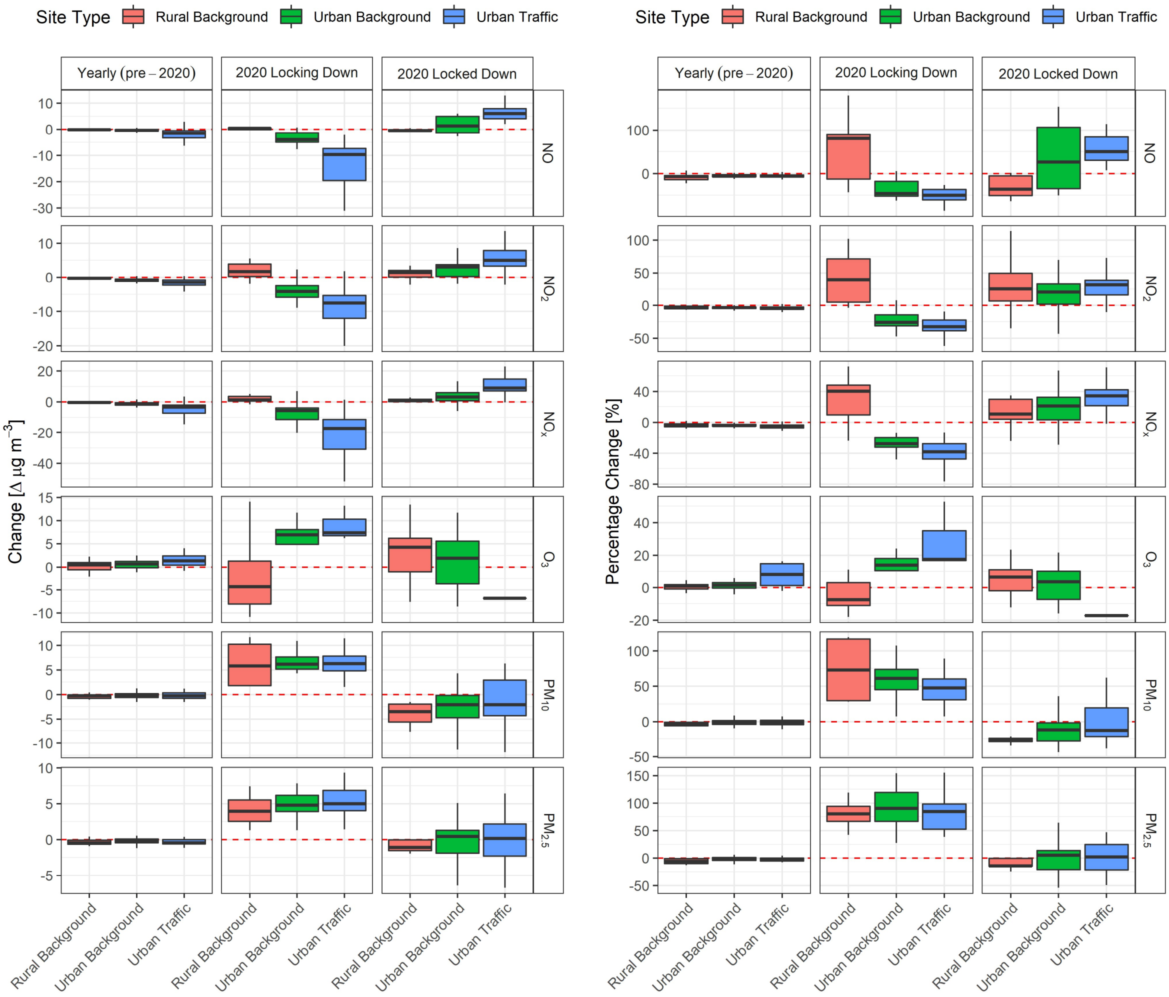

Figure S4: Overall trends for NO, NO$_2$, NO$_x$, O$_3$, PM$_{10}$ and PM$_{2.5}$ at UK AURN sites (Left absolute changes, Right percent changes): for each site, Average Yearly Change (pre-2020) are the average annual change as determined by Theil-Sen analysis for the period 01 January 2015 to 31 December 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. (See also Footnotes on Table 1 regarding calculation and comparison of percent changes.)

Figure S5: NO Trends observed at individual AURN Stations: 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.

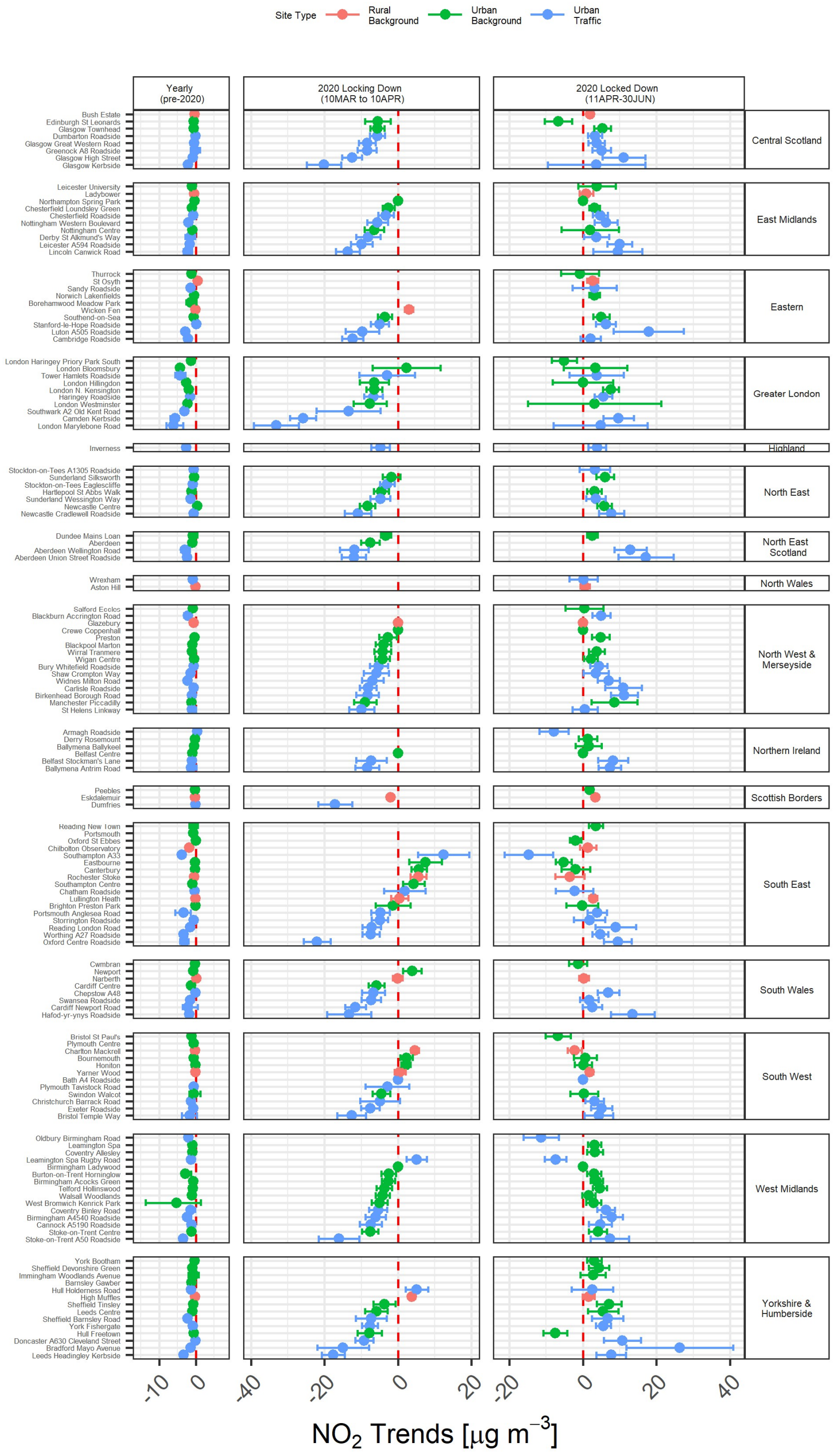

Figure S6: NO₂ Trends observed at individual AURN Stations: Average Yearly Change (pre-2020) are the average annual change as determined by Theil-Sen analysis for the period 01 January 2015 to 31 December 2019, and Change Locking Down and Change while Locked Down are determined as the net sum of changes due for break-points/segments detected during the periods 10 March to 10 April 2020 and 11 April to 30 June 2020, respectively.

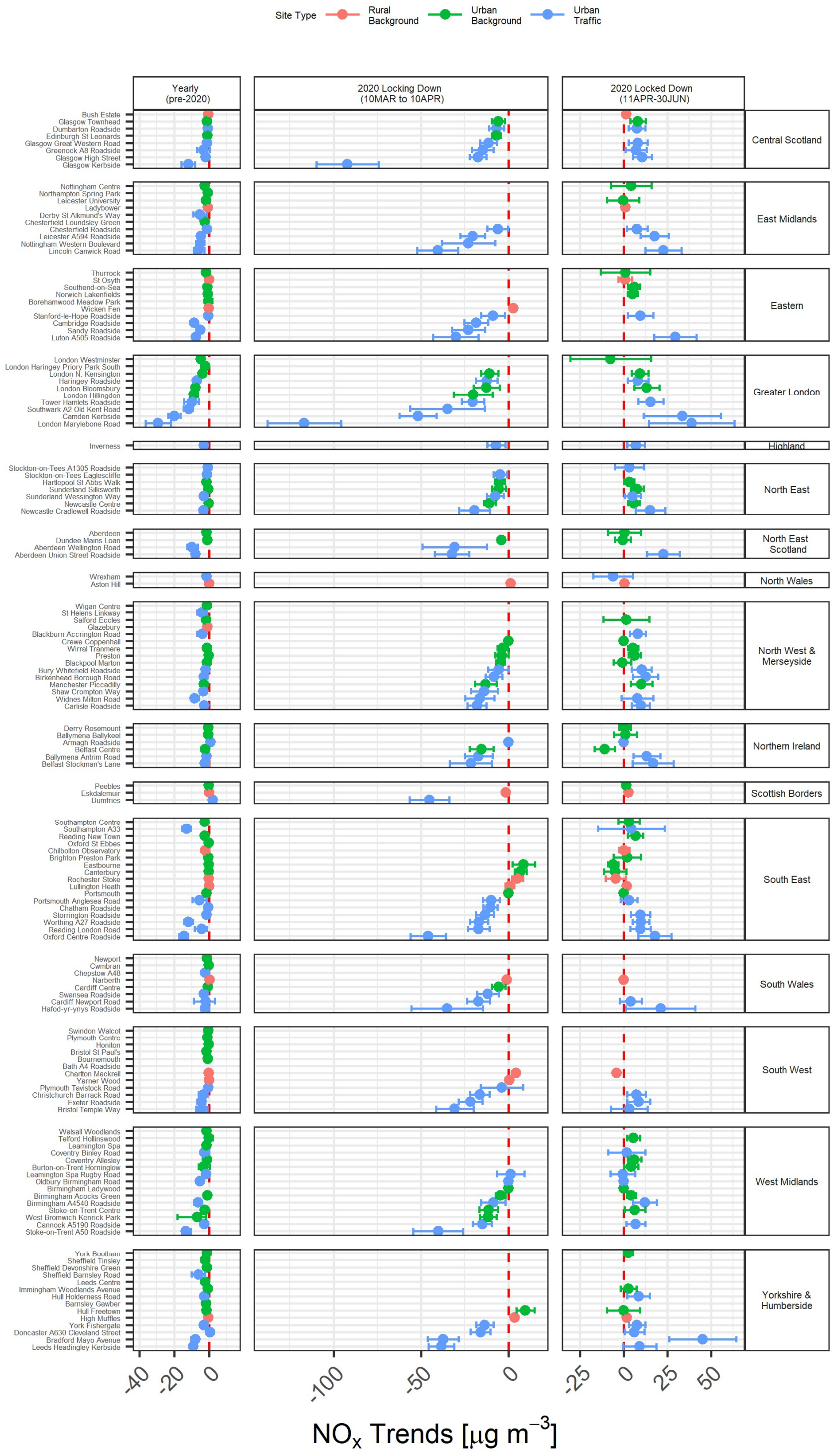

Figure S7: NO_x Trends observed at individual AURN Stations: Average Yearly Change (pre-2020) are the average annual change as determined by Theil-Sen analysis for the period 01 January 2015 to 31 December 2019, and Change Locking Down and Change while Locked Down are determined as the net sum of changes due for break-points/segments detected during the periods 10 March to 10 April 2020 and 11 April to 30 June 2020, respectively.

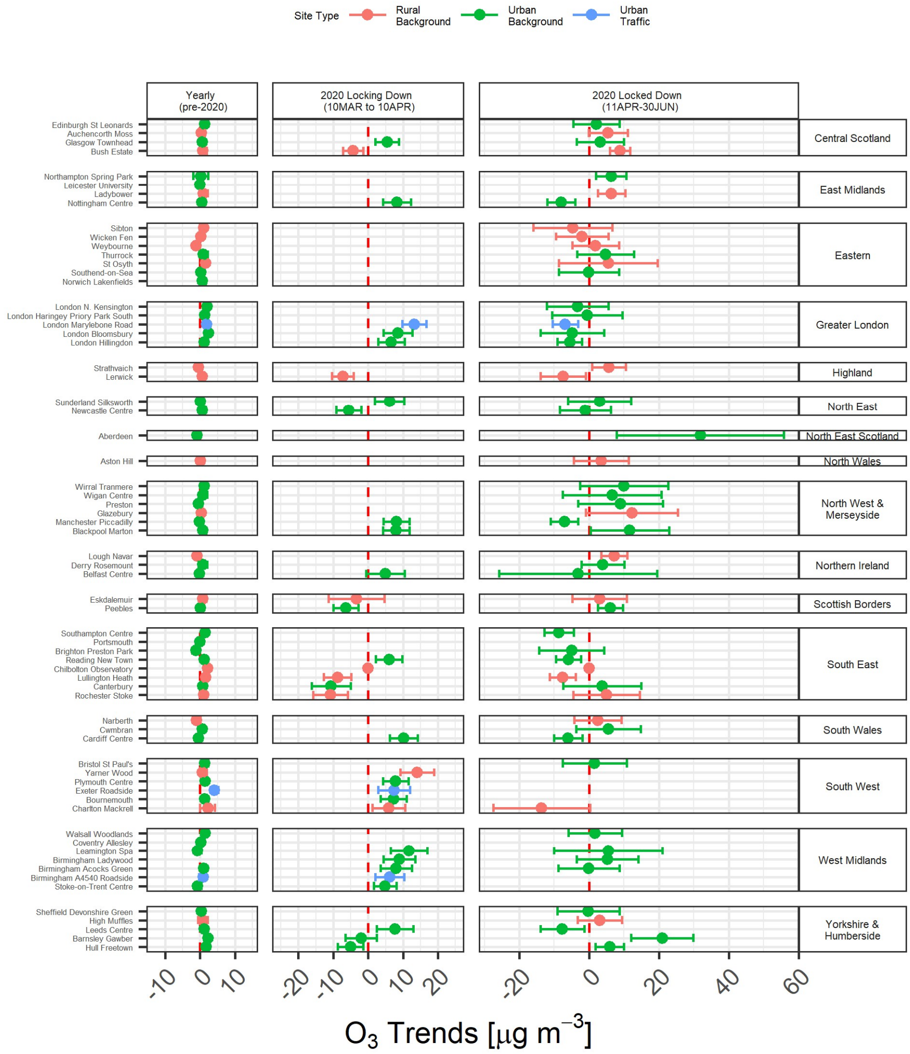

Figure S8: O$_3$ Trends observed at individual AURN Stations: Average Yearly Change (pre-2020) are the average annual change as determined by Theil-Sen analysis for the period 01 January 2015 to 31 December 2019, and Change Locking Down and Change while Locked Down are determined as the net sum of changes due for break-points/segments detected during the periods 10 March to 10 April 2020 and 11 April to 30 June 2020, respectively.

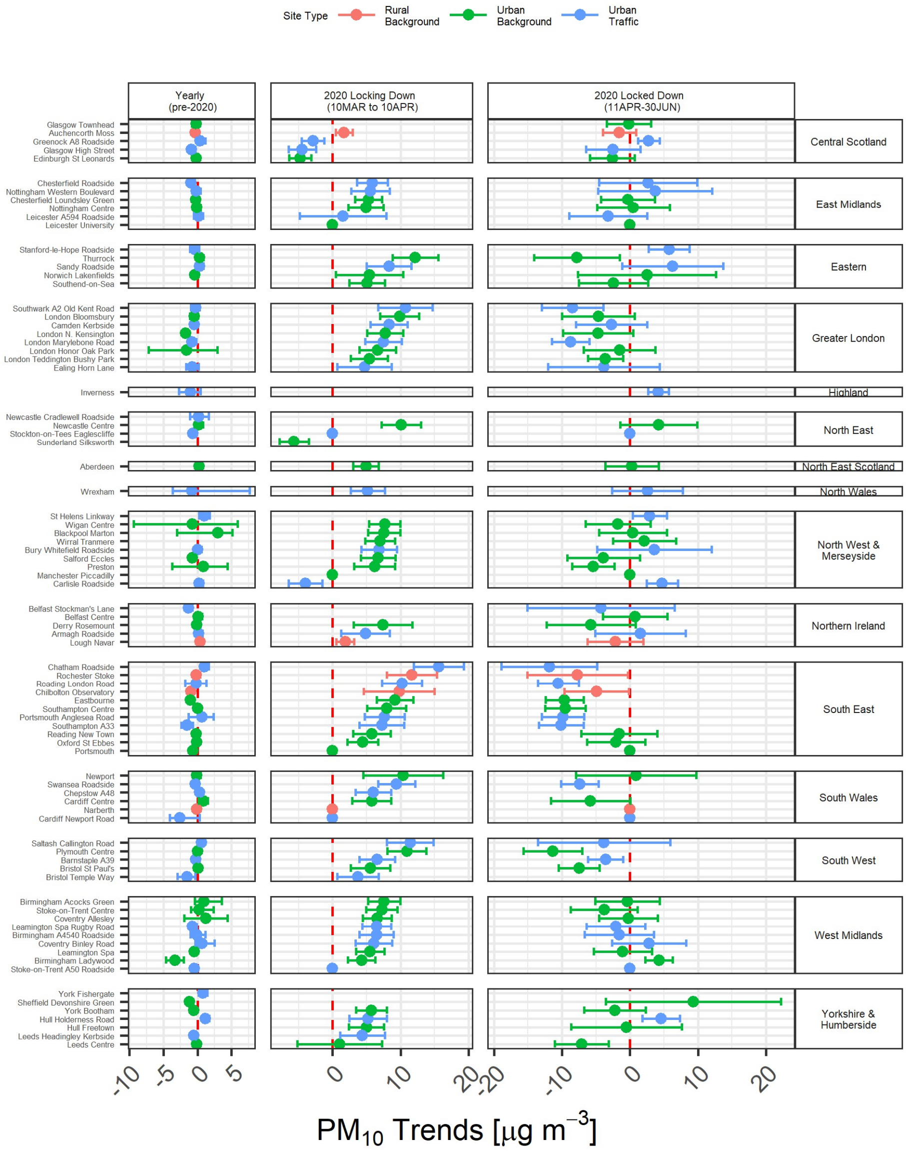

Figure S9: PM$_{10}$ Trends observed at individual AURN Stations: Average Yearly Change (pre-2020) are the average annual change as determined by Theil-Sen analysis for the period 01 January 2015 to 31 December 2019, and Change Locking Down and Change while Locked Down are determined as the net sum of changes due for break-points/segments detected during the periods 10 March to 10 April 2020 and 11 April to 30 June 2020, respectively.

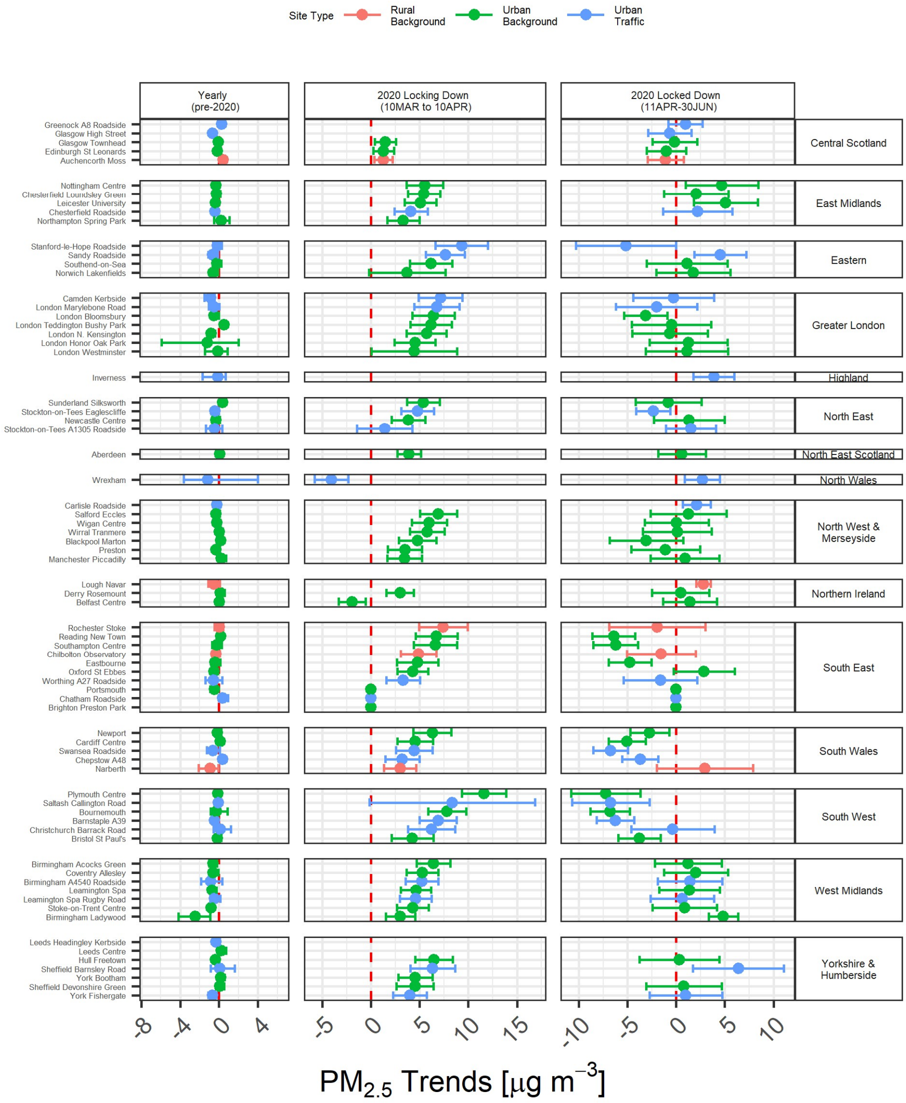

Figure S10: $PM_{2.5}$ Trends observed at individual AURN Stations: Average Yearly Change (pre-2020) are the average annual change as determined by Theil-Sen analysis for the period 01 January 2015 to 31 December 2019, and Change Locking Down and Change while Locked Down are determined as the net sum 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.

Table S2: UK AURN Monitoring Sites and NOAA Meteorological Stations paired for use in Theil-Sen and Break-Point/Segment analyses, and distances between site-station pairs. The AURN sites are Automatic Urban and Rural Network air quality monitoring stations operated in UK by Defra (https://uk-air.defra.gov.uk/), and the Meteorological stations are Meteorological stations operated in the UK but with data archived in the National Oceanic and Atmospheric Administration (NOAA) Integrated Surface Database (ISD (https://www.ncdc.noaa.gov/isd). Here, code and WBAN-USAF are the unique archive identifiers for the individual AURN and NOAA datasets, respectively. The nearest NOAA dataset with >90% data capture for 1-hour resolution wind speed, wind direction and air temperature data for the period 01 January 2015 to 30 June 2020, was paired with the AURN with data for same period. Please note: Not all AURN sites monitor all species studied here and not all were operating throughout the full study period, and not all NOAA stations provided sufficient data coverage for the full time period, and there are nearer site-station pairs for some of these AURN sites. Similarly, not all analyses (Theil-sen, break-point and break-segment) could be conducted on all data from all stations, so not all pairings generated all result types.

AURN Sites					Meteorological Stations				Distance (km)
Name	**Code**	**Site Type**	**Latitude**	**Longitude**	**Name**	**WBAN-USAF**	**Latitude**	**Longitude**	
Aberdeen	ABD	Urban Background	57.15736	-2.09428	Dyce	030910-99999	57.20133	-2.20433	8.24
Aberdeen Union Street Roadside	ABD7	Urban Traffic	57.14456	-2.10647	Dyce	030910-99999	57.20133	-2.20433	8.64
Aberdeen Wellington Road	ABD8	Urban Traffic	57.13389	-2.0942	Dyce	030910-99999	57.203	-2.200	9.99
Auchencorth Moss	ACTH	Rural Background	55.79216	-3.2429	Edinburgh Gogarbank	031660-99999	55.933	-3.350	17.03
Birmingham Acocks Green	AGRN	Urban Background	52.43717	-1.83	Birmingham	035340-99999	52.454	-1.748	5.86
Aston Hill	AH	Rural Background	52.50385	-3.03418	Shobdon Airfield	035200-99999	52.250	-2.883	30.03
Armagh Roadside	ARM6	Urban Traffic	54.35373	-6.65456	Glenanne No.2	039230-99999	54.233	-6.500	16.76
Ballymena Antrim Road	BAAR	Urban Traffic	54.85149	-6.27496	Portglenone	039150-99999	54.867	-6.450	11.33
Ballymena Ballykeel	BALM	Urban Background	54.8616	-6.25087	Portglenone	039150-99999	54.867	-6.450	12.76

Barnsley Gawber	BAR3	Urban Background	53.56292	-1.51044	Emley Moor No.2	033460-99999	53.600	-1.667	11.13
Bath Roadside	BATH	Urban Traffic	51.39113	-2.35416	Bristol	037243-99999	51.383	-2.719	25.33
Birkenhead Borough Road	BBRD	Urban Traffic	53.38851	-3.02501	Crosby	033160-99999	53.500	-3.067	12.71
Borehamwood Meadow Park	BDMP	Urban Background	51.66123	-0.27067	Northolt	036720-99999	51.5515	-0.4175	15.86
Belfast Stockman's Lane	BEL1	Urban Traffic	54.57259	-5.97494	Aldergrove	039170-99999	54.65533	-6.21633	18.06
Belfast Centre	BEL2	Urban Background	54.59965	-5.92883	Aldergrove	039170-99999	54.65533	-6.21633	19.51
Bath A4 Roadside	BHA4	Urban Traffic	51.39092	-2.35503	Bristol	037243-99999	51.383	-2.719	25.27
Birmingham Tyburn	BIR1	Urban Background	52.51172	-1.83058	Birmingham	035340-99999	52.454	-1.748	8.51
Birmingham A4540 Roadside	BIRR	Urban Traffic	52.47609	-1.87502	Birmingham	035340-99999	52.454	-1.748	8.95
Birmingham Tyburn Roadside	BIRT	Urban Traffic	52.51219	-1.83086	Birmingham	035340-99999	52.454	-1.748	8.56
Blackburn Accrington Road	BLAR	Urban Traffic	53.74775	-2.45272	Blackpool	033180-99999	53.767	-3.033	38.21
Blackpool Marton	BLC2	Urban Background	53.80489	-3.00718	Blackpool	033180-99999	53.767	-3.033	4.54
Birmingham Ladywood	BMLD	Urban Background	52.48135	-1.91824	Birmingham	035340-99999	52.454	-1.748	11.93
Oldbury Birmingham Road	BOLD	Urban Traffic	52.50244	-2.0035	Birmingham	035340-99999	52.454	-1.748	18.12
Bournemouth	BORN	Urban Background	50.73957	-1.82674	Bournemouth	038620-99999	50.783	-1.833	4.85
Bottesford	BOT	Rural Background	52.93028	-0.81472	Cranwell	033790-99999	53.0315	-0.4915	24.39
Burton-on-Trent Horninglow	BOTR	Urban Background	52.82105	-1.63572	Nottingham East Midlands	034185-99999	52.831	-1.328	20.7
Barnstaple A39	BPLE	Urban Traffic	51.07479	-4.04192	Chivenor	037070-99999	51.083	-4.150	7.6
Bristol Temple Way	BR11	Urban Traffic	51.45797	-2.58398	Bristol	037243-99999	51.383	-2.719	12.54

Bristol St Paul's	BRS8	Urban Background	51.46284	-2.58448	Bristol	037243-99999	51.383	-2.719	12.88
Brighton Preston Park	BRT3	Urban Background	50.84084	-0.14757	Shoreham	038760-99999	50.833	-0.283	9.55
Bury Whitefield Roadside	BUR W	Urban Traffic	53.55903	-2.29377	Rostherne No.2	033510-99999	53.367	-2.383	22.15
Bush Estate	BUSH	Rural Background	55.86228	-3.20578	Edinburgh Gogarbank	031660-99999	55.933	-3.350	11.94
Camden Kerbside	CA1	Urban Traffic	51.54421	-0.17527	City	037683-99999	51.505	0.055	16.52
Hafod-yr-ynys Roadside	CAE6	Urban Traffic	51.68058	-3.13351	Cardiff	037150-99999	51.397	-3.343	34.7
Cambridge Roadside	CAM	Urban Traffic	52.20237	0.124456	Mildenhall RAF	035770-35046	52.362	0.486	30.33
Cannock A5190 Roadside	CANK	Urban Traffic	52.6873	-1.98082	Birmingham	035340-99999	52.454	-1.748	30.34
Canterbury	CANT	Urban Background	51.27399	1.098061	Manston	037970-35047	51.350	1.333	18.39
Cardiff Centre	CARD	Urban Background	51.48178	-3.17625	Cardiff	037150-99999	51.397	-3.343	14.91
Carlisle Roadside	CARL	Urban Traffic	54.89483	-2.94531	Spadeadam	031650-99999	55.050	-2.550	30.56
Chilbolton Observatory	CHBO	Rural Background	51.14962	-1.43823	Middle Wallop	037490-99999	51.150	-1.567	8.98
Christchurch Barrack Road	CHBR	Urban Traffic	50.73545	-1.78089	Bournemouth	038620-99999	50.783	-1.833	6.43
Chesterfield Loundsley Green	CHLG	Urban Background	53.24413	-1.45495	Nottingham/Watnall	033540-99999	53.000	-1.250	30.4
Chepstow A48	CHP	Urban Traffic	51.63809	-2.67873	Bristol	037243-99999	51.383	-2.719	28.5
Chesterfield Roadside	CHS7	Urban Traffic	53.23172	-1.45694	Nottingham/Watnall	033540-99999	53.000	-1.250	29.23
London Bloomsbury	CLL2	Urban Background	51.52229	-0.12589	City	037683-99999	51.505	0.055	12.66
Cardiff Newport Road	CNPR	Urban Traffic	51.49096	-3.15231	Cardiff	037150-99999	51.397	-3.343	16.85
Coventry Allesley	COAL	Urban Background	52.41156	-1.56023	Coleshill	035350-99999	52.483	-1.683	11.5

Coventry Binley Road	COBR	Urban Traffic	52.40771	-1.49008	Church Lawford	035440-99999	52.367	-1.333	11.58
Crewe Coppenhall	COPP	Urban Background	53.11594	-2.45349	Rostherne No.2	033510-99999	53.367	-2.383	28.31
Shaw Crompton Way	CW	Urban Traffic	53.57928	-2.09379	Emley Moor No.2	033460-99999	53.600	-1.667	28.26
Cwmbran	CWMB	Urban Background	51.6538	-3.00695	Bristol	037243-99999	51.383	-2.719	36.11
Dundee Mains Loan	DCC1	Urban Background	56.47543	-2.95986	Leuchars	031710-99999	56.3865	-2.8675	11.4
Doncaster A630 Cleveland Street	DCST	Urban Traffic	53.51824	-1.13806	Doncaster Sheffield	034054-99999	53.475	-1.004	10.09
Derry Rosemount	DERR	Urban Background	55.00282	-7.33118	Magilligan No.2	039070-99999	55.16	-6.948	30
Derry	DERY	Urban Background	55.00123	-7.32912	Magilligan No.2	039070-99999	55.15	-6.933	30.16
Derby St Alkmund's Way	DESA	Urban Traffic	52.92298	-1.46951	Nottingham East Midlands	034185-99999	52.831	-1.328	13.96
Dumbarton Roadside	DUMB	Urban Traffic	55.9432	-4.55973	Glasgow Bishopton	031340-99999	55.900	-4.533	5.08
Dumfries	DUMF	Urban Traffic	55.07003	-3.61423	Eskdalemuir	031620-99999	55.317	-3.2	38.02
Dewsbury Ashworth Grove	DYAG	Urban Background	53.6931	-1.63711	Emley Moor No.2	033460-99999	53.600	-1.667	10.54
Ealing Horn Lane	EA8	Urban Traffic	51.51895	-0.26562	Northolt	036720-99999	51.5515	-0.4175	11.11
Stockton-on-Tees Eaglescliffe	EAGL	Urban Traffic	54.51667	-1.35855	Leeming	032570-99999	54.296	-1.534	27.04
Eastbourne	EB	Urban Background	50.80578	0.271611	Herstmonceux West End	038820-99999	50.9	0.317	10.95
Salford Eccles	ECCL	Urban Background	53.48481	-2.33414	Rostherne No.2	033510-99999	53.367	-2.383	13.49
Edinburgh St Leonards	ED3	Urban Background	55.94559	-3.18219	Edinburgh Gogarbank	031660-99999	55.933	-3.35	10.54
Edinburgh Nicolson Street	EDNS	Urban Traffic	55.94476	-3.18399	Edinburgh Gogarbank	031660-99999	55.933	-3.35	10.42

Eskdalemuir	ESK	Rural Background	55.31531	-3.20611	Eskdalemuir	031620-99999	55.317	-3.2	0.43
Exeter Roadside	EX	Urban Traffic	50.72508	-3.53247	Dunkeswell Aerodrome	038400-99999	50.867	-3.233	26.31
Great Dun Fell	GDF	Rural Background	54.68423	-2.4508	Great Dun Fell No.2	032270-99999	54.683	-2.45	0.15
Glasgow Great Western Road	GGWR	Urban Traffic	55.87204	-4.27094	Glasgow	031400-99999	55.872	-4.433	10.11
Glasgow High Street	GHSR	Urban Traffic	55.86094	-4.23821	Glasgow	031400-99999	55.872	-4.433	12.22
Greenock A8 Roadside	GKA8	Urban Traffic	55.94408	-4.73442	Glasgow Bishopton	031340-99999	55.907	-4.531	13.33
Glasgow Kerbside	GLA4	Urban Traffic	55.85917	-4.25889	Glasgow	031400-99999	55.872	-4.433	10.96
Glazebury	GLAZ	Rural Background	53.46008	-2.47206	Rostherne No.2	033510-99999	53.367	-2.383	11.91
Glasgow Townhead	GLKP	Urban Background	55.86578	-4.24363	Glasgow	031400-99999	55.872	-4.433	11.83
Harwell	HAR	Rural Background	51.57108	-1.32528	Benson	036580-99999	51.6165	-1.0895	17.05
Haringey Roadside	HG1	Urban Traffic	51.5993	-0.06822	City	037683-99999	51.505	0.055	13.51
London Haringey Priory Park South	HG4	Urban Background	51.58413	-0.12525	City	037683-99999	51.505	0.055	15.26
London Hillingdon	HIL	Urban Background	51.49633	-0.46086	Heathrow	037720-99999	51.47967	-0.45733	1.87
High Muffles	HM	Rural Background	54.33494	-0.80855	Fylingdales	032810-99999	54.367	-0.667	9.84
Honiton	HONI	Urban Background	50.79229	-3.1967	Dunkeswell Aerodrome	038400-99999	50.867	-3.233	8.69
London Westminster	HORS	Urban Background	51.49467	-0.13193	City	037683-99999	51.505	0.055	12.99
London Honor Oak Park	HP1	Urban Background	51.44967	-0.03742	City	037683-99999	51.505	0.055	8.88
London Harrow Stanmore	HR3	Urban Background	51.61733	-0.29878	Heathrow	037720-99999	51.47967	-0.45733	18.83
Hartlepool St Abbs Walk	HSAW	Urban Background	54.68324	-1.20384	Loftus	032750-99999	54.567	-0.867	25.24

Hull Freetown	HUL2	Urban Background	53.74878	-0.34122	Leconfield	033820-99999	53.867	-0.433	14.46
Hull Holderness Road	HULR	Urban Traffic	53.75897	-0.30575	Leconfield	033820-99999	53.867	-0.433	14.63
Immingham Woodlands Avenue	IMGM	Urban Background	53.61924	-0.21332	Humberside	033735-99999	53.574	-0.351	10.39
Inverness	INV2	Urban Traffic	57.48131	-4.24145	Aviemore	030630-99999	57.2	-3.833	39.74
London N. Kensington	KC1	Urban Background	51.52105	-0.21349	Northolt	036720-99999	51.5515	-0.4175	14.51
Ladybower	LB	Rural Background	53.40337	-1.75201	Emley Moor No.2	033460-99999	53.6	-1.667	22.58
Leamington Spa	LEAM	Urban Background	52.28881	-1.53312	Church Lawford	035440-99999	52.367	-1.333	16.14
Leamington Spa Rugby Road	LEAR	Urban Traffic	52.29488	-1.54291	Church Lawford	035440-99999	52.367	-1.333	16.36
Leicester University	LECU	Urban Background	52.61982	-1.12731	Nottingham East Midlands	034185-99999	52.831	-1.328	27.09
Leeds Headingley Kerbside	LED6	Urban Traffic	53.81997	-1.57636	Leeds Bradford	033463-99999	53.866	-1.661	7.55
Leeds Centre	LEED	Urban Background	53.80378	-1.54647	Leeds Bradford	033463-99999	53.866	-1.661	10.21
Leicester A594 Roadside	LEIR	Urban Traffic	52.63868	-1.12423	Nottingham East Midlands	034185-99999	52.831	-1.328	25.41
Lerwick	LERW	Rural Background	60.13922	-1.18532	Lerwick	030050-99999	60.133	-1.183	0.7
Lullington Heath	LH	Rural Background	50.7937	0.18125	Herstmonceux West End	038820-99999	50.9	0.317	15.18
Lincoln Canwick Road	LIN3	Urban Traffic	53.22137	-0.53419	Waddington	033770-99999	53.1705	-0.5235	5.7
Lough Navar	LN	Rural Background	54.43951	-7.90033	Finner	039780-99999	54.483	-8.233	22.04
Luton A505 Roadside	LUTR	Urban Traffic	51.89229	-0.46211	High Wycombe HQAIR	036600-99999	51.683	-0.8	32.89
Liverpool Queen's Drive Roadside	LV6	Urban Traffic	53.44694	-2.9625	Crosby	033160-99999	53.5	-3.067	9.09

Charlton Mackrell	MACK	Rural Background	51.05625	-2.68345	Yeovilton	038530-99999	51.0045	-2.636	6.64
Manchester Piccadilly	MAN3	Urban Background	53.48152	-2.23788	Rostherne No.2	033510-99999	53.367	-2.383	15.96
Market Harborough	MKTH	Rural Background	52.55444	-0.77222	Wittering	034620-99999	52.615	-0.4715	21.4
London Marylebone Road	MY1	Urban Traffic	51.52253	-0.15461	Northolt	036720-99999	51.5515	-0.4175	18.47
Newcastle Cradlewell Roadside	NCA3	Urban Traffic	54.98641	-1.59536	Newcastle	032433-99999	55.038	-1.692	8.42
Newcastle Centre	NEWC	Urban Background	54.97825	-1.61053	Newcastle	032433-99999	55.038	-1.692	8.43
Norwich Lakenfields	NO12	Urban Background	52.61419	1.301976	Norwich	034920-99999	52.676	1.283	6.99
Nottingham Centre	NOTT	Urban Background	52.95473	-1.14645	Nottingham/Watnall	033540-99999	53	-1.25	8.57
Newport	NPT3	Urban Background	51.6012	-2.97728	Bristol	037243-99999	51.383	-2.719	30.14
Northampton Kingsthorpe	NTN3	Urban Background	52.27189	-0.8799	Bedford	035600-99999	52.217	-0.483	27.7
Northampton Spring Park	NTN4	Urban Background	52.27226	-0.91661	Bedford	035600-99999	52.227	-0.464	31.22
Nottingham Western Boulevard	NWBV	Urban Traffic	52.96938	-1.18885	Nottingham/Watnall	033540-99999	53.005	-1.25	5.7
St Osyth	OSY	Rural Background	51.77798	1.049031	Shoeburyness Landwick	036930-99999	51.55	0.833	29.4
Oxford Centre Roadside	OX	Urban Traffic	51.75175	-1.25746	Benson	036580-99999	51.6165	-1.0895	18.98
Oxford St Ebbes	OX8	Urban Background	51.74481	-1.26028	Benson	036580-99999	51.6165	-1.0895	18.5
Peebles	PEEB	Urban Background	55.65747	-3.19653	Edinburgh Gogarbank	031660-99999	55.933	-3.35	32.1
Narberth	PEMB	Rural Background	51.78178	-4.69146	Pembry Sands	036050-99999	51.717	-4.367	23.47

Plymouth Centre	PLYM	Urban Background	50.37167	-4.14236	Plymouth/Mountbatte	038270-99999	50.35	-4.117	3.01
Plymouth Tavistock Road	PLYR	Urban Traffic	50.41106	-4.13029	Plymouth/Mountbatte	038270-99999	50.354	-4.12	6.39
Portsmouth	PMTH	Urban Background	50.82881	-1.06858	Thorney Island	038720-99999	50.817	-0.917	10.73
Portsmouth Anglesea Road	POAR	Urban Traffic	50.79834	-1.09556	Thorney Island	038720-99999	50.814	-0.921	12.39
Preston	PRES	Urban Background	53.76559	-2.68035	Blackpool	033180-99999	53.767	-3.033	23.18
Reading New Town	REA1	Urban Background	51.45309	-0.94407	Benson	036580-99999	51.6165	-1.0895	20.77
Reading London Road	REA5	Urban Traffic	51.4549	-0.94038	Benson	036580-99999	51.618	-1.0965	21.11
Southampton A33	SA33	Urban Traffic	50.92027	-1.46348	Middle Wallop	037490-99999	51.15	-1.567	26.55
Saltash Callington Road	SASH	Urban Traffic	50.41146	-4.22768	Plymouth/Mountbatte	038270-99999	50.35	-4.117	10.41
Sandy Roadside	SDY	Urban Traffic	52.13242	-0.30031	Bedford	035600-99999	52.217	-0.483	15.61
Sheffield Barnsley Road	SHBR	Urban Traffic	53.40495	-1.45582	Emley Moor No.2	033460-99999	53.612	-1.667	26.93
Sheffield Devonshire Green	SHDG	Urban Background	53.37862	-1.4781	Emley Moor No.2	033460-99999	53.6	-1.667	27.61
St Helens Linkway	SHLW	Urban Traffic	53.45183	-2.74213	Liverpool	033233-99999	53.334	-2.85	14.93
Sibton	SIB	Rural Background	52.2944	1.463497	Wattisham	035900-99999	52.122	0.9615	39.21
Southwark A2 Old Kent Road	SK5	Urban Traffic	51.4805	-0.05955	City	037683-99999	51.505	0.055	8.39
Stockton-on-Tees A1305 Roadside	SOTR	Urban Traffic	54.56582	-1.3159	Loftus	032750-99999	54.567	-0.867	28.94
Southampton Centre	SOUT	Urban Background	50.90814	-1.39578	Middle Wallop	037490-99999	51.15	-1.567	29.44
Stoke-on-Trent A50 Roadside	STKR	Urban Traffic	52.98044	-2.1119	Leek Thorncliffe	033300-99999	53.133	-1.983	19.03
Stoke-on-Trent Centre	STOK	Urban Background	53.02821	-2.17513	Leek Thorncliffe	033300-99999	53.133	-1.983	17.33

Storrington Roadside	STOR	Urban Traffic	50.91693	-0.44955	Shoreham	038760-99999	50.833	-0.283	14.96
Sunderland Silksworth	SUN2	Urban Background	54.88361	-1.40688	Newcastle	032433-99999	55.038	-1.692	25.02
Sunderland Wessington Way	SUNR	Urban Traffic	54.91839	-1.40839	Newcastle	032433-99999	55.038	-1.692	22.46
Strathvaich	SV	Rural Background	57.73446	-4.77658	Loch Glascarnoch	030310-99999	57.717	-4.883	6.61
Swansea Roadside	SWA1	Urban Traffic	51.6327	-3.94737	Mumbles Head	036090-99999	51.567	-3.983	7.71
Swindon Walcot	SWHO	Urban Background	51.55806	-1.76568	Lyneham	037400-99999	51.503	-1.992	16.81
Telford Hollinswood	TDHD	Urban Background	52.67347	-2.43669	Shawbury	034140-99999	52.799	-2.6675	20.89
London Teddington	TED	Urban Background	51.42099	-0.33965	Heathrow	037720-99999	51.47967	-0.45733	10.44
London Teddington Bushy Park	TED2	Urban Background	51.42529	-0.34561	Kenley Airfield	037810-99999	51.3	-0.083	22.95
Tower Hamlets Roadside	TH2	Urban Traffic	51.52253	-0.04216	City	037683-99999	51.505	0.055	7
Thurrock	THUR	Urban Background	51.47707	0.317969	City	037683-99999	51.505	0.055	18.47
Wirral Tranmere	TRAN	Urban Background	53.37287	-3.02272	Liverpool	033233-99999	53.334	-2.85	12.25
Walsall Woodlands	WAL4	Urban Background	52.60562	-2.03052	Coleshill	035350-99999	52.483	-1.683	27.17
West Bromwich Kenrick Park	WBKP	Urban Background	52.50834	-1.98601	Birmingham	035340-99999	52.454	-1.748	17.21
Weybourne	WEYB	Rural Background	52.95049	1.122017	Weybourne	034880-99999	52.95	1.133	0.74
Wicken Fen	WFEN	Rural Background	52.2985	0.290917	Mildenhall RAF	035770-35046	52.362	0.486	15.02
Wigan Centre	WIG5	Urban Background	53.54914	-2.63814	Rostherne No.2	033510-99999	53.367	-2.383	26.37
Wrexham	WREX	Urban Traffic	53.04222	-3.00278	Hawarden	033210-99999	53.167	-2.983	13.94
Widnes Milton Road	WSMR	Urban Traffic	53.36539	-2.73168	Liverpool	033233-99999	53.334	-2.85	8.59

Worthing A27 Roadside	WTHG	Urban Traffic	50.83295	-0.37992	Shoreham	038760-99999	50.836	-0.29533	5.95
York Bootham	YK10	Urban Background	53.96751	-1.08651	Linton On Ouse	032660-99999	54.0495	-1.2515	14.12
York Fishergate	YK11	Urban Traffic	53.95189	-1.07586	Linton On Ouse	032660-99999	54.0495	-1.2515	15.8
Yarner Wood	YW	Rural Background	50.5976	-3.71651	Plymouth/Mountbatte	038270-99999	50.35	-4.117	39.51