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The impact of COVID-19 control measures on air quality in China

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Abstract

The outbreak of Coronavirus Disease 2019 (COVID-19) in China in January 2020 prompted substantial control measures including social distancing measures, suspension of public transport and industry, and widespread cordon sanitaires ('lockdowns'), that have led to a decrease in industrial activity and air pollution emissions over a prolonged period. We use a 5 year dataset from China's air quality monitoring network to assess the impact of control measures on air pollution. Pollutant concentration time series are decomposed to account for the inter-annual trend, seasonal cycles and the effect of Lunar New Year, which coincided with the COVID-19 outbreak. Over 2015–2019, there were significant negative trends in particulate matter ($PM_{2.5}$, -6% yr^{-1}) and sulphur dioxide (SO_2, -12% yr^{-1}) and nitrogen dioxide (NO_2, -2.2% yr^{-1}) whereas there were positive trends in ozone (O_3, $+2.8\%$ yr^{-1}). We quantify the change in air quality during the LNY holiday week, during which pollutant concentrations increase on LNY's day, followed by reduced concentrations in the rest of the week. After accounting for interannual trends and LNY we find NO_2 and PM concentrations were significantly lower during the lockdown period than would be expected, but there were no significant impacts on O_3. Largest reductions occurred in NO_2, with concentrations 27.0% lower on average across China, during the lockdown. Average concentrations of $PM_{2.5}$ and PM_{10} across China were respectively 10.5% and 21.4% lower during the lockdown period. The largest reductions were in Hubei province, where NO_2 concentrations were 50.5% lower than expected during the lockdown. Concentrations of affected pollutants returned to expected levels during April, after control measures were relaxed.

1. Introduction

The outbreak of Coronavirus Disease 2019 (COVID-19) began in the megacity of Wuhan (population 11 million) in central China, with cases first being reported on December 27, 2019. Media reports of an unknown pneumonia outbreak began to appear on December 31, with the outbreak officially being reported to the World Health Organisation (WHO) on the same day (WHO 2020). The cause of the disease was confirmed as a novel coronavirus on January 7 2020 (Wu and Mcgoogan 2020). The Chinese government quickly implemented control measures, such as isolation, quarantine and social distancing. Dramatic actions to control the disease were taken, as entire cities were quarantined across China. This began with Wuhan being 'locked-down' on January 23, followed by another 14 cities in Hubei province the next day (Kraemer *et al* 2020). Cases of the disease were soon reported in China's other provinces, with every other province reporting their first case between January 18 to 25 (Liu *et al* 2020). Public transport networks, schools and entertainment venues were suspended (Tian *et al* 2020), and the Lunar New Year (LNY) national holiday was extended, to delay the return of hundreds of millions to their cities of work, and citizens were encouraged to work from home.

The control measures are likely to have resulted in a substantial decrease in air pollutant emissions across China. In the industrial sector, widespread suspensions of production resulted in the largest ever decrease in the Purchasing Managers Index, which tracks industrial output in China (CFLP 2020,

Prescott 2020). The monthly growth rate in industrial production, which in 2019 had averaged $+0.5\%$, fell to -2.78% in January 2020 and -26.63% in February 2020 (National Bureau of Statistics 2020b). In the power generation sector, electricity generation in January and February dropped by 8.2%, compared with 2019. As restrictions began to be eased during March, the economy started to recover, with March power generation lower by 4.6% compared with the previous year (National Bureau of Statistics 2020a). CO_2 emissions may have decreased by 25% during the first few weeks of lockdowns (CarbonBrief 2020).

The control measures and resultant emission reductions are likely to have influenced China's air quality, and impacts have been widely reported in the media. According to measurements made by NASA's TROMPOMI satellite, there was a 20% larger than previous year's drop in Nitrogen Dioxide (NO_2), between the period before LNY to the period after (Liu *et al* 2020). However, understanding the impacts of control measures on air quality is complicated by several compounding factors. The control measures coincided with the LNY, the largest holiday in China. The LNY is typically a week long and results in well-documented impacts on air pollution (Tan *et al* 2009, Gong *et al* 2014, Lai and Brimblecombe 2017). China's air quality has been changing rapidly in recent years, with large reductions in SO_2 and PM concentrations and increased O_3 (Van Der A *et al* 2017, Lu *et al* 2018, Silver *et al* 2018). These trends in pollutants are due to declining emissions (Zheng *et al* 2017, Ding *et al* 2019, Silver *et al* 2020), and need to be accounted for when analyzing any impact of the lockdown on pollutant concentrations.

Although China's air quality has improved in recent years, it continues to suffer a severe health burden caused by indoor and outdoor air pollution, with 12% of deaths in China in 2017 attributable to this risk factor (James *et al* 2018). Understanding trends in air quality is essential to assess the effectiveness of recent air quality measures and help inform future air pollution mitigation (Zhao *et al* 2017). The application of control measures during the COVID-19 outbreak provides an opportunity to analyse the potential air quality improvements resulting from a reduction in emissions, as well as a 'natural experiment' from which theories of chemistry-climate interactions can be tested.

To understand the impact of the control measures instigated during the COVID-19 outbreak, it is necessary to compare pollutant concentrations in 2020 with expected concentrations had the COVID-19 outbreak not occurred. Here, we use time series of China-wide measurements of key pollutant concentrations between January 2015 an April 2020 to isolate changes that occurred during the COVID-19 lockdown period compared with concentrations that would otherwise be expected based on recent trends, seasonality, and the effects of LNY. We do not assess the relative contribution of emissions and meteorology to observed changes during the lockdown.

2. Methodology

2.1. Data

We obtained data from China's national network of air quality monitoring stations, which is operated by the China National Environmental Monitoring Center (CNEMC). The network consists of 1640 automatic measurement stations located throughout mainland China, which report measurements of particulate matter ($PM_{2.5}$ and PM_{10}), nitrogen dioxide (NO_2), ozone (O_3), sulphur dioxide (SO_2) and carbon monoxide (CO). The data was downloaded from https://quotsoft.net/ (formerly http://beijingair.sinaapp.com/), which aggregates the real-time data reported on the official website of the CNEMC. The dataset covers the period from January 2015 to April 2020. For this study, stations with a timeseries of >58 months and >90% data availability were used. We used the same data quality methods as in Silver *et al* (2018), excluding data with high proportion of repeat measurements and periods of very low variability. The number of excluded stations is provided in the supplementary table 1 (available online at stacks.iop.org/ERL/15/084021/mmedia).

2.2. Time series decomposition

When comparing the air quality in China during the lockdown in 2020, to the same period of previous years, it is necessary to account for several interacting factors, including interannual trends, seasonal cycle and the effects of Chinese LNY. LNY is based on the lunar calendar, so in the Gregorian calendar, the holiday falls on a different date between late January and late February each year.

The time series are decomposed separately for each pollutant at each station, using daily data. The 2015–2019 time series are used to calculate the trend, seasonal cycle and effect of LNY, for each pollutant at each station, and these patterns are applied to 2020. The 2020 residuals are then analysed to assess the extent to which pollutant concentrations were affected during the lockdown period.

Figure 1 shows this method for NO_2, and the remaining pollutants are shown in supplementary figure 1. The data is analysed and visualised using the Python libraries *pandas* and *matplotlib* (Hunter 2007, Mckinney 2010). The trend is calculated using the method in Silver *et al* (2018), using the Theil–Sen estimator to calculate the monotonic, linear trends (Sen 1968, Carslaw and Ropkins 2012). The trend is subtracted from the daily mean data, and the resulting detrended data is smoothed using locally weighted scatterplot smoothing (LOWESS) using the *statsmodels* Python library (Cleveland 1979, Seabold and Perktold 2010). A 30-day window for the LOWESS filter is used to approximate the background seasonal

concentration. The period between 14 d prior and 21 d after LNY is removed and replaced with interpolated data. Both the seasonal smoothing and LNY data are averaged across years, to give separate seasonal cycle and LNY effect timeseries. These time series are subtracted from the detrended data, to give the residual time series, which represents departures from the expected concentration based on the trend, seasonal cycle, and LNY effect.

The residual concentrations are used to assess how much the concentration of pollutants deviated from their expected concentration, based on long-term trends, seasonality and LNY impacts. At each station, we apply a 7 day centered rolling mean to the residual time series, giving a time series of 7 d mean residuals (7DMR). We express this in relative terms (%) by dividing the residual timeseries by the sum of the trend, seasonal and LNY components. Taking the median during the lockdown period (defined below) allows for comparison between different pollutants and regions. The 7DMR represents a longer-term deviation from the expected concentration, averaging out day-to-day variability. Supplementary figure 3 the effects of using different averaging periods.

To analyze the influence of the COVID-19 control measures, we define the 'lockdown period' as January 23 to March 31, 2020. The lockdown was officially lifted in Wuhan on April 8th, though restrictions were eased in other parts of China earlier than this, and some social distancing measures have remained in place. Generally, restrictions were lifted gradually, so it is likely that emissions will gradually return to normal. We analyse data at the national level and for the following regions: the Mid-Yangtze Basin (MYB) in central China (which includes Hubei province); the North China Plain (NCP) which includes the capital Beijing, as well as Tianjin municipality and Hebei province; the Yangtze River Delta (YRD) which includes Shanghai; the Sichuan Basin (SCB) which includes Chengdu and Chongqing; the Fenwei Plain (FWP) which includes Xi'an; and the Pearl River Delta (PRD), which includes Guangzhou and Shenzhen.

3. Results

3.1. Inter-annual trends
There are significant inter-annual trends in air pollutant concentrations. Our previous work, Silver *et al* (2018) found that during 2015–2017 across much of China, there were significant negative trends in $PM_{2.5}$ and SO_2, whereas for O_3, there were widespread significant positive trends. Here we show that significant trends have continued across much of China.

Figure 2 shows the 2015–2019 trends in air pollutants across China. SO_2 has the strongest negative trend, with 89% of stations reporting significant reductions and a median trend of -12.0% yr^{-1} or

-2.6 μg m^{-3} yr^{-1}. For $PM_{2.5}$, 81% of stations report a significant reduction, with a median trend of -6.0% yr^{-1} or -3.0 μg m^{-3} yr^{-1}. For NO_2, 44% of stations report a significant reduction, with a median trend of -2.2% yr^{-1} or -0.7 μg m^{-3} yr^{-1}. Unlike the other pollutants, O_3 concentrations have increased, with 47% of stations reporting a significant positive trend, and a median trend of 2.8% yr^{-1} or 1.6 μg m^{-3} yr^{-1}. Changes in air pollutant concentrations are pervasive, with all analysed regions showing increased O_3 and decreased $PM_{2.5}$ and SO_2.

The variability of the magnitude and direction of trends highlights the importance of accounting for the inter-annual trend at each station individually, as we do here. For example, at a station with a positive trend, we might expect a decrease in concentration during the outbreak to be moderated, while at one with a negative trend, we account for the fact that the concentration likely would have been reduced under normal circumstances.

3.2. Seasonal cycle
Figure 3 shows the mean seasonal cycle of pollutant concentrations during 2015 to 2019. In general, the pollutants concentrations peak in the winter, except for O_3, which peaks in early summer. The effect of LNY is visible for some pollutants, especially NO_2. However, since this is not caused by seasonal changes and does not occur on the same date each year, we extract this signal from the seasonal cycle (shown as the red dotted line) and analyse separately.

3.3. Lunar New Year
Figure 4 shows the impact of LNY on pollutant concentrations. PM, CO, and SO_2 concentrations all increase on the first day of LNY, likely caused by emissions from fireworks (Jiang *et al* 2015, Feng *et al* 2016, Lai and Brimblecombe 2017). On this day, $PM_{2.5}$ and PM_{10} concentrations are on average 46 and 53 μg m^{-3} higher, respectively. During the remainder of LNY, concentrations of all pollutants except O_3 are lower than usual. $PM_{2.5}$ and PM_{10} concentrations are 6.7 and 15.2 μg m^{-3} lower respectively. NO_2 is on average 14.5 μg m^{-3} lower during the LNY holiday. O_3 concentrations are higher during LNY, and are negatively correlated with NO_2. This likely demonstrates a reduction in the NO_x (NO_2 + NO) titration effect, where O_3 is removed in the presence of high concentrations of NO.

The effects of LNY mean that simply comparing monthly averages between different years during this period could be misleading. In some years LNY occurs in January whereas in other years it occurs in February. Controlling for the LNY effect is important, as it allows comparison across years.

3.4. Residual analysis
Figure 5 shows the anomaly in pollutant concentrations after the inter-annual trend, seasonal cycle and

Figure 1. Average of the NO_2 (μg m^{-3}) time series (blue), decomposed into its the trend (yellow), seasonal cycle (green), Lunar New Year (LNY) effect (red) and residual (purple) components. The time series show the average concentration across all stations included in the study from the China National Environmental Monitoring Centre network. A 30-day rolling mean has been applied to smooth the data.
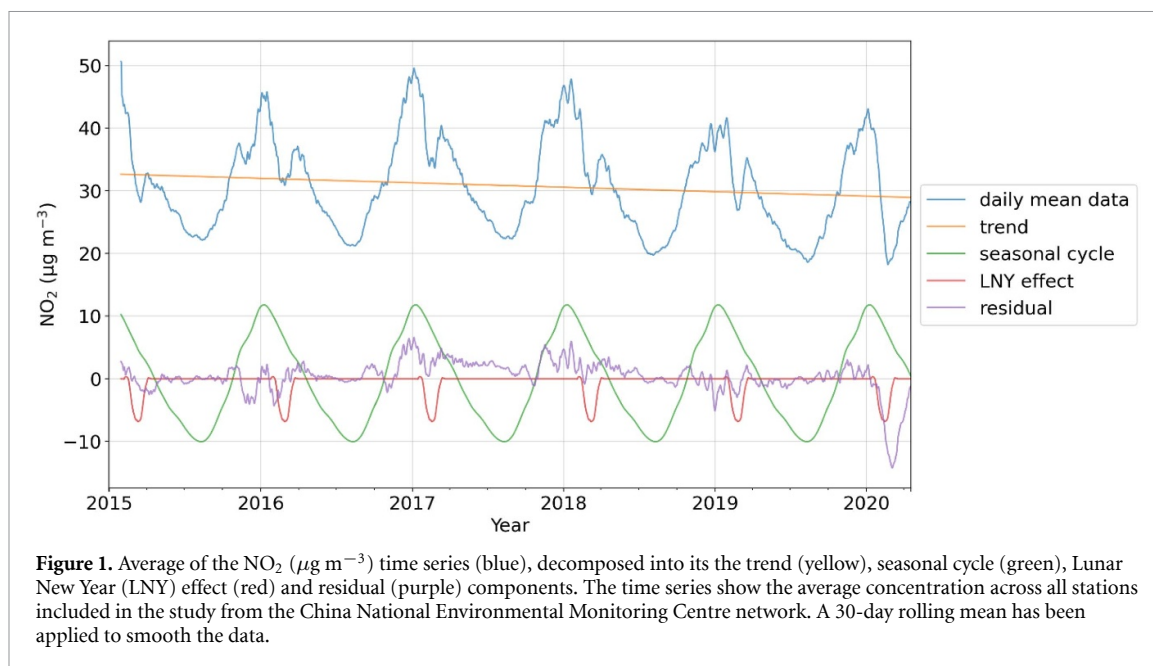
LNY effect have been removed. Results before, during and after the lockdown period, are displayed as the 7DMR concentration. Full results for each province and city are attached as *csv* files in the supplement.

3.4.1. NO_2

For NO_2, 46.0% stations across China record their lowest 7DMR during the lockdown period (table 1). During the lockdown period, the median 7DMR concentration was -27.0% (-8.0 μg m^{-3}) (table 2), with a maximum difference of -56.2% occurring on February 16. The median z-score of the 7DMR during lockdown is -2.3, and falls below -5 (figure 6). The minimum z-score during the lockdown was lower than for any previous time over the period analysed (supplementary figure 2), indicating that the lockdown resulted in an unusually extreme negative anomaly. A decrease in NO_2 during lockdown was observed across China, ranging from -25.9% in the YRD to -30.5% in the SCB. The most negative residuals occurred in Hubei (-50.5%, figure 7). Here, the end of LNY was changed to March 10, extending it for 5 weeks (Chen *et al* 2020), whereas in the rest of China it was extended for 1 week.

3.4.2. Particulate matter

A median negative residual in PM concentration across China occurred during the lockdown, although it is not as extreme as that for NO_2. For $PM_{2.5}$, 26.8% of stations recorded their minimum 7DMR concentration. During the lockdown period, the median 7DMR concentration was -10.5% (-3.7 μg m^{-3}) (table 2), with a maximum difference of -39.4% occurring on February 18. Across different regions, the decrease in $PM_{2.5}$ during the lockdown is quite variable, ranging from -17.2% in the PRD, to -2.0% in the NCP.
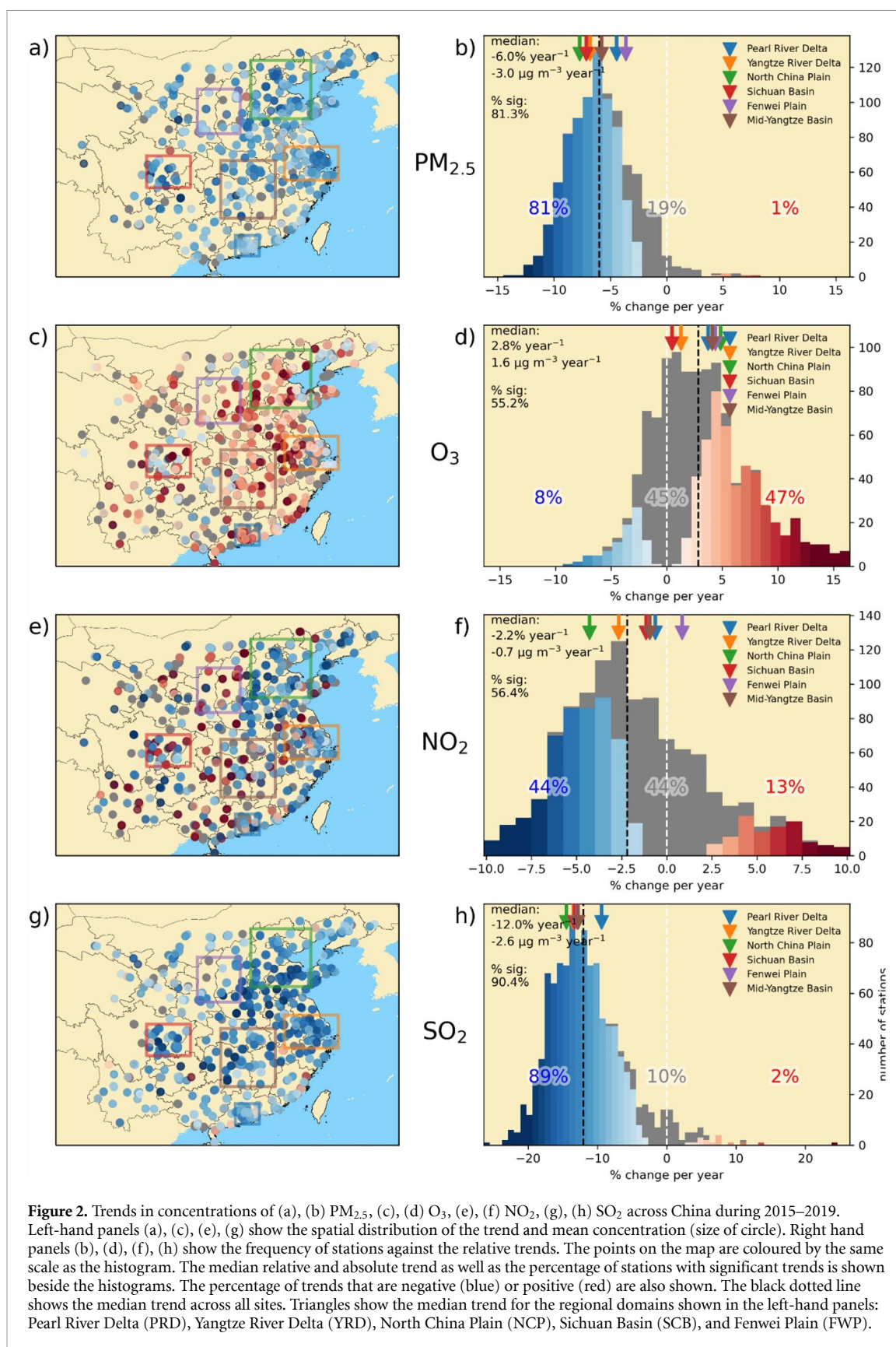
The median z-score of the 7DMR during lockdown is -0.7 (table 2), with a minimum of -2.7. This indicates that during most of the lockdown period, $PM_{2.5}$ concentrations were low, but not to the same extent as NO_2. However, when comparing the lockdown period to other periods of the same length (69 d), the lockdown period experienced the most negative average residual recorded in the last 5 years (supplementary figure 2). The PM_{10} residual timeseries shows a similar temporal pattern to that of $PM_{2.5}$, but its relative residual concentration is around twice as extreme as $PM_{2.5}$.

PM concentrations recover to normal levels earlier than NO_2 (figure 5), though the initial reduction in concentrations is of similar magnitude to NO_2 in some regions, with the PM in the YRD, PRD and MYB being ~60% lower in mid-February.

Prior to lockdown, during in mid-January, $PM_{2.5}$ residual concentrations are unusually high in some regions of China, with the FWP, YRD and NCP all reaching a z-score of over $+2$ during January, and concentrations ~50%–100% above the trend-adjusted seasonal mean. Figure 7 shows that some stations, mostly in north-Eastern China, experienced high positive anomalies during lockdown of >40%.
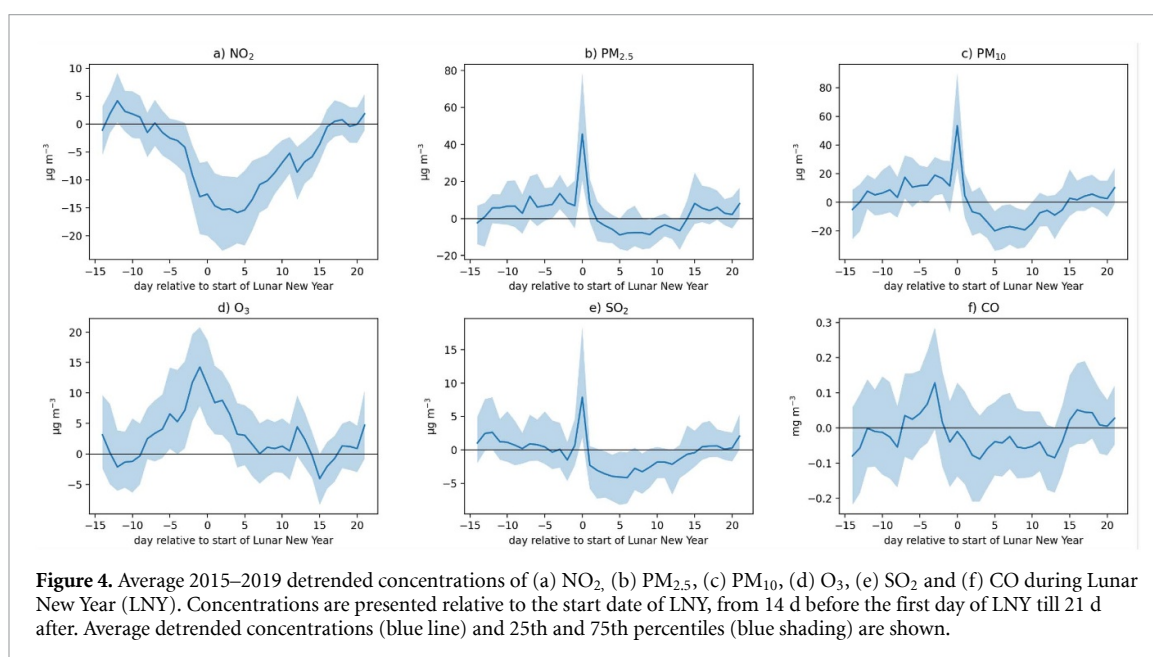
3.4.3. O_3

For O_3, 1.5% of stations recorded their minimum 7DMR concentration during the lockdown period, while 1.5% recorded their maximum. These proportions are much lower than for NO_2 or PM, indicating that that O_3 residual concentrations were less extreme. Across China the median O_3 7DMR during the lockdown was $+0.2\%$,

Figure 2. Trends in concentrations of (a), (b) PM$_{2.5}$, (c), (d) O$_3$, (e), (f) NO$_2$, (g), (h) SO$_2$ across China during 2015–2019. Left-hand panels (a), (c), (e), (g) show the spatial distribution of the trend and mean concentration (size of circle). Right hand panels (b), (d), (f), (h) show the frequency of stations against the relative trends. The points on the map are coloured by the same scale as the histogram. The median relative and absolute trend as well as the percentage of stations with significant trends is shown beside the histograms. The percentage of trends that are negative (blue) or positive (red) are also shown. The black dotted line shows the median trend across all sites. Triangles show the median trend for the regional domains shown in the left-hand panels: Pearl River Delta (PRD), Yangtze River Delta (YRD), North China Plain (NCP), Sichuan Basin (SCB), and Fenwei Plain (FWP).

with a range of −2.4 to 5.1% between the six regions.

It should be noted that unlike the other pollutants, winter is the seasonal minimum for O$_3$ concentrations across much of China (figure 3) (Gao *et al* 2020). During winter, O$_3$ production across much of China may be primarily volatile organic compound (VOC)-limited, while during spring and summer, more regions become NO$_x$ limited (Jin and Holloway 2015). Formation regimes of O$_3$ also vary across

Figure 3. Comparison of the detrended concentrations for (a) NO$_2$, (b) PM$_{2.5}$, (c) PM$_{10}$, (d) O$_3$, (e) SO$_2$ and (f) CO. The data is smoothed using a LOWESS filter. The 2015–2019 average is shown as a solid red line, the dotted line shows data after the Lunar New Year effect has been removed and replaced with interpolated data. Individual years are shown as shades of red and 2020 is shown as a black line.

Figure 4. Average 2015–2019 detrended concentrations of (a) NO$_2$, (b) PM$_{2.5}$, (c) PM$_{10}$, (d) O$_3$, (e) SO$_2$ and (f) CO during Lunar New Year (LNY). Concentrations are presented relative to the start date of LNY, from 14 d before the first day of LNY till 21 d after. Average detrended concentrations (blue line) and 25th and 75th percentiles (blue shading) are shown.

the country based on both emissions of precursors and climate (Wang *et al* 2020). The spatial and temporal heterogeneity of O$_3$ production regimes, and the array of precursors involved in O$_3$ formation, results in a complex response of O$_3$ to the change in emissions during lockdown.
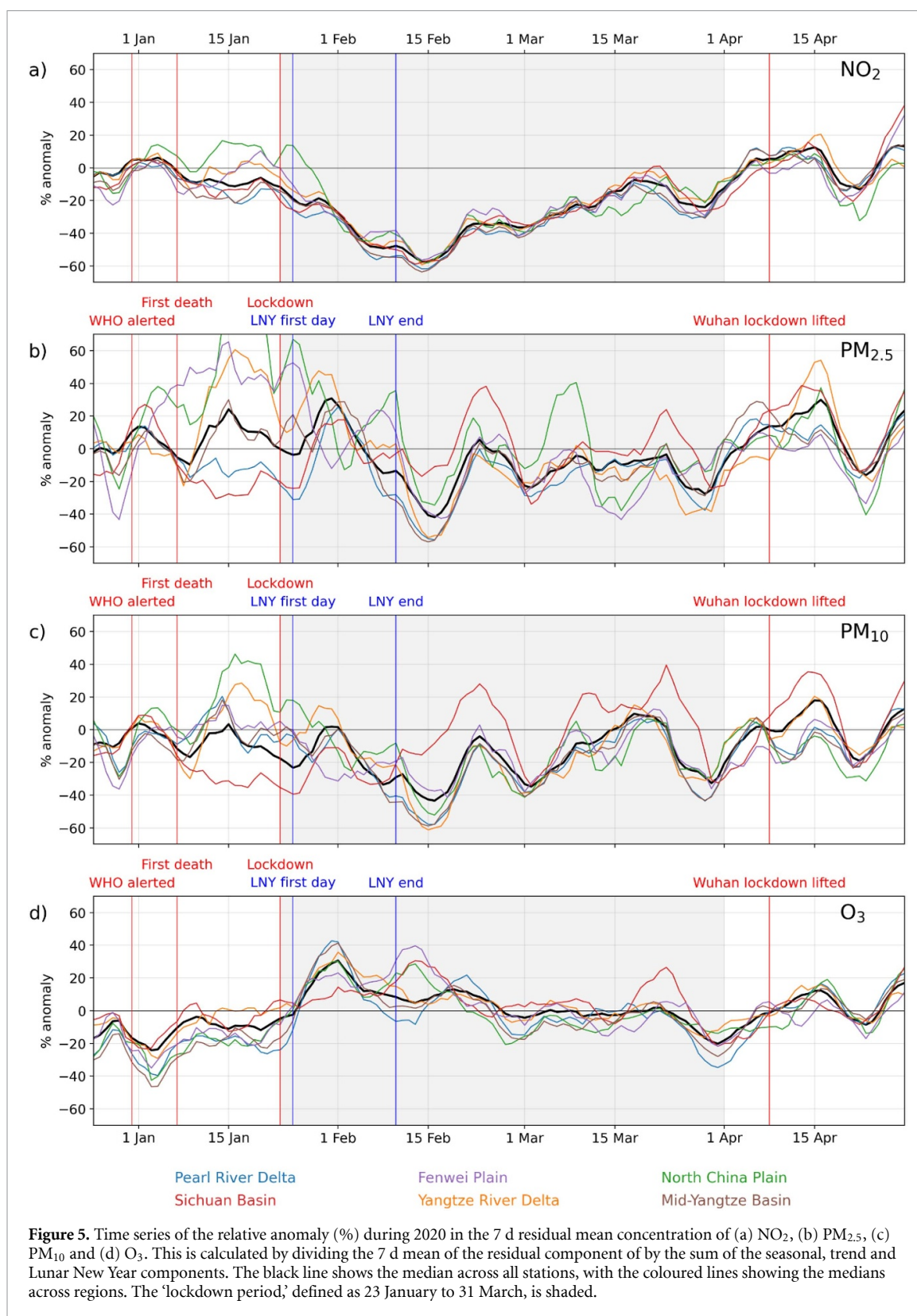
3.4.4. CO
A median negative residual in CO is also recorded during the lockdown period, although it is not as

Table 1. The proportion of stations that record their minimum and maximum 7 day mean residual during the lockdown period.

	minimum (% of stations)	maximum (% of stations)
NO$_2$	46.0	0.4
PM$_{2.5}$	26.8	1.2
PM$_{10}$	40.2	0.1
SO$_2$	18.5	0.2
O$_3$	1.5	1.5
CO	14.8	1.4

Table 2. Median 7 d mean residual (7DMR) concentrations during the lockdown period. For each pollutant, the residual is expressed in absolute (μg m^{-3}) and relative (%) terms, and a z-score. Results shown for all China and individual regions.

		China	Pearl river delta	Yangtze river delta	North China plain	Sichuan basin	Fenwei plain	Mid-Yangtze basin
NO$_2$	residual (μg m^{-3})	−8.0	−10.1	−9.4	−11.3	−8.6	−11.8	−9.5
	relative residual (%)	−27.0	−30.1	−25.9	−28.5	−30.5	−26.6	−28.1
	z-score	−2.3	−2.0	−2.0	−1.9	−2.0	−1.8	−2.0
PM$_{2.5}$	residual (μg m^{-3})	−3.7	−7.5	−4.4	−0.8	−1.4	−4.7	−4.5
	relative residual (%)	−10.5	−17.2	−12.1	−2.0	−3.9	−10.5	−11.1
	z-score	−0.7	−0.9	−0.7	−0.3	−0.2	−0.4	−0.5
PM$_{10}$	residual (μg m^{-3})	−14.7	−16.8	−15.0	−18.0	−8.4	−20.3	−16.5
	relative residual (%)	−21.4	−20.8	−20.3	−17.5	−9.9	−18.6	−18.4
	z-score	−1.3	−1.0	−1.1	−0.8	−0.5	−0.9	−0.9
O$_3$	residual (μg m^{-3})	0.1	−1.3	2.1	−1.6	2.8	1.6	−0.6
	relative residual (%)	0.2	−2.4	3.3	−2.8	5.1	2.7	−1.0
	z-score	−0.1	−0.2	0.2	−0.3	0.4	0.1	−0.1
CO	residual (mg m^{-3})	−0.1	−0.1	−0.1	−0.1	−0.1	−0.2	−0.1
	relative residual (%)	−12.1	−13.5	−11.2	−7.8	−12.8	−16.5	−14.3
	z-score	−1.3	−1.2	−1.0	−0.4	−1.2	−0.8	−1.0

Figure 5. Time series of the relative anomaly (%) during 2020 in the 7 d residual mean concentration of (a) NO$_2$, (b) PM$_{2.5}$, (c) PM$_{10}$ and (d) O$_3$. This is calculated by dividing the 7 d mean of the residual component of by the sum of the seasonal, trend and Lunar New Year components. The black line shows the median across all stations, with the coloured lines showing the medians across regions. The 'lockdown period,' defined as 23 January to 31 March, is shaded.

extreme as that for NO$_2$. For CO, 14.8% of stations recorded their minimum 7DMR concentration. During the lockdown period, the median 7DMR concentration was −12.1% (table 2), with a maximum difference of −28.5% occurring on February 20. Across different regions, the decrease in CO during the lockdown is quite variable, ranging from

−16.5% in the FWP to −7.8% in the NCP. The CO time series are shown in supplementary figures 5 and 6.

3.4.5. SO$_2$

Rapid reductions in SO$_2$ during 2015–2019 (figure 2, −12% yr^{-1}) result in reduced amplitude of seasonal

Figure 6. Time series of *z*-score during 2020 for (a) NO_2, (b) $PM_{2.5}$, (c) PM_{10} and (d) O_3. The black line shows the median across all stations, with the coloured lines showing the medians across regions. The 'lockdown period,' which is defined as 23 January to 31 March, is shaded.
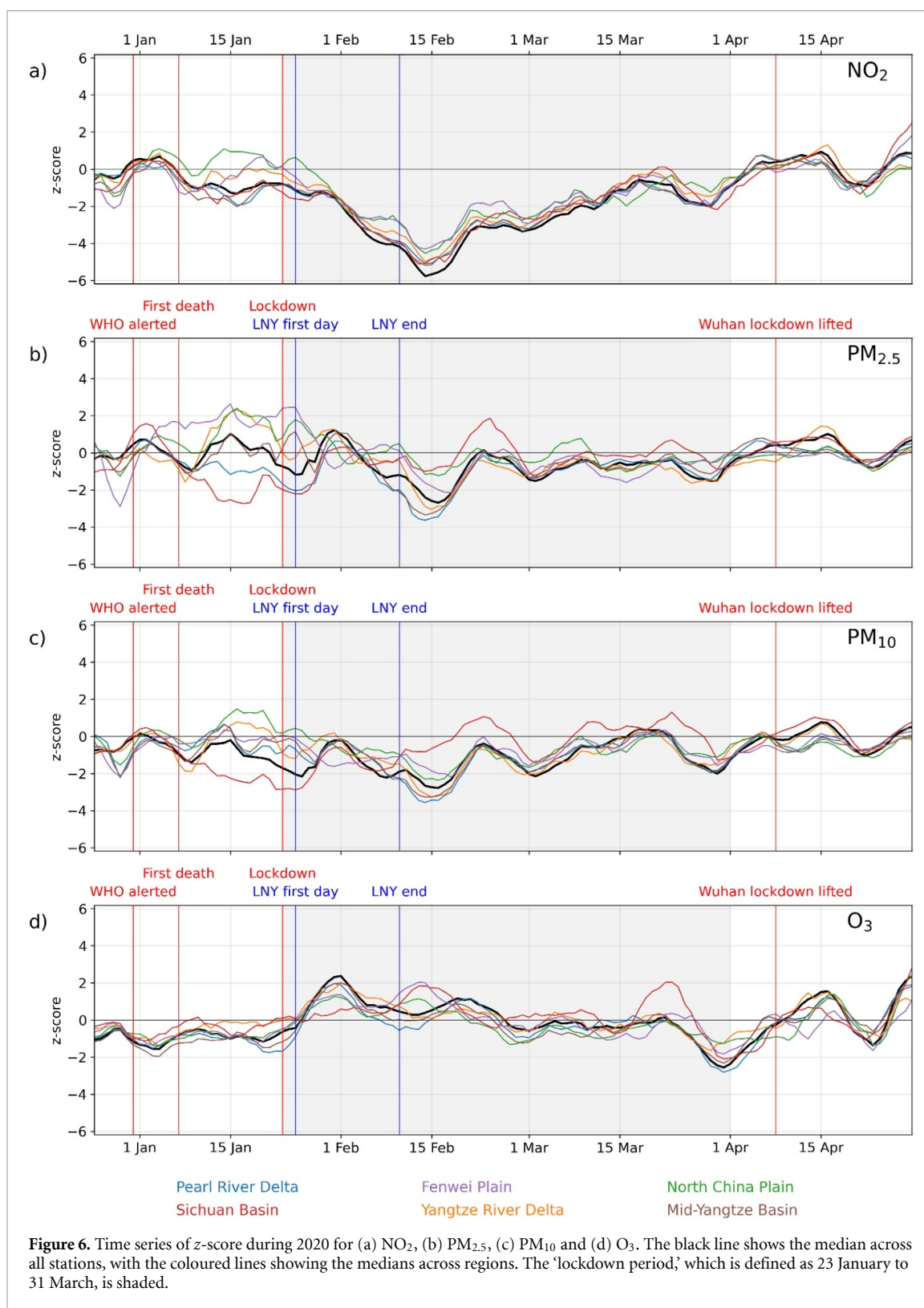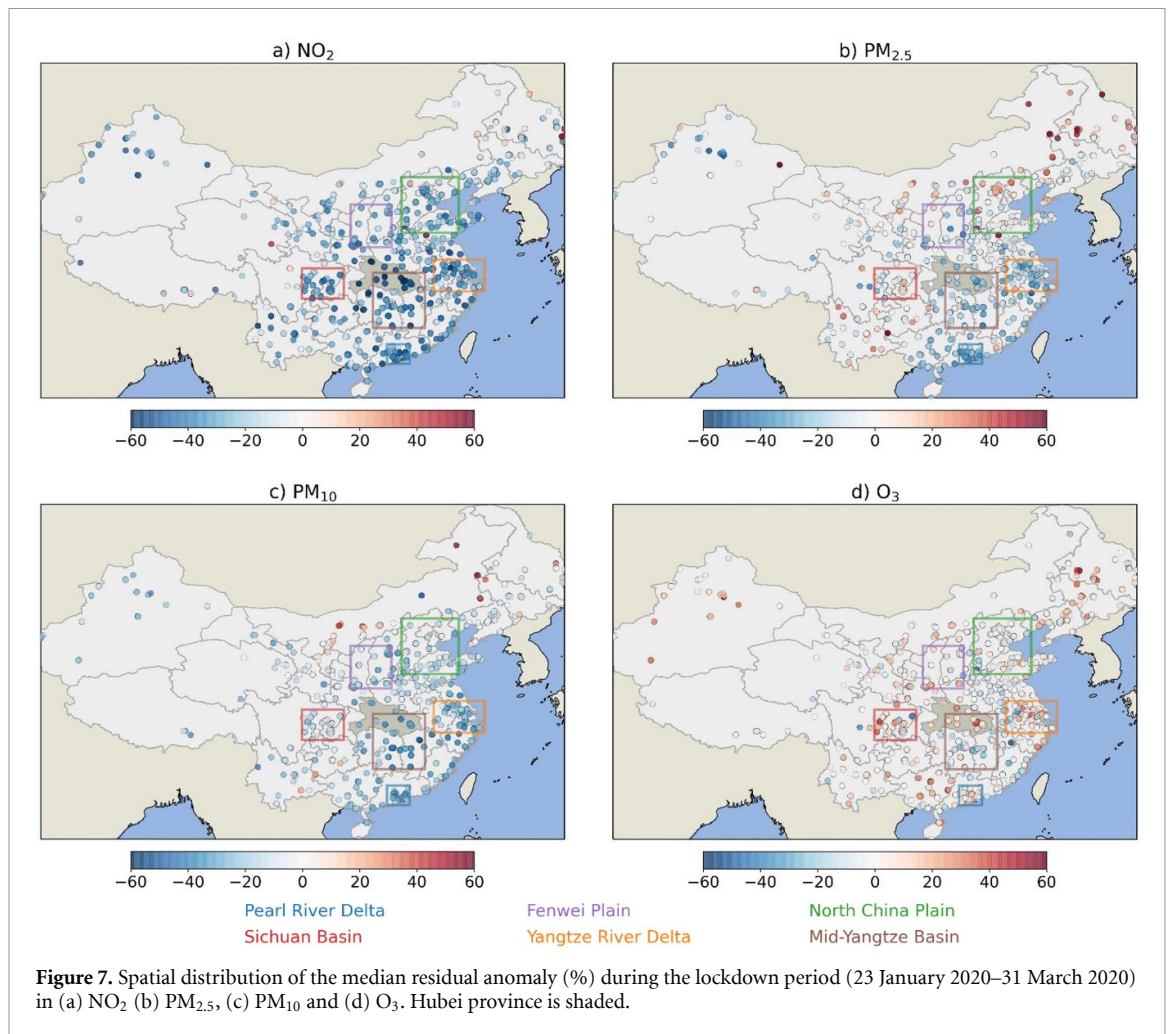
cycle (figure 3). This rapid change in seasonal cycle means that extracting the average 2015–2019 seasonal cycle impacts the residuals calculated in 2020. Therefore, although the residual concentration remains negative throughout the lockdown period, it cannot be shown that this was an unusual departure from the expected concentration based the interannual-trend

and seasonal cycle. The SO_2 time series are shown in supplementary figures 5 and 6.

4. Discussion and conclusions

We analysed air pollutant concentrations from China's air quality network to examine the impact

Figure 7. Spatial distribution of the median residual anomaly (%) during the lockdown period (23 January 2020–31 March 2020) in (a) NO_2 (b) $PM_{2.5}$, (c) PM_{10} and (d) O_3. Hubei province is shaded.

of the COVID-19 control measures on air quality. We show that quantifying the impact of the lock down requires careful consideration of interacting factors, including interannual trends, seasonal cycle and the LNY.

Large changes in air pollutant concentrations have occurred in China in recent years. We show strong reductions in $PM_{2.5}$, PM_{10}, SO_2 and NO_2 and increased in O_3 concentrations during 2015–2019. These long-term changes in air pollutants continue previously identified trends during 2015–2017 (Silver *et al* 2018). These long-term changes in pollutant concentrations are largely driven by changes in emissions (Zheng *et al* 2017, Ding *et al* 2019, Silver *et al* 2020).

We show that LNY holiday results in consistent changes in pollutant concentrations across China during 2015–2019, with all pollutant concentrations except O_3 are lower than normal. Similar effects have been reported for Nanjing (Kong *et al* 2015) and Taiwan (Tan *et al* 2009). Gong *et al* (2014) reported a 9% reduction in PM_{10} concentrations during LNY across 323 stations in eastern China. Reductions in PM, SO_2 and NO_2 concentrations are attributed to lower emissions from traffic and coal

combustion, and increased O_3 due to NO_x titration. The coincidence of LNY and COVID-19 control measures means it is important to account for LNY impacts when assessing the impacts of control measures.

We estimated that COVID-19 control measures resulted in reductions in NO_2, PM and CO concentrations during the lockdown period, defined here as January 23 to March 31, 2020. After accounting for the long-term trend, seasonal cycle and LNY, we estimated that China-wide concentrations in major air pollutants were reduced, with NO_2 reduced by 27.0%, $PM_{2.5}$ by 10.5%, PM_{10} by 21.4% and CO by 12.1%. We found little change in O_3 concentrations.

By comparing the residual concentrations during the lockdown period in 2020 to those during the previous five years, we show that unusual air pollution concentrations occurred during the lockdown. It is likely that these unusual concentrations, most notably for NO_2, were caused by emissions changes rather than unusual meteorological events, due to the extended duration (NO_2 stays below -2 z-score for a month), the consistency of the result across most of China, reports of substantially decreased

activity in emissions sectors, and the co-occurrence of unusual concentrations with the enforcement and lifting of the lockdown. A full assessment of the role of meteorology is now needed to clarify the relative contributions of emissions and meteorology to observed concentrations during the lockdown.

Chinese NO_x emissions are dominated by transport (35%), industry (35%), and power generation (19%) (Zheng *et al* 2018), all of which are likely to have been affected by the lockdown. Reduction in emission from these dominant sectors and short lifetime together explain the larger reduction in NO_2 compared to other pollutants. $PM_{2.5}$ concentrations in China are heavily influenced by residential emissions (Reddington *et al* 2019), which are likely to have been less influenced by the control measures. The larger relative reductions in PM_{10} and CO compared to $PM_{2.5}$, may be due to a greater reduction in primary emission sources and the greater contribution of secondary aerosol to $PM_{2.5}$. Reductions in emissions of VOC and NO_x combined with changes in PM concentrations result in little overall change in O_3 concentrations.

Despite decreases in pollutant concentrations during the last 10 years, China continues to suffer from poor air quality and a large disease burden resulting from air pollution (Zhao *et al* 2018). The control measures and associated emissions reductions during the COVID-19 outbreak provide a useful natural experiment. Analysing the change in pollutant concentrations during this period can help us understand the impacts of emission reductions on air quality. Future work quantifying emission reductions and simulating atmospheric chemistry during this period, will help elucidate how emissions reductions change PM composition and radical chemistry, as well examining the influence of meteorology.

Acknowledgments

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