COVID-19 Lockdowns Improve Air Quality in the South-East Asian Regions, as Seen by the Remote Sensing Satellites

Abirlal Metya^{1,2*}, Panini Dagupta^{1,3}, Santanu Halder^{1,2}, S. Chakraborty^{1,2}, Yogesh K. Tiwari^{1,2}

¹ Center for Climate Change Research, Indian Institute of Tropical Meteorology, MoES, Pune, India

² Department of Atmospheric and Space Sciences, Savitribai Phule Pune University, Pune, India

³ Department of Meteorology and Oceanography, College of Science and Technology, Andhra University, Visakhapatnam, Andhra Pradesh, India

ABSTRACT

The appearance of COVID-19 in December, 2019 in China and its rapid spread all over the globe, forced the governments to severely curb the social and economic activities of their respective countries. Barring the essential services, most of the business activities and transport sectors have been suspended and an unprecedented lockdown imposed over major economies in the world. South-East Asian regions, such as India and China, were no different. As a result, the pollutant level has gone down over these regions, and the air quality improved somewhat better than it was before the lockdown. This study uses satellite retrievals and attempts to estimate the extent of the reduction of major pollutants, like carbon monoxide (CO), nitrogen dioxide (NO₂) and sulfur dioxide (SO₂) in India and China during January to April, 2020. We have calculated anomalies of pollutants during the lockdown period relative to their long-term records. NO₂, which has significant emissions from the transport sector, is reduced on an average by 17% over India and 25% over China. SO₂, which mainly emits from power plants, shows significant reductions (approx. 17%) especially over the Eastern sector of India. CO is found to be reduced by 6.5% over north-central China. The differential reduction was attributed to man made versus natural activities. This study is helpful to policy makers in mitigating the air-pollution on a long-term perspective.

Keywords: SARS-CoV-2; Coronavirus; COVID-19; Air quality; CO; NO₂; SO₂.

INTRODUCTION

Coronavirus disease 2019 (COVID-19) is a novel pneumonia caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). COVID-19 is the seventh coronavirus known to affect humans (Andersen *et al.*, 2020). This novel coronavirus was first reported in December, 2019 in Wuhan, the capital of China's Hubei province. Since then, it has transmitted across the nations within a very short time. Due to the rapid spread across the globe, the World Health Organization (WHO) declared COVID-19 as a pandemic on March 11, 2020. Till April 29, 2020, 3,018,952 cases have been confirmed globally, with 207,973 deaths, according to WHO (2020). International travel is believed to have potential effects (Bogoch *et al.*, 2020) in the rapid spreading of the virus across the globe.

Lockdown measures have been implemented by the governments and regulatory agencies across the world to

maintain person to person 'social distancing' to minimize the virus infection. As a result, economic activities, such as social events, agricultural practices, travel, and tourism, etc. have come to a near halt. Business activities are drastically reduced, and people are forced to 'work from home'. Such a situation has resulted in an unprecedented effect on the environment. Due to the strict enforcement of vehicular movement, the emission level has dramatically reduced. As a result, air quality has significantly improved. Few previous instances show short time emission control measures (ECM) improved regional air quality. For example, ECM imposed during 2008-Olympic and Paralympic games held in Beijing, China, improved air quality over Beijing and surrounding regions for almost two months (July–September). A reduction of 43%, 13% and 12% in total column NO₂ (T_{NO2}), boundary layer SO₂ (BL-SO₂) and 700 hPa CO (CO₇₀₀) with respect to the last three years was observed over Beijing and surrounding regions due to strict traffic movements and controls on pollutant emission (Witte *et al.*, 2009). Air quality improvement during 2008-Beijing Olympics was also reported by Wang *et al.* (2010) and Shen *et al.* (2011). Temporary restriction in traffic movements was found to improve air quality in the 2004 Athens Olympics (Frantzeskakis and Frantzeskakis 2006; Shen *et al.*, 2011), the 2002 Busan Asian

* Corresponding author.

Tel.: 9732789387

E-mail address: abirmetya92@gmail.com

Games (Lee *et al.*, 2007) and the 1996 Atlanta Olympics (Friedman *et al.*, 2001). Recently, a significant drop in pollutant levels has been reported; for example, Spain, one of the badly infected countries, reported a 90% drop in vehicular traffic and a corresponding level of pollution (Barbuzano 2020).

Very strict lockdown measure was implemented by the Indian and the Chinese governments due to their vast population (1.35 and 1.39 billion respectively). Hence its effect on air quality is expected to be significant and such kind of studies have been recommended (Saraswat and Saraswat 2020). To study the “lockdown effect” on the pollutants, we have analyzed the remote sensing data of a few atmospheric pollutants; these are Carbon Monoxide (CO), Sulfur dioxide (SO₂) and the oxides of nitrogen (NO_x), mainly the NO₂. Air pollution has an impact on air quality (Monks *et al.*, 2009), climate, health (WHO 2016), and visibility (Wang *et al.*, 2012). Carbon monoxide (CO), Nitrogen dioxide (NO₂) and Sulfur dioxide (SO₂) are very toxic, gaseous air pollutants and produced by anthropogenic activities like—vehicular emission, power plants, manufacturing, real estate activities etc. as well as natural sources like- biomass burning, soil emission, and lightning. These pollutants can be emitted locally or can be reached by large-scale transport due to meteorology, depending upon pollutant lifetime, chemical reactivity, and wind circulation (Maas *et al.*, 2016; Sawlani *et al.*, 2019). In this study, we used satellite retrieved Carbon Monoxide (CO), Sulfur dioxide (SO₂), and Nitrogen Dioxide (NO₂) concentration to explore COVID-19 induced lockdown effect on these gases over the South-East Asian region mainly over India and China.

DATA AND METHODOLOGY

Study Area

Fig. 1(a) shows the two study areas, India, and eastern China, where the virus was believed to have originated. The population density is shown by blue shading. Population data was taken from Socioeconomic Data and Applications Center (SEDAC, <https://sedac.ciesin.columbia.edu/data/col>

lection/gpw-v4). The geographical extent of the study areas denoted as (a) India box (IN-box): 70–92°E and 8–33°N and (b) China box (CH-box): 103–122°E and 22–40°N. IN-box includes a major portion of India (except north-east India), Bangladesh, Nepal, Bhutan, part of Sri Lanka, part of Pakistan and part of Tibetan plateau. Eastern China is the main part of the CH-box. It is evident that the total population in IN-box increased sharply in the last twenty years than the CH-box. Moreover, these two boxes, which cover almost an area of ~1.37% of the earth, contain ~33% of the total population of the globe. These two regions saw rapid industrialization and socio-economic growth in the last few decades. Moreover, EDGAR v4.3.2 emission inventory data show a shift of top CO, SO₂, and NO_x emission regions from USA and Europe in 1970 to India and China in 2012 (Crippa *et al.*, 2018). As a result, these two regions suffer from poor air quality.

As mentioned earlier, the government of both countries took very strict measures to contain the spread of the deadly virus. Mass movements were restricted by curbing public transports (bus, train, airplane, etc.), large gatherings were banned, school colleges were closed, and the people were obliged to stay at home. Such measures prove sufficient promises to slow down the spreading of the virus as well as improve air quality in several parts of the world.

Air Quality Data

The Atmospheric Infrared Sounder (AIRS), polar-orbiting Aqua satellite launched by NASA on May 4, 2002, was aimed to monitor global water and energy cycles. As a part, it measures atmospheric CO. This sun-synchronous satellite has a 16-day repeat cycle. AIRS provides daily level-3 global CO averaged over 1° × 1° grid cells associated with 24 standard pressure levels. We used a version-6 ascending product of the satellite. The data quality and stability can be found in (Susskind *et al.*, 2014). AIRS CO products are most sensitive to the mid-troposphere. Hence, we have taken CO from 700 hPa level in the study and denoted as CO₇₀₀.

Ozone Monitoring Instrument (OMI) was launched in July, 2004 onboard NASA’s Aura satellite. It is a Dutch-Finnish nadir-viewing hyperspectral imaging spectrometer

Fig. 1. Shows population density (persons/sq. km). Two densely populated areas (IN-box and CH-box) are marked by squared boxes. (b) shows a change in the total population of IN-box and CH-box in the last 20-years by the red and green line respectively. Bars are the percentage of the world population that lives within the two regions.

flying on a sun-synchronous orbit crossing the local equator between 13:40 and 13:50 LT. OMI measures in the UV-visible wavelength range (270–500 nm) at a nadir resolution of 13×24 km. OMI obtained atmospheric SO₂ measurement in the UV-wavelength (310.5–340 nm) and NO₂ measurements in the 405–460 nm (Visible-range).

OMI tropospheric column NO₂ daily data, OMNO2d (Krotkov *et al.*, 2017), is obtained from NASA-GES-DAAC (https://disc.gsfc.nasa.gov/datasets/OMNO2d_003/summary). It is a level-3 gridded product with $0.25^\circ \times 0.25^\circ$ grid resolution. OMI boundary layer SO₂ daily data, OMSO2e (Krotkov *et al.*, 2015), is obtained from NASA-GES-DAAC (https://disc.gsfc.nasa.gov/datasets/OMSO2e_003/summary). The level-3 gridded product of $0.25^\circ \times 0.25^\circ$ grid resolution is obtained from an improved Band Residual Difference Algorithm (BRD). Tropospheric NO₂ and boundary layer SO₂ is denoted by ^{TC}NO₂ and ^{BL}SO₂ hereafter.

Moderate Resolution Imaging Spectroradiometer (MODIS) onboard NASA's Terra and Aqua satellites provides data from February, 2000 (Terra) and June, 2002 (Aqua). MODIS fire-products provide the location, timing, instantaneous radiative power, and smoldering ratio of actively burning fires (Kaufman *et al.*, 1998). Near real-time (NRT) MODIS Thermal Anomalies / Fire locations - Collection 6 processed by NASA's Land, Atmosphere Near real-time Capability for EOS (LANCE) Fire Information for Resource Management System (FIRMS), using swath products (MOD14/MYD14). The NRT fire data is replaced with data extracted from the standard MCD14ML Active Fire/Thermal Anomalies locations (vector data), as it becomes available, usually after 2 months. Hence, fire-counts used in the text from 2013–2019 is standard product (MCD14ML) and data of 2020 is NRT product (MCD14DL).

The Emissions Database for Global Atmospheric Research (EDGAR) is a bottom-up emission database that provides country level as well as gridded emissions from several sectors for air pollutants as well as greenhouse gases from 1970 (Crippa *et al.*, 2018).

Detrend the Datasets

The pollutants CO, NO₂, and SO₂ show strong seasonality as well as annual trends. Some places show negative trends due to strong mitigation policies. While a lack of mitigation compliance leads to positive trends in other places. Hence, the data has been detrended on every $5^\circ \times 5^\circ$ grid box using a nonlinear regression model suggested by (van der A *et al.*, 2017). In the present study, we have resampled the daily satellite data to a 10-day average for NO₂ and monthly-average for CO and SO₂. Hence, the nonlinear regression fitted to 10-day averaged data is:

$$y_t = A + \frac{1}{36} BX_t + C \sin(\omega X_t + \phi) + R_t \quad (1)$$

And, the equation for the monthly dataset is,

$$y_t = A + \frac{1}{12} BX_t + C \sin(\omega X_t + \phi) + R_t \quad (2)$$

where, y_t represents the 10-day or monthly averaged time series of the pollutant, X_t is 10-day or months from January 1, 2010, R_t is the remainder and A, B, C, ϕ are the fit parameters. A is constant of the fit, B is an annual trend, C is seasonal amplitude, $\omega(2\pi/36)$ is frequency, and ϕ is a phase shift. B is the slope or linear trend of the time series. Then the time series were detrended by subtracting observed time series by $\frac{1}{36} BX_t$ or $\frac{1}{12} BX_t$ for a 10-day averaged or monthly dataset respectively.

RESULTS AND DISCUSSION

Carbon Monoxide (CO₇₀₀)

Carbon monoxide (CO), an important air pollutant, is not only chemically colourless, odourless, and tasteless but also a toxic gas which is considered as an indirect greenhouse gas. Higher levels of CO can lead to serious health problems (Raub and Benignus, 2002). CO enters into the atmosphere from incomplete combustion of carbon mainly due to household combustion, industrial activities, road transport, and agricultural waste burning. The lifetime of CO is 1–3 months (Cooper *et al.*, 2002). The indirect radiative forcing of CO due to production of ozone (O₃) and carbon-di-oxide (CO₂) as well as modulating the lifetime and abundance of atmospheric methane (CH₄) is estimated to be 0.23 (0.18–0.29) Wm⁻² (Myhre *et al.*, 2014). CO emission from China is found to be stable (2005–2009) despite the rapid increase in energy consumption and industrial economy due to improvements in energy efficiency and emission control regulations (Zhao *et al.*, 2012). We found a decrease in CO₇₀₀ over China, the rate is -1.58 ppb yr⁻¹ and the rate over India is -0.433 ppb yr⁻¹ during 2010–2020. Hence, the monthly-mean dataset was detrended using Eq. (2).

Figs. 2(a), 2(c), and 2(e) show the monthly anomaly of CO₇₀₀. The climatology (2010–2020) of CO₇₀₀ of January–February–March is shown in the supplementary section (Fig. S1(a)). China emits more CO than India. CO₇₀₀ shows a clear seasonality over both regions. Both the areas show similar seasonality with maximum CO₇₀₀ in spring (March–April–May) and minimum in summer (June–July–August–September). Monthly anomaly (in %) of January, February, and March, 2020 of CO₇₀₀ (Fig. 2, left column) as well as MODIS fire-count (Fig. 2, right column) is shown. Fig. 2(a) shows a positive anomaly in the central part of CH-box in January, 2020. While Figs. 2(c) and 2(e) show a strong negative anomaly of -12 to -20% in different regions of north-central China. A strong positive anomaly is observed at the same time in south-China becoming more positive in March. MODIS fire-count data shows a positive anomaly over the Indo-China peninsula, which turns out to be more positive in February and March. Monthly wind vectors at 700 hPa level obtained from NCEP-NCAR reanalysis are also shown in Fig. 2 (left column).

Fig. 3(a) shows the change of CO₇₀₀ over a smaller region of north-central China (106 – 122° E and 30 – 40° N, shown in Fig. 2(c), denoted by squared box). The length of the bars presents a change in percentage from the long-term mean (2010–2020) in January (red), February (blue), and March

Fig. 2. Monthly anomaly of CO₇₀₀ for (a) January–2020 and (c) February, 2020 (e) March, 2020. Corresponding winds at 700 hPa are shown as vectors taken from NCEP-NCAR. Monthly anomaly of MODIS fire-count in (b) January, 2020 (d) February, 2020 and (e) March, 2020.

Fig. 3. Percentage change in CO₇₀₀ relative to the mean (2010–2020) of individual years over (a) north-central China. Red: January, Blue: February, Green: March. (b) and (c) shows the percentage change in TCNO₂ relative to the mean (2010–2020) of individual years over CH-box and IN-box, respectively. (d) shows the percentage change in BL SO₂ relative to the mean (2010–2020) of individual years over east-India.

(green). North-central China shows a significant reduction in CO₇₀₀ in February and March. The maximum reduction is observed in February, about ~6.5% from long term mean (2010–2020). March is also associated with a moderate decrease of about ~5.1%. The absolute values for north-central China are also shown in Table 1. A significant reduction

can be observed in the table during February (158.8 ppb) and March (164.7), 2020.

Global CO sources are mainly from anthropogenic activities (500–600 Tg yr⁻¹) and biomass burning (300–600 Tg yr⁻¹) (Zhang *et al.*, 2020). Biomass burning plays an important role in global CO concentrations. On a regional scale, the

Table 1. Time series of CO₇₀₀, ^{TC}NO₂ and ^{BL}SO₂ in January–April for the last 5-years. Significance (p-value) of the anomaly is derived using z-statistics ($z = x - \mu/\sigma$).

	2016	2017	2018	2019	2020	
					Mean	Anomaly
CO ₇₀₀ (ppb) for north-central China						
January	166.63	160.45	153.61	157.19	164.74	3.67 (p = 0.27)
February	169.55	161.41	165.34	166.77	158.87	−11.035 (p = 0.06)
March	187.38	176.69	171.62	167.6	164.68	−8.86 (p = 0.07)
^{TC} NO ₂ (μmol m ^{−2}) for CH-box						
January	169.05	154.75	194.31	176.22	156.87	−33.27 (p = 0.08)
February	118.0	137.05	114.26	126.4	101.37	−35.07 (p = 0.09)
March	120.1	132.07	117.77	125.02	113.85	−15.42 (p = 0.12)
^{TC} NO ₂ (μmol m ^{−2}) for IN-box						
February	25.1	24.02	28.13	22.42	23.41	−0.05 (p = 0.5)
March	26.35	26.84	27.83	22.98	20.97	−4.1 (p = 0.05)
April	26.31	26.0	24.58	23.33	21.47	−2.68 (p = 0.03)
^{BL} SO ₂ (μmol m ^{−2}) for east-India						
February	169.5	172.28	164.49	158.16	158.52	0.32 (p = 0.48)
March	137.54	144.64	139.35	144.64	156.82	18.2 (p = 0.01)
April	125.56	119.21	121.48	124.16	96.82	−20.0 (p = 0.01)

influence of biomass burning is also important in East Asia (Kang *et al.*, 2019) and Southeast Asia (Yin *et al.*, 2019). Hence, fire in the Indo-China peninsula with strong 700 hPa wind produce positive CO anomaly over south-east China. On the other hand, the industry and transportation sector is the dominant CO emitter in the eastern and north-central China (Zhao *et al.*, 2012). Hence, a decrease in CO over north-central China in February and March is most likely driven by a massive lockdown regulation. The lockdown effect is nearly absent in south-eastern China due to biomass burning in the Indo-China peninsula.

Tropospheric NO₂(^{TC}NO₂)

NO₂ is considered as one of the crucial atmospheric pollutants due to its severe effects on human health and plant growth (Sabljić, 2009). High NO₂ levels can cause photochemical smog, acid rain, and nitrate aerosols. Indirectly it can affect the greenhouse gas budget by producing tropospheric ozone. High temperature combustion processes such as power plants and transport sectors emit NO_x. The top emitting NO₂ centres have been shifted from the USA, Europe to India, and China from 1970–2012. Though NO₂ lifetime is highly dependent on meteorology, length of night, temperature, OH and H₂O concentration, daytime NO₂ lifetime is ~4 to ~8 hours (Beirle *et al.*, 2011). Even though the satellite provides a total column density of NO₂ (upto ~10–13 km), the majority of NO₂ molecules lie within the boundary layer, within lowermost ~1–2 km (Boersma *et al.*, 2009). Short lifetime and sensitivity to the boundary layer contribute to ^{TC}NO₂ as most sensitive to surface emission. Previous studies found an increasing trend in NO₂ over India (Ramachandran *et al.*, 2013; Ghude *et al.*, 2008). In the last decade (2010–2020) an increasing trend of +0.33 μmol m^{−2} yr^{−1} in ^{TC}NO₂ over the IN-box was observed. Stringent regulatory enforcement by China (Liu *et al.*, 2016) led to a significant reduction of NO₂ from 2011 onwards. We found −4.26 μmol m^{−2} yr^{−1} reduction of ^{TC}NO₂ during 2010–2020 over the CH-box.

The 10-day anomaly of ^{TC}NO₂ in percentage is shown in Figs. 4(a)–4(d). The date shown in the figure title is the day one of the 10-day anomalies i.e., Fig. 4(a) shows the mean anomaly of January 1 to January 10, 2020. A significant negative anomaly is evident during February over a large portion of China. However, the anomaly reduces from March fourth week and becomes positive in April. While a negative anomaly appears over India in March fourth week, it further intensified in April. The latitude-time plot, widely known as the Hovmöller diagram, is shown in Figs. 4(e) and 4(f). The negative anomaly was found all over the CH-box and concentrated between January second week to March first week (Fig. 4(e)). Large-scale negative anomaly persists over the IN-box from the third week of March (Fig. 4(f)). A nationwide lockdown was initiated by the Indian government from March 25, 2020, which forced about a billion people to stay at home, and restricted vehicular movements. The effect of lockdown is also seen in Fig. 4(c) and 4(d), which shows a large negative anomaly almost all over the IN-box. Google mobility data (Fig. S(3)) also shows a large decrease in mobility over India and neighbouring regions (Pakistan, Nepal, Sri-Lanka, and Indo-China region) from the third week of March. The retail and recreation sector, as well as transit stations, showed a substantial decrease (~80%) from baseline over India during lockdown (from 3rd week of March, 2020).

Fig. 3(b) shows a ~25% reduction of ^{TC}NO₂ in CH-box in February. Moreover, a significant reduction is also seen in January and March (~17% and ~12%). This massive reduction of ^{TC}NO₂ in consecutive three months is seen for the first time in the last 5-years. On the other hand, IN-box also experienced a large reduction in ^{TC}NO₂ for the first time in the previous 5-years. Quantitatively ~17% and ~11% reduction is observed over IN-box during March and April.

Table 1. shows area averaged ^{TC}NO₂ for January–March for the last 5-years (2016–2020) over CH-box. CH-box receives 101.37 and 113.85 μmol m^{−2} ^{TC}NO₂ in February

Fig. 4. 10-day anomaly of $^{TC}NO_2$ in percentage for period (a) 01 to 10-January, 2020; (b) 20 to 29-February, 2020; (c) March 31 to April 9, 2020 and (d) April 10 to 19, 2020. Time-Latitude plot over CH-box and IN-box is shown in (e) and (f).

and March, 2020, lowest in the last 5-years. The average $^{TC}NO_2$ over IN-box was 20.97 and 21.47 $\mu mol\ m^{-2}$ in March and April, 2020. These average values are also the minimum seen in the last 5-years.

The transport sector is an essential source of NO_2 in China and India (Garg *et al.*, 2001; Crippa *et al.*, 2018). Sector wise emission from EDGAR v4.3.2 shows ~15% emission from transport, ~41% from the energy sector, ~24% from

manufacturing industries and construction over China in 2012 (Fig. S2(b)). Transport (~24%), energy sector (~44%), and manufacturing industries and construction (~14%) were also major NO_x emitters of India in 2012 (Fig. S2(a)). Massive reduction of NO_2 over IN and CH-box during lockdown is most likely driven by decrease in vehicular movement. However, the energy sector is the largest emitter of NO_2 , and this sector shows little variation in regional scale.

Boundary Layer SO_2 ($^{\text{BL}}\text{SO}_2$)

~33 million people lived in areas with substantial SO_2 pollution (Li *et al.*, 2017). SO_2 forms sulfate (SO_4^{2-}) aerosols by oxidation and results in acid deposition through sulfuric acid (H_2SO_4). Moreover, the sulfate aerosols lead to historic “London smog” and lead to more than one million premature deaths each year (Lelieveld *et al.*, 2015). China alone is responsible for 30% emission of global SO_2 (Klimont *et al.*, 2013). Moreover, 90% of SO_2 in China is produced by coal consumption (Chen and Xu, 2010). Coal is widely used in thermal power plants, various industries (steel, cement, and glass) and residential activities. Power plants are responsible for 30–40% of total emission and industry for another 50–60% over China (He *et al.*, 2012). EDGAR v4.3.2 emission database shows ~33% emission from power plants, ~45% from manufacturing industries and construction, ~7% from residential ~0.18% from transport in 2012 (Fig. S4(b)). Steady growth in emission from power plants and a decrease from the residential sector is also evident in 1970–2012 time span. A similar characteristic is also found for India. Power plants are responsible for ~65% SO_2 emission, and manufacturing industries contribute ~24% in India SO_2 share (Fig. S5(a)).

Advances in satellite measurements provide an opportunity to study over large regions with improved accuracy. Many studies have used SO_2 data from OMI due to its superior ground resolution (Fioletov *et al.*, 2013). Long-term (2010–2020) monthly climatology of $^{\text{BL}}\text{SO}_2$ shows high concentration over IN and CH-box in January–February–March with a strong seasonality (Fig. S5(a) and S5(b)). Several previous studies found that China had reduced SO_2 emission through

desulfurization of coal-fired power plants in 2005/2006 (Li *et al.*, 2010; Xu, 2011). On the other hand, India had increased its SO_2 emission (Lu *et al.*, 2013; Li *et al.*, 2017) due to growing electricity demand and lack of regularization. We have also found an increase of $+1.12 \mu\text{mol m}^{-2} \text{yr}^{-1}$ $^{\text{BL}}\text{SO}_2$ over IN-box and a decrease of $-8.76 \mu\text{mol m}^{-2} \text{yr}^{-1}$ $^{\text{BL}}\text{SO}_2$ over CH-box. Hence, $^{\text{BL}}\text{SO}_2$ is also detrended similar to $^{\text{TC}}\text{NO}_2$ using Eq. (1).

Figs. 5(a) and 5(e) show locations of coal-based large (> 2000 Mw) power plants over China and India. It is evident that most of the power plants are clustered around east-India (80°E and 19°N) and north-central China (106°E and 30°N). A positive anomaly is found over east-India in March (Fig. 5(b)) which becomes negative in April (Fig. 5(c)). While, the negative anomaly is found over north-central China surrounded by positive anomaly in February (Fig. 5(e)). Moreover, positive anomaly acquires completely north-central China in April (Fig. 5(f)).

$^{\text{BL}}\text{SO}_2$ is sensitive to strong anthropogenic sources and regional pollution. While the lifetime of SO_2 is short, typically 4–48 hours (Lee *et al.*, 2011), the $^{\text{BL}}\text{SO}_2$ is used as a proxy for the location of SO_2 emissions. Long-time climatology (Fig. S5(a)) shows high $^{\text{BL}}\text{SO}_2$ around power plants and coal dependent (or consuming) industries, which is also found in previous studies (Li *et al.*, 2017; van der A *et al.*, 2017). Power System Operation Corporation (POSOCO, India, “https://posoco.in/”) shows a reduction in evening peak power demand from March 22, onwards (Fig. S(6)). The decrease is very distinct and was not found in previous 4-years (2017–2020). This unusual phenomenon may be caused by

Fig. 5. Position of large (> 2000 Mw) coal based power plants over India and China is shown in (a) and (d). Monthly anomaly of $^{\text{BL}}\text{SO}_2$ over India for (b) March, 2020; (c) April, 2020. Monthly anomaly of $^{\text{BL}}\text{SO}_2$ over China for (e) February, 2020 and (f) April, 2020.

large-scale lockdown in India from March 25, 2020. As a result, we found a large decrease in $^{BL}SO_2$ over east-India. Quantitatively 17% (Fig. 3(d)) reduction of $^{BL}SO_2$ from long term mean is observed over east-India during April. Averaged density of SO_2 is $96.82 \mu mol m^{-2}$ (Table 1), lowest in the last five-years. While, area averaged $^{BL}SO_2$ does not show significant reduction in February, 2020, despite fragmented negative anomaly found over north-central China. Hence, the recent scenario of $^{BL}SO_2$ leads to conclude that recent lockdown reduced the SO_2 level on a regional scale, where cluster of thermal power stations observed, due to less demand for electricity.

SUMMARY

CO over north-central China showed a significant reduction during the lockdown period. Whereas CO_{700} over south-east China did not get affected by lockdown, as the biomass burning in Indo-China peninsula remained high. A 6.5% (5.1%) reduction in CO_{700} is observed over north-central China in February (March), 2020. Satellite data shows, NO_2 decreases significantly during the current lockdown period over China (in February–March, 2020) and India (in March–April, 2020) loosely denoted as CH-box and IN-box in the text. China experienced a maximum reduction in NO_2 in February 2020. India (China) shows a maximum reduction, 17% (25%) from the last 10-years (2010–2020) mean, in March (February), 2020. The reduction is maximum in the last 5-years (2016–2020). NO_2 shows large-scale reduction (country level) while SO_2 shows reduction in much lower scale (state level). NO_2 and SO_2 have almost similar anthropogenic sources, i.e., burning of coal or oil. Power plants are a major contributor for both the pollutants. The main difference is traffic, which is more important for NO_2 . NO_x emission factor (emission/fossil fuel unit) is higher from the transport sector than energy and industry (Crippa et al., 2018). Hence, a large reduction of NO_2 over India and China shows that vehicular transport was maximum affected during the lockdown period. While the less demand of energy during lockdown leads to less emission of SO_2 from regions where coal fired power plants are dominant. A 17% reduction of $^{BL}SO_2$ is observed in east India, a region having several power plants. Moreover, few regions also show higher than normal SO_2 emission during the lockdown period.

The large-scale lockdown invoked in two major Asian economies caused a significant reduction in air pollution. Our analysis demonstrated that wide spread restriction of vehicular movement was responsible for a significant reduction of large-scale NO_2 emission. While, lesser demand of energy led to a reduced level of atmospheric SO_2 over a smaller spatial scale.

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SUPPLEMENTARY MATERIAL

Supplementary data associated with this article can be found in the online version at <https://aaqr.org/>

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