

## Article

# Unprecedented Temporary Reduction in Global Air Pollution Associated with COVID-19 Forced Confinement: A Continental and City Scale Analysis

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**Abstract:** Shortly after the outbreak of the novel infectious disease (COVID-19) started at the end of 2019, it turned into a global pandemic, which caused the lockdown of many countries across the world. Various strict measures were adopted to reduce anthropogenic activities in order to prevent further spread and infection of the disease. In this study, we utilized continental scale remotely sensed data along with city scale in situ air quality observations for 2020 as well as data from the baseline period (2015–2019) to provide an early insight on air pollution changes in response to the COVID-19 pandemic lockdown, by combining both continental and city scales. For the continental scale analysis, data of NO<sub>2</sub>, SO<sub>2</sub>, and O<sub>3</sub> were acquired from the ozone monitoring instrument (OMI) and data of aerosol optical depth (AOD) were collected from the moderate resolution imaging spectroradiometer (MODIS). For city scale analysis, data of NO<sub>2</sub>, CO, PM<sub>2.5</sub>, O<sub>3</sub>, and SO<sub>2</sub> were derived from ground-based air quality observations. Results from satellite observations at the continental scale showed that concentrations of NO<sub>2</sub>, SO<sub>2</sub>, and AOD substantially dropped in 2020 during the lockdown period compared to their averages for the baseline period over all continents, with a maximum reduction of ~33% for NO<sub>2</sub> in East Asia, ~41% for SO<sub>2</sub> in East Asia, and ~37% for AOD in South Asia. In the case of O<sub>3</sub>, the maximum overall reduction was observed as ~11% in Europe, followed by ~10% in North America, while a slight increase was found in other study regions. These findings align with ground-based air quality observations, which showed that pollutants such as NO<sub>2</sub>, CO, PM<sub>2.5</sub>, and SO<sub>2</sub> during the 2020 lockdown period decreased significantly except that O<sub>3</sub> had varying patterns in different cities. Specifically, a maximum reduction of ~49% in NO<sub>2</sub> was found in London, ~43% in CO in Wuhan, ~38% in PM<sub>2.5</sub> in Chennai, and ~48% in SO<sub>2</sub> in Beijing. In the case of urban O<sub>3</sub>, a maximum reduction of ~43% was found in Wuhan, but a significant increase of ~47% was observed in Chennai. It is obvious that restricted human activities during the lockdown have reduced the anthropogenic emissions and subsequently improved air quality, especially across the metropolitan cities.

**Keywords:** COVID-19; lockdown; geospatial correlation; ambient air pollutants; OMI; MODIS

## 1. Introduction

According to current estimations, the global population has reached about 7.8 billion and continues to increase by more than 81 million people per year in recent years [1]. The fast-growing population around the world increases pressure on daily anthropogenic activities such as industrial and processing activities [2,3] to fulfill the daily demands of more food, shelter and other services [4,5], which subsequently threatens the sustainability of the global ecosystem [6,7]. Nowadays, more than 55% of the global population is living in metropolitan areas [8]. Along with the population boost, power generation, industrialization, transport demand, and transport quantities have also been increasing. Massive anthropogenic emissions from these sectors have resulted in various environmental issues in terms of harmful effects on human health [9–11], worsened outdoor air quality [12,13], and an altered climate system [14,15]. In the list of the world's most polluted cities, most of the top 30 most polluted cities are located in Asia, especially in India, Pakistan, and China [16–21]. One of many causes leading up to outdoor air pollution is that the developing countries around the world do not adopt the standard operating protocols to run industrial units [22]. Another cause is the use of low-quality fuel in transport vehicles, which consequently releases various air pollutants to the atmosphere [23–26]. In the major metropolitan cities, nitrogen dioxide ( $\text{NO}_2$ ), sulfur dioxide ( $\text{SO}_2$ ), particulate matters (e.g.,  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$ ), tropospheric ozone ( $\text{O}_3$ ) and carbon monoxide ( $\text{CO}$ ) are among the foremost vulnerable air pollutants [27–29].  $\text{SO}_2$  is mainly induced by natural phenomenon (volcanoes) and anthropogenic sources such as the burning of fuels, power generation, and metal smelting [30]. Its presence in the low troposphere can degrade air quality and is also a precursor gaseous source of sulfate aerosols that can further affect the cloud reflectivity [31]. In the atmosphere, presence of hydrogen peroxide ( $\text{H}_2\text{O}_2$ ) and  $\text{O}_3$  can predominantly oxidize the  $\text{SO}_2$  in the aqueous phase to formulate sulfuric acid ( $\text{H}_2\text{SO}_4$ ), which can further lead to particulate sulfate [31]. Moreover, sulphates are key components of particulate matters ( $\text{PM}_{2.5}$ ) and compose 11%–65% of aerosol mass [32]. Combustion of fossil fuels in industries, transportation and other human sectors lead to the formation of  $\text{NO}_2$  [33], which can further play an important role as a catalyst in tropospheric  $\text{O}_3$  formation and serve as a precursor of inorganic aerosols ( $\text{PM}_{2.5}$ ) [10,34,35]. Several legislations have been implemented over the past several years to reduce the air pollution around the globe; however, the current air pollution level is still exceeding the World Health Organization (WHO) air quality standards over most major metropolitan cities.

On the other hand, the outbreak of COVID-19 that started in late December of 2019, spread quickly to many countries (212 countries and territories) over the world and eventually turned into a global pandemic [36–40]. The World Health Organization had to declare a global health emergency on 30 January 2020 [41,42]. Many major human activities, in the areas of culture, education, transportation, and industrial manufacturing were constrained globally [43,44] to prevent the further spread of COVID-19 disease [45–48]. The ongoing restrictions of anthropogenic activities in many countries have largely reduced the industrial production as well as energy consumption by 30% or so within a few weeks, as strict lockdown measures were imposed for public health concerns [49,50]. Restricted human activities during the pandemic lockdown have reduced the emissions of pollutants into the atmosphere [51] and thus decreased the pollution level across the global metropolitan cities [52,53]. This provides a unique chance to investigate the impacts of these restricted anthropogenic emissions on air quality, as well as to better understand the complex response of the atmospheric environment to anthropogenic activities.

Ground-based air quality observations provide accurate estimates of mass concentration of air pollutants but are short of spatial representativeness, which restricts our understanding of air pollution changes in response to COVID-19 pandemic lockdown at the continental scale. To better address this problem, satellite observations along with ground-based data during COVID-19 pandemic lockdown at continental and city scales—as indicated in other studies [54,55]—can provide a unique chance to detect real-time changes in air pollution globally. Moderate resolution imaging spectroradiometer (MODIS) and ozone monitoring instrument (OMI) have facilitated the observation of particulate matters and pollutants at high spatial and temporal resolutions [56,57]. Mass concentrations

of air pollutants observed from these space missions revealed a significant reduction in NO<sub>2</sub>, SO<sub>2</sub>, and PM<sub>2.5</sub>, coinciding with the strict quarantine measures, as was pointed out by some recent publications [44,58–61]. Recent imageries from MODIS on Terra satellite launched by the National Aeronautics and Space Administration (NASA) reported a reduction in aerosol optical depth (AOD) over Asia in April (2020) compared with its average over past years [44]. However, certain limitations did exist in the aforementioned studies. For example, most of these studies analyzed the changes in the mass concentration of air pollutants in 2020 by comparing with the data of just the previous year, 2019, as a baseline, which may be subject to the effects of inter-annual climatic variability and bring uncertainty in results. Therefore, there is a critical need to consider the data from the past several years as a baseline to reduce the effects of inter-annual climatic variability. Moreover, most studies were conducted on a regional scale rather than on a global scale.

This study compiled the global scale data from multi missions of satellites (MODIS and OMI) along with city scale data from ground-based air quality observations to investigate the changes of air pollution in response to the COVID-19 pandemic lockdown by comparing 2020 data from the lockdown period with the baseline period (2015–2019). By combining continental scale and city scale data, we formed a scale hierarchy for a more detailed analysis on the impact of the COVID-19 induced global lockdown on air quality. The main objective of this study is to shed light on uneven changes in air pollution under the potential effects of restricted human activities during the lockdown period.

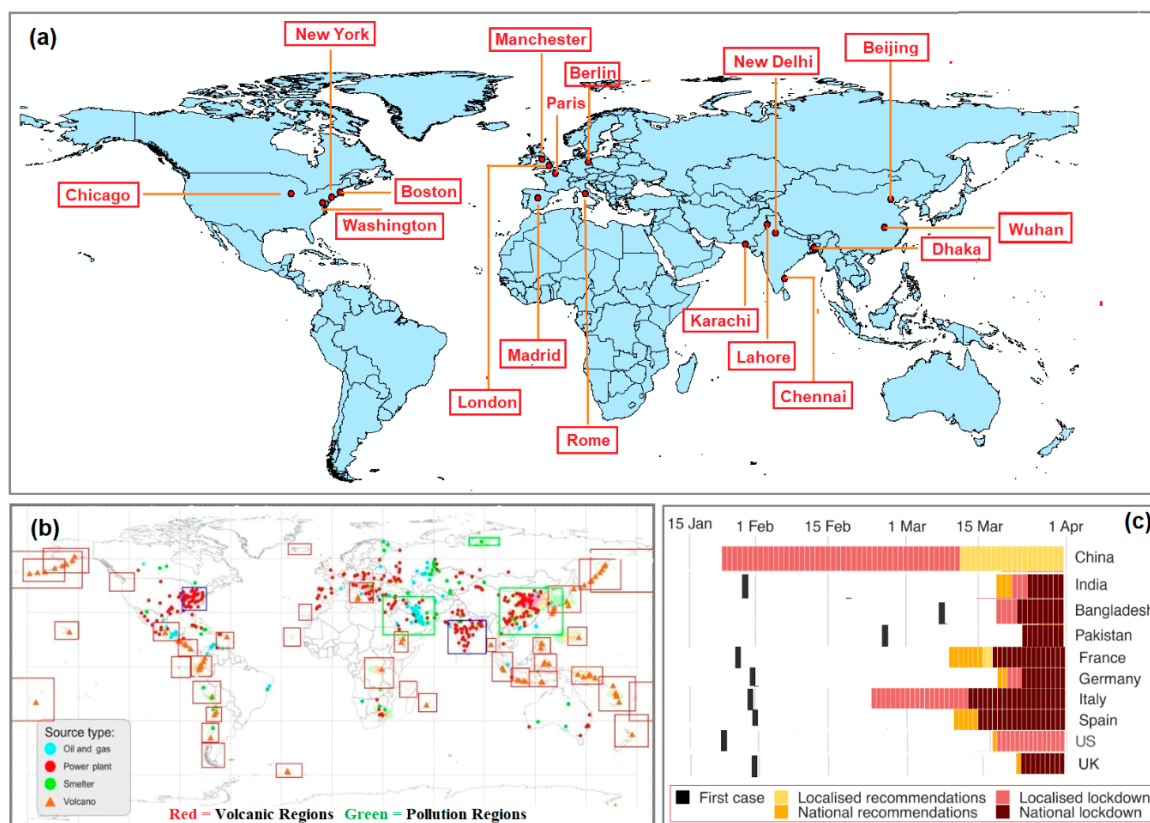
## 2. Materials and Methods

### 2.1. Study Area

This study was carried out over a global scale, especially covering three main continents: North America, Europe, and Asia. We did not include South America and Africa because from our examination on satellite retrieved data, the abnormal change in these two continents is not as significant as other continents. Therefore, we mainly focused on ten countries: Three countries from South Asia (Pakistan, India, and Bangladesh), one from East Asia (China), five from Europe (Spain, France, Italy, Germany, and the UK) and one from North America (United States of America). In Figure 1a, dots drawn in red color show the locations of countries selected in this study. In order to investigate air pollution changes at the city scale, we selected 16 major metropolitan cities around the world based on (i) the historical level of air pollution in the city, (ii) emission sources of pollution, (iii) geographical setting, (iv) COVID-19 cases in that city, (v) the city lockdown history, (vi) NASA evidence on effects of national lockdown on city pollution and (vii) population density among others. Figure 1b illustrates the origins and spatial distributions of different types of emission sources in the world. Most of the air pollution in selected study regions is mainly induced by transport, smelter, oil, gas, and power plants. Figure 1c highlights the dates of lockdown and severity restricted internal movement by countries.

### 2.2. Ground-Based Air Quality Monitoring

For the city scale analysis of air quality, data of five main pollutants, NO<sub>2</sub>, CO, PM<sub>2.5</sub>, O<sub>3</sub>, and SO<sub>2</sub>, were used to investigate the changes in air quality over metropolitan cities before and after the lockdown measures. Air quality data of these pollutants were obtained from World's Air Pollution: Real-time air quality index (WAQI project, <https://aqicn.org/>). These data were compiled from more than 12,000 ground-based monitoring stations, spatially distributed over 1000 major cities in more than 100 countries in the world. New dedicated worldwide COVID-19 datasets of air quality, updated 3 times a day, and covering about 380 major cities in the world were also collected from Air Quality Open Data Platform (available at [aqicn.org/data-platform/covid19/](https://aqicn.org/data-platform/covid19/)). However, some air quality parameters are missing from the WAQI project, especially for North America. Therefore, in order to fill in the gap of missing data, we collected air quality data of PM<sub>2.5</sub>, NO<sub>2</sub>, and CO from the United States Environmental Protection Agency (EPA) (available at [www.epa.gov/outdoor-air-quality-data/](https://www.epa.gov/outdoor-air-quality-data/)).



**Figure 1.** Illustration of study regions with some relevant details: (a) Locations of studied metropolitan cities, (b) spatial distribution of different emission sources of Sulphur, and (c) dates of lockdown and severity restricted internal movement by countries.

In the present study, we used the daily concentration of five pollutants ( $\text{NO}_2$ ,  $\text{CO}$ ,  $\text{PM}_{2.5}$ ,  $\text{O}_3$  and  $\text{SO}_2$ ) from 1 January–15 May for the year of 2015–2019 (defined as baseline period) and 2020, for sixteen selected cities located in South Asia, East Asia, Europe, and North America (Figure 1a). The pre-assumption behind the baseline period was that the air quality in this period mainly responded to regular conditions of anthropogenic emissions while changes in the air quality during January–May 2020 was caused primarily by effects of country-specific lockdown measures when most of the anthropogenic activities were stopped [51,55,62]. Also, using past multi-year data as baseline helps to reduce the effects of inter-annual climatic variability in air pollution [63]. Therefore, we compared the air quality data of the baseline period (2015–2019) with the data of 2020 in the same time frame to shed light on uneven improvement in the air quality under strict lockdown measures.

### 2.3. Space Observations Data

Satellites in space provide global observation data for air quality monitoring over the Earth. For continental scale analysis, we used global datasets of tropospheric  $\text{NO}_2$ ,  $\text{SO}_2$ ,  $\text{O}_3$ , and AOD. Tropospheric  $\text{NO}_2$ ,  $\text{SO}_2$ , and  $\text{O}_3$  data were collected from OMI onboard the NASA Aura satellite, available from October 2004 to present. OMI sensor provides the measurement of backscattered radiations from the Earth's surface as well as atmosphere layer with a spectral resolution of  $\sim 0.5$  nm, wavelength range from 270 to 500 nm, and spatial resolution of  $13 \times 24$  km<sup>2</sup>, at daily global coverage [64]. Scientific applications of OMI sensors provide data in monitoring tropospheric pollution of pollutants like  $\text{SO}_2$ ,  $\text{NO}_2$ , and  $\text{O}_3$ . We used the gridded products of OMI/AURA satellite, (1) the planetary boundary layer (PBL)  $\text{SO}_2$  vertical column density (OMSO2.v003), (2) tropospheric  $\text{NO}_2$  (OMNO2d.v003) and (3) total ozone columns (OMDOAO3.v003). The original OMI PBL  $\text{SO}_2$  products have a high noise level [65,66]; therefore, a new operational OMI PBL  $\text{SO}_2$  product produced

with the principal component analysis (PCA) algorithm was used, because it performed better with smaller bias [67].

The tropospheric NO<sub>2</sub> columns and total ozone column observations were retrieved from OMI based on the differential optical absorption spectroscopy (DOAS) technique within 405–465 nm [68–71]. Moreover, detailed description of the DOAS analysis and algorithm, data filtering, and quality control methods are available at <http://disc.gsfc.nasa.gov/Aura/OMI/>. On a global scale, the average uncertainty between OMI retrieved columns and ground-based column observations was found to be less than 2% [72], however, the relative difference can be larger at individual stations [73]. NO<sub>2</sub> (OMNO2d.003) data were used due to the improved algorithms and sensitivity of OMI for NO<sub>2</sub> detection at the lower atmosphere. It has been found that there is good agreement between in situ measurements and OMI satellite observations for NO<sub>2</sub> [67,74,75], SO<sub>2</sub> [67,76], and for O<sub>3</sub> [69,77–79]. In the present study, daily records of standard Level 3 OMI grid products at 0.25-degree resolution were acquired globally for the period of 1 January–15 May (2015–2020) from the NASA Goddard Earth Sciences (GES) Data and Information Services Center (DISC).

MODIS onboard NASA's Terra and Aqua satellites provides dataset to monitor AOD and the size distribution of the ambient aerosol. AOD is retrieved using two algorithms dark target (DT) and deep blue (DB) [80–82]. Several improved algorithms have been incorporated in the latest MODIS collections (V6.1) to mitigate the uncertainties as compared to previous products [83–85]. Detailed descriptions about aerosol products, aerosol retrieval, calibration procedure, and uncertainties can be found in the literature [86–88]. It has been well established that both MODIS DT and DB AOD measurements at 550 nm are in good agreement with ground observations [87,89]. In this study, latest records of daily AOD (MOD08\_D3) at 550 nm of MODIS onboard NASA's Terra sensor were acquired globally at 1° × 1° spatial resolution for the period of 1 January–15 May (2015–2020) from the NASA GES DISC. A detailed description of satellite products used in this study is listed in Table 1.

#### 2.4. Supplementary Data

Mobility index data of different human activities were tracked from Google reports covering January–May 2020 to understand the anthropogenic changes caused by the pandemic lockdown as well as the lockdown scenario in different countries. Time series datasets of COVID-19 were collected from WHO concerning the COVID-19 cases, numbers of death and the recovered since the epidemic started [42].

#### 2.5. Methods

Daily data of tropospheric NO<sub>2</sub>, SO<sub>2</sub>, O<sub>3</sub>, and AOD were processed using NASA Giovanni user interface. Giovanni is a web application that provides a simple, intuitive way to visualize, analyze, and access Earth science remote sensing data, particularly from satellites. Time series maps were made from daily acquired data for January–April, averaged over the past years during 2015–2019, as the baseline data and compared with the data of the same dates from 2020 in different lockdown scenarios. Daily time series of tropospheric NO<sub>2</sub>, SO<sub>2</sub>, O<sub>3</sub>, and AOD averaged over selected regions were acquired using NASA Giovanni from 1 January–15 May. Daily anomaly changes were computed using absolute difference, of which the formula was shown as follows:

$$\text{Anomaly} = \text{Daily values (2020)} - \text{Daily values (averaged over 2015–2019)} \quad (1)$$

Daily concentration of ground-based air quality data acquired from the United States Environmental Protection Agency (EPA) was usually expressed in mass density. Therefore, the following standard equations were applied to convert the concentration of mass density into volume mixing ratio:

$$\text{Concentration (mg/m}^3\text{)} = \text{concentration (ppm)} \times (\text{molecular mass/molar volume}) \quad (2)$$

$$\text{Concentration (ug/m}^3\text{)} = \text{concentration (ppb)} \times (\text{molecular mass/molar volume}) \quad (3)$$

**Table 1.** Detailed description of the data used in this study.

| Scale of Study         | Datasets                                                          | Spatial Resolution   | Temporal Resolution | Acquisition Date    | Sensor/<br>Observations                                     | Data Sources                                                                                                                                                                                                                                                       |
|------------------------|-------------------------------------------------------------------|----------------------|---------------------|---------------------|-------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Continental and Global | NO <sub>2</sub> , SO <sub>2</sub> , and O <sub>3</sub>            | 0.25 × 0.25          | Daily and monthly   | 2015–2020 (Jan–Apr) | Ozone monitoring instrument (OMI)                           | <a href="https://disc.gsfc.nasa.gov/datasets/">https://disc.gsfc.nasa.gov/datasets/</a><br><a href="https://giovanni.gsfc.nasa.gov/giovanni/">https://giovanni.gsfc.nasa.gov/giovanni/</a>                                                                         |
|                        | Aerosol optical depth (AOD)                                       | 1° × 1°              | Daily and monthly   | 2015–2020 (Jan–Apr) | Moderate resolution imaging spectroradiometer (MODIS) Terra | <a href="https://disc.gsfc.nasa.gov/datasets/">https://disc.gsfc.nasa.gov/datasets/</a>                                                                                                                                                                            |
| City scale             | NO <sub>2</sub> , CO, PM2.5, O <sub>3</sub> , and SO <sub>2</sub> | Average over city    | Daily               | 2015–2020 (Jan–May) | Ground-based                                                | <a href="https://aqicn.org/">https://aqicn.org/</a> .<br><a href="https://www.epa.gov/outdoor-air-quality-data/">aqicn.org/data-platform/covid19/</a><br><a href="https://www.epa.gov/outdoor-air-quality-data/">https://www.epa.gov/outdoor-air-quality-data/</a> |
| Country scale          | Mobility index                                                    | Average over country | Daily               | 2020 (Jan–Jun)      | Google reports                                              |                                                                                                                                                                                                                                                                    |
| Country scale          | COVID-19 dataset                                                  | Average over country | Daily               | 2020 (Jan–Jun)      | World health organization (WHO)                             | <a href="https://covid19.who.int/">https://covid19.who.int/</a>                                                                                                                                                                                                    |

### 3. Results

In this section, satellite observation and ground-based air quality data along with some supplementary data (COVID-19 and mobility) were analyzed to understand changes of global air pollution from a spatial and temporal point of view (both continental and city scale) in response to COVID-19 lockdown measures. The time series of data averaged on 1 January–15 May from 2015 to 2019 as baseline were compared with the data derived from the same duration in 2020. For the continental scale analysis of perspective pollutants, the results averaged over the area were used, while for the city level analysis the averaged time series data from different ground-based air quality monitoring stations in the specific city were used to explore the air pollution changes in response to COVID-19 lockdown.

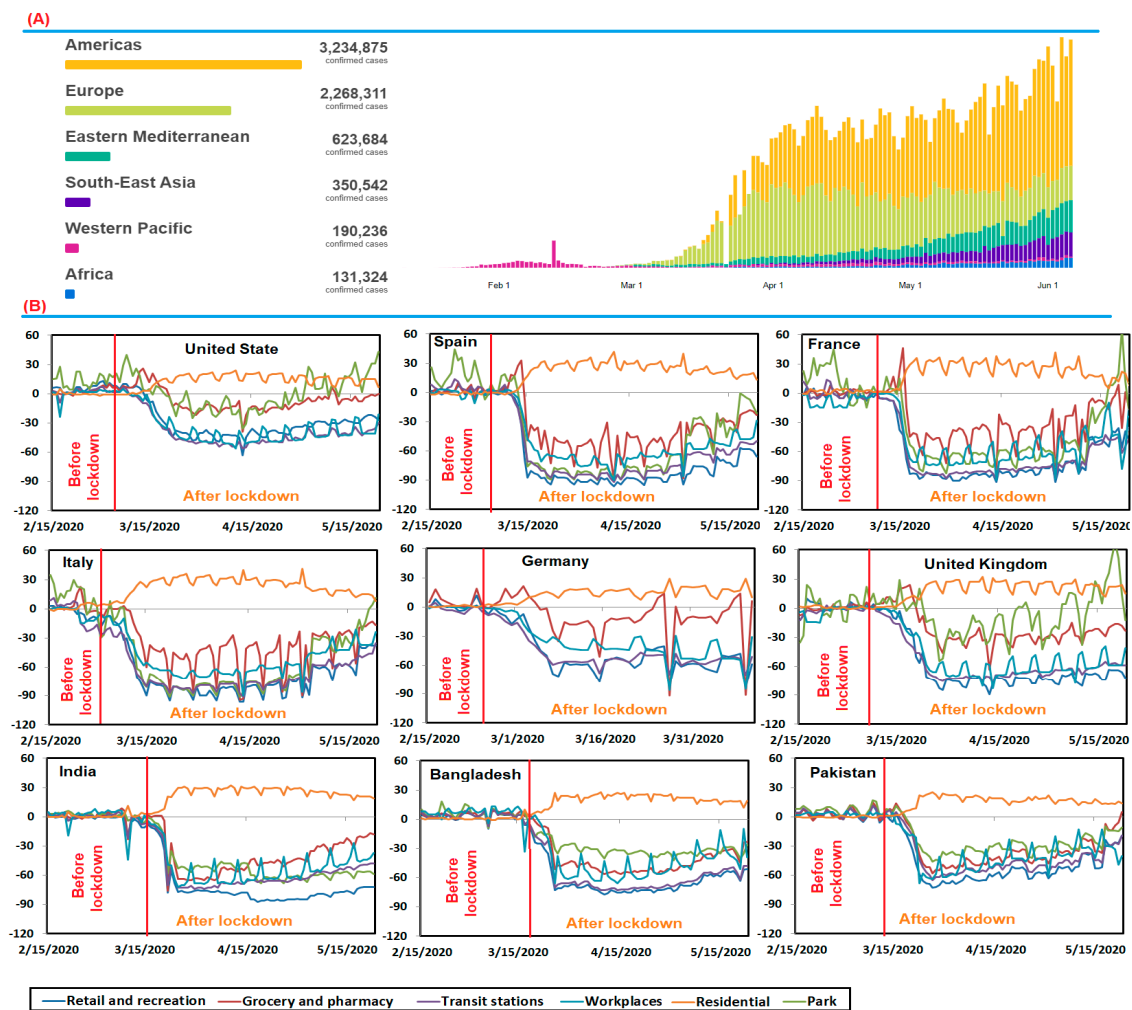
#### 3.1. COVID-19 Pandemic Lockdown and Anthropogenic Mobility

Time series of COVID-19 pandemic along with mobility index of different human activities were adopted to investigate the impacts of pandemic lockdown stages on human activities. The outbreak of COVID-19 started in late December of 2019. At the beginning stage, COVID-19 cases were mainly detected in Asian countries. But a few weeks later, it turned into a global pandemic and started to spread not only in Asia but also in other countries (Figure 2a). The World Health Organization (WHO) reported that the COVID-19 cases recorded in America were as high as 3,234,875 followed by Europe recorded as 2,268,311 until 4 June, 2020 [90]. With the rapid spread of COVID-19, strict lockdown measures were imposed by more and more countries all over the world to prevent the massive infections of the virus between people. Figure 2b illustrates the changes in mobility index with time in terms of different human activities for 9 of the 10 countries selected for this study. The Google mobility index divides usual mobility activities into different specific categories as follows: Retail and recreation, grocery and pharmacy, transit stations, workplaces, residential, and park. It can be observed clearly that all the activities including transport, industries, social places, and educational sectors were running normally before lockdown, but after the lockdown was imposed, the mobility index of human activities decreased by a large extent while the mobility index for residential increased since the lockdown began. The decline of mobility index for the selected countries was observed as 70–90% in workplaces followed by 60–85 % in transit stations till 25 May, 2020 since the pandemic started. However, the UK, France, Spain, and Italy exhibited larger drops in these activities.

#### 3.2. Change in Air Pollution at Global and Continental Scale from Satellite Observations

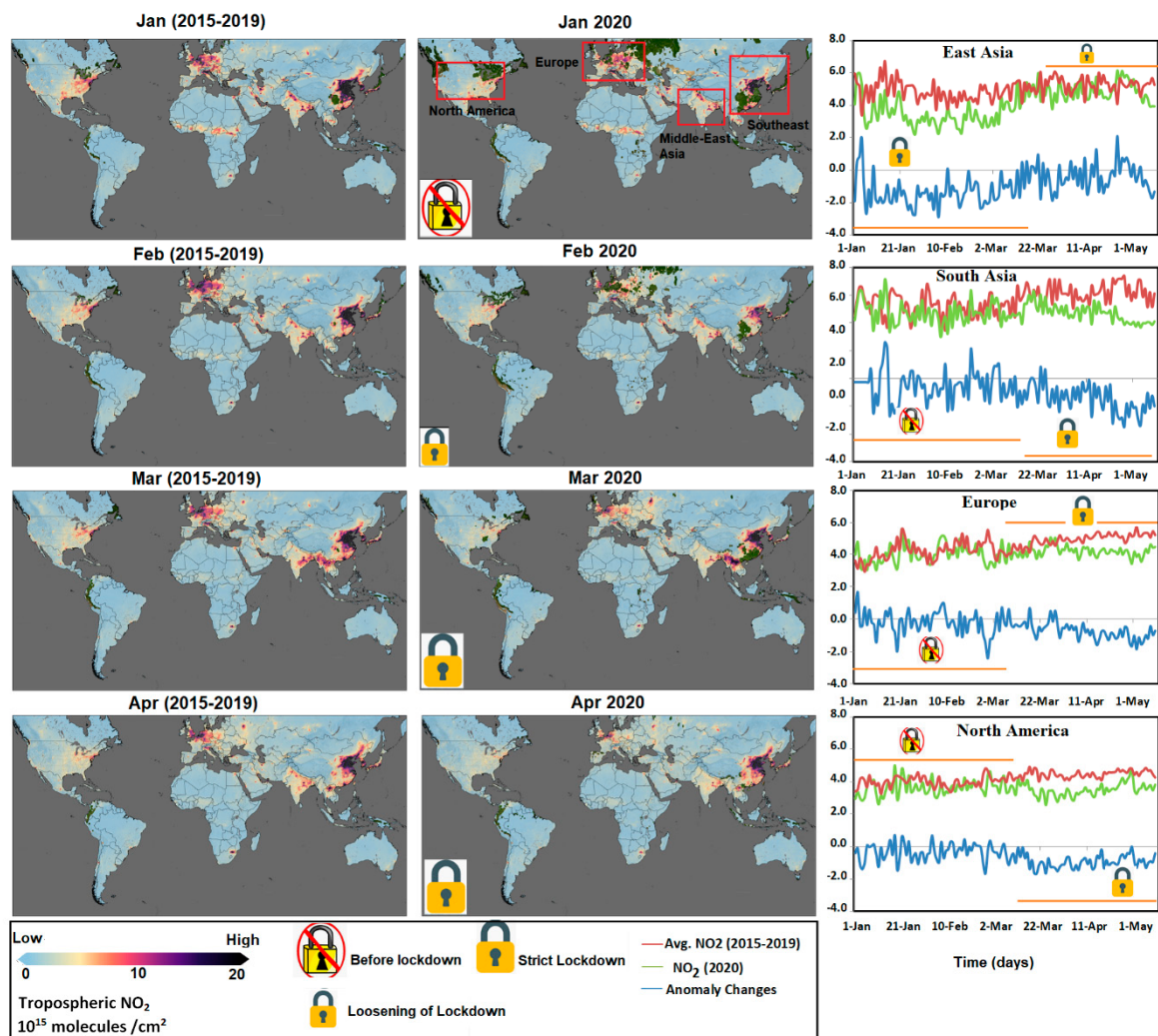
Spatial-temporal variations of airborne NO<sub>2</sub> before and after lockdown in 2020 compared with the baseline are presented in the left two columns of Figure 3. The right column in Figure 3 illustrates the comparison of daily averaged time series data during the baseline period with the daily data from the same dates of 2020. The maps of the NO<sub>2</sub> concentration clearly exhibit that the highest level of NO<sub>2</sub> concentration appeared in East Asia and Europe in contrast to a relatively lower level of NO<sub>2</sub> concentration in South Asia and North America. Moreover, the NO<sub>2</sub> pollution level is very unevenly distributed throughout East Asia as well as over North America. However, the NO<sub>2</sub> level is more evenly distributed over South Asia and Europe. A higher level of NO<sub>2</sub> observed over Europe can be explained by higher contributions from transport sectors, since the transport sector is considered as the largest contributor to NO<sub>x</sub> emissions in European cities [91]. The higher NO<sub>2</sub> level over Asia and Europe probably can be attributed to the contribution of NO<sub>x</sub> emissions, 40% of which is from automobile exhaust and road transport [92]. Seven compounds are contained within the NO<sub>x</sub> family, but EPA only regulates NO<sub>2</sub> as a surrogate for its family. The reason is that the most prevalent form of NO<sub>x</sub> in the atmosphere generated by anthropogenic activities is NO<sub>2</sub> [93]. Spatial maps clearly reveal that the level of NO<sub>2</sub> has largely decreased in the 2020 lockdown period, especially from March–Apr 2020 compared to the baseline period. For example, in Europe, an NO<sub>2</sub> level of about 10 to 20 (10<sup>15</sup> molecules/cm<sup>2</sup>) was observed in an extensive area over European countries (Spain, France, Italy, Germany, and the UK) during March–April in the baseline period. While in 2020, during the lockdown

period (March–April), not only the NO<sub>2</sub> emission level was reduced to about 10 ( $10^{15}$  molecules/cm<sup>2</sup>) but also its spatial extent largely decreased over all countries studied.



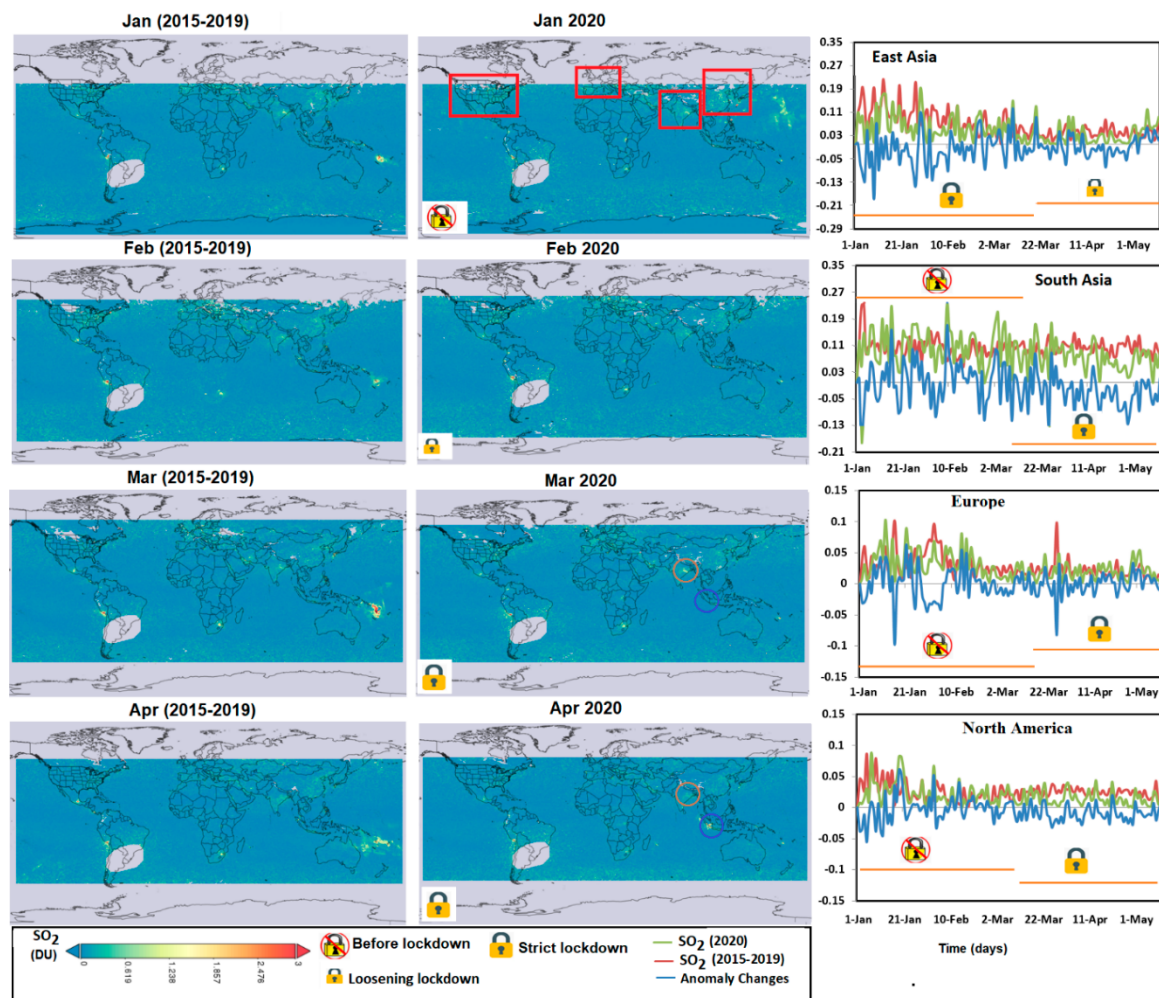
**Figure 2.** Mobility index of different human activities before and after the lockdown being put into effect. (A) The daily data of cases confirmed with COVID-19 in different regions of the world. (B) The mobility index changes of different human activities with time in different cities.

It is clear from time series graphs that NO<sub>2</sub> level before the lockdown period in 2020 was showing a similar behavior in fluctuation trend as it was in the baseline period, while after the lockdown was imposed, time series of mean NO<sub>2</sub> began to drop down compared to the baseline level. Moreover, it can also be observed that anomaly variations in NO<sub>2</sub> before the lockdown were fluctuating with positive (increasing trend) and negative (decreasing trend) values around the zero baseline (gray line), while after the lockdown was imposed, it showed negative values continuously below the baseline due to strict lockdown measures. One interesting finding is observed in East Asia (mainly in China), where we can see a significant decline of NO<sub>2</sub> between January to March followed by a sharp increase to the same emission level as averaged in previous 5 years, which is associated with the lockdown being lifted starting from mid-March [61]. The decline in the NO<sub>2</sub> emission level is generally associated with the local mobility trend.



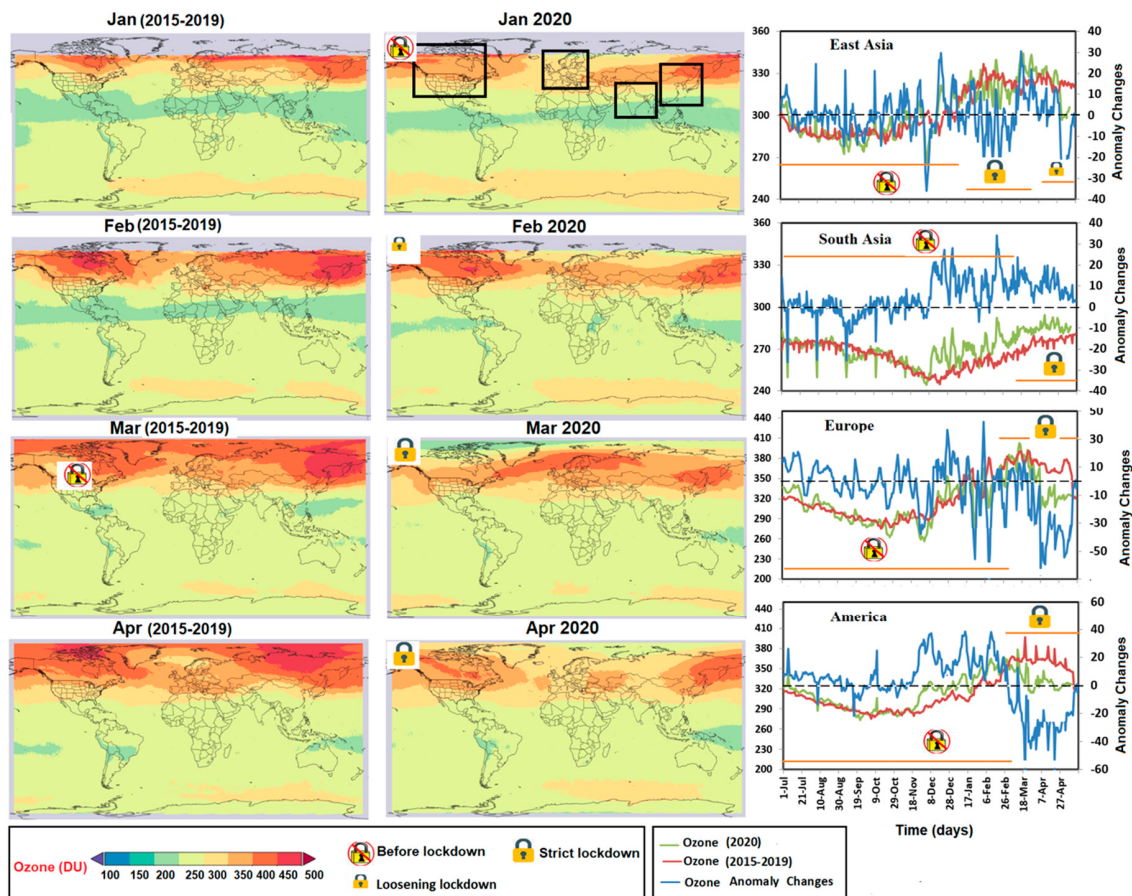
**Figure 3.** Spatial and temporal variations of NO<sub>2</sub> before and after the lockdown in 2020 compared with the baseline (2015–2019 averaged data). The left two columns represent the spatial views and the right column represents the time series view.

Figure 4 exhibits the spatial and temporal variations of SO<sub>2</sub> compared with the baseline before and after lockdown in 2020. SO<sub>2</sub> is measured by the Dobson unit (DU), which is a unit of the amount of gas measured in a vertical column through the Earth's atmosphere. We can see that in general, a higher level of SO<sub>2</sub> emission was found in East and South Asia regions compared to other regions, followed by Europe. The high level of SO<sub>2</sub> in East and South Asia regions is related to the abundant power plants and smelters, as shown in Figure 1b. Spatial maps of SO<sub>2</sub> show a substantial reduction, especially over South Asia and Europe during the lockdown (March–April 2020) compared to the baseline. For example, in South Asia (marked with a brown circle in Figure 4), SO<sub>2</sub> hotspots can be clearly observed with concentration > 1.5 DU in March of 2020 (before the strict lockdown) while these hotspots disappeared due to the reduction of SO<sub>2</sub> level to < 0.6 DU in April of 2020 (during the strict lockdown). Variation of SO<sub>2</sub> emission over the Sumatra region (marked with a blue circle in Figure 4) was almost invisible from January–March of 2020. However, in April 2020, some visible spots of SO<sub>2</sub> emissions can be seen over the Sumatra region, which may reflect the unusual weather conditions in April 2020. As shown in Figure 1b, Sumatra lies in a volcanic region and SO<sub>2</sub> air pollution is mainly induced by volcanic activities caused by climatic variations due to its unique location near to the Indian Ocean. From daily variations of SO<sub>2</sub> level, we can also find that reduction in SO<sub>2</sub> is related to lockdown status which is more significant over the two Asia regions compared to Europe and North America.



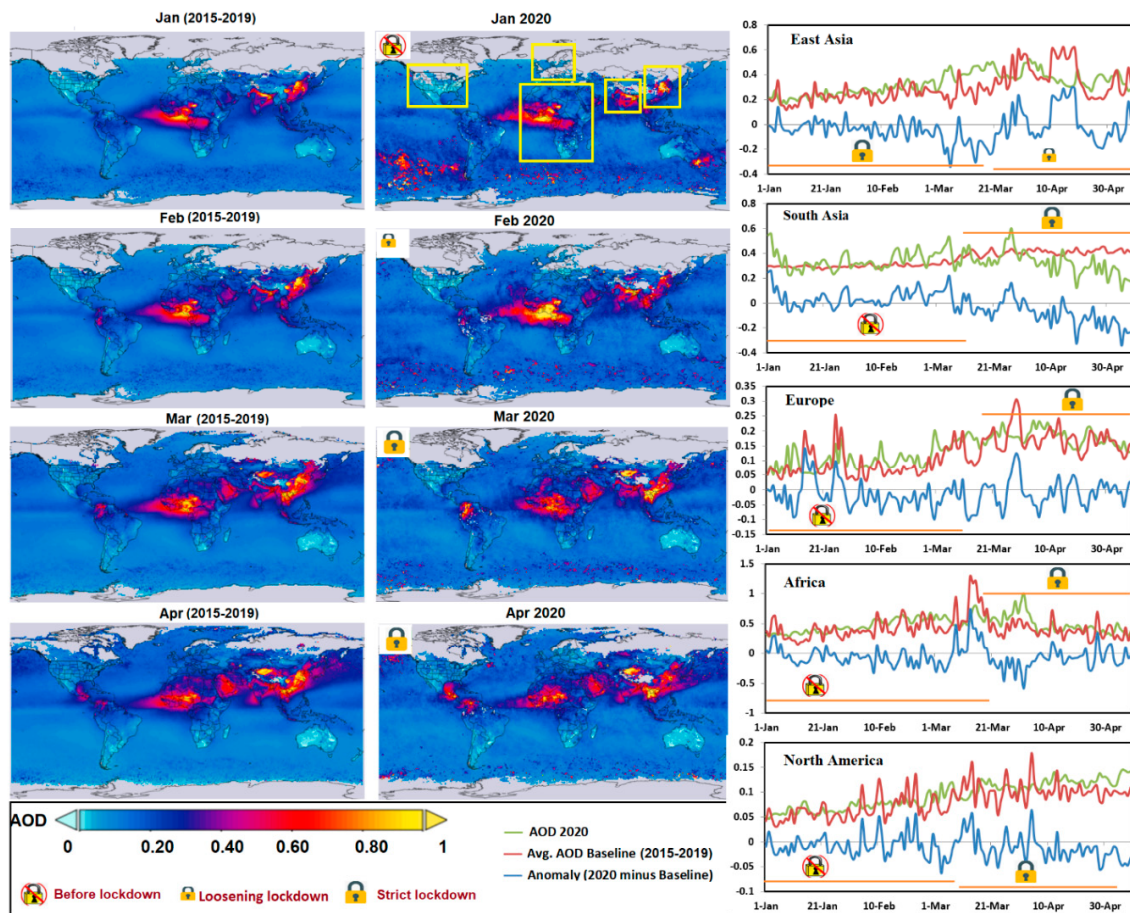
**Figure 4.** Spatial and temporal variations of SO<sub>2</sub> before and after the lockdown in 2020 compared with the baseline condition (2015–2019 averaged data).

Figure 5 exhibits the spatial and temporal variations of the total ozone column (O<sub>3</sub>) compared with the baseline level during 2015–2019 before and after lockdown in 2020. These maps reveal that the spatial extent and magnitude of O<sub>3</sub> over the North Americas and Europe significantly reduced during March–April 2020 (lockdown period) compared to the baseline. It can be seen that O<sub>3</sub> level over North America was close to the baseline level during January–February, 2020. But from March–April, a significant decline of O<sub>3</sub> occurred. For example, in April (2015–2019) O<sub>3</sub> level was more than 370 DU over North America while in April (2020) it reduced to less than 310 DU. However, a substantial increase of O<sub>3</sub> was observed for the period of March–April of 2020 over the South Asia region (Mainly India and Pakistan). Daily time series of average O<sub>3</sub> and its anomaly during February–March 2020 (before lockdown in most countries) fluctuated around their respective baselines (for the anomaly, its baseline is the black dot line at zero) over North America and Europe. However, after the lockdown was imposed, a sharp decline was observed as the anomaly fluctuated below the baseline level during this period. In the case of South Asia, the time series of average O<sub>3</sub> was above the baseline level and the anomaly was increasing during January–April (2020). However, it decreased to the baseline level after the lockdown was imposed in those countries of the region. For example, from 1 January–20 March, O<sub>3</sub> anomaly time series could reach 29 DU but after the lockdown was imposed from 20 March, it declined to 5 DU on the 15th May.



**Figure 5.** Spatial and temporal variations of the total ozone column compared with the baseline level before and after the lockdown being put into effect in 2020. Gray dotted line in the time series graphs indicates the zero line for anomaly time series.

Figure 6 presents the spatial and temporal variations of AOD before and after lockdown in 2020 compared with the baseline. AOD maps clearly depict that its spatial extent and magnitude were much higher in East Asia, South Asia, and Africa compared with Europe and North America. No significant changes in AOD were found over North America and Europe before and after the lockdown period since the values of AOD were already too low over these two regions. It seems that lockdown did not pose significant effects on AOD in Europe and North America but had more influence over the two Asia regions. In South Asia, the spatial extent of the AOD level as well its magnitude was higher during January–February, 2020 (before lockdown) with a value  $> 0.8$  but dropped to  $< 0.6$  in March–April 2020 during the lockdown. The daily mean AOD dataset and its anomaly changes in South Asia show that during the first 10 weeks of 2020 the AOD was increasing, but it abruptly decreased right after the lockdown was imposed. In East Asia, traditional Chinese New Year is usually around mid-January to late February each year, which often causes a decline in emissions, the average level of AOD in the past years over this duration was relatively low. Therefore, no significant decline of AOD in these two months of 2020 was observed. But from March, when Chinese New Year is usually over, the AOD level often increases as shown by the baseline but we can see a clear decline of AOD level after Chinese New Year in 2020. We can also see a significant surge in the AOD level after the lockdown was partially lifted in East Asia (mainly China) [61] around April.



**Figure 6.** Spatial and temporal variations of aerosol optical depth (AOD) before and after the lockdown in 2020 compared with the baseline (2015–2019).

Table 2 summarizes the averaged  $\text{NO}_2$ , AOD,  $\text{O}_3$ , and  $\text{SO}_2$  levels from January to April of 2020 compared to the baseline at a continental scale. This table shows percentage reductions of air pollutants during the pandemic lockdown, which were calculated and compared to baseline values to infer how much the data in 2020 increased (+) or decreased (−) compared to baseline. Continental scale data depict the maximum amount of reduction in  $\text{NO}_2$  to be ~33% (East Asia), in  $\text{SO}_2$  to be ~41% (East Asia) and in AOD to be ~37% (South Asia). In the case of  $\text{O}_3$ , the maximum reduction was ~11% (Europe), followed by ~10% (North America) while in other regions it increased slightly. We can see that in general, lockdown has posed significant impacts on the decline of pollutants like  $\text{NO}_2$  and  $\text{SO}_2$ , as well as AOD. But  $\text{O}_3$  appeared not to be affected as much by the reduction of human activity during the lockdown as the other three indicators. Even after strict lockdown, the  $\text{O}_3$  level only declined slightly relative to baseline but for some regions, it increased. This was probably related to the combined factors triggered by abnormal weak upper atmospheric wave events from December 2019 to March 2020 as reported by NASA. Note that the total column ozone is used for the continental scale analysis for  $\text{O}_3$ , which could also partially lead to our finding. Ground-based observation data lack spatial representative and cannot be used to cover large areas such as continental scale, so a remote sensing approach is required when it comes to continental scale data analysis.

**Table 2.** Percentage reduction of NO<sub>2</sub>, AOD, O<sub>3</sub>, and SO<sub>2</sub> when comparing the level of 2020 during lockdown period with the baseline (the same period in 2015–2019). (\*: Since other parameters for Africa have no significant change, they were skipped in this study. Only AOD was provided as significant changes of AOD occurred in Africa).

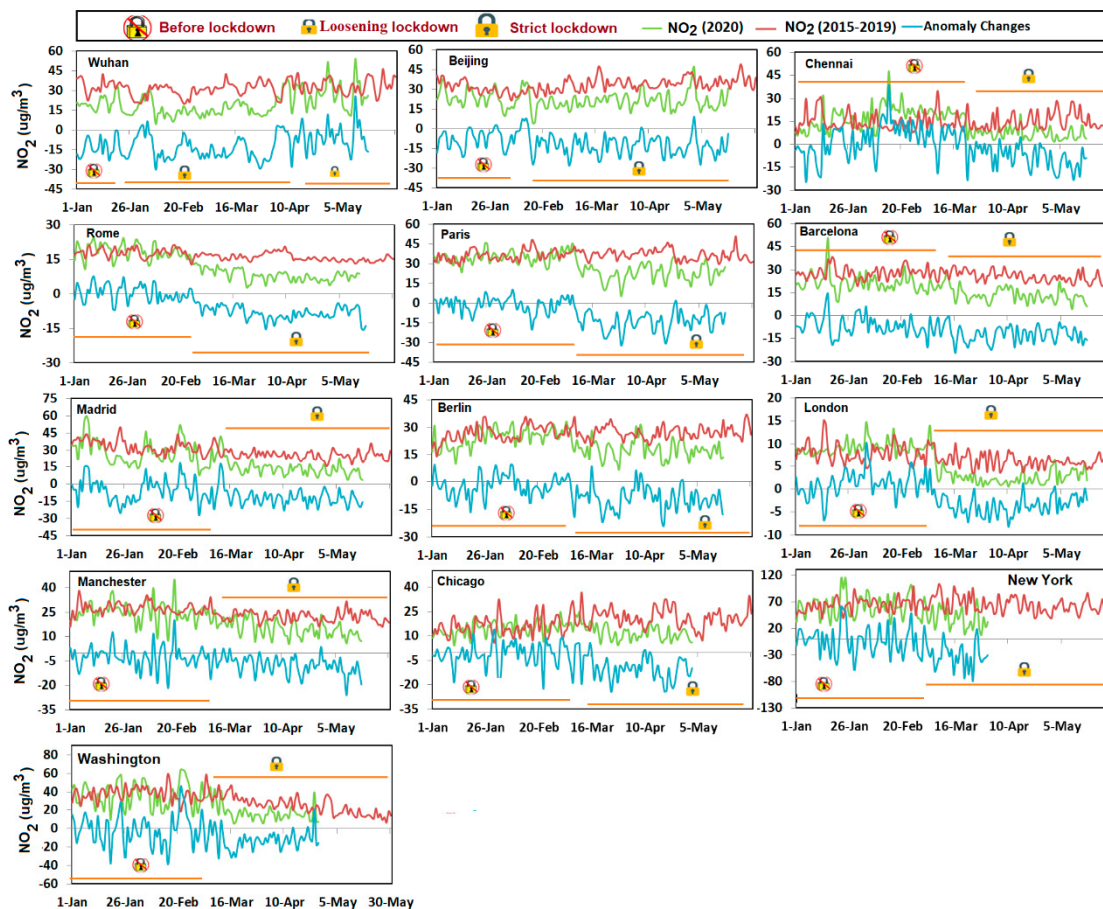
| Study Regions | Month | NO <sub>2</sub> | AOD    | O <sub>3</sub> | SO <sub>2</sub> | Lockdown Stages    |
|---------------|-------|-----------------|--------|----------------|-----------------|--------------------|
|               |       | %               | %      | %              | %               |                    |
| East Asia     | Jan   | −27.40          | −6.10  | 1.37           | −30.40          | Lockdown           |
|               | Feb   | −32.64          | −15.01 | −2.09          | −24.01          | Strict lockdown    |
|               | Mar   | −14.30          | −29.80 | 1.70           | −9.57           | Strict lockdown    |
|               | Apr   | −3.69           | 6.37   | 1.43           | −40.71          | Loosening lockdown |
| South Asia    | Jan   | −3.28           | −13.73 | 3.32           | 3.25            | No lockdown        |
|               | Feb   | −11.71          | 2.54   | 4.97           | 2.43            | No lockdown        |
|               | Mar   | −12.37          | −0.48  | 4.32           | −3.21           | Lockdown           |
|               | Apr   | −25.28          | −37.17 | 3.38           | −31.65          | Strict lockdown    |
| North America | Jan   | −11.05          | −13.20 | 6.44           | 0.79            | No lockdown        |
|               | Feb   | −6.38           | −4.40  | 5.55           | 0.98            | No lockdown        |
|               | Mar   | −19.89          | −7.25  | −6.39          | −22.98          | Lockdown           |
|               | Apr   | −29.39          | −12.61 | −9.55          | −35.53          | Strict lockdown    |
| Europe        | Jan   | −1.39           | 1.33   | 1.83           | 5.49            | No lockdown        |
|               | Feb   | −6.23           | −19.18 | −3.36          | −6.50           | No lockdown        |
|               | Mar   | −7.46           | −9.16  | −0.55          | −18.43          | Strict Lockdown    |
|               | Apr   | −26.86          | −9.10  | −10.53         | 3.32            | Lockdown           |
| Africa *      | Jan   | NA              | −9.88  | NA             | NA              | No lockdown        |
|               | Feb   | NA              | −16.64 | NA             | NA              | No lockdown        |
|               | Mar   | NA              | −3.91  | NA             | NA              | Lockdown           |
|               | Apr   | NA              | −19.30 | NA             | NA              | Strict lockdown    |

### 3.3. Change in Air Pollution at City Scale from Ground-Based Observations

For city scale analysis of air quality, ground-observed data of five main air pollutants NO<sub>2</sub>, CO, PM<sub>2.5</sub>, O<sub>3</sub>, and SO<sub>2</sub> were used to investigate the changes of air quality in metropolitan cities before and after lockdown. Since some data of five main air pollutants for some cities are still missing, we ignored those pollutants of those cities in graphs. Figure 7 illustrates the daily mean NO<sub>2</sub> dataset and its anomaly changes observed from January to May of 2020 compared to the baseline over the different global metropolitan cities.

It can be seen that all cities showed a significant drop in mean emission of NO<sub>2</sub> and its anomaly after the lockdown was imposed in these cities, however, reduction in Madrid, Rome, Barcelona, Berlin, and Wuhan were relatively larger. Before lockdown, human activities were running normally in terms of both normal daily activities and emitting pollutants, which should be the reason why time series of anomaly changes were fluctuating around the zero line. However, after the strict lockdown measures were imposed, abrupt reduction of human activities during pandemic lockdown resulted in sharp decreases in NO<sub>x</sub> emissions and thus time series of anomaly changes moved down below the baseline continuously. For those cities that were severely impacted by COVID-19 and strict measures for lockdown were imposed, dramatic drop of emissions during lockdown and rapid increase of emissions shortly after the lockdown was gradually lifted can be seen clearly from the figure, such as Wuhan and Beijing.

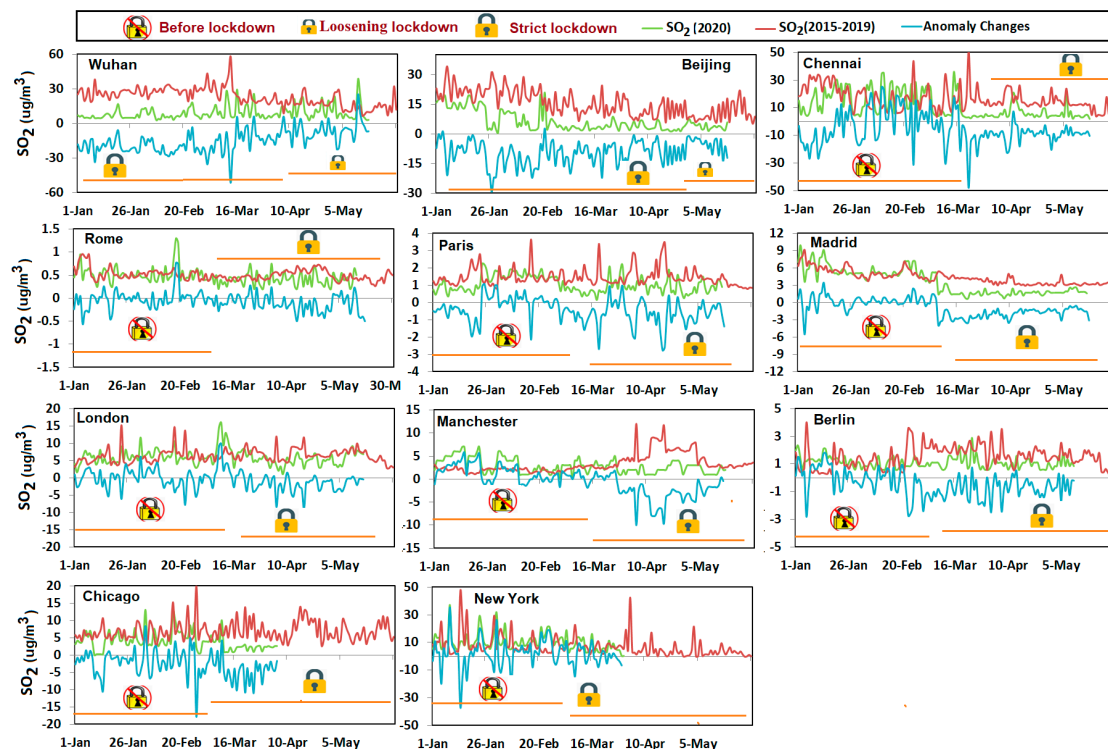
Figure 8 shows the daily mean SO<sub>2</sub> changes in different major cities from January to May of 2020 compared to the baseline. For the labels in the figure please refer to the explanations for Figure 7 of NO<sub>2</sub>. Quite similar to the variations of NO<sub>2</sub> in terms of daily mean as well as anomaly, for most cities, such as Wuhan and Beijing, Madrid, Chicago, Chennai, and Paris, lockdown immediately resulted in significant decrease of SO<sub>2</sub> emission. However, for cities like Rome, and London, there were only very slight decline in SO<sub>2</sub> even after the lockdown was imposed, because the emissions level of SO<sub>2</sub> was relatively low in these regions over the past years.



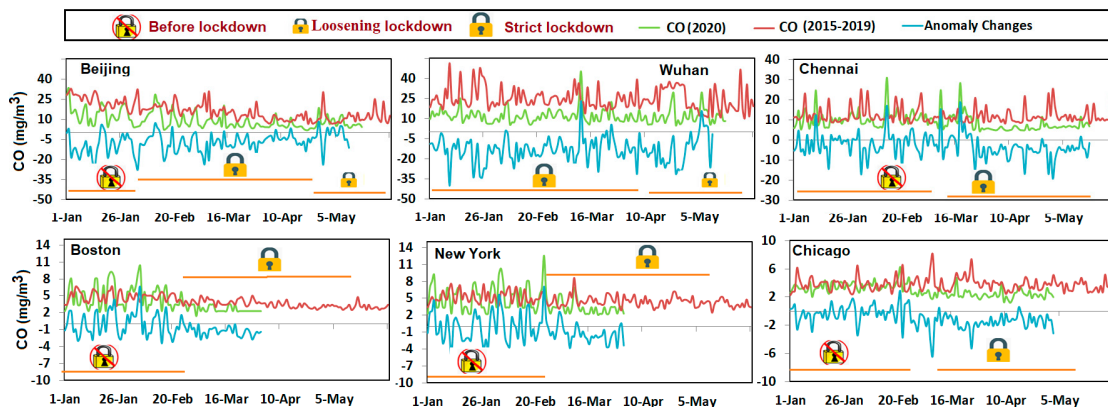
**Figure 7.** Daily mean  $\text{NO}_2$  dataset and its anomaly changes in different global metropolitan cities from January to May of 2020 against baseline value (average of 2015–2019 data). The bigger lock icon with a stop sign indicates the time before lockdown in 2020. The bigger lock icon indicates the period when lockdown is strictly enforced, and the smaller lock icon indicates the period when lockdown is still enforced but different stages of reopening already started. The light black line in the figure represents the zero line.

Figure 9 plots the daily mean variations of CO and its anomaly changes in different major cities from January to May of 2020 compared to the baseline. Since the CO data are not sufficiently available as the data of other pollutants for our chosen metropolitan cities, only six cities with available data were taken as examples in this study. Decrease of CO was found for all studied cities after lockdown, the declining trend is obvious for Beijing, Wuhan, and Chennai probably owing to more CO related emissions. The CO concentration in Wuhan was about 6 times higher than that averaged in Chicago, but both declined approximately 40% after lockdown. An increasing trend in CO anomaly compared to baseline before the lockdown period was found for cities like Boston, New York, and Chicago. After the lockdown was imposed, slight decrease in CO level appeared over these cities.

Figure 10 plots the daily mean dataset of  $\text{PM}_{2.5}$  and its anomaly changes compared to the baseline from January to May of 2020 over different major cities. In general,  $\text{PM}_{2.5}$  fluctuated obviously between different cities. The concentration of  $\text{PM}_{2.5}$  dropped considerably from 38.19% to 16.90% compared to the baseline during pandemic lockdown for all major cities presented in the graph. Before lockdown, the  $\text{PM}_{2.5}$  in 2020 over most cities overlapped with the baseline, which implies that  $\text{PM}_{2.5}$  pollution levels were similar between 2020 and 2015–2019 before lockdown. But after lockdown, the daily  $\text{PM}_{2.5}$  in 2020 was lower than the baseline. Cities in Asia decreased more significantly in  $\text{PM}_{2.5}$  after lockdown than those major cities in North America and Europe.



**Figure 8.** Daily mean  $\text{SO}_2$  dataset and its anomaly changes compared to the baseline values in different global metropolitan cities in 2020 (i.e., average values of  $\text{SO}_2$  from different ground-based monitoring stations on the same dates of 2015–2019).

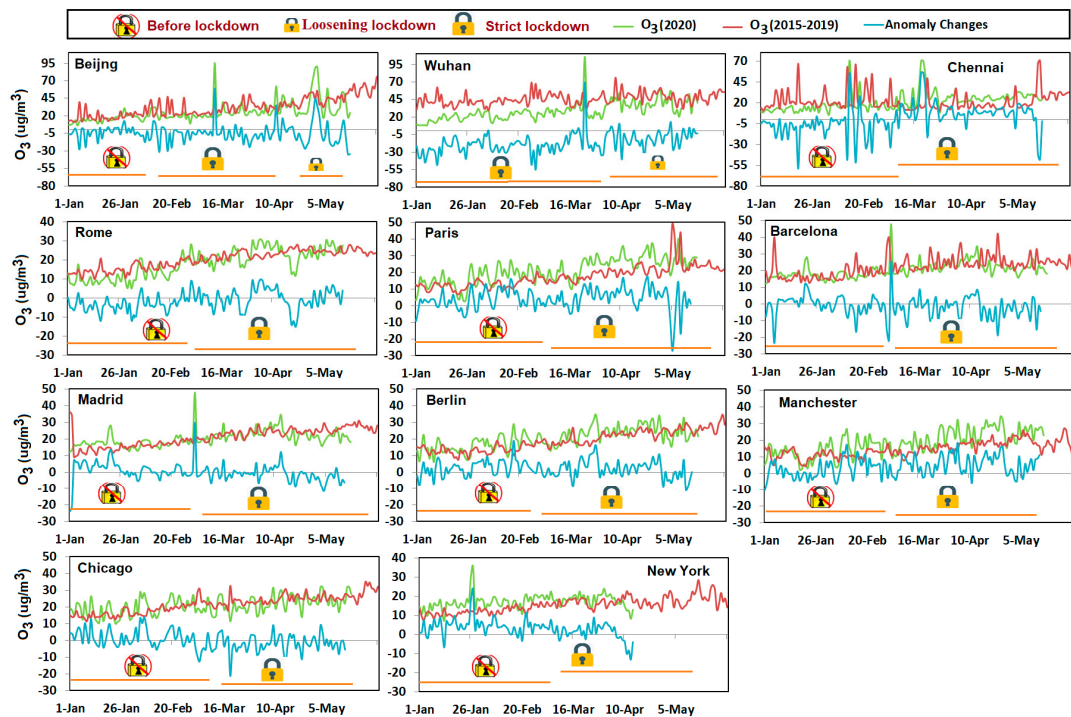


**Figure 9.** Daily mean dataset of CO and its anomaly changes in different global metropolitan cities in 2020 against the baseline (average of 2015–2019).

Figure 11 illustrates the daily mean dataset of tropospheric  $\text{O}_3$  concentration and its anomaly changes compared to the baseline from January to May of 2020 over different major cities. Higher concentration of  $\text{O}_3$  was observed in the Asian cities especially Beijing and Wuhan compared to cities in Europe and North America, which can be explained by the higher contribution of vehicle exhaust emission for  $\text{O}_3$  formation.  $\text{O}_3$  concentration was much lower than the baseline in Wuhan after the lockdown was imposed. However, for Chennai city in South Asia, the  $\text{O}_3$  concentration increased compared to previous years' data after lockdown. The same phenomenon was also observed in European cities like Rome, Paris, and Manchester. In Barcelona and Madrid where slight decline occurred after the first week of April 2020. The increase of  $\text{O}_3$  in many European cities compared to Asian cities can be explained by their lower  $\text{NO}_x$  emissions which might lead to a lower titration of  $\text{O}_3$  under the controlled transport emissions caused by the lockdown.



**Figure 10.** Daily mean dataset of PM2.5 and its anomaly changes over different major cities in 2020 against the baseline (the averaged value of PM2.5 for 2015–2019).



**Figure 11.** Daily mean ozone ( $\text{O}_3$ ) and its anomaly changes compared to the average of past years (2015–2019) over different major cities in 2020.

Table 3 lists the percentage change of NO<sub>2</sub>, CO, SO<sub>2</sub>, O<sub>3</sub> and PM2.5 concentrations comparing the emission level of 2020 during lockdown period with the baseline (the same period in 2015–2019) over the 16 major cities selected. From this table, clear drops in air pollution caused by lockdown can be observed. Overall results indicate that concentrations of pollutants dropped over all of the studied cities during the lockdown period. The maximum reduction in NO<sub>2</sub> was ~49% (London), CO was ~43% (Wuhan), PM2.5 was ~38% (Chennai) and SO<sub>2</sub> was ~48% (Beijing). In the case of urban O<sub>3</sub>, the maximum reduction was ~43% in Wuhan, but a significant increase of ~47% was also observed in Chennai. Combined with the WHO COVID-19 case confirmed number data, we can observe a general trend that the more cases confirmed in a city, the stricter level of lockdown was enforced and the greater the improvement in air quality.

**Table 3.** Percentage changes in NO<sub>2</sub>, CO, SO<sub>2</sub>, O<sub>3</sub>, and PM2.5 concentrations when comparing 2020 lockdown period to the same period in 2015–2019 across the different global metropolitan cities.

| Cities     | Month   | NO <sub>2</sub> | CO     | PM2.5  | SO <sub>2</sub> | O <sub>3</sub> | Lockdown Status    |
|------------|---------|-----------------|--------|--------|-----------------|----------------|--------------------|
| Beijing    | Jan–Feb | −26.54          | −32.18 | −16.34 | −37.15          | −18.11         | Loosening lockdown |
|            | Ma–Apr  | −38.88          | −40.12 | −33.19 | −48.18          | −10.79         | Strict lockdown    |
| Wuhan      | Jan–Feb | −43.89          | −39.25 | −34.26 | −47.46          | −43.42         | strict lockdown    |
|            | Mar–Apr | −36.86          | −42.45 | −28.83 | −39.85          | −28.21         | Loosening lockdown |
| New Delhi  | Jan–Feb | NA              | −10.15 | −7.29  | NA              | NA             | Before lockdown    |
|            | Mar–Apr | NA              | −29.71 | −33.08 | NA              | NA             | Strict lockdown    |
|            | Jan–Feb | NA              | NA     | −1.87  | NA              | NA             | Before lockdown    |
| Dhaka      | Mar–Apr | NA              | NA     | −19.12 | NA              | NA             | Strict lockdown    |
| Chennai    | Jan–Feb | 2.97            | NA     | −9.46  | −2.07           | −33.42         | Before lockdown    |
|            | Mar–Apr | −30.62          | NA     | −38.19 | −25.96          | 47.13          | Strict lockdown    |
| Rome       | Jan–Feb | 3.50            | NA     | 14.08  | −2.63           | −24.01         | Before lockdown    |
|            | Mar–Apr | −41.38          | NA     | −16.95 | −17.55          | −2.29          | Strict lockdown    |
| Paris      | Jan–Feb | −4.91           | NA     | −9.85  | −11.94          | 29.58          | Before lockdown    |
|            | Mar–Apr | −32.95          | NA     | −31.47 | −41.23          | 30.20          | Strict lockdown    |
| Barcelona  | Jan–Feb | −15.04          | NA     | NA     | NA              | −2.59          | Before lockdown    |
|            | Mar–Apr | −44.31          | NA     | NA     | NA              | −8.57          | Strict lockdown    |
| Madrid     | Jan–Feb | −9.32           | NA     | 15.24  | 4.42            | −19.71         | Before lockdown    |
|            | Mar–Apr | −43.04          | NA     | −30.36 | −43.06          | −0.07          | Strict lockdown    |
| Berlin     | Jan–Feb | −8.75           | NA     | −17.00 | 1.65            | 19.88          | Before lockdown    |
|            | Mar–Apr | −28.44          | NA     | −31.87 | −39.11          | 15.15          | Strict lockdown    |
| London     | Jan–Feb | 14.99           | NA     | 4.26   | −2.45           | NA             | Before lockdown    |
|            | Mar–Apr | −49.02          | NA     | −29.33 | −5.74           | NA             | Strict lockdown    |
| Manchester | Jan–Feb | −8.73           | NA     | −6.08  | 12.10           | 24.01          | Before lockdown    |
|            | Mar–Apr | −31.79          | NA     | −19.23 | −30.79          | 32.63          | Strict lockdown    |
| Chicago    | Jan–Feb | −7.06           | −6.96  | −1.68  | −11.80          | 13.72          | Before lockdown    |
|            | Mar–Apr | −39.36          | −39.07 | −22.46 | −42.17          | −9.94          | Strict lockdown    |
| New York   | Jan–Feb | −11.57          | 7.66   | −4.78  | 9.18            | 38.24          | Before lockdown    |
|            | Mar–Apr | −29.00          | −24.70 | −23.45 | −2.70           | 4.17           | Strict lockdown    |
| Boston     | Jan–Feb | NA              | 2.78   | NA     | NA              | NA             | Before lockdown    |
|            | Mar–Apr | NA              | −34.71 | NA     | NA              | NA             | Strict lockdown    |
| Washington | Jan–Feb | 1.9             | NA     | 2.43   | NA              | NA             | Before lockdown    |
|            | Mar–Apr | −33.45          | NA     | −21.67 | NA              | NA             | Strict lockdown    |

#### 4. Discussions

The results from in situ ground-based observation agree well with the results from the satellite observation, which was not only confirmed in this study but also in other studies [61]. This provides a foundation for us to discuss the findings from different observation methods together. In our study,

past multi-year data were used as the baseline to help reduce the effects of inter-annual climatic variability in air pollution [63].

#### 4.1. Satellite Observation

We can see from the satellite observation results that the strict lockdown measures facilitated substantial reductions in NO<sub>2</sub>, SO<sub>2</sub>, and AOD. Strict lockdown measures imposed during the COVID-19 epidemic not only decreased the power generation and energy consumption but also lowered the oil demand, consequently posing positive implications on the ecosystem [94,95]. NO<sub>2</sub> in 2020 remained at the same level as the baseline before lockdown but declined obviously after lockdown. Recent evidence from imageries published by the ESA (European Space Agency) and NASA also reported that NO<sub>2</sub> emission during 2020 lockdown had dramatically dropped for about 30% over the Northeast US and 40–49% over Asian countries (mainly China, India, and Pakistan) compared to 2019 data during the same time period [58].

SO<sub>2</sub> concentration of this year was overall higher than that of the past several years before lockdown, but declined unevenly over all regions after lockdown. Similar evidence was also provided by NASA [61] and ESA [44], which showed a strong decline in SO<sub>2</sub> emissions, especially over South Asia and East Asia. Recent declines in air pollution across all global regions are associated with less consumption of fossil fuels [22,96], which ultimately reduced the level of pollutants in the atmosphere during the lockdown period [51,53,97].

The AOD maps indicated that the values were much higher in both Asia regions compared to Europe and North America, which might contribute to Europe and North America's low response in AOD to lockdown. AOD level over East Asia (mainly China) exhibited significant drop during the first 7 weeks of 2020, which highlights a clear impact of reduced anthropogenic activities on the AOD level during both Chinese New Year and the pandemic lockdown period [61]. However, after the lockdown was gradually and partially lifted, the AOD level started to increase and approached to past years' average values [98,99]. Similar behavior of AOD was also observed in South Asia. The majority of the aerosols formed in the Indo-Pak region are associated with anthropogenic emissions such as emissions from vehicles, coal-fired power plants, industrial sources, and burning agricultural farms [100]. During the pandemic lockdown, the restricted use of fossil fuels has decreased the emission sources of airborne particles in the atmosphere [51] and these changes can be proxies for the decline in AOD [31,101].

We used total column ozone data only for continent scale analysis and used ground-based observation data which is tropospheric ozone for city scale analysis. Ground-based observation data lack spatial representativeness and cannot be used to cover large areas such as continental scale, so a remote sensing approach is required when it comes to continental scale data analysis. However, separating between tropospheric ozone and stratosphere ozone to acquire only tropospheric ozone using reflectance spectra in remote sensing is difficult [94]. Because only total ozone column data can be acquired without substantial calculation for extracting tropospheric ozone, we chose to only use total column ozone from the OMI sensor for continental level ozone analysis. A large portion of the total ozone column consists of stratospheric ozone that is mostly naturally induced and is sensitive to clouds and weather phenomena. A smaller portion of the total column ozone consists of tropospheric ozone [102–104] and it is mainly generated from air pollution, which means that it is mainly affected by human activities. While using total column ozone alone to assess the impact of lockdown on tropospheric ozone may create bias since a bigger portion of ozone in the total column is not primarily affected by human activity, we did not mean to use it in direct quantitative analysis for the tropospheric ozone. We only used this data to assess the change in overall O<sub>3</sub> condition globally and qualitatively to imply its influence on tropospheric ozone. By taking into consideration the inter-annual variability and seasonal changes of stratospheric ozone, we minimized the bias in qualitative analysis of the relationship between lockdown and tropospheric ozone level indicated from total column O<sub>3</sub>. Decline in total column O<sub>3</sub> was observed over the North America region while

only slight decline was observed in some locations over East Asia during the first 9 weeks of 2020. In general, our result indicated that  $O_3$  in 2020 decreased compared to the baseline.  $O_3$  levels from both the baseline and 2020 were higher in March and April, which exactly coincided with recent evidence provided by NASA scientists that the unusual weather in 2020 led to a low-level of ozone [44] and that stratospheric  $O_3$  is thicker in March and April. Studies conducted by [105,106] revealed a positive correlation between  $NO_2$  and stratosphere  $O_3$ , which would partially explain the decrease of  $O_3$  in North America and Europe since those two regions had larger decline in  $NO_2$ .  $SO_2$  is one of the ozone-depleting chemicals [107] and less decline in  $SO_2$  in North America and Europe will also lead to the decline of  $O_3$ .

#### 4.2. Ground-Based Observation

We used ground-based air quality data over metropolitan cities along with the satellite observed data for the following reasons: Firstly, satellite datasets used in this study do not reflect changes in pollutant concentration at city scale with finer details due to their  $0.25^\circ \times 0.25^\circ$  spatial resolution. Secondly, some pollutants like  $PM_{2.5}$  cannot be measured directly from space satellites. The changes in air pollution might also be induced by meteorological effects [105]; however, the air pollution over the city level are mainly prejudiced by anthropogenic emissions and chemical mechanisms [108,109]. Ground-based observations in this study revealed that strict lockdown measures caused substantial reduction in  $NO_2$ , CO,  $PM_{2.5}$ , and  $SO_2$  over the studied metropolitan cities.

Larger decline in  $NO_2$  was seen over the metropolitan cities in Europe, which can be explained by the reduced contribution of  $NO_2$  emission from transport sectors, the largest contributor to  $NO_2$  emission in European cities [91]. In East Asia (mainly China),  $NO_2$  emission dropped by ~39% (Beijing) and ~37% (Wuhan) and remained at a low level till April 2020, but the  $NO_2$  level started to recover to the level of baseline since April. Rise in  $NO_2$  can be explained by the partial lifting of lockdown and resuming of anthropogenic activities that contribute to primary  $NO_2$  emission, since the fossil fuel consumption and road traffic are the major sources of air pollution in these cities [92].

Metropolitan cities located in South and East Asia exhibited bigger reduction in  $PM_{2.5}$  compared to those from Europe and North America. Anthropogenic emissions (e.g., coal consumption, industrial harboring of iron, and smelting steel) are the major contributors (about 67%) to  $PM_{2.5}$  compared to the transport sector which only contributes 5% [92,110]. Mainly in East Asian cities (Beijing and Wuhan), the higher reduction in  $PM_{2.5}$  can be considered proxies to the controlled emissions from coal combustion and industrial activities during the lockdown [61]. The  $SO_2$  level declined significantly over all studied cities while maximum decline was observed over Wuhan (~48%) and Beijing (~49%). The main sources of  $SO_2$  emissions are power generation, smelter, and burning of fossil fuels. As explained in Figure 1b, the higher density of power plants and smelters in South and East Asia contributed to higher  $SO_2$  emissions, but reduced emissions from the source during lockdown lowered the  $SO_2$  level largely.

Ground-based city scale surface ozone data was used to accurately analyze the impact of lockdown on ozone pollution [111]. Tropospheric  $O_3$  increased primarily over Rome, Paris, Berlin, and Manchester; however, a visible drop remains to be seen over Barcelona, Beijing, and Wuhan. Because tropospheric  $O_3$  mainly forms from the chemical reaction between  $NO_x$  and volatile organic compounds (VOCs) in the presence of ultraviolet radiations from sunlight, a lack of sunshine will result in the reduction of  $O_3$ . In urban regions, formation of  $O_3$  mainly depends on the VOC- $NO_x$  ratio, which implies that reduction in VOC can decrease the  $O_3$  formation, while the reduction in  $NO_x$  can increase the  $O_3$  formation over the Earth's surface [112]. In cities,  $O_3$  is mainly depleted by the  $NO_x$  emission from the transport sector [113]. Strict lockdown measures especially over the metropolitan cities have reduced the  $NO_x$  emission which ultimately has increased the tropospheric  $O_3$  production [63,114]. Generally, the increase in  $O_3$  over the European cities can be explained by the decrease of road traffic emissions following the strict lockdown measures, because the overall contribution of road traffic emissions to  $O_3$  levels is about 12–35% over some European cities [115].

The varying pattern in the O<sub>3</sub> level can be explained by different conditions in weather (sunshine), NO<sub>x</sub> emission, and VOC level. For example, even though the huge reduction in NO<sub>x</sub> around the globe would normally lead to the increase in surface O<sub>3</sub> as exhibited in many cities, the production of O<sub>3</sub> in cities like Wuhan is also largely restrained by VOC [63]. In addition, both the generally cloudy weather ([http://tianqi.2345.com/wea\\_history/57494.htm](http://tianqi.2345.com/wea_history/57494.htm)) and the high AOD level in Wuhan during January–March 2020 contributed to the reduction of sunshine that is needed to form O<sub>3</sub>, thus partially leading to the reduced level of O<sub>3</sub> in 2020 compared to the baseline. In general, our findings agree with those reported by some recent studies, the controlled human activities have reduced the anthropogenic emissions [116] and improved the air quality for 40–54% over the metropolitan and industrialized regions [51,53,117–119] due to strict quarantine measures [95].

## 5. Conclusions

This study attempted to compile the data from multiple missions (MODIS and OMI) along with ground-based air quality data to investigate the changes in air pollution in response to COVID-19 pandemic lockdown at continental and city scales. While satellite datasets used in this study cover the whole globe and have a relatively higher spatial resolution, they do not reflect changes in pollutant concentration at the city scale; therefore, we supplemented satellite data with ground-based in situ observed air quality data.

Results of satellite observations at the continental scale depict that concentrations of NO<sub>2</sub>, SO<sub>2</sub>, and AOD substantially dropped in 2020 during the lockdown period compared to their averages in the baseline period over all continents, where a maximum reduction of ~33% for NO<sub>2</sub> was found in East Asia, ~41% for SO<sub>2</sub> also in East Asia, and ~37% for AOD in South Asia. In the case of O<sub>3</sub>, a maximum reduction was observed as ~11% in Europe followed by ~10% in North America, while a slight increase was found in other study regions. These findings align with ground-based air quality data in this study, which showed that pollutants such as NO<sub>2</sub>, CO, PM<sub>2.5</sub>, and SO<sub>2</sub> during the 2020 lockdown period decreased significantly except for O<sub>3</sub> which increased over the South and East Asia regions. Specifically, a maximum reduction of ~49% for NO<sub>2</sub> emission was found in London, ~43% for CO emission in Wuhan, ~38% for PM<sub>2.5</sub> in Chennai, and ~48% for SO<sub>2</sub> in Beijing. In the case of urban O<sub>3</sub>, a maximum reduction of ~43% was found in Wuhan, but a significant increase of ~47% was also observed in Chennai. It is generally observed that pollutants that are contributed more by industrial emissions have a larger decline after lockdown.

By combining different scales of data, we analyzed and discussed the effect of lockdown measures on air pollutants and air quality at different scales. This study revealed an overall decline in pollutants around the globe during lockdown time and had some interesting findings, which are in agreement with other regional studies. To fully explore the long-term effect of COVID-19, more follow-up studies using a longer period of pollutant data will be required. We hope this paper can inspire further studies on the topic of COVID-19, one of the largest global pandemics that, for the first time in history, paused human activity for such a long time.

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