Article

How Does COVID-19 Lockdown Impact Air Quality in India?

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Abstract: Air pollution is a severe environmental problem in the Indian subcontinent. Largely caused by the rapid growth of the population, industrialization, and urbanization, air pollution can adversely affect human health and environment. To mitigate such adverse impacts, the Indian government launched the National Clean Air Programme (NCAP) in January 2019. Meanwhile, the unexpected city-lockdown due to the COVID-19 pandemic in March 2020 in India greatly reduced human activities and thus anthropogenic emissions of gaseous and aerosol pollutants. The NCAP and the lockdown could provide an ideal field experiment for quantifying the extent to which various levels of human activity reduction impact air quality in the Indian subcontinent. Here, we study the improvement in air quality due to COVID-19 and the NCAP in the India subcontinent by employing multiple satellite products and surface observations. Satellite data shows significant reductions in nitrogen dioxide (NO2) by 17% and aerosol optical depth (AOD) by 20% during the 2020 lockdown with reference to the mean levels between 2005–2019. No persistent reduction in NO2 or AOD is detectable during the NCAP period (2019). Surface observations show consistent reductions in PM2.5 and NO2 during the 2020 lockdown in seven cities across the Indian subcontinent, except Mumbai in Central India. The increase in relative humidity and the decrease in the planetary boundary layer also play an important role in influencing air quality during the 2020 lockdown. With the decrease in aerosols during the lockdown, net radiation fluxes show positive anomalies at the surface and negative anomalies at the top of the atmosphere over most parts of the Indian subcontinent. The results of this study could provide valuable information for policymakers in South Asia to adjust the scientific measures proposed in the NCAP for efficient air pollution mitigation.

Keywords: air quality; AOD; PM2.5; NO2; COVID-19; India subcontinent

1. Introduction

The fast growth in the population has led to rapid industrialization and urbanization in developing countries during the past several decades, which has resulted in considerable increases in anthropogenic emissions of gases and particulates and, consequently, exacerbates air quality [1,2]. As the world’s second most populous country, India has experienced a severe air pollution problem in the past two decades [3], which can have significant harmful impacts on human health [4,5]. The World Health Organization (WHO) reported that nine of the world’s top ten most polluted cities were from India [6]. Moreover, 99.5% of the 640 districts in India exceeded the WHO guideline for annual mean Particulate Matter (PM2.5) concentration (i.e., 10 µg/m3) in 2016 [7]. Deteriorating air quality may have caused about 1.54 million premature mortality per year in India alone [2].

To mitigate and prevent air pollution, the Indian government launched the National Clean Air Programme (NCAP) in January 2019 [8]. The NCAP aims to augment the
existing air quality monitoring network across the country and to reduce anthropogenic emissions of nitrogen dioxide (NO$_2$), sulfur dioxide (SO$_2$), carbon monoxide (CO), ozone (O$_3$), ammonia (NH$_3$), PM$_{2.5}$, and PM$_{10}$ [9]. The objectives of the NCAP are (1) to ensure stringent implementation of mitigation measures for prevention, control, and abatement of air pollution; (2) to augment and enhance effective and proficient ambient air quality monitoring across the country to ensure quality data collection; (3) to promote public awareness and capacity-building measures that encompass data dissemination and public outreach programmes, for the purpose of inclusive public participation ensuring proper training and infrastructure building. The NCAP targets a national reduction of 20–30% of PM$_{2.5}$ and PM$_{10}$ concentrations by 2024 as compared to 2017 levels.

Concentrations of particulate matter in India often exceed the unhealthy threshold stipulated by the WHO. For example, annual mean PM$_{2.5}$ concentrations are often more than 100 µg m$^{-3}$ in Delhi, consistently exceeding the corresponding WHO standard [10]. In the 640 districts in India, PM$_{2.5}$ concentrations from more than 45% of the districts exceeded 40 µg m$^{-3}$ (the NCAP standard) in 2010, and the fraction increased to 63% in 2016. 99.5% of the districts also exceeded the WHO guideline of 10 µg m$^{-3}$ in 2016 [7]. During the burning season (October–November), PM$_{2.5}$ concentrations could skyrocket to 547 µg m$^{-3}$, which results in an enhancement of aerosol optical depth (AOD) by 0.1–0.3 over the Indo-Gangetic Plain. Therefore, studies on the sources and impacts of air pollution in India are warranted [2,7,11–14].

Based on observation and chemical transport models, previous studies have revealed that pollutant emissions are dominated by domestic cooking and heating, followed by industry and agriculture in Northern India [15]. Direct emissions, particularly diesel soot, are the main sources of primary PM [16]. Moreover, secondary inorganic components including nitrate, sulfate, and ammonia are major contributors to PM$_{2.5}$, followed by dust, vehicle emissions, and biomass burning [17]. It is shown that meteorological factors, such as relative humidity and wind speed, could also exert significant effects on air quality over India [18]. However, questions remain unanswered about the contributions of natural and anthropogenic factors to the air pollution levels in India.

In January 2020, the WHO declared a global health emergency due to the outbreak of the novel coronavirus pneumonia (COVID-19). As of 26 November 2021, there have been about 259,502,031 confirmed cases of COVID-19 in the world, including 5,183,003 deaths (WHO reported at https://covid19.who.int/, accessed on 31 November 2021). To curb the spread of the epidemic, governments in South Asia, including India, launched national emergency responses to reduce population movement and mass gatherings. Transportation, energy consumption, and industrial production were significantly reduced during this period. The consequent dramatic reduction of anthropogenic emissions during the lockdown period provided an ideal and natural experiment for studying the control and prevention of air pollution issues in India. Investigating the air quality changes during COVID-19 (2020) and NCAP (2019) can provide useful information for policy makers in South Asia to inform the design of air pollution mitigation strategies.

During the COVID-19 lockdown in India, the prohibition of unnecessary anthropogenic activities led to significant concentration reductions of atmospheric air pollutants (PM$_{2.5}$, PM$_{10}$, NO$_2$ and CO) [19–23]. For example, Muhammad et al. [24] reported that air pollution levels in India were reduced by up to 30% due mainly to the corresponding mobility reductions. Mahato et al. [19] found that surface PM$_{10}$ and PM$_{2.5}$ concentrations declined by more than 50% in Delhi. Meanwhile, a significant reduction of PM$_{10}$ concentrations from 189–278 to 50–60 µg m$^{-3}$ was observed during lockdown over the Dwarka river basin in Eastern India. Moreover, Agarwal et al. [25] reported that the reduction of PM$_{2.5}$ was gradual compared with the almost instantaneous reduction in NO$_2$. However, O$_3$ pollution levels over Delhi remained high during the lockdown period, which can be attributed to non-linear ozone chemistry and dynamics under low aerosol loading [26]. Further, Datta et al. [23] showed that the variation in ambient O$_3$ concentrations over Delhi and Kolkata could be explained primarily by spatial variation rather than the lockdown.
For carbonaceous aerosols, their relative changes were positive over the high-altitude Himalayan region, which was caused by the enhanced formation of secondary OC through photochemical reactions involving biogenic emissions [27].

At present, most studies are mainly focused on the changes in air pollution levels for specific cities during the lockdown period over India, and an overview of the changes in aerosols and their effects over the entire Indian subcontinent are still lacking (e.g., radiative forcing). Meanwhile, such large-scale changes in aerosol characteristics have the potential to modulate the radiation budget through direct and indirect radiative effects and subsequently impact the regional climate, so detailed investigations are needed [18,28]. Further, meteorological conditions are known to significantly influence regional air quality, and changes in aerosol characteristics also reversely impact meteorology, but such impacts during COVID-19 remain under-investigated. Additionally, most previous studies focused on a shorter period, i.e., starting from 16 March to 14 April 2020, which did not coincide with the actual lockdown period. In this study, we utilize multiple satellite products and surface observations to investigate and compare the changes in air quality over the Indian subcontinent due to NCAP and the 2020 lockdown. The entire lockdown period (March 24–June 30) was considered here. By contrasting aerosol changes during 2020 and 2019, we aim to quantify the following: (1) the contribution of human activities to the total column and surface aerosol abundances, then (2) the potential impacts of meteorological conditions on air quality, and (3) radiation responses to COVID-19 emission reductions.

2. Data and Methods

2.1. OMI

The Ozone Monitoring Instrument (OMI) onboard the Aqua satellite is a nadir-viewing solar backscatter. It measures solar irradiance and Earth radiance from 270 to 500 nm (ultraviolet (UV) to visible (VIS)) at high spectral and spatial resolutions with daily global coverage [29]. The entering light is split into the following two channels using a scrambler: the UV channel with the range 270–380 nm and the VIS channel that covers 350–500 nm. OMI provides the column tropospheric amounts of trace gases (i.e., NO2) and ozone. Generally, NO2 has a short lifetime and is primarily emitted from anthropogenic sources, including industries, powerplants, transportation, and residential combustion [30,31]. It serves as a key precursor for both secondary aerosol formation and ozone production [31–33]. NO2 is often used to indicate surface air quality during specific events, such as the 2008 Olympic Games in Beijing [34], and the 2014 Asia-Pacific Economic Cooperation summit in Beijing [35]. Here, the level-3 daily global gridded tropospheric NO2 at 0.25° × 0.25° from OMNO2d is used as a surrogate for human activities. The OMI tropospheric NO2 has been shown to correlate well with ground-based and in-situ NO2 measurements and bottom-up emission inventories [36]. In this study, tropospheric NO2 retrieved from OMI was used to quantify the contribution of human activities.

2.2. MODIS

The MODIS instruments onboard the Aqua and Terra satellites observe the Earth system in 36 spectral bands ranging from 0.4 to 14.4 μm and provide a nearly global coverage within 1 to 2 days owing to their wide swath of 2330 km [37]. MODIS AOD is retrieved from the deep blue (DB) algorithm over bright land (e.g., desert) and dark target (DT) algorithms over both vegetated lands and waters [38–42]. In MODIS collection 6.1, the DB algorithm is updated to produce a dynamic surface reflectance dataset depending on the normalized difference vegetation index (NDVI); the DT algorithm is updated to reduce the biases in urban areas based on a surface reflectance model [43]. In MODIS collection 6.1, a “merged” dataset of AOD at 550 nm is produced by combining the DT and DB retrievals to increase the data spatial coverage [44,45]. In this study, the merged daily AOD data with the resolution of 1° × 1° between 2005–2020 are used to analyze aerosol changes.
2.3. CERES

The Clouds and the Earth’s Radiant Energy System (CERES) instruments measure Earth’s radiation budget and cloud properties in 15 shortwave (SW, 0.2 to 4.0 µm) and 12 longwave (LW, 2.850 µm to 1 cm) spectral bands. The radiation fluxes at the top of atmosphere (TOA) and the Earth’s surface are assessed using delta-two stream radiation transfer model [46] under clear-sky (without clouds and aerosols) and cloudy-sky (with clouds and aerosols). The TOA radiation fluxes are derived using satellite-derived aerosol and cloud properties together with a radiative transfer model and observed radiances together with angular distribution models [47]. The surface fluxes are computed with cloud properties derived from geostationary satellites (GEO) and MODIS [47]. In this study, daily radiation flux data from 2005 to 2020 are used to quantify radiation response to emission reductions. Flux datasets are derived from Level 3 SYN1deg products with a spatial resolution of 1° × 1° [48]. Here, we have considered radiation fluxes at the surface, in the atmosphere (computed as a residual term), and at the TOA.

2.4. Surface Observation

Surface observational data are retrieved from 230 operational stations in Indian National Air Monitoring Network (https://app.cpcbccr.com/AQI_India/, accessed on 31 November 2021). Generally, the air quality is continuously monitored by sophisticated instruments. Therefore, the chemical method is used to measure SO\textsubscript{2} and NO\textsubscript{2}, and the high-volume sampler is being widely used for particulate matter measurement. In this study, hourly surface concentrations (units: µg/m\textsuperscript{3}) of PM\textsubscript{2.5}, PM\textsubscript{10}, NO\textsubscript{2}, NH\textsubscript{3}, SO\textsubscript{2}, CO, and O\textsubscript{3} were used. Based on the availability of measurements from 2015 to 2020, observations from seven cities were selected for analysis—Ahmedabad, Bengaluru, Hyderabad, Mumbai, Lucknow, Chennai, and Delhi to quantify the contribution of human activities to surface air pollution.

2.5. ERA5

The fifth generation ECMWF reanalysis (ERA5) is the latest generation of atmospheric reanalyses of the global climate. It can provide dozens of commonly used atmospheric and land-surface variables with temporal coverage from 1950 to now [49]. Many studies have proved that ERA5 can provide reasonable temporal and spatial variability of meteorological fields (i.e., wind and precipitation) on a large scale by assimilating remote sensing data, atmospheric sounding data, and ground-based observations. Also, ERA5 with reasonable temporal and spatial variability can be used as the background input of the proposed correction-downscaling model. In this study, variables of the precipitation, wind speed, planetary boundary layer and relative humidity from ERA5 are used to analyze the impact of meteorological conditions on air pollution levels in India. Although the meteorological field from ERA5 is shown reasonable in the spatiotemporal distributions, we also further compare the wind speed, planetary boundary layer, and relative humidity with the corresponding variables from the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), and the precipitation from the Global Precipitation Measurement (GPM).

2.6. Method

India reported the first COVID case on 30 January 2020, and the number of confirmed cases increased to 519 on March 24 (Table 1). To curb the spread of COVID-19 in the Indian subcontinent, a strict lockdown was enforced. The first phase was officially announced on 24 March 2020 and lasted for 21 days from 25 March to 14 April 2020. The lockdown was further extended to 30 June 2020. Here, the following two periods are defined: the pre-lockdown period (1 January–23 March) and the lockdown period (24 March–30 June). As the city locks down, the aerosol mass changes obviously due to the reduction of anthropogenic emissions. To quantify aerosol changes in the Indian subcontinent, daily anomalies of AOD and tropospheric NO\textsubscript{2} are calculated from 1 January to 30 June in 2019 and 2020.
based on the fifteen-year climatology mean (2005–2019). Corresponding daily anomalies of meteorological fields, and radiation fluxes are also calculated. The anomalies in 2019 and 2020 represent NCAP-induced and city-lockdown-induced changes, respectively. The anomalies during 2019 and 2020 are further compared for two periods—pre-lockdown and lockdown, to investigate the potential impacts of COVID-19 lockdown on air quality and radiation. Note that although pre-lockdown and lockdown periods are defined for the year of 2020, these two periods are also selected for 2019 for comparison purposes. Additionally, the Indian subcontinent is divided into the following three sub-regions: North, Central, and South (Figure 1b), based mainly on population density.

**Table 1.** The dates of key COVID-19 events in India, including confirmed cases, deaths, and implementation of governmental policies.

| Date              | Confirmed Cases | Deaths | The Government’s Policy                                      |
|-------------------|-----------------|--------|-------------------------------------------------------------|
| 30 January 2020   | 1               | \     | \                                                          |
| 24 March 2020     | 519             | 9      | Nationwide lockdown from 25 March to 14 April 2020          |
| 14 April 2020     | 10,815          | 353    | Nationwide lockdown Extended to 3 May 2020                  |
| 4 May 2020        | 42,533          | 1373   | Nationwide lockdown extended to 31 May 2020                 |
| 31 May 2020       | 181,827         | 5185   | Nationwide lockdown extended to 30 June 2020                |
| 30 June 2020      | 585,792         | 17,410 | Nationwide unlock                                           |

![Figure 1.](image-url) Column abundance of tropospheric NO$_2$ climatology (2005–2019) and anomaly (2019 and 2020). (a–c): pre-lockdown period and (d–f): lockdown period. The anomaly is defined as the deviation of tropospheric NO$_2$ over 1 January–23 March and 24 March–30 June from the climatological value, and the anomalies in 2019 and 2020 are calculated based on 2005–2019 climatology. Pre-lockdown and lockdown are defined as periods of 1 January–23 March 2020 and 24 March–30 June 2020, respectively. DU is the Dobson unit, which is equivalent to ~0.45 mmol m$^{-2}$. Data are retrieved from the Ozone Monitoring Instrument (OMI). The asterisks in (a,d) represent major cities in the Indian subcontinent.
3. Results
3.1. Changes in Satellite Retrieved Tropospheric NO$_2$ and AOD

Dramatic reductions in air pollution levels during the 2020 lockdown can be observed by satellite retrieved concentrations of NO$_2$ in the troposphere. The main sources of tropospheric NO$_2$ are transportation and industrial activities, thus tropospheric NO$_2$ is a good indicator of anthropogenic emissions [30,31]. The spatial distributions of climatological (2005–2019) tropospheric NO$_2$ are also shown in Figure 1a,b for the pre-lockdown and lockdown periods. The spatial distributions of tropospheric NO$_2$ concentrations generally follow population density as follows: the highest concentrations over the Indo-Gangetic Plain (IGP) are found in the North Indian subcontinent, followed by the Central Indian and lower concentrations over the South Indian subcontinent.

An analysis of tropospheric NO$_2$ anomalies strongly suggests significant reductions in anthropogenic emissions in 2020 during the lockdown period (Figure 1c–f). In 2019, tropospheric NO$_2$ anomalies did not show spatially consistent differences in any of the three aforementioned sub-regions during either pre-lockdown or lockdown periods, implying that NCAP did not make substantial differences in air quality during the first half of 2019. However, in 2020, tropospheric NO$_2$ anomalies during the pre-lockdown period showed negative values in large areas of Central and East India, suggesting reductions in anthropogenic emissions likely due to NCAP. Moreover, tropospheric NO$_2$ in 2020 showed larger (~2 times) reductions during the lockdown period than during the pre-lockdown period across most regions of the Indian subcontinent, with the largest reductions in IGP, followed by the Central and South subcontinent. A total reduction of 7.1% (~0.006 DU) in tropospheric NO$_2$ concentrations was detected over the entire three sub-regions in comparison with the 2005–2019 climatology.

The time series of tropospheric NO$_2$ during the pre-lockdown and lockdown periods over the three sub-regions is shown in Figure 2a–c (left). To better show the trend in tropospheric NO$_2$, we calculated the de-trended tropospheric NO$_2$ over the three sub-regions. Tropospheric NO$_2$ levels in 2020 are the smallest due to the reductions in anthropogenic emissions during the lockdown period (light-red dots), in which the regional mean tropospheric NO$_2$ is 0.067, 0.076, and 0.045 DU (Figure S3). In comparison with the averaged tropospheric NO$_2$ of 2015–2019 (Figure S3), tropospheric NO$_2$ over the three sub-regions changed by -0.011 (-13.9%, North), -0.016 (-18.5%, Central), and -0.011 DU (-23.1%, South) during the lockdown, respectively. Also, the interannual variability of regional mean tropospheric NO$_2$ during the pre-lockdown period over the three sub-regions is similar to that of the lockdown period. However, tropospheric NO$_2$ in 2020 over the three sub-regions changed by 0.002 (2.9%, North), -0.012 (-12.5%, Central), and -0.008 (-14.9%, South) DU during the pre-lockdown, which may be caused by the reductions in anthropogenic emissions due to NCAP. Further, the time series of daily mean tropospheric NO$_2$ over the three sub-regions are shown in Figure 3a–c (left). The daily mean tropospheric NO$_2$ in 2019 is close to climatology during most of the days in the three sub-regions. However, the daily mean tropospheric NO$_2$ in 2020 is far below climatological levels during the lockdown period in all three sub-regions, despite that it is close to climatological levels during the pre-lockdown period over the North and South Indian subcontinents, with generally lower levels in the Central Indian subcontinent. Also, the reductions in tropospheric NO$_2$ are more apparent during the first three to four weeks of the lockdown. It is worth noting that daily mean tropospheric NO$_2$ in 2020 during the lockdown period in all three sub-regions is possible within the fifteen-year spread of tropospheric NO$_2$ (gray shadings), which is the minimum and maximum tropospheric NO$_2$ levels between 2005–2019, and they can include larger uncertainties of tropospheric NO$_2$. With the reductions in anthropogenic emissions during COVID-19 lockdown, tropospheric NO$_2$ in the 2020 lockdown period is expected to decrease significantly. Moreover, the tropospheric NO$_2$ and AOD are almost out of phase in all presented regions during the lockdown period, which could be partially attributed to the influences of natural aerosol loadings (i.e., dust aerosol) on AOD [50].
In addition to tropospheric NO$_2$ concentrations, the satellite-retrieved AOD is another useful variable for investigating persistent haze issues, which can well represent the aerosol loadings. Figure 4a,b shows the climatology of the averaged AOD during the pre-lockdown and lockdown periods. It shows that the high AOD occurs over North India along the southern slope of the Himalayas, which is similar to the spatial feature of tropospheric NO$_2$ climatology. In order to better understand the improvement in air quality due to city-lockdown, AOD anomalies are illustrated in Figure 4c–f. Significantly, positive AOD anomalies are generally observed over the Indian subcontinent in 2019 and 2020 during the pre-lockdown period. The regional mean of AOD anomalies over the three Indian sub-regions is about 0.03 (North), 0.07 (Central), and 0.001 (South) in 2019, respectively (Figure S3). However, during the lockdown period, the AOD anomalies in 2019 turned into negative values, especially over the Indus plain. The reduction of aerosol loading over the Indus plain is mainly induced by the decrease in dust aerosol loading, as shown in a previous study [50]. In 2020, however, the decrease in aerosol loading is mainly observed over the Indo Gangetic Plain and the Ganges Delta, which are mainly induced by anthropogenic pollution emissions. Those larger negative AOD anomalies are closely related to the reduction of emissions from the traffic and manufacturing sectors, which are expected to be substantially impacted by the city lockdown [18,19]. The consistent positive anomalies of tropospheric NO$_2$ and AOD during the lockdown period of 2020 implies that the dramatic reductions in tropospheric NO$_2$ and other anthropogenic emissions played more important roles than the variations of meteorological conditions in leading to negative AOD anomalies. Quantitatively, in 2020, AOD was reduced by about 22.6% (0.05, North),...
2.9% (0.11, Central), and 20.1% (0.02, South) over the three Indian sub-regions during the lockdown period, which is about 1.7 (North), 1.6 (Central), and 20 (South) times of that in 2019, respectively.

The annual time series of AOD exhibits increasing trends over the Central and South Indian subcontinent during the pre-lockdown and lockdown periods from 2005 to 2019, as shown in Figure 2d–f (right). In 2020, AOD during the lockdown period are the smallest in comparison with 2005–2019 climatology. Moreover, the AOD in 2020 during the lockdown period was 0.38, 0.41, 0.29 versus 0.50, 0.45, 0.39 of the fifteen-year average. This observation may indicate that aerosol loading has dramatically decreased due to the reductions in anthropogenic emissions during the lockdown period. Further, the time series of daily mean AOD exhibits an increasing trend from April to June, despite a decreasing trend in tropospheric NO2 (Figure 3d–f). The reason is attributed to the more contributions of natural sea salt aerosol and dust emitted from the Thar Desert and eastward transported to AOD [50], and enhancement of the photolysis of NO2 due to the warmer and more humid conditions [51,52]. During the pre-lockdown period in 2020, AOD was almost located within the climatological ranges of the three sub-regions. However, during the lockdown period in 2020, a significant decrease in AOD was observed over the North and South Indian subcontinent, especially in the first few weeks of the lockdown period. Over the Central Indian subcontinent, close-to-climatology AOD is found in the first few weeks during the lockdown period. This unexpected high AOD is induced by positive anomalies in mid-tropospheric relative humidity [18]. Overall, the decreases of AOD induced by
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city-lockdown are the most significant over North Indian subcontinent, where population is the densest and thus anthropogenic emissions are the highest. Also, daily AOD within the fifteen-year spread is naturally due to the larger range of AOD variation in the past fifteen years.

Figure 4. The same as Figure 1, but for total column AOD. Data are from MODIS.

3.2. Changes in Gaseous Emissions near the Surface

Observed surface concentrations of NO$_2$, PM$_{2.5}$, O$_3$, SO$_2$, and CO from surface stations are also utilized to demonstrate the impact of COVID-19 on air quality. Due to data availability, data from seven stations operated by the Pollution Control Board (CPCB, https://www.cpcb.nic.in/, accessed on 31 November 2021) are selected across India from 2015 to 2020 (Figure 5). Data anomalies during the lockdown period (with reference to 2015–2019) are shown in Figure 5. For NO$_2$, reductions are observed in all cities, with the highest reduction over Bengaluru (city 2, 22.8 µg/m$^3$ and a 48.3% reduction), followed by city 1 (14.3 µg/m$^3$ and 39.8%) and city 7 (15.4 µg/m$^3$ and 50.7%). However, the highest reduction in the tropospheric NO$_2$ is over Ahmedabad (city 1, 0.1 DU and 40%), followed by city 2 (0.037 DU and 30%) and city 5 (0.036 DU and 33%) (Figure S4a). For PM$_{2.5}$, decreases are detected in all cities except for city 4, with the highest decrease being over Ahmedabad (city 1, 70 µg/m$^3$, and 58%). These observations are generally consistent with the changes in satellite retrieved AOD, which also show a significant decreasing trend (Figure 5c). The highest reduction in column AOD is observed over Delhi (city 7, 0.16 and 25%), followed by city 1 (0.13 and 19%) and city 2 (0.13 and 37%) (Figure S4a). Generally, PM$_{2.5}$ concentrations decrease by about 39 µg/m$^3$ (52%) over North India, 20 µg/m$^3$ (45%) over Central India, and 27 µg/m$^3$ (41%) over South India, respectively. As for O$_3$, reductions are observed in all cities except for cities 1, 2, and 6. The increases in O$_3$ in these three cities may
be related to the variations of VOCs and other factors that can influence the production and/or consumption of tropospheric O$_3$. For SO$_2$ and CO, the largest reductions were seen in Bengaluru, a pattern consistent with the reductions in NO$_2$ and PM$_{2.5}$. While over other cities, the changes in SO$_2$ and CO are much smaller. Overall, the surface observed changes in NO$_2$ and PM$_{2.5}$ are consistent with the reductions in satellite retrieved NO$_2$ and AOD. Additionally, the relative changes of meteorological conditions within the same time periods show that precipitation (except Bengaluru and Delhi), wind speed, and planetary boundary layer (except Hyderabad) decrease, while the relative humidity increases (except Hyderabad) (Figure S4e). Moreover, the largest reduction in precipitation is observed over Hyderabad (city 3, 1.46 mm/day and 40%), followed by city 4 (1.31 mm/day and 23%). For the wind speed, the largest reduction is found over Mumbai (city 4, 0.83 m/s and 25%), followed by city 5 (0.58 m/s and 18%) and city 3 (0.56 m/s and 36%). For the planetary boundary layer and relative humidity, the largest reduction and increment are found over Delhi (city 7; 167 m and 21%; 10.3% and 20%), followed by city 1 (130 m and 17%; 9.7% and 19%), respectively.

![Population Density](image)

**Figure 5.** (a) Population density ($\times 10^3$ persons/km$^2$). (b–f) The changes (lockdown minus climatology) of near surface NO$_2$, PM$_{2.5}$, O$_3$, SO$_2$, and CO at 7 cities in 2020 (light-red bar). Data are from surface station observations.

### 3.3. Potential Impacts of Meteorological Fields on Air Quality

Meteorological conditions could affect air pollution levels [18,53]. For example, particulate matter levels in northern China during the city-lockdown period increased significantly and even led to several severe haze formations [53]. The unexpected air pollution was induced by the anomalously high humidity and uninterrupted emissions from petrochem-
ical facilities and power plants, whose emissions could promote aerosol heterogeneous chemistry. The unexpected AOD increase in the central part of India is likely due to the simultaneous increase in relative humidity and decrease in wind speed [18]. Here, the climatology of meteorological conditions is analyzed to study the potential impacts of meteorological fields on air quality over the Indian subcontinent, based on ERA5. Firstly, we evaluated ERA5 data against GPM and MERRA-2. The results show that ERA5 can well represent the precipitation and wind filed at 10 m over the India-subcontinent (Figures S5 and S6). Generally, the climatology of precipitation is mainly distributed over the Northeastern and Southwestern Indian subcontinents, with a maximum value of 40 mm/day during the lockdown period (Figure 6). Also, fractional changes ((lockdown minus 2005–2019 climatology)/(climatology average)) in precipitation, circulations, boundary layer height, and relative humidity during the 2020 lockdown period are shown in Figure 7. Compared to climatology for the year 2020, there is a significant increase in precipitation over the Indian subcontinent, with a maximum increase of 100%. The mean fractional changes over North, Central, and South India are 9.6%, 9.7%, and 0.3%, respectively, which indicate the reductions of aerosol particles by wet scavenging. Simultaneously with the precipitation, the fractional changes in wind speed show a decreasing trend of 30–50% over the whole Indian subcontinent, which is consistent with the observed results in Pandey and Vinoj [18]. In general, the prevailing wind at 10 m during the lockdown period over South India is westerly, which turns northwesterly over North India (Figure 6). The mean wind speeds are 1.3, 2.0, and 1.7 m/s over North, Central, and South India. The reductions in wind speed could provide a conducive environment for the stagnation of air-pollutants and increase fire counts over this region [18]. Here, the correlations between AOD, precipitation, and wind speed are also examined, and the day-to-day variation of AOD is associated with the two aforementioned meteorological variables. Clearly, the decreased (increased) AOD is consistent with the increased (decreased) precipitation a few days ago and the increased (decreased) wind during the lockdown period speed (Figure S7).

Figure 6. Climatology of meteorological conditions between 2005 and 2019. (a): precipitation (units: mm/day), (b): wind at 10 m (units: m/s), (c): relative humidity (units: %), and (d) planetary boundary layer height (units: m). Data retrieved from ERA5 reanalysis.
Figure 7. Fractional changes (%) ((lockdown minus climatology)/(climatology average)) in (a) precipitation, (b) wind speed (m/s), (c) relative humidity, and (d) planetary boundary layer. Data retrieved from ERA5 reanalysis.

Humidity is an important atmospheric parameter and can strongly influence AOD through chemical reaction processes [54]. The relative humidity at 2 m is significantly higher over the Indian coastal zones than in the inland areas (Figure 6), and the maximum relative humidity along the coastal regions can reach over 90%. Compared to climatology, the fractional changes show an increasing tendency. Notably, the increase in relative humidity is prominent over North and Central India. Compared to climatology, the fractional changes in relative humidity over North, Central, and South India show increasing variations of 9.6%, 9.7%, and 0.3%, respectively. Pandey and Vinoj [18] have reported that the increase in AOD that occurred over Central India is due to the increase in relative humidity. The larger negative anomalies of tropospheric NO2 and AOD that occurred over North India were also because of the higher relative humidity (Figure 7). Similar to the increase in relative humidity, the planetary boundary layer in the Indian subcontinent generally declined during the lockdown period, which could favor the accumulation of pollutants (Figure 6). Even so, the AOD shows a decreasing tendency. The reason is mainly attributed to the reduction of anthropogenic emissions during the lockdown period. It is worth noting that aerosols can reduce planetary boundary layer height via radiative effects due to the positive feedback to the meteorology. Also, the day-to-day variation of AOD over the three sub-regions is significantly associated with variations in relative humidity and planetary boundary layer height during the lockdown period (Figure S7).

To illustrate the correlations between daily AOD and the four meteorology variables in the three sub-regions during the lockdown period, their scatter plots and correlations are provided in Figure 8. The orthogonal linear regression is used to calculate the correlation coefficients between AOD and meteorological variables, and the statistical significance of the coefficients is evaluated using the two-tailed Student’s t-test. No statistically significant
A correlation between daily AOD and precipitation and wind speed was detected at the 95% confidence level. Relatively, AOD over North and Central India is highly correlated with relative humidity (positive). However, over South India, the correlation between AOD and relative humidity is not a statistically significant correlation. Over Central India, AOD has a highly negative correlation with the planetary boundary layer, but the correlation is not statistically significant over the other two regions. These results indicate that AOD over North and Central India could be conditioned on the relative humidity and planetary boundary layer, though how to disentangle these multiple effects is challenging and beyond the capability of this analysis.

Figure 8. Relationships between daily mean AOD with precipitation, wind speed, radiative humidity, and planetary boundary layer height over North, Central, and South India during the lockdown period. Correlation coefficients (r) are calculated via the orthogonal linear regression, and the statistical significance (p) is using the two-tailed Student’s t-test. Inhere, the statistical significance level at 95% (p < 0.05) is marked with the asterisk (red color).

3.4. Radiation Response to COVID-19 Emission Reductions

The considerable reductions in anthropogenic emissions due to COVID-19 lockdown could be strong enough to cause changes in the regional radiation budget. The changes (lockdown minus 2005–2019 climatology) in radiation fluxes at clear sky conditions for shortwave, longwave, and net at the top of the atmosphere (TOA), in the atmosphere, and at the surface are shown in Figure 9. For SW radiation at the surface, positive anomalies are observed over the northeastern (10–15 W m\(^{-2}\)) and western (5–10 W m\(^{-2}\)) Indian subcontinents (Table 2), which is consistent with the spatial patterns of decreases in AOD (Figure 4). Less SW radiation is absorbed by the atmosphere, which is likely caused by reductions in absorbing aerosols such as black carbon. Negative radiation anomalies at the TOA indicate a higher planetary albedo (i.e., more scattering), which can also be attributed to reductions in absorbing aerosols in the atmosphere. For longwave radiation at the surface, changes in radiation fluxes have much weaker magnitudes and opposite directions at the surface and in the atmosphere, but the same direction of change at the TOA. For net radiation, it generally follows the changes of shortwave radiation with a slightly smaller magnitude.
Table 2. Changes (lockdown minus climatology) of the shortwave (SW), longwave (LW), and NET (SW + LW) radiation flux at the top of atmosphere, in the atmosphere, at the surface over North, Central, and South Indian subcontinent (Figure 1) during the lockdown period in 2020. Data are retrieved from the Clouds and the Earth’s Radiant Energy System (CERES). The lockdown period is defined as 1 January–23 March in 2020, and the climatology is the same date range from 2005 to 2019.

| Radiation (W m$^{-2}$) | Top of Atmosphere | Atmosphere | Surface |
|------------------------|-------------------|------------|---------|
|                        | SW    | LW    | NET   | SW    | LW    | NET   | SW    | LW    | NET   |
| North                  | –2.3  | –0.7  | –3.0  | –8.2  | +1.0  | –7.2  | +5.9  | –1.7  | +4.2  |
| Central                | –0.7  | –0.7  | –1.4  | –3.0  | +0.4  | –2.6  | +2.3  | –1.1  | +1.2  |
| South                  | –3.2  | –0.6  | –3.8  | –11.8 | +0.1  | –11.7 | +8.6  | –0.7  | +7.9  |

4. Conclusions and Discussion

In this study, we investigate the impacts of COVID-19 and the NCAP on the air quality in the Indian subcontinent by using multiple satellite retrievals from OMI and MODIS and surface observation datasets from the Indian National Air Monitoring Network. The results show a significant reduction of 10% and 15% in tropospheric nitrogen dioxide (NO$_2$) and aerosol optical depth (AOD) during the 2020 lockdown period compared to their climatological levels (2005–2019) due to restricted human activities in many regions in India. The surface observations further demonstrate that PM$_{2.5}$ and NO$_2$ have significant reductions by 33–50% and 41–58% during the 2020 lockdown period in seven cities over the India subcontinent, except for Mumbai in Central India. However, no significant reduction has been detected for tropospheric NO$_2$ and AOD during the same period in 2019. Moreover, the potential impacts of meteorological fields on air quality, such as precipitation, wind...
speed, relative humidity, and planetary boundary layer height, have also been examined. The increase in relative humidity could, respectively, enhance aerosol hygroscopic growth and induce a more stable boundary layer, which favors the accumulation of pollutants. However, total AOD over the Indian subcontinent decreases by more than 20% compared to climatology. These findings suggest air pollution levels over the Indian subcontinent are significantly influenced by anthropogenic emissions. Further, the analysis of radiation demonstrates an overall increase in surface net radiation over the Indian subcontinent, with decreases in atmosphere-absorbed net radiation and decreases in radiation entering the TOA. The increase in surface net radiation is consistent with a surface temperature increase (0.04–0.07 K) over the South Indian subcontinent in March–May of 2020 [55,56]. These results provide valuable information for policymakers on the effectiveness of the measures proposed in the NCAP in improving air quality compared to the nationwide shutdown due to COVID-19.

However, such city-lockdown induced reductions in air pollutants are conflicted with economic development. Further observation-based analysis and model simulations are needed to investigate more economically efficient measures to mitigate aerosol pollution in the Indian subcontinent and to address the associated climatic and economic impacts.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/rs14081869/s1, Figure S1: The changes of tropospheric NO\textsubscript{2} in 2020 (a and d), 2019 (b and e), 2018 (c and f) as compared with that in 2017. (a)–(c): pre-lockdown period and (d)–(f): lockdown period. Pre-lockdown and lockdown are defined as periods of January 1–March 23, 2020 and March 24–June 30, 2020, respectively. Data are from the Ozone Monitoring Instrument (OMI); Figure S2: Annual series of the regional mean tropospheric NO\textsubscript{2} and total column AOD from 2005 to 2020 over three subregions in the Indian subcontinent (Figure 1). (a)–(c): NO\textsubscript{2} and (d)–(f): AOD. The black and light-red lines respectively represent the period of January 1–March 23 and March 24–June 30. The light-red dotted line represents average value of 2015–2019 during the period of March 24–June 30. The light-red dot shaded represents the value of 2020 during the period of March 24–June 30; Figure S3: Same as Figure S1, but for total column AOD. Data are from MODIS; Figure S4: The changes (lockdown minus climatology) of the tropospheric NO\textsubscript{2}, AOD, precipitation, wind, relative humidity, and planetary boundary layer at 7 sites in 2020 (light-red bar); Figure S5: Spatial distribution of precipitation for the period of 2015-2020. (a): ERA5 during the per-lockdown period, (b): ERA5 during the lockdown period, (c): GPM during the per-lockdown period, and (d) GPM during the lockdown period; Figure S6: Spatial distribution of wind at 10 meter for the period of 2015-2020. (a): ERA5 during the per-lockdown period, (b): ERA5 during the lockdown period, (c): MERRA2 during the per-lockdown period, and (d) MERRA2 during the lockdown period; Figure S7: Time evolution of AOD, precipitation, wind, relative humidity and planetary boundary layer in 2020 over three subregions in the Indian subcontinent. The black, light-blue, and light-red lines respectively represent North, Central, and South Indian subcontinent.

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