Aerosol Characteristics during the COVID-19 Lockdown in China: Optical Properties, Vertical Distribution, and Potential Source

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Abstract: The concentration changes of aerosols have attracted wide-ranging attention during the COVID-19 lockdown (CLD) period, but the studies involving aerosol optical properties (AOPs) are relatively insufficient, mainly AOD (fine-mode AOD (AODf) and coarse-mode AOD (AODc)), aerosol absorption optical depth (AAOD), and aerosol extinction coefficient (AEC). Here, the remote-sensing observations, Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) products, backward-trajectory, and potential-source-contribution models are used to assess the impact of AOPs, vertical distribution, and possible sources on the atmosphere environment in North China Plain (NCP), Central China (CC), Yangtze River Delta (YRD), Pearl River Delta (PRD), and Sichuan Basin (SB) during the CLD period. The results demonstrate that both AOD (MODIS) and near-surface AEC (CALIPSO, <2 km) decreased in most areas of China. Compared with previous years (average 2017–2019), the AOD (AEC) of NCP, CC, YRD, PRD, and SB reduced by 3.33% (10.76%), 14.36% (32.48%), 10.80% (29.64%), 31.44% (22.68%), and 15.50% (8.44%), respectively. In addition, MODIS (AODc) and MERRA-2 (AODc) decreased in the five study areas compared with previous years, so the reduction in dust activities also contributed to improving regional air quality during the epidemic. Despite the reduction of anthropogenic emissions (AODf) in most areas of China during the CLD periods, severe haze events (AODf > 0.6) still occurred in some areas. Compared to previous years, there were increases in BC, OC (MERRA-2), and national raw coal consumption during CLD. Therefore, emissions from some key sectors (raw coal heating, thermal power generation, and residential coal) did not decrease, and this may have increased AODf during the CLD. Based on backward-trajectory and potential source contribution models, the study area was mainly influenced by local anthropogenic emissions, but some areas were also influenced by northwestern dust, Southeast Asian biomass burning, and marine aerosol transport. This paper underscores the importance of emissions from the residential sector and thermal power plants for atmospheric pollution in China and suggests that these sources must be taken into account in developing pollution-mitigation plans.

Keywords: COVID-19; AOD; AAOD; AEC; potential sources; air quality

1. Introduction

On the eve of the Spring Festival in January 2020, the first coronavirus-related pneumonia was reported in Wuhan, China. Subsequently, this new type of coronavirus pneumonia
was officially named COVID-19 by the World Health Organization (WHO) [1]. Currently, the epidemic has evolved into a global crisis [2]. Wuhan implemented a precautionary lockdown on 23 January to curb the spread of the virus among humans, followed by other cities in China. The nationwide COVID-19 lockdown (CLD) lasted three weeks [3]. During the CLD period, many public places were closed, most industries and businesses were closed, traffic was highly reduced, and the population was confined at home. The CLD measures reduced trace gases and aerosols, and air quality in many cities in China has been dramatically improved [4–6].

Aerosols, both natural and anthropogenic, play an essential role in air quality and the climate [7,8]. Although reductions in anthropogenic fine particulate emissions during the CLD periods improved air quality in most cities of China [9], some areas still suffer from air pollution (AOD > 0.7). From the perspective of satellite remote sensing, it is necessary to retrieve the fine-mode AOD (AODf) and coarse-mode AOD (AODc) to assess the impact of the CLD measures on the regional/global atmospheric environment [10]. In addition, previous studies have found that winter haze in the North China Plain (NCP) is often accompanied by high aerosol loads, which are associated with coal-consuming emissions from factories, power plants, and residents during the heating season [11,12]. The National Energy Administration released the national power industry statistics from January to March 2020, showing that thermal power generation and heating coal consumption increased by 4.3% and 3.6%, respectively (http://www.nea.gov.cn/2020-04/23/c_139002144.htm, accessed on 23 March 2022). It is worth noting that many absorbent aerosols (organic and black carbon) are produced by the above coal-burning emissions [13], but few scholars have analyzed the light-absorbing aerosols during the CLD period. Moreover, the long-range transport of dust from Northwest China in winter [14] and the cross-border transit of biomass burning in Southeast Asia in spring [15] can disturb the atmospheric environment in some regions of China. Therefore, it is urgent to study the impact of absorptive aerosols (dust, organic and black carbon) on regional/global air quality during the CLD period. Several studies have further found that the CLD measures led to a reduction of anthropogenic primary pollutant emissions, but the enhanced secondary pollution offset this decline and caused the severe haze in China [16–18]. However, the assessment of regional air quality during the CLD period only considers anthropogenic emissions. It does not focus on natural sources (dust, clear continent, and clear marine), which may lead to significant uncertainty in analyzing and predicting the atmospheric environment [19]. Accordingly, discussing the effects of anthropogenic and natural source aerosols on regional air quality reduces this uncertainty during the CLD period. The AOD and aerosol absorption optical depth (AAOD) characterize useful information concerning atmospheric aerosol loading but little information on the aerosol vertical distribution [20]. Previous studies have found that detecting the aerosol vertical distributions by CALIPSO satellite can provide further insight into the effects of aerosols on climate and air quality [21,22]. Consequently, the vertical distribution characteristics of aerosols during the epidemic are worthy of in-depth study.

Many scholars have used satellite remote-sensing products to evaluate changes in the atmospheric environment and global climate change, but the data have limitations under cloudy conditions [23]. Reanalysis products are another reliable method for conducting aerosol studies and are of great significance in areas lacking observations. The Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2), is the latest reanalysis of data produced by the Global Modeling and Assimilation Office (GMAO). Numerous studies have shown that the aerosol concentration and optical properties from MERRA-2 products can characterize the air quality and make up for the lack of information about satellite products due to cloud cover [24,25].

This study aimed to assess the impact of aerosol optical properties (AOPs), vertical distribution, and potential sources on the atmospheric environment during the epidemic through remote-sensing observations, MERRA-2 data, and backward-trajectory models. The paper is organized as follows: Section 2 briefly introduces the research materials, the datasets, the research method, the backward trajectory, and the potential source model.
Section 3 contains the impact of aerosol on the atmospheric environment on different spatiotemporal scales, mainly involving the AOPs, vertical distribution, and potential aerosol sources. Sections 4 and 5 close the paper with a discussion and the main conclusions.

2. Materials and Methods
2.1. Observation Areas and Study Periods

The outbreak of COVID-19 in China coincides with the traditional Chinese Lunar New Year (a 7-day national holiday). Previous studies have noted a reduction in anthropogenic emissions due to production shutdowns for the holiday, but air pollution quickly returns to normal levels after the holiday [26]. In order to reduce the impact of such holidays, many scholars compare the annual average of the same period in the past 3–5 years with the 2020 CLD, including the Lunar New Year [3,23]. Since 16 January, large-scale population migration across the country to celebrate the New Year has accelerated the spread of COVID-19 to a certain extent [27]. Figure 1 summarizes the number of confirmed cases from 23 January to 8 April 2020. It is shown that the number of those cases is relatively concentrated in areas with high population density. These areas are the NCP (34°N–41°N and 113°E–119°E), Central China (CC, 26°N–32°N and 112°E–117°E), Yangtze River Delta (YRD, 29°N–33°N and 119°E–122°E), Pearl River Delta (PRD, 21°N–25°N and 112°E–117°E), and Sichuan Basin (SB, 28°N–33°N and 103°E–110°E). More confirmed cases have adopted stricter lockdown policies, further affecting travel activities, factory resumption, and regional air quality [28,29]. Therefore, we selected the above five regions with the most significant number of confirmed cases for research. Moreover, to explore the AOPs, vertical distribution, and potential sources in different CLD periods, this study divided the focused period into three parts, namely Pre-CLD, CLD-I, and CLD-II, as illustrated in Table 1.

![Figure 1](image-url)  
**Figure 1.** Colorbar represents China’s population density (people per km²) map, with 1.4 billion people. The circles represent the cumulative number of cases reported by 8 April 2020, 76 days after the Wuhan lockdown on 23 January. Location of regions in study areas (black square), including NCP, CC, YRD, PRD, and SB. The blue dots represent Beijing (1), Wuhan (2), and Guangzhou (3), respectively.
Table 1. The study period for 2020.

| Variables | Periods (Start to End) | Description |
|-----------|------------------------|-------------|
| Pre-CLD  | 2020-01-03 to 2020-01-23 | 21 days before Wuhan’s lockdown |
| CLD-I    | 2020-01-24 to 2020-02-13 | The entire country goes into lockdown |
| CLD-II   | 2020-02-14 to 2020-04-08 | Wuhan was unblocked on 8 April |

2.2. Observation and Reanalysis of Data

2.2.1. MODIS AOD, AODf, and AODc

The medium-resolution imaging spectrometer (MODIS) on board the Terra and Aqua satellites is an essential instrument with a wide spectral range, high spatial resolution, and near-daily global coverage to monitor the ambient AOD over the oceans and the continents. MODIS mainly obtains the AOD through two different algorithms, dark target (DT) and dark blue (DB). Many researchers have assessed the AOD products of two updated algorithms in MODIS Collection 6.1 (C6.1) and believed both algorithms could better retrieve AOD [30,31]. Supplementary Figure S1 shows the AOD at 550 nm in comparison to AERONET and MODIS during the CLD period. The results indicate a good agreement between them, with the coefficient of determination at $R^2 = 0.83$ and the Root Mean Square Error at RMSE = 0.17. Therefore, the AOD by MODIS DB algorithm inversion was selected to assess the aerosol optical properties during the epidemic. Several validation studies overland in AERONET locations revealed that about 72% of the retrievals fall within expected uncertainty levels of $\pm 0.05 \pm 0.15 \times$ AOD [32,33].

MODIS retrievals from the same sensor and the same algorithm (DB) during the out-break can provide information on the latest trends in AODc ($= \text{AOD} - \text{AODf}$) and AODf [10]. AODc, MODIS Aqua/Terra dust optical depth, is column-integrated extinction by mineral particles. In this study, the daily AODc was retrieved from MODIS DB aerosol products (AOD, single-scattering albedo ($\omega$), and the Ångström exponent ($\alpha$)). To separate dust from scattered aerosols (e.g., sea salt), the single scattering albedo of dust at 470 nm was less than 0.99. In short, the AODc ($\lambda = 550$ nm) was retrieved by using the following equation by Pu et al. [34]:

$$
\text{AODc}(\lambda) = \text{AOD}(\lambda) \times (0.98 - 0.5098\alpha + 0.512\alpha^2)
$$

2.2.2. CALIPSO PDR, CR, and VFM

The Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) was launched on 28 April 2006 to assess the impact of aerosols on the global climate [35]. CALIPSO can detect clouds and aerosol macroscopic, microscopic, and optical properties and provide high-confidence information on their global vertical distribution (>90%). In this study, the method adopted by Winker et al. [36] was used to carry out quality control for all of the results from the CALIPSO satellite. This study mainly used the L2 aerosol profile product (L2_05 kmApro_V4_20), which provides vertical aerosol extinction profiles on which the particle depolarization ratio (PDR) and color ratio (CR) can be further calculated [37]. The PDR and CR are the key parameters in aerosol and cloud characterizations, distinguishing the degree of irregularity of aerosol particles and the dynamic change of the particle size [38]. The calculation formulas of PDR and CR are as follows.

$$
\text{CR}(r) = \frac{\beta_{1064,p}(r)}{\beta_{532,p}(r)}
$$

$$
\text{PDR}(r) = \frac{\beta_{532,p,\perp}(r)}{\beta_{532,p,\parallel}(r)}
$$

where CR ($r$) is the ratio of the backscatter coefficient of particles at a wavelength of 1064 nm ($\beta_{1064,p}(r)$) to those at 532 nm ($\beta_{532,p}(r)$). The larger the CR value, the larger the particle radius. The PDR($r$) is the depolarization only by two polarization planes ($\beta_{532,p,\perp}(r)$)
and $\beta_{532, r}(r)$ at a 532 nm wavelength can be calculated, where $\beta$ and $r$ are backscatter coefficients and distance from the satellite to observing altitude, respectively. The larger the PDR value, the stronger the non-spherical tendency of aerosol particles.

The CALIPSO vertical feature mask (L2_VFM_V4_10) product was classified based on the physical characteristics of the aerosol and cloud [37,39]. The detected aerosols are classified into six types: clear marine, dust, polluted continental, clear continental, polluted dust, and smoke [40]. In this study, we organized these six aerosols into anthropogenic aerosols (AA, including polluted dust, smoke, and polluted continental) and natural aerosols (NA, including clean marine, dust, and clean continental) according to the previous study [41].

The dominant aerosol can embody the characteristics of the seasonal occurrence of aerosol in the area [41,42]. To this end, the aerosol that dominates each period is defined as the most frequent aerosol type. We used Equation (4) to calculate the frequency (Freq) of each different aerosol at different altitudes [39]:

$$Freq = \frac{N_{\text{aerosol}(i)}}{N_{\text{total}}}$$ (4)

where $N_{\text{aerosol}(i)}$ is the number of the CALIPSO profiles for each aerosol subtype, and $N_{\text{total}}$ represents the lidar profiles for all of the aerosol subtypes collected in the study area.

2.2.3. MERRA-2

The MERRA-2 provides real-time global atmospheric reanalysis datasets beginning in 1980, with a resolution of approximately $0.5^\circ \times 0.625^\circ$. The Georgia Institute of Technology–Goddard Global Ozone Chemistry Aerosol Radiation and Transport (GOCART) aerosol scheme is used. GOCART treats the sources, sinks, and chemistry of 15 externally mixed aerosol mass mixing ratio tracers: dust, sea salt, black and organic carbon (BC and OC), and sulfate ($SO_4$) [43]. As an important step toward a complete Integrated Earth Systems Analysis (IESA), in addition to meteorological observations, MERRA-2 now includes the assimilation of aerosol optical depth (AOD) from the various ground- and space-based remote-sensing platforms [43]. Previous studies have shown that MERRA-2 AOD (550 nm) exhibited good agreement with the ground station ($r = 0.6$–0.91) and satellite data ($r = 0.75$–0.85) [19,24]. Our validation also showed that MERRA-2 AOD correlated well with ground stations during CLD ($R^2 = 0.44$, RMSE = 0.31) (Supplementary Figure S1). In addition, we also evaluated the comparison of MODIS (AAOD), MERRA-2 (AAOD), and AERONET site data during the city closure. Unfortunately, AAOD (MODIS) was not studied because of the small amount of data. Although the correlation between AAOD (MERRA-2) and AERONET sites performed poorly (Supplementary Figure S1), the continuity of MERRA-2 data and previous good validation results [24] led us to choose it to analyze the spatial and temporal distribution characteristics of absorbing aerosols during the CLD. In addition, we also used MERRA-2 data to assess the AODf (=AOD - AODc) and AODc (MERRA-2 dust AOD) during CLD. Therefore, the hourly aerosol column concentration data products (MERRA-2-2D-tavg-aer***) were used in this study. The relationship between aerosol absorption optical depth (AAOD), AOD, and aerosol single scattering albedo (SSA) can be expressed by Equation (3), where $\lambda$ is the wavelength.

$$AAOD(\lambda) = [1-SSA(\lambda)] \times AOD(\lambda)$$ (5)

2.3. Backward Trajectory

The cluster analysis is a statistical analysis method of multiple variables that can classify air mass trajectories according to the speed and direction of the air mass movement [44]. The angular distance analysis method of MeteoInfoMap [45] was used to prove the air-mass transport direction of the study areas during the CLD period. Three representative cities (Beijing, Wuhan, and Guangzhou) were selected as the backward starting point, with simulated heights of 500 and 2500 m and an airflow trajectory calculation time of 48 h. Meteorological data came from the Global Data Assimilation System (GDAS) provided by
the United States National Center for Environmental Prediction. The backward trajectories combined with PM\textsubscript{2.5} (https://www.aqistudy.cn/historydata/, accessed on 23 March 2022) concentrations (potential source contribution function (PSCF) and concentration weighted trajectories (CWTs) model) were used to determine the source location and main transport route of pollutants [46]. The PSCF calculation formula is as follows.

$$PSCF_{ij} = \frac{m_{ij}}{n_{ij}}$$ (6)

The number of all trajectories passing through the study area in the grid \((i,j)\) is defined as \(n_{ij}\), and the number of pollution tracks in the grid \((i,j)\) passing through the research area is \(m_{ij}\). This paper used the average PM\textsubscript{2.5} concentration during the CLD period as the pollution tracking. The higher the PSCF value, the higher the probability that the pollution trajectory is located in the grid. The PSCF method cannot distinguish the contribution of grids with the same PSCF value to the pollution degree of the observation area. The CWT can make up for the lack of PSCF and quantitatively reflect the pollution degree on different trajectories [47]. When the \(n_{ij}\) value is small, the weight function, \(w_{ij}\), can effectively reduce PSCF and CWT errors and uncertainties (WPSCF and WCWT) [48].

3. Results
3.1. AOD, AODf, and AODc

Figures 2 and 3 show the AOD, AODf, AODc, and their differences (compared with 2017–2019) in all study areas provided by MODIS and MERRA-2 during different periods, due to the dense population, heavy traffic, and factories in the NCP, CC, YRD, PRD, and SB, which are vulnerable to anthropogenic emissions [49], with high aerosol loading (Figure 2). During the CLD-I period, it is established that the CLD measure has reduced the emissions of trace gases and aerosols, and the air quality of many cities in China has improved in the short term [50]. Except for the SB, the AODf (and also in total AOD) from MODIS of the other four regions has dropped compared to the Pre-CLD period (Table 2). Moreover, the difference between CLD-I and the same window in previous years indicates that the CLD measures have improved the atmospheric environment in most parts of China, in which the AODf (AOD) retrieved by MODIS in the CC, YRD, PRD, and SB areas has dropped by 8.14% (14.36%), 3.38% (10.80%), 30.04% (31.44%), and 16.11% (15.50%), respectively (Table 2). However, the AODf (MODIS) in the NCP increased during the CLD-I period compared to previous years. Previous studies have shown that the increase in AODf during the CLD may be driven by increased secondary pollution [16]. During the CLD-II period, the AODf (AOD) of NCP, CC, and the YRD displays a continued downward trend compared with the Pre-CLD period in Figure 3a. Furthermore, compared with the average of previous years, statistics demonstrate that the three regions have decreased by 16.11% (22.26%), 8.57% (14.12%), and 20.37% (28.93%), respectively (Table 2). In contrast, the AODf (AOD) retrieved by MODIS in the PRD region has increased rapidly during the CLD-II period. We found that this increase could be attributed to the increased transport of smoke aerosols from Southeast Asia (Supplementary Figure S2). During the CLD-II period, the AOD and AODf from MODIS in the SB area increased by 9.00% and 13.85%, respectively, compared with previous years, but the AODc did not increase. The SB, covering an area of 260,000 km\textsuperscript{2}, is located immediately east of the Tibetan Plateau, with a significant drop exceeding 3000 m in elevation over a short horizontal distance. Previous studies have explored the effect of unique deep basins on haze pollution through two sets of simulations with and without the basin topography. The results show that the SB topography increases 48 \(\mu g\) m\textsuperscript{−3} in the basin-averaged surface PM\textsubscript{2.5} concentrations [51]. Therefore, the complex terrain and special local meteorological conditions of SB and the increase in anthropogenic emissions may worsen air quality.
were overestimated in four other regions (Figure 2 and Supplementary Table S1). The poor performance of MERRA-2 during haze may result from several combined factors. The relatively small number of AOD observations available for assimilation in MERRA-2 during this period and the model itself has too-weak emissions (the lack of nitrate) and mistimed aqueous production [43]. Although the missing nitrate in the aerosol module of MERRA-2 data causes it not to be a good representative of all haze events, MERRA-2 dust aerosol shows good performance for dust events [24]. Figure 3 shows the decreasing trend of AODc in MODIS and MERRA-2 in all five study areas compared to previous years, so reducing dust aerosols may also improve the atmospheric environment in the study areas.

**Figure 2.** (a) Spatiotemporal distribution of AOD, AODf, and AODc at 550 nm from MODIS during the Pre-CLD (a1–a3), CLD-I (a4–a6), and CLD-II (a7–a9) periods. (b) MERRA-2 provides the AOD, AODf, and AODc at 550 nm during the Pre-CLD (b1–b3), CLD-I (b4–b6), and CLD-II (b7–b9) periods. The study area’s boundaries and the locations of critical cities were displayed in Figure 1.

**Table 2.** Statistical analyses of AOD, AODf, and AODc from MODIS and AAOD (MERRA-2) variables.

| Names   | Periods Variables | NCP       | CC        | YRD       | PRD       | SB        |
|---------|------------------|-----------|-----------|-----------|-----------|-----------|
| Pre-CLD | AOD              | 0.75 (0.46) | 0.50 (0.46) | 0.59 (0.42) | 0.34 (0.38) | 0.21 (0.44) |
|         | AODf             | 0.50 (0.27) | 0.32 (0.29) | 0.44 (0.25) | 0.25 (0.27) | 0.15 (0.32) |
|         | AODc             | 0.25 (0.19) | 0.18 (0.17) | 0.15 (0.16) | 0.09 (0.09) | 0.06 (0.12) |
|         | AAOD             | 0.039 (0.037) | 0.038 (0.040) | 0.034 (0.037) | 0.016 (0.021) | 0.036 (0.042) |
| 2020 (Avg.) | AOD              | 0.69 (0.72) | 0.35 (0.41) | 0.38 (0.43) | 0.28 (0.42) | 0.29 (0.34) |
|         | AODf             | 0.62 (0.54) | 0.26 (0.29) | 0.27 (0.30) | 0.21 (0.30) | 0.21 (0.25) |
|         | AODc             | 0.07 (0.18) | 0.09 (0.12) | 0.11 (0.13) | 0.07 (0.12) | 0.08 (0.09) |
|         | AAOD             | 0.049 (0.041) | 0.038 (0.034) | 0.037 (0.031) | 0.022 (0.019) | 0.034 (0.036) |
| CLD-I   | AOD              | 0.43 (0.55) | 0.40 (0.47) | 0.37 (0.52) | 0.46 (0.43) | 0.36 (0.33) |
|         | AODf             | 0.32 (0.38) | 0.30 (0.33) | 0.29 (0.37) | 0.33 (0.31) | 0.27 (0.24) |
|         | AODc             | 0.11 (0.17) | 0.10 (0.14) | 0.08 (0.15) | 0.13 (0.13) | 0.09 (0.09) |
|         | AAOD             | 0.038 (0.042) | 0.042 (0.038) | 0.034 (0.037) | 0.040 (0.032) | 0.036 (0.034) |
| CLD-II  | AOD              | 0.43 (0.55) | 0.40 (0.47) | 0.37 (0.52) | 0.46 (0.43) | 0.36 (0.33) |
|         | AODf             | 0.32 (0.38) | 0.30 (0.33) | 0.29 (0.37) | 0.33 (0.31) | 0.27 (0.24) |
|         | AODc             | 0.11 (0.17) | 0.10 (0.14) | 0.08 (0.15) | 0.13 (0.13) | 0.09 (0.09) |
|         | AAOD             | 0.038 (0.042) | 0.042 (0.038) | 0.034 (0.037) | 0.040 (0.032) | 0.036 (0.034) |
Table 2. Cont.

| Names | Periods Variables | Regionals |
|-------|------------------|-----------|
|       |                  | NCP       | CC        | YRD       | PRD       | SB        |
| Pre-CLD |                 | AOD 0.29 (64.15) | 0.04 (9.20) | 0.17 (41.93) | −0.04 (−9.79) | −0.23 (−53.19) |
|         |                  | AODf 0.23 (86.60) | 0.03 (11.70) | 0.19 (74.66) | −0.02 (−8.30) | −0.17 (−52.52) |
|         |                  | AODc 0.06 (30.82) | 0.01 (7.08) | −0.01 (−7.38) | 0 (−0.04) | −0.17 (−53.94) |
|         |                  | AAOAD 0.002 (6.29) | −0.002 (−5.16) | −0.003 (−6.83) | −0.005 (−24.51) | −0.006 (−13.42) |
| Change |                 | AOD −0.02 (−3.33) | −0.006 (−14.36) | −0.05 (−10.80) | −0.13 (−31.44) | −0.05 (−15.50) |
| CLD-I  |                  | AODf 0.08 (14.09) | −0.02 (−8.14) | −0.03 (3.38) | −0.09 (−30.04) | −0.04 (−16.11) |
|         |                  | AODc −0.11 (−61.11) | −0.03 (−25.00) | −0.02 (−15.38) | −0.05 (−39.69) | −0.01 (−13.41) |
|         |                  | AAOAD 0.008 (18.27) | 0.004 (12.32) | 0.006 (19.35) | 0.003 (17.64) | −0.002 (−6.02) |
| CLD-II |                  | AOD −0.12 (−22.26) | −0.07 (−14.12) | −0.15 (−28.93) | 0.02 (5.31) | 0.03 (9.00) |
|         |                  | AODf −0.06 (−16.11) | −0.03 (−8.57) | −0.07 (−20.37) | 0.02 (4.97) | 0.03 (13.85) |
|         |                  | AODc −0.03 (−15.69) | −0.04 (−28.57) | −0.07 (−46.67) | 0 (0) | 0 (0) |
|         |                  | AAOAD −0.003 (−8.30) | 0.004 (10.69) | −0.003 (−7.63) | 0.008 (25.43) | 0.001 (3.80) |

The brackets indicate (%) the comparison of AOD, AODf, AODc, and AAOD with the average value of the same window period in previous years.

Figure 3. (a) The AOD, AODf, and AODc retrieved by MODIS are compared with the 3-year average (2017–2019) of the same window in previous years during the Pre-CLD (a1–a3), CLD-I (a4–a6), and CLD-II (a7–a9) periods. (b) Same comparison as (a), but for MERRA-2 data.
During the haze occurrence in the NCP (Pre-CLD and CLD-I), MERRA-2 underestimated the AOD in this area compared with MODIS and AERONET (Supplementary Figure S1). Conversely, comparisons of MODIS with MERRA-2 showed that AOD and AODf were overestimated in four other regions (Figure 2 and Supplementary Table S1). The poor performance of MERRA-2 during haze may result from several combined factors. The relatively small number of AOD observations available for assimilation in MERRA-2 during this period and the model itself has too-weak emissions (the lack of nitrate) and mistimed aqueous production [43]. Although the missing nitrate in the aerosol module of MERRA-2 data causes it not to be a good representative of all haze events, MERRA-2 dust aerosol shows good performance for dust events [24]. Figure 3 shows the decreasing trend of AODc in MODIS and MERRA-2 in all five study areas compared to previous years, so reducing dust aerosols may also improve the atmospheric environment in the study areas.

3.2. Light-Absorbing Aerosols and Scattering Aerosols

3.2.1. AAOD

The AAOD indicates the light attenuation due to aerosol absorption and is a useful parameter for studying the spatial and temporal distribution of absorbing aerosols [52]. The higher the absorptive aerosol content, the greater the AAOD value. Figure 4 shows the spatial–temporal distribution of AAOD from MERRA-2 products. In the Pre-CLD period, the areas with high AAOD values were mainly concentrated in the NCP, CC, YRD, and SB, with a high consumption of coal and fossil fuels (Figure 4). By analyzing the optical properties of absorbing aerosols in China over 38 years, Sun, et al. [53] found that the highest AAOD (0.045–0.06) over China occurred in the densely populated and industrially developed NCP, CC, YRD, and SB. Figure 4 also shows similar regional distribution characteristics of absorbing aerosols during the Pre-CLD and CLD-I periods. In the CLD-I period, AAOD, in contrast to AOD, did not decrease significantly relative to the Pre-CLD period in all study areas (Table 2). The AAOD of the four regions (NCP, CC, YRP, and PRD) increased compared with the average of the previous years in Table 2 (18.27%, 12.32%, 19.35%, and 17.64%). According to the National Energy Administration statistics, the national heating consumption of raw coal and thermal power generation increased by 3.6% and 4.3% compared with previous years during the epidemic (http://www.nea.gov.cn/2020-04/23/c_139002144.htm, accessed on 23 March 2022), and this may contribute to increased absorption aerosols during the CLD period in China [54,55]. Previous studies have suggested that industrial and transportation emissions are major contributors to PM$_{2.5}$ pollution in China, but reductions in emissions from this industry did not prevent air pollution during the CLD period. In fact, the underlying sectors, some of which emit significant amounts of pollutants, did not reduce their operations, contributing to the increase in absorptive aerosols [54]. During the CLD-II period, the CLD measures in most parts of China slowed down, and traffic and factories began to recover. Therefore, the absorptive aerosols in the NCP, CC, YRD, and SB returned to the Pre-CLD level (Table 2). There was a significant increase in light-absorbing aerosols in the PRD (Figure 4c3). Previous results indicated that biomass burning in Southeast Asia significantly impacts downwind regions during the dry season (November–April), such as South China and Southwest China [56,57]. Therefore, the increase in AAOD in the PRD may result from the cross-region transfer of pollutants emitted from biomass burning in Southeast Asia (Supplementary Figure S2).
3.2.2. Dust, BC, OC, and SO$_4$

The absorption of solar radiation due to aerosol particles is mainly caused by dust and carbonaceous particles (BC and OC). Because absorptive aerosols strongly absorb solar radiation, this can heat and alter the stability of the atmosphere, which plays an important role in climate and air quality [58,59]. Dust primarily comes from natural sources via wind erosion, and the other part comes from anthropogenic sources altering landscape or disturbing soil [60]. BC and OC mainly result from incomplete combustion of fossil fuels and biomass burning [13].

Figures 5 and 6 describe the spatial distribution AOD of absorbing (BC, OC, and dust) and scattering aerosol (SO$_4$) provided by MERRA-2 in the Pre-CLD, CLD-I, and CLD-II periods and the absolute changes, respectively. In the CLD-I period, the highest dust AOD appeared in the dust source areas of Western China in Figure 5. A BC AOD between 0.04 and 0.08 could be observed in NCP, CC, YRD, and SB, which is consistent with the distribution characteristics of AAOD. In addition, the BC AOD of all regions increased to varying degrees compared to the Pre-CLD period (Figure 7). Previous studies have shown that residential coal burning (28%) is the largest source of BC in China, followed by residential biofuel combustion (22.7%), coke production (17.6%), diesel vehicles (8.2%), and brick kilns (7.4%) [55]. Therefore, the increase in residential coal burning and residential biomass emissions during the CLD period may increase the AOD of BC and OC. In the CLD-II period (spring), with the frequency of dust activities, most areas in Northern China suffered from the impact of dust transmission across regions. However, the intensity of dust activities in 2020 had decreased compared with previous years (Figures 3 and 6).
Southern China, BC and OC AOD increased compared with the Pre-CLD period and the average value of prior years (2017–2019) (Figure 6). Previous studies have found that BC and OC emissions increase in wet and sub-humid areas in spring, related to the increase in biomass burning [59].

The scattered aerosol (sulfate AOD) shows a lower characteristic in Northern China than in Southern China (Figure 5), and this may be due to the influence of the solar radiation intensity and precipitation [61]. Compared with BC and OC, the variation of sulfate AOD shows more complicated characteristics during the CLD periods (Figure 6). The CLD measures resulted in a decrease in sulfate AOD over CC, YRD, and PRD. However, the sulfate AOD increases in the NCP and SB regions. The heavy use of coal and biomass fuels in the NCP region through the CLD may have led to increased BC, OC, and sulfate. A high sulfate AOD was also found in the SB surrounded by high mountains, and this may result from frequent, persistent inversions and stagnant air circulation, leading to high levels of pollution from anthropogenic emissions in the region [62]. Figure 7 shows the BC, OC, dust, and sulfate AOD in five study areas provided by MERRA-2, as well as the ratio between the fine absorption mode (BC and OC) and the total fine mode (SO$_4$ + BC + OC). The AOD of BC and OC, and the ratio (~93%) in the PRD increased significantly compared with other regions, which may be more susceptible to cross-border transmission of biomass burning (Supplementary Figure S2). In addition, most areas had some increase in the fine absorption mode/the total fine mode (~2 to 34%) compared to previous years. Therefore, the increase in absorbing aerosols during the CLD may have contributed to the deterioration of regional air quality.

![Figure 5. AOD of dust (a1–a3), BC (b1–b3), OC (c1–c3), and SO$_4$ (d1–d3) from MERRA-2 during the Pre-CLD, CLD-I, and CLD-II periods. The study area’s boundaries and the locations of key cities were shown in Figure 1.](image-url)
Figure 6. Difference (AOD) of the three absorbing aerosols (dust \(a_1-a_3\), BC \(b_1-b_3\), and OC \(c_1-c_3\)) and scattering aerosol (SO\(_4\) \(d_1-d_3\)) during the Pre-CLD, CLD-I, and CLD-II periods, with the mean values of the same window in previous years (2017–2019). The study area’s boundaries and the locations of key cities were shown in Figure 1.

Figure 7. AOD of dust, BC, OC, and SO\(_4\) in NCP, CC, YRD, PRD, and SB in 2020 and the average value of previous years (2017–2019). The percentage on the bar represents \((BC + OC)/(BC + OC + SO_4)\).
3.3. CALIPSO

3.3.1. Aerosol Extinction Profile and Vertical Distribution of Each Aerosol Type

The extinction coefficient profiles of 532 nm in different study areas were evaluated during the Pre-CLD, CLD-I, and CLD-II periods and the same window data in previous years (Figure 8). The aerosol extinction coefficient (AEC) represents the distribution of aerosol absorption and scattering cross-sections with height and reflects particulate matter content [55]. The CALIPSO satellite inversion results confirm that aerosol particles decay exponentially with altitude, and aerosol particles mainly concentrate in the atmosphere below 2 km in all study areas. It is divided into four height ranges (0–2 km, 2–4 km, 4–6 km, and 6–8 km) in the vertical direction to assess the impact of the CLD measures on the AEC (Table 3). In the CLD-I period (Figure 8), the near-surface AEC (<2 km) of all study areas decreased compared with the Pre-CLD period and 3-year averages, with the largest decrease in CC (32.48%). The near-ground AEC (<2 km) of NCP, CC, and YRD during the CLD-II period continued to decline compared with the Pre-CLD and CLD-I periods. However, at a height of 0–2 km, the AEC of PRD and SB increased compared to the CLD-I period (Table 3). Figure 9 shows that the influence of marine aerosols causes the AEC of PRD to grow at the near-surface. The complex terrain and special local meteorological conditions in the SB may deteriorate air quality [63]. The NCP was mainly affected by dust at the high altitude (2–8 km) during the CLD period. YRD and PRD were greatly disturbed by smoke and contaminated dust (Figure 9).

Figure 8. Profiles of AEC for five studies areas from CALIPSO retrievals in the Pre-CLD, CLD-I, and CLD-II periods. The red curve represents the 2020 data, and the blue curve represents the 2017–2019 data average.

Figure 9. The frequency distribution of each aerosol type within an 8 km altitude for five study areas during the Pre-CLD, CLD-1, and CLD-II periods in 2020. The different colors represent the six aerosol types.
Table 3. Statistics of AEC of different layers.

| Periods | Altitudes | NCP  | CC   | YRD  | PRD  | SB   |
|---------|-----------|------|------|------|------|------|
|         | 0–2 km    | 0.47 | 0.51 | 0.51 | 0.28 | 0.47 | 0.47 |
|         | 2–4 km    | 0.16 | 0.11 | 0.07 | 0.09 | 0.47 | 0.47 |
|         | 4–6 km    | 0.12 | 0.10 | 0.26 | 0.32 | 0.06 | 0.06 |
|         | 6–8 km    | 0.04 | 0.09 | 0.47 | 0.07 | 0.47 | 0.47 |
| CLD-I   | 0–2 km    | 0.42 | 0.21 | 0.25 | 0.25 | 0.25 | 0.25 |
|         | 2–4 km    | 0.07 | 0.16 | 0.09 | 0.07 | 0.07 | 0.07 |
|         | 4–6 km    | 0.36 | 0.36 | 0.06 | 0.06 | 0.06 | 0.06 |
|         | 6–8 km    | 0.02 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |
| CLD-II  | 0–2 km    | 0.25 | 0.19 | 0.09 | 0.09 | 0.09 | 0.09 |
|         | 2–4 km    | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 |
|         | 4–6 km    | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 | 0.09 |
|         | 6–8 km    | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 | 0.05 |

The brackets represent the comparison between the AEC (%) at different CLD periods in 2020 and the AEC of the Pre-CLD period.

Figure 8. Profiles of AEC for five studies areas from CALIPSO retrievals in the Pre-CLD, CLD-I, and CLD-II periods. The red curve represents the 2020 data, and the blue curve represents the 2017–2019 data average.

Figure 9. The frequency distribution of each aerosol type within an 8 km altitude for five study areas during the Pre-CLD, CLD-I, and CLD-II periods in 2020. The different colors represent the six aerosol types.

3.3.2. Anthropogenic and Natural Aerosols

Figure 10 is the scatter density diagram of the layer-integrated PDR and CR of the five study areas during different study periods, distinguishing the impact of AA and NA on regional air quality. The number density of the green, yellow, and red data points is 0.4 to 1.0, accounting for more than 85% of the total data points. The data of five areas in
different periods are mainly concentrated (~85 to 90%) in the lower-left area, indicating that the particle size is small and spherical, as is consistent with the characteristics of AAs, which are mainly fine-modal and spherical particles [22]. There are about 10% aerosols in the range of PDR (~0.2–0.42) and CR (~0.5–1.1) during the CLD-II period in the NCP. The research results of Freudenthaler et al. [64], the ~10% PM$_{2.5}$ may be dust aerosol. The data distribution in the PRD region is a similar scattered pattern in the anthropogenic polluted areas. However, due to the influence of a fraction of larger-sized sea salt, the CR is relatively higher than that of contaminated anthropogenic aerosols [58].

![Figure 10](image1.png)

**Figure 10.** Scatterplots of PDR and CR in different lockdown stages in the five study areas, in which the black line represents the 1:1 line. The sample size (N) is also provided.

Figure 11 shows the occurrence frequency of each aerosol subtype contributed to the total aerosol type in the vertical direction in five regions during the CLD periods. During the CLD-I period, the ratios of AA in NCP, CC, and PRD increased compared with the Pre-CLD period. The noticeable increase in AA of NCP and CC areas is the polluted continental aerosols, while PRD is mainly due to external sources of smoke. Compared with the same window period of previous years, the proportion of AA in NCP, CC, PRD, and YRD is more significant than that in last years, but the ratio of NA is smaller than that of previous years. The proportion of AA in CC has increased the most (30.03%) compared with prior years. The increase in AA is mainly because of the increased polluted continental
aerosols (37.86%), while the decrease in NA is primarily related to the decline in dust aerosols (31.57%). Supplementary Figure S3 shows that the highest frequency of AA in the CC area (0.88 km) is lower than that of NA (4.0 km). Previous studies have testified that AA annual average maximum frequency in CC is 1.3 km, more significant than 0.88 km during the CLD-I period, so the CC is more vulnerable to anthropogenic pollution near-surface than in previous years [41]. Considering the frequent occurrence of dust in spring, the proportion of dust aerosols in all regions during the CLD-II period in 2020 is remarkably more significant than that in the Pre-CLD and CLD-I periods. However, the proportions of AA and NA during the CLD-II period did not change much compared to the same period in previous years.

Figure 11. (a) Occurrence frequencies of each aerosol subtype contributed to the total aerosol type in the vertical direction for five study areas during Pre-CLD, CLD-I, and CLD-II periods, and (b) the same window contribution data in previous years.

3.4. Backward Trajectory and Potential Sources of Aerosol

To further investigate whether the polluted areas were influenced by local emissions, we looked at aerosol transport from external seasonal dust or biomass burning emissions. Therefore backward-trajectory and potential-source-contribution models were used to assess the impact of possible sources of aerosols on the atmospheric environment in Beijing, Wuhan, and Guangzhou. Figures 12 and 13 show the clustering of backward trajectories, MODIS fire radiative power (FRP), and PM$_{2.5}$ potential source contributions in Beijing (39.87°N, 116.43°E), Wuhan (30.57°N, 114.36°E), and Guangzhou (23.11°N, 113.27°E) during the CLD-I and CLD-II periods, respectively. The results of clustering trajectories in Beijing showed that the long-distance transportation trajectories from the northwest in the CLD period are dominant. Their frequencies are 44.84% (CLD-I) and 75.77% (CLD-II). The airflow from the desert area in the northwest to Beijing will bring more dust aerosols and cause more polluted dust [14]. To further evaluate the potential source areas and contributing concentrations that affect atmospheric pollution in Beijing, the WPSCF and WCWT of PM$_{2.5}$ were calculated. During the CLD-I period, the potential source areas (WPSCF $\geq$ 0.7) were banded and mainly concentrated in the NCP and Inner Mongolia, densely populated and heavily polluted by heavy industries and traffic. The WPSCF can only involve the impact of the potential source area on the study area and cannot reflect the specific contribution concentration of the pollution grid. Therefore, the WCWT method resolves the concentration-weighted trajectory of air pollutants with different particle sizes in Beijing during the CLD period. The results of WCWT are similar to those of WPSCF, and the regions with higher WCWT values are still unchanged. During the CLD-I and CLD-II periods, the PM$_{2.5}$ potential source area in Beijing significantly expanded from
NCP and Inner Mongolia to Northeast China. Wuhan was affected by local air mass and long-distance air mass transport during the CLD period. In the CLD-I and CLD-II periods, the local air mass accounted for 38.25% and 74.14% of the entire trajectory. Local air masses generally appear when the regional meteorological conditions are relatively stable, and the diffusion capacity of the atmosphere is usually weak, so the pollutants near the ground tend to accumulate; thus, Wuhan had a severe pollution event during the CLD-I period (Figure 2). The long air mass mainly came from the heavily polluted NCP, YRD, and Southwest China (a significant smoke source area) [65]. By combining the results of the WPSCF and WCWT, it can be seen that the potential source areas of high concentrations of PM$_{2.5}$ present a distribution pattern centered on Wuhan. Therefore, air pollution in CC is mainly destroyed by local emissions and partial region transport, including pollutants in NCP and absorbing solid particles in the southern biomass burning region. During the CLD period, the near-surface of Guangzhou was mainly affected by the local air mass (75.50%), but the long-distance northwest air mass (9.76%) and the Southeast Asian air mass (1.59%) also disturbed the atmospheric environment. Previous studies have confirmed that long-distance air masses from Northwest and Southeast Asia can transport dust and smoke aerosols to the region, respectively [56,66]. The CALIPSO inversion results have shown that the area is affected by dust and smoke (Figures 9 and 11). In particular, we further analyzed the 2500 m backward trajectory and found that the PRD at high altitudes is largely affected by smoke aerosols in Southeast Asia (Supplementary Figure S2). In addition, Guangzhou is also affected by maritime air masses (13.35% and 49.69%), so marine aerosols can also affect this area. Through WPSCF and WCWT, it can be seen that the main potential source areas of this area are the southeast coastal and northwest dust-source areas.

Figure 12. Mean 48 h backward-trajectory clusters (500 m) of Beijing, Wuhan, and Guangzhou and distribution of potential source of PM$_{2.5}$ during CLD-I period. The bottom map of the first column of backward-trajectory air masses is the MODIS FRP.
Figure 13. The same as Figure 12 but for the CLD-II period.

4. Discussion

The CLD measures in China in early 2020 slowed traffic activity and forced many factories to shut down, so anthropogenic emissions were expected to decrease [3]. According to the results of MODIS and CALIPSO inversion, it can be seen that the AOD and near-surface AEC (<2 km) in most areas of China decreased compared with the Pre-CLD period and previous years. In terms of quantifying and understanding the impact of CLD measures on the atmospheric environment, the inversion of interest is the AODf. Therefore, the AOD, AODf, and AODc provided by MODIS and MERRA-2 were used to evaluate the aerosol optical properties during the epidemic. Although the accuracy of the AODf (MODIS) inversion is limited for separating AOD into fine (AODf: pollution, wildfire) and coarse (AODc: dust, sea salt) modes, the changes to the signal are significant and detectable [10,34]. During the CLD, AODf (AOD) from MODIS decreased in most cities of China. During the haze occurrence of NCP, MERRA-2 underestimated the AOD in this area compared with MODIS and AERONET. In contrast, the comparison of MODIS and MERRA-2 showed that both AOD and AODf were overestimated in the other four regions. However, MERRA-2 had a decreasing trend in AODc in all five study regions—the same trend as MODIS AODc. Therefore, the reduction in dust activity may also have improved the atmospheric environment in the study area. Although most of China reduced anthropogenic emissions (AODf) during CLD, severe haze events still occurred in some regions (NCP, AODf > 0.6). Previous studies believed that the haze was driven by secondary pollution enhancements and unfavorable meteorological conditions. Our results further revealed that NCP was mainly caused by local anthropogenic emissions (AODf/AOD = 90%) and was also affected by northwest dust transport, but AODc decreased by 61.11% compared with previous years. In addition, the analysis of MERRA-2 AAOD data showed that the concentrations of absorbing aerosols in the five study areas increased to different degrees during the CLD period, and this increase was mainly due to the rise in BC and OC. Previous studies pointed
out that, although MERRA-2 underestimated the AAOD over China (bias = −0.011) [25], it could still characterize the spatiotemporal distribution of absorptive aerosols, so the actual situation may be that more absorptive aerosols were emitted during the epidemic. In particular, the ratio between the fine absorption mode (BC and OC) and the total fine mode (SO$_4$ + BC + OC) also showed an increase (~2–34%) in most areas. This increased absorptive aerosol is likely to come from industries/sectors that continued to work (raw coal heating, thermal power generation, and residential coal use) during the lockdown, leading to an increase in AODf. The lockdown measures have resulted in people being confined to their homes and reduced transport and industrial emissions, but the residential sector may not have been hit hard, so residential emissions may have contributed to the pollution [54]. Therefore, residential emission control plans and improved power plant emissions should be developed and implemented to address air pollution in China. When analyzing regional air quality, we should consider the effects of AA and NA. Based on the CALIPSO satellite retrieval results, the five study areas are mainly affected by anthropogenic emissions, and particular regions are affected by north-west dust, biomass burning in Southeast Asia, and marine aerosol transport.

The study has several shortcomings. The uncertainty of meteorological conditions may lead to inaccuracies in the retrieval of AOPs. The MERRA-2 dose does not capture all haze events, due to several factors, including inappropriate anthropogenic emissions, the lack of nitrate aerosols in the GOCART aerosol program, and the relatively small amount of remote-sensing data used for assimilation that does not account for changes in aerosol composition. These factors combined limit the impact of aerosol assimilation during pollution events. In addition, space and time coverage of CALIPSO VFM data is limited (16-day repetition period at a specific location). It may miss the opportunity to detect certain high-altitude aerosols.

5. Conclusions

This study introduced and evaluated the spatiotemporal distribution characteristics of AOD, AODf, and AODc provided by MODIS and MERRA-2 during the CLD period and compared them with the mean data of previous years (2017–2019). In addition, we also used CALIPSO and backward-trajectory models to further analyze the vertical extinction characteristics and potential sources of aerosols during the CLD. In general, aerosol concentrations declined in most parts of China during the lockdown, partly due to reduced anthropogenic emissions and decreased dust activity. During the CLD periods, the increase in AODf in the NCP region is likely to come from emissions from some sectors (raw coal heating, thermal power generation, and residential coal) that continued to operate during the lockdown. These results also highlight the need to control residential and power plant emissions.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/rs14143336/s1. Figure S1: (a) The blue asterisk represents the location of AERONET Xianghe site. AERONET vs. MODIS (b1) and AERONET vs. MERRA-2 (b2) AOD at 550 nm during 24 January 2020 to 8 April 2020. AERONET vs. MODIS (c1) and AERONET vs. MERRA-2 (c2) AAOD at 550 nm during 24 January 2020 to 8 April 2020. Only the temporally and spatially matched data are used. The dashed line denotes the 1:1 line. The sample size (N), coefficient of determination (R2), and root mean square error (RMSE) are also provided; Table S1: Statistical analyses of AOD, AODf, AODc from MODIS and AAOD (MERRA-2) variables; Figure S2: Mean 48 h backward trajectory clusters (2500 m) of Beijing, Wuhan and Guangzhou during CLD-I and CLD-II period. The bottom map of the first column of backward trajectory air masses is the MODIS FRP; Figure S3: The average occurrence frequencies of AA (red line) and NA (blue line) within 8 km altitude for five studies areas during the CLD periods in 2020. The dashed line indicates the altitude of the largest occurrence frequency.
Author Contributions: Conceptualization, methodology, and writing—original draft, Y.J.; conceptualization and writing—review and editing, Y.M.; methodology and writing—review and editing, M.Z., Y.L. and X.L.; writing—review and editing, S.J. and B.L.; data curation, A.S. and J.Z.; supervision, Q.F. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Key Research and Development Program of China (Grant No. 2019YFC0214605), Guangdong Major Project of Basic and Applied Basic Research (Grant No. 2020B0301030004), Science and Technology Program of Guangdong Province (Science and Technology Innovation Platform Category) (Grant No. 2019B121201002), and the National Natural Science Foundation of China (Grant No. 42075181).

Data Availability Statement: CALIPSO (www.eosweb.larc.nasa.gov, accessed on 5 July 2022), MODIS (www.ladsweb.modaps.eosdis.nasa.gov, accessed on 8 April 2022), and MERRA-2 (https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2, accessed on 20 April 2022) The other data presented in this study are available upon request from the corresponding author.

Acknowledgments: The authors are grateful to NASA for providing the remote-sensing satellite data used in this study, the United States National Center for Environmental Prediction for providing GADS data, and the China National Environmental Monitoring Center for giving the ground-based PM data.

Conflicts of Interest: The authors declare no conflict of interest.

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