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Article

Analyzing aerosol variation during the COVID-19 pandemic lockdown using satellite data

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SUMMARY

The COVID-19 pandemic caused lockdowns worldwide throughout many cities, implementing numerous restrictions on human activity. Previous studies have shown that various anthropogenic pollutants have decreased in many regions from these lockdowns, which should translate into aerosol levels, measured by aerosol optical depth (AOD), also having a large reduction. However, AOD levels over metropolitan areas during the lockdown periods have not been sufficiently documented. Using NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) AOD data, we analyzed AOD level variances during the pandemic over 13 selected metropolitan areas in Europe, India, and China. We hypothesized that reduced human activities from the pandemic lockdowns would also result in a large decrease in AOD levels in metropolitan areas. So, we compared the average AOD levels during the lockdown to the previous five-year average during the city's corresponding lockdown dates in order to investigate the statistical significance of variations. For European cities, there were few changes in AOD levels observed during the pandemic lockdown periods. As for the Indian cities, three showed slight decreases in AOD levels (~0.5%–7.4%) and one showed an 11% increase. However, compared to Indian and European cities, all of the cities in China showed noticeable reductions in AOD levels during the lockdown (~11%–30%). Statistical analysis did not show statistical significance for most of the cities due to the large variation of AOD, suggesting that the AOD level decrease attributed to the reduction of human activities does not exceed the range of natural AOD level variation.

INTRODUCTION

During the year 2020, the COVID-19 pandemic forced global lockdown periods upon the world to slow the spread of the virus. This provided a unique opportunity to measure the magnitude of human activity on the atmosphere, specifically anthropogenic pollutants such as NO_x, NO_2, which is part of the NO_x family, and SO_2.

Anthropogenic pollutants such as NO_x, NO_2, and SO_2 are precursors to aerosols, which are particles of either solid or liquid that remain suspended in the atmosphere for varied amounts of time. Aerosol levels can be measured with various methods, including measuring Particulate Matter (PM) levels, which measures the concentration of liquid and solid particles in the air, as well as through Aerosol Optical Depth (AOD), which provides a more general picture by measuring the light extinction by aerosols throughout an entire atmospheric column (1). Aerosols are a direct indicator of atmospheric cleanliness because they encompass both human-generated factors, such as NO_x and SO_2, which can be turned into aerosols through atmospheric chemical reactions, as well as natural particles such as sea salt, dust, and volcanic ashes (2-5). High aerosol concentrations can potentially cause many risks including cardiovascular disease, lung cancer, climate change, etc., and can even be attributed to a decreased life expectancy (6). By studying the variation in aerosol levels during these periods of reduced human activities, a larger picture can be inferred regarding the impact of human activities on general levels of atmospheric particles, providing reference to policymakers in order to help combat this problem of excessive anthropogenic pollution.

During pandemic lockdown periods in 2020, there have been signs of a clear reduction in NO_2 and SO_2 levels throughout Eurasia. In Kazakhstan for example, NO_2 levels decreased by roughly 35% during the pandemic period (7). According to Clemente *et al.*, the average NO_x concentration during pandemic lockdown periods in 2020 was approximately 60% lower than the average value during corresponding months for the years 2015–2019 (8). In Lanzhou, China, there was a reduction in SO_2 levels from 18.8 ± 7.4 μg/m^3 before the pandemic started to 17.0 ± 8.9 μg/m^3 during the pandemic (9). Additionally, results also showed a 70% decrease in SO_2 levels in the transport sector across Chinese territories (10). Thus, levels of anthropogenic pollutants such as NO_x and SO_2 experienced a noticeable decrease during periods of decreased human activities.

PM levels throughout Eurasia were also measured during the pandemic. The results yielded a substantial decrease in PM levels in many cities. For example, in Kazakhstan, there was a reduction in PM2.5, a measurement of PM 2.5 μm or less in diameter, concentration by around 21% during the lockdown periods in the country, compared to the period before the lockdown (7). In Spain, PM10, a measurement of PM 10 μm or less in diameter, concentrations also experienced a sizable drop of 35% during the lockdown periods compared to five years prior to the shutdowns (8). Furthermore, sites in China experienced an even greater decrease in PM levels, with one site experiencing PM2.5 concentrations that dropped from 63.7 ± 17.0 μg/m^3 before the lockdown to 33.8 ± 12.7 μg/m3 during the lockdown, a decrease of roughly 47% (9).

Given the clear reductions in PM, as well as precursors of aerosols such as NO_x and SO_2, we hypothesized that reduced human activities from the pandemic lockdown would also result in a large decrease in AOD levels in metropolitan areas. Remote sensing data has provided long-term, global

AOD level measurements in the past decades. Through the analysis of NASA satellite AOD data, this paper provides insight into the extent to which anthropogenic activities have contributed to AOD levels by analyzing AOD level variations of 13 different cities in Eurasia during pandemic lockdown periods, as well as how different levels of lockdown policies could affect AOD level variation.

RESULTS

Thirteen cities from three different regions (Europe, China, and India) were selected in this study to obtain a representative sample of Eurasia. Spain and Italy constitute the selected sample in Europe from media and past literature, and will be referred to as the European study region throughout this study. Each region had its own unique AOD level variation patterns and different lockdown policies and time periods. The name, location, population, and lockdown dates of these cities are listed below (**Table 1**).

During this study, we relied on NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) Multi-Angle Implementation of Atmospheric Correction (MAIAC) data (11). MODIS is a satellite sensor onboard the NASA Earth Observing System Terra and Aqua satellites. These two satellites work together to provide comprehensive Earth observing data. The MAIAC algorithm is a new generation atmospheric correction algorithm which harnesses both temporal and spatial information to jointly retrieve surface reflectance, AOD levels, as well as other geophysical parameters (12).

Annual and Seasonal AOD Level Variations

The 12-year time series of monthly AOD levels within the European study region shows low AOD levels for all observed cities, with an average around 0.10 (**Figure 1A-D**). There were also seasonal variations present, in which all cities had a higher AOD level during the summer months and lower levels during the winter months. During this 12-year time period, the AOD levels are relatively stable and there were no noticeable trends.

In the monthly averaged AOD levels for India during the timescale of 2010–2021, consisting of the cities of New Delhi, Lucknow, Kanpur, and Raipur respectively, seasonal variations were still present, however, for New Delhi, Kanpur, and Raipur, there was a noticeable upward trend in the AOD levels (**Figure 1E-H**). The monthly AOD level values in these cities were much higher than those in European cities, varying between 0.4 to more than 1.5. They also showed more complicated seasonal patterns because the variations are not as uniform and predictable compared to other panels. In the monthly averaged AOD levels for 2010–2021 in China, consisting of the cities of Beijing, Lanzhou, Zhengzhou, Wuhan, and Chengdu, there was a downward trend in all cities in China, with a more noticeable negative sloping trend in Chengdu, Zhengzhou, and Wuhan (**Figure 1I-M**). As for Zhengzhou and Wuhan, there was a notable difference in the patterns of AOD levels for the years before 2015 and the years after 2015; the variation before 2015 was much higher than after 2015, as seen by the range of AOD level variation that was much greater before 2015 than after. Still, seasonal variations were present and observable, as depicted by the annual oscillating pattern.

Taking into consideration all cities in the study, the benchmark period was selected to be from 2015–2019 to minimize annual AOD level variations, especially in the Indian and Chinese study regions. Thus, the benchmark average value was calculated with the AOD level values of the dates that corresponded to each respective city's lockdown period during the period from 2015–2019 (**Table 1**).

AOD Level Variation During the Pandemic

In order to examine the AOD level changes during the pandemic lockdown, the average AOD levels during the dates of the lockdown periods annually as well as during the lockdown in 2020 (AODpan) of each respective city for the years 2015–2021 was plotted. The pandemic lockdown policies were no longer in effect in 2021, however, the cities were still under the impact of the pandemic, so the year 2021 was also plotted for comparison.

In the average AOD levels during each European city's individual lockdown for each year during the period 2015–2021, no city showed a notable deviation from the benchmark values for the years 2020 and 2021 (**Figure 2A-D**). In the

City	Location	Population (millions)	Size (km^2)	Lockdown Dates
Elche, Spain	(38°16'N, 0°42'W)	0.2	4 x 6	3/14/20–3/29/20
Madrid, Spain	(40°4'N, 3°42'W)	3.2	17 x 15	3/14/20–5/17/20
Milan, Italy	(45°29'N, 9°12'E)	1.4	15 x 15	3/9/20–5/17/20
Rome, Italy	(41°14'N, 12°30'E)	2.9	11 x 13	3/9/20–5/18/20
New Delhi, India	(28°37'N, 77°12'E)	26	28 x 40	3/25/20–5/17/20
Lucknow, India	(26°51'N, 80°57'E)	3.9	15 x 15	3/25/20–5/17/20
Kanpur, India	(26°27'N, 80°20'E)	3.2	10 x 15	3/25/20–5/17/20
Raipur, India	(21°15'N, 81°38'E)	1.8	11 x 11	3/25/20–5/17/21
Beijing, China	(39°55'N, 40°25'E)	21.5	30 x 20	6/16/20–7/20/20
Lanzhou, China	(36°03'N, 103°50'E)	3.8	10 x 13	2/1/20–3/31/20
Zhengzhou, China	(34°45'N, 113°42'E)	10.3	20 x 20	2/1/20–3/31/20
Wuhan, China	(30°35'N, 114°18'E)	11.1	50 x 50	1/23/20–4/8/20
Chengdu, China	(30°40'N, 104°05'E)	16.3	16 x 16	2/1/20–3/31/20

Table 1. Selected cities and background information.

Indian study region, it can be seen that there was also not a heavy variation in AOD levels for the years 2020 and 2021 during the lockdown period, as the graph remains relatively close to the benchmark average (**Figure 2E-H**). A slight increase in AOD levels can be observed in New Delhi and Raipur (**Figure 2E-H**). However, all five cities in the Chinese study region showed a noticeable unanimous reduction in AOD levels during the lockdown periods in 2020 and 2021 compared to the benchmark period before (**Figure 2I-M**).

The comparison of lockdown AOD levels and benchmark AOD levels was summarized, which also shows the statistical analysis component of the variation of AOD levels during the pandemic years compared to the benchmark value (**Figure 3A-B**). The benchmark was determined to be the 5-year period

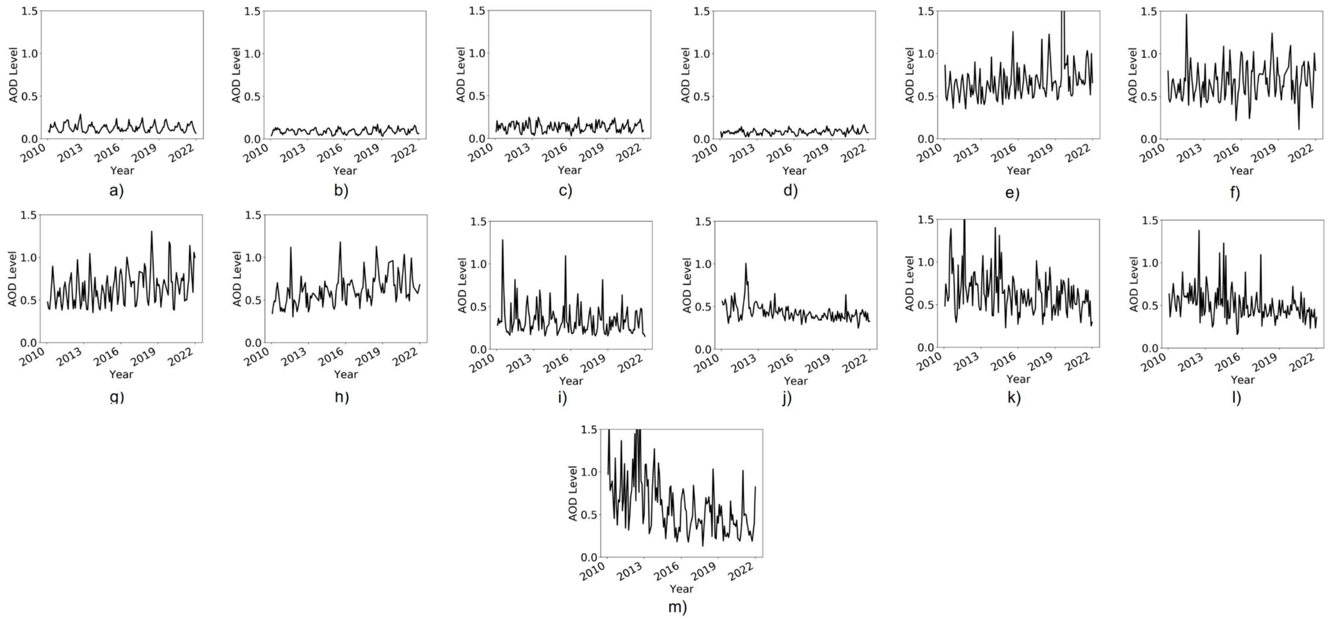

Figure 1: Monthly averaged AOD levels during 2010–2021. a) Elche, Spain, b) Madrid, Spain, c) Milan, Italy, d) Rome, Italy, e) New Delhi, India, f) Lucknow, India, g) Kanpur, India, h) Raipur, India, i) Beijing, China, j) Lanzhou, China, k) Zhengzhou, China, l) Wuhan, China, and m) Chengdu, China. Line graphs showing changes in monthly AOD levels for the cities in the 3 study regions (4 in Europe, 4 in India, and 5 in China).

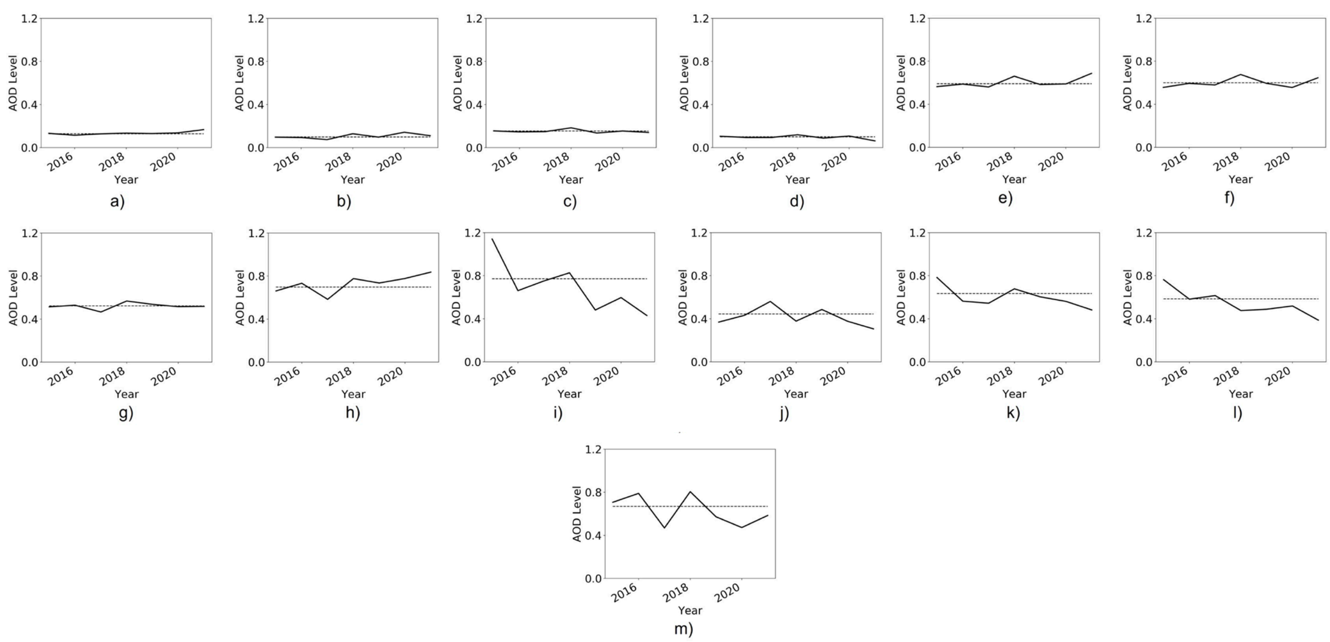

Figure 2. Averaged AOD levels during the pandemic lockdown periods during 2015–2021. a) Elche, Spain, b) Madrid, Spain, c) Milan, Italy, d) Rome, Italy, e) New Delhi, India, f) Lucknow, India, g) Kanpur, India, h) Raipur, India, i) Beijing, China, j) Lanzhou, China, k) Zhengzhou, China, l) Wuhan, China, and m) Chengdu, China. The lockdown periods for each city are listed in table 1. Line graph showing variation of averaged AOD levels for the 5-year benchmark period during each city's respective lockdown month for cities in the 3 study regions (4 in Europe, 4 in India, and 5 in China). Dotted line represents the 5-year benchmark average AOD level.

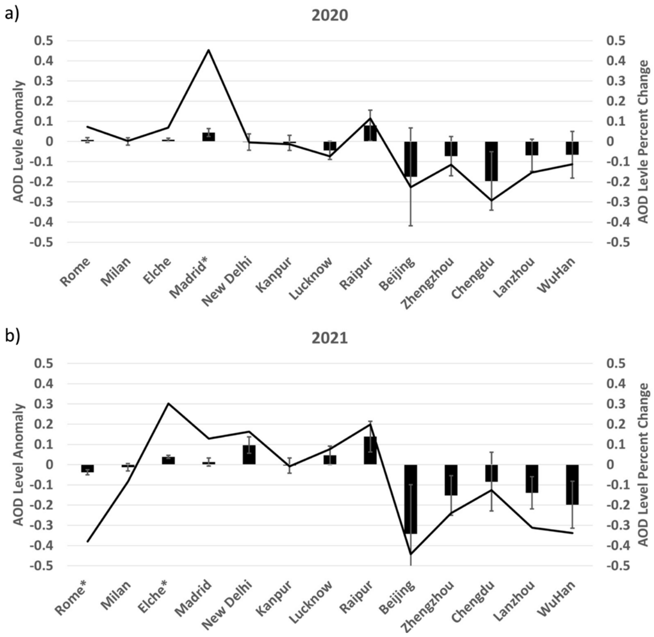

Figure 3: Lockdown AOD level anomalies for selected 13 cities. a) 2020 and b) 2021. The anomaly was defined as the difference between the lockdown AOD level and the benchmark AOD level. Cities with statistically significant AOD level variations (p-value less than 0.05) are denoted with a * next to the city name. The line graph represents AOD Level Percent Change on the right vertical axis. The AOD Level Anomaly is shown in the bar plot, marked on the left vertical axis. The error bars are also shown in each individual bar.

from 2015–2019 before the pandemic struck to minimize annual and seasonal variation, representing a control value to compare back to. The AOD level variations in China were much larger than the variations observed in Europe and India. Even though the p-values did not show statistical significance of these reductions due to the large standard deviation, there was still a 11%–30% decrease in AOD levels in China compared to the benchmark value (**Figure 3A-B**). The large standard deviation could be attributed to various factors, such as the natural transportation of aerosols, aerosol life expectancy, and satellite data uncertainty.

Spatial Patterns of AOD Level Variation

The spatial patterns of AOD level variation were also examined throughout this study. First, a 100km x 100km area around each city was selected. For every 1 km pixel, the benchmark AOD level value was calculated with the preceding five-year mean AOD levels, drawn in the left image of each panel. Next, the lockdown period AOD levels were also calculated for each 1 km pixel, depicted in the image on the right of each panel. For every region—Europe, India, and China—the spatial patterns were very similar within the region. However, each region had its own unique spatial patterns, which were represented with a 100km x 100km selected area for a sample city in each region (**Figure 4**).

In Madrid, the selected city from the European study zone, there was a slight unanimous increase in AOD levels, however this increase was less than 0.05, which was more likely explained by natural AOD level variations and cannot be attributed to the lockdown (**Figure 4A**). The images of New Delhi, the selected city from the Indian study zone, exhibited the mixed features of AOD level variation in the Indian study zone, as part of the region in and around the red box showed an increase, while there was also a general decrease in the image (**Figure 4B**). This characteristic was repeatedly observed in all cities in the Indian study zone, as the AOD level variation was non-uniform. On the other hand, in Chengdu, the selected city from the Chinese study zone, it was obvious that the entire region experienced a clear decrease of AOD levels (**Figure 4C**).

DISCUSSION

In this study, 13 cities were selected from three different regions in Eurasia: India, China, and Europe consisting of Spain and Italy. These regions represent different AOD levels

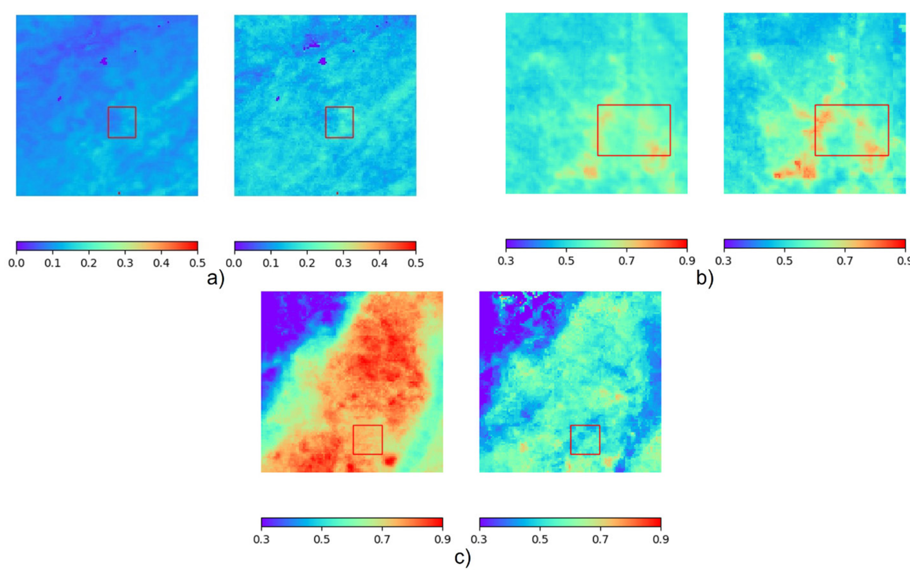

Figure 4. Comparison of AOD Level Spatial Variations before and during the pandemic lockdown periods. a) Madrid, Spain, b) New Delhi, India, and c) Chengdu, China. The left panel of each tile represents benchmark values while the right panel represents values during the lockdown for each city and the red box represents the city location from Table 1.

throughout different regions in Eurasia, each with their own unique characteristics and variations, and their own lockdown policies and time periods. After an initial analysis of each city's 10-year AOD level variations, taking into account seasonal variations as well, a benchmark value of the previous 5 years was calculated to better evaluate the changes in AOD level during the pandemic lockdown periods in each city. Average AOD levels for the AODpan were utilized across all years within the benchmark period to better compare the AOD levels during the lockdown period and the AOD levels throughout all the control years, as well as to account for seasonal variation. For example, if the lockdown period mainly happened in March, the average AOD levels for the month of March were compared together in order to minimize error from seasonal changes.

In Europe, the average AOD levels during the benchmark period were generally around 0.1–0.2, which was already relatively low considering that AOD levels generally fall into the standard range of 0–2. As a result, there was not a large variation observed during the lockdown periods within the European study region. Although Clemente *et al*. discovered a large reduction in traffic patterns in Elche the results show that it did not have a large impact on AOD levels (8). The large percentages observed in Spain are due to the generally lower AOD levels. The absolute AOD level changes are below 0.05, which was already below the uncertainty of satellite AOD level data, so it can be ruled as insignificant. From the spatial analysis, a very stable pattern can be observed throughout the entire region before and during the pandemic lockdown periods.

In India, the average AOD levels were much higher than in Europe, with average AOD levels being ~0.5–0.7. Mixed results were observed: three out of the four cities selected showed slight decreases of 0.5%–7.5% in AOD levels compared to the benchmark value, while one of the cities showed an 11% increase in 2020. There was a noticeable increase of AOD levels in 2021 for New Delhi, Lucknow, and Raipur, which could be related to the resumption of human activities in 2021. Although Ranjan *et al*. discovered a 45% reduction in AOD levels across the entire Indian territory, this reduction was not observed in the four cities that were studied (13). This could be explained by the spatial heterogeneous variation of AOD levels.

In the Chinese study region, the average AOD levels were around 0.5–0.7, which are similar to the average values in India. There was a noticeable decrease in AOD levels of roughly 11%–30% in 2020 when the pandemic first hit. It is worth noting that in 2021, the reductions are even larger, reaching 44% in Beijing, which may be because the lockdowns were continued into 2021. Furthermore, the spatial patterns in China show a unanimous decrease throughout the entire region.

Out of the 13 selected cities, the size and population density did not have any impact on AOD level variation. Europe, India, and China instead showed unique patterns. European AOD levels are generally low, so the variation patterns do not show clear changes. Indian and Chinese AOD levels are generally higher, yet they show distinct patterns: the variation patterns in India are mixed, while the patterns in China exhibit a universal decrease.

The difference in the AOD level variation patterns may be linked to the differing regulations in lockdown procedures throughout each study zone as well as the different aerosol sources in each region. There are relatively low levels of European anthropogenic pollution in the first place as explained by the low average AOD levels to begin with, so a reduction in human activities as produced by the lockdown would not create a noticeable change in AOD levels. However, India and China exhibit relatively higher levels of anthropogenic pollution, so a reduction in human activities would yield a larger impact on overall AOD levels. Moreover, the dramatic decrease of AOD levels in China may also be associated with their strict lockdown procedures that reduced human activities more seriously than in other regions.

The statistical analysis showed p-values of greater than 0.05 for almost all the cities due to high variations in AOD levels, which does not show statistical significance. This was because AOD level reflects the combination of both natural, such as sea salt, and anthropogenic sources. The reduction in solely anthropogenic sources through the lockdown does not necessarily generate a significant change in aerosol levels.

In some of the cities, the AOD level variations during the pandemic lockdown were not consistent with the PM reductions reported in the literature. For example, in Elche, Spain, the AOD levels during the lockdown slightly increased while Clemente *et al*. found a 35% drop in PM10 (8). This discrepancy could be related to aerosol vertical profiles or meteorological fields, which need to be further studied.

In summary, by comparing the AOD levels during pandemic lockdown periods with benchmark AOD levels in 13 cities in Eurasia, we found that cities in Europe and India did not show noticeable AOD level reductions. However, in Chinese cities, where a stricter lockdown policy was implemented, a much higher AOD level reduction (11%–30%) was observed, indicating that minimizing human activities through strict procedures could reduce AOD levels. However, this reduction still does not exceed the sensitivity of AOD natural variation, implying that to reduce air pollution, minimizing human activities may not be very effective as this lockdown policy is obviously not sustainable in the long term. Thus, new technological breakthroughs should be pursued.

MATERIALS AND METHODS

We used NASA's MODIS MAIAC Collection 6.1 1-km resolution AOD level data from the years 2010–2021 (11). The variation in AOD levels was analyzed in this meta-analysis for certain cities in Eurasia. To account for the size variation in each individual city, the population of each city and dimensions of the study region were included to represent small to large city sizes. Additionally, the geographical coordinates and the respective lockdown periods of each city were also included for further insight.

We used Python code version 3.6.7, utilizing the SciPy and pandas packages to extract the AOD levels over each city. After selecting a rectangular area that covered the specified city and isolating the AOD levels, the average AOD levels were calculated for each city daily to generate the monthly AOD levels from 2010–2021. These monthly AOD levels were then used to evaluate the variation of seasonal and annual AOD level variation to create a benchmark period of AOD levels that could be used as a control value.

A python SciPy stats package statistical z-score analysis version 1.2.1 was also performed using z-scores and corresponding p-values to determine variation and statistical significance of the AOD level reductions. The code has been uploaded to a GitHub page for further reference and can be found at: https://github.com/Arthurw2004/AOD-level-variation-during-COVID-19-lockdowns. Z-scores were defined as the following:

$$Z = \frac{x - \mu}{\sigma}$$

where Z was the z-score, x was the observed AOD average level of the specified year, μ was the benchmark AOD average value, and σ was the standard deviation of AODpan during the benchmark years. In this study, the p-value was a statistical measure of the significance of AOD level changes, and a value of 0.05 or lower was considered statistically significant.

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