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Impact analysis of COVID-19 pandemic control measures on nighttime light and air quality in cities

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\textbf{ABSTRACT}

The COVID-19 pandemic has profoundly affected human society on a global scale. COVID-19 pandemic control measures have led to significant changes in nighttime light (NTL) and air quality. Four cities that were severely impacted by the pandemic and that implemented different pandemic control measures, namely, Wuhan (China), Delhi (India), New York (United States), and Rome (Italy), were selected as study areas. The Visible Infrared Imaging Radiometer Suite (VIIRS) and air quality data were used to study the variation characteristics of NTL and air quality in the four cities in 2020. NTL brightness in Wuhan, Delhi, New York, and Rome decreased by 8.88\%, 17.18\%, 8.21\%, and 6.33\%, respectively, compared with pre-pandemic levels; in the resumption phase Wuhan and Rome NTL brightness recovered by 13.74\% and 3.38\%, but Delhi and New York decreased by 16.23\% and 4.99\%. Nitrogen dioxide (NO\textsubscript{2}) concentrations in the lockdown periods of Wuhan, Delhi, New York, and Rome decreased by 65.07\%, 68.75\%, 55.59\%, and 56.81\%, respectively; PM\textsubscript{2.5} decreased by 49.25\%, 69.40\%, 52.54\%, and 66.67\%. Air quality improved, but ozone (O\textsubscript{3}) concentrations increased significantly during the lockdown periods. The methods presented herein can be used to investigate the impact of pandemic control measures on urban lights and air quality.

1. \textbf{Introduction}

In 2020, the COVID-19 pandemic had a profound impact on the societies, economies, and ecological environments of countries around the world. All countries have implemented measures to contain the spread of COVID-19. Wuhan (China), Delhi (India), New York (United States), and Rome (Italy) implemented lockdowns among cities with serious pandemics, requiring home quarantine and reducing non-essential production, that led to declines in economic activity. It is estimated that the COVID-19 pandemic may slow global economic growth by 3\%–6\% in 2020 (Jackson \textit{et al.}, 2021). The lockdown measures also led to changes in urban air quality. The stagnation of urban transportation, industrial production, and commercial activities has affected the concentrations of harmful gases such as PM\textsubscript{2.5}, PM\textsubscript{10}, nitrogen dioxide (NO\textsubscript{2}), sulfur dioxide (SO\textsubscript{2}), and tropospheric ozone (O\textsubscript{3}) that are the most threatening to human health (Sicard \textit{et al.}, 2020). However, there are few studies in this area at present, and none that have illuminated the dynamic changes and spatial differences of NTL and air quality at various spatiotemporal scales.

Free access to National Polar-Orbiting Partnership-Visible Infrared Imaging Radiometer Suite (NPP-VIIRS) data and air quality data

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provides opportunities for the development of relevant research. These two types of data can be used to study the effectiveness of pandemic control measures at different scales and their impacts on socioeconomic activities and environmental elements in the associated regions. In recent years, NPP-VIIRS data have been used to detect the dimming of lights caused by war (Li et al. 2015, 2018), natural disasters (Fan et al., 2019; Zhao, 2018), humanitarian crises (Jiang et al., 2017), and public health emergencies. Particularly in the field of public health emergencies, researchers have used NPP-VIIRS data to study the changes of light levels in China and India during the pandemic and to examine the impact of COVID-19 on the economy, environment, and citizens’ activities (Elvidge et al., 2020; Ghosh et al., 2020; Liu et al., 2020). However, domestic and foreign researchers studying the impact of COVID-19 using NTL data have focused on a particular month pre-pandemic and during the pandemic without discussing the complete data; the study areas have been cities in a given country, and no comparisons have been made between different cities at a global scale. There is thus a lack of studies on the general impact of pandemic control measures on NTL and air quality.

In addition, the COVID-19 pandemic has also had a significant impact on urban air quality. Pandemic control measures have caused changes in concentrations of urban air pollutants PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$, and tropospheric O$_3$, and long-term exposure to air pollution has led to an increase in the COVID-19 mortality rate (Kumari and Toshniwal 2020; Stafoggia et al., 2020; Wu et al., 2020). Different cities around the world have implemented various pandemic control measures, while implementation differs among residents in each country, leading to varied changes in NTL and air quality in different cities, with changes in the concentrations of air pollutants being the most rapid and visual elements. The study of changes in air pollutant concentrations can reflect the impact of pandemic control measures on air quality in different cities.

This study is based on NPP-VIIRS monthly composite data and time series air quality data from different periods: pre-pandemic, during the pandemic, and resumption of work and production phases in Wuhan, Delhi, New York, and Rome. We used statistical analyses, two-dimensional scattergrams, and NTL difference images in an attempt to determine whether the pandemic control measures caused changes in urban light and air quality. What differences exist in NTL changes in the context of COVID-19 control measures in the four cities? What impact did the pandemic control measures have on urban air quality? This study is intended to provide a reference for decision makers in environmental management during public health emergencies that may occur in the future.

2. Materials and methods

2.1. Study areas

Four cities severely impacted by COVID-19 were selected as study areas: Wuhan in China, Delhi City in India, New York City in the United States, and Rome in Italy (Fig. 1). Wuhan is the capital city of Hubei Province and was selected as one of China’s “Top 10 Nighttime Economic Cities” in 2019. Wuhan was the first region in China to discover the outbreak of COVID-19 and to implement control measures, thereby providing a reference for other countries in pandemic control. Delhi City is known as the National Capital Region (NCR) and is composed of the Indian capital Delhi and neighboring satellite cities Gurgaon, Faridabad, Ghaziabad, and Noida (simply as Delhi in this article). Delhi is one of the most severely infected cities in India, and it has become a focal region in the world for pandemic control due to the rapid increase in cases. New York City is the largest city in the United States and consists of the five boroughs Bronx, Brooklyn, Queens, Manhattan, and Staten Island, and it was the most severely infected city in the early period of the pandemic outbreak and was typical of pandemic control in the United States. Italy was the center of the European pandemic at the beginning of the outbreak. Rome is the capital of Italy and is one of the most severely infected cities in southern Italy. Table 1 describes the basic information of the four cities, with the city lockdown and resumption work dates from the International Monetary Fund.
This study was conducted based on NPP-VIIRS monthly composite data and air quality data (Table 2). The NPP-VIIRS data derived from the National Oceanic and Atmospheric Administration (NOAA) were scanned and imaged by the Suomi National Polar Partnership satellite equipped with the Visible Infrared Imaging Radiometer Suite (VIIRS). The VIIRS instrument can be used to collect radiance images of land, atmosphere, ice, and ocean in the visible and infrared bands with two operating modes of medium and high resolution; the day/night band (DNB) range of 0.5 μm–0.9 μm is normally used to detect the information of nighttime light sources (Elvidge et al., 2017; Miller et al., 2012).

2.2. Dataset and workflow

The basic situation in Wuhan, Delhi, New York, Rome and Rome in 2020.

Table 1

| Population | GDP (billion) | Climate | Lockdown Start Date | Resumption of Work and Production Date | Blocking Time (day) |
|------------|---------------|---------|---------------------|---------------------------------------|---------------------|
| Wuhan      | 11,212,000    | $245.02 | Subtropical monsoon climate | 1/23/2020                            | 4/8/2020            | 76 |
| Delhi      | 30,200,000    | $195.98 | Tropical monsoon climate | 3/25/2020                            | 5/18/2020           | 55 |
| New York   | 8,620,000     | $1025.24| Temperate continental climate | 3/20/2020                            | 6/8/2020            | 81 |
| Rome       | 3,800,000     | $180.15 | Mediterranean climate    | 3/10/2020                            | 5/4/2020            | 56 |

Although the VIIRS monthly data filter out noise such as stray light, moonlight, and cloud cover, transient lights such as auroras, fishing boats, fires, and other background noises still exist. To improve the accuracy of monitoring NTL changes in Wuhan caused by COVID-19, the background noise needed to be rectified. Currently, there are three main types of methods for NPP-VIIRS noise processing. One is denoising with the support of DMSP/OLS NTL images; the second is mask denoising with the help of annual global NTL composite data (DMSP-OLS) data, NPP-VIIRS data have higher spatial and spectral resolution accuracy. The spatial resolution of the NPP-VIIRS monthly composite data is about 500 m, and the spectral resolution is 14 bits. The spatial resolution of the DMSP-OLS data is 1 km and the spectral resolution is 6 bits. In addition, the professional NTL satellite remote sensing Luojia-1 launched by China can obtain NTL images with high spatial resolution of 130 m and spectral resolution of 15 bits, but the data continuity is poor.

The air quality data (PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$ and O$_3$) were derived from environmental monitoring stations in each country. The monthly mean air quality data indices were calculated using daily or hourly data from city atmospheric ground monitoring stations. However, there exist monitoring stations with missing data. Wuhan air quality data from the PM$_{2.5}$ historical data network (https://www.aqistudy.cn/historydata) were calculated using hourly data from the China National Environmental Monitoring Centre and were obtained from August 2019 to August 2020 in this study. Delhi air quality data were derived from Central Control Room for Air Quality Management in India (https://app.cpcbccr.com/). Using the data from the Delhi Pusa Station as the main source and the Dwarka Sector 8 Station to supplement the missing data of April, monthly mean data for 2020 were calculated from daily data. New York air quality data were derived from the U.S. Environmental Protection Agency (https://aqs.epa.gov/) through downloading daily data to obtain monthly data for 2020. Rome air quality data were derived from the Regional Environmental Protection Agency of Lazio (https://www.arpalazio.it/), and the monthly mean air quality data for Rome were obtained using monthly average data from 11 monitoring stations. Fig. 1 shows the spatial distribution of the air quality monitoring stations used in this study, with all stations within the urban areas.

To avoid deformation of the NPP-VIIRS monthly composite data, we performed Albers equal-area projection and resampled the data to a 500 m × 500 m raster cell. Aiming to obtain NTL data within the study area, we used the mask of city administrative district to extract the NPP-VIIRS data. The radiance value of the lightless areas should be 0, so the grid cells with negative values in the NPP-VIIRS data were set to the background value of 0 (Bennett and Smith 2017). To improve data accuracy, we used different processing methods to rectify noise and outliers before final analyses of the processing results.

In the processing of air quality data, we used daily and hourly PM$_{2.5}$, PM$_{10}$, NO$_2$, SO$_2$, and O$_3$ data from monitoring stations to calculate the monthly averages, and the daily averages of air quality data from surface monitoring stations can reflect the air quality during VIIRS night overpass (~1:00 a.m. local time (Fu et al., 2018; Wang et al., 2016). Average of monitoring data from multiple stations as monthly mean air quality data when multiple station existed. Fig. 2 shows the complete workflow of the data acquisition process.

2.3. Denoising based on the empirical threshold method

To avoid deformation of the NPP-VIIRS monthly composite data, we performed Albers equal-area projection and resampled the data to a 500 m × 500 m raster cell. Aiming to obtain NTL data within the study area, we used the mask of city administrative district to extract the NPP-VIIRS data. The radiance value of the lightless areas should be 0, so the grid cells with negative values in the NPP-VIIRS data were set to the background value of 0 (Bennett and Smith 2017). To improve data accuracy, we used different processing methods to rectify noise and outliers before final analyses of the processing results.

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and calculated the average values of the sample points as the minimum threshold (Table 3) and set the radiance values lower than the minimum threshold to zero to eliminate the background noise.

2.4. Outlier handling by convolution smoothing

After the background noise rectification of NPP-VIIRS monthly composite data, the outliers in the data needed to be processed, and the convolutional smoothing method was used to handle the outliers of Wuhan, Delhi, New York, and Rome NTL data. In the study of light radiance in China during the past 20 years (Xu et al., 2015), the maximum values occurred in Beijing and Shanghai, and thus Wuhan city light radiance values in each month should not be higher than the maximum values for Beijing or Shanghai (Table 4). The maximum thresholds for Delhi, New York, and Rome were set based on the latest annual global VIIRS data published by EOG for 2012–2019, the data were filtered to eliminate external features such as biomass burning, auroras, and background noise, while using the median value for the whole year to remove outliers (Elvidge et al., 2021). This study was based on the 2019 global VIIRS data, extracting annual NTL data for Delhi, New York, and Rome. The maximum radiance value of NTL in each city in 2019 was used as the maximum threshold to handle outliers for monthly composite data. Table 5 shows maximum radiance thresholds for 2019.

To smooth the grid cell radiance values $DN_{ij}$ in the Wuhan, Delhi, New York, and Rome VIIRS DNB images that were higher than the maximum threshold value, a $3 \times 3$ filter was built to replace the value with the mean value for the eight neighboring cells, with the grid cell as the center. If the mean value in eight neighborhoods was still higher than the maximum threshold, then we used the maximum value in the eight neighborhoods as the new center to replace the outlier with the mean value in the neighborhoods, and so on until the convolution value was less than the maximum threshold.

$$D = DN_{i,j-1} DN_{i,j} DN_{i,j+1} 1/8 1/8 1/8$$

$$D = DN_{i-1,j} DN_{i,j} DN_{i+1,j} 1/8 0 1/8$$

where $C = 1/8 1/8 1/8$.

The filter constructed in the study is a low-pass filter to smooth outliers in the image for the purpose of eliminating them. The result of the outlier grid cells after convolution is $R_{(i,j)}$:

$$R_{(i,j)} = D_{(i,j)} C$$

In the formula, $C$ is the filter and $D$ is the eight-neighborhood image region centered on $DN_{ij}$ where $i$ and $j$ represent the rows and columns of grid cells.

| Data Name                  | Data Type | Data Time    | Spatial Resolution | Data Source                                           |
|----------------------------|-----------|--------------|--------------------|-------------------------------------------------------|
| NPP-VIIRS                  | Raster    | 2019 and 2020| Approximately 500 m| Earth Observation Group                                 |
| Wuhan air quality data     | Statistical| 8/2019-8/2020|                    | China National Environmental Monitoring Centre         |
| Delhi air quality data     | Statistical| 2020         |                    | Central Control Room                                   |
| New York air quality data  | Statistical| 2020         |                    | U.S. Environmental Protection Agency                   |
| Rome air quality data      | Statistical| 2020         |                    | Regional Environmental Protection Agency of Lazio      |
Table 3
Minimum radiances thresholds for the four cities by month.
(Radiance: nW·cm$^{-2}·sr^{-1}$).

| Name   | Aug.2019 | Dec.2019 | Jan.2020 | Feb.2020 | Mar.2020 | Apr.2020 | May.2020 | Jun.2020 | Jul.2020 | Aug.2020 | Sep.2020 |
|--------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
| Wuhan  | 2.61     | 2.86     | 3.02     | 3.55     | 3.46     | 4.04     | 3.28     | 2.86     |          |          |          |
| Delhi  | 2.03     |          | 2.41     | 2.50     |          | 2.39     | 2.48     | 2.59     |          |          |          |
| New York| 7.74     | 8.48     | 7.55     | 7.91     |          |          | 5.84     | 7.95     |          |          |          |
| Rome   | 1.65     | 1.84     | 2.07     | 1.70     | 1.94     | 1.61     | 1.71     | 1.65     |          |          |          |
Wuhan NTL decreased significantly in January 2020 at the early lockdown period. After the resumption of work and production, there was an upward trend in both cities NTL. The monthly lights in Delhi and New York showed declines from the pandemic outbreak to the lockdown period, and after the resumption of work. The method calculates the difference between pairs of monthly composite brightness. The NTL difference images method was based on the monthly composite data of the three phases of pre-pandemic, lockdown period, and after the resumption of work and production. Pairs of different phases of monthly radiance were set as X and Y axes, and comparisons of the slopes of regression lines were made to observe the changes in NTL brightness. The NTL difference images method was based on the monthly composite data of the three phases of pre-pandemic, lockdown period, and after the resumption of work. The method calculates the difference between pairs of monthly composite data, and visualizes the changes of NTL brightness via the hypsometric method.

3. Results

3.1. Monthly light patterns

From the histograms of monthly light amounts for Wuhan, Delhi, New York, and Rome (Fig. 3), we can see that the monthly light amounts in Wuhan and Rome during the lockdown period showed a declining trend compared to the pre-pandemic period, and the Wuhan NTL decreased significantly in January 2020 at the early lockdown period. After the resumption of work and production, there was an upward trend in both cities NTL. The monthly lights in Delhi and New York showed declines from the pandemic outbreak to the resumption of work and production phases. The difference between the maximum and minimum values of monthly light in Wuhan, Delhi, New York, and Rome were 34773 nW·cm⁻²·sr⁻¹, 60477 nW·cm⁻²·sr⁻¹, 10002 nW·cm⁻²·sr⁻¹ and 28454 nW·cm⁻²·sr⁻¹, respectively, indicating that the light changed more in Delhi and Wuhan than in New York or Rome.

3.2. NTL change analysis method

For the analysis of NTL changes, we used statistical analyses, two-dimensional scattergrams, and the NTL difference images method to compare and visualize the NTL changes. The statistical method was performed according to the pandemic situations of different cities to select different times of the monthly composite data for rectification and calculating the sum-of-lights (SOL). The two-dimensional scattergrams method was based on the city pandemic control timeline to select the monthly average radiance of the three phases of pre-pandemic, lockdown period, and after the resumption of work and production. Pairs of different phases of monthly radiance were set as X and Y axes, and comparisons of the slopes of regression lines were made to observe the changes in NTL brightness. The NTL difference images method was based on the monthly composite data of the three phases of pre-pandemic, lockdown period, and after the resumption of work. The method calculates the difference between pairs of monthly composite data, and visualizes the changes of NTL brightness via the hypsometric method.

3.3. NTL brightness variation

Based on the monthly average radiance values for Wuhan, Delhi, New York, and Rome, we constructed scattergrams of group “a” for the pre-pandemic and lockdown period and group “b” for the lockdown period and resumption phases in the four cities (Fig. 4). The scattergrams show December 2019 radiance values on the X axis, March 2020 radiance values on the Y axis, and the slope of the regression line is denoted by K. K < 1 means that the night light brightness of March 2020 on the Y axis is dimmer compared with December 2019. In the Figs. 4 and 1b scattergrams, K > 1 means that the night light brightness of May 2020 (Y axis) was brighter than in March 2020 (X axis), and the angle indicates the magnitude of change. In the Figs. 4 and 2a scattergrams, K < 1 means that the night light brightness of April 2020 was dimmer compared to January 2020. In the Figs. 4 and 2b scattergrams, K < 1 means that the brightness of August 2020 continued to be dimmer. In the Figs. 4, 3a and 3b scattergrams, K < 1 means that the lockdown policy caused dimming of lights, and the light levels did not recover quickly, even after the resumption of work and production. In the Fig. 4 and a scattergrams, K < 1 means that the lockdown policy caused March 2020 night light brightness to be dimmer compared to January 2020. In the Fig. 4 and b scattergrams, K > 1, but the magnitude of the change is small, meaning that May 2020 night light brightness was slightly higher compared to March 2020. In general, Wuhan and Delhi had large changes in night light brightness, while New York and Rome had smaller changes.

3.4. NTL brightness variation

Based on the monthly composite data of Wuhan, Delhi, New York, and Rome, we constructed group “a” NTL difference images for the lockdown period and pre-pandemic and group “b” NTL difference images for the resumption phase and lockdown period in the four cities (Fig. 5). The qualitative analysis was corroborated through the quantitative analysis shown in Table 6. In the NTL difference images, the gains in brightness have been colored red and the declines in the brightness are shown in blue. From the group “a” NTL difference images, we can see that in the four cities, night lights dimmed during the lockdown period compared to the pre-pandemic. Figs. 5, 1a and 2a show large dimming magnitudes of 8.88% and 17.18%, respectively, and Figs. 5, 3a and 4a have smaller dimming magnitudes of 8.21% and 6.33%, respectively. The four cities showed clear dimming of lights in their commercial centers such as Jianghan commercial district in Wuhan, the New Delhi area in Delhi, Manhattan in New York, and the capital region in Rome, but some
areas in the suburbs of the cities were brighter. From the group “b” NTL difference images, we can see that in Wuhan and Rome, the night lights increased by 13.74% and 3.38%, respectively, compared to the lockdown period after the government implemented the resumption work and production policy; in Delhi and New York (Figs. 5, 2b and 3b), night lights decreased by 16.23% and 4.99%, respectively, after the resumption of work and production policy was implemented. The NTL difference images comparisons of the four cities indicate that Wuhan and Delhi had large changes in night light brightness. The NTL in Wuhan was clearly dimmed during the lockdown period and rapidly become brighter after the resumption of work and production, while the NTL in Delhi continued to be dim.

Fig. 3. Monthly light amounts: (a) Wuhan; (b) Delhi; (c) New York; (d) Rome.
during the lockdown period and after the resumption of work and production. The NTL in New York continued to be dimmed during the lockdown period and the resumption of work phase, but the decline was small. The NTL in Rome during the lockdown period showed a small dimmer rate, and after the resumption of work and production, the night light brightness slowly recovered. In general, the Wuhan NTL brightness changed significantly at each period of the pandemic control.

Fig. 4. Monthly average radiance scattergrams: (1a, 1b) Wuhan; (2a, 2b) Delhi; (3a, 3b) New York; (4a, 4b) Rome.
Fig. 5. NTL difference images of group a and b for each city: (1a, 1b) Wuhan; (2a, 2b) Delhi; (3a, 3b) New York; (4a, 4b) Rome.


3.4. **Air quality changes due to city lockdown**

Fig. 6 shows the time series variation of monthly mean air quality data during the pandemic period for Wuhan, Delhi, New York, and Rome. The qualitative analysis was corroborated through the quantitative analysis shown in Fig. 7. The orange and green bar charts in Fig. 7 show the percent differences in air pollutant concentrations between the lockdown periods and the pre-pandemic period, the resumption of work and production phase, and the lockdown period in each city. Fig. 7 indicates that PM$_{2.5}$, PM$_{10}$, NO$_2$, and SO$_2$ concentrations declined, while O$_3$ concentrations increased significantly during the lockdown period in the four cities compared to the pre-pandemic periods. In the four cities, the NO$_2$ concentrations decreased more than those of other pollutants, among which the largest decline was 68.75% in Delhi followed by Wuhan, Rome, and New York at 65.07%, 56.81%, and 55.59%, respectively. The PM$_{2.5}$ concentration declines in Delhi was greater than in Rome, New York, and Wuhan, being 69.40%, 66.67%, 52.54%, and 49.25%, respectively; PM$_{10}$ concentration decline in Delhi was greater than in Rome, Wuhan, and New York. In comparisons of the air pollutant concentrations during the lockdown period, some concentrations in the resumption phase in cities began to increase, with NO$_2$ concentrations increasing 63.64%, 26.33%, and 5% in Wuhan, Delhi, and New York, respectively. In general, PM$_{2.5}$, PM$_{10}$, NO$_2$, and SO$_2$ concentrations in the four cities decreased during the lockdown period compared with pre-epidemic levels, and concentrations of some pollutants began to increase after the resumption of work and production compared to the lockdown period.

| Name  | Percentage Difference (March 2020 Brightness Minus December 2019 Brightness) | Percentage Difference (April 2020 Brightness Minus January 2020 Brightness) | Percentage Difference (May 2020 Brightness Minus January 2020 Brightness) | Percentage Difference (August 2020 Brightness Minus April 2020 Brightness) |
|-------|--------------------------------------------------------------------------|-------------------------------------------------|------------------------------------------------------------------------|------------------------------------------------------------------------|
| Wuhan | -8.88                                                                   | 13.74                                           | -16.23                                                                | -16.23                                                                |
| Delhi | -17.18                                                                  |                                                 | -4.99                                                                 |                                                 |
| New York | -8.21                                                                 |                                                 | -6.33                                                                  | 3.38                                                                   |
| Rome  | -                                                                          |                                                 |                                                                        |                                                                        |

4. **Discussion**

The spread of COVID-19 in 2020 had significant impacts on socioeconomic, environmental, and human health conditions on a global scale (Sarkodie and Owusu 2021). All countries have implemented control measures to cope with COVID-19, but due to the differences in social environments and natural conditions, the effectiveness of control measures and their impacts on NTL and air quality have been significantly different among countries. The aim of this study was to investigate the impact of COVID-19 control measures on urban lights and air quality. Based on NPP-VIIRS and air quality data, the present study examined the dynamic changes and spatial differences in NTL and air quality in Wuhan, Delhi, New York, and Rome at several spatiotemporal scales, with the aim of comprehensively understanding the responses to pandemic control measures and providing a reference for decision makers in environmental management.

Wuhan lockdown start date (January 23, 2020) is only one week away from the end of January, but Wuhan NTL values declined significantly in January, which was not only affected by the lockdown, but also related to the approach of the Chinese New Year, many people leave the city and return to their provinces (Elvidge et al., 2020). During the lockdown period in Wuhan NTL brightness decreased the most, which was closely related to the effectiveness of national pandemic control measures, voluntary compliance with quarantine policy by citizens, and reduced non-essential production activities. The NTL continued to be dim in Delhi during the resumption phase, this was associated with failure to achieve significant results in pandemic control measures and the increasing number of cases leading to the worsening of the pandemic in rural areas (Sahoo et al., 2020). New York night light levels were decreased significantly during the pandemic and failed to recover quickly, even after the implementation of the resumption of work and production policy. This was caused by the reduction of non-essential production activities during the lockdown period leading to an increase in unemployment, and unemployment rate remained at 23.62% on June 8, 2020, when the first phase of the resumption of work policy was implemented (Chetty et al., 2020), in addition to the case rebound in early summer that slowed down the resumption of work and production progress. The pandemic control measures in Rome contained the COVID-19 spread in the early stages of the outbreak, and the night lights began to brighten after the government implemented a series of measures during the resumption phase. In general, the NTL brightness in four cities across three continents was significantly dimmer during the lockdown period compared to the pre-pandemic period, with large decreases in Wuhan and Delhi indicating that the implementation of pandemic control measures had a significant impact on the production activities of citizens. NTL began to brighten in Wuhan and Rome in the economic recovery phase, but lights in Delhi and New York continued to be dimmed, and this was closely related to the effects of cities’ resumption of work and production (Yin et al., 2021). This suggests that the state of economic recovery can be monitored by NTL to some extent.

The pandemic control measures not only caused changes in urban light levels but also improved urban air quality; this helped to improve the respiratory health of residents and inhibited the spread of the epidemic. PM$_{2.5}$, PM$_{10}$, NO$_2$, and SO$_2$ concentrations decreased significantly during the pandemic in Wuhan, Delhi, New York, and Rome, with the largest declines being in NO$_2$ concentrations as fossil fuel combustion produces the main pollutants, indicating that travel activities of citizens in the four cities were dramatically reduced during the lockdown period. The increase in O$_3$ concentration was mainly due to the reduction in NO$_2$ leading to a lower O$_3$ titration by NO and the reduction in PM pollutant concentrations resulting in enhanced solar radiance conducive to O$_3$.
formation (Sicard et al., 2020; Zhang et al., 2020). NO₂ concentrations in Wuhan, Delhi, and New York increased in the resumption phase, and the magnitude of the decline in Rome decreased, this was closely related to the increase in anthropogenic activities such as traffic, and exhaust emissions after the resumption phase. Improvements in urban air quality due to reductions in human activity during the lockdown period provide a valuable reference for policy makers in post-pandemic environmental management.

The pandemic had not ended in the cities when the NTL and air quality data used for this study were obtained. NTL remote sensing data from high latitudes is affected by cloud cover and stray light, resulting in reduced quality of the raw data (Elvidge et al., 2021).

Fig. 6. The time series variations of monthly mean air quality data during the pandemic (rectangular areas are city lockdown period): (a) Wuhan; (b) Delhi; (c) New York; (d) Rome.
Seasonal variation, differences in image angles, and moonlight contamination also need to be considered when calculating the sum of light (Coesfeld et al., 2018). Therefore, more work could be done to investigate the impact of COVID-19 control measures for the complete period in typical cities around the world after the end of the pandemic. Such research should include (1) using time-series NTL data and air quality to study the socioeconomic impacts of pandemic control measures on countries during the entire pandemic period; (2) implementing more stringent data quality control procedures to improve data accuracy; when higher accuracy Luojia series data or other data are published, we will conduct a similar study using high accuracy NTL data; (3) NTL remote sensing data combined with socioeconomic data to monitor global economic recovery for the post-pandemic era; (4) analysis of changes in air pollutant concentrations during the lockdown period, as this provides an opportunity to study the correlation between COVID-19 and air pollutant concentrations (Naqvi et al., 2021).

5. Conclusions

Based on NPP-VIIRS data and air quality data, the present study investigated the impact of pandemic control measures on NTL and air quality in Wuhan, Delhi, New York, and Rome, where cases were concentrated and spatially representative of conditions at the beginning of the outbreak. From the analysis results, we conclude the following:

(1) The NTL brightness and air quality in Wuhan, Delhi, New York, and Rome changed as a result of the pandemic control measures, and the responses differed between cities.

(2) The NTL in the four cities was dimmed during the lockdown period, especially in Wuhan. After the resumption of work and production, the NTL in Wuhan and Rome become brighter, while the NTL in Delhi and New York failed to recover as quickly. This suggest that the changes in NTL in the four cities were associated with the pandemic control measures.

(3) Wuhan, Delhi, New York, and Rome NTL values during the lockdown period were reduced by 8.88%, 17.18%, 8.21%, and 6.33%, respectively, compared with the pre-pandemic levels, and the lights in commercial centers were significantly dimmer in cities and brightened in some areas of the outer suburbs, indicating that Wuhan and Delhi control measures reduced a large number of non-essential production activities. After the resumption of work and production, the light brightness of Wuhan and Rome increased by 13.74% and 3.38% compared with the lockdown period, while Delhi and New York still decreased by 16.23% and 4.99%.

(4) PM$_{2.5}$, PM$_{10}$, NO$_2$, and SO$_2$ concentrations in the four cities showed decreasing trends during the lockdown period compared to the pre-pandemic period, with the largest decrease in NO$_2$, while the O$_3$ concentrations increased significantly. In the resumption phase, the concentrations of some pollutants began to rise, with NO$_2$ increasing significantly. In general, urban air quality improved and control measures were effective in reducing social activities that produced anthropogenic pollutants, for...
example reducing traffic and industrial production, and Wuhan and Delhi outperformed Rome and New York. As human activity increased during the economic recovery phase, some air pollutant concentrations began to increase, as observed in Wuhan and New York. (5) The spatial scale of the study area revealed that the COVID-19 pandemic has had profound impacts on NTL and air quality in countries around the world.

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Ethical approval

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Author contributions

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Consent to publish

All authors consent to the publication of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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