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Lockdown induced night-time light dynamics during the COVID-19 epidemic in global megacities

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ABSTRACT

The lockdown of cities against the COVID-19 epidemic directly decreases urban socioeconomic activities. Remotely sensed night-time light (NTL) provides a macro perspective to capture these variations. Here, taking 20 global megacities as examples, we adopted the NASA’s Black Marble NTL data with a daily resolution to investigate their spatio-temporal changes. We collected daily NTL products for four weeks (one month) before and after the date of lockdown in each city, which were then summarized as weekly and monthly averaged NTL images after pre-processing (cloud removing, outlier detection, etc.). Results show that NTL overall decreased after the lockdown of cities, but with regional disparities and varying spatial patterns. Asian cities experienced the most obvious reduction of NTL. Particularly, the monthly averaged NTL in Mumbai, India, decreased by nearly 20% compared to one month before. However, there was no significant decline in NTL in European cities. African cities also experienced stable changes of NTL. Spatially, city centers darkened more obviously than the urban periphery. Facing emergencies, NTL data has broad applications in monitoring socioeconomic dynamics and assessing public policies in a near real-time manner.

1. Introduction

The COVID-19 epidemic swept the world and continued to spread. As of April 30th, 2021, the accumulative confirmed cases worldwide exceeded 150 million with more than 3 million deaths (Dong et al., 2020). Without effective medical treatments and vaccine during the initial outbreak of the pandemic, local governments in various countries had to lock down cities and adopt non-pharmaceutical inventions, such as the stay-at-home order, social distancing, and so on (Kraemer et al., 2020; Tian et al., 2020). The lockdown ban and its related inventions were aimed to reduce the frequency of residents’ activities and the intensity of interaction, so as to prevent the spread of the diseases. In practice, the lockdown ban effectively restrained the spread of the pandemic (Jia et al., 2020; Lai et al., 2020). Meanwhile, the lockdown ban significantly changed the rhythm of daily life and social activities of urban residents, bringing unprecedented influences on our natural environments and socioeconomic systems (Straka et al., 2021).

Numerous studies have assessed spatio-temporal changes of natural environments during this epidemic, such as the improved air quality and water quality (Venter et al., 2020; Xu et al., 2021). However, the impact of the lockdown of cities on our socioeconomic systems is more complicated and hidden (Beyer et al., 2020). Taking into account differences in various countries, without objective and consistent indicators, it is difficult to compare the socioeconomic impact on a global level. Benefiting from the development of earth observation technologies, such large-scale changes in socioeconomic activities are enough to be captured by satellites through remotely sensed night-time lights (NTL) (Bennett and Smith, 2017; Elvidge et al., 2017; Li et al., 2019). NTL reflects the dynamics and intensity of socioeconomic activities, which has been widely used in mapping urban areas, estimating population and GDP, and monitoring disasters and conflicts (Chen and Nordhaus, 2011; Chen et al., 2017; Levin et al., 2020; Li and Li, 2014; Li et al., 2015; Ou et al., 2019; Wang et al., 2020).

In the global fighting against the COVID-19 epidemic, NTL data has been used to assess its broad and profound impacts (Small and Sousa, 2021). Generally, the decline in night lights after lockdown was observed worldwide (Jechow and Holker, 2020). Elvidge et al. (2020) found that 82% of the population lived in administrative units where...
lighting dimmed because of the lockdown of cities in China. A similar study in India reported that 87% of the population lived in administrative units that became dimmer after the lockdown compared to one month before (Ghosh et al., 2020). In Africa, 75% of the natural protected areas (tourism economic zones) experienced a decline in light intensity (Anand and Kim, 2021). The correlation between the intensity of dimming in NTL and COVID-19 confirmed cases varies in countries. In China, they were not correlated because all cities adopted lockdown measures almost at the same time after the lockdown of Wuhan, Hubei (Elvidge et al., 2020; Ghosh et al., 2020; Lan et al., 2021). However, higher COVID-19 infection rates were associated with a larger decline in NTL intensity at the district level in India (Beyer et al., 2021). The NTL data was also employed to assess the recovery of cities. Although the NTL recovered somewhat subsequently, but it was still lower than the previous normal (Shao et al., 2021).

These previous studies only analyzed NTL changes in small numbers of cities in a single country, without international comparisons. In addition, the decrease and increase of NTL radiance are widely measured, but the detailed spatial structure in NTL changes within a city is still unclear. In this study, we select 20 global megacities, with more than ten million urban residents there, as examples. These cities have higher population densities and a higher frequency of human movements, making them more vulnerable to infectious diseases (Rocha et al., 2015; Stier et al., 2021). These megacities also adopted lockdown measures in their own countries at an early time. We first use daily NTL products (NASA’s Black Marble) to synthesize monthly and weekly averaged NTL images for 20 sample cities, respectively. Then we compare spatial disparities of NTL changes before and after the lockdown of cities. Particularly, we use the concentric-ring analysis to reveal the spatial structure (center-periphery) of NTL changes. We further quantify the relatively long-term temporal changes in NTL to show its recovery or a second-wave decline.

2. Materials and methods

2.1. Global megacities

A megacity usually refers to a city residing more than ten million people (Demographia, 2020; Nations, 2015). There are more than 30 megacities in the world at present and most of them are located in Asia. Considering the evenness and representativeness of sample cities, we excluded the majority of Asian megacities, particularly megacities in China, such as Shanghai, Guangzhou, Shenzhen, etc. Then, after an initial inspection on the quality of NTL data, cities with poor data quality, such as Lagos and Kinshasa in Africa, were excluded. Thirdly, these cities were indeed locked down for a period in the early outbreak of the COVID-19 epidemic (Hale et al., 2021). Based on the above criteria, our final sample cities are 20 global megacities with their spatial distributions in Fig. 1.

We searched online and checked the specific date of lockdown in each city according to local governmental regulations and news (Table 1). We collected locations of city centers from The Atlas of Urban

Table 1

| Continent | City          | Country     | Lockdown Date |
|-----------|---------------|-------------|---------------|
| Asia      | Beijing       | China       | Jan. 25, 2020 |
|           | Manila        | Philippines | Mar. 15, 2020 |
|           | Seoul         | South Korea | Mar. 22, 2020 |
|           | Karachi       | Pakistan    | Mar. 24, 2020 |
|           | Kolkata       | India       | Mar. 25, 2020 |
|           | Mumbai        | India       | Mar. 25, 2020 |
|           | Bangkok       | Thailand    | Mar. 26, 2020 |
|           | Dhaka         | Bangladesh  | Mar. 26, 2020 |
|           | Ho Chi Minh   | Vietnam     | Apr. 1, 2020  |
|           | Tokyo         | Japan       | Apr. 7, 2020  |
| Europe    | Paris         | France      | Mar. 17, 2020 |
|           | London        | United Kingdom | Mar. 23, 2020 |
|           | Moscow        | Russia      | Mar. 30, 2020 |
| Africa    | Cairo         | Egypt       | Mar. 19, 2020 |
|           | Johannesburg | South Africa| Mar. 26, 2020 |
| North     | Los Angeles   | United States| Mar. 19, 2020 |
| America   | New York      | United States| Mar. 22, 2020 |
| South     | Buenos Aires  | Argentina   | Mar. 20, 2020 |
| America   | Sao Paulo     | Brazil      | Mar. 24, 2020 |
|           | Mexico City   | Mexico      | Mar. 30, 2020 |

Fig. 1. Spatial distributions of 20 global megacities. The population data is from the Demographia website (http://www.demographia.com/). The continental boundary is from the template data of ArcGIS10.6. The monthly composites of NPP-VIIRS night-time light data of February 2020 are used as the base map (https://eopdata.mines.edu/nighttime_light/). Note that the monthly NPP-VIIRS data is only used as the background of global night-time lights and it is not used in further analysis.
Expansion (http://www.atlasofurbanexpansion.org) (Angel, 2016), and then we checked these centers using Google Map and local road networks. We also collected the urban extent of each sample city from the Atlas of Urban Expansion (Xu et al., 2020). The urban extent was used to calculate the averaged NTL intensity within their urban areas.

2.2. Black Marble NTL products and pre-processing

We need an NTL product with a high temporal granularity so as to analyze the dynamic impact of the lockdown ban on urban socio-economic activities. The NASA’s Black Marble product suite is processed on a daily basis within 3–5 h of acquisition, which means it is time-efficient enough to meet the need for real-time monitoring (Román et al., 2020). These daily NTL products are generated with data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) on-board the Suomi National Polar-orbiting Platform (SNPP). The NASA’s Black Marble product suite includes the daily at-sensor top of atmosphere night-time radiance product (VNP46A1) and the daily moonlight-adjusted NTL product (VNP46A2) (Román et al., 2018). Although the VNP46A2 product has a higher quality with further corrections of clouds, atmospheric conditions, etc., but it had not been updated to the lockdown time when we conducted this study.

This study acquired the VNP46A1 product four weeks before and after the date of lockdown, resulting in a period of eight weeks (56 d) of NTL changes for each sample city. These daily NTL products are at a 500 m spatial resolution with 26 scientific data sets layers, which are publicly accessed from the NASA’s LAADS DAAC data center (https://ladsweb.modaps.eosdis.nasa.gov/). We obtained the DNB radiance of the NTL from “DNB_At_Sensor_Radiance_500m” band, and corrected it by other datasets bands. Data pre-processing includes cloud removing and outlier detection. According to the cloud quality flag band, we filtered the DNB radiance and removed pixels with high and medium cloud mask quality. We also removed water background and shadow. After removing clouds, DNB quality flag bands were used to check whether there were abnormal pixels in the image and to adjust moon illumination fractions (Lan et al., 2021; Zheng et al., 2021).

After data pre-processing, we used the daily NTL products to generate monthly and weekly averaged NTL images. We further analyzed spatio-temporal variations of NTL before and after the lockdown ban in these 20 global megacities. The overall workflow is shown in Fig. 2.
2.3. Monthly/weekly averaged NTL images

We calculated monthly/weekly averaged images to make up for data shortages and data gaps resulting from pre-processing (Lan et al., 2021; Shao et al., 2021). For each sample city, we generated a pair of monthly averaged and four weekly averaged NTL images before and after the date of lockdown. The monthly/weekly averaged images are generated pixel by pixel following steps shown in Fig. 3.

For the same location (in red border), there are \( P \) pixels in total. Note that \( P \) equals 28 and 7 for the monthly and weekly NTL images, respectively. We first count the median of all non-empty pixels, and then set the pixel value greater than three times of the median as 0. The remaining non-empty pixels are effective pixels (\( Q \)). If effective pixels account for more than a quarter (\( Q \) greater than 1/4\( P \)), we calculate the mean value of these \( Q \) effective pixels; otherwise, the mean value of this pixel is set to 0. Then, we choose 1000 nW cm\(^{-2}\)sr\(^{-1}\) as the threshold to exclude extremely high DNB radiance. The mean value greater than 1000 is set to 1000; otherwise, the mean value remains unchanged. The number of pixels with DNB radiance greater than 1000 nW cm\(^{-2}\)sr\(^{-1}\) accounts for less than 1% of the entire image. Finally, the steps are repeated for all other pixels with the same location, resulting in the monthly/weekly averaged NTL images. Taking Dhaka, Bangladesh, as an example, the monthly averaged NTL images before and after the lockdown ban are shown in Fig. 4. It clearly shows NTL radiance has decreased after the lockdown ban in Dhaka (the white rectangles).

We further conducted the raster calculation to generate a monthly difference image, so we can investigate spatial disparities of NTL changes within a city. The monthly difference image is defined as formula (1):

\[
\text{Radi}_{\text{Diff}} = \text{Radi}_{\text{After}} - \text{Radi}_{\text{Before}}
\]  

(1)

where \( \text{Radi}_{\text{Diff}} \) is the monthly difference DNB radiance, \( \text{Radi}_{\text{After}} \) is the monthly averaged DNB radiance after the lockdown ban, and \( \text{Radi}_{\text{Before}} \) is the monthly averaged DNB radiance before the lockdown ban.

2.4. Concentric-ring analysis

The agglomeration of population and socioeconomic elements forms the center of the city, which also determines the macro-spatial structure of the city, that is, the center-periphery structure (Guérois and Pumain, 2008). The concentric-ring analysis does well in capturing the center-periphery structure (Guérois and Pumain, 2008). The concentric-ring analysis means dividing urban areas into a series of concentric rings from the city center and analyzing urban dynamics in different rings (Wu et al., 2021; Xu et al., 2019a). We build two types of concentric rings to analyze monthly and weekly averaged NTL images, respectively. The first one is a series of concentric rings with an equal interval of 2 km, which is used for monthly averaged NTL images (Fig. 4). The second concentric rings with four divisions (3 km, 5 km, 10 km, and 20 km) are used to analyze NTL dynamics of weekly averaged NTL images. Some cities are located in coastal areas with irregular shapes, and their multi-rings cover water bodies. In addition, if the city center is located on the edge of the city, its multi-rings cover the nearby cities. Considering influences of the urban form and the location of city centers, we use the urban extent to clip the concentric rings. We focus on NTL dynamics in concentric rings within urban extents (Fig. 4).

We calculate the mean and standard deviations of NTL radiance in concentric rings using the following two formulas:

\[
\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}
\]  

(2)

\[
\sigma_{\text{ring}} = \sqrt{\frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n}}
\]  

(3)

where \( x_i \) is the NTL radiance of pixel \( i \), \( n \) is the number of pixels in the ring, \( \bar{x} \) and \( \sigma_{\text{ring}} \) are mean value and standard deviations of NTL radiance of all pixels in the same ring.

3. Results

3.1. Spatial disparities of NTL changes

The monthly difference NTL images of 20 global sample cities are presented in Fig. 5, which shows spatial disparities of NTL changes after the lockdown of cities. The monthly difference NTL image is the result of monthly averaged NTL images after lockdown subtracting from that before lockdown (Formula (1)). Pixels with negative values experienced dimmed lights, while pixels with positive values got brighter after the lockdown of city. Considering uncertainties in original data and pre-processing, this study defines pixels in the difference image ranging from –20 to 20 as changes with uncertainties. We further calculate the average values and percentage changes of DNB radiance within their urban extents before and after lockdown policies in all sample cities.
We divide 20 sample cities into three categories according to their changes of monthly NTL radiance (Fig. 5, Table 2).  

(1) **NTL-Decreased cities**: The monthly NTL radiance obviously decreased after the lockdown of cities in these 10 cities, including Mumbai, Dhaka, Manila, Karachi, Kolkata, New York, Tokyo, Mexico City, Ho Chi Minh City, and Los Angeles. Some cities like Mumbai, Dhaka, Manila, and Karachi experienced a widespread decline in NTL radiance from central urban to suburban areas. The monthly NTL radiance decreased the most in Mumbai (India) with a nearly 20% decline. In addition, most NTL-Decreased cities are located in Asia.  

(2) **NTL-Scattered cities**: There is no obvious spatial pattern of NTL radiance changes in this category of cities, including Johannesburg, Bangkok, Buenos Aires, Cairo, and Beijing. For instance, NTL radiance decreased in central urban areas in Bangkok, Cairo, and Beijing, but it increased in suburban areas.  

(3) **NTL-Increased cities**: The monthly NTL radiance increased to some extent in this category of cities, including Sao Paulo, Paris, Moscow, London, and Seoul. Although the NTL radiance decreased around the city center in Sao Paulo and Paris, most areas outside experienced an increased NTL radiance. Pixels with increased NTL radiance dominate in Moscow, London, and Seoul. The three European sample cities are all NTL-increased cities.

### 3.2. Spatial structure of NTL changes

We perform the concentric-ring analysis on the monthly NTL difference image with 30 concentric circles at 2-km intervals. Fig. 6 shows the mean and standard deviation of NTL radiance changes in each ring within 60 km from the city center. The mean (black line) of NTL radiance changes is the average of the pixel values in the same ring, and the error bar is one standard deviation of the pixel values in the same ring. Cities in the first two rows in Fig. 6 are NTL-Decreased cities, cities in the third row are NTL-Scattered cities, and cities in the last row are NTL-Increased cities.

The concentric-ring analysis clearly reveals the spatial structure of the NTL radiance changes. Firstly, on the whole, the NTL radiance around the city center reduced the most. The city center is the most intensive area of social and economic activities in the city. The lockdown of the city reduced the concentration of population and the intensity of activities. As a result, the intensity of night lights in the city center experienced the most obvious decline. In several cities like Mumbai, Karachi, Cairo, and Paris, the NTL radiance in the city center dropped by more than 100 nW/cm²/sr. Secondly, changes of the NTL radiance are getting smaller and smaller from the city center to the periphery. The spatial range of significant NTL changes is within 20 km from the city center. Thirdly, changes of NTL radiance varied across cities. For NTL-Decreased cities, NTL radiance declined in varying degrees in different rings and the intensity of decline generally decreased with the distance to the city center. For NTL-Scattered cities (the third row), their averages of NTL changes fluctuated around the horizontal line of 0 (red lines). For NTL-Increased cities (the last row), night lights in Moscow and Sao Paulo limtedly increased around the city center, or even decreased in Paris, while the peak of the increase in lights appears around 15 km to the city center. For the spatial structure of NTL changes in London and Seoul, we provide detailed explanations combining results of their temporal variations (Fig. 7).

### 3.3. Temporal variations of NTL

The temporal variations of weekly averaged NTL radiance four weeks before and after the lockdown of cities are shown in Fig. 7. We calculate the average NTL radiance in different concentric rings (within 3 km, 3–5 km, 5–10 km, and 10–20 km). The light blue area corresponds to four weeks after the lockdown, and the light yellow area corresponds to four weeks before the lockdown. The order of cities in Fig. 7 is the same as that in Table 2.

The temporal variations of NTL reveal its dynamics from a finer time granularity. Firstly, most cities experienced a declined NTL radiance after the lockdown of city. The NTL radiance of Mumbai declined the most. Secondly, the time of responses to the lockdown varied across cities. For instance, the NTL of Manila quickly declined in the first week after the lockdown, while New York’s NTL dropped sharply in the second week after the lockdown. More importantly, the NTL in London and Seoul dropped significantly before the lockdown, which shows that although the government did not adopt a lockdown ban, the people had already taken actions against the COVID-19 epidemic. This can explain why the NTL radiance increased in a large area in London and Seoul in Fig. 5. Thirdly, the varying trends of the weekly averaged NTL radiance in different rings are relatively consistent, verifying the reliability of data preprocessing.
For further analysis, we selected three cities (Beijing, Johannesburg, and New York) and extended the time span to 16 weeks (4 weeks before and 12 weeks after the lockdown). The relatively long-term variations of NTL radiance are shown in Fig. 8. In Beijing, the NTL radiance in different rings slightly increased in the two weeks after the lockdown. The outbreak of the COVID-19 epidemic in China exactly met the Chinese New Year (The Chinese New Year’s Eve was January 24, 2020). The increased NTL radiance in Beijing is closely related to holiday lights. After that, the light continued to decline for four weeks (one month). From the eighth week (mid-March in 2020) after the lockdown, the NTL radiance in Beijing began to increase, showing a recovery of the city. For Johannesburg, the lockdown started on March 26, 2020, and the lockdown period was initially set as 21 days, and then it was extended for another two weeks to April 30. The lighting of Johannesburg was less...
affected by the lockdown. After a slight drop in the first three weeks after the lockdown, it recovered or even slightly exceeded its original level. After the outbreak of the COVID-19 epidemic in New York, the night light experienced two significant declines in the second week and the 10th week after the lockdown of the city.

4. Discussion

The lockdown of cities was widely adopted to fight against the COVID-19 epidemic globally, which changed our natural systems as well as socioeconomic systems. Such a large-scale change in social and economic activities can be captured by satellites. This study took 20 global megacities as examples and investigated spatio-temporal changes of NTL before and after the lockdown using NASA’s Black Marble daily NTL data. Pixels with abnormal values were removed in the pre-processing, so we summarized the daily data into monthly/weekly averaged images to improve the reliability of data analysis. The monthly averaged NTL images were used to analyze spatial disparities of NTL changes. By subtracting one month from another, it is possible to identify areas where lighting either dimmed or brightened. Particularly, we used the

Table 2
Monthly averaged NTL radiance and its changes within urban extents before and after the lockdown.

| Category          | City          | Before Lockdown* | After Lockdown* | Difference# | Change Percent## |
|-------------------|---------------|------------------|-----------------|-------------|-----------------|
| NTL-Decreased cities (10) | Mumbai       | 123.7            | 100.6           | −23.1       | −18.67%         |
|                   | Dhaka         | 82.9             | 69.8            | −13.1       | −15.80%         |
|                   | Manila        | 149.4            | 127.7           | −21.7       | −14.52%         |
|                   | Karachi       | 174.2            | 151.0           | −23.2       | −13.32%         |
|                   | Kolkata       | 107.4            | 98.6            | −8.8        | −8.19%          |
|                   | New York      | 150.1            | 138.4           | −11.7       | −7.79%          |
|                   | Tokyo         | 135.4            | 128.8           | −6.6        | −4.87%          |
|                   | Mexico City   | 233.9            | 223.5           | −10.4       | −4.45%          |
|                   | Ho Chi Minh City | 137.7     | 132.7           | −5.0        | −3.63%          |
|                   | Los Angeles   | 293.8            | 273.5           | −20.3       | −6.91%          |
|                   | Johannesburg | 161.4            | 156.9           | −4.5        | −2.79%          |
|                   | Bangkok       | 146.0            | 144.6           | −1.4        | −0.96%          |
|                   | Buenos Aires  | 306.1            | 303.6           | −2.5        | −0.82%          |
|                   | Cairo         | 183.1            | 183.5           | 0.4         | 0.22%           |
|                   | Beijing       | 123.2            | 127.1           | 3.9         | 3.17%           |
| NTL-Scattered cities (5) | Johannesburg | 234.5            | 243.9           | 9.4         | 4.01%           |
|                   | Bangkok       | 193.7            | 201.9           | 8.2         | 4.23%           |
|                   | Buenos Aires  | 139.7            | 147.8           | 8.1         | 5.80%           |
|                   | Cairo         | 150.5            | 112.2           | 6.7         | 4.15%           |
|                   | London        | 105.5            | 112.2           | 6.7         | 6.35%           |
|                   | Seoul         | 207.0            | 221.3           | 14.3        | 6.91%           |
| NTL-Increased cities (5) | Sao Paulo     | 243.9            | 253.2           | 9.4         | 4.01%           |
|                   | Paris          | 193.7            | 199.1           | 5.4         | 2.79%           |
|                   | Moscow         | 139.7            | 147.8           | 8.1         | 5.80%           |
|                   | London         | 150.5            | 112.2           | 6.7         | 4.15%           |
|                   | Seoul          | 207.0            | 221.3           | 14.3        | 6.91%           |

* The monthly averaged NTL radiance was calculated within the urban extent of each city, and the unit of NTL radiance is nW/cm²·sr⁻¹.
# Difference = After Lockdown−Before Lockdown.
## Change Percent = Difference/(Before Lockdown) × 100%.

Fig. 6. Changes of monthly averaged NTL radiance and its changes within urban extents before and after the lockdown of cities in concentric rings with the distance to the city center. The black line is the mean of changes of NTL radiance in concentric rings. The error bar is one standard deviation of changes of NTL radiance in concentric rings.
concentric-ring analysis to quantify the center-periphery structure of NTL changes. The weekly averaged NTL images were adopted to reveal temporal variations of NTL changes. We further showed a relatively long-term variation of NTL in Beijing, Johannesburg, and New York to show its recovery or a second-wave decline.

We found varying NTL changes in different cities. Generally speaking, night lights in Asian cities weakened more significantly. After the lockdown of Mumbai, India, night lights reduced by nearly 20%. Night lights in European cities were not significantly weakened, and even rose after the city was closed. Since the epidemic had spread to the country or the city, urban residents had reduced their social activities in advance. This can explain why Seoul and London had already seen a decline in NTL in the week before the lockdown. In terms of the spatial structure of NTL changes, the weakening of the lights in the city center is the most obvious. This is mainly because the city center is a dense commercial area. The periphery of the city is generally a residential area, and the reduction of lights is relatively weak in this area (Shao et al., 2021).

Disparities in NTL changes reflect different effects of the lockdown ban in different countries. Further study could investigate the relationship between NTL changes and strictness of lockdown bans (Hale et al., 2021).

This study also has limitations. Firstly, we investigate the spatial disparities and spatial structure of NTL dynamics, without distinguishing the difference among diverse functional areas. A case study in Wuhan, China, found that commercial centers experienced lower NTL radiance values, while residential areas recorded increased levels of brightness after the beginning of the lockdown (Liu et al., 2020). Secondly, this study only adopted NTL data to assess the socioeconomic impact of the lockdown of the city. In the future, multi-source data can be combined to evaluate its impact more comprehensively, such as electricity consumption data, human mobility data, etc. (Bustamante-Calabria et al., 2021; Demirguc-Kunt et al., 2020; Li et al., 2020; Ruan et al., 2020). Lastly, this study selects limited samples; it does not take into account the differences between small and medium cities.

5. Conclusions

This study contributes to quantifying global responses to the COVID-19 epidemic using remotely sensed night-time lights (NTL). We analyzed NTL changes in 20 megacities caused by the lockdown of cities with international comparisons. The NTL generally decreased after the lockdown but with varying regional disparities and spatial patterns. Asian cities experienced the most obvious reduction of NTL radiance, while there was no significant decline in European cities. Spatially, the NTL radiance around the city center reduced the most. The Black Marble daily NTL data has potential applications to monitor urban socioeconomic dynamics for real-time prediction and assessment.

CRediT authorship contribution statement

Gang Xu: Conceptualization, Investigation, Methodology, Writing -
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