Article

Long-Term Impacts of COVID-19 Lockdown on the NO₂ Concentrations and Urban Thermal Environment: Evidence from the Five Largest Urban Agglomerations in China

Ninghui Zhang ^{1,2,†}, Haipeng Ye ^{1,2,3,†} , Ji Zheng ⁴, Xuejing Leng ^{2,5} , Dan Meng ¹ and Yu Li ^{1,2,*}

¹ Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China; zhangninghui21@mailsucas.ac.cn (N.Z.); yehp.19s@igsrr.ac.cn (H.Y.); mengd.18s@igsrr.ac.cn (D.M.)

² College of Resources and Environment, University of Chinese Academy of Sciences, Beijing 100049, China; xjleng_st@rcees.ac.cn

³ Institute of Geomatics, Department of Civil Engineering, 3S Centre, Tsinghua University, Beijing 100084, China

⁴ Department of Urban Planning and Design, The University of Hong Kong, Pokfulam, Hong Kong, China; zhengji@hku.hk

⁵ State Key Laboratory of Urban and Regional Ecology, Research Centre for Eco-Environmental Sciences, Chinese Academy of Sciences, Beijing 100085, China

* Correspondence: liy@igsrr.ac.cn

† These authors contributed equally to this work.

Abstract: Under the threat of COVID-19, many regions around the world implemented lockdown policies to control the spread of the virus. This restriction on both social and economic activities has improved the quality of the environment in certain aspects. However, most previous studies have only focused on the short-term impact of lockdown policies on the urban environment. The long-term effects of lockdown require a more focused exploration and analysis. Thus, five major urban agglomerations in China were selected as the research area; changes in the numerical and spatial distribution of NO₂ concentration and surface temperature during four different lockdown stages in 2019, 2020, and 2021 were investigated to analyze the long-term effects of lockdown policies on the urban environment. The results indicated that the impact of shorter lockdowns was short-term and unsustainable; the NO₂ concentrations increased again with the resumption of production. Compared with air pollutants, thermal environmental problems are more complex. The effect of the lockdown policy was not reflected in the decrease in the area proportions of the high- and sub-high-temperature regions but rather in the spatial distribution of the high-temperature area, which was manifested as a fragmentation and dispersion of heat source patches. In addition to the severity of the lockdown, the impact of the lockdown policy was also closely related to the level of development and industrial structure of each city. Among the urban environments of the five agglomerations, the most affected were the Yangtze River Delta and Yangtze River Middle-Reach urban agglomerations, which had the largest decline in NO₂ concentrations and the most notable fragmentation of heat source patches.

Keywords: urban thermal environment; COVID-19; lockdown; nitrogen dioxide; urban agglomeration

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1. Introduction

Since detection of the first official case of COVID-19 on 31 December 2019 in Wuhan [1], the pandemic has caused an unprecedented global health and socioeconomic crisis [2–4]. This unexpected pandemic has threatened the health of global populations and also caused widespread panic. Simultaneously, humans have been confronted with several noticeable ecological and environmental issues, such as chronic air quality problems and expansions of the regional urban heat island [5–8]. Ambient air pollutants carrying microorganisms make pathogens more invasive to humans and make people more susceptible to pathogens [9].

While people exposed to long-term thermal problems are more likely to suffer from digestive and nervous system diseases [10], environmental problems are associated with an increased risk of death or severe illness among people with COVID-19 infection [10]. The exacerbation of environmental problems may exacerbate the spread of the pandemic [11,12], pose negative effects on health, resulting in increased morbidity and mortality [8,13].

To prevent the spread of COVID-19 in China, the national government first declared a state of emergency and implemented a lockdown policy in Wuhan City on 23 January 2020, restricting the daily activities of approximately 11 million people, including maintaining social distance, restraining economic activities, banning public transportation, and prohibiting private and public gatherings [14,15]. Other cities and countries around the world have followed this strategy to varying extents since February 2020 [16]. According to statistics, lockdown policies were implemented in 194 countries. Lockdowns have not only suppressed the growth rate of COVID-19 cases but also reduced the intensity of human activities. Owing to the decline in traffic and shutdown of intensive industries during the pandemic, there has been a significant reduction in anthropogenic pollutants and heat emissions.

Recently published studies have reported that partial or complete lockdown policies, implemented in response to the pandemic, have improved the air quality of areas, as well as their thermal environments. There has been a significant global reduction in air pollution for a variety of noxious particles and gases [17–19]. The results revealed that, for major urban areas located in Europe (i.e., Madrid, Milan, Paris, and Naples [20]); Asian (i.e., Almaty [21], Baghdad [22], Wuhan [21], Seoul [23], and Hat Yai [24]); and America (São Paulo [25], Peru [26], and New York [27]), there has been substantial associated reductions in NO₂ levels when compared with the previous year, many of the order of 6%–83%. Negative changes in NO₂ concentration were also obvious at the national level, of which the decrease rate was 30% in China [28], 32% in the UK [29], 15–25% in rural India [30], and 36.7% in the United States [31].

On the other hand, anthropogenic heat released by human activities (e.g., human metabolism, building energy consumptions, and vehicle traffic emissions) and solar radiation are two major sources of urban heat [32]. Therefore, the restriction of production and living caused by lockdown policy also had a positive impact on the urban thermal environment. Recent analyses have shown that the temperature of impervious surfaces in the San Francisco Bay Area declined by 3 °C during the lockdown period [33], while the mean land surface temperature of Dehradun decreased by 5.42% on average compared with the two previous years [34]. Coincidentally, there was an evident declining effect on surface urban heat islands in Pakistan and the United Arab Emirates during the pandemic [35,36]. In Wuhan, the extent of the decline was 9.41% of the normalized surface urban heat island compared with normal workdays [37]. Therefore, the lockdown policy notably affected the thermal environment through human anthropogenic heat release.

The lockdown policy undoubtedly had a significant impact on the urban environment. However, most existing research has only compared the performance of the lockdown period with previous years. Therefore, it remains unknown whether the lockdown would influence the urban environment or change resident behaviors for an extended period. The performance after lockdown requires deep exploration and analysis [38].

Comparing the changes in the air pollution and thermal environment from three periods, i.e., before, during, and after lockdown, is a future research direction. For China, lockdown restrictions have loosened with the gradual control of the pandemic. The transition from lockdown to semi-normal life has provided an opportunity to systematically assess the long-term influence of the lockdown on the air quality and thermal environment. The long-term effects of the lockdown policy can be obtained by monitoring the performance of NO₂ and thermal environment at different stages to judge whether the policy only changes people's behavior temporarily or has a more profound impact on people's long-term habits. This study focuses on the long-term phenomenon of the urban environment and clearly showed differences between the three periods, helping to elucidate

whether the COVID-19 lockdown imposed a profound long-term influence and figure out whether lockdown policy change people's long-term habits or just short-term behavior.

NO₂ is a key factor in atmospheric chemistry and is an important precursor for both ozone production and secondary aerosol formation [36]. The land surface temperature (LST), with continuous spatial coverage, has been an important parameter in manifesting urban thermal environments in recent decades [39]. Hence, this study selected NO₂ and night LST data from remote sensing applications as the air quality and thermal environment indices to assess the indirect effect produced by the COVID-19 pandemic in five typical urban agglomerations in China. The study areas include four first-class urban agglomerations recognized by the State Council of China, namely the Beijing–Tianjin–Hebei (BTH), Yangtze River Delta (YRD), Pearl River Delta (PRD), and Cheng-Yu (CY), as well as the hardest-hit region caused by COVID-19, Yangtze River Middle-Reach (YRMR) urban agglomeration. Many studies have documented reductions in air pollutants during the lockdown period in these regions, with reductions in NO₂ ranging from 33% to 61% [28,40]. Besides, there was thermal environment change analysis carried out in some individual cities of urban agglomerations, such as Wuhan [41].

2. Materials and Methods

2.1. Study Areas

This article focuses on the five largest urban agglomerations in China: the Beijing–Tianjin–Hebei (BTH), Yangtze River Delta (YRD), Pearl River Delta (PRD), Cheng-Yu (CY), and Yangtze River Middle-Reach (YRMR). The first four are first-level urban agglomerations recognized by the State Council of China, whereas the YRMR covers the most severely affected areas centered on Wuhan City.

As shown in Figure 1, the BTH, YRD, and PRD are all located on the North China Plain and the Yangtze and Pearl River Deltas, respectively. CY is located in the Sichuan Basin, and the YRMR is located in the middle reaches of the Yangtze River. As regions with the fastest economic development, these five urban agglomerations only account for 10.3% of the total area of China but contributed to 42.9% and 60.2% of the total population and gross domestic product (GDP) in 2020, respectively (Table 1). Rapid urbanization significantly impacts land cover properties, surface heating, and air pollutant emissions [42,43], accompanied by severe urban ecological problems, such as urban heat islands and air pollution [44].

However, during the pandemic, cities in the five urban agglomerations implemented strict control measures to contain the spread of the pandemic; most provinces issued lockdown policies. The shutdown of social and economic activities had a positive impact on the urban environment. From January to June 2020, human activities in China transitioned from a peak to a trough and then gradually recovered.

By comparing the differences before, during, and after the pandemic, these five urban agglomerations can be used as typical representatives to reflect the impact of lockdown policies, analyze the long-term effects of lockdown policies on urban environments, and provide relevant reference information for the governance of and improvements to the urban environment.

Table 1. Socioeconomic statuses of the five most developed urban agglomerations in China in 2020.

Urban Agglomeration	Total Area (km ²), (Proportion)	Core Cities	Total Population(Million), (Proportion)	GDP (Billion USD), (Proportion)
Beijing–Tianjin–Hebei urban agglomeration (BTH)	218,000, 2.3%	Beijing, Tianjin	107, 7.4%	1299.6, 8.3%
Yangtze River Delta urban agglomeration (YRD)	211,700, 2.2%	Shanghai	188.0, 13.0%	3936.1, 25.2%

Table 1. Cont.

Urban Agglomeration	Total Area (km ²), (Proportion)	Core Cities	Total Population(Million), (Proportion)	GDP (Billion USD), (Proportion)
Yangtze River Middle-Reach urban agglomeration (YRMR)	326,100, 3.4%	Wuhan, Changsha, Hefei, Nanchang	105.8, 7.3%	1000.9, 6.4%
Cheng-Yu urban agglomeration (CY)	185,000, 1.9%	Chengdu, Chongqing	86.2, 6.0%	1707.7, 10.9%
Pearl River Delta urban agglomeration (PRD)	56,500, 0.6%	Guangzhou, Shenzhen, Hong Kong	132.3, 9.2%	1461.2, 9.3%

Note: Proportion represents the percentage of urban agglomeration index values for the entirety of China. These statistical data can be obtained from the National Ministry of Housing and Urban-Rural Development of Statistics (<http://www.mohurd.gov.cn/xytj/tjzljshxytjgb/jsfjnj/>; accessed on 15 November 2021).

Figure 1. (a) Locations of the five urban agglomerations. (b–f) Digital elevation models of the five urban agglomerations: Beijing–Tianjin–Hebei (BTH), Yangtze River Delta (YRD), Pearl River Delta (PRD), Cheng–Yu (CY), and Yangtze River Middle-Reach (YRMR).

2.2. Data Collection and Preprocessing

2.2.1. TROPOMI/Sentinel-5p Data (NO₂)

The atmosphere is divided vertically into layers according to temperature changes with height. The troposphere is the layer closest to the ground, the temperature of which decreases with height. Its upper layer is called the tropopause, namely the transition layer between the troposphere and stratosphere. In 1957, the World Meteorological Organization defined the thermodynamic tropopause as the lowest height at which the temperature decline rate is reduced to 2 °C/km or less, and the average temperature decline rate from this height to any height within 2 km above it does not exceed 2 °C/km [45].

Sentinel-5p is a global air pollution monitoring satellite launched by the European Space Agency (ESA) on 13 October 2017. The tropospheric observatory of sentinel-5P (Tropospheric Monitoring Instrument, TROPOMI) is capable of daily coverage for trace gases, such as NO₂, O₃, and SO₂, on a global scale. It is as an air pollution sensor characterized by the highest spatial resolution at present [46,47]. There are three spectral regions and seven bands in TROPOMI that provide measurements of ultraviolet and visible (270–500 nm), near-infrared (675–775 nm), and short-wave infrared (2305–2385 nm) spectral bands. A visible channel (400–496 nm) was used for NO₂ retrieval. The NO₂ inversion results were calibrated by monitoring the NO₂ concentration on the ground to confirm the accuracy.

In this article, the NO₂ product was further processed based on the Google Earth Engine (GEE) platform; we selected reliable pixels and high-quality data with “cloud_fraction” < 0.20 for the “tropospheric_NO₂_column_number_density”. According to the mean calculation of the four stages from 2019 to 2021, a total of 12 NO₂ concentration composite images were generated. The native measurement unit for the tropospheric vertical column of NO₂ was then converted from mol/m² to μmol/m² for further investigation.

2.2.2. MODIS Data (LST)

The Terra and Aqua satellites, both of which carry MODIS sensors, were launched in 1999 and 2002, respectively. The transit times are approximately 15:30 and 1:30 for the Aqua satellite and 10:30 and 22:30 for the Terra satellite, providing four basic observation datasets to explore the thermal environment. The 8-day LST composite products (MYD11A2 product), with a 1-km spatial resolution, were calculated using a generalized split-window algorithm [48,49], which has good agreement with ground satellite observations at an error of <1 K in most cases [48,50].

The generalized split-window algorithm (GSW) is the most commonly used method for LST retrieval from satellite data [51]. There are 36 spectral channels with wavelengths ranging from 0.4 to 14.4 μm (2 bands at 250 m, 5 bands at 500 m, and 29 bands at 1-km spatial resolution) in the MODIS data. The MYD11A2 LST product was calculated as follows:

$$LST = a_0 + (a_1 + a_2 \frac{1 - \bar{\epsilon}}{\bar{\epsilon}} + a_3 \frac{\Delta\epsilon}{\bar{\epsilon}^2}) \frac{T_{31} + T_{32}}{2} + (a_4 + a_5 \frac{1 - \bar{\epsilon}}{\bar{\epsilon}} + a_6 \frac{\Delta\epsilon}{\bar{\epsilon}^2}) \frac{T_{31} - T_{32}}{2} \quad (1)$$

where T_{31} and T_{32} represent the top-of-the-atmosphere (TOA) brightness temperatures of MODIS channels 31 and 32, respectively, $\bar{\epsilon}$ and $\Delta\epsilon$ represent the mean and differences in emissivity from channels T_{31} and T_{32} , respectively, and a_i is a coefficient of the GSW algorithm.

Considering that the daytime surface temperature is strongly affected by solar radiation, while the nighttime surface temperature is more closely related to human activities [52]; the nighttime LST was selected as the basic dataset to measure the thermal environment. The night LST data were obtained based on the GEE platform using the QC_NIGHT band for image quality control to ensure an average LST error of <1 K. The temperature was then converted from Fahrenheit to Celsius. Similarly, according to the mean calculation of the four stages from 2019 to 2021, a total of 12 LST composite images were generated.

2.3. Methods

2.3.1. Calculation of NO₂ Time Effect

To determine the impact of the lockdown on the urban environment, other factors that also contributed to changes, such as interannual trends, should be excluded. Hence, this article defined the study scope from 2019 to 2021, with the implementation of the 2020 lockdown policy node as a reference to obtain the four stages (i.e., pre-lockdown, lockdown, partial-lockdown, and post-lockdown). Hence, there were 12 time stages in the pre-pandemic (2019), in-pandemic (2020), and post-pandemic (2021) years, which were used to calculate the time-varying effects of the air quality and thermal environmental issues:

$$\text{Change rate (\%)} = ((X_t - X_{t-1}) / X_{t-1}) * 100\% \quad (2)$$

where X_t is the NO₂ concentration for the selected periods, and t represents year 2020 or 2021.

2.3.2. Reclassification of LST

Each urban agglomeration was considered as a single study area, and the mean-standard deviation method was adopted to quantitatively classify the temperature. The standard deviation reflected the extent of deviation from the average temperature, whereas the combination of mean and standard deviation reflected the level of different dynamic temperatures. Based on this theory, the temperature images in the study area were divided into five categories: high-temperature, sub-high-temperature, medium-temperature, sub-low-temperature, and low-temperature regions. Low-temperature areas were considered cold sources, whereas high-temperature areas were considered heat sources. Table 2 lists the specific classifications. Table 2 lists the specific classifications, where T represents the temperature value of pixel, and p and std represent the mean and standard deviation of temperature value of all pixels, respectively.

Table 2. Classification of the thermal environment landscape.

Category	Abbreviation	Description
Low	L areas	$T \leq p - 1.5std$
Sub-low	S-L areas	$p - 1.5std < T \leq p - 0.5std$
Median	M areas	$p - 0.5std < T \leq p + 0.5std$
Sub-high	S-H areas	$p + 0.5std < T \leq p + 1.5std$
High	H areas	$T > p + 1.5std$

2.3.3. Quantification of LST Patch Aggregation

To better describe the spatiotemporal patterns of the thermal environment, this study selected four landscape metrics to analyze the aggregation of heat sources. Table 3 lists the details of the indices [53]. The values of the number of patches (NP), aggregation index (AI), and cohesion index (CI) metrics were obtained using the Fragstats v4.2 software at the class level.

Table 3. Metrics used to measure the aggregation of heat sources.

Metrics	Formula	Description
Number of patches (NP)	$NP = n_i$ [54] n_i = number of patches in the landscape of patch type (class) i .	Number of patches: more patches indicate more fragmentation.

Table 3. Cont.

Metrics	Formula	Description
Aggregation Index (AI)	$AI = \left[\sum_{i=1}^m \left(\frac{g_{ij}}{\max g_{ij}} \right) P_i \right] (100) \quad [54]$ <p> g_{ij} = number of similar adjacencies (joins) between pixels of patch type (class) i based on the single-count method. $\max g_{ij}$ = maximum number of similar adjacencies (joins) between pixels of patch type (class) i based on the single-count method. </p>	Aggregation of the landscape: a larger value indicates a higher extent of aggregation.
Cohesion Index (CI)	$CI = \left[1 - \frac{\sum_{i=1}^n P_{ij}}{\sum_{i=1}^n P_{ij} \sqrt{a_{ij}}} \right] \cdot \left[1 - \frac{1}{\sqrt{Z}} \right]^{-1} \cdot (100) \quad [54]$ <p> p_{ij} = perimeter of patch ij in terms of number of cell surfaces. a_{ij} = area of patch ij in terms of the number of cell surfaces. n = total number of cells in the landscape </p>	Dispersion and interspersed of the landscape: a higher value reflects higher clustering.

3. Results

3.1. Temporal Variation in NO₂

During the COVID-19 outbreak (2020), owing to the implementation of control measures, the concentration of NO₂ was significantly lower than the 2 years before and after the pandemic (Figure 2). The average NO₂ concentrations of the entire study area in 2020 decreased by 52.64%, 25.00%, and 5.30% during pre-lockdown, during-lockdown, and partial-lockdown periods compared to 2019. As the spread of the epidemic was controlled, the lockdown policy eased such that the difference in NO₂ concentration between the 2019 and 2020 in the post-lockdown periods was not as notable as before. In 2021, with the full resumption of human activities and industrial production, no significant changes were observed, and the NO₂ concentration appeared to return to its original level.

To reflect the temporal variation of NO₂ in the five urban agglomerations, Figure 2 shows the average concentrations corresponding to the different stages in each urban agglomeration from 2019 to 2021. The NO₂ concentration decreased significantly in the outbreak year (2020), especially during the lockdown period. Among the study areas, the NO₂ concentrations in the YRD, YRMR, and PRD decreased by more than 50% to 58.96%, 54.14%, and 52.94%, respectively. This phenomenon reveals that the degree of urban development and severity of the pandemic jointly affected environmental improvements resulting from the lockdown policy.

In the post-lockdown stage, the NO₂ concentrations were almost identical to the pre-pandemic levels. The NO₂ concentrations returned to their original emissions levels in response to the resumption of human activities. Therefore, in the partial-lockdown and post-lockdown stages, the NO₂ concentrations in 2021 were almost identical to those in 2019. However, in the BTH and CY agglomerations, the air quality during the pre-lockdown stage deteriorated significantly compared with the 2 previous years, which was caused by retaliatory production and consumption after the pandemic was under control. This indicates that, for a certain period, the lockdown policy changed daily human behavior, not their habits. The impact of the lockdown on daily lifestyle changes, such as working from home, online learning, and online socializing, which displayed decreasing mobility and economic activity, were only short-term lifestyle under restriction measures. Although the lockdown policy effectively improved the air quality, its influence was short-term and unsustainable.

Figure 2. Temporal changes in the NO₂ concentrations. (a) Entire study area, (b) BTH, (c) YRD, (d) YRMR, (e) CY, and (f) PRD.

We note that, except for the significant reduction in the during-lockdown stage of 2020, the overall pattern of each urban agglomeration during each stage of each year still showed a downward trend. The NO₂ concentration was the highest in the pre-lockdown stage and lowest in the post-lockdown stage. The concentration of the former was almost two-fold higher than that of the latter, which indicates that changes in the annual stage of each urban agglomeration were basically identical. This also reflected that NO₂ was closely related to the intensity of human activities, especially those affected by coal burning during the warm season.

3.2. Temporal Variation in LST

Based on changes in the area proportions of the S–H and H temperature regions in the entire study area (Figure 3), we found that the values of the temperature regions remained in a relatively stable state. Before, during, or after the pandemic, the proportion of the middle-and high-temperature regions during the four different time stages was >28%. Additionally, the thermal environment also showed a certain annual temporal variation, with a slight upward trend each year. This indicates that improvements to the thermal environment were more difficult than improving the air pollutant situation. The reduction in anthropogenic activity in terms of alleviating the heat island problem was less effective than expected.

Figure 3. Changes in the area proportions of the S–H and H temperature regions. (a) Entire study area, (b) BTH, (c) YRD, (d) YRMR, (e) CY, and (f) PRD.

However, compared with the stage variations across the entire region, no evident rule was observed with respect to the change in individual urban agglomerations, either from interannual or stage perspectives. Among the five study areas, the thermal environment problem was more serious in the BTH and YRD. Regardless of the period, the proportion of high-temperature areas was >25%. Based on the proportion of high-temperature areas, the lockdown policy did not improve the thermal environment. This phenomenon also reflects the fact that the thermal environment is a complex system. The overall situation is closely related to changes in the radiation energy and energy states caused by different land cover types.

3.3. Spatial Pattern Analysis of NO₂

Considering that the distribution of heavily polluted area caused by NO₂ was conspicuously aggregated, the change in NO₂ before and after lockdown policy implementation was analyzed in the high-value NO₂ areas in each urban agglomeration during the 2019 pre-lockdown stage (Figure 4). NO₂ was mainly concentrated to the south of the BTH: Shijiazhuang, Xingtai, and Handan were the most prominent regions. In the YRD, NO₂ was mainly aggregated in the north and west, categorized as two areas, i.e., an eastern region, as represented by Suzhou and Shanghai, and a northwestern region, as represented by Xuzhou and Huaibei. However, the high NO₂ areas in the YRMR were scattered and mainly concentrated in the capital and industrial cities. Chengdu and Chongqing had the highest NO₂ concentrations in the CY. In the PRD, NO₂ was mainly distributed in the center of the bay, including Zhongshan, Jiangmen, Shenzhen, Dongguan, and Hong Kong.

Figure 4. Map of NO₂ concentrations in the pre-lockdown stage (1 January to 22 January) of 2019. (a) Entire study area, (b) BTH, (c) YRD and YRMR, (d) CY, and (e) PRD.

Figure 5 shows the distribution of the differences in the NO₂ concentrations during the lockdown period between 2020 and 2019, 2021 and 2020, and 2021 and 2019. The areas with notable fluctuations corresponded to the areas with high NO₂ values. In contrast,

the changes in the values of the rest of the region were characterized by a small range of normal fluctuations. This indicates that the decline in the overall NO₂ concentration was mainly due to a few major cities. The YRMR, YRD, and PRD were the most affected areas, because the amplitude of the NO₂ change exceeded 20 $\mu\text{mol}/\text{m}^2$.

Figure 5. Map of NO₂ concentrations in the during-lockdown stage (23 January to 23 February) of 2019. (a) NO₂ concentration of 2020 minus NO₂ concentration of 2019, (b) NO₂ concentration of 2020 minus NO₂ concentration of 2021, and (c) NO₂ concentration of 2021 minus NO₂ concentration of 2019.

During the lockdown period in 2020, most areas in the five urban agglomerations showed a slight increase compared with 2019, whereas high-value NO₂ areas showed a significant decline. In the BTH region, Baoding, Shijiazhuang, and Xingtai showed a series

of regional declines. In the YRMR, Wuhan and Xiaogan showed a large-scale decline, while Nanchang, Changsha, and other cities also showed a small-scale decline centered on a certain point. In the YRD, there was a decrease in the NO₂ concentration in the Shanghai–Suzhou–Zhenjiang–Nanjing–Chuzhou cluster. The CY was not significantly affected; only Chengdu and Chongqing showed a small degree of decline. In the PRD, the NO₂ concentration in the circular contiguous area, as formed by Foshan, Jiangmen, Zhongshan, Dongguan, and Shenzhen, decreased significantly, where Foshan and Guangzhou had the largest areas of the change areas.

In 2021, with the pandemic under control, the areas where NO₂ had previously declined due to the lockdown policy experienced a rebound; a decrease at a specific location in 2020 corresponded precisely to an increase at that same location in 2021. We note that the NO₂ in some cities characterized by non-notable changes had a significant increase, e.g., Beijing, Tianjin, Tangshan, and Qinhuangdao in the BTH region, as well as Chengdu and Chongqing in the CY region. However, the areas in Hubei Province most affected by the pandemic characterized by the most notable improvements in the air quality during the lockdown stage, such as Wuhan and Xiaogan, had no observable rebound effect with respect to NO₂ in 2021.

By comparing the data for 2019 and 2021, it was observed that the overall NO₂ increase in the BTH and CY was due to the influence of Tianjin, Tangshan, Qinhuangdao, Chengdu, and Chongqing. These cities were not severely affected during the lockdown but had a significant increase in their NO₂ emissions. Although the NO₂ in other urban agglomerations showed a rebound trend, as the high-value area did not recover to its original level, the overall level of NO₂ showed a downward trend compared with that in 2019.

The NO₂ distribution under the influence of the pandemic was closely related to the intensity/duration of the lockdown and the industrial structure of the city; highly industrialized cities with high activity intensities were more affected. Wuhan and Xiaogan in the YRMR, the hardest hit areas in the pandemic, had the most stringent lockdown policies, resulting in the most notable reduction in anthropogenic NO₂ emissions. The YRD, which is adjacent to the YRMR, may have been affected by trade; thus, industrial NO₂ emissions also decreased significantly. In the BTH region, shutdowns under the lockdown policy significantly improved the air quality in most industrial cities of Hebei Province. The sudden increase in the NO₂ concentrations in Chengdu, Chongqing, Beijing, and Tianjin may have resulted from the impact of industrial relocation caused by the disruption of production activities in other regions.

3.4. Thermal Environment Spatial Pattern Analysis

Except for the proportion of the S–H and H temperature areas, the distribution mode of the heat source was also related to thermal comfort. In the previous discussion of this article, there was no notable correlation between the lockdown policy and overall proportion of heat sources. Except for the proportion of the S–H and H temperature areas, the distribution mode of the heat source was also related to thermal comfort. Therefore, a simple analysis of the numerical changes in the heat source area cannot fully reflect the impact of the lockdown policy. Figure 6 shows the spatial distribution of the different temperature categories during the in the during-lockdown phase over three years. We investigated whether the reduction in human activities, including factory closures and traffic restrictions, had an impact on the thermal environment of spatial distribution of thermal environment.

Figure 6. Maps of the different temperature regions for each class level in the during-lockdown stage. (a–c) the NO₂ concentration of BTH in each year, (d–f) the NO₂ concentration of YRD in each year, (g–i) the NO₂ concentration of YRMR in each year, (j–l) the NO₂ concentration of CY in each year, and (m–o) the NO₂ concentration of PRD in each year.

Generally, the heat source and the cold source areas for all of the urban agglomerations were mostly distributed in the south and north, respectively, which was mainly affected by the climate rule under the difference in latitude. No matter in which year, the H patches were surrounded by the S–H areas, which proved that the distribution of temperature has a certain continuity. In 2019, the graded centers of the heat island intensity in the

urban agglomerations showed “contiguous heat island centers, which are connected to form bands of high temperature zones, especially in YRD and YRMR. However, the spatial distribution characteristics of heat source in the other three urban agglomerations were more scattered with less numbers of patches.

The thermal environment of the BTH region did not change significantly between 2019 and 2020. However, in 2021, the H areas swallowed the S–H areas region in the southwest, and a longitudinal distribution of heat sources appeared. We noted that, for the CY, large heat sources appeared in the southern direction in 2019. In 2020, the heat source area in the CY shifted to the left with an expansion trend; the location of the heat source returned to its original position by 2021. For the PRD, the H areas continuously engulfed the surrounding S–H areas during the study period.

In conclusion, the spatial distribution changes of BTH, CY, and PRD were not significant during the lockdown period in 2020. Although the H areas of CY have expanded to some extent and have a tendency to shift westward, the heat sources were still located in the southern part of the entire urban agglomeration. For PRD, the heat source patches were enlarged, but the location of the main areas remained unchanged. The three urban agglomerations mentioned above were less affected by the epidemic, i.e., shorter lockdown periods and more lenient lockdown policies. The reason for the change in these agglomerations was likely due to climate influences.

However, the YRD and YRMR, i.e., the areas most affected by the pandemic, showed notable changes in their thermal environments (Figure 6). During the lockdown period, the high-temperature patches with a high contiguity and concentration in the YRD and YRMR were significantly fragmented and dispersed, which lasted until 2021. The distribution of the cold sources appeared to be more stable and less changeable than those of the heat sources because these areas corresponded to areas of industrial underdevelopment characterized by a small degree of change in the human activities. To better understand the spatiotemporal distribution of the thermal environment, our analysis was mainly aimed at the aggregation of patches in the heat source region (Table 4).

Table 4. Landscape metric values for the heat sources.

Year	NP	CI	AI
2019	1739	98.65	84.27
2020	3887	92.50	74.38
2021	2332	96.47	81.20

Table 4 shows the different landscape metrics values of the lockdown stage for each year; it illustrates that the NP of the heat sources was highest, and the values of CI and AI were lowest in 2020, which means the lockdown policy reduced the connection degree of the high temperature region by fragmenting and dispersing heat source patches. The heat source region dominated by a single center gradually evolved into multi-center modes.

4. Discussion

To stop the spread of COVID-19 pandemic, the Chinese government implemented a series of policies including the shutdown of non-essential businesses, mandating social distancing, and the prohibition of large gatherings. The lockdown measures caused non-negligible influences on the air pollution and the anthropogenic heat emissions. This paper analyzed the spatiotemporal patterns and changes of NO₂ concentration and thermal environment during the four lockdown periods of five urban agglomerations, since the first-level public health emergency response was activated in China.

Analysis of the spatiotemporal variations of the air quality in the study areas indicated that the change of NO₂ concentration presented highly time consisting with the lock-down policies. Once the lockdown policy was implemented, the NO₂ concentration showed a significant reduction. When the lockdown policy was eased, the NO₂ concentration returned to its normal level compared to previous years, which was consistent with the

results of relevant studies in other areas, except China [55]. Compared with 2019, satellite observations around BTH, YRD, YRMR, CY, and PRD showed a 47.63%, 58.96%, 54.14%, 37.89%, and 52.94% drop in the concentration of NO₂, which was higher than most of other regions. For example, Khurram Shehzad assessed NO₂ in New Delhi and Mumbai and discovered a 40–50% reduction in NO₂ in 2020 compared to the same dates of 2019 [56]. Berman and Ebisu recorded a 26% decline of the NO₂ concentration in the continental United States [57]. In California, NO₂ declined 38% during the COVID-19 pandemic compared to historical years [55]. The drops in NO₂ were more significant in the five urban agglomerations than China overall (16%), which could be attributed to the influence of the lockdown policy that was closely related to the level of urban development and industrial structure, while the study areas were the most developed urban areas in China [58].

For the thermal environment, previous published studies mostly focused on the average land surface temperature or mean intensity of surface heat island. Bikash Ranjan Parida conducted that land surface temperature decreased by 1 to 2 °C over Europe and North America by implementing a lockdown policy. The mean intensity of daytime SUHI in the Middle East during the lockdown period showed a decreased trend, especially in small metropolitans (e.g., Jeddah, Beirut, Muscat, and Makkah) [59]. In Gauteng Province, South Africa, the LST and surface urban heat island intensity were much lower compared to those of the previous year [60]. However, considering that heat source area plays the most important role in the urban thermal environment, this study took the spatial distribution and area proportion of the high temperature area as the key research object. The results showed that the distribution of heat source patches changed significantly during lockdown period, showing more decentralized and fragmented. This suggested that a simple analysis of the value change of the temperature is not enough; hence, the further exploration of the spatial distribution characteristics of the thermal environment is essential.

This study has its limitations. The change of the urban environment during the COVID-19 lockdown cannot only be attributed to restrictive measures; other factors, such as weather and socioeconomic variables also matter. The research did not take these extra factors into consideration. Therefore, further studies that conduct a quantified analysis of the weather and socioeconomic impacts on the urban environment are desirable. In addition, comparison studies across regions with different levels of urbanization are recommended.

5. Conclusions

According to a previous study, transport (35%), industry (35%), and power generation (19%) are the main producers of Chinese NO_x emissions [61]. Affected by strict Chinese lockdown policies, significant declines in the NO₂ concentrations were observed in the study areas during the outbreak year of the pandemic (2020), especially in the during-lockdown period (23 January–23 February). However, our findings suggest that improvements to the air quality in most regions are short-term and unsustainable. The NO₂ concentration increased again rapidly with the resumption of production. Although production, living, and movement were restricted for a certain period, there has not been a change in the daily habits of society.

Compared with NO₂, variations in the urban thermal environment were substantially more complex. There was no similar declining variation pattern in the high- and sub-high-temperature area proportions during the lockdown period of the pandemic. The effect of the lockdown policy did not reflect the changes in the heat source areas; rather, they were mainly reflected in the distribution of the heat source. By calculating the thermal landscape metrics, the results showed that the values of the CI and AI were the lowest in 2020, which indicated that the lockdown policy reduced the connection degree of the high-temperature region by fragmenting and dispersing heat source patches.

Among the five urban agglomerations, the most notable urban environmental changes were detected in the YRMR and YRD. In terms of the air pollution, the NO₂ concentration in the YRD and YRMR decreased by >50%, reaching 58.96% and 54.14%, respectively. Additionally, the NO₂ concentrations in the YRD and YRMR did not rebound to their

original levels after the end of the lockdown policy but remained at a lower concentration. In terms of the urban thermal environment, by analyzing the landscape patches of the heat source, we observed that heat source patches originally concentrated in the southern region spread to other regions during the lockdown stage in 2020 in both the YRMR and YRD. Meanwhile, the fragmentation and dispersion extent of the heat source patches were also the most prominent among the five urban agglomerations.

In addition to the difference in the strictness of the lockdown policies caused by the severity of the pandemic, the impact of the lockdown policies was closely related to the level of urban development and the industrial structure. Changes in the NO₂ concentrations of the entire urban agglomeration were mainly caused by several major cities. Highly developed cities with large populations and intensive human activities, such as Changsha and Nanchang in the YRMR; Shanghai, Suzhou, and Nanjing in the YRD; and Shenzhen and Hong Kong in the PRD, experienced a large decrease in NO₂ emissions owing to the lockdown policy. Industrial cities with relatively high proportions of secondary industries, such as Baoding in the BTH; Zhenjiang and Chuzhou in the YRD; and Foshan, Dongguan, and Zhongshan in the PRD, exhibited a significant reduction in NO₂ emissions due to suspended industrial production during the pandemic period.

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