Impact of COVID-19 restrictions on air quality and surface urban heat island effect within the main urban area of Urumqi, China

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RESEARCH ARTICLE

Abstract
The outbreak of coronavirus in 2019 (COVID-19) posed a serious global threat. However, the reduction in man-made pollutants during COVID-19 restrictions did improve the ecological environment of cities. Using multi-source remote sensing data, this study explored the spatiotemporal variations in air pollutant concentrations during the epidemic prevention and control period in Urumqi and quantitatively analyzed the impact of different air pollutants on the surface urban heat island intensity (SUHII) within the study area. Urumqi, located in the hinterland of the Eurasian continent, northwest of China, in the central and northern part of Xinjiang was selected as the study area. The results showed that during COVID-19 restrictions, concentrations of air pollutants decreased in the main urban area of Urumqi, and air quality improved. The most evident decrease in \( \text{NO}_2 \) concentration, by \( 77 \pm 1.05\% \) and \( 15 \pm 0.98\% \), occurred in the middle of the first (January 25 to March 20, 2020) and second (July 21 to September 1, 2020) COVID-19 restriction periods, respectively, compared with the corresponding period in 2019. Air pollutant concentrations and the SUHIIs were significantly and positively correlated, and \( \text{NO}_2 \) exhibited the strongest correlation with the SUHIIs. We revealed that variations in the air quality characteristics and thermal environment were observed in the study area during the COVID-19 restrictions, and their quantitative relationship provides a theoretical basis and reference value for improving the air and ecological environment quality within the study area.

Keywords Surface temperature · Urban heat island intensity · Pollutant concentration · TROPOMI · Sentinel-5P

Introduction
The global spread of coronavirus 2019 (COVID-19) has not only threatened human life, but also caused economic recessions and soaring population mortality globally (Alqasemi et al. 2021; Ali et al. 2021). Many countries adopted strict prevention and control measures to reduce the spread of COVID-19, and studies showed that stringent control measures temporarily reduced the human-induced emission of air pollutants (El Kenawy et al. 2021; Li et al. 2020; Xin et al. 2021). Atmospheric pollutants (PM\(_{2.5}\), NO\(_2\), CO, and SO\(_2\)) contain many hazardous materials which destroys the ozone layer, produces corrosive acid rain, and accelerates global warming and also cause human and biological poisoning and death (Lin et al. 2017). NASA and the European Space Agency reported that the NO\(_2\) concentrations in North America and Europe were reduced by 65%, and the PM\(_{2.5}\) and NO\(_2\) concentrations in the UK, France, and Germany were both reduced by 45% in 2020 compared with the corresponding period in 2019 (Chen et al. 2020; Karuppasamy et al. 2020). Copernicus Atmosphere Monitoring Service data showed that China’s NO\(_2\) concentrations for the first half of 2020 were 35–45% lower than the average concentrations within the corresponding period over the preceding 5 years. Otmani et al. (2020) used Sentinel-5P remote sensing data and measured data to reveal the significant improvement in air quality and significant decline in air pollutant concentrations in major Iranian cities during the COVID-19 outbreak control period. The air quality in Wuhan, China, was also significantly improved during the COVID-19 prevention and control periods, and the
concentrations of PM$_{2.5}$, NO$_x$, SO$_2$, and CO were reduced by 35%, 47%, 11%, and 30%, respectively. There were also large reductions in PM$_{2.5}$ and CO within the suburbs of urban areas. It is evident that the global stringency measures employed resulted in reductions in air pollutant emissions and diminished the regional transport effects of air pollutants (Zheng et al. 2020). However, although many studies have shown notable decreases in the concentrations of major air pollutants and improvements in air quality during the epidemic prevention and control periods, they did not have evidence of changes in the air pollutant concentrations during such periods and determined that the concentrations of some air pollutants increased by nearly 20% compared with the normal period (Li et al. 2020). Therefore, studying changes in air pollutant concentrations and air quality during the strict epidemic control periods is a focus of current research in atmospheric and environmental sciences, and epidemic control has provided a natural laboratory for these studies.

The urban heat island (UHI) effect causes severe weather to damage the atmospheric environment, resulting in secondary disasters which affect human lives and endanger human health (Moradi et al. 2018). Anthropogenic air pollutants and heat emissions play an important role in urban temperature increases, and a reduction in air pollutant concentrations may weaken the UHI effect (Dantas et al. 2020; Kerimray et al. 2020; Ranjan et al. 2020). In this respect, Liu et al. (2022) analyzed Moderate Resolution Imaging Spectroradiometer (MODIS) surface temperature and surface observation data and determined that in 2020, the surface urban heat island intensity (SUHII) decreased significantly in more than 300 cities in China compared to 2017–2019, with declines in intensity of surface urban heat island during the day and intensity of surface urban heat island at night of 0.25 °C and 0.39 °C, respectively. However, most current research has focused on assessing air quality during the epidemic prevention and control period, while studies analyzing the effects of air pollutants on the urban SUHII and the causes of abnormal changes in SUHII are rare. In addition, the study area is an important city in western China, surrounded by mountains on three sides with complex terrain and dry climate. The comprehensive factors such as industrial and agricultural structure, urbanization, and pollutant discharge in the study area resulted in certain particularity and representativeness in the study area. In 2020, two COVID-19 outbreaks and subsequent strict control measures were implemented in Urumqi, China. According to Urumqi’s regulations on the level of response to epidemic prevention and control, January 25 to March 20, 2020, was the first strict epidemic prevention and control period, March 21 to July 20 was the recovery period, and July 21 to September 1, 2020, was the second period of strict prevention and control of the epidemic. This study used 2020 as the outbreak period in the study area and 2019 as the normal reference year to conduct related research. During the epidemic prevention and control period, traffic flow significantly reduced, and at times, no vehicles passed, which provided a basis for studying the impact of traffic flow changes on air quality.

This study employed multi-source remote sensing data to assess the spatiotemporal characteristics of air pollutant concentrations in Urumqi during the COVID-19 restriction periods and their potential impact on the UHI effect. We also investigated whether improvements in air quality weakened the UHI effect in the study area. The results provide a theoretical basis for research on urban air pollution prevention and control, air quality improvement, and studying the urban thermal environment in the northwestern arid zone of China.

**Study area and data**

**Study area**

Urumqi (42°45′32″–44°08′00″N, 86°37′33″–88°58′24″E), located in the hinterland of the Eurasian continent, is surrounded by mountains to the east, south, and west (with high terrain in the southeast and low terrain in the northwest). It is situated at an altitude of 376–4900 m, with an average altitude of 800 m in the main city (Sun et al. 2022). Urumqi is characterized by a mid-temperate continental arid climate, with average annual precipitation of 236 mm and average temperatures of 25.7 °C in July and August and −15.2 °C in January (Zhong et al. 2022). Urumqi is the capital of the Xinjiang Uygur Autonomous Region and the political, economic, and cultural center of Xinjiang. Urumqi comprises seven districts and one county (Tianshan District, Shiyibake District, Xinshi District, Shuimogu District, Toutunhe District, Dabancheng District, Midong District, and Urumqi County), and the population and key industrial areas are concentrated in the Tianshan, Shiyibake, Xinshi, Toutunhe, and Shuimogu Districts (Fig. 1). By 2018, the urbanization rate in Urumqi had reached 90.2%, and the urban built-up area covered 365.88 km$^2$ (Shi et al. 2021). Urumqi is an important area for China’s opening to the west and associated exchanges. It has unique geopolitical and locational advantages, and its position and role in the economic development of western China and Central Asia are increasing (Li et al. 2021).

**Data and data processing**

The MOD11A2 dataset was selected to evaluate land surface temperature (LST) and SUHII in the study area because it provides an absolute error of ±1 K (Gow et al. 2016; Pablos and Martinez-Fernandez. 2016). In this study, daytime surface temperature data for every 8 days between 2018 and 2020 were extracted from MOD11A2.
and processed to obtain monthly and annual average surface temperatures. The MCD19A2 product is a terrestrial aerosol optical depth (AOD) dataset produced using MODIS Terra combined with Aqua, and it employs the Multi-angle Implementation of Atmospheric Correction (MAIAC) algorithm (Mao et al. 2021). These data have been used to monitor ground-level PM2.5 concentrations (Zhou et al. 2021). In this study, the AOD daily product data in the blue band (0.47 μm) of MCD19A2 from 2019 to 2020 were used, owing to the high accuracy of the AOD retrieved from this band (Jia et al. 2020). Sentinel-5P, a global atmospheric pollution monitoring satellite launched by the European Space Agency on October 13, 2017, carries the Tropospheric Monitoring Instrument (TROPOMI) to effectively observe trace gas components in the atmosphere globally and provide important indicators, such as NO₂, O₃, SO₂, HCHO, CH₄, and CO, which are closely related to anthropogenic activities (Cheng et al. 2019; Li et al. 2019). TROPOMI is currently the world’s most advanced atmospheric monitoring spectrometer, possessing the highest spatial resolution and an imaging resolution of 7 × 3.5 km (Veefkind et al. 2012). This study selected daily product data of NO₂, SO₂, and CO concentrations between 2019 and 2020 with TROPOMI tertiary products as indicators for evaluating air quality in the study area. The product quality and cloud cover control dataset were fully employed to conduct the NO₂, SO₂, and CO data
analyses. These were then checked and filtered to retain cells with good quality and cloud cover of < 0.2. Batch format and projection transformation was performed for all data (Han et al. 2008). The process of synthesizing month-scale and annual-scale data and filtering and analyzing invalid values and outliers was realized by using the Google Earth Engine (GEE) platform. Land use and nighttime lighting data (https://esa-worldcover.org/en/data-access, https://doi.org/10.7910/DVN/YGIVCD) were used to distinguish the main urban area from non-main urban areas (arable land, shrub land, grassland, and woodland) and establish a 10-km buffer zone from the outline of the main urban area as a suburb. Digital elevation model (DEM) data (https://www.gscloud.cn) were reused to remove bare land and other land types with altitudes higher than 1000 m to avoid the interference of the cold island effect on the SUHII (Hu and Brunsell 2013). The air quality and temperature observations used for the validation of this study were mainly obtained from the China Environmental Monitoring Station (CEMS): https://www.cnemc.cn. See Table 1 for the details and sources of the above data.

**Methods**

This study employed the Sentinel-5p and MODIS time series product data to analyze the change in trend and relationship between air quality and SUHII before and after the COVID-19 epidemic prevention and control period in the study area. The technical route is illustrated in Fig. 2.

**SUHII calculation**

Based on a comprehensive consideration of land use types, night lights, and DEM in the study area, the MOD11A2 dataset was used to extract the average LST values of the main urban area and suburbs in the normal reference year and the outbreak period. The mean LST difference in the suburbs was calculated as the SUHII per cell as follows:

\[
SUHII = \overline{LST_{urban}} - \overline{LST_{suburbs}}
\]

where \(\overline{LST_{urban}}\) represents the average LST value of the main urban area in the study area and \(\overline{LST_{suburbs}}\) represents the suburban average LST (excluding water bodies, bare land, and mountains with an altitude greater than 1000 m).

**Mann–Kendall test**

The Mann–Kendall (M–K) test is a nonparametric test that is commonly used to detect trends in environmental, climatic, and hydrological data (Qi et al. 2021; Song et al. 2018; Shikwambana et al. 2021; Wu et al. 2022). The

![Fig. 2 Workflow flowchart adopted in the present study](image-url)

**Table 1 Data used and associated sources**

| Datasets        | Data source                                      | Data resolution | Data type            | Time of interest |
|-----------------|--------------------------------------------------|-----------------|----------------------|------------------|
| MOD11A2         | Google Earth Engine (GEE)                        | 1000 m/8 d      | LST_day_1 km         | 2018–2020        |
| MCD19A2         | Google Earth Engine (GEE)                        | 1000 m/1 d      | 0.47 μm              | 2019–2020        |
| Sentinel-5P TROPOMI | [1000 m/2 d (downscaled)]                  |                 | NO₂, SO₂, CO         | 2019–2020        |
| Land use data   | [https://esa-worldcover.org/en/data-access](https://esa-worldcover.org/en/data-access) | 10 m/yr         | Cultivated, forest land, grassland, shrubland, water bodies, construction Area, barren land, others | 2020 |
| Nighttime light data | [An extended time series (2000–2020) of global NPP-VIIRS-like nighttime light data](https://doi.org/10.7910/DVN/YGIVCD) | 500 m          | —                    | 2019–2020        |
| DEM             | [https://www.gscloud.cn](https://www.gscloud.cn) | 30 m            | —                    | 2020             |
| Measured data   | [https://www.cnemc.cn](https://www.cnemc.cn)     | —               | Air quality and air temperature measured data | 2018–2020        |
advantages of the M–K test are that it does not require samples to satisfy a certain distribution, and it is not disturbed by a few outliers. In this study, the M–K test was used to detect variation patterns in surface temperature in Urumqi from 2018 to 2020 and temporal abrupt change points and was calculated as follows:

\[
UF_k = \begin{cases} 
\frac{S+1}{\sqrt{VAR(S)}}, & S > 0 \\
0, & S = 0 \\
\frac{S-1}{\sqrt{VAR(S)}}, & S < 0 
\end{cases}
\]  

(2)

where \(S\) is the test statistic and \(UF_k\) is the standardized test statistic. In addition, \(UB_k = -UF_k, UF_k, \) or \(UB_k\) greater than 0 and less than 0 mean that the variable is on an upward and downward trend, respectively. When \(UF\), the UB curves have an intersection in the confidence interval, and the intersection is a mutation point. When the \(UF\) or \(UB\) curve exceeds the confidence interval, a significant change in this variable is indicated. Usually \(UF\) and \(UB\) are abbreviated as \(UF\) and \(UB\), where \(UF\) is the order column of sequential time series and \(UB\) is the order column of reverse order time series. The \(UF\) or \(UB\) value exceeds the 0.05 level of significance, indicating a significant upward or downward trend. The range beyond the 0.05 significance level line was defined as the time region in which the mutation occurred. When the intersection of the \(UF\) and \(UB\) curves is within the 0.05 significance level interval, that is, between \([-1.96 \text{ and } 1.96]\), the time corresponding to their intersection is the time when the mutation begins.

**Statistical analysis**

When conducting a statistical analysis, the Pearson correlation coefficient, \(r\), is widely used to measure the degree of correlation between two variables, and its value lies between \(-1\) and 1 (Vadim et al. 2021). The coefficient of determination, \(R^2\), indicates the degree to which the dependent variable is explained by the independent variable in the regression relationship, and its value is equal to the square of the correlation coefficient, \(r\). The larger the value, the higher the degree of explanation. In this study, the Pearson correlation coefficient, \(r\), was used to evaluate the correlation between the SUHII and air pollutant concentrations, and \(R^2\) was used to test the fitting degree of the regression model between the SUHII and air pollutant concentrations.

**Results**

**Temporal and spatial changes in air quality during the epidemic prevention and control period**

During the strict epidemic prevention and control periods implemented in the study area in 2020, the vertical column concentrations of \(NO_2\), \(CO\), and \(SO_2\) exhibited downward trends compared with the corresponding period in 2019; in particular, there was a clear decline in the \(NO_2\) concentration (Fig. 3a). As shown in Fig. 4a, there were decreases in \(NO_2\) concentration of \(77 \pm 1.05\%\) and \(15 \pm 0.98\%\) in the first (January 25 to March 20, 2020) and second strict periods (July 21 to September 1, 2020), respectively, compared with the corresponding period in 2019, and the normalized abnormal curve showed a peak during these two periods. The strict prevention and control measures for the epidemic reduced the emission of pollutants that were mainly caused by anthropogenic activities, and this was the primary reason for the obvious decline in the vertical column concentration of \(NO_2\).

As shown in Fig. 3b, the overall AOD of the study area in 2020 was slightly lower than in 2019, and it was particularly evident in the Midong, Toutunhe, Xinshi, and Shayibake Districts. The AOD change curve in Fig. 4b showed a decrease in the AOD of \(61 \pm 0.9\%\) and \(32 \pm 1.45\%\) during the first and second strict periods in 2020, respectively, compared with the corresponding period in 2019.

Figure 3c shows that \(CO\) was mainly distributed in the Toutunhe, Xinshi, and Midong Districts, as well as the western part of Shuimogou District and the northern part of Urumqi County in the study area, and there were minimal differences in its spatial distribution. However, temporally, the atmospheric \(CO\) concentration decreased by \(26.3 \pm 0.6\%\) and \(28.1 \pm 0.32\%\) during the first and second strict periods in 2020, respectively, compared with the corresponding period in 2019.

Figure 3d shows the highly heterogeneous spatial distributions of the \(SO_2\) concentration in the study area during the epidemic prevention and control period in 2020 and in the corresponding period in 2019. However, compared to the corresponding period in 2019, the \(SO_2\) concentrations in the main urban area decreased slightly during the two strict periods in 2020. As shown in Fig. 4d, the maximum and minimum \(SO_2\) concentrations decreased by \(5.6 \pm 1.27\%\) and \(7 \pm 1.21\%\), respectively, during the two strict periods in 2020 and the corresponding periods in 2019. In general, during the epidemic prevention and control period in 2020, the concentration of air pollutants in the study area decreased, and air quality improved.

**Changes in LST and SUHII during COVID-19 restriction periods**

The M–K method was used to detect changes in average surface temperature data (138 sample data) of the study area every 8 days from January 1, 2018, to December 31, 2020. We determined that most of the \(UF–UB\) curves were within the confidence interval of the significance level of \(\alpha = 0.05\) (Fig. 5). The two intersection points of the \(UF–UB\) curve in 2020 were also within the 0.05 confidence interval, and
the mutation detection results were statistically significant, indicating that the time corresponding to the two intersection points was the start time of the mutation of the surface temperature in the study area. The times corresponding to the first and second intersection points occurred in the first strict period (January 25 to March 20) and first recovery period (March 21 to July 20). Combining the trends and magnitudes of the UF–UB curves showed that the UF–UB corresponding to the first intersection point in 2020 was greater than 0. After this intersection point, the UF–UB curves tended toward the 0 axis, indicating a decreasing trend in the increasing surface temperature within the study area after this intersection point. The UF–UB corresponding to the second intersection point in 2020 was less than 0. After this intersection point, the UF–UB curves moved rapidly away from the 0 axis, indicating that the increase in the decreasing surface temperature trend within the study area after this intersection point continued until the beginning of September 2020 (the end of the second strict period) when the surface temperature began to gradually rise. This analysis indicates that there was a slight decrease in the surface temperature during the 2020 epidemic compared with the corresponding period in 2019. Combined with the results of the M–K test, the strict prevention and control measures of the epidemic largely reduced the trend of increased surface temperature within the study area. Further, this indirectly shows that surface temperature is largely related to anthropogenic activities.

The spatial distribution characteristics of the SUHII in the study area presented in Fig. 6 reveal that the average SUHII in the study area during the first strict period in 2020 and during the corresponding period in 2019 were −2.49 °C and −3.26 °C, respectively. The average SUHII in the study area during the first recovery period and during the corresponding period in 2019 were 3.08 °C and 2.76 °C, respectively. The average SUHII in the second strict period in 2020 and during the corresponding period in 2019 were 3.49 °C and 5.13 °C, respectively. During the first strict period in 2020 and the corresponding period in 2019, the highest SUHII values occurred in the Dabancheng District and Urumqi County in the southern part of the study area, mainly because much of the land in these regions is bare and a high surface temperature during the daytime manifests as heat island effect. The average SUHII in the study area during the first and second strict periods in 2020 decreased by 0.77 °C and 1.64 °C, respectively, compared with the corresponding period in 2019, while there was no significant change in the SUHII within the study area during the recovery periods in 2020 compared with the corresponding periods in 2019. Overall, the SUHIIs in the study area showed increasing trends from January 25 to September 1, 2020, and for the corresponding period in 2019; they were closely related to the changes in temperature and air quality in different seasons (Liu et al. 2022), indicating that the two strict periods in the study area in 2020 decreased to varying degrees compared with the corresponding period in 2019. These findings demonstrate that the surface temperature and heat island intensity in the study area decreased to varying degrees during the strict prevention and control of the two epidemics in 2020.

**Relationship between SUHII and atmospheric pollutant concentrations**

Although preliminary conclusions regarding the effects of air pollutants on the UHI effect have been obtained in some studies, the extent and mechanisms involved vary due to considerable differences between cities, and quantitative explanations for the extent of both effects are lacking. Therefore, to further analyze the reasons for the decline in the SUHII during the strict periods of 2020, we analyzed gridded (12 × 12 km) monthly SUHII, NO2, AOD, CO, and SO2 data in the study area from 2019 to 2020, as well as the correlation between the SUHII in all grids in the district and the corresponding NO2, AOD, CO, and SO2, respectively. The SUHII in the study area was significantly and positively correlated with NO2, AOD, CO, and SO2, indicating that the SUHII was enhanced with increasing concentrations of NO2, AOD, CO, and SO2 (Fig. 7). The strongest correlation of the SUHII was with NO2 concentration ($R^2 = 0.83, p < 0.01$), followed by CO concentration ($R^2 = 0.78, p < 0.01$). Based on these results, significant correlation was observed between the concentration of air pollutants and SUHII in the study area which was mainly due to the absorption of short-wave radiation by atmospheric pollutants emitted from anthropogenic activities. This increases the urban surface temperature and results in an increase in the UHI effect (Liang et al. 2020; Yuan et al. 2020).

**Discussions**

**Validation**

We used measured data obtained in the study area from 2018 to 2020 to validate the accuracy of the remote sensing products used to obtain NO2, CO, SO2, AOD, and LST (Fig. 8). The measured data included NO2, CO, SO2, PM2.5, and air temperature. The verification results showed
that Sentinel-5P data was well correlated with the monthly mean data of NO$_2$, CO, and SO$_2$ at the measured site, with $R^2$ values of 0.87, 0.61, and 0.91, respectively ($p < 0.01$). Studies have shown that AOD and PM$_{2.5}$ are strongly correlated and consistent in this respect (Yuan et al. 2020). The measured PM$_{2.5}$ data used to test the MCD19A2 AOD in the study area exhibited evidence of a strong correlation between AOD and PM$_{2.5}$ ($R^2 = 0.60$). In addition, surface and air temperatures demonstrated a good linear correlation. Air temperature can be used to estimate surface temperature using associated statistical relationships, and the error is within $\sim 3$ °C (Yuan et al. 2015). The verification results of this study showed that the LST product of MOD11A2 correlated well with the monthly average air temperature ($R^2 = 0.93$). In conclusion, the satellite product data used in this study were found to be consistent with the measured data and thus met the accuracy requirements of this study.
Analysis of the causes that changed air quality and SUHII during COVID-19 restrictions and uncertainty factors

To control the epidemic and spread of COVID-19, the government implemented a series of strict preventive and control measures, including the temporary closure of entertainment venues, maintaining social distance, prohibiting residents from gathering and ordering them to stay at home, and interrupting and stopping all non-essential transportation, production, and commercial activities. Many studies have shown that these measures played a positive role in COVID-19 restrictions and simultaneously reduced the emissions of man-made pollutants and heat sources to certain extents, thereby improving air and environmental quality (Karuppasamy et al. 2020; Li et al. 2020).

In 2020, Urumqi City implemented two strict epidemic prevention and control measures that provided the opportunity to study the impact of the epidemic prevention and control period on air quality and the urban SUHII. Aerosols can be divided into two types, primary aerosols based on their origin (in the form of particles directly entering the atmosphere from the source (such as sandstorm particles and other fine dust)) and secondary aerosols generated from the transformation of primary pollutants in the atmosphere, such as those from anthropogenic sources (the burning of fossil and non-fossil fuels, transportation, and smoke and dust emitted by various industries). Aerosols in Urumqi mainly originated from anthropogenic activities and are thus secondary aerosols (Abdumtalifu et al. 2018). It is evident from the results of this study that the strict epidemic prevention and control measures were attributed to the decline in AOD in the study area, correlating with other similar studies (Abdumtalifu et al. 2018; He and Wang 2009; Parida et al. 2021). Previous research shows that the CO concentration reflects the effect of anthropogenic activities to a certain extent (Li et al. 2019) because CO is mainly derived from vehicle exhausts, steelmaking, ironmaking, gas stations, and waste gas emitted from solid waste incineration. Such activities were shut down in the study area during the strict periods in 2020, which resulted in a significant drop in the CO concentration. The most evident downward trend in 2020 was the NO$_2$ concentration in Urumqi (compared to CO, SO$_2$, and AOD), which decreased during the first and second strict periods by 77% and 15%, respectively, compared with the corresponding period in 2019 (Fig. 4a); these results are consistent with other studies (Berman and Ebisu 2020; Yuan et al. 2020). Concentration of NO$_2$ in Urumqi in 2020 was mainly derived from urban areas that were highly and densely populated, with developed industries and commerce enterprises (Fig. 3a). Most of the NO$_2$ in the atmospheric troposphere was derived from emissions associated with human production and living within industrially developed and densely populated areas, although a small amount was derived from lightning and soil microbial emissions (Bai and Wang 2021; Otmani et al. 2020). In conclusion, the strict prevention and control measures implemented during COVID-19 in the study area during 2020 improved air quality.

There was a decline in the concentration of air pollutants, an improvement in air quality, and a weakening of the urban SUHII during the COVID-19 restrictions, compared with the corresponding period in 2019. The
weakening of the SUHII in the study area was related to the improvements in air quality during the urban prevention and control periods. However, the weakening of SUHII in the study area cannot be entirely attributed to improvements in air quality during the epidemic prevention and control periods, because changes in the SUHII in this area are related to long-term climate change, land use/land cover type, population density, urban structure, industrial layout, urban–rural economic development level, and other factors. In addition, although this study considered the impact of air quality on the urban surface SUHII in the vertical direction during COVID-19 restrictions, the impact of differences between the main urban area and the outer suburbs and villages on the SUHII in the study area requires further investigation on a horizontal gradient. It is also evident that differences in natural and human elements and level of urbanization result in varying SUHII characteristics within different cities and in different periods, and this requires further investigation. It is anticipated that this study will be followed by others that will further examine the impact of epidemic prevention and control measures on air quality and the UHI effect in Urumqi.

Conclusions

This study used satellite remote sensing data products to evaluate spatiotemporal variations in air quality and their characteristics before and after implementation of COVID-19 epidemic prevention and control measures in Urumqi City in 2020. Their relationship with the SUHII was investigated through a correlation analysis. The following conclusions were drawn:
During COVID-19 restriction periods, air pollutant concentrations in the study area decreased significantly and air quality improved. There were significant declines in the vertical column concentrations of NO₂, 77% and 15%, during the first and second strict periods, respectively, in 2020 compared to the corresponding periods in 2019. In addition, AOD decreased by 61% and 32%, respectively; CO vertical column concentrations decreased by 26.3% and 28.1%, respectively; and the SO₂ concentration decreased slightly during the first and second strict periods in 2020.

Although the change in surface temperature in the study area from 2018 to 2020 was not significant, the surface temperature in 2020 was slightly lower than that in 2018 and 2019. The average SUHII was slightly weakened by 0.77 °C and 1.74 °C during the first and second strict periods in the study area in 2020, respectively, compared to the corresponding period in 2019. The
weakening of the average SUHII was associated with changes in anthropogenic activity.

(3) During the epidemic prevention and control period in the study area, the air pollutant concentration and SUHII decreased, and there was a strong correlation between them. There was a high correlation between the SUHII and NO2, AOD, CO, and SO2 in the study area ($R^2$ values were all greater than 0.60, $p < 0.01$), which indicated that the SUHII decreased with a decline in air pollutant concentrations. The results obtained can be used to improve urban air quality by optimizing and improving transportation, industrial production, and energy consumption, with the aim of reducing the urban thermal environment and improving the quality of the urban environment.

With the continuation of the COVID-19, long-term data can be used to analyze the relationship between urban SUHII and air quality before and after the epidemic, in order to obtain more objective and accurate conclusions. In addition, for the mechanism between urban SUHII and air pollutants, future model simulations and actual observations can be used for in-depth discussions.

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